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Machine Learning techniques for Supply Chain Management: A Systematic Literature Review

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Abstract. This paper presents a systematic review of the development of research on Machine Learning (ML) applications in supply chain management (SCM), particularly demand forecasting. The objective is to bridge the gap between current and potential ML methods that can improve the performance of the demand forecasting operation in three SCM industries: industry, agriculture, and services, by analyzing published work in the last decade in several numerical databases. Five aspects were covered: the research trend on ML applications in SCM; the ML algorithms most used by researchers for demand forecasting; the advantages of ML algorithms over traditional forecasting approaches; the ML techniques considered most adopted at the demand forecasting operation, as well as the SCM industry sector that benefited most from these applications. We have focused on providing an overview of the applications of ML in demand forecasting and asserting its powerful role in the evolution of SCM effectiveness, in order to provide a reference for future research and applications of SCM in different economic sectors.

Keywords: Machine learning, supply chain management, demand forecasting, search trend, economic sectors

1. Introduction

In the current economic context, especially with the globalization; the inter-penetration of markets; and the trend of outsourcing/offshoring, the company of the 21st century should be able to confront a new environment defined by (Bennett & Lemoine, 2014; Packowski, 2013) as the acronym VUCA (Volatility- Uncertainty- Complexity- Ambiguity). The supply chain, which incorporates the management of a company's processes from planning to distribution, it works to assure the optimal management of such processes in order to maintain a matching offer to the demand, is considered the first to be affected in this environment (Sasser, 1976; Chandra & Fisher, 1994; Mahmoud 2021).

According to (Milgrom & Roberts, 1988) uncertainty of demand is considered one of the most important components of its environmental, which increases the risk of mismatching between offer and demand. (Chen et al., 2007) suggest that demand uncertainty spills thrueghout processes, reducing the efficiency of the supply chain. (Spalanzani et al., 2006) define demand uncertainty as the inability to specify the exact quantities to produce in order to cover the markets needs at the specified time (timing of) of that demand. There are several actions to be adapted to the uncertainty of demand, the most known one is the increase in the level of stocks, which means, the production process (make to stock) (Milgrom & Roberts, 1988). However, this solution is not the best, because it rounds up the stationary costs related to the stock and affects the financial health of the company. There is another mechanism to reduce the imbalance between the offer and the demand, it is the improvement of the forecast of the demand. As (Haberleitner et al., 2010) argue, demand forecasting is the starting point for all planning activities and execution processes across the supply chain. Therefore, obtaining forecasts is a complicated process which need a great care in each full field phase, including the data retrieval and analysis step, which is the key to producing a good forecast.

The excessive use of technologies, associated with the usage of mobile internet and Internet of Things (IoT), have increased the data of several characteristics called Big Data. This latter is a data set distinguished with the five Vs: Volume, Velocity, Variety, Veracity, and Value (White, 2012; Jeble et al., 2017; Affia et al., 2019; Anu et al., 2021). Data analysis refers to the use of mathematical and statistical tools offering an available data analysis to extract symptomatic information helping in decision making. However, if the data continues growing simultaneously, it will be managed difficultly (Anu Dahiya et al., 2021). Traditional statistical methods failed to analyse these new and potentially invaluable data sets in order to generate good forecasts. (Jeble et al., 2017) confirmed that the presence of big data in the supply chain has created remarkable complexity in the demand forecasting operation.

Artificial intelligence has been one of the most popular techniques for many years, its power has been demonstrated in many applications (Min, 2010; Oke, 2004; beom kim, 2019). The definition of artificial intelligence is differentiated according to the context in which it is used (Riahi et al., 2021), AI can be generally defined as « any artificially created intelligence, i.e. a software system that simulates human thinking on a computer or other devices » as defined (Čerka et al., 2015).The ability of AI-based automation technologies to manage and analyze large amounts of big data, has highlighted his role as a decision-making tool (Dwivedi et al., 2021), and has increased the creativity of the supply chain (Wilson & Daugherty, 2018) becoming more and more artificial for the company (Tarafdar et al., 2017). Machine learning is a subdomain of artificial intelligence able to learn from the data in order to produce predictions. According to many researches, Machine Learning can be applied to several stages of supply chain management, including demand forecasting as well as predictive analysis tasks (H. Bousqaoui et al., 2017; Raguseo, 2018). ML algorithms can interpret the complex non-linear relationships between so many causal factors affecting demand, in the presence of big data (Ampazis, 2014; Tanaka, 2010), and increase the efficiency of supply chain processes (Minis & Ampazis, 2006; Risi et al., 2018).

The importance of research on machine learning (ML) and supply chain management (SCM) has led to an excessive number of publications in recent years. Several researches have recently focused on the integration of machine learning techniques in the supply chain, such as (Bousqaoui et al., 2017; Feki et al., 2016; Mori et al., 2012), while others have described their applications for demand forecasting, such as (Waller & Fawcett, 2013; Carbonneau et al., 2008; Weng et al., 2019). Although machine learning has potential score, the number of publications in the area of demand forecasting remains modest. (Manyika et al., 2011) conforms that ML was applied in one or more SC activities in only 15% of firms. This could be due to a misunderstanding of ML concepts in the corporate culture, ambiguity of how it could be applied, knowledge of guidelines for selecting appropriate ML techniques for supply chain researchers and practitioners, as well as the inability to have appropriate data (Ni et al., 2020).

In fact, there are a few papers focused on systemic research of AI applications in SCM (Min, 2010; Riahi et al., 2021). (Ni et al., 2020) are the only ones to have established a review of ML applications in SCM, but their study was limited only to applications in the industry domain. Therefore, we have not found any reviews dedicated entirely to ML applications in demand forecasting.

For this purpose, this study attempts to complement the research of (Ni et al., 2020), by conducting a more in-depth systematic review of the applications of the 10 most widely used ML algorithms in demand forecasting, in the three main economic sectors: industrial sector, agricultural sector, and service sector in order to fill the gap between ML and SCM, and provide a comprehensive sample for researchers and practitioners in the field of SCM.

To reach this objective, we are called to establish a systematic review of the last ten years of publications in several major international databases, in order to answer five key questions of this research:

RQ1: What are the general research trends on applications in demand forecasting?

RQ2: Which ML algorithms are often used in demand forecasting?

RQ3: What are the advantages of ML algorithms compared with traditional approaches?

RQ4: Which ML algorithms are considered to be the most effective in demand forecasting?

RQ5: In which sectors and activities are these ML algorithms frequently used?

The rest of this paper will be organized as follows: section 2 presents the literature review about this study. Section 3 describe the Systematic review process followed in this study. Section 4, presents the results of analysis. Section 5 concludes, by proposals for future researchers.

2. Literature Review

2.1. Demand forecasting impact on the supply chain

Research in the field of operation management, has confirmed the role of effective supply chain management on the variability and continuity of many organizations in today's competitive market (Burinskiene 2018). (Fatorachian & Kazemi, 2018) points out that in order to keep pace with customer demands in a highly competitive environment, the supply chain should increase resilience and efficiency across processes. (Ivanov & Rozhkov, 2020) advocates that changes in demand profiles affect the operational politics of the supply chain by inducing disruptive queues on inventory dynamics. In recent years, world-class organizations have succeeded in always occupying the first place, because they have been able to interpret the expectations of its customers and follow the rapid evolution of technology, such as Google, Netflix, Airbnb, Amazon and Uber (Iansiti & Lakhani, 2020). Nevertheless, there are other organizations who had to stop their activities because they were not able to follow the technological trend and satisfy the demand of consumers, for example: Blockbuster in the United States. Thus, it can be deduced that the more efficient and responsive the supply chain is, the more competitive advantages the organization can gain. A critical factor in the effectiveness of supply chain management is the accuracy of demand forecasting (Chong et al., 2017). Several researches have discussed the effects of demand forecasting on supply chain performance, an accurate demand forecast synchronizes flows, ensures proper supply chain management and improves customer satisfaction by avoiding stock-outs (Kumar et al., 2020). (Fleischmann et al., 2002) considered demand estimation as a decision support tool, allowing the organization of the company's supply chain on all the time horizons and at all levels. (Oliva & Watson, 2009) approved that the improvement of the demand forecasting mechanism allows the increase of the stock turnover rate and the reduction of 50% of the available stocks, the organization of the transport flows (Rai et al., 2019), and the growth of distribution activity (Shareef et al., 2016), by increasing financial benefits and return on investment (Gunasekaran et al., 2004; Clarke, 2006). While other researches have studied the negative effects of poor forecasting on the supply chain, (Lee et al., 1997; Wan & Evers, 2011; Mason-Jones & Towill, 1999) have shown that the order amplification called bullwhip effect (BWE) is among the most responsive effects of poor demand estimation. The (BWE) increases the overall cost and decreases the efficiency of the supply chain processes (Chopra & Meindl, 2007). Therefore, demand planning becomes one of the biggest challenges for companies (Moon et al., 2003; Mccarthy et al., 2006). In addition, in an effort to save production costs, companies have shifted to sourcing products from distant markets around the world (Christopher & Holweg, 2017). This, in turn, has caused an extension of both production and product sourcing times. According to (Armstrong, 1986; Simchi-levi & Zhao, 2005), as the forecasting horizon gets longer, the accuracy of demand forecasts tends to decrease. The quest for reliable customer demand forecasting is one of the most dynamic problems in supply chain management (Chong al., 2017). Traditional forecasting methods, such as moving average, time series, exponential smoothing, and Box-Jenkins methods, have relied heavily on the accuracy and consistency of historical data, which is not always the case in most of the time. They do not easily capture the non-linearity associated with time series data, as seasonality, trends, etc. Although historical data is always elementary for predicting future demand, there are multiple variables called dependent variables that are related to demand in a direct and indirect way and that must be taken into account during forecasting calculations. Nevertheless, traditional statistical methods are unable to capture non-linear relationships. For this reason, Supply Chain Management can leverage machine learning to overcome the limitations of statistical approaches to produce more reliable and efficient forecasting models.

2.2. Machine learning methods for demand forecasting

Demand forecasting is a discipline of predictive analytics that focuses on understanding customer demand for goods and services. In the field of demand forecasting, popular traditional models, including time series methods: ARIMA (Autoregressive Integrated Moving Average,) Moving average, weighted moving average, Croston model, etc… have dominated for a long time and have taken their place in many real-world applications. They are considered effective when the data series is stationary and takes a linear model. However, most real-world problems have nonlinear characteristics, drawing attention to nonlinear techniques (Aras & Kocakoç, 2016). Traditional methods can only generate results based on past and current data, without considering external demand factors as inputs. Therefore, Machine Learning

(ML) methods can be a promising solution to address the limitations of traditional approaches and produce more reliable forecasts.

Machine learning, invented by Samuel (1959), emerged as a technique for allowing computers to acquire knowledge from data without being explicitly programmed (Ratner, 2000). ML models are able to capture non-linear relationships in data, without the limitations of time series. There are many different ML algorithms, which can generally be divided into two main categories: supervised and unsupervised learning. They are used to accomplish four main tasks: classification, regression, association and clustering (Kone & Karwan, 2011). In the case of supervised learning, the input data is labelled, that is to say, the model already knows what it is looking for in the data. During the learning process, the accuracy of the algorithm must also be adjusted to find the link between the inputs and outputs in order to achieve a good performance. Unlike supervised learning, unsupervised context must operate from unlabelled data. The role of the algorithm is to pursue cohesion within the data and to classify it into distinct groups as possible (Goodfellow et al., 2016). Machine learning algorithms are packages found in many popular programming languages, they were invented by researchers in the field, based on mathematical models built from data samples (beom kim, 2019). For example, Vapnik is the inventor of Support Vector Machine (SVM) and Huang guangbin is the inventor of Extreme Learning Machine (ELM) etc... They can be combined with other mathematical models, but their operating principles remain the same. (Ni et al., 2020) are the only ones to have conducted a review systematic review of the articles published during the period 1998/01/01-2018/12/31, on six academic databases: Emerald Insight, IEEE Xplore, Scopus, Science Direct, Wiley and Springer, with Google Scholar. The results showed that demand forecasting is the largest beneficiary of ML applications among the 6 SCM activities, and there is 10 ML algorithms which are the frequently used in the field of supply chain: Extreme Learning Machine (ELM), Random Forest (RF), k-nearest neighbor (KNN), Decision Tree (DT), Logistic Regression (LR), K-means , Naive Bayes Classifier (NBC), Neural Networks, Ensemble Algorithms (ESM). Among these algorithms, there are Neural Network (NN) methods and Support Vector Machine (SVM) which gather the most number of works carried on demand forecasting. For this reason, this study attempts to complement the research of (Ni et al., 2020), by conducting a more in-depth systematic review of the applications of the 10 most widely used ML algorithms in demand forecasting, in the three main economic sectors: industrial sector, agricultural sector, and service sector.

3. Systematic Review Process

This research focuses on the literature review of past and current applications of machine learning techniques in the field of demand forecasting. In our literature research, we followed the Systematic Literature Review method (SLR), as a well-adapted methodology to searching, classifying and exploring scientific articles from digital databases (Brereton et al., 2007; Kitchenham, 2004). A systematic review is the rigorous and reproducible synthesis of the results of all existing original studies addressing the same research question (Colombet, 2015), it is an in-depth research process that reduces the risk of duplication of articles, making it more efficient than traditional research (Tranfield et al., 2003), SLR generally involves three successive stages: planning, elaboration, and presentation of results. The planning part consists of determining the keywords of the topic being addressed and rephrasing them as a research question, and the digital sources on which we will address our research. The elaboration of the methodology concerns the study of the selected articles which contains the stage of the definitions of the criteria of inclusion and exclusion, and the stage of the Quality Assessment where we must determine Quality assessment questions and finally the stage of extraction of the necessary data for our study. Finally, we have the results part where we present all the results of this systemic study.

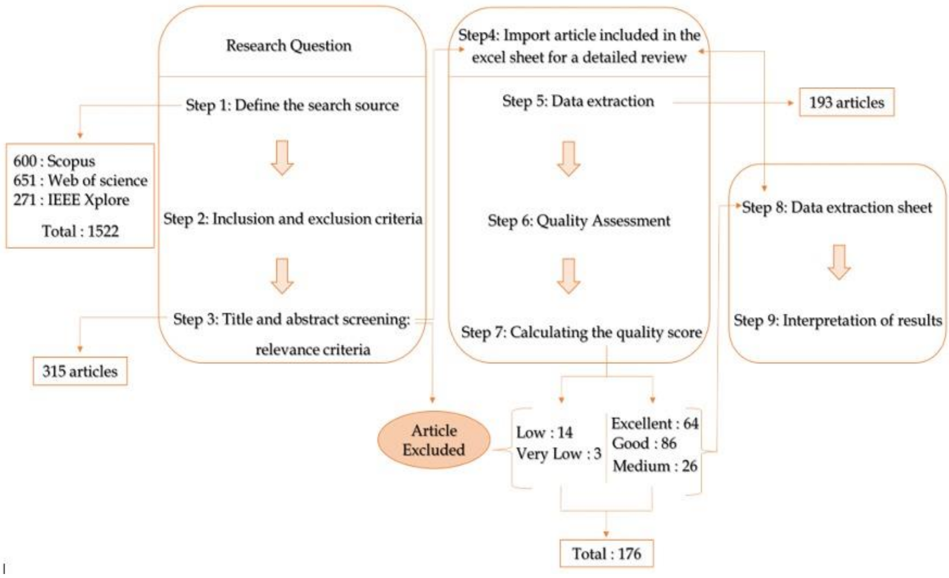

Fig. 1: Stages of review protocol

Applying these steps, the string (machine learning OR linear regression OR neural network Extreme Learning Machine OR Random Forest OR k-nearest Neighbor OR Decision Tree OR Logistic Regression OR K-means OR Naive Bayes Classifier OR Neural Networks OR Support Vector Machine OR Ensemble Algorithms) AND (demand forecasting) was used to retrieve articles from three digital databases Scopus (www.scopus.com) and Web of Science (www.webofscience.com), IEE Xplore (www.ieeexplore. ieee.org). These tree databases are considered among the largest sources of various types of documentations, namely scientific journals, books and conferences, and they allow to dedicate a universal view of the progress of scientific and technological research. The search for articles was limited to the last 10 years, from 2010 to 2020. We limited our query to journals and conferences with a good academic reputation. The first list of articles retrieved from the search strings was 1522 articles, as shown in Figure 1: 600 from Scopus, 651 from Web of Science, and 271 from IEE Xplore as a first selection, and according to our determined inclusion and exclusion criteria we kept 315 articles, then, after downloading the articles, we submitted them to a quality assessment the number of articles becomes 176.

3.1. Justification of the selection process

We refined the selection of studies by reading the titles, abstracts, and keywords. Implementation of the inclusion and exclusion criteria on our first selection reduced the total number to 315 articles.

We defined the following inclusion and exclusion criteria:

3.1.1. Inclusion criteria

The following inclusion criteria was established: (i) journals and conference papers dealing with the intersection of demand forecasting and Machine Learning algorithms, containing the search terms in the title, abstract or keywords (ii) journals and conference papers written in English; (iii) journals and conference papers published since 2010.

3.1.2. Exclusion criteria

For the quality assessment of the study, the following exclusion criteria was defined for: (i) papers using the term machine learning outside of demand forecasting, (ii) papers without evaluation criteria for the forecasting methods used, (iii) papers containing the keywords in the abstract just to present the study context; (iiii) paper without electronic document.

3.1.3. Quality assessment

Quality assessment, is an operation that requires a comprehensive review of the articles selected in the previous steps, there is no universal definition of parameters of the quality of the studies to be followed, but it has been defined by the fact that the biases are the minimum possible and the internal and external validation is maximum (Centre for Reviews & Dissemination, 2001). Distinguishing the studies that answer our research questions (RQ) and supporting the process of inclusion/exclusion are the main reasons for which the quality assessment was carried out. Quality assessment is suggested as a tool to enhance individual work as it allows us to interpret the results obtained and establish comparative analyses, for future research direction in the field of software engineering (Brereton et al., 2007). Following the list proposed by Kitchenham our quality assessment (QA) questions are specified below:

Table 1: Quality assessment questions

No.	Question
QA1	Does the study define the context in which the research was established?
QA2	Are the objectives of the research adequately defined?
QA3	Does the study identify the research questions?
QA4	Is the research plan in line with the research objectives?
QA5	Is the literature review appropriate to the research question?
QA6	Have the supply chain sector and the type of demand to be predicted been well defined?
QA7	Is the source of the data sets indicated?
QA8	Can the data collected address the research question?
QA9	Are the prediction techniques used justified?
QA10	Does the study specify the best performing method?
QA11	Are there clear statements of results and conclusions?
QA12	Are the limitations of the research addressed?
QA13	Is the study useful for research or practice?

Each quality assessment question will be scored according to three possible options: (1) the problem is completely addressed, (0.5) partially addressed, (0) no longer addressed. Then, a quality score will be calculated by summing the scores of the responses on each quality question. The quality assessment of the studies relevant to this research was performed, and disagreements on the results were discussed among the researchers, in order to retain only those with a quality score. The articles are subsequently classified, according to the calculation of scores into four categories: Excellent (12 ≤ score ≤ 13, Good (10,5 ≤ score ≤ 11.5), Medium (9,5 ≤ score ≤ 10), Low (6.5 ≤ score ≤ 9), Very low (4,5 ≤ score ≤ 7).

Table 2: Relevant study quality measurement

Quality level	# Of studies	Percent
Excellent (12 ≤ score ≤ 13)	64	33%
Good (10,5 ≤ score ≤ 11.5)	86	45%
Medium (9,5 ≤ score ≤ 10)	26	13%
Low (6.5 ≤ score ≤ 9)	14	7%
Very low (4,5 ≤ score ≤ 7)	3	2%
Total	193	100%

Following the quality assessment measure, 17 articles with a Low and very Low score were excluded from our final list. We finally end up with 176 qualified articles for the data extraction stage.

3.2. Data extraction

The extraction strategy for the selection of studies, we required that the quality score be higher than 9. Indeed, as shown in Table 2, we believe that the selected studies are of high quality since about 94% (184 out of 193) of the selected studies are of excellent or good or Medium quality level. In order to collect the data we need to answer the research questions of this study, we first examined the content of each article and then designed a form in the form of a card (Table 3) to organize and facilitate the pilot extraction of data. The elements of the table are distinguished (source of publication; year of publication of the article; authors; target industry of the research; type of demand to be forecasted, motivation for the use of machine learning; research method; sample of the experiment; ML methods used; evaluation factors of the chosen forecasting model; impacts and benefits of the application of machine learning on demand forecasting in the targeted domain).

All these elements are classified and grouped, in such a way, to answer each research question. The extracted data were rechecked and discussed among the researchers before filling in the form for each item that will be used later for a data synthesis.

Table 3. Data extraction form

Source of publication Year of publication of the article Authors Sector of activity targeted by the research Type of demand to be predicted Sample of the experiment ML methods used Evaluation factors of the selected forecasting model Impacts of the chosen ML model application on the target domain RQ1: What are the general research trends on applications in demand forecasting? The year of publication of the articles allows us to group them by year which can show us the growth or the decrease of research on ML applications in demand forecasting. RQ2: Which ML algorithms are often used in demand forecasting? ML techniques most appropriate for producing effective demand forecasts RQ3: What are the advantages of ML algorithms compared to traditional approaches? Comparison between ML vs. non-ML models Sample of the experiment strengths of ML algorithms RQ4: Which ML algorithms are considered to be the most effective in demand forecasting? Type of demand to forecast Comparison between ML models RQ5: In which sectors and activities are these ML algorithms frequently used? Target industry of the research Impacts of the application of the selected ML model on the targeted domain

4. Results and Discussion

4.1. General research trends on ML applications in demand forecasting (RQ1)

Fig. 2, shows the trend of papers published over the last ten years on machine Learning and demand forecasting. We observe that there is a remarkable fluctuation in the last three years. The 76 papers published in 2018 and half of 2021 alone accounted for 48% of the total publications over the past ten years. This shows that ML holds more popularity in the SC domain, especially in demand forecasting.

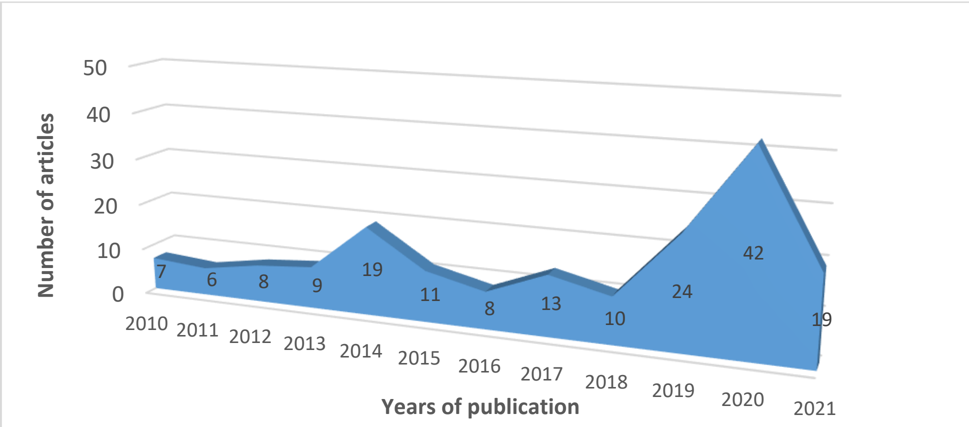

Fig. 2: Number of papers published on machine learning between 2010 and 2021

Fig. 3, presents the evolution of research during the last ten years on ML and SCM on the Internet, according to Google Trends, which is a tool that allows to follow the trends related to a defined topic. We can see that our results are compatible with those of Google Trends, where the frequency of searches on ML has had a significant jump in the last three years.

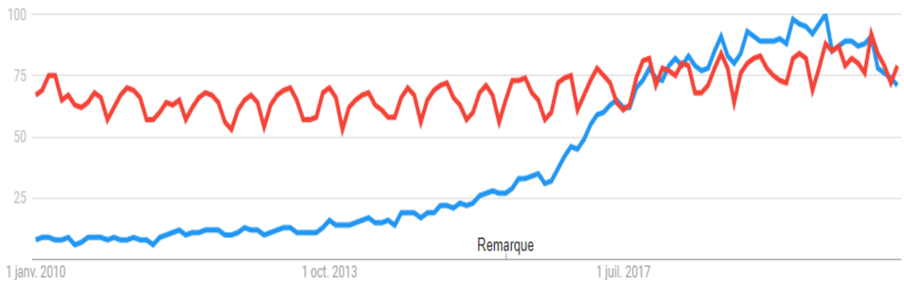

Fig. 3: Google research on the growth of interest in machine learning and supply since 2010

4.2. Identification of frequently used algorithms in demand forecasting (RQ2)

From the selected papers, we identified eleven ML methods that were applied to estimate demand forecasts. They are presented below:

- Artificial Neural Networks (ANN)
- Support Vector Machin (SVM)
- Random Forest (RF)
- Extreme Learning Machine (ELM)
- EXtreme Gradient Boosting (XGBoost)
- k-Nearest Neighbor (K-NN)
- Decision Tree (DT)
- Linear Regression (LR)
- Naïve Bayes Classification (NBC)
- Ensemble learning (ESM)
- Genetic algorithm (AG)

The analysis of the identified papers shows that neural networks and support vector machine are the most used algorithms, with 53% and 21% of the total papers reviewed, which shows the popularity of these algorithms in this field. The other algorithms are between 1% and 5%, however, these algorithms are able to produce good forecasts, but it may simply be due to the lack of popularity for demand forecasting in each of these three areas. The details of research attention to each ML technique over the past decade are presented in Table 4.

Several researchers have tested the demand forecasting performance of these less popular algorithms against the most frequently used ones. For example, (Huang et al., 2019) have compared four learning methods, support vector regression (SVR), extreme machine learning (ELM), EXtreme Gradient Boosting (XGBoost), and linear regression (LR) for energy demand forecasting of residential buildings. The authors have observed that (ELM) provides the best performing results by reducing the error rate on the forecasts. Similarly, (Jin et al., 2020) proposed a hybrid model based on the Kernel extreme learning machine (KELM), variational mode decomposition (VMD), autoregressive moving average (ARMA) model for short-term forecasting of the number of air passengers in Beijing, Guangzhou and Pudong airports. The performance of this model was compared with the hybrid model composed with Support Vector Machine (SVM). The test showed the strength of the Extreme Learning Machine (ELM) based algorithm. As a result, a primordial call is made to researchers in the field of supply chain to give more importance to the less popular machine learning algorithms in the different economic sectors.

4.3. ML algorithms vs traditional approaches (RQ3)

Since ML is a data-driven technique, the construction and the model chosen are based on the nature and size of the data in the ML project. Thus the evaluation of the ML model depends on the dataset. In addition to the dataset the metrics used to measure the accuracy of the ML model must be taken into consideration. There are different metrics for measuring the accuracy of ML methods, so it is important to choose the appropriate metrics to evaluate the performance of the predictions. In this study, the selected studies showed that correlation coefficient, Root Mean Square Error (RMSE), Mean Average Percentage Error (MAPE), and absolute error (MAD) are the most popular evaluation metrics to measure the accuracy and performance of developed models.

Table 4: Summary of publications on machine learning algorithms

Machine Learning Algorithms	Scientific article reference	Number of articles
Artificial Neural Network (ANN)	(Kumar et al., 2020); (Vijai & Sivakumar, 2018) ; (Runge et al., 2020); (Uyar et al., 2016) ; (Liu et al., 2021); (Hošovský et al., 2021) ; (Y.-C. Hu, 2020); (Yi Yang et al., 2016); (Abba & Elkiran, 2017); (Wu et al., 2021) ; (Ofori-Ntow Jnr et al., 2021); (Fu & Chien, 2019); (Hribar et al., 2019); (Sharifzadeh et al., 2019) ; (Szul et al., 2020); (Prado et al., 2020); (Haq et al., 2020); (Kantasa-ard et al., 2020); (Chen et al., 2019); (Gao & Lee, 2019); (Weng et al., 2019); (Dave et al., 2021); (Bedi & Toshniwal, 2018); (Domingos, Ojeme, & Daramola, 2021); (Jintao Ke et al., 2017);(Chong, Han, & Park 2017) ; (Ribeiro et al. 2020); (He 2017); (H. Wang et al. 2018); (Kilimci et al., 2019); (C. Zhang et al., 2020); (Ayub et al., 2020); (G. Zhang et al., 2020); (Nasser et al., 2020); (Sajjad et al., 2020); (Abbasimehr et al., 2020); (J. Liu et al., 2020); (X. Li et al., 2020); (Chang et al., 2011); (Chaturvedi et al., 2015); (C.-F. Chen et al., 2012) ; (Jaramillo-Morán et al., 2013); (Kaytez et al., 2015); (Lau et al, 2013); (H. Li et al., 2013); (P. Li et al., 2014) ; (Lou & Dong, 2015) ; (Lu et al., 2012) ; (Mohammadi et al.,2014) ; (Niu et al., 2012) ; (Romano & Kapelan, 2014) ; (Shahrabi et al., 2013); (Teixeira & Fernandes, 2012); (Unsihuay-Vila et al., 2010); (Venkatesh et al., 2014); (C. Xia et al., 2010) ; (Catal et al., 2015) ; (T. Chen & Wang, 2012) ; (Du et al., 2015) ; (Yadav & Srinivasan, 2011); (Cheng & Wei, 2010); (Kotillova et al., 2012); (Ampazis, 2014); (Shao et al., 2014) ; (Haque et al., 2012); (Daniel et al., 2016) ; (J. Xu et al., 2018) ; (A. Y. Chen et al., 2016) ; (C. Liu et al., 2017); (Slimani et al., 2015); (Sahay et al., 2016); (Marinescu et al., 2014); (Hossen et al., 2018); (Toqué et al., 2017) ; (Ai et al., 2019) ; (Delorme-Costil & Bezian, 2017) ; (Varanasi & Tripathi, 2016); (Ramos-Carrasco et al., 2019); (Ren et al., 2010); (Bejarano-Luque et al., 2021); (UNUTMAZ et al., 2021); (Wanchoo, 2019) ; (Saini et al., 2020) ; (Selvi & Mishra, 2020) ; (Al-Ghamdi et al., 2021) ; (Laaroussi, et al., 2020) ; (Kanavos et al., 2021) ; (Feizabadi, 2020) ; (Livieris et al., 2019) ; (J. Wang & Duggasani, 2020) ; (Y. Xu et al., 2019) ; (Ahmad et al., 2020) ; (Shi, 2020) ; (L. Huang et al., 2021) ; (Chandriah & Naraganahalli, 2021) ; (J.-F. Chen, Lo, &	108

	Do, 2017) ; (Guo et al., 2021) ; (Hamzacebi et al., 2019) ; (Y.-C. Hu et al., 2019) ; (Z. Huang et al., 2019) ; (Chauhan & Hanmandlu, 2010) ; (Ma & Luo, 2021) ; (Bin & Tianli, 2020) ; (Das, 2017) ; (Kankal & Uzlu, 2017); (Shilaja & Arunprasath, 2020); (Ao, 2011); (Germi et al., 2014) ; (Feizabadi, 2020); (Souza, Wanke, & Correa, 2020)	
Support Vector Machin (SVM)	(Al-Musaylh et al., 2018); (Priyadarshi et al., 2019); (Aktepe et al., 2021); (Allawi et al., 2019); (Beyca et al., 2019); (Solyali, 2020); (Jawad et al., 2020); (Abolghasemi et al., 2020); (L.-Y. Chen, 2014) ; (W.-C. Hong et al., 2011) ; (Z. Hu et al., 2014) ; (Lu, 2014) ; (Yeh et al., 2014) ; (X. Yu et al., 2013) ;(W.-C. Hong et al., 2013) ; (Sarhani & El Afia, 2015); (Villegas et al., 2018); (Idowu et al., 2016); (Eseye & Lehtonen, 2020); (Abera & Khedkar, 2020) ; (Bolandnazar et al., 2020); (Y. Fu et al., 2015); (Gonçalves et al., 2021); (Nuaimi, 2014); (Vink et al., 2020); (Y. Wang, 2011); (Qiao et al., 2019) ; (M. S. Li et al., 2015) ; (Xue et al., 2018) ; (Tabrizchi et al., 2021) ; (Vahdani et al., 2016) ; (Fan et al., 2020) ; (Fan et al., 2021)	33
Random Forest (RF)	(Punia et al., 2020); (Johannesen et al., 2019); (Qiu et al., 2017) ; (Herrera et al., 2010) ; (Lahouar & Ben Hadj Slama, 2015) ; (J. Kim et al., 2018) ; (Kang et al., 2017) ; (Yin et al., 2020);	8
Extreme Learning Machine (ELM)	(Jin et al., 2020); (J. Kumar & Singh, 2020) ; (Choi et al., 2014) ; (M. Xia et al., 2012) ; (Y. Huang et al., 2019) ;	5
EXtreme Gradient Boosting (XGBoost)	(Moroff et al., 2021); (Ji et al., 2019) ; (Almaghrebi et al., 2020) ; (Sidhu et al., 2020)	4
k-Nearest Neighbor (K-NN)	(Panagopoulos et al., 2020) ; (Al-Qahtani & Crone, 2013) ;	2
Decision Tree (DT)	(Van Nguyen et al., 2020) ; (Bozkir & Sezer, 2011); (Laik et al., 2014);	3
Linear Regression (LR)	(Zhu et al., 2018); (Merkuryeva et al., 2019); (Amin et al., 2019); (Ciulla & D'Amico, 2019) ; (Demiriz, 2014); (Yandong Yang, 2015); (Francis & Kusiak, 2017); (H. Lee et al., 2014) ; (T. Hong et al., 2010) ; (Akpinar & Yumusak, 2017)	10
Naïve Bayes Classification (NBC)	(Chu, 2014)	1
Ensemble learning (ESM)	(Vanichrujee et al., 2018)	1
Genetic algorithm (AG)	(Ghanbari et al., 2013) ; (Azadeh et al., 2014)	2

The review of the selected papers showed that, based on the evaluation metrics, the researchers demonstrated that machine learning methods can produce better forecasts compared to traditional SCM demand forecasting methods. We can cite, (Hošovský et al., 2021) compared weekly gas demand forecasts produced by traditional ARMA and SARMA models and a genetic algorithm-optimized regression wavelet neural network (REGWANN) ML method, for three buildings with different profiles. The researchers used the daily gas consumption in the three buildings over a five-year period. The researchers showed using the mean absolute error (MAE) measures the superiority of the ML model, then that it allowed the reduction of the error values by 22.6%, 17.7% and 57% for the three buildings. Similarly, (Moroff et al., 2021) who applied two statistical time series forecasting methods namely seasonal auto regressive integrated moving average (SARIMAX), Triple exponential smoothing (ETS) and three ML methods Random Forest (RF), Extreme Gradient Boosting (XGBoost), Long short term memories (LSTM), for forecasting the demand of five products, in the area of industry 4.0, using six years' sales history of each product. The performance of the forecasts is measured using RMSE values, where the ML models produced the most accurate demand forecasts than traditional methods, with even lower error rates for the (LSTM) method. Also, (Lau et al., 2013) applied artificial neural network (ANN) and exponential smoothing and multiple regressions, for gasoline demand forecasting. The researchers used historical monthly gasoline demand in millions of gallons from Ontario from 1960 to 1975. Using the MSE, the researchers showed that the ANN model was able to produce the most optimal forecast.

The advantages of ML algorithms are diverse, such as the ability to learn from a large amount of multidimensional data, the ease of manipulation and the support for decision making in a shorter time compared to traditional approaches. This conclusion has been supported by several studies reported in the literature, where researchers have compared the predictions produced by the ML method and traditional approaches. From our list of selected articles, we can cite: (Gonçalves et al., 2021) automotive electronics assembly product demand, (Moroff, Kurt, & Kamphues, 2021; Ji et al., 2019) E-commerce product demand, (Kantasa-ard et al., 2020) agricultural SC internet network demand, (A. Kumar, Shankar, & Aljohani, 2020) electronic product demand, (Abbasimehr, Shabani, & Yousefi, 2020) furniture demand etc.

Other researchers such as (Fradinata et al. 2019; Jaipuria & Mahapatra 2014) have studied the ability of ML techniques to reduce the bullwhip effect in SCM. The authors confirmed that more accurate predictions produced lower amplification of the bullwhip effect across members of a supply chain.

4.4. Performance comparison between ML algorithms in demand forecasting (RQ4)

The Fig. 3, shows that 61% of the researches done over the last ten years, applied neural networks, followed by the support vector machine algorithm at 19%. This result is consistent with several systemic studies under the same research axis (Aamer, Eka Yani, & Alan Priyatna, 2020; EL Filali et al., 2021; Ni et al., 2020; Bousqaoui et al., 2017).

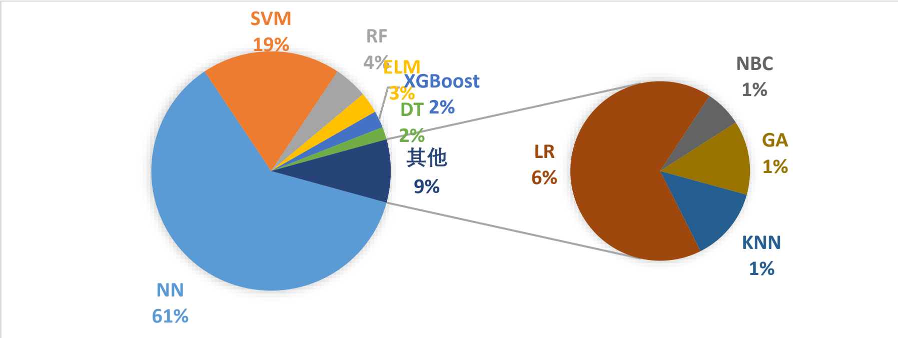

Fig. 3: Distribution of article publications by machine learning method

This can be interpreted by the fact that most researchers use NNs to compare the performance of predictions, such as (Solyali, 2020) who have applied four ML algorithms: artificial neural network (ANN), adaptive neuro-fuzzy inference system (ANFIS), support vector machine (SVM), and multiple linear regression (MLR), on real historical data of electricity consumption in 2016 and 2107, for the electricity demand forecasting in the long and short run. Temperature, humidity, solar irradiation, population, gross national income (GNI) per capita, and electricity price per kilowatt-hour were chosen as the input parameters for the ML algorithms. The results of the long-term and short-term studies show that SVM and ANN are more reliable than other ML methods, however ANN model is the most superior in terms of accuracy. (Sharifzadeh, Sikinioti-Lock, & Shah, 2019), have compared Artificial Neural Networks (ANN), Support Vector Regression (SVR) and Gaussian Process Regression (GPR), for solar, wind and electric energy demand prediction. The authors applied a sensitivity analysis for each algorithm to adjust its parameters and obtain the most optimal results. All models were able to produce good predictions of solar and wind energy demand, but only the neural network method was able to predict electricity demand. Similarly for (Hribar et al., 2019) have compared the residential natural gas demand forecast of an urban area produced by : Linear regression (LR), Recurrent neural networks (ANN) and the extreme learning machine. The results show that accuracy is much higher when the model learns the forecasted weather data and Recurrent Neural Networks (ANN) were found to be the best performers for demand forecasting in this energy sector. Other researchers have compared the forecasts produced by the artificial neural network (ANN) algorithm versus the support vector machine (SVM), as in the paper by (Abera & Khedkar, 2020), the authors have applied both algorithms to forecast the electrical demand of individual household electronics, and they showed that the SVM provided more accurate and much better forecasting results than previous work in the same area. Similarly, for (Beyca et al., 2019) who applied multiple linear regression (MLR), artificial neural network (ANN) and support vector regression (SVR) for natural gas demand forecasting, in the largest natural gas consuming megacity Istanbul province in Turkey. The results showed that SVR provided the most reliable and accurate results compared to ANN technique. Other researchers have chosen to combine NN with other statistical or ML models in order to further improve forecasting performance, as in the case of (Barzegar et al., 2020; Sajjad et al., 2020; J. Ke et al., 2017; Ayub et al., 2020; Mohammadi et al., 2014). The unbalanced distribution of ML algorithms, is common for items from all databases used in this study, as stated (Ni et al., 2020; Bousqaoui et al., 2017). Other algorithms have just appeared, such as ELM which is frequently used for decision support in the financial domain (M.-J. Kim, 2012), nevertheless, it is little applied in the SCM domain, this can be translated by the ambiguity carried on these algorithms regarding the over-interpretation of data which can cause catastrophic results in this domain. In general, in answering question 4, the analysis of our study confirms that NNs are the most appropriate methods to produce efficient demand forecasts in the SCM domain.

4.5. ML models by economic sector and ML application area (RQ5)

Table 5, contains a total of 176 articles identified through our systematic search. Each article is classified according to the field of application of the supply chain, and affected to one of three sectors of economic activity, namely, the industry sector, the service sector and the agriculture sector. In order to give a global view of the economic sectors and under sectors most benefited by the applications of new technologies.

Table. 5. Distribution of articles by sector of activity and Machine Learning algorithm used

Machine Learning Algorithm	Reference	Total articles	% algorithm	% Sub-sector	% Sector
Industry sector					66%
Residential gas demand		5		4%	
Artificial Neural Network (ANN)	(Hribar et al., 2019); (Hošovský et al., 2021)	2	40%		
Support Vector Machine (SVM)	(Beyca et al., 2019) ; (Qiao et al., 2019)	2	40%		
Linear Regression (LR)	(Akpinar & Yumusak, 2017)	1	20%		
Crude oil demand		1		1%	
Artificial Neural Network (ANN)	(Shao et al., 2014)	1	100%		

Water demand		12		10%	
Artificial Neural Network (ANN)	(Vijai et al., 2018) ; (Nasser et al., 2020); (Romano & Kapelan, 2014); (Delorme-Costil & Bezian, 2017) ; (Ren et al., 2010); (Al-Ghamdi et al., 2021) ; (Y. Xu et al., 2019) ; (Chen et al., 2019) ;	8	67%		
Support Vector Machine (SVM)	(Allawi et al., 2019)	1	8%		
Random Forest (RF)	(Herrera et al., 2010) ;	1	8%		
XGBoost	(Sidhu, Kumar, & Rana, 2020)	1	8%		
Electricity demand		48		41%	
Artificial Neural Network (ANN)	(Runge et al., 2020) ; (Yang et al., 2016) ; (Ofori-Ntow Jnr et al., 2021) ; (Wang et al., 2018) ; (Ayub et al.,2020); (Chang et al., 2011); (Chaturvedi et al., 2015); (Jaramillo-Morán et al., 2013); (Kaytez et al., 2015); (Li et al., 2013); (Li et al., 2014); (Lou & Dong, 2015); (Niu et al., 2012); (Unsihuay-Vila et al., 2010); (Xia et al., 2010); (Yadav & Srinivasan, 2011); (Kotillova et al., 2012); (Sarhani & El Afia, 2015); (Haque et al., 2012); (Sajjad et al., 2020); (Daniel et al., 2016) ; (Bedi & Toshniwal, 2018) ; (C. Liu et al., 2017); (Sahay et al.,2016); (Marinescu et al., 2014); (Hossen et al., 2018); (Selvi & Mishra, 2020) ; (J.-F. Chen et al., 2017) ; (Hamzacebi et al., 2019) ; (Chauhan & Hanmandlu, 2010) ; (Germi et al., 2014);	31	65%		
Support Vector Machine (SVM)	(Al-Musaylh et al., 2018); (Solyali, 2020);(Hu et al., 2014); (Hong et al., 2013); (Fu et al., 2015); (Jawad et al., 2020); (Vink et al., 2020); (M. S. Li et al., 2015) ; (Fan et al., 2020) ; (Villegas et al.,2018);	10	21%		
Linear Regression (LR)	(Zhu et al.,2018) ; (T. Hong et al., 2010) ; (Lee et al., 2014)	3	6%		
k-Nearest Neighbor (K-NN)	(Al-Qahtani & Crone, 2013)	1	2%		
Random Forest (RF)	(Lahouar & Ben Hadj Slama, 2015); (Yin et al., 2020);	2	4%		
Algorithme génétique	(Azadeh et al., 2014)	1	2%		
Energy demand				25%	
Artificial Neural Network (ANN)	(Sharifzadeh et al., 2019) ; (Szul et al., 2020) ; (Prado et al., 2020) ; (Ribeiro et al., 2020) ; (Zhang et al., 2020) ; (G. Zhang et al., 2020) ; (Yeh et al., 2014) ;	17	59%		

	(Chen & Wang, 2012); (Cheng & Wei, 2010); (Haq et al., 2020); (He, 2017); (Ai, et al., 2019) ; (Varanasi & Tripathi, 2016); (UNUTMAZ et al., 2021); (Ahmad et al., 2020) ; (Kankal & Uzlu, 2017); (Shilaja & Arunprasath, 2020); (Das, 2017)				
Support Vector Machine (SVM)	(Abera & Khedkar, 2020); (Eseye & Lehtonen, 2020) ; (Tabrizchi et al.,, 2021) ; (Idowu et al., 2016)	4	14%		
XGBoost	(Almaghrebi et al., 2020)	1	3%		
Random Forest (RF)	(X. Qiu et al., 2017) ; (Johannesen et al., 2019)	2	7%		
Extreme Learning Machine (ELM)	(Huang et al., 2019)	1	3%		
k-Nearest Neighbor (K-NN)	(Panagopoulos et al., 2020)	1	3%		
Algorithme génetique	(Ghanbari et al., 2013)	1	3%		
Linear Regression (LR)	(Ciulla & D'Amico, 2019) ; (Amin et al., 2019)	2	7%		
dry freight demand		1		1%	
Artificial Neural Network (ANN)	(Uyar et al., 2016)	1	100%		
Magnesium material demand		1		1%	
Artificial Neural Network (ANN)	(Hu, 2020)	1	100%		
Oxygen demand of the wastewater treatment plant		1		1%	
Artificial Neural Network (ANN)	(Abba & Elkiran, 2017)	1	100%		
Semi-conductor demand		1		1%	
Artificial Neural Network (ANN)	(Fu & Chien, 2019)	1	100%		
Goods demand		1		2%	
Artificial Neural Network (ANN)	(Weng et al., 2019) ; (Feizabadi, 2020)	2	100%		
Furniture demand		1		1%	
Artificial Neural Network (ANN)	(Abbasimehr et al., 2020)	1	100%		
Aircraft spare engines demand		1		1%	
Artificial Neural Network (ANN)	(Liu et al., 2020)	1	100%		
Construction machinery spare parts		3		3%	
Linear Regression (LR)	(Francis & Kusiak, 2017)	1	33%		
Random Forest (RF)	(J. Kim, Lee, & Choi, 2018)	1	33%		
Support Vector Machine (SVM)	(Aktepe et al., 2021)	1	33%		
Pharmaceutical products demand		1		1%	

Linear Regression (LR)	(Merkuryeva et al., 2019)	1	100%		
Beauty Demand		1		1%	
Fuzzy inference system	(Souza et al., 2020)	1	100%		
Automobile electronic assembly products demand		2		2%	
Linear Regression (LR)	(Gonçalves et al., 2021)	1	50%		
Artificial Neural Network (ANN)	(Chandriah & Naraganahalli, 2021)	1	50%		
Clothing industry demand		5		4%	
Artificial Neural Network (ANN)	(Kilimci et al., 2019); (Liu et al., 2021); (Du et al., 2015)	3	60%		
Extreme Learning Machine (ELM)	(Choi et al., 2014); (Xia et al., 2012)	2	40%		
Cosmetic product demand		1		1%	
Support Vector Machine (SVM)	(Vahdani, Razavi, & Mousavi, 2016)	1	100%		
Workload demand		1		1%	
Extreme Learning Machine (ELM)	(Kumar & Singh, 2020)	1	100%		
Agriculture sector		4			2%
Energy demand in agriculture		2		50%	
Artificial Neural Network (ANN)	(Saini et al., 2020)	1	50%		
Support Vector Machine (SVM)	(Bolandnazar et al., 2020)	1	50%		
Agricultural product demand		1		25%	
Support Vector Machine (SVM)	(Priyadarshi et al.,2019)	1	100%		
Physical Internet networks of the agricultural SC demand		1		25%	
Artificial Neural Network (ANN)	(Kantasa-ard et al., 2020)	1	100%		
Services Sector					32%
Transport demand				18%	
Artificial Neural Network (ANN)	(Wu et al., 2021); (Gao & Lee, 2019); (J. Xu et al., 2018); (A. Y. Chen et al., 2016) ; (Toqué et al., 2017) ; (Vanichrujee et al., 2018) ; (Bejarano-Luque et al., 2021); (Z. Huang et al., 2019)	8	80%		
Random Forest (RF)	(Kang et al., 2017)	1	10%		
Linear Regression (LR)	(Yandong Yang, 2015)	1	10%		
Newspaper/magazine demand		1		2%	
Support Vector Machine (SVM)	(Yu et al., 2013)	1	100%		
Passenger demand		7		12%	

Artificial Neural Network (ANN)	(Ke et al., 2017); (Li et al., 2020) ; (Laaroussi et al., 2020) ; (Kanavos et al. 2021)	4	57%		
Extreme Learning Machine (ELM)	(Jin et al., 2020)	1	14%		
Support Vector Machine (SVM)	(Wang, 2011)	1	14%		
Decision Tree (DT)	(Laik et al., 2014)	1	14%		
online movie rental demand		1		2%	
Artificial Neural Network (ANN)	(Ampazis, 2014)	1	100%		
E-commerce product demand		4		7%	
Artificial Neural Network (ANN)	(Lau et al.,2013) ; (Ao, 2011)	2	50%		
XGBoost	(Moroff et al., 2021) ; (Ji et al., 2019)	2	50%		
Food products demand		1		2%	
Support Vector Machine (SVM)	(Abolghasemi et al., 2020)	1	100%		
Tourism demand		7		18%	
Artificial Neural Network (ANN)	(Chen et al., 2012); (Shahrabi et al., 2013); (Teixeira & Fernandes, 2012); (Ramos-Carrasco et al. 2019); (Livieris et al., 2019) ; (Shi, 2020) ; (Y.-C. Hu et al., 2019)	7	70%		
Support Vector Machin (SVM)	(Hong et al., 2011); (Fan et al., 2021)	2	20%		
Classificateur Naive Bayes (NBC)	(Chu, 2014)	1	10%		
Future export demand				4%	
Artificial Neural Network (ANN)	(Dave et al., 2021); (Bin & Tianli, 2020)	2	100%		
Retail demand		5		9%	
Random Forest (RF)	(Punia et al., 2020)	1	20%		
Neural Network (NN)	(Slimani et al., 2015); (Wanchoo, 2019), (Feizabadi, 2020)	2	40%		
Support Vector Machine (SVM)	(Xue et al., 2018)	1	20%		
Linear Regression (LR)	(Demiriz, 2014)	1	20%		
Electronic Product demand		5		9%	
Decision Tree (DT)	(Van Nguyen et al., 2020)	1	20%		
Support Vector Machine (SVM)	(Chen, 2014); (Lu, 2014)	2	40%		
Artificial Neural Network (ANN)	(Lu et al., 2012);(Kumar et al., 2020)	2	40%		
Food demand		4		7%	
Decision Tree (DT)	(Bozkir and Sezer, 2011)	1	25%		
Artificial Neural Network (ANN)	(L. Huang et al., 2021) ; (Guo et al., 2021) ; (Ma & Luo, 2021)	3	75%		

Hotel reservation demand				2%	
Artificial Neural Network (ANN)	(J. Wang & Duggasani, 2020)	1	100%		
Healthcare Service Demand				2%	
Support Vector Regression (SVR)	(Nuaimi, 2014)	1	100%		
Emergency items demand				2%	
Artificial Neural Network (ANN)	(Mohammadi et al.,2014)	1	100%		
cash demand at ATMs		3		5%	
Artificial Neural Network (ANN)	(Venkatesh et al., 2014); (Catal et al., 2015); (Domingos et al., 2021) ;	3	100%		
stock market demand		1		2%	
Artificial Neural Network (ANN)	(Chong et al., 2017)	1	100%		
Total		176			100%

The results of our analysis as shown in Table 5, shows that (66%) of the research works on ML applications for demand forecasting are concentrated in the industrial sector, where electricity and energy demand forecasting hold more importance in the industrial sector with (41%) and (25%), respectively. Followed by water forecasting (10%) and clothing industry demand (4%), residential gas demand (4%), construction machinery spare parts (3%).However, a small number of papers studied the demand forecast of pharmaceutical industry (1%), automotive industry (2%), Beauty demand (1%), Cosmetic product demand (1%) and Workload demand (1%). According to (Ni, Xiao, & Lim 2020), the lack of appropriate and sufficient data needed for the success of these applications, ambiguity on the guidelines to be followed by CS practitioners allowing the selection of appropriate ML methods in order to improve demand forecasting, are among the main factors for the low applications of ML in companies in the industrial domain. ANNs are the most used algorithms in the industrial sector, over the last ten years, with a percentage of 60%, followed by SVM algorithms (17%) .This result is consistent with several systemic studies under the same research axis (Aamer, Eka Yani, & Alan Priyatna, 2020; Ni, Xiao, & Lim, 2020).

The service sector is in second place with a percentage of 32%, due to the increase in mobile technologies, excessive use of the Internet and online services. The service sector occupies the second place with a percentage of 42%, due to the increase of mobile technologies, excessive use of the Internet and online services. We can find more ML applications for demand forecasting in tourism 18%, transportation 25%, e-commerce products 8%, electronic products 13%, cash demand in ATMs 8%, and retail 5%. As in the industrial sector, ANN algorithms are among the most used with a percentage of 65%, there are also regression algorithms 44% such as support vector regression 16%, decision tree (DT) (5%)and Random forest 4% which have also been used for supervised and unsupervised demand forecasting in the service sector, This is due to the development of technologies that allow the collection of data retrieved through various tools, websites and connected objects and online applications used by customers, allowing the aggregation of sales history according to the categories of purchases made.

The results of our analysis showed that there is only 2% of research work in the field of ML in the Agriculture sector. This is an alarming figure in this important sector due to the low use of new technologies in the agricultural industry, this calls for researchers and supply chain practitioners to take advantage of the benefits of ML techniques for demand forecasting to improve the agricultural sector.

4.6. Research challenges and future research directions

Our study contributes to an in-depth investigation of the applications of ML techniques in SCM and more specifically in demand forecasting in three leading economic sectors: industrial, agricultural and service sectors. 176 articles were retrieved from three digital databases, Scopus, Web of Science and IEE Xplore, and then divided according to the year of publication, the ML method applied and the application domain.

Although we were able to answer the research questions as expected, the study has some limitations. First, only three databases were taken as sources. It is likely that there are other relevant articles to consider. For this reason, other academic databases should be included. Second, the 10 ML algorithms considered in this study are based on the systemic review established by (Ni al., 2020) in the field of SCM, there might be other low frequency ML algorithms in SCM, but they might be really useful for SCM. To this end, the list of algorithms should be updated regularly. Third, based on our systemic study, one of the trends of ML applications in forecasting is the dominance of neural network methods in 61% of the applications, this could be due to the ability of neural networks to produce more accurate forecasts compared to other algorithms such as linear regression (LR) and decision tree (DT). This result does not imply the ultimate superiority of neural networks, it all depends on the nature of the data to be processed and the context of the application (Goodfellow, Bengio, & Courville, 2016). 66% of the analyzed works were found in the industrial sector, 41% between these applications were concentrated in the field of electricity and very low publications in the automotive industry 2%, and the pharmaceutical industry 1%. The service sector occupies 32% of the publications and very low applications in the agricultural sector 2%. This number is alarming for an important sector such as agriculture. It is therefore necessary to call on researchers to deepen research in the SCM of the agricultural sector, as this is necessary for the economic development of countries.

From our analysis, most of the works have established comparison applications between ML methods with each other’s or with statistical methods, in order to show the performance of ML techniques without proposing a strategy for integrating these techniques in the real world or studying the effects of these applications on the effectiveness of SCM. (Kilimci et al., 2019) are the only ones who have proposed an actual strategy for including a deep learning model in SCM.

Considering the disruption of the global economy and supply chain due to the COVID-19 pandemic, and drought, research in SCM should also be conducted in the service sector, and in the pharmaceutical and water industry to establish effective and transparent collaborative forecasting and replenishment strategies along the supply chain.

5. Conclusion

This study adopted a systematic review of recent trends in ML applications in SCM to answer the five research questions presented at the beginning of this study. The research articles in this study published in the last ten years were searched in three major academic databases: Scopus, Web of Science, and IEE Xplore. As a result, 176 articles were selected and closely analyzed. The result of the analysis showed that ML applications in SCM have experienced a remarkable increase in the last three years, and these methods have demonstrated their capabilities to provide more accurate forecasts at lower costs compared to traditional demand forecasting approaches. The distribution of papers by type of ML algorithm applied, showed a remarkable imbalance among the 10 frequently used ML algorithms in the SCM field. Neural network methods are the most dominant in 61% of the articles studied, followed by SVMs 33%. Similarly, the industrial sector receives the most attention from machine learning researchers where electricity and energy demand forecasting occupy a more important place with (41%) and (25%) respectively in this sector, while 4% of research was devoted to the automotive industry and 1% to the pharmaceutical industry. The service sector has the second largest number of applications with 32%, while the agricultural sector has the lowest number of searches (2%). We believe that machine learning can play an important role in improving efficiency throughout the supply chain of organizations. For this reason, this seminal study, can be a reference of what has been done in the three economic sectors for researchers and policy makers to move from statistical methods to ML methods to improve SCM efficiency for the three economic sectors.

Table 6: Quality score of studies

Reference	QA1	QA2	QA3	QA4	QA5	QA6	QA7	QA8	QA9	QA10	QA11	QA12	QA13	Total score
(Kaytez *et al.*, 2015)	1	1	0	1	1	1	1	1	0.5	1	0.5	0	1	10
(Lau *et al.*, 2013)	1	1	0	1	1	1	1	1	1	1	1	1	1	12
(Li *et al.*,2013)	1	1	0	1	1	1	1	1	1	1	1	1	1	12
(Li *et al.*, 2014)	1	1	0	1	1	1	1	1	1	1	1	1	1	12

(Lou & Dong, 2015)	1	1	0	1	1	1	1	0.5	0.5	0.5	1	0	1	9.5
(Lu *et al.*, 2012)	1	1	1	1	1	1	1	1	1	1	1	1	1	13
(Lu, 2014)	1	1	0	1	1	1	1	1	1	1	1	0	1	11
(Mohammadi *et al.*, 2014)	1	1	0	1	1	1	1	1	1	1	1	0	1	11
(Niu *et al.*, 2012)	1	0.5	0	1	1	1	1	1	1	1	1	0	0.5	10
(Romano & Kapelan, 2014)	1	1	1	1	1	1	1	1	1	1	1	1	1	13
(Shahrabi *et al.*, 2013)	1	1	1	1	1	1	1	1	1	1	1	1	1	13
(Teixeira & Fernandes, 2012)	1	1	1	1	0.5	1	1	0	0.5	1	1	0	0.5	9.5
(Unsihuay-Vila *et al.*, 2010)	1	1	0	0.5	1	1	1	1	1	1	1	0	1	10,5
(Venkatesh *et al.*, 2014)	1	1	0	1	1	1	1	1	1	1	1	0	1	11
(Xia *et al.*, 2010)	1	1	0	1	1	0.5	1	1	1	1	1	0	1	10,5
(Xia *et al.*, 2012)	1	1	0	1	1	1	1	1	1	1	1	1	1	12
(Yandong Yang, 2015)	1	1	0	1	1	1	1	1	1	1	1	0	1	11
(Yeh *et al.*, 2014)	1	1	0	1	0	1	1	1	1	1	1	0	1	11
(Yu *et al.*, 2013)	1	1	0	0.5	1	1	1	0.5	0.5	1	1	0	1	9.5
(Bakker *et al.*, 2013)	1	1	0	0.5	0.5	1	1	1	1	0.5	0.5	0	1	9
(Catal *et al.*, 2015)	1	1	0	0.5	1	1	1	1	1	1	1	0.5	1	11
(Chen & Wang, 2012)	1	1	0	1	1	1	1	0.5	1	1	1	0.5	1	11
(Du *et al.*, 2015)	1	1	0	1	1	1	1	1	1	1	1	1	1	12
(Ghanbari *et al.*, 2013)	1	1	0	1	1	1	1	1	1	1	1	1	1	12
(Hassan *et al.*, 2015)	0.5	0.5	0	1	1	1	1	0.5	1	1	0.5	0	0.5	8.5
(Hong *et al.*, 2013)	1	1	0	0.5	1	1	1	1	1	1	1	1	1	11.5
(Joseph & Larrain, 2012)	1	0.5	0	0.5	0.5	1	1	1	0.5	1	1	0	1	9
(Yadav & Srinivasan, 2011)	1	1	0	1	1	1	1	1	1	1	1	1	1	12
(Cheng & Wei, 2010)	1	1	0	1	1	1	1	1	1	1	1	0	1	11
(Hassan, *et al.*, 2013)	1	0.5	0	0.5	1	1	1	1	1	1	1	0.5	1	10.5

(Kotillova, *et al.*, 2012)	1	0.5	0	0.5	1	0.5	1	1	0.5	1	1	0.5	1	9.5
(Sarhani and El Afia, 2015)	1	1	0	1	1	1	1	0.5	1	1	1	0	1	10,5
(Abba & Elkiran, 2017)	1	1	0	0.5	0.5	1	1	0.5	1	1	1	0	1	9.5
(Abbasimehr, *et al.*, 2020)	1	1	0	1	1	1	1	1	1	1	1	1	1	12
(Abera & Khedkar, 2020)	1	1	0	1	1	1	1	1	1	1	1	0	1	11
(Abolghasemi *et al.*, 2020)	1	1	0	1	1	1	1	1	1	1	1	0	1	11
(Ahmad & Chen, 2019)	1	1	0	0.5	1	1	0.5	0.5	1	0.5	0.5	0	1	8.5
(Aktepe *et al.*, 2021)	1	1	0	1	1	1	1	1	1	1	1	0.5	1	11.5
(Allawi *et al.*, 2019)	1	1	0	1	1	1	1	1	1	1	1	1	1	12
(Almaghrebi *et al.*, 2020)	1	1	1	1	1	1	1	1	1	1	1	1	1	13
(Al-Musaylh *et al.*, 2018)	1	1	0	1	1	0	1	1	1	1	1	1	1	12
(Al-Qahtani & Crone, 2013)	1	1	0	0.5	1	0	1	1	1	1	1	1	1	11.5
(Amin *et al.*, 2019)	1	1	0	0.5	1	0	1	1	1	1	0.5	1	1	10
(Ampazis, 2014)	1	1	0	1	1	1	1	1	1	1	1	0	1	11
(Ayub *et al.*, 2020)	1	1	0	1	1	1	1	1	1	1	1	0.5	1	11.5
(Azadeh *et al.*, 2014)	1	1	0	1	1	1	1	1	1	0.5	1	0	1	10.5
(Bedi & Toshniwal, 2018)	1	1	0	1	1	1	1	1	1	1	1	0.5	1	11.5
(Beyca *et al.*, 2019)	1	1	0	1	1	1	1	1	1	1	1	0	1	11
(Bolandnazar, *et al.*, 2020)	1	1	0	1	1	1	1	1	1	1	1	0	1	11
(Bozkir and Sezer, 2011)	1	1	0	1	0.5	0.5	0.5	1	0.5	1	1	1	1	10
(Boriratrit *et al.*, 2018)	1	1	0	1	1	0.5	0	1	0	0	1	0	1	7.5
(Cankurt, 2016)	1	1	0	1	0	0.5	1	0.5	0	0	1	0	1	7
(Chang *et al.*, 2011)	1	1	0	1	1	1	1	1	1	0.5	1	0.5	1	11
(Chaturvedi, *et al.*, 2015)	1	1	0	1	1	1	1	1	1	1	1	0	1	11
(Chen *et al.*, 2012)	1	1	0	1	1	1	1	1	1	1	1	0	1	11

(Chen et al. 2019)	1	1	0	1	1	1	1	1	1	1	1	0	1	11
(Chen, 2014)	1	1	0	1	1	1	1	1	1	1	1	0.5	1	11.5
(Choi *et al.*, 2014)	1	1	0	1	1	1	1	1	1	1	1	1	1	12
(Chong *et al.*, 2017)	1	1	0	1	1	1	1	1	1	1	1	0	1	11
(Chu, 2014)	1	1	0	1	1	1	1	1	1	1	1	1	1	12
(Ciulla & D'Amico, 2019)	1	1	0	1	1	1	1	1	1	1	1	1	1	12
(Dave *et al.*, 2021)	1	1	0	0.5	1	0.5	1	1	1	1	1	1	1	11
(Demiriz, 2014)	1	1	0	1	0.5	1	1	1	0.5	1	1	0	1	10
(Domingos, *et al.*, 2021)	1	1	0	1	1	1	1	1	1	1	1	1	1	12
(Eseye & Lehtonen, 2020)	1	1	0	1	1	1	1	1	1	1	1	1	1	12
(Francis & Kusiak, 2017)	1	1	0	1	1	1	1	1	1	1	1	1	1	12
(Fu & Chien, 2019)	1	1	0	1	1	1	1	1	1	1	1	1	1	12
(Fu *et al.*, 2015)	1	1	0	1	1	1	1	1	1	1	1	0	1	11
(Gao & Lee, 2019)	1	1	0	1	1	1	1	1	1	1	1	0	1	11
(Gonçalves *et al.*, 2021)	1	1	0	1	1	1	1	1	1	1	1	1	1	12
(Guo *et al.*, 2017)	0.5	1	0	1	0.5	0.5	0.5	1	1	1	1	0	0.5	8.5
(Haq *et al.*, 2020)	1	1	0	1	0.5	1	0.5	0.5	1	1	1	1	1	10.5
(Haque et al. 2012)	1	1	0	1	0.5	1	0.5	1	1	1	1	0	1	10
(He, 2017)	1	1	0	1	0.5	1	1	1	1	0.5	1	0	1	10.5
(Herrera *et al.*, 2010)	1	1	0	1	1	1	1	1	1	1	1	1	1	12
(Hong *et al.*, 2011)	1	1	0	1	1	1	1	1	1	1	1	1	1	12
(Hošovský *et al.*, 2021)	1	1	0	1	1	1	1	1	1	1	1	0	1	11
(Hribar *et al.*, 2019)	1	1	0	1	1	1	1	1	1	1	1	0	1	11
(Hu, 2020)	1	1	0	1	1	1	1	1	1	1	1	0	1	11
(Hu *et al.*, 2014)	1	1	0	1	1	1	1	1	1	1	1	0	1	11
(Huang *et al.*, 2019)	1	1	0	1	1	1	1	1	1	1	1	0	1	11
(Idowu *et al.*, 2016)	1	1	0	1	1	1	1	1	1	1	1	0	1	11

(Jaramillo-Morán, *et al.*, 2013)	1	1	0	1	1	1	1	1	1	1	1	0	1	11
(Jawad *et al.*, 2020)	1	1	0	1	1	1	1	1	1	1	1	1	1	12
(Ji *et al.*, 2019)	1	1	0	1	1	1	1	1	1	1	1	1	1	12
(Jin *et al.*, 2020)	1	1	0	1	1	1	1	1	1	1	1	1	1	12
(Johannesen, *et al.*, 2019)	1	1	0	1	1	1	1	1	1	1	1	1	1	12
(Kantasa-ard *et al.*, 2020)	1	1	0	1	1	1	1	1	1	0.5	0.5	0	1	10
(Ke *et al.*, 2017)	1	1	0	1	1	1	1	1	1	1	1	0.5	1	11.5
(Kilimci *et al.*, 2019)	1	1	0	1	1	1	1	1	1	1	1	1	1	12
(Kumar *et al.*, 2020)	1	1	0	1	1	1	1	1	1	1	1	1	1	12
(Kumar & Singh, 2020)	1	1	0	1	1	1	1	1	1	1	1	0	1	11
(Lahouar & Ben Hadj Slama, 2015)	1	1	0	1	1	1	1	1	1	1	1	1	1	12
(Laik, *et al.*, 2014)	1	1	0	0.5	0.5	1	1	1	1	0.5	1	0	1	9.5
(Lee *et al.*, 2014)	1	1	0	1	1	1	1	1	1	1	1	0.5	1	11.5
(Li *et al.*, 2020)	1	1	0	1	1	1	1	1	1	1	1	0.5	1	11,5
(Liu *et al.*, 2020)	1	1	0	1	1	1	1	1	1	1	1	1	1	12
(Liu *et al.*, 2021)	1	1	0	1	1	1	1	1	1	1	1	1	1	12
(Merkuryeva *et al.*, 2019)	1	1	0	1	1	1	1	1	1	1	1	1	1	12
(Moroff *et al.*, 2021)	1	1	1	1	1	1	1	1	1	1	1	1	1	13
(Nasser *et al.*, 2020)	1	1	0	1	1	1	1	1	1	1	1	0	1	11
(Nuaimi, 2014)	1	1	0	1	1	1	1	1	1	1	1	0.5	1	11.5
(Ofori-Ntow Jnr, Ziggah, & Relvas 2021	1	1	0	1	1	1	1	1	1	1	1	1	1	12
(Ozerdem *et al.*, 2017)	1	0.5	0	0.5	0.5	0.5	1	1	1	1	1	0	1	9
(Panagopoulos *et al.*, 2020)	1	1	0	1	1	0.5	1	1	1	1	1	0	1	10.5
(Prado *et al.*, 2020)	1	1	0	1	1	1	1	1	1	1	1	1	1	12
(Priyadarshi *et al.*, 2019)	1	1	0	1	1	1	1	1	1	1	1	1	1	12

(Punia *et al.*, 2020)	1	1	0	1	1	1	1	1	1	1	1	1	1	12
(Qiu *et al.*, 2017)	1	1	0	0.5	1	1	1	0.5	1	1	1	1	1	11
(Ribeiro *et al.*, 2020)	1	1	0	1	1	1	1	1	1	1	1	1	1	12
(Runge *et al.*, 2020)	1	1	0	1	1	1	1	1	1	1	1	1	1	12
(Solyali, 2020)	1	1	0	1	1	1	1	1	1	1	1	1	1	12
(Sharifzadeh, *et al.*, 2019)	1	1	0	1	1	1	1	1	1	1	1	1	1	12
(Sajjad *et al.*, 2020)	1	1	0	1	1	1	1	1	1	1	1	1	1	12
(Szul *et al.*, 2020)	1	1	0	1	1	1	1	1	1	1	1	1	1	12
(Shao *et al.*, 2014)	1	1	0	1	1	1	1	1	1	1	1	1	1	12
(Uyar *et al.*, 2016)	1	1	0	1	1	1	1	1	1	1	1	0	1	11
(Vijai & Bagavathi Sivakumar, 2018)	1	1	0	1	1	1	1	1	0.5	0.5	1	0	1	10
(Villegas *et al.*, 2018)	1	1	0	1	1	1	1	1	1	1	1	1	1	12
(Vhatkar & Dias, 2016)	0.5	0.5	0	1	1	1	1	1	1	0.5	0.5	0	0	8
(Van Nguyen, 2020)	1	1	0	1	1	1	1	1	1	1	1	1	1	12
(Vink *et al.*, 2020)	1	1	0	1	1	1	1	1	1	1	1	1	1	12
(Wang *et al.*, 2018)	1	1	1	1	1	1	1	1	1	1	1	1	1	13
(Weng *et al.*, 2019)	1	1	1	1	1	1	1	1	1	1	1	1	1	13
(Wu *et al.*, 2021)	1	1	1	1	1	1	1	1	1	1	1	0	1	12
(Wang, *et al.*, 2015)	1	0.5	0	0	0.5	1	1	1	0.5	0.5	1	0	1	8
(Wang, 2011)	1	1	0	0.5	0.5	1	1	1	1	1	1	0	1	10
(Yang *et al.*, 2016)	1	1	0	1	1	1	1	1	1	1	1	1	1	12
(Yin *et al.*, 2020)	1	1	0	1	1	1	1	1	1	1	1	0	1	11
(Zhu *et al.*, 2018)	1	1	0	1	1	1	1	1	1	1	1	1	1	12
(G. Zhang *et al.*, 2020)	1	1	0	1	1	1	1	1	1	1	1	0	1	11
(Zhang *et al.*, 2020)	1	1	0	1	1	1	1	1	1	1	1	1	1	12
(Daniel, Kasun, & Milos 2016)	1	1	0	1	1	1	1	1	1	1	0.5	0	1	10.5

(J. Xu et al. 2018)	1	1	0	1	1	1	1	1	1	1	1	1	1	12
(T. Hong et al. 2010)	1	0	0	1	1	1	1	1	1	1	1	0.5	1	10.5
(A. Y. Chen et al. 2016)	1	1	1	1	1	1	1	1	1	1	1	1	1	13
(Qiao et al. 2019)	1	1	0	1	1	1	1	1	1	1	1	1	1	12
(Hamid & Rahman 2010)	1	0.5	0	1	1	0.5	1	1	0.5	0.5	0	0.5	0.5	8
(Ray, Mishra, & Lenka 2016)	1	0	0	1	1	0.5	0	1	1	1	0.5	0	0.5	7.5
(C. Liu et al. 2017)	1	0	1	1	1	1	1	1	1	1	1	1	1	12
(Slimani, El Farissi, & Achchab 2015);	1	1	0	1	0.5	1	1	1	1	1	1	0	1	10.5
(Sahay, Sahu, & Singh 2016)	1	1	0	1	1	1	1	1	1	0	0	0.5	1	9.5
(Marinescu et al. 2014)	1	1	0	1	1	1	1	1	1	1	1	1	1	11
(Hossen et al. 2018)	1	1	0	1	1	0.5	1	1	1	1	0.5	0	1	10
(Bala 2010)	1	1	0	1	1	0.5	0.5	0.5	1	1	0.5	0	0.5	8.5
(Toqué et al. 2017)	1	1	0	1	1	1	1	1	1	1	0.5	0	1	10.5
(M. S. Li et al. 2015)	1	1	0	1	1	1	1	1	1	1	0.5	0	1	10.5
(Ai, Chakravorty, & Rong 2019)	1	1	0	0.5	1	1	1	1	1	1	1	0	1	10,5
(Delorme-Costil & Bezian 2017)	1	1	0	0.5	0.5	1	1	1	1	1	1	1	1	11
(Singh, Singh, & Paliwal 2016)	1	0.5	0	0.5	0.5	1	0.5	1	1	1	0.5	1	0.5	9
(Vanichrujee et al. 2018)	1	1	0	1	1	1	1	1	1	1	1	0.5	1	11.5
(Varanasi & Tripathi 2016)	1	0.5	0	1	1	1	1	1	1	1	0.5	0.5	1	10.5
(Ramos-Carrasco et al. 2019)	1	1	0	1	1	1	1	1	1	1	0.5	0.5	1	11
(Ren et al. 2010)	1	1	0	1	1	1	1	1	1	0.5	0.5	0	1	10
(Bejarano-Luque et al. 2021)	1	1	0	1	1	1	1	1	1	1	1	1	1	12

(H. Yu et al. 2021)	1	1	0	1	1	1	0.5	1	0.5	0.5	0	0	1	8.5
(UNUTMAZ et al. 2021)	1	1	0	1	1	1	1	1	1	0.5	1	0	1	10.5
(Weisbach et al. 2020)	1	1	0	0.5	0.5	1	1	1	0	O.5	0.5	0	1	8
(Xue et al. 2018)	1	1	0	1	1	1	1	1	1	1	1	0	1	11
(Wanchoo 2019)	1	1	0	1	1	1	1	1	0.5	0.5	1	0	1	10
(Selvi & Mishra 2020)	1	1	0	1	1	1	1	1	0.5	0.5	1	1	1	11
(Al-Ghamdi, Kamel, & Khayyat 2021)	1	1	0	1	1	1	1	1	1	1	1	1	1	12
(Laaroussi, Guerouate, & sbihi 2020)	1	1	0	1	1	1	1	1	1	1	1	0	1	11
(Kanavos et al. 2021)	1	1	0	1	1	1	1	1	1	1	1	0.5	1	11.5
(Feizabadi 2020)	1	1	1	1	1	1	1	1	1	1	1	1	1	13
(Livieris et al. 2019)	1	0.5	0	1	0.5	1	1	1	0.5	1	1	0	1	10
(J. Wang & Duggasani 2020)	1	1	0	1	1	1	1	1	1	1	1	0	1	11
(Y. Xu et al. 2019)	1	0.5	0	1	1	1	1	1	1	1	1	0	1	11
(Ahmad et al. 2020)	1	1	0	1	1	1	1	1	1	1	1	0	1	11
(Shi 2020)	1	1	0	1	1	1	1	1	1	1	1	0	1	11
(Tabrizchi, Javidi, & Amirzadeh 2021)	1	1	0	1	1	1	1	1	1	1	1	0	1	11
(Sidhu, Kumar, & Rana 2020)	1	1	0	1	0.5	1	0.5	1	0.5	1	1	0	1	9.5
(L. Huang et al. 2021)	1	1	0	1	1	1	1	1	1	1	1	0	1	11
(Chandriah & Naraganahalli 2021)	1	1	0	1	1	1	1	1	1	1	0.5	0	1	10.5
(J.-F. Chen, Lo, & Do 2017)	1	1	0	1	1	1	1	1	1	1	1	0	1	11
(Guo et al. 2021)	1	1	0	1	1	1	1	1	1	1	1	0	1	11
(Hamzacebi, Avni, & Cakmak 2019)	1	1	0	1	1	1	1	1	0.5	0.5	0.5	0	1	9.5

(Y.-C. Hu, Jiang, & Lee 2019)	1	1	0	1	1	1	1	1	1	1	1	0	1	11
(Chauhan & Hanmandlu 2010)	1	1	0	0.5	1	1	1	1	0.5	0.5	1	0	1	9.5
(Ma & Luo 2021)	1	1	0	1	1	1	1	1	1	1	1	0	1	11
(Bin & Tianli 2020)	1	1	0	1	0.5	1	1	1	1	1	1	0	1	10.5
(Das 2017)	1	1	0	1	0.5	1	1	1	1	1	1	0	1	10.5
(Kankal & Uzlu 2017)	1	1	0	1	1	1	1	1	1	1	1	0	1	11
(Shilaja & Arunprasath 2020)	1	1	0	1	1	1	1	1	1	1	1	0	1	11
(Olmedo 2016)	1	0.5	0	0.5	0.5	1	1	1	0	1	1	0	1	8.5
(Ao 2011)	1	1	0	1	1	1	1	1	1	1	1	0	1	11
(Germi et al. 2014)	1	1	0	1	1	1	1	1	1	1	1	0	1	11
(Vahdani, Razavi, & Mousavi 2016)	1	1	0	1	1	1	1	1	1	1	1	1	1	12
(Souza, Wanke, & Correa 2020)	1	1	0	1	1	1	1	1	1	0.5	0.5	0	1	10
(Fan et al. 2020)	1	1	0	1	1	1	1	1	1	1	1	0	1	11
(Fan, Jin, & Hong 2021)	1	1	0	1	1	1	1	1	1	1	1	1	1	12
(Saini et al. 2020)	1	0.5	0	1	1	1	1	1	1	0.5	0.5	0	1	9.5
(Akpinar & Yumusak 2017)	1	1	0	1	0.5	0.5	1	1	1	1	1	0	1	10

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