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Reviewing the Applications of Neural Networks in Supply Chain: Exploring Research Propositions for Future Directions

Ieva Meidute-Kavaliauskiene [1,*], Kamil Taşkın [2], Shahryar Ghorbani [3], Renata Činčikaitė [1] and Roberta Kačenauskaitė [4]

1 Faculty of Business Management, Vilnius Gediminas Technical University, 10223 Vilnius, Lithuania; renata.cincikaite@vilniustech.lt
2 Department of Business, University of Sakarya, Sakarya 54050, Turkey; ktaskin@sakarya.edu.tr
3 Department of Production Management, University of Sakarya, Sakarya 54050, Turkey; mg.shahryar@gmail.com
4 Logistics Command Garrison Base Service, Mindaugo Str. 26, 03215 Vilnius, Lithuania; kacenauskaiter@gmail.com
* Correspondence: ieva.meidute-kavaliauskiene@vilniustech.lt

Abstract: Supply chains have received significant attention in recent years. Neural networks (NN) are a technique available in artificial intelligence (AI) which has many supporters due to their diverse applications because they can be used to move towards complete harmony. NN, an emerging AI technique, have a strong appeal for a wide range of applications to overcome many issues associated with supply chains. This study aims to provide a comprehensive view of NN applications in supply chain management (SCM), working as a reference for future research directions for SCM researchers and application insight for SCM practitioners. This study generally introduces NNs and has explained the use of this method in five features identified by supply chain area, including optimization, forecasting, modeling and simulation, clustering, decision support, and the possibility of using NNs in supply chain management. The results showed that NN 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 NN applications in SCM.

Keywords: neural network; decision support; supply chain management; systematic review

Citation: Meidute-Kavaliauskiene, I.; Taşkın, K.; Ghorbani, S.; Činčikaitė, R.; Kačenauskaitė, R. Reviewing the Applications of Neural Networks in Supply Chain: Exploring Research Propositions for Future Directions. *Information* **2022**, *13*, 261. https://doi.org/10.3390/info13050261

Academic Editor: Aneta Poniszewska-Maranda

Received: 11 April 2022
Accepted: 18 May 2022
Published: 20 May 2022

1. Introduction

A company may hold inventory such as raw materials, elements, semifinal, or final products. These may be held for reasons including creating buffers to deal with uncertainty in supply and demand, using the advantages of a smaller number of purchases with higher volumes, and reducing transportation costs [1,2].

Recently, many researchers have focused on developing models that will eliminate inventories and reflect inventory management costs in the supply chain. People use neural networks in response to areas that somehow require machine intelligence [3,4]. Their acceptable performance in terms of speed and accuracy in predicting trends in financial markets, handwriting identification, or plastic explosives in aircraft passengers' baggage has made them famous as a unique AI technique [5–8].

It is not surprising that the ability of neural networks has inevitably been exaggerated. However, this tool is capable of resolving the uncertainty in inventory management. In the present study, a generalized neural network was introduced, and then some of its uses were investigated in supply chain management [9]. Moreover, it was found that neural networks are the best tools for performing other techniques such as expert systems, math planning, simulation, etc. Finally, the issues that led to neural networks' deficient performance were discussed [10–12].

In the past decade, there have been many changes in supplier management in the business world, and corporate dependency on suppliers has become more significant than ever. In the meantime, companies face many items to be purchased and potential suppliers. Additionally, given the various things required, the same policies for deciding on different suppliers do not seem reasonable. The need for additional policies states that various shopping items and suppliers are needed [13]. Categorizing suppliers allows differentiation between suppliers to allocate orders [14]. Suppliers are classified into three groups—desirable, average, and undesirable—by a neural network model [15,16].

Selecting the right supplier that can provide the buyer with the right quality, price, and timely volume is one of the essential activities for building a proper supply chain. The nature of these decisions is usually complex and unstructured [17].

Providers are one of the essential parts of the supply chain whose performance directly impacts customer satisfaction. Because customer demands vary with organizations, organizations must consider different criteria for selecting their suppliers. Many studies have been conducted in this area using various criteria and methods [7].

There are several literature reviews of NN applications in SCM, but most focus on a specific operational function of the supply chain. For instance, O'Donovan et al. (2015), Dutta and Bose (2015), and Babiceanu and Seker (2016) conducted literature reviews on material flow in production operations, while Wamba et al. (2015) focused on applications in the logistics area. Literature reviews that take a broad view of the supply chain and cross-maps with NN techniques in SCM are yet scarce. A systematic literature review was delivered by discussing papers on NN and SCM. Existing literature has driven the implementation and discussion of SCs and NN to enable organizational procedures to achieve efficiency in SC processes. Therefore, the current research was conducted to improve insight into previous literature that has identified the impact of NN in SCs.

Our literature review presented a classification framework that identifies and connects supply chain challenges with levels of analytics, NN models, and methods. Our review domain aims to fully understand where and how NNs have been applied in supply chain management by mapping NN models and approaches to supply chain functions. To achieve the objective, the literature review tries to address the following questions:

(1) In which fields in supply chain management are NNs being applied?
(2) What are the current research trends associated with NNs and SCM?
(3) What are the future research directions for an SC based on NNs?

2. Methodology

Some techniques can be used to evaluate the literature. In this regard, the citation analysis method and citation and traditional bibliometric methods have been used many times in various management areas [18,19]. Therefore, according to the trend set out in Figure 4, this study examines the subject under investigation. Based on Figure 1 and the trend identified, using the two databases Scopus and Web of Science, and based on the keywords supply chain and artificial neural network shown in Table 1, the most important challenges that can be solved in this the area were identified using artificial neural network methods including logistics network design, inventory control, supply chain design, demand forecasting, supplier selection, and risk management.

As shown in Table 1, 214 articles have dealt with supply chain problem solving using artificial neural networks. Then, in these two databases, utilizing the combination of the keywords "artificial neural network" AND "logistics network" AND "supply chain design", "artificial neural network" AND "inventory" AND "supply chain control", "artificial neural network" AND "supply chain design", "artificial neural network" AND "demand forecast" AND "supply chain", "artificial neural network" AND "supplier selection" AND "supply chain", and "artificial neural network" AND "risk" AND "supply chain", according to Table 1, the number of articles in each of these areas of the supply chain was determined. Finally, by reviewing and evaluating the papers, the most appropriate articles were selected to explain how to solve these challenges through artificial neural networks.

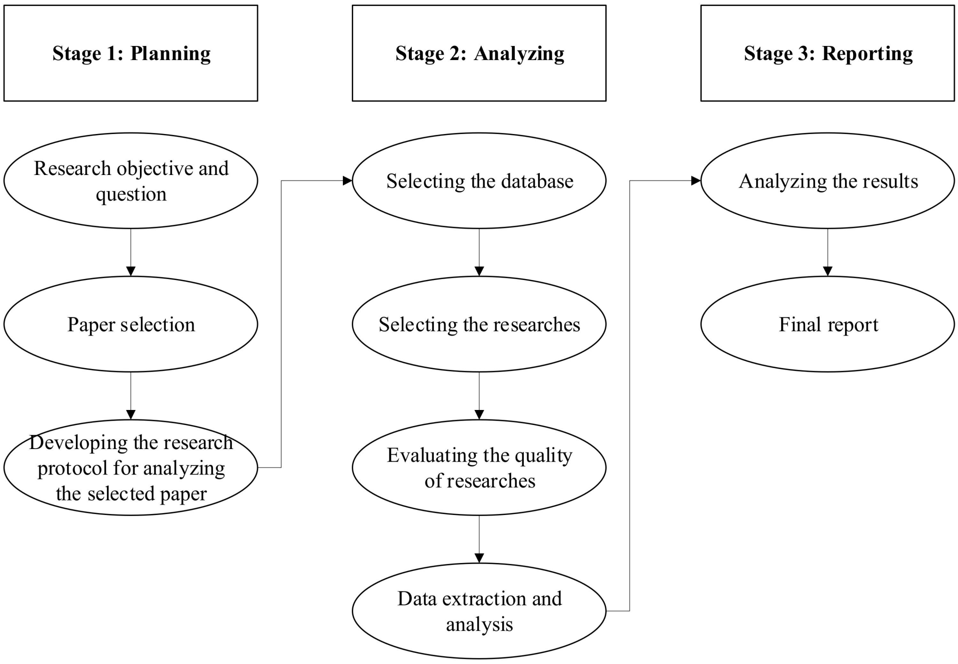

Figure 1. Steps of the literature review process.

Table 1. The used keywords.

No.	Keywords	Number of Papers
1	"Artificial neural network" AND "Supply chain"	214
2	"Artificial neural network" AND "Logistic network" AND "Supply chain"	52
3	"Artificial neural network" AND "Inventory control" AND "Supply chain"	18
4	"Artificial neural network" AND "Supply chain network design"	16
5	"Artificial neural network" AND "Demand forecasting" AND "Supply chain"	74
6	"Artificial neural network" AND "Supplier selection" AND "Supply chain"	57
7	"Artificial neural network" AND "risk" AND "Supply chain"	11

Neural networks are widely used in various fields, especially management. The supply chain consists of different parts. The purpose of supply chain management is to manage each of these components. In this regard, neural networks have helped solve the supply chain problems. The number of articles that used artificial neural networks to solve the supply chain's challenges were reviewed based on the studies. The results showed that the highest number of articles in this field in 2009, 2017, and 2018 was 13, 24, and 27, respectively. In mid-2022, 26 papers have been published, and due to the use of neural networks, it is predicted that the number of science products in the field of supply chains will increase significantly.

The main element of a neural network is a mathematically modeled artificial Tron created by McCulloch and Pitts in 1943 [20,21]. Figure 2 shows how an artificial neuron works. Each neuron has several inputs and one output. Each input is multiplied by a predefined weighting factor [10]. Then, the output is determined by a mathematical function f (x) which is the sum of the product of inputs and weighting factors. Therefore, how a specific brain cell is imitated is determined by computation. Interestingly, suppose an artificial neuron with a slight difference in the combination of weighing factors and n (f) is created for the same set of inputs. In that case, the output may be somewhat different. This may seem relatively simple, but when these translations connect inappropriate topologies with suitable selection factors, they build a foundation for a robust computing paradigm. Most research on neural networks and their applications focuses on studying network topologies and determining weight factors [22]. It has been proved that in solving classification and regression problems, considering the nonlinearity of the relationship between input and output variables, it is possible to estimate any function effectively under certain conditions.

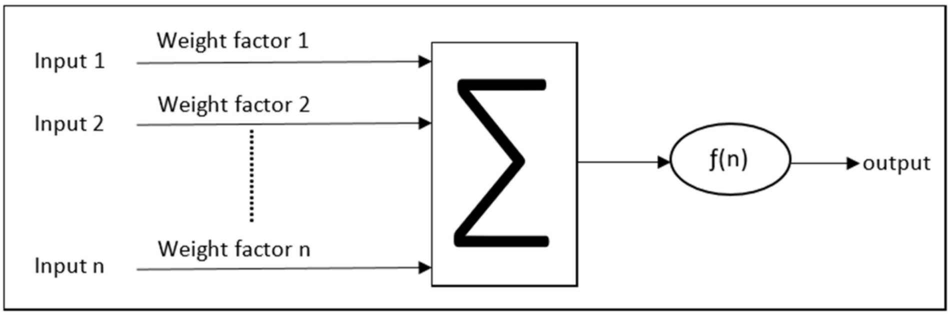

Figure 2. McCulloch–Pitts neuron.

Figure 3 demonstrates one of the network topologies that is most widely is used, which is termed the three-layer feed-forward network [23]. Every hidden layer neuron is directly linked to every input layer signal. Such links are also found between the hidden layer and the output layer.

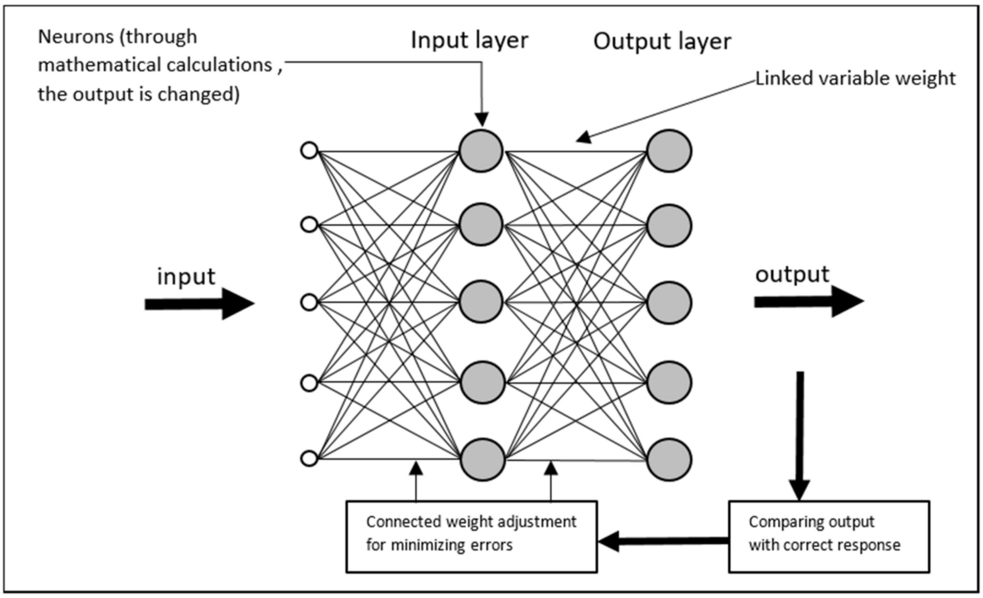

Figure 3. A three-layer neural network.

The development of a functional neural network is performed in two chapters: training and operation, in which the activity of a network is carried out as follows [24]:

1. Random values are determined for weight factors.
2. Input and output samples are presented respectively to the input and output layers.
3. Weighting factors are adjusted to match the input/output pair properly.
4. This procedure is repeated for other input–output teams in the actual sample.
5. As weight adjustment for each pair of output–input influences, steps three and four should be repeated so that each team in the sample is matched based on the predefined error rate. In other words, this is the stage for convergence of weight and network stability factors.

Due to these capabilities, neural networks are used to solve problems in different areas, such as time series forecasting. In particular, it has been shown that these networks have outstanding results for prediction. Among the successful applications of neural networks is operation management, which has led to considerable savings in inventory costs [23,25–27].

Several features have been identified in the supply chain, and neural networks can be used to solve them. These features can be summarized as follows [17]:

2.1. Optimization

This is similar to setting restrictions. Let us suppose a set of conditions in which the aim is to obtain a set that satisfies all constraints and minimalizes the cost function. The most prominent example is the travelling salesman problem (TSP). The scenario is that there are several cities; the goal is to find the shortest possible route which visits every town. Here, an intuitive approach includes counting all solutions, evaluating distances, and identifying the shortest route. Clearly, as the number of cities increases, possible combinations increase faster. In this way, the main focus of the research is on discovering a well-estimated correct solution. Experience has shown that, in most cases, the most commonly used keys are acceptable and almost optimal. Therefore, neural network use is one of the most accepted methods in finding either optimal or near-optimal solutions. Earlier studies have confirmed specific usages of neural networks in the TSP: workshop arranging, batch production programming, and vehicle and warehouse routing problems [28].

This concept is related to supply chain management in the context of some main activities of an integrated logistics intelligence system. Sometimes, it is difficult to equate the performance of different algorithms regarding optimization problems. However, neural networks' adaptation capability is now a fascinating topic, as original restrictions may be calculated in a very dynamic environment once they occur. This would be especially critical so far as it relates to supply chain management. JIT transport management in a supply chain demonstrates that the system should tackle restrictions that emerged from other centers' present situations within the chain. In companies, multiple scheduling activities are needed to react to problems such as high demand inconsistency or unpredicted disturbances in the same vein. Furthermore, data mining and neural networks are applied to resolve the inventory issue [28,29].

2.2. Forecasting

One of the main coordination goals in supply chains is improving forecasting accuracy. The techniques commonly used to predict supply chain demand are simple forecast, average, moving average, trend, multiple linear regression, and neural networks. As one of the most natural prediction methods, simple estimates will use the last achieved value as the best guess for the next value. The moving average forecast uses the average of a certain number of previous periods to predict future demand. Trend-based forecasting uses a simple regression model that considers time as an independent variable. In recent years, companies have recognized the importance of sharing information and integrating all stakeholders in the supply chain [30]. Despite these measures to reduce forecasting errors, none are complete, and forecasting errors still exist. Interactive forecasting allows the company and its supplier to coordinate decisions by exchanging models and support strategies, which helps to integrate predictions and production schedules [31]. However, in the absence of interactive forecasting, companies will develop traditional forecasts and production timing. Even if the final customer demand has a predictable pattern, forecasting demand while the company's market oscillates randomly in these circumstances becomes a challenge known as the "bullwhip effect," which results from asymmetric information [32]. Therefore, imprecise forecasting has undesirable effects on a company and unwanted effects on a company and the entire supply chain. Therefore, accurate forecasting is essential for supply chain management [33]. With the specific features of the neural networks in forecasting, it is supposed that this approach can provide a reasonably good solution. Moreover, in this paper, researchers have used neural networks to predict the sale of the article to reduce inventory and manage it better [34].

Using several past demand observations as independent variables, a multiple regression model predicts demand changes. These techniques are called traditional techniques. However, using moving averages by simple forecasting will reduce the bullwhip effect [35,36]. However, we expect advanced methods to work better than more traditional methods for two reasons: First, advanced techniques incorporate nonlinear models that provide better estimates than linear models. Secondly, because of behavioral complexities, it is expected that there will be significant nonlinear behavior in demand behavior [37].

Due to the numerous successes achieved by neural networks in forecasting the performance of financial markets, forecasting is considered the most helpful area from the perspective of users of neural networks. Referring to the various applications presented in the literature, the realm of the neural network is quite broad in forecasting [38].

In terms of development, neural networks' use can indeed be seen in designing complex systems that are not clear and understandable by the rules governing the systems' actions. Together with other methods for analyzing time series, such systems may be modeled through expert systems and statistical techniques. Nevertheless, these conventional strategies are not predominantly effective due to the enlightenment in certain parts of the models [39].

An instinctive description of neural networks' application in predicting is provided. Let us suppose specific previous information is applied to evaluate particular system behavior, which is used to train a neural network. The system's response time can be compared to other parameters.

Therefore, this considers a particular pattern in the input data set so that the neural network may realize if similar models have occurred before. Then, depending on what would be likely to occur, one or two phases are anticipated. Even though this is a fairly simple representation of neural networks' application in forecasting. Over recent years, the method appeared to be a mature methodology based on different applications. Assuming that a pattern may not be effectively developed in certain situations, experience has revealed that a neural network strategy may arrange for a more precise forecast than expert models or mathematical equations [40].

Thus, forecasting technique analyses are very important for companies [41]. Instead, autoregressive linear prediction has been shown to reduce the bullwhip effect and implement exponential smoothing methods [42].

2.3. Modeling

Forrester Theory [43] has been used extensively to describe supply chain dynamics. This method is formulated in supply chain analysis utilizing the theory of system dynamics proposed by Towill [17], providing significant improvement in the local decision-making of a center, which influences the overall view of the chain. Different case simulations have also been applied to scrutinize supply chain dynamics [44]. Although both approaches have been confirmed to be practical in the design and resolution of supply chain issues, there are still underlying uncontrolled issues. Such problems involve nonlinear system behavior and a large proportion of process input and output variables. In analyzing dynamic systems, both approaches are regarded to be more or less classical.

From a neural network experiment on the modeling, analysis, and control of dynamic systems, it has been found that several characteristics make the neural network more attractive than the theory of system dynamics. Specifically, the neural network technique is well suited to situations that cause problems such as those mentioned above. For this reason, neural networks have been widely used to control and model the contexts in which class system theories have not been able to provide satisfactory solutions [45]. The use of neural networks as a meta-analysis for the simulation of isolated events is one of the things yielding encouraging results [46].

2.4. Clustering

The concept of clustering in a network means that multiple servers provide the same service simultaneously, and each server can be considered a cluster. Of course, the application and implementation of this concept in the network have many advantages. One of the benefits of using clustering is speeding up service delivery [47–49]. This occurs because when a request arrives at the clustered set, if the first server fails to respond to the request, the request is referred to the next server (failover clustering). If all the servers respond to the requests without ansy problems, the processing times of the requests are distributed between the servers, which results in load balancing, eventually leading to faster response times.

2.5. Decision Support

Two characteristics classify decision-making through information technology. On one side, there is a great deal of data according to which the decision has been made, and on the other side, the data are typically imperfect. The findings on the management of the supply chain, as it proceeds, permit these characteristics if NNs can produce essential solutions [50].

Most studies on decision support systems relate to the management and analysis of data to support a decision [51]. The data indexing pattern for data repossession is not clear enough in a supply chain likely to distribute data across the entire network. The unique capabilities of neural networks in pattern recognition, data categorization, and self-organization have made them ideal for performing searches in databases. For example, consider supply chain management that one could quickly formulate and analyze using a neural network approach in the form of a classification problem.

The extraction of relationships from data without prior knowledge about the proper models for the data set is another essential aspect of the decision support system [51]. Sometimes, this problem is grouped in the category of nonconservative issues. The deductive learning of neural networks is due to their self-organization and generalization features. They are, therefore, accepted as a very influential tool in solving problems. Classical applications in this area can be demonstrated by applying neural networks to imitate expert judgment processes. When formulating, there are certain principles for a decision using techniques such as expert systems when there are problems or the answers are not accurate.

Regarding supply chains, controlling chain functions is also a potential application area for the use of neural networks due to a large amount of data a large amount of data being available but data modeling being complicated.

In this regard, in [52], to identify the faithful customers in the entire electronics supply chain and maximize the total profit of the chain, the researchers used a self-organized neural network to explore consumer behavior data and cluster them. Then, by identifying features of the customer of each cluster, marketing strategies are presented to them, thus supporting management decisions on marketing strategies.

Figure 4 shows the trend of published papers from 2002 to mid-2022 in the selected journals. From Figure 4, it is apparent that the number of published articles related to NNs in SCM increased slowly from 2000 to 2015. There has been a drastic change in the number of publications in the selected journals after that. Furthermore, NNs have received increasing attention in the last decade; it is noted that in the year 2021, the number of publications rose sharply, with more than 35 produced. This indicates that research on the application of NNs in the field of SCM is attracting growing attention. The reason behind an increase in studies in NN and SCM could be explained by the rising focus on big data in 2013.

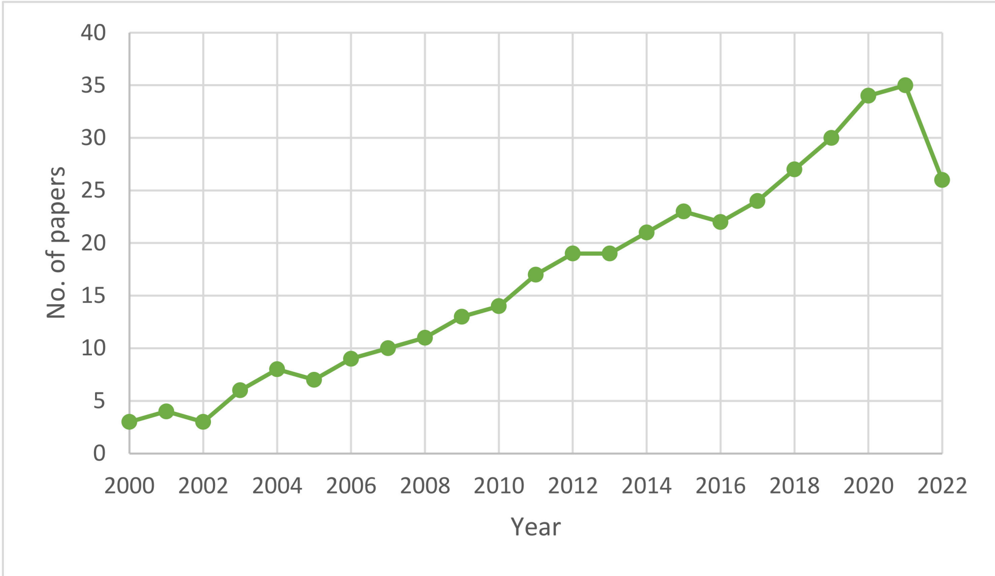

Figure 4. Trends of published papers in the selected fields of the study.

There are many applications of neural networks in supply chain management. In this paper, we investigated some of them regarding supplier selection.

One of the most critical issues in supply chains is choosing the best supplier. The process of supplier selection that can provide the buyer with the right quality products at the right price, at the right time, and in the right volume is one of the essential activities in creating a suitable supply chain. Deciding on supplier selection plays a significant role in the production and management of corporate logistics. Many experienced companies believe that supplier selection is the most critical activity of an organization. As a result, incorrect decisions regarding the selection of suppliers will have many negative consequences for the company. Supplier decision-making and selection is essentially a multicriteria issue. For most organizations, this is of strategic importance. The nature of such decisions is usually complex and unstructured. Management science techniques can be helpful in deciding these issues.

In this paper, the ANN was used for predicting the performance measure values for selecting the best supplier. The network architecture for this area is in Figure 5.

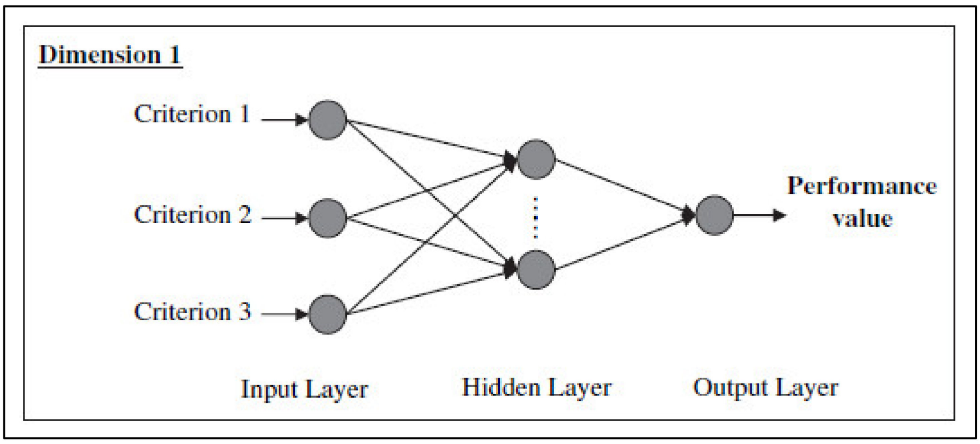

Figure 5. Network architecture.

Table 2 shows the literature review for supplier selection based on neural networks (2009 to present).

Table 2. Literature review for supplier selection based on neural networks.

Reference	Topic	Research Method	Case Study
[53]	Supplier selection: A hybrid model using DEA, decision tree, and neural network	DEA, decision tree, and neural network	Railway industry
[54]	A neural networks approach for forecasting the supplier's bid prices in the supplier selection negotiation process	neural networks and MCDM	China industry
[10]	Integration of particle swarm optimization-based fuzzy neural network and artificial neural network for supplier selection	particle swarm optimization and ANN	Computer company
[23]	An approach based on ANFIS input selection and modeling for the supplier selection problem	ANFIS and ANN	Textile firm
[27]	Sustainable supplier selection based on self-organizing map neural network and multi-criteria decision-making approaches	self-organizing map, fuzzy AHP, ANN	Automotive industry
[55]	Application of decision-making techniques in supplier selection	Artificial intelligence (A.I.) techniques	
[56]	Multi-Criteria Supplier Selection Using Fuzzy PROMETHEE Method	PROMETHEE and ANN	
[21]	A hybrid group decision support system for supplier selection using the analytic hierarchy process, fuzzy set theory, and neural network	fuzzy AHP—ANN	
[57]	MCDM tools application for selection of suppliers in manufacturing industries using AHP, Fuzzy Logic, and ANN	AHP, fuzzy logic, and ANN	Manufacturing industries
[28]	Nonlinear genetic-based model for supplier selection: a comparative study	DEA-ANN-gene expression programming	Comparative study
[58]	Forecasting efficiency of green suppliers by dynamic data envelopment analysis and artificial neural networks	ANN and dynamic DEA	Naniwa Co
[59]	A hybrid model for supplier selection: integration of AHP and multi expression programming (MEP)	AHP and MEP	
[17]	A hybrid approach using data envelopment analysis and an artificial neural network for optimizing 3PL supplier selection	DEA and ANN	
[60]	A hybrid ensemble and AHP approach for resilient supplier selection	AHP—ANN	Plastic raw material

Because ANN and SCM belong to different research domains, there are many journals in which papers on those topics could be released. Table 3 shows the list of nine journals in which at least three papers concerning ANN applications in SCM were printed. It is shown that a high incident of articles was with Expert Systems with Applications (32.8%). Additionally, Applied Soft Computing made the second most significant (12.8%) contribution to the ANN applications in SCM. This might be caused by the superior performance in production demand forecasting.

Table 3. Distribution of articles based on journals.

Journals	Numbers	Percent
Expert Systems with Applications	18	32.8
Applied Soft Computing	7	12.8
Decision Support Systems	6	10.9
European Journal of Operational Research	6	10.9
Applied Intelligence	5	9.1
Engineering Applications of Artificial Intelligence	4	7.3
Expert Systems	3	5.4
Neural Computing & Application	3	5.4
International Journal of Production Research	3	5.4
Total	55	100

Regarding research trends of NN applications in supply chain management, this result found that there were two research summits (between 2010 and 2011, 2015 and 2016 respectively) over 24 years (1998/01/01–2022/04/01); the top researchers were Chung Kim and H. Lau. To explore the relationship between all researchers of this field, a co-citation network of cited authors is presented in Figure 6. The minimum citation is set at 21; 25 authors are chosen. As indicated in the figure, a larger circle means more authority. Thus, the number of available sources in the field of NN applications in SCM increases.

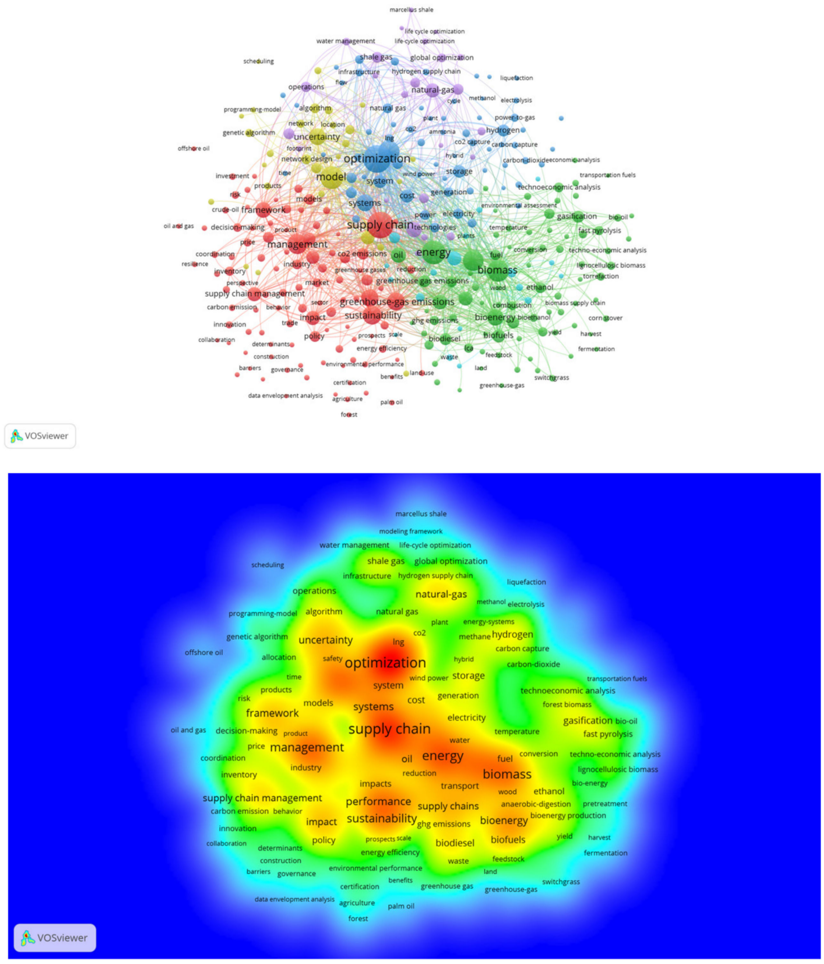

Figure 6. Co-occurrence map of the keywords.

VOS Viewer recognizes 8476 verbs. Then, after refining irrelevant results and also merging synonyms, 247 items remained, which are visualized according to the following map:

VOS Viewer can also produce a bibliometric mapping of NN related to SCM. The bibliometric mapping of the keywords used is shown in Figure 7. The bibliometric analysis shows several widely used keywords in the paper that are the research object. The more keywords that appear, the wider the circle indication will be, while the line relationship between keywords shows how much they are related to other keywords.

The most used keywords—"Optimization", "Supply Chain", and "Supplier Selection"—had the highest co-occurrence. Based on the closer network visualization in VOS viewer, "Optimization" was more strongly interlinked with two keywords: "Supply chain" and "Forecasting". These could be considered the essential topics in optimization research for SCM.

A total of 3459 authors were found that conducted research in NN and SCM. Figure 7 shows the bibliographic coupling map of the 75 selected authors. These authors were distributed into seven clusters.

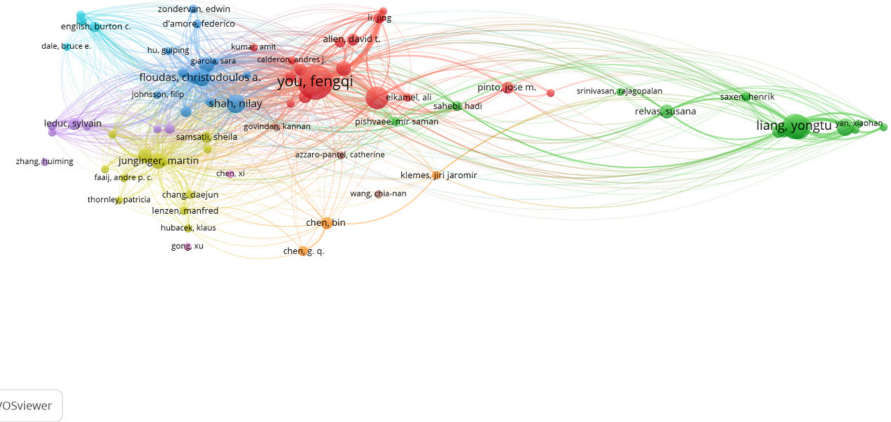

Figure 7. Bibliographic coupling map of the authors.

The larger the shape and the brighter the color, the more writings related to NNs published by the author. The appearance of cluster density depends on the level of yellow light brightness. It identifies that the yellow color on the map depends on the number of items associated with other things. It is possible to interpret the authors who have published the most from the map. Based on these results, the bigger and brighter the author's name, the more papers they published. The author with the most printed publications related to NN based on bibliometric mapping, shown in cluster 1, was Fengqi You, with 38 documents published on this subject.

Based on the citation type of analysis which used VOS viewer software to illustrate the visual map produced from bibliographic data, the cited author unit was analyzed by the complete counting method. The minimum number of documents of an author was six; of 3857, only 68 authors met the threshold. For each of the 68 authors, the total strength of the citation links with other authors was calculated. Therefore, Figure 8 demonstrates the documents of an author with the best full link strength. Therefore, Fengqi You was the most published author with 37 papers and a total link strength of 590.

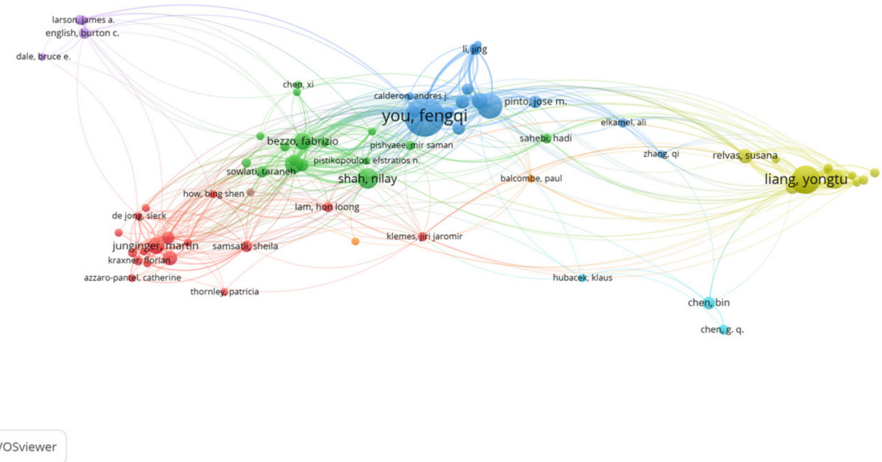

Figure 8. Citation map of the authors.

3. Discussion

While the use of neural networks in some areas of supply chain management is desirable, it is worthwhile to discuss and ask questions about how to deal with existing techniques, such as expert systems and other analytical approaches, in displaying similar issues. To answer this question, neural networks are not an alternative, but an instrument for completing existing techniques. From a functional point of view, neural networks are best suited for software call procedures because they can be used anywhere in the software. Predictably, neural networks will be integrated into the industrial field. In particular, neural networks are often combined with expert systems to create solutions that a technique alone cannot provide.

For instance, an intelligent system to manage real-life distribution in supply chains may split into two phases. The initial stage is to incorporate products into groups according to properties like storage supplies and product natures. The action mechanism at this point is relatively straightforward; thus, the strength of the expert systems should be applied to that end. Neural networks may be utilized at that point to resolve fleet routing problems to minimize the distance, time, the required number of trucks for transport, and so forth.

In common intelligent mechanisms, the scope of neural networks is not restricted to those that are able. The integration of neural networks with various other strategies to deal with real-world issues was examined by Materi et al. [61]. The integrated problem-solving approaches' instances are illustrated in Figure 9. Neural networks' capacity to be combined with current technologies is crucial from an industrial standpoint. It allows the employment of advanced tools; this seems to be a simplified approach to introducing any novel technology.

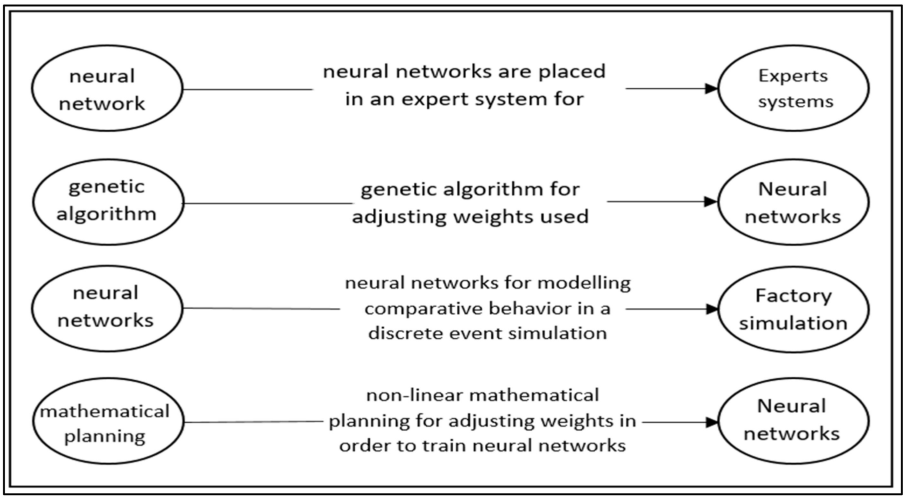

Figure 9. Combined intelligent system.

Several studies on neural network applications have recommended using neural network solutions for interesting technical issues. However, there is a general feeling that the number of neural network applications can be less than that. Therefore, awareness of the known disadvantages of neural networking for installation in operational systems is essential for their successful development in supply chain management. Marco [62] notes that the weaknesses of the neural network are of two types. The first disadvantage is that neural networks can provide solutions that do not help the user's understanding; this is the essential disadvantage when comparing neural networks with expert systems. Gradually, researchers are trying to overcome this problem. The second disadvantage is that it is often difficult to obtain valuable quality data for the proper training of neural networks. Sometimes, the required data are not easily accessible; in many cases, the information is available, but the way it is managed completely disrupts the process.

Unfortunately, this process sometimes leads management to think that this unique feature is not described or calculated correctly. However, in recent years, a new technology called radio frequency identification (RFID), which contains necessary information such as product code and manufacturer, has been developed. The technology will generate countless data about the business, which can be considered a rich foundation for use in neural networks.

This research has suggested a framework (Figure 10) that comprises eight emerging research areas for SCM and the integration of NN methods. The research framework describes the advantages of integrating NNs to attain efficiency in SCM.

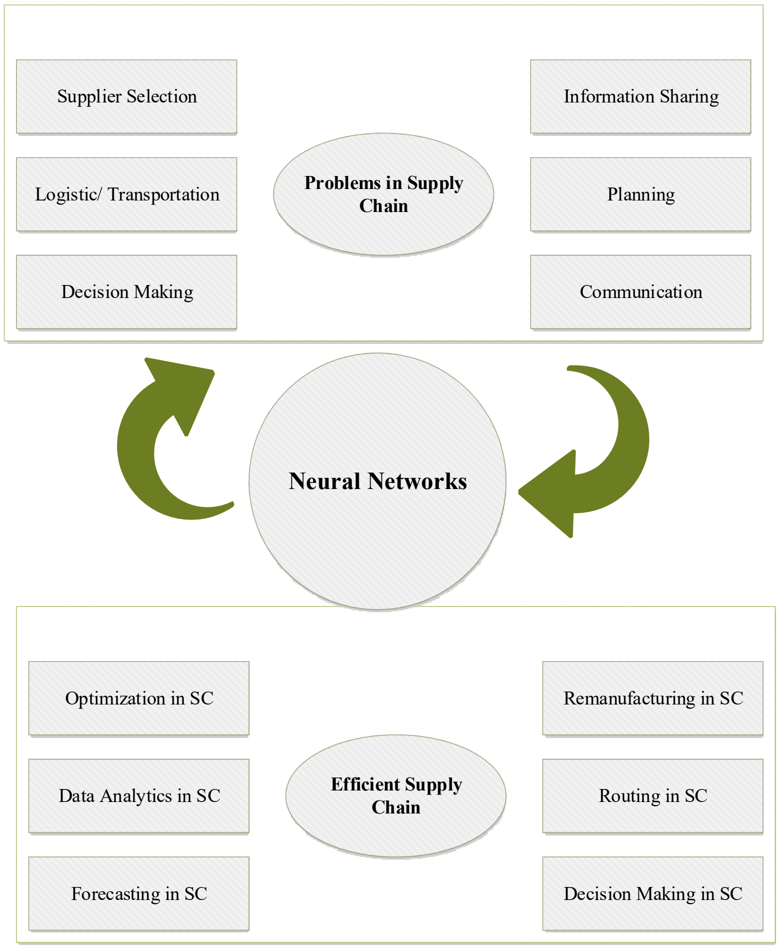

Figure 10. A suggested research framework for NNs in SCM.

4. Conclusions

Neural networks remain very committed to practical uses and significant enhancements to engineering, although they proceed to be a powerful technology. From the perspective of supply chain management, this study proposed several aspects that can significantly contribute to neural networks. One of the most critical aspects of supply chain management is increasing the coordination of participating companies in the chain to achieve lower costs and higher customer satisfaction through on-time delivery. It was also argued that the studies showed that neural networks could provide more accurate results, such as simple forecast, average, moving average, and even an excellent linear regression method, than traditional techniques.

In this study, based on the classification of supply chain challenges, the application of artificial neural networks in each of the challenges and how to solve them through artificial neural networks was expressed. According to the results, the highest number of published articles in solving supply chain challenges using the artificial neural network was in demand forecasting, supplier selection, and logistics network design. The lowest number of published articles was in risk and inventory control. Therefore, it can be concluded that solving the challenge of risk management and inventory control in the supply chain through artificial neural networks has received less attention and can be considered a topic for future research.

It was also explained that due to the various limitations and capabilities of different tools, the integration of artificial neural networks with other existing techniques could lead to improved results. It is believed that the industry can take advantage of this inspirational tool f so that the strategies offered by the technology can be used to improve management.

The methods and applications of neural network techniques in supply chain management should be evaluated. Multicriteria decision-making methods should be used to assess effectiveness and usefulness. Since ANNs work on the same model as the human brain, which has been studied for generations, we can break down the processes and inner workings to a level that any audience can grasp and go on to create insights to streamline their supply chain. For inventory management, logistics network routing, and demand planning, deep learning and neural networks are the future. The digital supply chain of the future will have NNS at the core of its strategic platform. Fueled by the provision of big data and the end-to-end electronic connectivity of global supply chains, NNs and AI will be utilized for any desired supply chain application.

This study will deliver a profound perception of SCM by integrating NNs and inspire managers to examine future suggestions. Future research can expand their review papers by combining other folds of SCM. This study is limited to only journal articles so that future research can contain other documents for a wider diversification of linked articles. This will also demonstrate interest in probing the challenges and obstacles in review papers based on NNs and SCM.

Author Contributions: Conceptualization, I.M.-K. and K.T.; methodology, S.G., R.Č. and R.K.; software, K.T.; validation, I.M.-K., formal analysis, S.G.; investigation, I.M.-K. and R.Č.; resources, S.G. and R.Č.; writing—original draft preparation, S.G. and K.T.; writing—review and editing, I.M.-K.; visualization, S.G. and R.K.; supervision, I.M.-K. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data of this study are available from the authors upon request.

Conflicts of Interest: The authors declare no conflict of interest.

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