

Forecasting Supply Chain Demand Approach Using Knowledge Management Processes and Supervised Learning Techniques

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ABSTRACT

In today's context (competition and knowledge economy), ML and KM on the supply chain level have received increased attention aiming to determine long and short-term success of many companies. However, demand forecasting with maximum accuracy is absolutely critical to invest in various fields, which places the knowledge extract process in high demand. In this paper, the authors propose a hybrid approach of prediction into a demand forecasting process in supply chain based on the one hand, on the processes analysis for best professional knowledge for required competencies. And on the other hand, the use of different data sources by supervised learning to improve the process of acquiring explicit knowledge, maximizing the efficiency of the demand forecasting, and comparing the obtained efficiency results. Therefore, the results reveal that the practices of KM should be considered as the most important factors affecting the demand forecasting process in supply chain. The classifier performance is examined by using a confusion matrix based on their accuracy and Kappa value.

KEYWORDS

Forecasting, Knowledge Management, Machine Learning, Prediction Models, Supply Chain Decision Support Systems, Supply Chain Management

INTRODUCTION

Over the last years, a Supply Chain Management (SCM) framework was presented as a new business model and a way to create competitive advantage by knowledge discovery from heterogeneous data of customers and suppliers. Similarly, SCM has become increasingly significant with the globalization of business, and competition (Silva et al. 2020; Ketchen & Guinipero, 2004). Typically,

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SCM has been widely recognized as a significant point for information technology investment in supporting supply chain processes (Tooranloo et al. 2018; Wu & Chuang, 2010). In the literature of supply chain management, multiple authors present various definitions. According to (Raghu Nath & Devi, 2018), SCM is about managing flows of material, information, and funds in a complex network of entities of suppliers, manufacturers, distributors, and customers. For Gonzalez-Loureiro et al. (2015), the supply chain is a set of activities that span enterprise functions from the ordering and receipt of raw materials through the manufacturing of products through the distribution and delivery to the customer. Additionally, SCM is defined as a set of entities directly involved in the activities associated with the upstream and downstream flows of products, services, finances, and/or information from a source to a customer (Aggarwal et al. 2020; Christopher, 2016; Islek & Oguducu, 2017). For Kong & Xue, (2013), SCM is a mode of operation which is new, advanced, and could improve the business competitiveness. Additionally, the supply chain is the network of organizations that are involved, through upstream and downstream linkages, in the different processes and activities that produce value in the form of products and services delivered to the ultimate consumer (Mentzer et al. 2001). At the same time, a supply chain can be regarded as a complex network spanning several companies and sectors. This latter has involved keeping extensive records of almost every aspect of its activities. Therefore, the success of a supply chain depends on the accuracy of the forecasts, especially those of the demand. According to (Stadtler & Kilger, 2008), Supply Chain Management (SCM) is defined as, the act of sharing material, information within organizational units, so as to meet customers' needs and as a result, enhance the entire supply chain involved. In the industrial world, (Mohseni et al. 2019) show that a strong there is no way for the industry to escape the adoption and to incorporate sustainability in SCM. Hence, it is needed to specify sustainability practices in SCM in accordance with industry characteristics.

In order to achieve the required supply chain, it is necessary to use intelligent technologies and tools namely Machine Learning (ML) which enables monitoring, evaluation of supply chain performance and anticipates the future. In this regard, Machine Learning (ML) has been one of the most promising technologies due to its multiple capabilities important for business success in terms of making accurate predictions, recognizing patterns, etc... In recent years, a number of practical logistic applications of Machine Learning (ML) have emerged, especially in SCM. Besides, Machine Learning techniques constitute a real asset for supply chains, since they give better forecasts than the more traditional approaches. As per our objective, the combination of ML methods and supply chain management concepts can improve supply chain efficiency and reduce costs with an optimized decision-making process by providing actionable information to the right decision-makers.

Currently, Knowledge Management (KM) process has been convincingly applied to some extent in logistics management, forecasting/demand planning, scheduling, inventory management, humanitarian logistics, and reverse logistics. Moreover, the demand knowledge derived from obtained data and factors knowledge which influence on it allow to manager to react more flexibly on-demand change, to plan more effectively, to increase the availability of products on the market, to increase the level of customer's services and to develop this competitive advantage. In most studies, knowledge sharing has been extensively studied as a key enabler for coordination and integration in supply chains in order to demonstrate its relevance and applicability for practitioners (Kiil et al. 2019; Posey & Bari, 2009).

In the same way, the forecasting concept is the news logistic concept that increases the potential of a global logistics solution through global interconnectivity stakeholders especially the connection among manufacturers, distributors, and consumers in the chain (Kantasa-ard et al. 2019). Apparently, forecasting is essential in investment, which places machine learning in high demand. In prior studies, various time series forecasting models have been widely applied in sales forecasting, such as exponential smoothing models, ARIMA models, expert systems, and Nearest Neighbors models. A case study carried out by (Annor-Antwi et al. 2019), illustrates that forecasting helps in the future prediction of the market trends, it also helps a business utilize resources more efficiently, manage inventory, remain competitive, evaluate its past and therefore be able to have a clearer focus on the

future. According to (Kamble et al. 2015), SCM relies on forecasts of future demand for decision making which are used in supply chain design, planning as well as in operations. In past decades, the ML methods have established themselves as serious contenders to classical statistical models in the area of forecasting. In reality, demand forecasts are very important for efficient supply chain planning. In theory, demand forecasting is the estimation of a probable future demand for a product or service. The term is often used interchangeably with demand planning, yet the latter is a broader process that commences with forecasting but is not limited to it (Baryannis et al. 2019). Indeed, demand forecasts information sharing between supply chain members may improve supply chain performance (Babu & Shah, 2013; Bousqaoui et al. 2019). Besides, demand forecasting enables an organization to take various business decisions, such as planning the production process and deciding the price of the product. Likewise, accurate demand forecasting is essential for a firm to enable it to produce the required quantities at the right time and arrange well in advance for various inputs (Pérez-Salazar et al. 2017).

In light of the above considerations, this study has sought to identify the main forecasting supply chain demand using, on the one hand, the processes analysis for practices knowledge and the strategic analysis for required competencies. And on the other hand, incorporating different data sources by supervised learning techniques like Nearest Neighbors, Bayesian Networks, and AdaBoostM1 improve the process of acquiring knowledge explicit.

The remainder of this paper is organized as follows: Section 2 presents the literature review of existing works. Section 3 presents proposed hybrid approach implementation details. Subsection 3.1 examines the level of knowledge management practice to forecasting supply chain demand. Subsection 3.2 describes data cleaning, preprocessing, model training, and evaluation. Section 4 concludes and summarizes the key findings.

2. RELATED WORK

Over the years, there have been numerous theories and practices that provide explanations and predictions of using Machine Learning (ML) and Knowledge Management (KM) in supply chain demand forecasting from different disciplines. This section will briefly prove some backgrounds done by various researchers regarding the use of Machine Learning (ML) techniques and Knowledge Management (KM) process in Supply Chain Management (SCM) and notably forecasting (demand and Time Series).

2.1. Machine Learning Used in Supply Chain

In the last few years, ML techniques are becoming the need of the company due to its smarter ways to grow revenue, and saving time in solving problems. One of the greatest use of ML in SCM is predicting the future demand of the manufacturers, distributors and customers (Weili, 2019). For instance, Guosheng, H., & Guohong, Z. (2008) have developed a model with better explanatory power to select ideal supplier partners based on support vector machine (SVM) and Back-Propagation Neural Networks (BPNN). Likewise, the prediction accuracies for BPNN and SVM methods are compared to choose the appreciating suppliers. The actual examples illustrate that SVM methods are superior to BPNN. The work done by in (Kuo et al. 2010), intends to develop a green supplier selection model, which integrates artificial neural network (ANN), and two multi-attribute decision analysis (MADA) methods: data envelopment analysis (DEA) and analytic network process (ANP). This model evaluation results indicate that the ANN–MADA hybrid method outperforms two other hybrid methods, ANN–DEA and ANP–DEA. Kocamaz et al. (2016) have presented the control of chaotic supply chain with Artificial Neural Network based controllers and the synchronization of two identical chaotic supply chains that have different initial conditions with Adaptive Neuro-Fuzzy Inference System (ANFIS) based controllers. Nguyen et al. (2018) recently published a survey of big-data analytics for supply chains that classifies the studies by supply chain functions, including

demand management, manufacturing, warehousing, and general supply chain management. The authors highlight that areas such as demand forecasting and machine maintenance are increasingly using ML. According to a study by (Makkar et al. 2019) on the seek various business applications of ML techniques in Supply Chain Management. The research reviews the cases where Machine Learning Techniques are being used in Supply chain optimization. According to one of the reports by (Wenzel et al. 2019), ML methods have applied with successfully in SCM in industry. The authors have assigns use cases of machine learning to the task model of SCM, resulting in an overview of ML applications within the different supply chain tasks. Another study by (Ni et al. 2019), it is to provide a systematic review of recent trends of the ML applications in SCM. For this study, the research articles, published during 1998/01/01–2018/12/31, were searched on six academic databases: Emerald Insight, IEEE Xplore, Scopus, Science Direct, Wiley and Springer, with Google Scholar as a complementary database. Another analysis by (Bateh, 2019), on the impact machine learning, Artificial Intelligence, and robotics has on the SCM. This analysis has put emphasize how machines transform our SCM with various segments including marketing, SCM innovations with AI, and even these innovations' overall impact. Melançon et al. (2019) have developed a system that uses ML to predict service level failures in a supply chain. The authors have implemented and tested the ML model and the user interface (UI) in the context of Michelin's supply chain, specifically the store-and-sell channel. Liu & Huang, (2020) have proposed an ensemble support vector machine model to solve the risk assessment of supply chain finance, combined with reducing noises method. The main characteristics of this approach include that (1) a novel noise filtering scheme that avoids the noisy examples based on fuzzy clustering and principal component analysis algorithm, and (2) support vector machine classifiers, based on the improved particle swarm optimization algorithm, are seen as component classifiers. Another study by (Ni et al. 2020), it is to provide a systematic review of recent trends of the ML applications in SCM. For this study, the research articles, published during 1998/01/01–2018/12/31, were searched on six academic databases: Emerald Insight, IEEE Xplore, Scopus, Science Direct, Wiley and Springer, with Google Scholar as a complementary database.

2.2. Machine Learning Used in Forecasting

In the literature, the most ML algorithms improve forecasting methods in accuracy and optimize replenishment processes. With these advances, companies are minimizing the cost of cash-in-stock and out-of-stock scenarios. In machine learning, the ability of a model to predict categorical values based on a training dataset is called classification. In the right context, the existing works in the general area of ML for demand forecasting are reviewed first to shed light on the models and techniques that are typically used for demand forecasting regardless of the application domain. Among the first studies to load forecasting, Carbonneau et al. (2008) have investigated the application of machine learning for supply chain demand forecasting in order to minimize the cost of inventory and to increase customer satisfaction by predicting the demand of products. The best predictor model was Recurrent Neural Network (RNN) and after that Support Vector Machine (SVM) and then Neural Network (NN), then Multiple linear Regression (MLR). In the study done by (Ahmed et al. 2010), it is to compare the following models: multilayer perceptron, Bayesian neural networks, generalized regression neural networks, K-nearest neighbor regression, CART regression trees, support vector regression and Gaussian processes. Another focus of the study is to examine preprocessing methods, used in conjunction with the machine learning forecasting models. Mora-López et al. (2011) have proposed the use of statistical models to obtain useful information about the significant information for a continuous time series and then they have used this information, together with ML models, statistical models and expert knowledge, for short-term forecasting of continuous time series. Sivalingam et al. (2016) have investigated forecasting gold price based on extreme learning machine. For predicting gold price some techniques such as neural network, fuzzy logic, genetic algorithm, particle swarm optimization and simulation annealing can be used. In the study done by (Xiaodong et al. 2016), it is to investigate stock market prediction via extreme learning machine (ELM). Besides the accuracy

of the models which predict stock market, speed plays a crucial role in online forecasting. In this research, the performance of ELM with SVM and Back Propagation Neural Network (BP-NN) based on one-year period with H-share metric of news articles compared. Fischer et al. (2018) have proposed a comprehensive simulation study design that allows for comparing the forecasting quality of eight ML models (two MLPs, logistic regression, naïve Bayes, k-nearest neighbors, decision trees, random forests, gradient-boosting) across to time series of eight data generating processes (DGPs) – reflecting different linear and nonlinear dependencies (base case). Another study by (Pavlyshenko, 2019) has used a ML models for sales time series forecasting. Sales prediction is rather a regression problem than a time series problem. The effect of ML generalization consists in the fact of capturing the patterns in the whole set of data. In the same way, Abolghasemi et al. (2019) have proposed to use machine learning models to disaggregate time series. Three machine learning (Artificial neural networks, extreme gradient boosting and support vector regression) algorithms are used to estimate the proportions of lower-level time series from the upper level.

2.3. Knowledge Management Used in Supply Chain

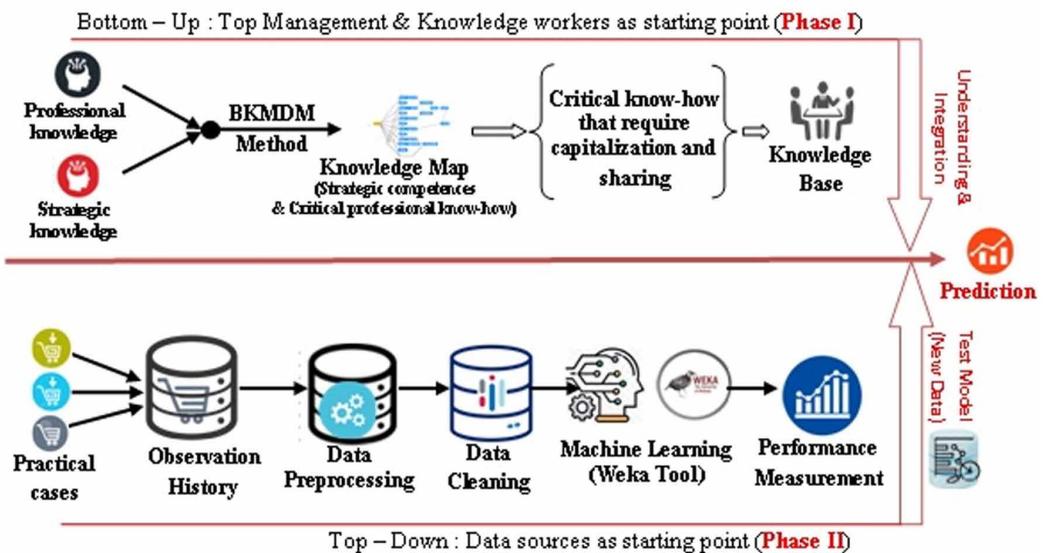
In theory, Knowledge Management (KM) practices can be defined as the set of management activities conducted in a firm with the aim of improving the effectiveness and efficiency of organizational knowledge resources (Kianto & Andreeva, 2012; Kianto et al. 2017). Reviewing the literature, we can see the importance of KM concept in the supply chain. KM process reduces variability across the supply chain, and results in better forecasting, coordinating, and customer service. According to (Schoenherr et al. 2014), supply chain knowledge is defined as “the use of knowledge resources obtained from supply chain members for economic gain”. As per our objective (Brahami & Matta, 2019; Brahami & Matta, 2018) highlights that it is fundamental to determine, acquire, use and convert tacit knowledge of supply chain experts to an explicit form to transform a firm’s knowledge assets into competitive capabilities. According to (Peng Wong & Yew Wong, 2011; Li et al. 2006), SCM and KM represent alternative approaches that have generated a lot of interests among organizations and researchers. The Researchers (Chengalur-Smith & Duchessi, 2014; Nyaga et al. 2010) have claimed that in modern supply chains, many companies are linked to their suppliers and customers through systems that enable knowledge sharing. In the study done by (Abu-Shanab, 2007), it is to develop a model that facilitates the process of future research in order to test performance changes with respect to implementing IS, and to what extent firms will benefit from information sharing in supply chain networks (SCN). In the study done by (Volpato & Stocchetti, 2007), it is to verify the presence of KM activities in five first-tier suppliers and to analyze the main features of the operational implementation of such activities, with the aim to evaluate the perception of the involved issue. Peng Wong & Yew Wong, (2011) have investigated how SCM practices and KM capabilities affect firm performance. This study has extended knowledge in the mainstream management and provides valuable clues on how to improve organizational effectiveness. Another research by (Zhang & Chen, 2013), is to study information sharing in a supply chain consisting of one supplier and one retailer, in which both the supplier and the retailer possess partial information on the demand. Another study by (Lotfi et al. 2013), it is to overview the effectiveness of knowledge sharing in SCM, in order to increase the efficiency of the organizational performance in the manufacturing sector. This study elaborates the benefits and barriers of knowledge sharing leading to enhanced supply chain integration among enterprises, as a result. Another research by (Attia & Salama, 2018), is to examine the effect of KM capabilities on SCM practices and organizational performance in firms, in addition to examining the effect of SCM on organizational performance. Almuie & Zawaideh, (2019) have employed the IA approach to facilitate automated knowledge acquisition for SCM decision making. In addition, the study framework is characterized by different levels of knowledge acquisition linked to SCM and knowledge reuse on the basis of the prior supply chain knowledge. According to a study by (Kő et al. 2019), knowledge creation patterns inherent in the supply chain of companies that operate in a networked environment in the Székesfehérvár region of Hungary. The main contributions of this

study of knowledge creation patterns in three dimensions: the Socialization – Externalization – Combination –Internalization (SECI) framework, supply chain processes and ICT solutions, which is a unique approach compared with the frameworks from the relevant literature. Most recently, Schniederjansa et al. (2020) have did a study which aims to understand future inquiries for scholars to broaden their perspectives and leveraging KM in order to enhance the supply chain digitization research paradigm. Moreover, this study was carried at the base a large-scale literature review as well as a textual analysis and forecasting on industry- and field-applications, technologies and topics in digitization. Another study by (Indriyani et al. 2020), is to determine the effect of knowledge sharing and supply chain management on opportunity recognition skill through management skill in the food industry in Surabaya. This study has conducted by examining the knowledge sharing, opportunity recognition skill and management skill and the data obtained were analyzed using PLS. Finally, Soetjipto et al. (2020) have determined the effect of variable mediation in this case the Supply Chain Strategic (SCS), on the influence of KM on Business Performance (BP) in the Small and Medium Enterprises (UKM) sector in Java Island of Indonesia.

3. APPROACH PROPOSED

Nowadays, many companies manage a huge amounts of sales and consumer behavior data in order to extract hidden information for making intelligent analysis and prediction. In contrast, demand forecasting is absolutely essential within supply chain activities management and decision making. Furthermore, KM is a fundamental enabler of SCM in highly competitive environments that are both information and knowledge-intensive. The main objective of this paper is to propose a hybrid approach of prediction into the demand forecasting process in supply chain management based on the one hand, on the processes analysis for best professional and practices knowledge and the strategic analysis for required competencies using BKMDM method. And on the other hand, the use of different data sources by machine learning techniques to improve the process of acquiring knowledge explicit (historical supply chain dataset), maximizing the efficiency of the demand forecasting and comparing the obtained efficiency results (see Figure 1).

Figure 1. Main Steps of the proposed hybrid approach



3.1. Knowledge Management Applied to Forecasting Supply Chain Demand (First Phase “Botton-Up”)

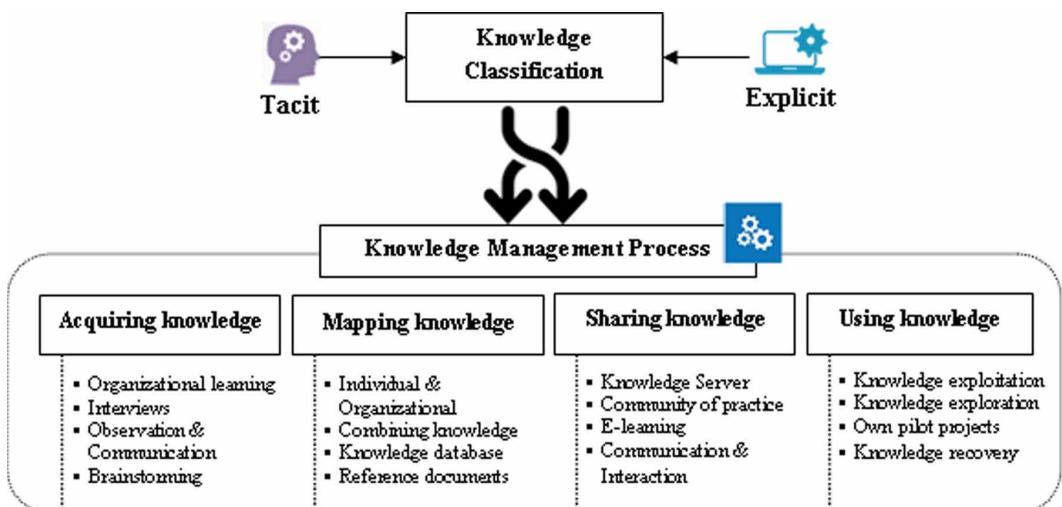
3.1.1. KM Processes Components

In today’s turbulent and highly competitive environments, KM (knowledge capitalization) is essential in the growing field of forecasting supply chain demand because multiple sectors are involved within the company. For this, this section of the paper discusses the link between KM process and forecasting supply chain demand. In doing this, it explores the factors that promote KM in organizations, with the coverage given to such factors as people, leadership, and the external environment. In the context of practical work mentioned above, this study used these four processes to assess the current KM implementation in hypermarkets, department stores, and grocery stores which are (see Figure 2): Acquiring knowledge (*knowledge acquisition is the process to capture tacit and explicit knowledge in order to add it to its knowledge assets and make it available for the future use* (Ohara & Bai, 2019)), Mapping knowledge (*knowledge mapping is a tool for knowledge representation visual in order to facilitate decision making* (Brahami et al. 2015; Brahami, 2020)). *On the other hand, knowledge mapping allows companies to enhance their efficiency and expertise by transforming created information into usable organizational knowledge and disseminating it to where it is*, Sharing knowledge (*knowledge transfer involves the sharing of all knowledge source* (Zheng, 2017)) and Using knowledge (*using knowledge concerns the actual applying of knowledge in performing tasks* (Cerchione & Esposito, 2017)). *Similarly, knowledge utilization refers to the process of employing the created, stored, coded, and presented information in problem-solving and decision-making* (Ginting et al. 2020). In this field, descriptive analysis has been started using the mean and the standard deviation in order to assess the level of each KM processes practice.

3.1.2. Research Materials and Methods

In contrast and in order to assess the importance of KM (knowledge capitalization) in each business area of forecasting supply chain demand namely a chain of hypermarkets, department stores, and grocery stores, it is important to firstly understand the key main of the BKMDM (*Boolean Knowledge Management guided by Data Mining*) method (Brahami et al. 2013; Brahami & Nada, 2018; Brahami & Matta, 2019; Brahami et al. 2020) in order to identify the contextual relationships among the factors. The main principle of the BKMDM method (*knowledge discovery and management*) is to identify

Figure 2. The practices related to the KM process

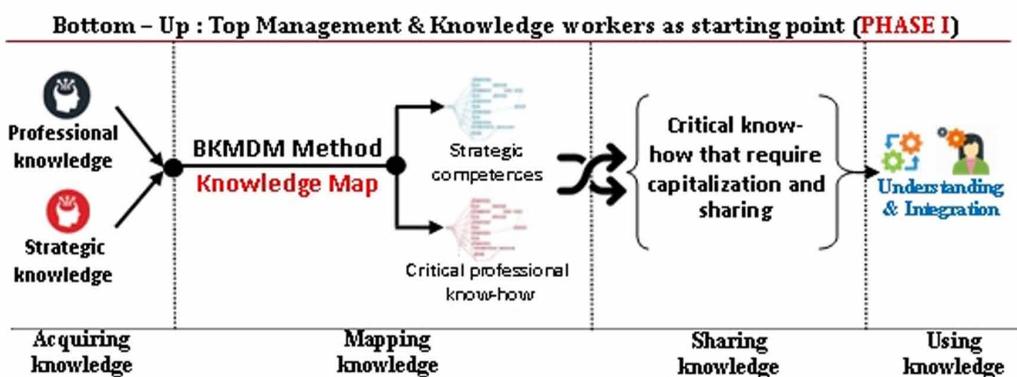


the best professional knowledge (*Tacit Knowledge*) and knowledge discovery from practical cases (*Explicit Knowledge*), to formalize them into models, and to ensure the sharing and using of know-how. Besides that, the advantages of BKMDM method based on the principle of Boolean modeling are automatic data retrieval from heterogeneous sources, the results of the mapping are simple to be reorganized and used by and for a process of machine learning and mixing expert knowledge and data in learning algorithms. Formally, the result obtained initially in a BKMDM method is a set of models and rules that formalize knowledge and which were elaborated through interviews with the knowledge workers (knowledge actors) and a process of knowledge discovery from practical cases (heterogeneous sources). Figure 3 summarizes the main steps of the first phase (Bottom - Up) of our hybrid approach which respects the KM process that we adopted in order to assess the current KM implementation in hypermarkets, department stores, and grocery. Moreover, this second phase (top management & knowledge workers) puts, on the one hand, the trade's actors (knowledge workers) at the center of any process of forecasting supply chain demand and as well its strategic competences and, on the other hand, the different data sources to improve the process of acquiring knowledge explicit (see Figure. 3).

Indeed, the research variables that represent KM processes and the questionnaire were adopted from a study conducted by (Brahami et al. 2013; Brahami et al. 2020). The questionnaire included 16 items (four items for each process) and used a 5-point Likert scale (1=Strongly Disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly Agree). To do that, the practical work has been carried out on the basis of three steps:

1. Group working sessions involving those concerned with discussion on a particular issue. During this session, we used the brainstorming technique. In the literature, brainstorming is a group activity in which all the members of a group suggest ideas and then discuss them as a brainstorming session (Gogus, 2012). When brainstorming, we used the Mind Maps concept by Mind Manager tool as a means of registration and organization in order to sure our creativity is well captured and enhancing the brainstorming process;
2. Individual interviews with nearly 35 people in department stores and grocery stores, concerned with various processes (knowledge actors). All the individuals interviewed therefore have a direct link with the logistics chain. Moreover, respondents can be selected on common factors/ attributes i.e. age, sex, education, etc. During this session, some support tools have been used as well as interviewing techniques. Likewise, we used the interview technique to gather data during face-to-face interviews in order to support knowledge sharing. In the meantime, all the responses are collected and processed using statistical processing software called SPSS. Primarily, the

Figure 3. Main Steps of knowledge formalization phase I (Bottom - Up)



SPSS tool was chosen for its wide choice of processing, crosstabs, and groupings. SPSS is also a versatile package that allows many different types of analysis data and execution of statistical tests. Moreover, we involve through our data analysis a reliability analysis in order to test the internal consistency of each construct variables;

3. As we all know, managers play a strategic role in a company’s performance and growth since they possess knowledge about hypermarkets product portfolio and procurement. Therefore, the demand planning team has monthly meetings where they present the demand forecast strategy to the managers. In the context of this study, a management interview mainly focuses on leadership skills and experience, but an interviewer also asks questions about background, qualifications, and communication skills. Interviews with managers (logistics manager, supply chain manager, production manager, sales manager and business manager) of hypermarkets to explain the procurement strategy, its goals, and communication in the organization. In contrast, the quality manager was interviewed with respect to the quality issues in procurement processes and their implementation in daily routines.

Once we finish knowledge formalizing, all results of the three steps have been validated with the participants and all the contributing experts. This step is nothing more than a transformation of the physical representation of the data gathered into the process model. The collected content is then reviewed to reach some quality standards. The next step is to demonstrate and analyze how the KM processes can support the forecasting supply chain demand.

3.1.3. Results and Discussion (Phase I)

In theory, an assessment of the normality of data is a prerequisite for many statistical tests because normal data is an underlying assumption in parametric testing (Darren & Mallery, 2010). As per our objective, an analysis was done through Kolmogorov–Smirnov, and Shapiro–Wilk test for normality in order and to confirm the normal data distribution. In fact, Table 1 depicting those static values of all variables in both tests was significant at a 95% confidence interval for the mean, which revealed that data was normally distributed (See Table 1). For this, the parametric tests must use if data shows the normal distribution.

Further, we conducted a reliability analysis using Coefficient Alpha or Cronbach’s alpha (Peters, 2014). As shown in Table 2, the overall values of Cronbach’s Alpha for KM processes were: Acquiring knowledge=0.811, Mapping knowledge=0.883, Sharing knowledge=0.778, and Using knowledge=0.831 (see Table 2).

These values show that data collected for KM processes in each business area of forecasting supply chain demand for this study are reliable and internally consistent. This research contributes to the extant literature in forecasting supply chain demand by enhancing our understanding of the ability of two domains to influence the best professional knowledge and knowledge from practical cases. Our findings offer significant insights into the best professional knowledge and knowledge from practical cases within forecasting supply chain demand, advance academic understanding, and

Table 1. Kolmogorov–Smirnov and Shapiro–Wilk tests for normality

	Kolmogorov–Smirnov			Shapiro–Wilk		
	Statistic	N	Sig.	Statistic	N	Sig.
Acquiring knowledge	.127	4	.000	.968	4	.000
Mapping knowledge	.224	4	.000	.970	4	.000
Sharing knowledge	.220	4	.000	.799	4	.000
Using knowledge	.123	4	.000	.937	4	.000

Table 2. Reliability Analysis Results

Indicator	Cronbach Alpha	No. of Items	Rule (Peters, 2014)
Acquiring knowledge	0.811	4	Good
Mapping knowledge	0.883	4	Good
Sharing knowledge	0.778	4	Acceptable
Using knowledge	0.831	4	Good

Table 3. Descriptive Analysis of Knowledge Management Processes

Variable (KM Processes)	Min	Max	M	SD
Acquiring knowledge	2.75	5.00	3.71	0.560
Mapping knowledge	3.00	5.00	3.90	0.620
Sharing knowledge	2.00	4.50	3.07	0.535
Using knowledge	2.00	4.25	2.76	0.544
Min: Average minimum level of agreement Max: Average maximum level of agreement M: Mean SD: Standard Deviation				

provide important implications for managers (logistics manager, supply chain manager, production manager, sales manager, and business manager). Overall, our study is important from both a theoretical and a practical perspective, enhancing the value of previous researches.

Besides that, Table 3 illustrates the results of the descriptive analysis of KM processes (See Table 3).

The results showed that the mean score of KM was 3.36 with a standard deviation of 0.29. The overall mean score for KM, including the four sub-constructs, were calculated by computing new variables in SPSS for the mean scores of all items of the sub-constructs. Among the four sub-constructs of KM, mapping knowledge showed the highest mean score (M = 3.9, SD = 0.62), followed by acquiring knowledge (M = 3.71, SD = 0.62) and sharing knowledge (M = 3.07, SD = 0.535). However, using knowledge showed the lowest mean score (M = 2.76, SD = 0.544).

As well, the correlation Table 4 shows the level of association and direction of the relationship among the variables (see Table 4).

Table 4. Correlation Analysis of KM Processes

Variable	Acquiring knowledge	Mapping knowledge	Sharing knowledge	Using knowledge
Acquiring knowledge	1			
Mapping knowledge	.726**	1		
Sharing knowledge	.583**	.740**	1	
Using knowledge	.572**	.738**	.733**	1
**Correlation is significant at 0.01 levels, N: 4				

The highest value of correlation coefficient ($r = .740$, $p < .01$) between knowledge mapping practices and knowledge sharing, followed by, between knowledge mapping practices and knowledge using ($r = .738$, $p < .01$), followed by, between the application of knowledge sharing and knowledge using ($r = .733$, $p < .01$), followed by, between knowledge acquisition and knowledge mapping practices ($r = .726$, $p < .01$), followed by, between knowledge acquisition and knowledge using ($r = .653$, $p < .01$) and finally knowledge acquisition and knowledge ($r = .587$, $p < .01$).

Indeed, the results of correlation analysis revealed that all variables were significantly correlated and no multi-co-linearity problem. According to (Shabbir & Gardezi, 2020; Hair et al. 2010), the correlation coefficient (r) must not go beyond .90 to get rid of the multi-collinearity problem.

The results showed that KM has a significant positive effect on forecasting supply chain demand. This shows that the increasing process of KM will make the forecasting supply chain demand better. The results also indicate that a strong application of the knowledge capitalization process will improve forecasting supply chain demand. Managers and knowledge workers who already have sufficient knowledge in forecasting supply chain demand will be able to share their knowledge and experience with employees and colleagues, and their expertise will also be able to develop the supply chain, especially for those related to the forecasting demand activities. Questionnaire survey and case study have been carried out, which aim at improving and testing the proposed KM model namely knowledge mapping step in order to facilitate understanding and embedding knowledge capitalize into the process in forecasting supply chain demand. In conclusion, since knowledge is a critical resource of sustainable innovation and competitive advantages for 21st-century enterprises, companies should invest heavily in formalizing knowledge by knowledge mapping methods and the creative workers through the employment of effective KM practices models.

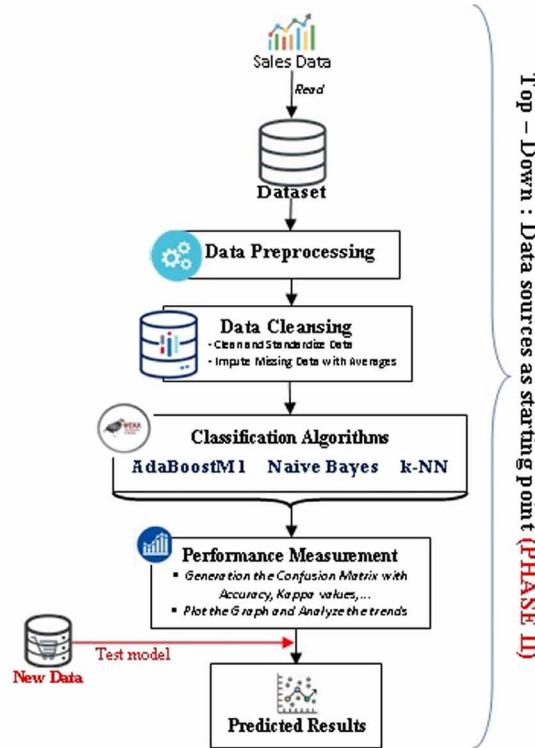
3.2. Machine Learning Applied to Forecasting Demand Data Sources (Second Phase “Top-Down”)

In the past decade, machine learning techniques offer immense help in managing the forecasting supply chain demand. Utilizing the pros of each technique allows a vast analysis and, later on, precise predictions of a broad variety of aspects. Indeed, recent advances in Machine Learning (ML) and the growing availability of datasets have initiated a steady stream of research combining machine learning and forecasting supply chain demand. In this respect, the top-down Machine Learning phase II of our proposed hybrid approach is shown in Figure. 4 (see Figure 4). After collecting, cleaning, and preprocessing the Walmart Dataset. As well, different classification learning techniques such as AdaBoostM1, Naive Bayes, and Nearest Neighbors are used. These ensemble techniques were applied to improve the performance of classification with an optimized decision-making process based on monitoring of the key performance indicators. The information set for forecasting supply chain demand was gathered and applied on every classifier to predict the forecasting and therefore the performance of the classifier is examined based on their Accuracy and Kappa value.

3.2.1. Data Understanding and Attributes

As we mentioned above, forecasting is used to predict future conditions and making plans accordingly. Moreover, forecasting is used in many businesses. In order to examine the effectiveness of various advanced ML techniques in forecasting supply chain demand, Walmart Shipment Datasets were prepared. In this context, the reason behind using Walmart data is Walmart's efficiency in Supply Chain Management (SCM). Over the past ten years, Walmart has reached as the world's largest and the most powerful retailer with the statistics of the highest sales per square foot, inventory turnover. With 45 stores across the world namely a chain of hypermarkets, department stores, and grocery stores, the data associated with it is huge in number. Similarly, this dataset is

Figure 4. The top-down phase II of machine learning



available on the Kaggle website. These Walmart Datasets contained information about the stores, departments, temperature, unemployment, CPI, isHoliday, and Markdowns (see Figure 5). For this study, the Walmart Shipment Dataset containing 1200 tuples and 12 attributes has been used for evaluation with multi-class classification models. The evaluations have been done with the help of Keel and WEKA tools.

Figure 5. Walmart Shipment dataset attributes detailed information

	Store	Date	Weekly_Sales	Temperature	Fuel_Price	Markdown1	Markdown2	Markdown3	Markdown4	Markdown5	CPI	Unemployment	IsHoliday
0	1	2010-02-05	1643690.90	42.31	2.572	NaN	NaN	NaN	NaN	NaN	211.096358	8.106	False
1	1	2010-02-12	1641957.44	38.51	2.548	NaN	NaN	NaN	NaN	NaN	211.242170	8.106	True
2	1	2010-02-19	1611968.17	39.93	2.514	NaN	NaN	NaN	NaN	NaN	211.289143	8.106	False
3	1	2010-02-26	1409727.59	46.63	2.561	NaN	NaN	NaN	NaN	NaN	211.319643	8.106	False
4	1	2010-03-05	1554006.68	46.50	2.625	NaN	NaN	NaN	NaN	NaN	211.350143	8.106	False
5	1	2010-03-12	1439541.59	57.79	2.667	NaN	NaN	NaN	NaN	NaN	211.360643	8.106	False
6	1	2010-03-19	1472515.79	54.58	2.720	NaN	NaN	NaN	NaN	NaN	211.215635	8.106	False
7	1	2010-03-26	1404429.92	51.45	2.732	NaN	NaN	NaN	NaN	NaN	211.018042	8.106	False
8	1	2010-04-02	1594968.28	62.27	2.719	NaN	NaN	NaN	NaN	NaN	210.820450	7.808	False
9	1	2010-04-09	1545418.53	65.86	2.770	NaN	NaN	NaN	NaN	NaN	210.622857	7.808	False

3.2.2. Data Cleansing

In general, the data obtained from the natural world is badly shaped. Some of the problems, such as outlier, may affect the ML models and produce biased results. Currently, data cleaning techniques, including missing value handling and outlier detection, were issued to tackle the problem. Similarly, they make the gathered data suitable as the input of the model. Therefore, the Walmart Dataset was scrubbed of any outliers or duplicates. Duplicated records were dropped after data aggregation had been performed. Records that contained multiple nulls or negative values for any of the attributes were removed. A small number of missing records with missing data were imputed with the mean of the attribute for the class within that feature.

3.2.3. Summary of Machine Learning Methods

In most literature, ML models have been employed in the last decade as serious competitors to classical statistical algorithms for prediction. In the right context, we explore in short using ML techniques to predict forecasting supply chain demand. We briefly discuss each method in turn before applying them to the forecasting of demand using a Walmart Shipment dataset.

1. Adaptive Boosting (AdaBoostM1)

The word AdaBoostM1 is derived from Adaptive Boosting. It is one of the most promising, fast convergence, and easy to be implemented ML algorithm (Wang, 2012). In fact, AdaBoostM1 is a meta-algorithm that is used to improve performance and solve the problem of unbalanced categories along with other learning algorithms (Alaoui & Elberrichi, 2018). Hence, the AdaBoostM1 algorithm multiple iteratively classifiers to improve the classification accuracies of many different data sets compared to the given best individual classifier (Lee et al. 2011; Fan & Wang, 2011). In this technique, the classification of each new stage is set for the benefit of wrong examples of classification in the previous steps. In sum, this technique allows classifying even high random error with a negative index in order to improve the overall performance.

2. K-Nearest Neighbor (K-NN)

K-Nearest Neighbor algorithm (K-NN) is widely used for classification and regression in recognition of patterns and consistency in data. In a family of algorithms, K-NN is a supervised learning algorithm for data/text classification. Furthermore, K-NN can be defined as a non-parametric, lazy learning algorithm as it uses a database that has the data points and is separated into several classes to predict the classification. As well, K-NN is a type of memory-based learning because hypotheses are built directly from training instances the neighbors are derived from the set of objects of a known class (Shouman et al. 2012). In contrast, the drawbacks of K-NN algorithm are it is not the fastest algorithm, works with less number of inputs; requires homogeneous features, delicate for the local alignment of the data.

3. Naïve Bayes (NB)

Naïve Bayes Algorithm is a collection of algorithms based on Bayes theorem of probability with naïve assumptions based on independent features instead of an analyzing single document. It helps to produce a more accurate model. It is one of the most popular supervised learning algorithms (Han et al. 2012). With Naïve Bayes (NB) classifier, the resultant model will give a high-performance with high training speed with the capabilities to predict the probability of the feature that belongs to the class (Boullé, 2007). The objective function of Naïve Bayes is to maximize the posterior probability given the training data to formulate a decision rule for new data.

3.2.4. Experimental Analysis and Results (Phase II)

In this section, experimental analysis, evaluation measures, and results of the study have been presented. In order to evaluate the predictive performance of classification algorithms based schemes on analysis, we applied 10-fold cross-validation on the entire dataset and use different performance measurements to evaluate the results. After cleaning and preprocessing the Walmart Dataset. This last has been used for simulation analysis and comparison of the two ML techniques with and without the AdaBoost technique. For our case, we use the Weka tool (Bouckaert et al. 2010). It is a collection of ML algorithms for data mining tasks. Weka supports several standard data mining tasks, more specifically, data pre-processing, clustering, classification, regression, visualization, and feature selection. For simulation analysis on the Walmart dataset with the K-NN algorithm, the accuracy and Kappa value are coming out to be the best when two nearest neighbors are taken. Nevertheless, the accuracy and kappa value is decreasing on increasing the number of nearest neighbors. Meanwhile, we show through Table 5 (see Table. 5) the trends in accuracy and kappa values for different nearest neighbors.

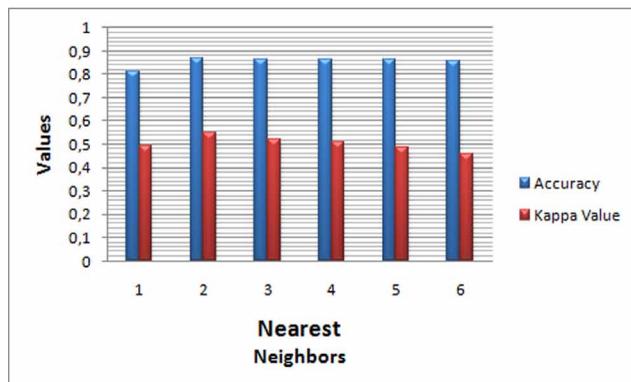
In the meantime, we report that the observation mentioned above has been proved by performing the cluster analysis of the dataset. For this, the cluster analysis of the dataset is giving the same result as the KNN. Indeed, this analysis showed that the entire dataset is coagulating into two clusters each having a centroid (it was used to further improve the performance of KNN), clearly indicating that the entire dataset has two nearest neighbors that are suitable for forecasting supply chain demand.

Similarly, Figure 6 (see Figure 6) show the graphical view of the accuracy and Kappa values for comparison.

Table 5. Accuracy and Kappa values for different neighbours

# Nearest Neighbors	Accuracy	Kappa value
1.	81.31	0.493
2.	86.91	0.551
3.	86.50	0.522
4.	86.30	0.511
5.	86.11	0.484
6.	85.60	0.457

Figure 6. Comparison of Kappa values and Accuracy for different neighbors



Combining classifiers to improve accuracy is a common phenomenon nowadays. Being simpler yet powerful algorithms both Naïve Bayes and KNN are ideal candidates for combination to achieve higher accuracy. In contrast, AdaBoostM1 can be used to boost the performance of any machine learning algorithm.

In the context of our study, we show through Table 6, the value of the kappa coefficient and accuracy by applying KNN and Naïve Bayes techniques with and without AdaBoostM1. As well, results show that the Naïve Bayes technique is more efficient in the present as well as in the absence of AdaboostM1.

In the machine learning concept, analysis and preprocessing of input data plays an important role prior to algorithm selection. Through data cleansing and preprocessing supply chain data, pruning decision spaces, the performance of the forecasting model can be improved. Thanks to machine learning techniques, supply chain management has entered a new level of transparency, operations efficiency, and builds competitive strengths, which are likely to be improved further.

4. CONCLUSION

Over the years, the problems that are most often attracting the attention of researchers and becoming the reasons for applying ML and KM in SCM are focused mainly on demand estimation. Similarly, theoretical and empirical researches have shown that improving performance in every firm is always possible by coupling KM practices and ML techniques initiatives with SCM programs. This research found in the first step that the practice of KM is modest in hypermarkets, department stores, and grocery stores. The findings showed that the practice of knowledge mapping was the highest, however, the practice of sharing and using knowledge that are the main objectives of KM was relatively low. In this regard, it can be concluded that these hypermarkets are threatened to lose their knowledge and competitive advantage unless they manage their knowledge more structurally.

Furthermore, there are various ML algorithms available to facilitate demand forecasting in SCM. Supervised Learning and its core constructs namely predictive analytics are ideally suited for providing insights into improving forecasting supply chain demand performance not available from previous technologies. This research was an attempt to highlight a few of these available techniques and the performance measures associated with them. The aim of this research has been to find the most suitable ML models in maximizing the efficiency of the demand forecasting and comparing the obtained efficiency results. In addition, it enables computing models to adjust to certain conditions, changes, and developments in a business environment with the ability to improve on its own over time. In this study, we restricted to using supervised learning techniques as KNN, Bayesian Networks, and AdaBoostM1 algorithms.

In summary, combining the strengths of ML and KM is proving to be a very effective technology that continually seeks to find key factors most affecting forecasting supply chain demand performance but also for understanding what drives sales and how customers are likely to behave under certain conditions. This study provides valuable knowledge crucial on what factors are important to predict the forecasting supply chain demand. For practice, this research has provided valuable information

Table 6. Comparison between Naïve Bayes classifier and K-Nearest neighbor

	Accuracy		Kappa Coefficient	
	<i>With AdaBoost</i>	<i>Without AdaBoost</i>	<i>With AdaBoost</i>	<i>Without AdaBoost</i>
Naïve Bayes Classifier	89.52	88.53	0.650	0.617
K-Nearest Neighbor	81,31	81.31	0.493	0.494

for the company to implement forecasting supply chain demand prediction and incorporate the result for their planning. All findings in this research are based on real-life data.

As a future work, we plan to enrich the set of features by gathering data from other sources like shopping trends, social media and location based demographic data of stores. New variety of data sources contributions to deep learning can be observed. One such attempt could be to check if using deep learning techniques such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) will enhance the model furthermore in terms of its demand forecasting performance.

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