# A systematic review of the research trends of machine learning in supply chain management

**Article** *in* International Journal of Machine Learning and Cybernetics · July 2020

DOI: 10.1007/s13042-019-01050-0



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International Journal of Machine Learning and Cybernetics
https://doi.org/10.1007/s13042-019-01050-0

ORIGINAL ARTICLE

# A systematic review of the research trends of machine learning in supply chain management

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Received: 18 June 2019 / Accepted: 8 December 2019


**Abstract**
Research interests in machine learning (ML) and supply chain management (SCM) have yielded an enormous amount of publications during the last two decades. However, in the literature, there was no systematic examination on the research development in the discipline of ML application, in particular in SCM. Therefore, this study was carried out to present the latest research trends in the discipline by analyzing the publications between 1998/01/01 and 2018/12/31 in five major databases. The quantitative analysis of 123 shortlisted articles showed that ML applications in SCM were still in a developmental stage since there were not enough high-yielding authors to form a strong group force in the research of ML applications in SCM and their publications were still at a low level; even though 10 ML algorithms were found to be frequently used in SCM, the use of these algorithms were unevenly distributed across the SCM activities most frequently reported in the articles of the literature. The aim of this study is to provide a comprehensive view of ML applications in SCM, working as a reference for future research directions for SCM researchers and application insight for SCM practitioners.

**Keywords** Machine learning · Supply chain management · Algorithms · Research trends · Application

## 1 Introduction

With the development of digitization, information, robotics, communication technology, and Artificial Intelligence (AI), the world is undergoing an age known as the "fourth industrial revolution" [42], which possesses a distinctive feature that machines gain intelligence to make decisions instead of human brain. Machine Learning (ML) is one of these techniques, which concern with the development and application of computer algorithms that "learn" from the experience [86]. ML was originated from the growing ability over the last two decades that machines could handle huge input information, and some machines could even find out the hidden patterns and complex relationships to make appropriate and reliable decisions where human beings could not, especially for disruptive and discontinuously information. The literature revealed that the machines could provide more accurate results than human beings in many domains of decision-making and even started to replace them [80] for e.g. cancer prediction and prognosis [24], drug discovery [71], and genetics and genomics [68].

The need to make decisions for uncertainty is an important issue in supply chains (SCs) [40]. Besides the large number of decisions, supply chain management (SCM) also suffers from uncertainty or information asymmetry, which is described as "bullwhip effect" of the upstream amplification in the demand variability. Therefore, it is hard to achieve an accurate preparation for each entity. In other words, the decision-making process in the flow of goods and service alongside SCM contains many complex decision-making processes and information barriers. ML really constitutes a real asset for SCM. First, ML is able to describe the non-linear relationship while traditional methods are not, for the training model of ML better describes how the output (y) changes with the input (x). In a non-ideal SC, the parameters associated with multiple explainer variables cannot be described exclusively by a linear model. For example, in a traditional demand-prediction model, the alcoholic beverage sales were thought to

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Published online: 21 December 2019

be related to temperature alone, which could be described by linear model $Y = a + bX$. However, research also found that other factors affected alcoholic beverage sales like tax policy [34]. When two factors are considered simultaneously, their relationship becomes nonlinear. In this case, ML has its advantages over a traditional linear model. Second, ML is able to deal with unstructured data sets where traditional models fail [90]. For instance, traditional linear regression model requires a sample size larger than the number of features in the data sets. However, a small company usually fails to gain enough sample size for their SC records. Third, ML and its core constructs are suitable for a better SCM performance prediction. If taking the strengths of unsupervised learning, supervised learning and reinforcement learning into consideration, ML is extremely effective in continually seeking the key factors most effecting SC performance. Forth, with the help of visual pattern recognition across a SC network, ML is able to explore a lot of potential applications in maintenance of physical assets and physical inspection. Although the applications of ML have so many merits and expectation of its application is high, and even some studies do indicate that ML has penetrated in SCM including Neural Networks [39], Support Vector Machine [11], Logistic regression [74], Decision Tree [30], and Extreme Learning Machine [81], a study recently reported that ML, with one or more SC functions, has been applied to merely 15% enterprises [78]. The inadequate use of ML in SC might be caused by the poor understanding of how ML could be applied, the low acceptance in company culture, and the inability to obtain suitable data. Thus, a systemic review is in urgent need to quantitatively analyze the latest research trends, to explore the ML algorithms frequently used in SCM, and to figure out the SCM activities most suitable for ML.

In order to provide a general picture of ML applications in SCM and to bridge the gaps between ML and SCM, this paper will systemically review the research trends by analyzing the publications in five major international databases, and will then explore the frequently used ML algorithms in SCM and the SCM activities often aided by ML algorithms as a reference for future research directions for SCM researchers and application insight for SCM practitioners.

This paper is consisted of five sections with the present section as the first. The second section will give a brief introduction to the background of ML algorithms applications in SCM and the third will introduce the research methodology of this study. The results are shown in the fourth section. The fifth section will present the conclusion that includes major findings, the limitations in this study and the suggestions for further research.

## 2 Literature review

In a modern era, digitization of shopping has reshaped customers' purchasing and buying habits, and then caused demands and sales information to become more disruptive and discontinuous than ever. These changes require business organizations involved to catch up to maintain their competitiveness by avoiding demand uncertainty and financial risk. Thus, a fluent SC to acquire materials, convert materials into finished goods, and deliver goods o customers is the key capability to success for an organization in the global competition [38]. In order to increase the key capability in upgrading the visibility along the SC, a lot of leading-edge organizations will share their data with their SC partners (e.g. inventory, selling data) and SCM is becoming more and more data-intensive. Realizing the increasing significance of data in SC, SCM researchers and practitioners have tried out every possible means to improve their data management along the SC to give better decisions [83]. One of these means is ML that has been applied for many years but is still far from being fully utilized in SCM.

The poor application of ML to SCM might be mainly due to the shortage in understanding of the latest development in ML algorithms, that is, in the knowledge of taxonomies or guidelines for SCM researchers and practitioners in selecting the right ML algorithms for the right SCM activities. Therefore, the main objectives of this study are to lucubrate on clarifying the research trends and the ML applications in SCM by analyzing the available research articles.

No systematic reviews have been found which were entirely devoted to the ML applications in SCM, but a number of articles [83, 89]; Francisco 2017; [105] on AI applications in SCM have mentioned ML algorithms as common mathematical modelling techniques, shedding some light on the ML applications in SCM.

Min [83] was the first author who conducted a review on AI applications in SCM. The author based on his or her personal knowledge of algorithms, selected 28 articles on the links between AI tools and SCM activities, and extracted seven AI tools and reviewed their applications in eight SCM activities. Although some ML algorithms like Neural Networks (NNs) were mentioned as mathematical modelling techniques in the paper, they were put in a parallel place with AI. In addition, Min took a conservative attitude to ML and even to AI. According to the review, both AI and ML could provide better prediction results for specific, narrowly focused SCM issues, but their solutions were very difficult for ordinary decision-makers to follow suit. Different from Min [83] in selecting the articles, Ngai et al. [89] objectively retrieved five databases and obtained

77 articles from 1994 to 2014 for reviewing the status quo of the applications of seven AI techniques in the SCM of textile and apparel industry. The results of this review claimed that the gaps between AI techniques and SCM were caused by the unbalanced applications of certain ML algorithms like NNs, for the unbalance increased the risk of hindering research-directed development of the industry. Although the articles in this review were selected in an objective way, the ML algorithms were listed out of seven AI techniques in a subjective way. Besides, Ngai et al. took textile and apparel industry for all the industries involving SCM, which was a partial representation. With the similar approach adopted by Ngai et al. in selecting the articles, Francisco (2017), in another review study, included more articles published over a longer time span. Moreover, the author created a framework to classify the 84 shortlisted articles from 1995 onwards by the types of applications, data source etc. This review took a pessimistic view to the applications of AI, for its results showed that AI took up only 11.9% of all the techniques in the evaluation of SCM performance' and thus ML algorithms were regarded merely as mathematical modelling techniques which had not yet linked independently with the evaluation of SCM performance. With an optimistic attitude towards the applications of AI and the ML algorithms in SCM, Syam and Sharma [105] carefully reviewed the approaches that changed the decision-making process in the sales prediction from the perspective of the applications of AI and ML algorithms under the background of the "fourth revolution". The results obtained in the paper confirmed that AI and the ML algorithms had a great impact on the routine, standard and repeatable SCM activities, but still Syam and Sharma claimed that it had a long way to go to fully replace human-decisions in SCM with AI or ML algorithms.

The articles reported above did take some snapshots of the ML applications in SCM, but they all failed to present a systematic review over multiple parameters. To be specific, the limitations of the previous studies could be mainly summarized as follows.

First, all the articles focused on the applications of AI in SCM one way or another, but none of them was devoted to systematically reviewing the developing trends of ML applications in SCM. Surely, these articles are not able to present a panorama view of ML applications in SCM for SCM researchers and practitioners. Second, the ML algorithms were selected and analyzed in a subjective way in traditional literature review only by searching the ML algorithms' keywords [83, 89], which would miss some articles with certain less frequently used ML algorithms, particularly the frequency of the each ML algorithm could not be obtained statistically in a reasonable way for the time being. The worst of all, the applications of ML algorithms were not well linked with the SCM activities in these studies, for which there might be two major reasons. One is that the ML algorithms were not clearly defined, or the relations between AI and ML algorithms were not clearly justified in particular; the other is that the industries involving SCM activities were not fully covered and discussed.

Therefore, to remedy these gaps, this study attempts to address the following three research questions:

1. What are the general research trends of ML applications in SCM?
2. What ML algorithms are frequently used in SCM?
3. In what activities of SCM are these frequently-used ML algorithms distributed?

## 3 Research methodology

This section will closely address the research questions in order as listed above.

First, as for the research trends of the ML applications in SCM, the relevant articles published on the ML applications in SCM are to be collected and retrieved, and then analyzed in a descriptive way in terms of publication year, top journals, top countries, top industrial sectors, active authors, research designs employed, and leading universities involved. Next, the ML algorithms employed in the articles are identified and statistically ranked by the frequency of their use in SCM. Finally, in response to the distribution of the frequently-used ML algorithms in SCM activities, the features of each ML algorithm are analyzed, and then the applications of these features are to be explored in six typical SCM activities, that is, demand/sales estimation, procurement & supply management, production, inventory & storage, transportation & distribution, and supply chain improvement.

### 3.1 Article selection process

This study will take a structured approach to filter the studies to be included in the systematic review. The collected studies are to be analyzed by a variety of variables in order to present a comparatively complete picture of the ML applications in SCM.

To achieve this aim, the majority of the articles were collected from the following six academic databases: Emerald Insight (www.emeralinght.com), IEEE Xplore (ieeexplore.ieee.org), Scopus (www.scopus.com), Science Direct (www.sciencedirect.com), Wiley (https://onlinelibrary.wiley.com) and Springer (https://link.springer.com), and a small part of the articles were obtained as an addition using Google Scholar (scholar.google.com) to ensure a complete coverage of the collection. The string—"machine learning" AND

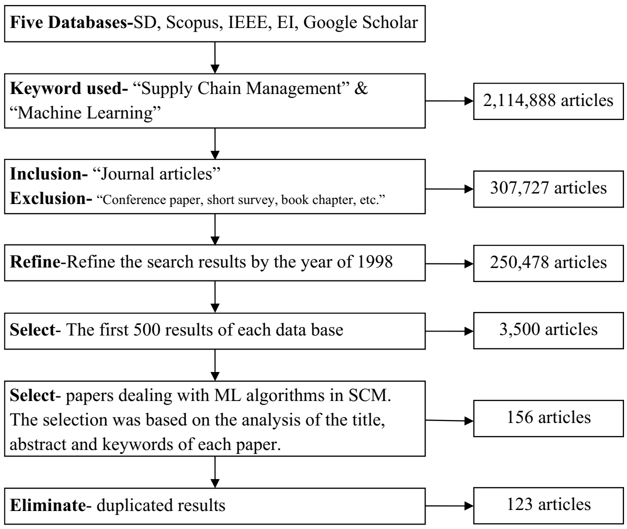



**Fig. 1** Process for selecting papers

"supply chain management" was employed for retrieving the articles in databases, and publications with these specific terms in their title, abstract or keywords were considered roughly qualified ones. As indicated in Fig. 1, the number of articles targeted amounted to 2,114,888. Despite the search specifications, there were still some unwanted publications, and then Filter 1 was introduced. For the first filter, such publications as short surveys, conference papers, and book chapters were excluded because they were not specified for treating the research questions. This visual search process gave a closer view to the theme and after the first filter, 307,727 articles were left for the second filtering. Since the concept of ML applied in SCM first emerged in 1998, second filter reduced the collection down to 250,478 ones published between 1998/01/01 and 2018/12/31. There were still too many articles for a review study; therefore the third filter was set to select the first, as a common practice, 500 results out of each data base, then five experts were asked to further select the ones that were best qualified for addressing those research questions during the fourth filter, and 156 articles were left. Finally, this study obtained 123 articles from 75 journals after deleting duplicated ones at the fifth stage.

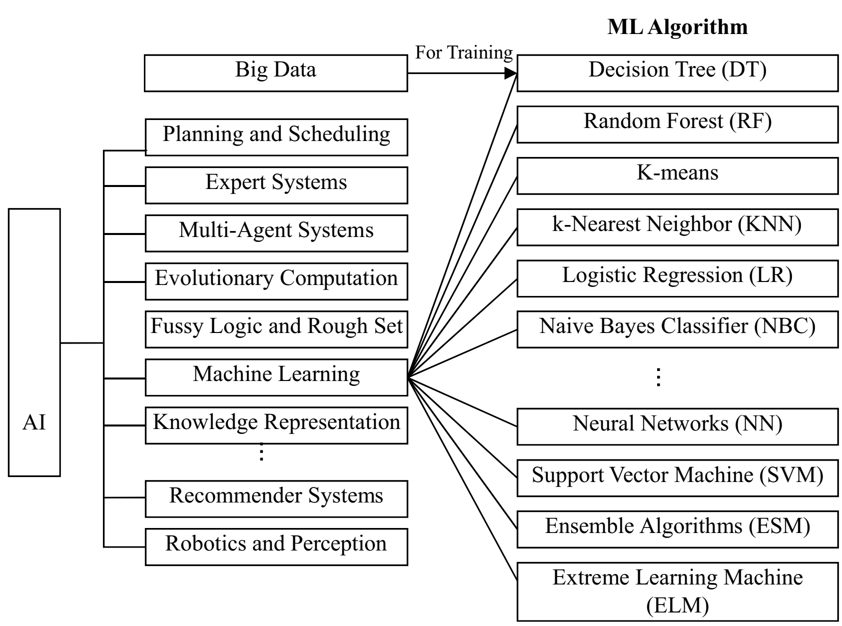
## 3.2 Justification of the selection process

### 3.2.1 Rules for selecting the theme

AI, Big data, ML and ML algorithms are four related taxonomies often used in SCM. However, ML, as a subset concept under the umbrella term AI and an independent research domain, is often mingled by people with the other three. Since this paper is to review how ML, and the ML algorithms, in particular are applied in SCM, ML is to be specially distinguished from the other three taxonomies, as indicated in Fig. 2.

As seen in Fig. 2, ML is a subbranch of AI that equips the machines with the capability to automatically learn from the data existing with no specific programming. Arthur Samuel was the first one to coin the term "Machine Learning" in 1959 [8]. He pointed out that ML was the study of algorithms and mathematical models that computer systems used to progressively improve their performance on a specific task. Tom M. Mitchell's famous definition has been wildly quoted: "*A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P if its performance at tasks in T, as*

**Fig. 2** Terms related to ML (Paraphrased from Huawei Enterprise Support Community)



*measured by P, improves with experience E.*" Unfortunately, this wildly-cited definition caused confusion by messing up AI with ML. Although it was an accurate conception at his age, with the development of all the intelligent methods, ML becomes an independent research branch. The status of ML, ML algorithms being the existing models for ML, is now in parallel to other AI tools like Expert Systems, Fussy Logic and Rough Set. To make it clear, Fig. 2 is thus drawn to clarify that ML is now only a part of AI, not the AI itself.

ML requires big sample size to train the examples, and big data sets are used to train ML models. However, the big data sets are not "big data analytic," and data sets which are "big" today may become not "big" enough several years later, and therefore ML is not a Big data equivalence and this study excludes the analysis of the size of data sets.

ML algorithm is a subbranch of ML, which consists of the existing models of ML created by previous researchers and widely used by academic researchers and industrial practitioners. ML algorithms normally have packages existing in the popular programming languages. Their function relies heavily on the mathematical models built of the sample data. They make predictions or decisions with no explicitly programmed instructions to perform a specific task. They are able to be altered and assembled with other mathematical tools, but their core ideology does not change. According to the survey of Christoph [21], there were 32 types of commonly recognized ML algorithms, and some frequently used ones are listed at the right side of Fig. 2: Decision Tree (DT) [25], Random Forest (RF), K-means [75], k-Nearest Neighbor (KNN), Logistic regression (LR) [37], Naive Bayes Classifier (NBC), Neural Networks (NN) [5], Support Vector Machine (SVM) [26], Ensemble Algorithms (ESM), and Extreme Learning Machine (ELM). Out of these algorithms, this study is to explore what are the frequently-used algorithms in SCM and how these frequently-used ML algorithms are applied to SCM activities.

#### 3.2.2 Identification of the algorithms frequently used in SCM

ML is known to explore the ways with the help of the computers in acquiring knowledge directly from data and in learning to solve the problems [96]. Of course, ML solves the problems with various ML algorithms. In general, some ML algorithms were promoted by the neurological studies, some by the process controlling human evolution, and some by structural optimization instead of experience optimization. The basic methodological approach adopted by the research articles on the ML applications in SCM is to compare the the proposed model's performance with the common ML algorithms [102]. In this case, there might be several ML algorithms involved in a single article.

In order to answer the second research question, three specialists in ML algorithms were invited to independently read the 123 shortlisted articles carefully and thoroughly, and then extracted the basic algorithms out of 32 commonly recognized ML algorithms by two rules. One was to define the "frequently used ML algorithms" as those that turned up at least twice in two different shortlisted articles, that is to say, those algorithms that only showed up once in a single article were not regarded as "frequently used ML algorithms." The other rule was to exclude those articles that only made some comments on certain ML theories but did not employed any specific algorithms, e.g. the articles concerning the building of Reinforcement Learning Models [84, 88] were not regarded as "frequently used ML algorithms." Two specialists would first read one shortlisted article and listed all the candidate algorithms extracted by the rules defined above. The extracted candidate algorithms that were identical between the two specialists were counted as the ML algorithms in this study. Those that were not identical were referred to the third specialist, and the three invited specialists discussed over the disparities and made a concordant decision. Finally, three specialists extracted and identified 10 frequently used ML algorithms in total from the 123 shortlisted articles.

## 4 Results

Three sections are devoted to presenting the study results, that is, research trends, frequently used ML algorithms, and the distribution of the ML algorithms in SCM activities, with a summary specific to each research question at the end of each section.

### 4.1 Research trends

#### 4.1.1 Year of publication

The 123 articles were shortlisted according to the year of publication over a period of 20 years (1998/01/01–2018/12/31). Although "Machine Learning" was a "new" concept reflourished toward the end of 1990s (Pat 2011), the applications, then, of ML algorithms in SCM were found to be very few. As shown in Fig. 3, the first peak appeared in 2008 indicates a strong practice of ML in SCM. This peak came into existence around the financial crises (2008–2009), when both developed and developing economies tried to explore the possibility of new decision-making methods by machines instead of by human beings. Researchers and practitioners began to understand that ML was able to bring true value for SCM, because ML proved more accurate than human beings in performance. The second peak came in the recent 2 years (2016–2017) because of the popularity of AI. The

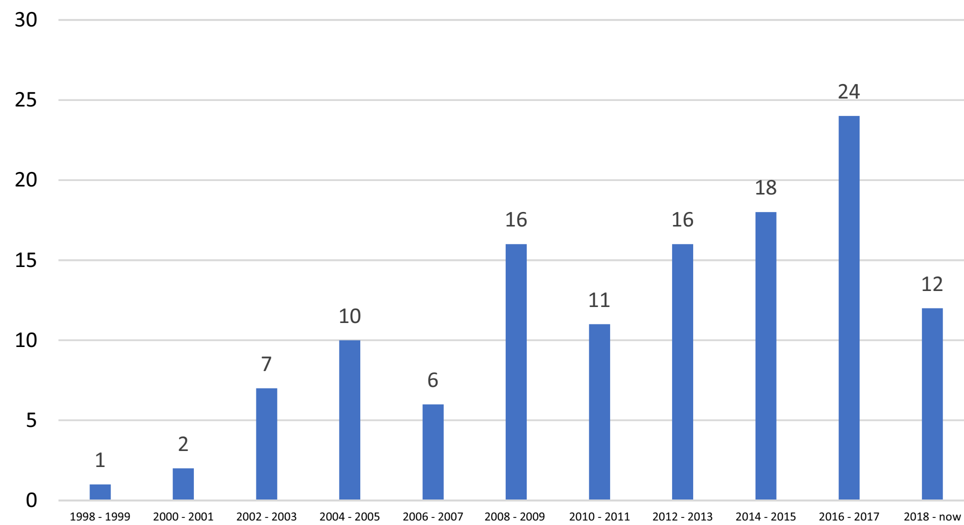



**Fig. 3** The distribution of publications over years

ML applications in SCM covered studies on finance [125], food [30] and manufacturing [54] industries. However, the total number in publications (less than 20 articles each of the 2 years) is still far from exciting, which indicates that ML is not being fully exploited and the attitude towards ML applied in SCM is still conservative.

#### 4.1.2 Journals

Because ML and SC belong to different research domains, there exist a variety of journals for an article to be published. Table 1 presents the list of 15 different journals in which at least two articles concerning ML applications in SCM were published in terms of the year of publication. It is seen that a relatively high occurrence of publications was with *Expert Systems with Applications* (18.70%). Since 2002, this journal, with engineering background, has published a large number of articles on ML applications in SCM. This journal is also seen to be focused on the application of time-series modeling, intelligent algorithms and their applications. To strongly integrate ML with SCM, *Int. J. Production Economics* has made its the second largest (4.88%) contribution to the ML applications in SCM. This might be caused by the superior performance in production demand forecasting of ML. This journal has focused on reporting studies of Economics and Econometrics, Industrial Manufacturing. Besides, the fuzzy theory and soft computing have been the key searching tools in ML for SCM optimization. These two

**Table 1** Distribution of articles based on journals

| Journals | Numbers | Percent (%) |
|---|---|---|
| Expert Systems with Applications | 23 | 18.70 |
| International Journal of Production Economics | 6 | 4.88 |
| Applied Soft Computing | 5 | 4.06 |
| Computers & Industrial Engineering | 3 | 2.44 |
| Decision Support Systems | 3 | 2.44 |
| Engineering Applications of Artificial Intelligence | 3 | 2.44 |
| European Journal of Operational Research | 3 | 2.44 |
| Journal of Manufacturing Technology Management | 3 | 2.44 |
| Applied Intelligence | 2 | 1.63 |
| Benchmarking: An International Journal | 2 | 1.63 |
| Electronic Commerce Research and Applications | 2 | 1.63 |
| Expert Systems | 2 | 1.63 |
| International Journal of Production Research | 2 | 1.63 |
| Neural Computing & Application | 2 | 1.63 |
| Transportation Research Part E | 2 | 1.63 |
| Others | 60 | 48.78 |
| Total | 123 | 100.00 |

key searching tools have been well-applied and discussed in *Applied Soft Computing* (4.06%), which has focused on computer science and its interdisciplinary applications.

### 4.1.3 Countries

Figure 4 reveals a wide coverage of publication for ML across 25 countries in the world. Among 123 shortlisted articles, China and USA led the research with 27 and 24 articles published respectively. This trend is in accordance with the belief that a large economy with demands more SC resources. Based on the number of countries, we can find that only a small part of the countries are involved in this research, this can be caused by the hard entrance level of machine learning. China is contributing more to the improvement of ML algorithms for better prediction performance in SCM by using the hybrid of multiple ML algorithms [32, 91, 117], while U.S scholars are trying to explore the possibility of the ML applications in more industrial sectors and cases [13, 58, 95]. Iran ranked the 3rd, this is accordant with its major export of natural resources and its levels of the machine learning researches. The countries that followed China and USA, Iran are Turkey, Korea, UK, Taiwan, India and Germany, which contributed a lot for the theoretical building of ML applications in SCM. The other countries listed in Fig. 4 are Malaysia, Finland, Austria, Chile, France, Greece, Norway, Serbia, Switzerland, whose adoption of ML in SCM research is comparatively low.

### 4.1.4 Research design

As the convention, the research design is analyzed based on either data sources for training ML algorithms (Francisco et al. 2017) or the learning methods [105] that ML belongs to.

According to data sources (presented in left plot of Fig. 5), the research design is further divided into six categories: specialists' judgments, data based on other studies, case study, historical data, simulated data, and historical data combined with simulated data. As indicated in Fig. 5, simulated data are the prime choice of research design in the ML applications in SCM (50%), followed by historical

**Fig. 4** Classification according to country of publication

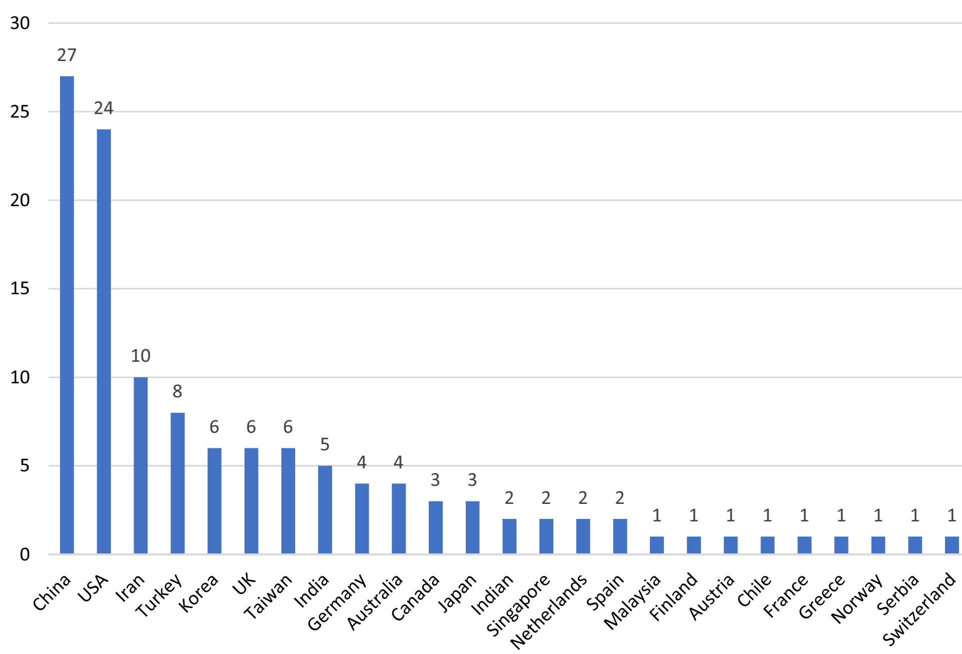
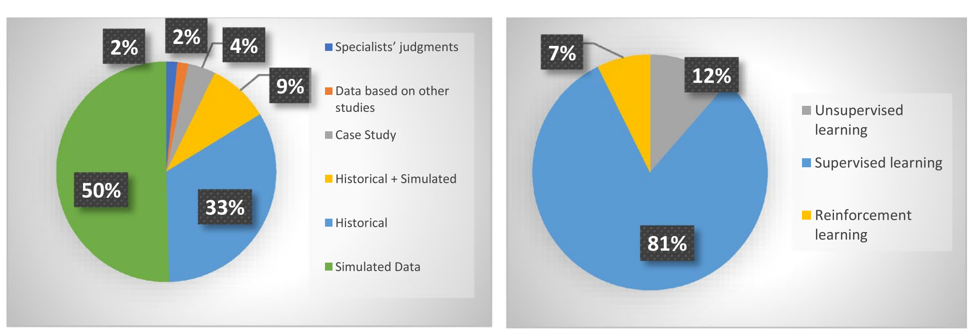



**Fig. 5** Classification according to research design



data (33%), and the mix of the research with a historical data (9%). The specialists' judgments, data based on other studies, and case study take up relatively small parts (2%, 2%, and 4% respectively). As we know, the research in supply chain shared a tradition of focusing on theoretical modelling. The researchers in this domain would rather address the simulation data than the historical data of a practical significance in SC. To the mind of these researchers, the historical data were sometimes bad in quality and difficult to collect.

Based on the learning methods, the research design is classified into supervised learning, unsupervised learning and reinforcement learning. Supervised learning was defined by Gareth et al. (2013) as the data sets having the "right answers," indicating that a bunch of input variables and their corresponding output variables are given to the machine. In unsupervised learning, the data sets are provided unstructured data and are not correspondingly related to "right answers." In other words, unsupervised learning requires the model to find the relationship itself. The difference between reinforcement learning and supervised learning focuses on the need for neither presenting the correct input/output pairs, nor explicitly correcting sub-optimal actions. Also, unlike unsupervised learning, focusing on performance or hidden patterns, reinforcement learning involves in keeping exploration (of uncharted territory) and exploitation (of current knowledge) in balance [50].

As shown in the right plot of Fig. 5, the most frequently used research design is supervised learning (87%), and the second and third ones are unsupervised learning (8%) and reinforcement learning (5%). Supervised learning takes the largest share because human beings feel easy in manipulating by telling a machine right from wrong, while to manipulate the unsupervised learning and reinforcement learning is really time-consuming for these research designs are brand-new to most of the researcher in this domain. Although the unsupervised learning only takes up 8% of all the articles, the ideas presented by the articles in this category shed some light, because unsupervised learning is able to spot the weakness of SCM in advance while human beings are not. For instance, Ha and Krishnan [43] used the neural clustering method, which performs unsupervised learning, to score each of the suppliers according to their performance. Compared with human decisions judged by experience; their model detected each supplier's advantages and weaknesses according to different criteria automatically and stably. Maleki and Cruz-Machado [77] used BNC to spot the performance weaknesses of the supply chain. BNC was found in the research to have learned the structures and parameters of supply networks and drawn inferences quite efficiently, which had never been achieved by human beings. SCM today is in urgent need for a new operating platform or architecture to make predictions on real-time data, and to offer SCM patterns and insights which have been invisible in the past with traditional analytic tools. ML will surely become an essential element in future SC platforms or architectures to revolutionize every aspect of SCM.

#### 4.1.5 Industries

Industries play a key role in contributing to a nation's economy. Every research appears to be incomplete if its applications are invisible and the research does not contribute to the development of the nation's economy [27]. That is to say, it is extremely significant for the research to identify how the ML can be applied across different industries.

As seen in Fig. 6, the grocery and food industries dominate the ML applications in SCM, followed by the automotive and fashion industries. This is different from the conclusion drawn by Francisco et al. (2017), which indicated that automobile took the first place and fashion industry took the second place in the ML applications in SCM. It reveals that ML applications has displayed a trend shifting from automobile and fashion industries towards other industries. That the grocery industry took the lead may be because ML combined with the traditional technologies used across SC operations is able to greatly low inventory and operations costs, and shorten response times to customers. And according to Brandenburg et al. [9], food industries need to possess an effective and efficient logistic performance because their products are perishable. Therefore the food industry taking the lead may be justified by food safety regulations and the increasing need for its transparency. SCM is a prior choice because food safety should be monitored and tested at every SC step. ML can be employed for easily tracking food products from farm to consumer to provide transparency. Also, more accurate forecasting with ML adds value to pricing and inventory of food industries. Similar to Francisco's conclusion, automobile and fashion also applied ML a lot because they were highly-customized industries with low inventory turnover [117]. As also is seen from the total number of publications, the ML applications in SCM are still very low in other industries.

#### 4.1.6 Leading universities

As indicated in Table 2, 102 universities in total offered 123 research articles to promote the ML applications in SCM. The top universities are The Hong Kong Polytechnic University, Yonsei University, followed by Concordia University, Ferdowsi University of Mashhad, University of Florida, Purdue University, University of South Australia, National Institute of Technology, National Taipei University of Technology. Most research are done in Hong Kong universities and South Korea, which is accordant with the situation that Asian countries are advanced with telecommunications techniques [45]. Such universities

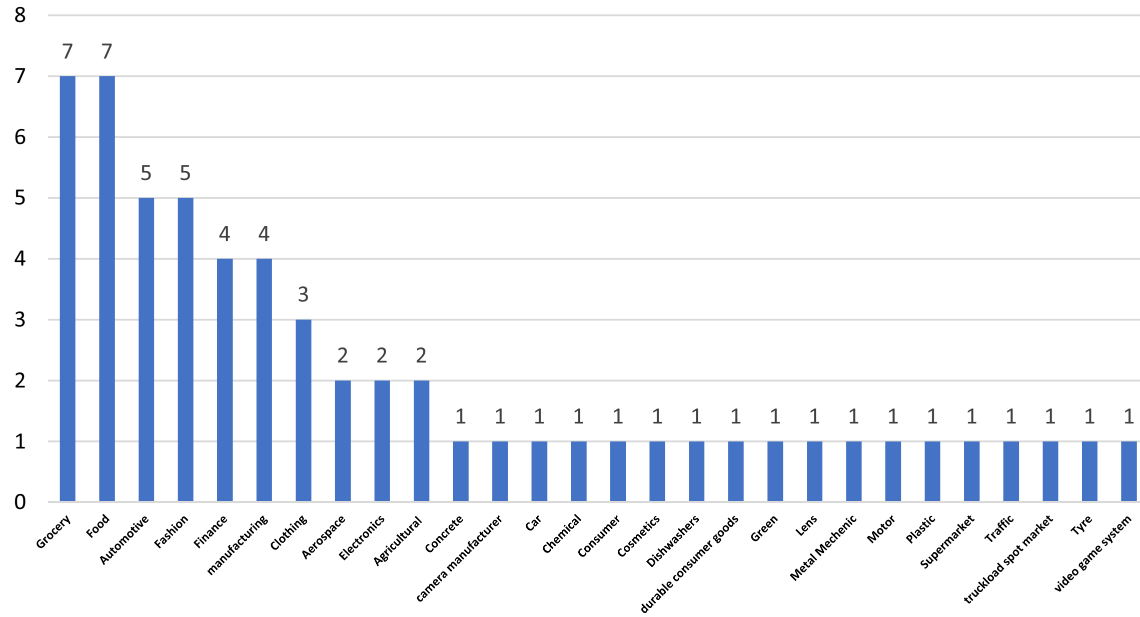



**Fig. 6** Classification according to focused industries

**Table 2** Leading Universities contributing to the ML applications in SCM

| Universities | Numbers | Percent |
|---|---|---|
| The Hong Kong Polytechnic University | 9 | 7.32 |
| Yonsei University | 3 | 2.43 |
| Concordia University | 2 | 1.63 |
| Ferdowsi University of Mashhad | 2 | 1.63 |
| National Institute of Technology | 2 | 1.63 |
| National Taipei University of Technology | 2 | 1.63 |
| Purdue University | 2 | 1.63 |
| University of Florida | 2 | 1.63 |
| University of South Australia | 2 | 1.63 |
| Hunan University | 2 | 1.63 |
| Islamic Azad University | 2 | 1.63 |
| University of Tehran | 2 | 1.63 |
| Islamic Azad University | 2 | 1.63 |
| Other universities in number | 89 | 72.36 |
| Total | 123 | 100.00 |

like Purdue university, National Institute of Technology are outstanding in engineering, which would surely give them the priority to try many ML algorithms in SC. It is also worth noting that many of these universities have independent departments of both engineering and business backgrounds, which would directly help in strengthening the ML applications in SCM practices and developing SCM strategies. However, judging from the publication number, even the top university published merely 9 articles in last 20 years. This reveals that the ML applications in SCM are yet far from fully exploited and have a lot of space to develop.

**Table 3** Leading first authors contributing to the ML applications in SCM

| Authors | Numbers | Percent |
|---|---|---|
| Chang Ouk Kim | 3 | 2.44 |
| H.C.W. Lau | 3 | 2.44 |
| R.J. Kuo | 3 | 2.44 |
| K.L. Choy | 2 | 1.63 |
| Matthew Chiu | 2 | 1.63 |
| Mojtaba Maghrebi | 2 | 1.63 |
| Other authors in number | 108 | 87.80 |
| Total | 123 | 100.00 |

#### 4.1.7 Contributing authors

As shown in Table 3, 114 first authors contributed the 123 articles shortlisted. The authors on top of the list are Chang Ouk Kim, H.C.W. Lau and R.J. Kuo, each of whom has three articles published. Chang Ouk Kim has been the leading researcher in building the theoretical foundation, developing conceptual framework and carrying out application-oriented studies on the ML applications in SCM; H.C.W. Lau and R.J. Kuo each contributed three articles covering the majority of SCM research threads. Similarly, K.L. Choy, Matthew Chiu, and Mojtaba Maghrebi also contributed articles with high research values. However, the three leading authors joined together published 9 out of the 123 articles.

According to the Price's Law (Price et al. 1982), if authors with three articles or more do not contribute to more than 50% of the total number of articles, there is no possibility to form a stable group of high-yielding authors in a research domain. By this law, a high-yielding authors' group does not exist at all in the study of ML applications in SCM.

As for the research trends of the ML applications in SCM, it is found that there were two research peaks (between 2008 and 2009, 2016 and 2017 respectively) over a time span of 20 years (1998/01/01–2018/12/31); the leading industries shifted from automobile and fashion industries towards others; simulated data were taken as the prime data source and supervised learning as the most frequently used research design; the key journals were *Expert Systems with Applications and Int. J. Production Economics*, and key countries were China and USA; the leading universities were the Hong Kong Polytechnic University and Yonsei University, while the leading authors were Chang Ouk Kim and H.C.W. Lau. However, the ML applications in SCM remained in a developmental stage since there were not enough high-yielding authors to form a strong research group in the field and their publications were still at a low level. To explore the relationship between all authors of these 123 articles, a co-citation network of cited authors is presented in Fig. 7, the minimum citation is set at 10; 30 authors are chosen out. As indicated in the figure, the bigger circle means more citations. As also shown in Fig. 7, the high-cited authors can be divided into two kinds. One is the inventors of certain ML algorithms, for example, Vapnik is the inventor of SVM, Huang guangbin is the inventor of ELM. The other one is the authors who mainly applied ML in SCM in an early stage, for instance, R.J. Kuo published his first NN applications in decision support system for sales forecasting in 1998; K.L Choy was the first to apply NN to supplier selection in 2002; Charles A. Weber was a pioneer in dealing with vendor selection in as early as 1991. Thus, the trial of ML applications in SCM raises their citations in this domain.

## 4.2 The frequently used machine learning algorithms

It is worth noting that only 10 out of 32 commonly recognized ML algorithms have been frequently applied in SCM. Some advanced ML algorithms were neglected, for example, deep learning algorithm, a well-known variation of NN [63] has not been identified as one of frequently used algorithms in our paper. This might be ascribed to the unfamiliarity of the SCM researchers and practitioners to the common ML algorithms, as García et al. [36] pointed out that ML algorithms often suffer from the low interpretability in application.

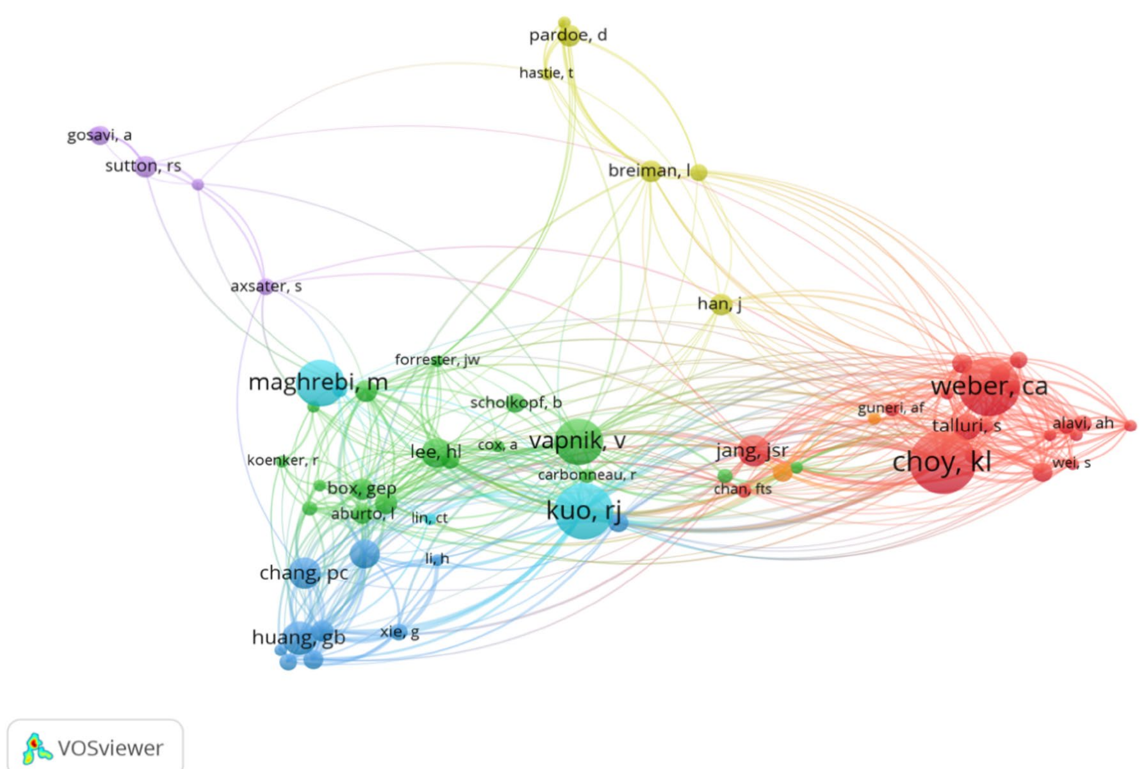



Fig. 7 The co-citation network of the cited authors

**Table 4** Brief overview of 10 ML algorithms

| Name | General usage | Advantage | Disadvantage |
|---|---|---|---|
| Decision Tree (DT) | Discriminant models; mutli-regression and classification; regularized Maximum Likelihood Estimate | 1. Easy calculation, being suitable to handle samples with deficient attribute values;<br>2. Able to assess an item with different features;<br>3. Strong interpretability | Easy to be over-fitting |
| Random forest (RF) | Classification | 1. Insensitive to missing and abnormal values;<br>2. High accuracy of training results;<br>3. Relative Bagging can converge to a small generalization error | 1. Over-fitting for large data noise;<br>2. Sensitive to the features with different values |
| K-means | Clustering; Classification | 1. Easy and fast;<br>2. Low complexity | 1. Only used when cluster mean values have been defined;<br>2. Actual line given by cluster K is sensitive to the initial values;<br>3. Sensitive to noise and outliers |
| K-Nearest neighbor (KNN): | Discriminant models; mutli-regression; classification | 1. Simple for classification and regression, particularly for nonlinear classification;<br>2. Low complexity;<br>3. Immune to outliers | 1. Need to preset K;<br>2. Unable to solve large unbalanced data sets |
| Logistic regression (LR) | Regression | 1. Simple to operate;<br>2. Easy calculation;<br>3. Small storage resources | Poor fitness and precision |
| Naive Bayes classifier (NBC) | Generative model | 1. Good at small-scale data sets.<br>2. Applicable to multi-classification | 1. Requiring conditional independence assumption, which leads to reduced accuracy;<br>2. Poor classification performance |
| Neural Networks (NN) | Regression; classification | 1. Strong nonlinear fitting ability, simple learning rules and strong robustness, with memory ability;<br>2. Strong self-study ability and error back propagation ability<br>3. Good parallelism | 1. Unable to explain the reasoning process and basis;<br>2. Unsuitable for insufficient data set;<br>3. Sensitive to initial values |
| Support vector machine (SVM) | Regression/classification | 1. Suitable for nonlinear classification;<br>2. Applicable both to classification and regression;<br>3. Easy to explain;<br>4. Fewer generalization errors | Sensitive to kernel functions and parameters |
| Ensemble algorithms (ESM) | Regression; classification | Good at assembling the advantages of NNs | Being dependent of the basic classifier |
| Extreme learning machine (ELM) | Regression; classification | 1. Fast learning;<br>2. Good generalization performance.<br>3. Simple to operate | Arguments in its definition, methodology and so on |

To help improve the situation, Table 4 provides a brief overview of these 10 ML algorithms to facilitate a clear understanding of these algorithms among SCM researchers and practitioners. In Table 4, the first column from the left lists the names of 10 ML algorithms; the second column presents the general usage of the 10 ML algorithms; and the third and fourth column summarize their advantages and disadvantages accordingly. In addition, more characteristic of these 10 frequently used ML algorithms are introduced in detail as follows:

1. Decision Tree (DT): DTs display possible consequences with different graphs. Each node of the graphs contributes to one specific feature [16]. DTs are normally used for discriminant models and multiple regression. Although DTs are simple to observe and

have low bias, they are easy to be over-fitting. That is where the RF comes in.

2. Random Forest (RF): RF uses different DTs trained with different data sets and selects the random subsets of features to make predictions by making use of the mean values of all the individual prediction results. DT and RF are the two decision methods which share the potential usage in SCM by listing the benefits of each decision and their probability of fulfillment. These two decision methods then make an overall presentation by doing lead-scoring for SC managers to allocate resources [74].
3. K-means: K-means is an unsupervised clustering method. This method is able to divide the data into k clusters that would decrease the square errors of each group [70]. K-means is time-and-cost-efficient with its low computational complexity, but the K needs to be preset in advance, which requires the prior knowledge of the data sets. What is worse, K-means is prone to being affected by outliers and noise.
4. K-Nearest Neighbor (KNN): Similar to K-means, KNN is also a clustering method that separates data into K clusters. However, being different from K-means, KNN is a supervised learning method, which is immune to noise. However, KNN is not able to handle large data sets and the data sets analyzed by KNN should be regular without any missing values. Anyhow, K-means and KNN, both are able to be used in SCM for the purpose of separating customers into frequent buyers and their purchase amount. These two ML algorithms select people more objectively and faster than human brain does [52].
5. Logistic Regression (LR): It is a variation of the massively used Linear Regression Model [37]. As compared to Linear Regression Model, LR is able to employ non-linear model to replace linear fitting model to fit every dependent variable and independent variable, but it still highly relies on the choice of the fitting model and has poor fitness. Since LR is good at predicting continuous data, it is used in sales forecasting of SCM.
6. Naive Bayes Classifier (NBC): NBC is based on the Bayesian Theorem, which is good at small-scale data sets. NBC has the potential application in SCM for identifying the credit of a stakeholder, telling whether he or she would break rules of contracts and thus provides a warning in advance for the other stakeholders.
7. Neural Networks (NN): NN started in the 1980s and were first applied in 1988 [5]. It was created to simulate human brain in learning to perform tasks [101]. NN is a powerful algorithm in identifying complex nonlinear input/output relationships so that it is able to be used by SCM to warn against the potential competitors. NN has many variations, like back propagation (BP) NN, Radial Basis Function (RBF) and convolutional neural network (CNN). All these variations are applicable to SCM. Take CNN as an example. CNN is the essential tool for deep learning and is commonly used to analyze imagery. In SCM it is employed to analyze the audio and video communication of customer-salesperson, and to do lead-time planning and customization. However, NNs have an intrinsic disadvantage, that is, because the computational results are obtained by repetitive training in a "black box", NNs are unable to explain their reasoning process.
8. Support Vector Machine (SVM): SVMs are able to make up for the disadvantage NNs have, for SVMs have characteristics of simple structure, replacing experience optimum with global optimum [15]. SVMs have the strong generalization ability and strong mathematical interpretability. Also, SVMs are suitable for hi-dimensional issues, which will provide SCM with cross-selling and up-selling opportunities. However, SVMs heavily rely on its kernels, which also need prior knowledge of the data sets involved.
9. Ensemble algorithms (ESM): To fully explore the advantages of these algorithms mentioned above, researchers also develop some integrated algorithms like Ensemble algorithms (ESM). ESM takes in the advantages of each basic classifier and provides predictive results better than any of the basic classifier alone [66]. ESM can be particularly valuable for SCM in the credit risk assessment of stakeholders since people can get a credit record more easily without enough credit evaluation in a fast developing environment [33].
10. Extreme Learning Machine (ELM): ELM is feed-forward NNs, which cut down half of the calculation compared to normal NNs. Most of its training is done in milliseconds, seconds, and minutes [48]. Also, all the parameters of the networks are tuned iteratively by ELM that no parameters need to be manually tuned. This makes ELM extremely easy to use. ELM is able to analyze big data sets for SCM within short time periods. However, although ELM can bring better results with simple calculation, some researchers have been arguing about its methodological approaches, and even about its definition.

Apart from the characteristics of these 10 frequently used algorithms in SCM introduced above, the detailed description for the concrete frequency of these ML algorithms is shown in Fig. 8. The figure demonstrates that NN is the most frequently used NN (54%), SVM (21%) is the second, then followed by LR (5%), DT (4%), ELM (4%), NBC (4%), KNN (2%), RF (2%), ESM (2%) and K-means (2%). The rank of frequently used ML algorithms obtained in this

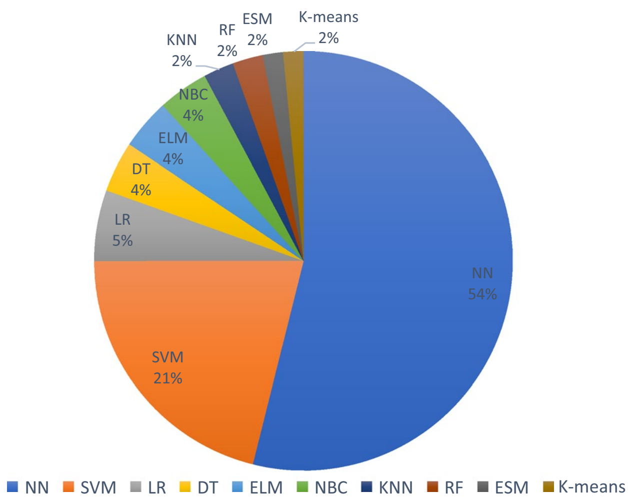



**Fig. 8** Classification according to ML algorithms based on frequency

paper is on the whole similar to that reported by Bousqaoui and Achchab [7], that is, NN was ranked the first and SVM the second, LR took the third place. It is also interesting to see that almost half of the shortlisted articles employed NNs as the ML algorithms. This is because most of the articles compared their results with NN performance or combined the NN model with their own model, as the BP NN invented in 1975 [116]. What's worse, NNs and SVM took up almost three-fourths of the frequently used ML algorithms, as SVM was also a mature algorithm which was invented by Vapnik [114]. The unbalanced applications of ML algorithms, as claimed by Bousqaoui and Achchab [7], are also common among the articles of the five databases. Other new algorithms like ESM and ELM, which are seen in good application in Fraud detection [72] and financial decision-making [53], are used rarely in SCM. The inadequate application might be caused by worries of over-interpretation by new algorithms of the data or finding patterns in the data that do not exist (Yan 2007) since SCM is a non-experimental science that controlled experiments cannot be implemented [10].

In response to the second research question, 10 algorithms were identified out of 32 as the frequently ones used in SCM, and the 10 ML algorithms were seen in unbalanced applications.

## 4.3 Distribution of the algorithms

Judging from the developmental trends of the ML applications in SCM and the analysis of frequently used ML algorithms in SCM, the potential of ML as a means of tackling complex problems and retrieving information in SCM has not been fully explored in the past. However, some researchers have made pioneering efforts at the ML applications in SCM, and some ML algorithms such as NNs and SVMs have been utilized to address certain SCM activities. In this section, six SCM activities are to be introduced to demonstrate the strong linkage between ML algorithms and SCM activities, and then to outline how those frequently used ML algorithms were distributed in the 6 SCM activities.

### 4.3.1 Demand/sales estimation

Planning is driven by demand/sales estimation in SCM. However, demand/sales estimation is difficult sometimes because a good demand forecast works as an estimation for all sales potential estimation, which is a complex estimation system. In this case, it is required to relate the parameters associated with multiple explanatory variables to their dependent variables in a highly nonlinear manner. By introducing non-linear analyses, ML algorithms is able to improve the accuracy of predicting and forecasting in sales, demand, and the degree how much inventory is required. Being different from those traditional methods like moving average, exponential smoothing, time-series methods and Box-Jenkins methods, ML algorithms do not heavily rely on the accuracy of historical data so that ML algorithms have been promoted as alternatives for demanding and planning in SCM. For instance, Ning et al. [91] developed the minimum description length optimal NNs which could accurately predict retailer demands with various time lags to change the replenishment strategy, which cannot be finished by traditional models. Thomassey [107] proposed different forecasting models which performed more reliable sales forecasts than traditional models did. These models built by advanced methods such as NNs, fuzzy logic and data mining, worked well under situations like strong seasonality of sales, volatile demand, the lack of historical-data backgrounds or the wide number of items with short life cycle. Compared with traditional methods, ML algorithms are able to remove the data sets' defects and provide non-linear models to suit the demand/sales curve in a more accurate way.

### 4.3.2 Procurement and supply management

It is the key to the success of any organization in procurement and supply management to satisfy the customers with high quality products at a low cost and in a short time. The main function by the ML applications in SCM is the supplier evaluation and selection. Traditionally, the suppliers who are able to provide the retailer with the right quantity of the right product/service at the right time in the right place are qualified as being suitable. However, the potential suppliers are rarely so clearly superior to their competitors. Thus, most business would adopt some kinds of supplier 'scoring' or assessment procedure, which requires the information about performance history of potential suppliers, about their credit history and other personal information. This sort of information is often not available to the public, and the data availability often causes such problems as small size of data-sets, inconsistent values, and errors, etc. The key advantage of some ML algorithms is the flexibility in coping with missing values.

Thanks to the dynamics and complexity of the above scenarios, the make-or-buy decision relies heavily on systematic decision-aid ML algorithms such as SVMs. For example, Mori et al. [87] used SVMs to find new business partners—suppliers and customers. They designed several features that might characterize customer–supplier relationships with a firm's profile and its transactional relationships. Compared with real data, the results obtained by Mori et al. indicated an F value of 84% plausible candidates. Similarly, Li et al. [67] used reasoning ESM to do the general competence trust diagnosis for some supplier companies. The results proved that instead of human making decisions in supplier selection, ESM was more stable in making final decisions with an accuracy of 88.82%. As a result, ML algorithms are able to handle the comprehensive information of the suppliers and make an objective judgement accurately.

#### 4.3.3 Production

By taking into account multiple constraints, ML algorithms will improve factory scheduling accuracy and production planning. ML algorithms will also make it possible to balance the constraints more effectively than those that were manually done in the past, particularly, for manufacturers who rely on build-to-order and make-to-stock production workflows. With the help of ML, manufacturers could reduce SC latency for components and parts used in their most heavily customized products. For example, faced with the different customization requirements and production regulation of each country, Chen et al. [15] put forward a solution with NNs to group similar customization needs. Then they used the existing inventory information to select the parts for production managers, which hugely reduced the cost during the SC compared to human decision. In a similar way, Juez et al. (2010) employed SVMs to considerate multiple factors to arrange production lead-time before manufacturing in aerospace industry. As a whole, the ML algorithms are able to yield the lead-time prediction in production with a shorter response time.

#### 4.3.4 Inventory and storage

SC inventory management (SCIM) and storage incur important costs. For instance, according to Timme and Williams-Timme [108], the annual spending on storage is about 15%–35% of its total business value. The goals of SCIM are to increase product variety, to improve customer service and to decrease costs as well. However, information concerning all these goals is hard to be precisely estimated, predicted and obtained with traditional decision rules for it is largely based on the sound judgment and experience of inventory managers themselves. Therefore warehouses are often faced with uncertain inventory input, which means a tool which will help human to overcome the uncertainty is necessary. ML algorithms are able to seek quick input comparable patterns with warehouse data sets. Gumus et al. [40] used NNs with the help of neuro-fuzzy demand to do a lead-time forecasting in a multi-echelon SC. The results showed that, the inventory management level was efficiently improved with their proposed model. ML has also proved to be effective at automating inspecting the damage inside logistics hubs, or in-house delivering. Wan et al. [115] used SVM and NBC in two small SC examples, results revealed that their model could increase their inventory safety. Overall, the ML algorithms are able to identify the hidden inventory patterns that have never been revealed in reducing saving cost.

#### 4.3.5 Transportation and distribution

One of the most popular ML applications in SCM is to solve the vehicle routing problems. The optimal routes out of multiple choices for a transporting vehicle to travel are really important for SC to deliver a product to the corresponding customers, and deciding the routes are in most cases beyond the ability of a human brain. ML algorithms and the apps running ML algorithms excel at analysing large, diverse data sets, providing results fast with high demand forecasting accuracy. Cirovic et al. [23] worked out a model for the routing of light delivery vehicles through logistics operators. To solve the problems of routing in the model, an adaptive NN was trained by a simulated annealing algorithm to assess the performance of the distribution network routes. Becker et al. [5] used a real-world simulation scenario on the basis of the Hamburg Harbor Car Terminal, a logistic site involving approximately 46,500 car-routing decisions. The simulation results yielded by Becker et al. showed that the neural-net model's performance was 48% better than that of the best heuristic routing tested in previous studies. Thus, ML algorithms are able to generate better deliver routes by objectively and timely exploring the pattern of consumers' behaviour, vehicles, transportation and infrastructures.

#### 4.3.6 Supply chain improvement

A more effective supply chain delivers services and products only when and where they are needed, which means customer feedback is essential for SC improvement or SC improvement is basically about adjusting the SC to become more consumer-centric. Various methods such as market research, surveys, and interviews are traditionally used to provide the opportunity for consumers to offer feedback within the retailer store. The fact is that, in the process of surveys and interviews, normal retailers do not attract large audience for consumers often avoid giving out comments face to face. Thus, their sample size is small. Those decisions for SC improvement based on a small sample are prone to being invalid. However there is substantial amount of consumer information presented by social media that may reflect the true opinions of customers. Social media data serve as a better channel of customers' feedback but they are often irregular and lack quality in nature and large in variety, volume and velocity. It is thus difficult to handle them manually [121]. In this situation, ML algorithms combined with IoT (Internet of things) sensors, advanced analytics, and real-time monitoring come up to provide end-to-end visibility across SC activities. For instance, [85] once extracted 1338,638 pieces of customers' views from Twitter data, carried out an sentiment analysis of the data using text mining and SVM and precisely direct the customers' complaints of problems like extra fat, presence of foreign particles, discoloration, and hard texture to the root causes in the upstream activities of the SC of beef products. Darren Law et al., aided by LR, NN and DT, completed a prior defect-discovery from 11,024 Amazon reviews of some brands of dishwashers, and found that the potential defects were highly correlated with the domain specific "smoke" and "sparkle" terms. Results showed that their tool spotted defects of dishwashers in advance with an accuracy of 94% which much improved the quality assurance on both the supply and demand side. Therefore, with the help of the data from sensors, ML algorithms can monitor SC synchronously while transportation can rule out the SC disruptions in advance.

The distribution of 10 frequently-used ML algorithms in the 6 SCM activities seen in the 123 articles shortlisted was presented in Table 5. As indicated in Table 5, it is known that:

1. The ML distribution is remarkably inclined to demand/sales estimation of the 6 SCM activities, as demand/sales estimation is the most frequently reported of the six SCM activities in the 123 articles shortlisted, transportation & distribution and procurement & supply management were the second, followed by supply chain improvement, production, and inventory & storage;
2. In Table 5, 24 out of 60 cross-blocks between 10 ML algorithms and 6 SCM activities are blank. This indicates that some ML algorithms have never been used in any of six SCM activities. For example, K-means has never been used in either transportation & distribution, production, procurement & supply management, inventory & storage, or SM improvement. In a similar way, there are SMC activities that have never turned to help from any ML algorithms, for instance, inventory & storage never involves any of DT, ELM, LR, ESM, KNN, RF, or K-means. The blank application of some ML algorithms in some SCM activities doesn't imply that these ML algorithms are not applicable in these activities, and the blank involvement of some SCM activities for some ML algorithms doesn't suggest that these SCM activities do not need any help of these ML algorithms either. The most probable reason for the blank application and involvement might be the insufficient knowledge for the linkage between ML algorithms and SCM activities. In other words, SCM researchers and practitioners might feel difficult to tailor the features or advantages of some ML algorithm specific to the needs of certain SCM activities.

In regard to the third research question, it is found that the distribution of the frequently-used ML algorithms in six SCM activities were pretty uneven. Some ML algorithms like NNs and SVMs piled up in a couple of SCM activities or notably in demand/sales estimation, while some SCM activities like production and inventory & storage only involved a couple of ML algorithms.

## 5 The future directions of machine learning in supply chain management

In this section, a number of potential directions of ML applications in SCM are suggested as follows:

*To make SCM research more "practical"*. As can be seen from Fig. 5, with a unbalanced 50% of the data source in SC comes from the simulation data, the research of ML applications in SCM till now has been concentrated only on mathematical modeling. This is because the city-scale and the synchronic SC data made the analysis of historical data very difficult. However, with the emergency of ML algorithms, researchers are increasingly empowered in analysing the data sets of different structures, sometimes even with missing data. Integrating the data sets from all parts of the supply chain and presenting them on a smart phone, dashboards will enable consumers to have more knowledge about the entire system. At the same time, managers can employ ML methods like deep learning neural methods to guide consumers in making more holistic and sustainable buying decisions. Besides, managers can employ visual data graphics in better interpreting important signals, and to use new metrics in measuring risk, sustainability and total costs. Thus, the studies combining "big data" with SC should be done to make SCM research more practical in the future.

*More "objectivity" in SCM research.* From top part of Table 5, it is easy to find that ML has been frequently used in prediction and supplier selection to provide guidance for managers. This is mainly because human might make mistakes on

**Table 5** 10 ML algorithms used in 6 SCM activities

| | Demand/sales estimation | Transportation and distribution | Production | Procurement and supply management | Inventory and storage | SC improvement |
|---|---|---|---|---|---|---|
| NN | Ning et al. [91], Pan et al. [93], Carbonneau et al. [11], Fasli and Kovalchuk (2011), Xia et et al. [120], Thomassey [107], Aburto and Weber [1], Sun et al. [103], Chiu and Lin [18], Carbonneau et al. [12], Garg et al. (2003), Cheng et al. [16], Garcia et al. [36], Trapero et al. [109], Jaipuria and Mahapatra [49], Arunraj and Ahrens [4], Kuo and Xue [57], Gao et al. [35], Kuo and Chen [55], Chiu and Lin [18], Lee and Park [65], Rohde [99] | Shervais et al. [100], Mercier and Uysal [82], Maghrebi and Sammut [76], Keller et al. [51], Noroozi et al. [92], Piramuthu [95], Alfian et al. [3], Cirovic et al. (2014), Liu et al. [69], Becker, et al. [5], Lee et al. [64], Ozkanand Inal (2014) | Chung et al. [22], Wu et al. [119], Liu et al. [69] | Golmohammadi et al. [39], Zuo et al. [126], Hong and Ha [46], Hu and Zhang (2008), Vahdani et al. [111], Aksoy and Ozturk [2], Wu [118], Kuo et al. [56], Tavana et al. [106], Lau et al. [60], Choy et al. [19, 20], Lau et al. [61], Hosseini and Khaled [47], Fallahpour [31], He et al. [44] | Shervais et al. [100], Gumus et al. [40], Chen et al. [2012], Haq and Kannan (2006) | Pan et al. [93], Raut et al. [97], Zhu et al. [125], Xie et al. [122], Chatzidimitriou et al. [14], Efendigil and Onut [28], Lau et al. [59], Vaat and Donk [112], Efendigil et al. [29], Swain and Cao [104] |
| SVM | Carbonneau et al. [12], Tsukamoto et al. (2014), Carbonneau et al. [11], Wu et al. [118], Garcia et al. [36], Zhao and Chen [123], Vahdani et al. [113] | Ma et al. [74], Maghrebi and Sammut [76], Bhattacharya [6], Ciccio et al. [26] | Estelles-Lopez et al. [30], Ko et al. [54], Juez et al. (2010), Chi et al. [17] | Zuo et al. [125], Mori et al. [87], Hu and Zhang (2008), Vahdani et al. [111], Chi et al. [17], Guo et al. [41], Tseng et al. [110], Fallahpour [31] | Wan et al. [115] | Singh [101], Chatzidimitriou et al. [14], Zhang et al. [124] |
| DT | Cheng et al. [16] | Maghrebi and Sammut [76], Keller et al. [51], Piramuthu [95] | – | Wu [118] | – | – |
| ELM | Martinez et al. (2016), Wong and Guo [117], Xia et al. [120], Lu and Kao [73], Sun et al. [103], Lau et al. [62] | – | – | – | – | – |
| LR | – | Ma et al. [74], Keller et al. [51] | Estelles-Lopez et al. [30], Ghasri et al. [37] | Hosseini and Khaled [47] | – | Xie et al. [122] |
| ESM | – | – | – | Li et al. [67] | – | Zhu et al. [125] |
| KNN | Kiekintveld et al. [52] | Maghrebi and Sammut [76] | Estelles-Lopez et al. [30] | – | – | – |
| RF | – | Ma et al. [74] | Estelles-Lopez et al. [30] | – | – | Zhu et al. [125] |
| NB | – | Piendl et al. [94] | Rodger et al. [98] | Mao et al. [79] | Wan et al. [115] | – |
| K-means | Lu and Kao [73] | – | – | – | – | Ko et al. [54] |

SC decisions by ration, ML can somehow improve the objectivity in decision-making. What is more, this important nature of ML is able to make integrated SC available for decision-making managers. If the whole SC would have been fully supported by a machine, the decisions made by the machine would help interpret the information from other supply chain stakeholders, to control bullwhip effect from how it is formed. In case of objectivity, those ML applications have promoted the urgent needs in improving decision-support tools for forecasting, early warning, and real-time disruptions monitoring in SCM.

*More "variety" is needed.* As also seen from the Table 5, few algorithms besides NN and SVM have been explored in SCM. So there is a definite large room where various ML algorithms should be applied into SCM research. Derivatively, another possible trend to cope with the new upcoming ML algorithms is to redesigning the SC structure. In particular, with the accurate help of ML, it is possible to reduce waste, emissions and risk along the supply chain, which provides more SC activities besides the six mentioned in Sect. 4 of this study. With the help of ML algorithms, it is also possible to reveal potential links between the complexity of a supply chain and the frequency of disruptions that might occur. In order to manage these links, research tailored to various needs, particularly those related to the risks and sustainability in SCM, can have a thriving future.

*More"robustness"is required.* It is extremely difficult for a single departments or company to deploy a new system by themselves, not to speak of ML, as a "black box", only providing accurate results without any explanations. This makes a department or a company harder to accept ML in SCM. Also, some ML methods are not able to perform well in a single case and their robustness will not be strong enough to last in the real-time applications. How can common end-users like suppliers and retailers be convinced to make a decision in choosing a proper ML method in SCM only on the basis of the comparisons between different ML algorithms? New research is needed to drill down into the interpretability of ML algorithms for dynamic settings to be tested in future.

In the end, the ML applications in SC are facing tremendous changes and require more acknowledgement among the researchers and improvement in robustness out of the research into reality. Thus, in a volatile and fast-paced supply environment, the ML applications would surely be equipped with a bright future in supply chain management.

## 6 Conclusion

This study conducted a systematic review of recent trends of the ML applications in SCM to answer three research questions as were presented at the beginning of this paper. To address the three research questions, the research articles, published during 1998/01/01–2018/12/31, were searched on six academic databases: Emerald Insight, IEEE Xplore, Scopus, Science Direct, Wiley and Springer, with Google Scholar as a complementary database. As a result, 123 research articles were obtained and closely analyzed. The analysis and its results indicated that, although there were two research peaks (between 2008 and 2009, 2016 and 2017 respectively) for ML applications in SCM over a time span of 20 years (1998–2018), the ML applications in SCM were still in an developmental stage since there were not enough high-yielding authors to form a group in this domain and their publications were still at a low level; and that, even though 10 ML algorithms were found to be frequently used in SCM, their applications were carried out in an unbalanced way, and the distribution of the frequently-used ML algorithms in six SCM activities were pretty uneven.

Although the three research questions have been addressed as expected and the conclusions obtained might be helpful for SCM researchers and practitioners, this paper possesses certain limitations. First, several precautions were taken in filtering the articles for review purpose, for example, merely five common databases were checked in this paper. It could be possible that some relevant articles might have been filtered. Therefore, more databases should be included for the further research on the ML applications in SCM. Second, only frequently used ML algorithms in SCM were counted in this review, and there might be some ML algorithms which were initially introduced to SCM but would be really helpful for SCM later on. For the further studies in this domain, the ML algorithms with low frequency should also be included for analysis. Third, the criteria for an ML algorithm to be included in our paper were entirely based on 32 commonly recognized ML algorithms presented by Christoph Koutschan in [21], it might be possible for some newly invented ML algorithms applied in SCM after 2015. Therefore, the list of ML algorithms should be brushed up regularly for the studies on the ML applications in SCM. The research on the ML applications in SCM is still in a developmental stage; there is great space to cover and fruitful research contents to see in this domain in the future.

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