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Predictive Big Data Analytics For Supply Chain Through Demand Forecasting

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Abstract—**Supply chain management (SCM) that makes use of BDA is becoming more prevalent. The wide range of SCM applications of BDA, including demand prediction, trend analysis, and consumer behaviour, is the reason for this. This study aims to enhance precision and efficiency in demand forecasting and SCM through the application of BDA. Despite advancements, challenges persist such as reliance on isolated datasets, underutilisation of advanced machine learning models, and limited incorporation of external variables. Demand forecasting, crucial for supply chain decisions like production planning and inventory control, is hindered by demand volatility influenced by factors such as promotions and market trends. This study leverages integrated, real-time data sources and sophisticated analytics to improve prediction accuracy and operational efficiency, thereby enabling businesses to better manage uncertainties in demand, supply, and costs. The research also identifies gaps in current literature, including the need for more robust models, comprehensive external variable analysis, and broader validation across industries. By addressing these gaps, the research contributes to a development of more resilient and responsive supply chains.**

Keywords—Big data analytics for supply chain, supply chain through demand* forecasting*, demand forecasting using supply chain.

I. INTRODUCTION

Precision marketing tactics are becoming more popular among modern businesses as a means to maintain or enhance profit margins and remain competitive. Due to this, precision marketing has made extensive use of demand forecasting models to ascertain and satisfy client demands [1][2]. An important part of SCM is the ability to communicate and use demand forecasts. Predicting future demand is the foundation for many supply chain management choices, such as order fulfilment, production planning, inventory management, and demand planning. It might be difficult to make accurate predictions at times because of the inherent volatility and fluctuating uncertainty. Demand volatility is caused by consumers' ever-changing behaviour [3]. Promotion, weather, market trends, and season are just a few of the elements that might influence customer behaviour and introduce uncertainty into demand [4] [5]. Demand may be quite unpredictable in the retail business, especially when it comes to promotions. There has been a plethora of research on how promotions affect demand dynamics. Demanding volatility is a logical consequence of the promotion. Promotional times are not immune to demand volatility and fluctuation. Supply chain managers and practitioners are starting to worry about demand volatility, which is a difficult risk to mitigate [6]. Researchers and practitioners have repeatedly highlighted the increasing unpredictability of demand as a significant threat to the supply chain. Demand volatility makes demand forecasting difficult and presents unnecessary expenses for inventory, stock-outs, and capacity utilisation [7]. Nevertheless, the research on demand forecasting in the supply chain has neglected to account for demand volatility. In order to reduce uncertainty at various stages of the supply chain, it is essential to provide forecasts that can represent the fundamental behaviour of unpredictable demand.

This literature review (meta-research) study primarily focuses on "demand forecasting" inside supply chains. Given the dynamic and unpredictable character of modern global supply chains, BDA (and ML) approaches are essential for demand forecasting. The importance of BDA is further underscored by the digitalisation of supply networks[8] and the use of Blockchain technology[9] For improved supply chain monitoring. SC data is multi-dimensional, produced at various stages of the supply chain for a wide range of uses (products, supplier capacities, orders, shipments, customers, retailers, etc.), processed rapidly because of the abundance of SC nodes, and in large quantities because of the diversity of SC suppliers, products, and consumers. Given these intricacies, traditional methods of demand forecasting have given way to more sophisticated intelligent models that can adapt to changing supply chain demands through learning from past data and identifying statistically meaningful trends (defined by mean and variance attributes) [10]. The fundamental links between demand data throughout SC networks are found, and forecasting rules are extracted via the use of BDA tools to build this capacity. Complex machine-programmed algorithms are needed to handle these methods, which are computationally demanding [11].

A. *Motivation and contribution of the study*

A motivation for this study stems from the critical need to enhance precision and efficiency in demand forecasting and SCM through the application of BDA. Despite significant advancements, the current landscape reveals persistent challenges such as reliance on isolated datasets, underutilisation of advanced machine learning models, limited incorporation of external variables, and inadequate validation methods across diverse industries. The significance of this study lies in its potential to leverage integrated, real-time data sources and sophisticated analytics to improve prediction accuracy and operational efficiency. The primary aim is to enable businesses to better manage uncertainties in demand, supply, and costs, thereby achieving a more resilient and responsive supply chain. The objectives include addressing gaps in current literature, developing more robust forecasting models, and incorporating comprehensive external variable analysis to enhance the overall effectiveness of supply chain management. The following contribution of this work as:

- **Enhanced Precision in Demand Forecasting:** The study uses BDA to significantly enhance an accuracy of demand prediction, addressing isolated datasets and utilising advanced machine learning models.
- **Operational Efficiency in Supply Chain Management:** The research enhances operational efficiency by integrating real-time data sources, reducing costs related to stock-outs, overstocking, and capacity utilisation.
- **Incorporation of External Variables:** It includes external variables like promotions, market trends, and seasonal variations in forecasting models, leading to more accurate and reliable demand predictions.
- **Identification of Literature Gaps:** The study highlights critical gaps in existing literature, advocating for more robust models and broader industry validation to improve demand forecasting.
- **Development of Resilient Supply Chains:** By improving forecasting accuracy and operational efficiency, the research supports the development of more resilient and responsive supply chains.

B. *Organized of this paper*

The remainder of this essay is as follows: Sections I, II, and III provide an overview of the BDA for the supply chain, data in the supply chain, and demand forecasting. Section VI offers a review of the literature on big data analytics for supply chains using demand forecasting. last section V provides the conclusion and future work of this work.

II. BIG DATA ANALYTICS FOR SUPPLY CHAIN

BDA involves using sophisticated analytics methods on massive data sets to discover insights and power data-driven decisions. Big Data Analytics consists of three levels of analytics: descriptive, predictive, and prescriptive reporting. Each level of analytics has a distinct function and goal[12].

- The application data gathered by Prescriptive Analytics comes from a wide variety of sources, including traditional ones like Manufacturing, Logistics, Transportation, and Warehousing, and more recent ones like Cyber-Physical Systems. The domains encompass forecasting, risk assessment, risk management, and procurement.
- Predictive analytics has its merits. Concerning the quantity of operations carried out by a system.
- The most leeway is provided by descriptive analytics. One use of descriptive analytics is the generation of human-friendly summaries and reports based on raw data. Historical data is the mainstay of descriptive analytics.

Improving and revolutionising supply chain operations is within the realm of possibility with an use of BDA. Leaders in today's dynamic corporate world would rather not depend on gut feelings when making choices, but rather on data-driven insights. The perceived advantages of BDA are a significant incentive for organisations to enhance their technical and organisational capabilities after extract value by data. While a phenomenon of "Big Data" is widely regarded as the most recent global sensation, it has not necessarily emerged spontaneously. Big Data Analytics and Its Applications in SCM has seen a significant surge in the last ten years in an use of various ICT for SCM [13].

A number of businesses that offer raw materials to producers, central organisations, wholesalers, retailers, consumers, and end users is known as a supply chain. A supply chain is made up of informational and financial movements in addition to the actual flows that involve the movement of goods and commodities. The term SCA refers to an use of BDA methods to uncover valuable information that is buried inside supply chains. Three categories of analytics exist for these types of data: prescriptive, predictive, and descriptive. Because they save expenses for sourcing, transportation, storage, stock out, and disposal, well-thought-out and executed actions immediately benefit the bottom line. Therefore, supply chain performance is positively and significantly affected by adopting BDA strategies to address issues in SCM. Supply and demand balance issues have long been addressed by academics and management via the use of statistical and operational research methods.

A. *Data in supply chain*

Customers, orders, sales, shipping, delivery, stores, and product data are the several types of data that may be found in a context of supply chains. A classification of data from the supply chain is shown in Figure 1. This means that SC data comes from a variety of sources, including transportation, warehousing, inventory, sales, and production. Thus, current predictions may underestimate or overestimate demand due to factors such as price volatility, technology advancement, customer commitments, and competition [14]. Consequently, demand projections may be more accurately made by digging into supply chain data to learn more about market trends, customer behaviours, suppliers, and technology. Reducing supply chain expenses is possible via the identification of patterns and trends in this data and their subsequent application to the improvement of forecast accuracy [15].

Fig. 1: Taxonomy of supply chain data

Information pertaining to supply chains may be classified into many types: product, store, client, shipment, delivery, order, sale, and delivery [16][17]. The supply chain data categorisation is shown in Figure 1. Data for SC comes from a variety of places, including sales, inventory, manufacturing, warehousing, and transportation. Under- or over-estimation of demand in previous predictions may result from factors such as price volatility, technology advancement, client commitments, and competition. Therefore, a comprehensive analysis of supply chain data is required to increase the accuracy of demand projections by gaining a deeper knowledge of market trends, customer behaviours, suppliers, and technology. Reducing supply chain expenses is possible via the identification of patterns and trends in this data and their subsequent application to the improvement of forecast accuracy[18][19].

III. DEMAND FORECASTING IN SUPPLY CHAINS

"Demand management" didn't have its first real-world use until the 1980s and 1990s. There have always been two main ways to handle demand control. Two approaches are available: one that looks forward at prospective demand over the next several years, and another that looks back at previous or current capabilities in response to demand. The term "demand forecasting" refers to the process of making educated guesses about how much of a product or service customers are likely to buy in the future. Both short-term and long-term choices on production, sales, investment, growth, workforce employment, etc. now need accurate demand forecasts. Its goal is to analyse and quantify the factors that impact product sales, both current and future. Businesses plot out their operations, manufacturing, or sales in preparation for future demand. Typically, when people think about demand forecasting, they picture sales projections and demand manipulation. The industry's sales predictions may be a useful tool for a company when developing its sales strategy and policy. As such, it plays a significant role in the company's strategic decision-making process. A thorough grasp of the various forecasting techniques is crucial for practical application in order to provide accurate forecasts[20].

A. Important Features of Demand Forecasts

The following are some of the most important aspects of demand forecasting.

- Predictions of future demand are expressed in terms of concrete amounts.
- The endeavour is conducted in an environment that is unpredictable.
- A forecast is created for a time frame that is long enough to allow for decision-making and action.
- It is predicated on historical data, previous sales, and other information.
- It just provides us with an estimated future demand for a product.
- It is predicated on certain suppositions.
- It cannot be entirely precise, as it pertains to predictions regarding future demand.

In order to establish appropriate production and inventory plans, etc., demand forecasting is necessary for determining whether demand is prone to cyclical swings or not. They have the potential to become roadmaps for choosing the path that will increase the company's profits. When market size, competitor sentiment, price movement, consumer preferences, potential new substitute product threats, and other external economic factors impact sales forecasting, internal factors such as advertising budget, pricing policy, product enhancements, sales efforts, and so on help manipulate demand. Management has to know how much the company's actions and the external economic climate contribute to sales if demand forecasting is to be used actively rather than passively.

B. Factors Affecting Demand Forecast

Numerous aspects are associated with demand forecasting, including past demand, anticipated advertising or marketing activities, economic conditions, product life cycle, planned price reductions, competitor efforts and pricing, credit policy, quality, and sales effort.

C. Components of Demand Forecasting

The choice of forecasting technique is influenced by a few primary aspects. They are as follows:

- Vulnerability to technology advances and shifts in product markets determine the duration of the projection. The categorisations are broad strokes. The company and the projection dictate the relative importance of short, medium, and long term.
- Daily to two-year time frames are typical for short to medium range predictions. Production and delivery timelines, as well as inventory counts, are often informed by these.
- Forecasts that are considered long-range often include a period of more than two years. Strategic planning is the usual application of these. The future course of the organisation is defined by its strategic planning. Plans for new goods, expansion into new markets, and the creation of new facilities and technologies are all part of the long-term objectives.

D. Behavior and The Possible Existence of Patterns

There are instances when demand acts erratically. On sometimes, it acts in a predictable manner. Predictable behaviour may be broadly classified into three primary types: trends, cycles, and seasonal patterns.

- A long-term increasing or decreasing trend in demand is characterised by a steady pattern. The consistent growth in PC sales over the last many years is an example of a contemporary trend.
- An increasing and decreasing demand pattern that occurs repeatedly over an extended period of time is called a cycle. The sales of automobiles seem to follow a periodic pattern.
- Repetitive shifts in demand that happen at regular intervals are called seasonal patterns. Seasonality is a key factor in the sales of winter sports equipment.

Predictions rely heavily on regression, which establishes a mathematical connection between many variables. Regression in its most basic form is known as linear regression. Another common method is multiple regressions.

IV. BDA FOR DEMAND FORECASTING IN SCM

A purpose of this study is to sift through all the published studies about SC demand and sales forecasting using big data, sort them according to the techniques used, and then list all the implementations. Our study shows that there is a lack of a systematic literature evaluation addressing SC demand forecasting from a data analytics and ML approach categorisation perspective. We did this by doing a comprehensive literature search in Elsevier, Scopus, and Google Scholar, covering publications with dates of publication between 2005 and 2019. Big data analytics, ML, sales forecasting, demand forecasting, and supply chain were the search terms utilised.

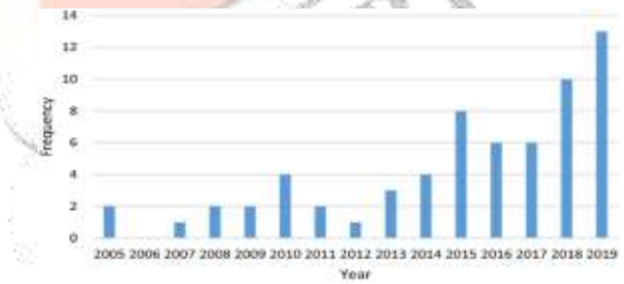

Fig. 2: Distribution of literature in supply chain demand forecasting from 2005 to 2019

Figure 2 displays the results of a trend analysis of SC demand forecasting papers published between 2005 and 2019. The number of publications has been rising from 2005 to 2019. Such expansion is anticipated to continue in 2020. We found 64 academic publications (not including books, chapters, or reviews) that focused on big data analysis or ML applied to SC demand forecasting in the last 15 years and classified them according to the methodology used for demand forecasting.

Table 1: Literature on BDA/machine learning techniques for supply chain demand forecasting (2005–2019)[18]

Rank	Technique	Frequency
1	Neural networks	30
2	Regression	27
3	Time-series forecasting (ARIMA)	13
4	Support vector machine	8
5	Decision tree	3

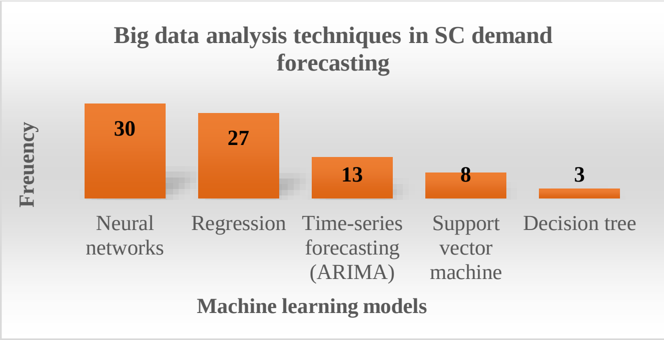

Fig. 3: Big data analysis techniques in SC demand forecasting

In Table 1 and Figure 3, the five most popular methods are shown, namely, the "NN," "Regression," "Time-series forecasting (ARIMA)," "SVM," and "DT" approaches. Based on this table, it seems that big data analytic methods are being increasingly used for demand forecasting in South Carolina. It should be noted that some articles used more than one of these methods. The use of BDA in SCM has been the subject of many literature review articles [18]. However, in order to explore BDA applications that are relevant to this field of study, this research mainly focuses on the subtopic of "demand forecasting" within SCM.

V. LITERATURE REVIEW

The research suggests that demand forecasting may benefit from big data collected from a variety of sources across supply chains.

For example, In, Khan et al., (2020) predictions are built from data that is gathered from many sources. The ML engine takes in information from many modules and uses it to predict the weekly, monthly, and quarterly needs for products and commodities. The results of the simulation show that the store may achieve an intelligent demand forecasting accuracy of up to 92.38% by using the planned solution with real-time organisation data[21].

In, Miranda-Ackerman and Colín-Chávezbc, (2018) used many different regression models, including RF, XGBoost, GBR, LightGBM, Bi-LSTM, Cat Boost Regressor, and LSTM. The results show that LSTM is the best method and that deep learning models may be used for predicting. Root Mean Squared Log Error (RMSLE) = 0.28, RMSE = 18.83, MAP) = 6.56%, and MAE = 14.18, to be exact[22].

In, Yu, Mirowski and Ho, (2017) the modelling and forecasting of these distinct residential electrical consumptions using sparse coding were examined in this research. The suggested techniques are examined using a dataset of 5,000 homes in a collaborative effort with the Chattanooga Electric Power Board, spanning the months of September 2011 through August 2013. In this difficult case, ridge regression with sparse code features increases the accuracy of total load forecasts for the next day and week by 10%. Furthermore, they assess the efficiency of more conventional approaches to forecasting, such as Holt-Winters smoothing and autoregressive integrated moving averages, on this particular forecasting issue[23].

In, Tian, Wang and E, (2021) submitted a KPI that, when used for demand forecasting, produces better results in relation to inventory costs. Considerations for logistic network supply reliability and seasonality indices discovered in historical demand patterns are made by this technique. Their real-world examples showed how the proposed method might improve forecasting and safety stock level efficiency by reducing the probability of stockouts and excess inventory[24].

In, Rabe et al., (2016) outlines a modelling methodology for cooperative route planning in supply chain modelling. A discrete event simulation model is used to provide a real-world illustration of how collaborative planning might be implemented. The potential benefits of collaborative planning for reducing the overall transport distance are assessed by contrasting the delivery concept on a model supply chain with and without cooperation[25].

In, Iftikhar and Khan, (2020) this study uses social media data from Facebook and Twitter to enhance supply chain demand forecasts. The proposed method for estimating product demand is an enhanced Bass emotion model that integrates predictive modelling using past sales data with the results of mood, trend, and word analysis derived from big social media data. It has been concluded that the proposed forecasting framework enhances the precision of demand forecasting in the supply chain[26].

Table 2: Big Data Analytics for Supply Chain Through Demand Forecasting

Ref	Methodology	Data Set	Performance	Limitations & Future Work
[27]	AI-based methods	Web of Science Core Collection (WoSCC) and Scopus.	The findings indicate a rising trend in articles on big data and predictive analytics as they relate to business intelligence.	• Only English articles from WoSCC and Scopus are included; more databases are needed in future research. • Insights based on Cite Space, limited to imported citation data. • Identifies academic contributors, excluding other measurement methods.
[28]	rolling forecasting methods	FMCG industry dataset	resulting in a net profit increase	The model was simply run with the expected product cost, disregarding any other associated expenses.
[29]	Seasonal Methods	Mendeley Data	The presented models fulfilled the assumed postulates	Predictive models are essential for preparing and meeting demands in sustainable supply chains.
[30]	SARIMAX, ARIMA, LSTM, and AR models	time-series dataset	Results for the United Arab Emirates (MAPE: 0.097, RMSE: 0.134), Saudi Arabia (MAPE: 0.158, RMSE: 0.199), and Kuwait (MAPE: 0.137, RMSE: 0.215) showed that the SARIMAX model was the most accurate in forecasting order volumes and trends.	Experimenting with other parameter ranges and doing more research into the impact of external factors on order volume prediction are potential areas for future investigation.
[31]	search methodologies, and analytical methods	SCI and SSCI databases	The findings indicate that, with respect to TP and TPR%, the main research fields were Engineering, Industrial (1854, 20.60%), Management (3071, 34.13%), and Operations Research & Management Science (2680, 29.78%).	The application practice is where SCM's limitations are most apparent.

A. Research gaps

Despite significant progress in demand forecasting and supply chain management, several research gaps persist. Current studies often rely on isolated datasets and lack integration of diverse, real-time data sources, limiting model robustness. The potential of newer deep learning architectures and hybrid models remains underexplored, as does the synergy between sparse coding and advanced feature engineering techniques. While some models consider external variables, a comprehensive examination of their full range of influences is lacking. Safety stock optimisation approaches need broader validation across various industries, and practical implementations of collaborative planning and route optimisation are scarce. Additionally, research often limits itself to English articles from specific databases, necessitating a more global perspective. Finally, forecasting models typically overlook a holistic range of costs, including logistics and storage, which are crucial for accurate profit assessments. Closing these gaps will greatly contribute to the development of better solutions for demand forecasting and SCM, providing more precise, faster, and feasible techniques.

VI. CONCLUSION AND FUTURE WORK

In conclusion, I want to accentuate how BDA can contribute to change in the field of demand forecasting and SCM. The combination of advanced analytics and near real-time data sources suggests increased accuracy and efficiency of the predictive capability of the business when managing uncertainty inherent in demand, supply, and cost data. This research aimed at analysing and classifying the different forms of BDA in relation to supply chain demand forecasting. With an eye on the methodologies and tools used for demand forecast, we compiled and reviewed these papers. The benefits and drawbacks of seven popular methods were examined. Among the numerous methodologies employed, regression analysis and neural networks are particularly prevalent. Optimisation models or simulations may be employed to optimise a cost function for fitting predictions to data, thereby enhancing forecasting accuracy, as indicated in the study. Despite notable advancements, the field still faces critical challenges, such as the reliance on isolated datasets, the underutilisation of sophisticated machine learning models, and the limited consideration of external variables that influence demand volatility. Solving these challenges is crucial for constructing more accurate and, therefore, reliable forecasting models. Also, this research points out the following directions for further research; there is a scarcity of external factors in current models, fresh deep learning networks which are yet to be probed, and the usage of new blended models that integrate conventional statistical studies with modern machine learning. There is still room for improvement in the sparse coding and feature engineering ideas; it can be considered to be an unexplored research direction.

Further research should attempt to construct and calibrate more accurate models of demand that utilise more extensive external covariates and encompass more sophisticated artificial neural network algorithms. It is necessary to examine the case of these models in various industries to determine the effectiveness of the models. For supply chains to be more transparent and trackable, future studies should look at real-time data analytics and how to integrate new technologies like blockchain. Research into how these sophisticated forecasting models affect supply chain risk mitigation and operational efficiency might be fruitful.

REFERENCES

[1] J. Thomas, "Enhancing Supply Chain Resilience Through Cloud-Based SCM and Advanced Machine Learning: A Case Study of Logistics," *J. Emerg. Technol. Innov. Res.*, vol. 8, no. 9, 2021.

[2] Z. You, Y. W. Si, D. Zhang, X. Zeng, S. C. H. Leung, and T. Li, "A decision-making framework for precision marketing," *Expert Syst. Appl.*, 2015, doi: 10.1016/j.eswa.2014.12.022.

[3] G. Walker and D. Weber, "A Transaction Cost Approach to Make-or-Buy Decisions," *Adm. Sci. Q.*, 1984, doi: 10.2307/2393030.

[4] M. Gilliland, "The Business Forecasting Deal: Exposing Myths, EliminatingBad Practices, Providing Practical Solutions," in *The Business Forecasting Deal*, 2010.

[5] J. Thomas, "The Effect and Challenges of the Internet of Things (IoT) on the Management of Supply Chains," *Int. J. Res. Anal. Rev.*, vol. 8, no. 3, pp. 874–878, 2021.

[6] M. Christopher, "The Agile Supply Chain: Competing in Volatile Markets," *Ind. Mark. Manag.*, 2000, doi: 10.1016/S0019-8501(99)00110-8.

[7] M. Christopher and M. Holweg, "'Supply Chain 2.0': Managing supply chains in the era of turbulence," *Int. J. Phys. Distrib. Logist. Manag.*, 2011, doi: 10.1108/09600031111101439.

[8] G. Büyüközkan and F. Göçer, "Digital Supply Chain: Literature review and a proposed framework for future research," *Comput. Ind.*, 2018, doi: 10.1016/j.compind.2018.02.010.

[9] N. Kshetri, "1 Blockchain's roles in meeting key supply chain management objectives," in *International Journal of Information Management*, 2018. doi: 10.1016/j.ijinfomgt.2017.12.005.

[10] Z. Michna, S. M. Disney, and P. Nielsen, "The impact of stochastic lead times on the bullwhip effect under correlated demand and moving average forecasts," *Omega (United Kingdom)*, 2020, doi: 10.1016/j.omega.2019.02.002.

[11] M. Bohanec, M. Kljajić Borštnar, and M. Robnik-Šikonja, "Explaining machine learning models in sales predictions," *Expert Syst. Appl.*, 2017, doi: 10.1016/j.eswa.2016.11.010.

[12] V. Rohilla, S. Chakraborty, and R. Kumar, "Car Auomation Simulator Using Machine Learning," *SSRN Electron. J.*, 2020, doi: 10.2139/ssrn.3566915.

[13] S. Sadeghi Darvazeh, I. Raeesi Vanani, and F. Mansouri Musolu, "Big Data Analytics and Its Applications in Supply Chain Management," in *New Trends in the Use of Artificial Intelligence for the Industry 4.0*, 2020. doi: 10.5772/intechopen.89426.

[14] J. Huber, A. Gossmann, and H. Stuckenschmidt, "Cluster-based hierarchical demand forecasting for perishable goods," *Expert Syst. Appl.*, 2017, doi: 10.1016/j.eswa.2017.01.022.

[15] M. M. Ali, M. Z. Babai, J. E. Boylan, and A. A. Syntetos, "Supply chain forecasting when information is not shared," *Eur. J. Oper. Res.*, 2017, doi: 10.1016/j.ejor.2016.11.046.

[16] F. Constante, F. Silva, and A. Pereira, "DataCo SMART SUPPLY CHAIN FOR BIG DATA ANALYSIS," 2019, doi: 10.17632/8gx2fvg2k6.5.

[17] V. Rohilla, S. Chakraborty, and R. Kumar, "Deep learning based feature extraction and a bidirectional hybrid optimized model for location based advertising," *Multimed. Tools Appl.*, vol. 81, no. 11, pp. 16067–16095, May 2022, doi: 10.1007/s11042-022-12457-3.

[18] M. Seyedan and F. Mafakheri, "Predictive big data analytics for supply chain demand forecasting: methods, applications, and research opportunities," *J. Big Data*, 2020, doi: 10.1186/s40537-020-00329-2.

[19] W. Bian, J. Shang, and J. Zhang, "Two-way information sharing under supply chain competition," *Int. J. Prod. Econ.*, 2016, doi: 10.1016/j.ijpe.2016.04.025.

[20] M. D. R. Pérez-Salazar, A. A. A. Lasserre, M. G. Cedillo-Campos, and J. C. H. González, "The role of knowledge management in supply chain management: A literature review," *Journal of Industrial Engineering and Management*. 2017. doi: 10.3926/jiem.2144.

[21] M. A. Khan *et al.*, "Effective Demand Forecasting Model Using Business Intelligence Empowered with Machine Learning," *IEEE Access*, 2020, doi: 10.1109/ACCESS.2020.3003790.

[22] M. A. Miranda-Ackerman and C. Colín-Chávezbc, "Food supply chain demand and optimization," in *Encyclopedia of Food Security and Sustainability*, 2018. doi: 10.1016/B978-0-08-100596-5.22278-6.

[23] C. N. Yu, P. Mirowski, and T. K. Ho, "A Sparse Coding Approach to Household Electricity Demand Forecasting in Smart Grids," *IEEE Trans. Smart Grid*, 2017, doi: 10.1109/TSG.2015.2513900.

[24] X. Tian, H. Wang, and E. E, "Forecasting intermittent demand for inventory management by retailers: A new approach," *J. Retail. Consum. Serv.*, 2021, doi: 10.1016/j.jretconser.2021.102662.

[25] M. Rabe, U. Clausen, A. Klueter, and M. Poeting, "An approach for modeling collaborative route planning in supply chain simulation," in *Proceedings - Winter Simulation Conference*, 2016. doi: 10.1109/WSC.2016.7822264.

[26] R. Iftikhar and M. S. Khan, "Social media big data analytics for demand forecasting: Development and case implementation of an innovative framework," *J. Glob. Inf. Manag.*, 2020, doi: 10.4018/JGIM.2020010106.

[27] S. M. Lee, D. Lee, and Y. S. Kim, "The quality management ecosystem for predictive maintenance in the Industry 4.0 era," *Int. J. Qual. Innov.*, 2019, doi: 10.1186/s40887-019-0029-5.

[28] V. Gorbachuk, A. Syrku, and S.-B. Suleimanov, "PRICE FORECASTING MECHANISMS OF MODERN ENERGY MARKETS," *Econ. scope*, 2020, doi: 10.32782/2224-6282/159-35.

[29] H. Sang, Y. Kotake, and S. Takahashi, "A dynamic modeling simulation for supply chain management inventory service: A case study on a rental housing unit manufacturing and logistics company," in *ACM International Conference Proceeding Series*, 2018. doi: 10.1145/3277139.3277178.

[30] K. Sundararajan *et al.*, "A contemporary review on drought modeling using machine learning approaches," *CMES - Computer Modeling in Engineering and Sciences*. 2021. doi: 10.32604/cmes.2021.015528.

[31] D. Mishra, A. Gunasekaran, T. Papadopoulos, and S. J. Childe, "Big Data and supply chain management: a review and bibliometric analysis," *Annals of Operations Research*. 2018. doi: 10.1007/s10479-016-2236-y.