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Application of Artificial Intelligence in performance Supply Chain Management

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Abstract: The volume of data generated by the various Supply Chain Management actors is considerable, the extraction, processing and analysis of this data becomes a priority for decision makers to better understand the origin of problems that sometimes cause disruptions in the decision-making process. At the same time, companies find themselves with increased competition, to persist, decision makers must act quickly by analysing their own data and those coming from outside their businesses. Traditional methods have shown their limits in terms of exploration and interpretation of this growing volume of data. The aim of this paper is to highlight the new applied methods of Artificial Intelligence in Supply Chain Management functions, we will identify the most well-known Machine Learning techniques and review the applications of Machine Learning algorithms in Supply Chain Management.

Keywords: Machine Learning; SCM; Artificial Intelligence; Decision making, Demand forecasting

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1. Introduction

Decision making in case of market uncertainty, customer solvency, changing customer trends, ensuring a sustainable relationship with suppliers, and finally detecting anomalies, represent a real challenge for Supply Chain Mangement (SCM) actors. In addition, SCM also suffers from the ambiguity or asymmetry of information that makes it difficult for the decision-maker to better exploit, process and analyse the data to ensure the performance and continuity of their business, hence the need for new and more effective tools in decision-making. Artificial Intelligence seems to be one of these powerful methods.

Arising in the 1950s, the term "Artificial Intelligence" (AI) began as the simple theory of human intelligence exhibited by machines (Bini, 2018), For (Simon, 1965) "Machines will be able to do any job a man can do", from that statement to the present day, Artificial Intelligence has undergone a remarkable evolution and has come much closer to what H. Simon predicted 57 years ago.

This evolution was started by Expert Systems (Ignizio, 1990) and Fuzzy Logic by Lotfi Zadeh in 1965, then after with the advent of new processing and analytical applications induced by Big Data in 2010, as well as the development of Machine Learning and Deep Learning algorithms, AI is becoming more modern and has raised the intention of companies to improve their business performance. Indeed, the cadence of AI applications has increased rapidly with attractive results as well as some uncertainties regarding the future of daily work and business management (Bughin, J., Seong, J., Manyika, J., Chui, M., Joshi, R., 2018).

Over the past decades, Supply Chain Management has undergone an important transformation.

Many companies are increasingly investing in the process of transforming their business processes to reap the benefits of AI in the occurrence of their end-to-end supply chain (Chui, M., Henke, N., Miremadi, M., 2019); SCM literature is still catching up with some recent efforts to integrate modern AI methods.

In most industries despite the size of the company small, medium, or large, AI is a field that includes the development of systems capable of performing tasks that normally require human intelligence. In the McKinsey report (Bughin, J., Seong, J., Manyika, J., Chui, M., Joshi, R., 2018) estimate that the economic contribution of AI technologies will be about $13 trillion by 2030 and could increase global GDP by about 1.2% per year. However, despite the potential to disrupt the way organisations operate, Gartner (2018) estimates that 37% of organisations are still trying to define their AI strategies, while 35% are struggling to find the right application.

The article under review addresses the following research question: What are the areas of application of AI in Supply Chain Management?

2. Methodology

To achieve our objective, 02 keys research questions are developed to highlight the relevance of this work (Whetten, 1989) and to describe the methodology adopted in this paper.

Q1: Why? Firstly, there are few researchers in economics or management who address the collaboration between AI and SCM e.g. the application of Machine Learning techniques and their relationship with prediction methods. Moreover, there is little generic conceptual framework to illustrate how data and information relate to the problem and decision situation from a systems perspective (Tan & Zhan, 2017).

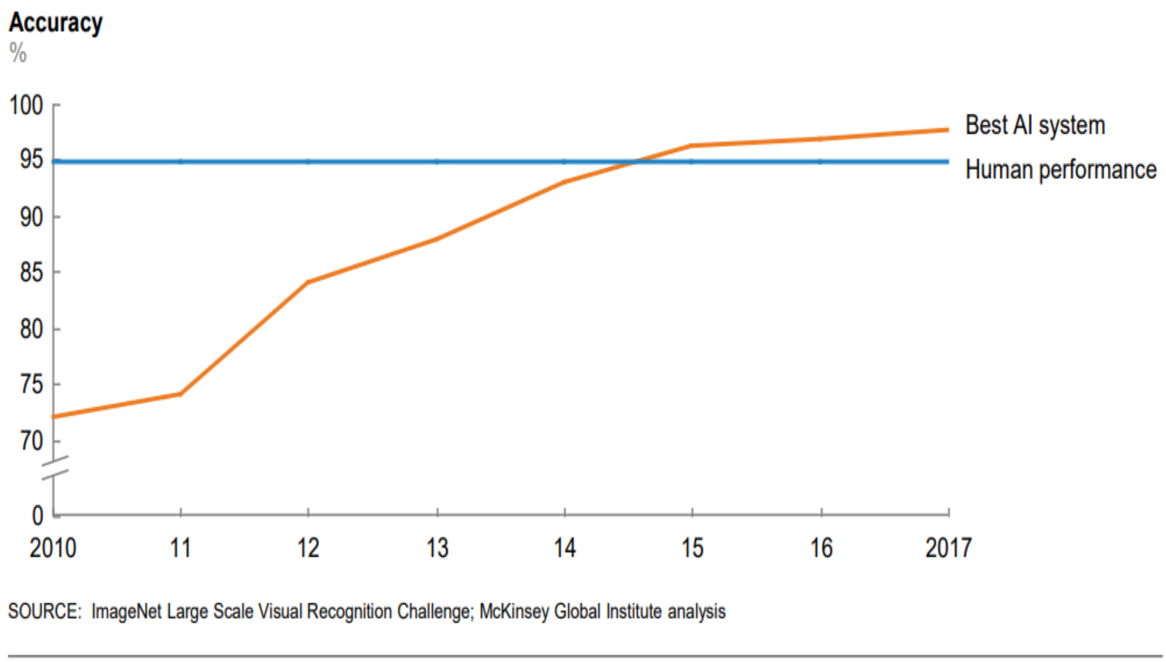
Q2: How? The topic of this paper is research on ML methods and techniques for operations applicable to SCM. In order to answer the conceptual and practical research questions we will start with a literature review (section 3.1) on AI and SCM, followed by the application of ML in SCM (section 3.2) and ML techniques (section 3.3).

3. Literature reviews

3.1 Artificial Intelligence and Supply Chain Management

In the Larousse Dictionary, AI is defined as *"the set of theories and techniques used to create machines capable of simulating human intelligence" (*larousse, s.d.).

Currently, in some areas, the ability of AI systems to recognise objects has improved significantly to the point where the best systems now outperform humans (Figure1)

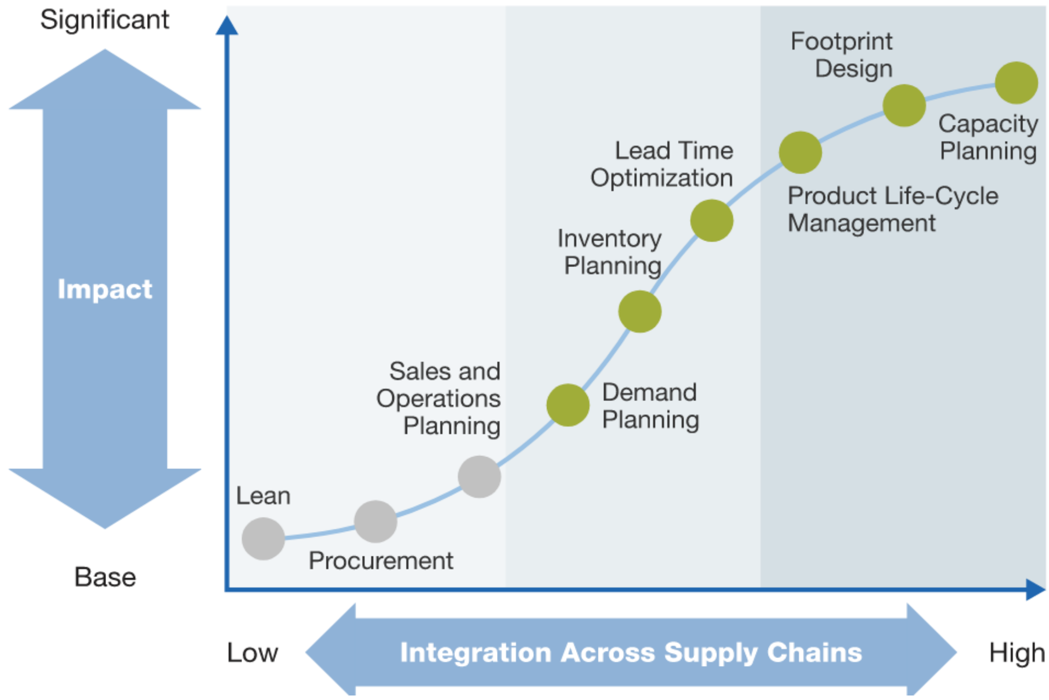


(Bughin, J., Seong, J., Manyika, J., Chui, M., Joshi, R., 2018)

Figure 1. Notes from the ai frontier insights from hundreds of use cases

According to the Association for Operations Management (APICS) dictionary, SCM has been defined as "*the design, planning, execution, control and monitoring of supply chain activities to create net value, build a competitive infrastructure, leverage global logistics, synchronise supply with demand, and measure performance on a global scale"*.

The role of demand planning capability is important because its impact is significant (Figure2), it represents a competitive advantage, and it is also a means of measuring business performance.



(Ashutosh Dekhne, Xin Huang, Apratim Sarkar, 2013)

Figure 2. Integration through SCM

The abundance and diversity of data that companies generate makes it difficult for decision makers to solve organisational problems.

The need to make decisions under uncertainty is a major problem in SCM ((Gumus et al., 2010). In addition to the variety, complexity, and number of decisions, SCM management also suffers from uncertainty or asymmetric information. This causes a bullwhip effect, which is summarised in the difficulties encountered in estimating the demand of each supply chain actor when order volumes fluctuate. (Provost & Fawcett, 2013) propose Data-Driven Decision-Making, which refers to the use of facts, metrics, and data to guide strategic business decisions in line with objectives and initiatives.

(Tan et al., 2015) argue the need for more sophisticated methods and analytics that can help supply chains gain competitive advantage by capturing data driven innovations.

Machine Learning is known for its ability to correlate large and diverse data sources. It is effective when it comes to finding patterns and trends in large amounts of data that occur on a daily basis. In the case of the SCM, it helps to address major issues, in this case predicting demand. Future customer needs can be anticipated by a multitude of variables or factors specific to the sector under study, i.e., the cross study of sales history, seasonality, geographical areas.

3.2 Application of Machine Learning in Supply Chain Management

Machine Learning (ML) is a branch of AI as shown in Figure 3, which focuses on using data and algorithms to simulate the way humans learn, gradually improving its accuracy.

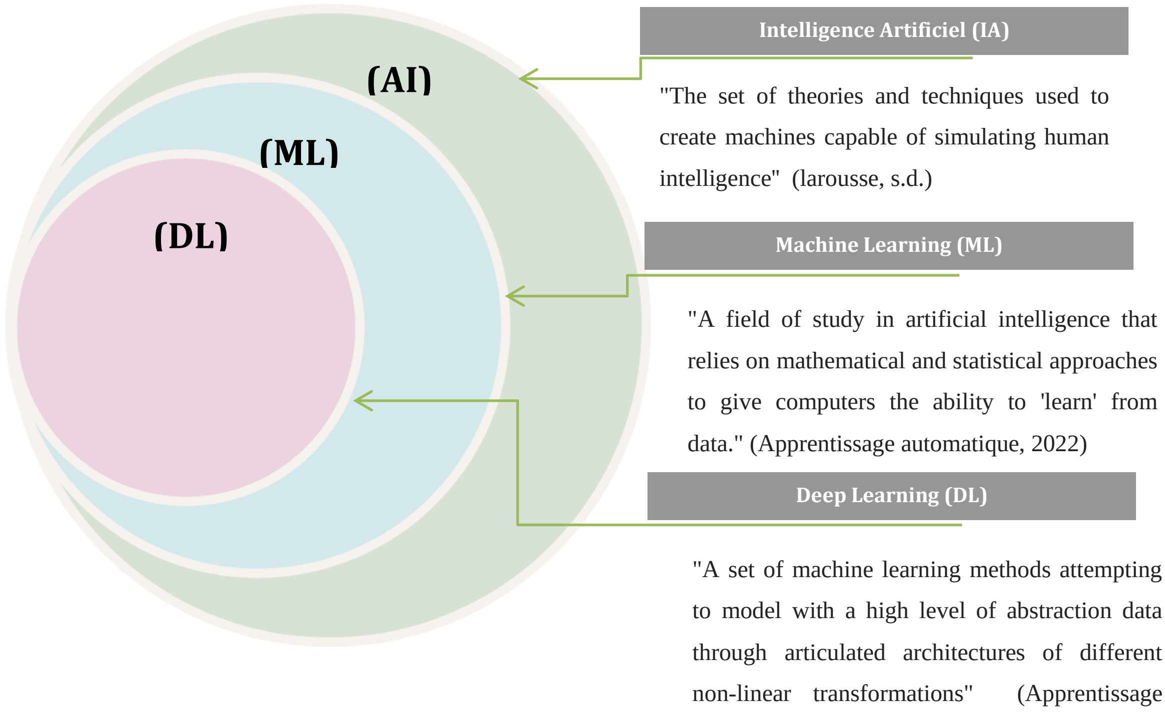


Figure 2 components of the AI

ML is a real advantage for SCM. It is able to describe the non-linear relationship while traditional methods are not, because the ML learning model better describes how the output (y) changes with the input (x). In a non-ideal SC, the parameters associated with several explanatory variables cannot be described exclusively by a linear model. For example, in a traditional demand forecasting model, it was thought that sales of alcoholic beverages were only related to temperature, which could be described by a linear model:

$$Y = a + bX$$

However, research has also shown that other factors affect alcohol sales, such as tax policy (Freeman, 2000).

3.2.1 Demand forecasting

Demand forecasting is a method of estimating the consumption of products or services for future periods.

"It will enable production to be planned in order to reduce delivery times and optimise stock levels. Demand forecasting is also a fundamental step in the establishment of an S&OP (Sales and Operations Planning) or a business model to analyze the economic viability of a project or a company"[1].

Nowadays, with the help of Web Scraping and Natural Language Processing (NLP) technologies (Eugene, 1984) even real-time discussions on forums and social networks have become easily accessible and analyzable (Chae, 2015a). Sales forecasts (Lau et al., 2018) are then refined and the life span of a product can be evaluated. Using clustering algorithms with decision trees (Sharma, R.,

[1] (2022, March 23). Prévision de la demande — Wikipédia. Fr. https://fr.wikipedia.org/wiki/Pr%C3%A9vision_de_la_demande

Kamble, S.S., Gunasekaran, A., Kumar, V., Kumar, A., 2000), it is also possible to extend the analysis to the prediction of the sales potential of a product in a specific setting.

3.2.2 Flow management

Demand forecasting not only improves sales management and thus finances, but also allows considerable optimisation of inventory by ensuring that the right amount of the right product is always in the right place.

By combining this information with the study of external factors such as raw material supply problems, goods traffic, or weather conditions, the risks of inventory shortages are largely minimised. This data can also be used to optimise delivery schedules or to assist in the decision-making process when choosing a supplier.

(Pasandideh, S.H.R., Niaki, S.T.A., Nia, A.R, 2011) proposed an Economic order Quantity (EOQ) model for a two-tier SCM in which the supplier delivers the retailer's orders in accordance with the demand. The proposed EOQ formulation is a non-linear integer programming model.

3.2.3 Optimising logistics performance

Logistics performance is a representation that encompasses all SCM activities. Its optimisation therefore requires many levers at different levels of the SCM actors (Figure 4)

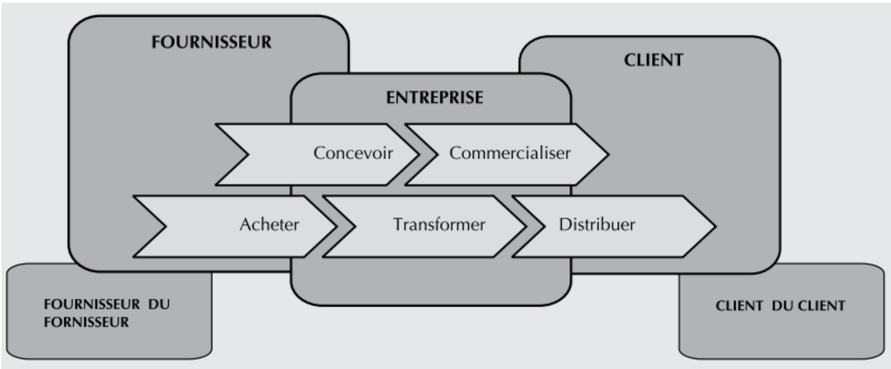


Figure 4. SCM actors

The performance of the SCM depends on the choice of its actors, the best selection of sustainable suppliers is central to a sustainable SCM (Amindoust et al., 2012), they propose criteria and sub-criteria for the selection of sustainable suppliers and develop a methodology to evaluate and rank a given set of suppliers using a fuzzy approach to address the subjectivity of the decision makers' evaluations.

Indeed, the analysis of the supplier order history allows to better know the quality of suppliers in terms of delivery time, compliance and quality standards of their products while grouping the appropriate purchases.

Robotic Process Automation (RPA) technologies enable the design of systems and machines to automate tasks that are difficult for humans to perform repeatedly or efficiently (Frey, C.B., Osborne, M.A, 2017). These help with inventory taking or customer order picking.

The optimisation of logistics performance also involves the detection and study of anomalies. In-depth analysis of processes and past orders may reveal recurring problems.
Optimising SCM performance also involves the detection and diagnosis of anomalies using radio frequency identification (RFID) technologies (Ma et al., 2018). With the rapid growth of the Internet of Things (IoT), the implementation of sensors and more sensitive connected objects is a real opportunity. Data from various equipment along the chain allows for real-time monitoring and control

of processes to prevent future anomalies (Ben-Daya, M., Hassini, E., Bahroun, Z, 2017). AI is involved in optimising planning and better resource allocation **(Ławrynowicz, 2007)**. In order to follow the evolution of the market or the deliveries to be made, AI algorithms distribute tasks in the best way to optimise productivities and avoid under or over staffing.

3.2.4 Improving the customer experience

Combined with ML, NLP can be adopted to analyze publicly available data (e.g. social media, blog posts, news) to provide insights into SCM operational challenges, sustainability risks, market and competitor performance, customer preferences and demand and future market trends (Chae, 2015b). Studying this data in conjunction with customer feedback analysis provides more visibility on what steps to take to further improve customer experience and satisfaction. NLPs allow customers to be segmented according to their profile and to be able to better target the services and promotional offers that will be offered to them, they generate Chatbots applications to facilitate interactions and conversations to better manage purchases.

In addition, the SCM has benefited from the contributions of AI, ML and Data Science advances at the very core of its activities. Through more efficient processes, the SCM has benefited in terms of processing time and in terms of costs that are significantly reduced.

Minimised risk and improved responsiveness to logistical contingencies has resulted in an overall improvement in customer service. Optimised performance and improved customer satisfaction: the perfect combination to move the logistics industry towards a proactive, predictive and personalised industry.

3.3 Different Types of Algorithms

As per (Tom, 1997) ML "is a field of investigation devoted to understanding and building methods that 'learn', i.e. methods that exploit data to improve performance on a set of tasks". ML algorithms create a model based on sample data, called training data, to make predictions or decisions without being explicitly programmed to do so. The choice of ML model differs from situation to situation depending on the problem to be solved and the discipline, such as medicine, banking to detect fraud, or e-mail filtering, speech recognition or sales prediction, where it is difficult or impossible to develop conventional algorithms to perform the necessary tasks (Hu, J.; Niu, H.; Carrasco, J.; Lennox, B.; Arvin, F, 2020). ML is associated with the development of algorithms capable of learning from training data to solve problems using knowledge gained from previous problems (Priore, P., Ponte, B., Rosillo, R., de la Fuente, D., 2019).

3.3.1 Machine Learning techniques

There are several categories of ML algorithms, we will focus on describing (02) types of them, which are often used by data scientists and theoretical researchers namely supervised learning and unsupervised learning (Overgoor, G., Chica, M., Rand, W., Weishampel, A., 2019).

3.3.1.1 Supervised Learning

Supervised learning finds alliances between the characteristics of a dataset and a target variable called Y to create a function of type:

$$\mathbf{f:X \rightarrow Y}$$

Y: An objective variable "Target

X: One or more characteristic variables "Features

In supervised mode, the algorithms work on the basis of data chosen by humans for their characteristics (X) and their known impact on the result (Y). For example: the influence of the outside temperature on the sales of drinks or the impact of outstanding orders on the delivery time. Sales forecasting models use this type of algorithm. The supervised learning workflow is illustrated in Figure 5

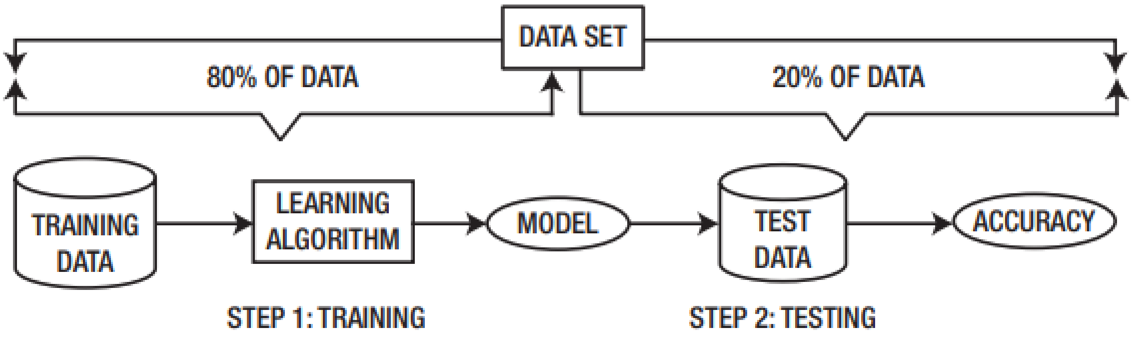


Figure 3. Figure 5 Supervised Learning (Kashyap, 2017)

In this model, human intervention is paramount, the use of the machine is limited in its computational capabilities.
Supervised learning models can mainly contain Decision Tree models, Linear Regression, support vector machines and Neural Networks (Cui et al., 2018).

3.3.1.2 Unsupervised learning

In unsupervised learning, the machine has only variable X, the models are left to their mechanism to better structure and present the data. The aim of the algorithm is to model the distribution in the data in order to look for consistency in the data within each category and to form dissimilar categories.
It is often used in clustering problems to identify similarities; this approach is called Clustering (Figure 6).

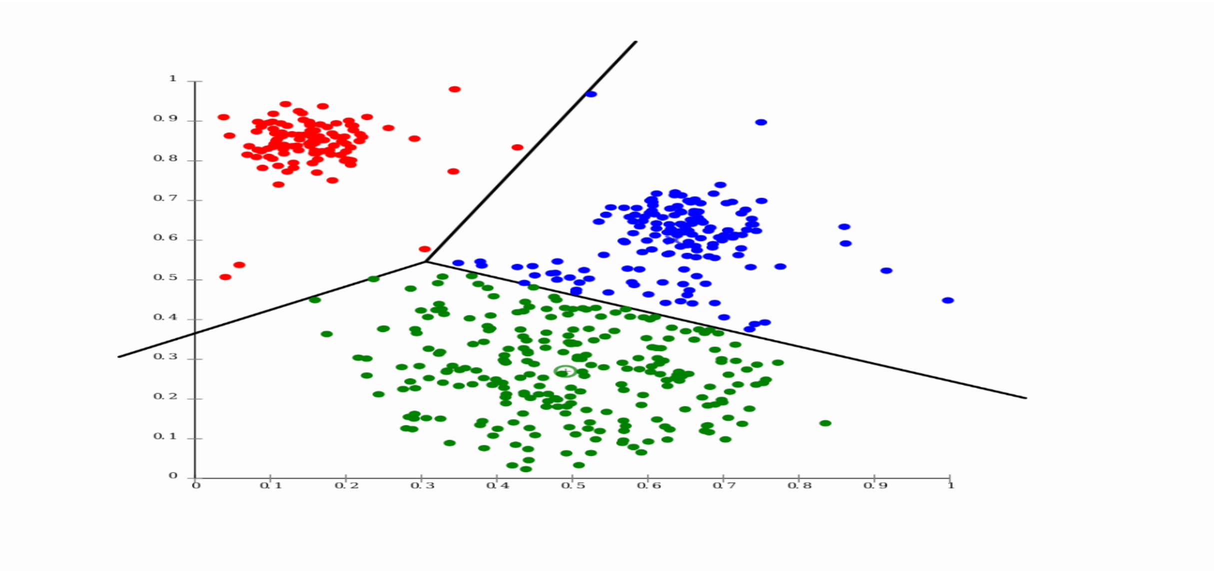


Figure 4. Data Divided into 3 categories (DBSCAN, 2020)

Algorithms are used to establish the diagnosis, while humans are involved in analyzing the data and determining the appropriate steps.
Also, the algorithms are used to solve a variety of problems such as production planning, inventory management, vehicle routing and warehouse management. On the other hand, the work of applying machine learning (ML) in SCM has recently seen increasing interest. Applications of ML in SCM

include demand forecasting, inventory planning, anomaly detection, transportation route optimization, production planning, and fraud detection. ML models can help improve the accuracy and efficiency of decision making in these areas. Table 1 represents a description of the most well-known algorithms used in the SCM fields.

Table 1. Frequently used ML algorithms.

Type of learning	Algorithms	Description
Supervised learning	Decision trees	Using related values, decision trees will classify attributes into different groups that can be applied for classification purposes (S. B. Kotsiantis, I. D. Zaharakis, and P. E. Pintelas, 2006)
	Naive Bayes	Naive Bayes algorithms can be better applied to cluster and classify objects (D. Lowd and P. Domingos, 2005).
	Support vector machines (SVM)	SVMs work on margin calculations, they can be better applied to classification purposes (A. Karatzoglou, D. Meyer, and K. Hornik, 2006)
	k-nearest neighbors	In k-nearest, the learner usually uses the training data. When the test data is presented to the learner, he or she compares the 2 data. Here, K the most correlated data is taken from a training set. (The majority of K is taken, which serves as a new class for the test data (Harrington, 2012))
	Supervised Neural Networks	Using the supervised neural network, the predicted and actual output will be compared, and depending on the error identified, the parameters will be changed and considered again as the input to the neural network (Dey, 2016)
Unsupervised learning	K-Means Clustering	Using the similarity of the data clusters, the K-means clustering algorithm (KM) defines K-clusters in which the cluster center is the average of the values. (S. Shalev-Shwartz, Y. Singer, N. Srebro, A. Cotter, 2011)
	Principal components analysis.	Analysis Principal component analysis can provide faster and easier calculations as it reduces the size of the data (Harrington, 2012)
	Unsupervised neural network	The unsupervised neural network categories the data according to their similarities. Since the output is unknown, UNN considers the correlations between different inputs and classifies them into different groups (Dey, 2016)

The table 2 showcases a variety of authors who investigate the benefits of utilizing ML technology in specific contexts, identifying areas where ML algorithms can provide the most effective solutions for problem-solving and performance improvement. The selected papers encompass research in various domains, including demand forecasting, inventory control, and production management, among others. This research aims to advance the development and application of ML techniques to address real-world challenges and optimize complex processes.

Table 2. ML applications in the SCM

ML applications	Auteurs
Demand forecasting and sales estimates	(R. Carbonneau, K. Laframboise, and R. Vahidov, 2008) (A. Ning, H. Lau, Y. Zhao, and T. T.Wong, 2009) (Y. Pan, R. Pavur, and T. Pohlen, 2016)
Transport and distribution	(M. Maghrebi, C. Sammut, and S. T. Waller, 2015) (S. Mercier and I. Uysal, 2018) (S. Shervais, T. T. Shannon, and G. G. Lendaris, 2003)
Production	(W. W. C. Chung, K. C. M. Wong, and P. T. K. Soon, 2007) (H. Wu, G. Evans, and K.-H. Bae, 2016.)
Inventory control	(S. Shervais, T. T. Shannon, and G. G. Lendaris, 2003) (A. T. Gumus, A. F. Guneri, and F. Ulengin, 2010)
Selection and segmentation of suppliers	(X. Guo, Z. Yuan, and B. Tian, 2009) (A. Valluri and D. Croson, 2005) (W. Jiang and J. Liu, 2018)

4. Conclusion

In conclusion, the elements of demand forecasting, flow management, logistics performance optimization, and customer experience improvement are all crucial for ensuring effective and efficient supply chain management. Demand forecasting is essential for ensuring that companies have enough products to meet customer needs. Flow management enables maximizing resource utilization and reducing costs. Logistics performance optimization contributes to improving quality, speed, and reliability of services. Finally, customer experience improvement is crucial for maintaining customer loyalty and attracting new customers.

By using Machine Learning techniques, these elements can be significantly improved. Demand forecasting algorithms can be trained on historical data to predict future demand with increased accuracy. Machine Learning techniques can also be used to optimize transport routes and improve production planning decisions. Finally, data analysis can help understand customer needs and preferences, allowing for more effective personalized offerings. In summary, applying Machine Learning techniques to these key elements further improves supply chain performance.

For future prospects, it is conceivable that advancements in artificial intelligence, natural language processing, and the Internet of Things will continue to drive innovation in supply chain management. The integration of these technologies would enable increased automation, real-time decision-making based on continuous data, and improved collaboration among supply chain partners. Furthermore, the use of machine learning would enhance systems' ability to adapt and continuously improve by quickly identifying trends, anomalies, and optimization opportunities. This would enable more agile, flexible, and responsive supply chain management, reducing costs, delays, and inefficiencies.

Additionally, the integration of artificial intelligence and machine learning into supply chains may lead to the development of more sophisticated predictive models capable of anticipating market trends and fluctuations with even greater accuracy. This would enable businesses to make more informed decisions regarding production, logistics, and inventory management, minimizing risks and optimizing overall performance.

The future of supply chain management relies on a deeper integration of artificial intelligence, machine learning, and emerging technologies, opening up new possibilities for enhanced efficiency, effectiveness, and strategic decision-making.

Table of Abbreviations

AI	Artificial Intelligence
EOQ	Economic order Quantity
IoT	Internet of Things
ML	Machine Learning
NLP	Natural Language Processing
RFID	Radio frequency identification
RPA	Robotic Process Automation
S&OP	Sales and Operations Planning
SCM	Supply Chain Management
SVM	Support vector machines

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