The Interplay Between Machine Learning Techniques and Supply Chain Performance: A Structured Content Analysis

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***Abstract*—Over recent years, disruptive technologies have shown considerable potential to improve supply chain efficiency. In this regard, numerous papers have explored the link between machine learning techniques and supply chain performance. However, research works still need more systematization. To fill this gap, this paper aims to systematize published papers highlighting the impact of advanced technologies, such as machine learning, on supply chain performance. A structured content analysis was conducted on 91 selected journal articles from the Scopus and Web of Science databases. Bibliometric analysis has identified nine distinct groupings of research papers that explore the relationship between the machine learning and supply chain performance. These clusters cover topics such as big data and supply chain management, knowledge management, decision-making processes, business process management, and the applications of big data analytics within this domain. Each cluster's content was clarified through a rigorous systematic literature review. The proposed study can be seen as a kind of comprehensive initiative to systematically map and consolidate this rapidly evolving body of literature. By identifying the key research themes and their interrelationships, this analysis seeks to elucidate the current state-of-the-art and to highlight potential directions for future research in this critical field.**

***Keywords*—Bibliometric analysis; machine learning; ProKnow-C methodology; supply chain performance**

I. Introduction

The convergence of digitalization, information technology, robotics, communication technologies, and artificial intelligence (AI) has marked the beginning of a transformative era known as the Fourth Industrial Revolution [1, 2]. This era is characterized by machines gaining intelligence and the ability to make decisions, replacing human cognitive capabilities [1, 3]. Machine Learning (ML) is a key technique within this revolution, involving the creation and implementation of computer algorithms that can "learn" from experience [4]. Indeed, ML has evolved alongside advancements in machine capabilities to process vast amounts of input data over the past few decades. Additionally, machines can now identify hidden patterns and intricate relationships, enabling them to make reliable and appropriate decisions even in the face of disruptive and discontinuous information, where human capabilities may fall short [5].

However, the inefficient implementation of ML in supply chain networks can be attributed to a lack of understanding of how to apply machine learning effectively, insufficient integration into the company's culture, and the challenge of obtaining relevant and appropriate data [5]. In addition, the low association of ML and SCP could be mainly related to the need to understand the latest developments in machine learning algorithms. Specifically, knowledge of taxonomies or guidelines for supply chain researchers and practitioners to select the correct machine learning algorithms for practical activities of supply chain performance [5]. Hence, there is an immediate requirement for a comprehensive assessment aimed at quantitatively examining the current research patterns, investigating commonly employed machine learning algorithms relevant to supply chain performance, and identifying the most suitable areas for applying machine learning techniques [5].

In this context, this paper conducts a systematic analysis of research publications retrieved from international databases such as Scopus and Web of Science. It examines the machine learning algorithms commonly utilized in the context of supply chain management (SCM), aiming to serve as a foundational reference for future research in this field. The study endeavors to offer a comprehensive overview of ML applications in SCM research, addressing current gaps regarding the impact of ML techniques on supply chain performance. The findings highlight the importance of balanced ML applications to mitigate discrepancies between ML implementations and supply chain outcomes. The imbalance in ML algorithm applications poses a heightened risk of impeding progress in research-driven industries. That is, this work represents a useful systematic review of ML applications and their impact on supply chain performance, emphasizing the critical need to bridge this gap in the literature.

This paper is structured in six sections, beginning with this introduction. Section II provides a succinct overview of existing research on machine learning and its influence on supply chain performance. Section III details the research methodology employed in this study. Section IV presents the findings derived from the research. Finally, Section VI concludes the paper by discussing the primary results in Section V, acknowledging the study's limitations, and offering recommendations for future research.

II. Literature Review

A. Machine Learning

The scientific exploration of algorithms and computational models that enable computers to improve their performance on specific tasks or make accurate predictions by leveraging experience is known as machine learning [6]. Unlike traditional programming approaches, machine learning relies on statistical techniques and data-driven processes, granting computer systems the ability to learn and adapt autonomously [7]. It is widely recognized as a powerful tool in various domains of scientific research [8]. According to Du and Sun [9], machine learning systems utilize labeled and unlabeled training data from diverse sources as inputs. The learning system's knowledge base is used to select an appropriate machine learning algorithm, while considering the organization's decision-making requirements [10].

According to Zhu et al. [11], machine learning can be broken down into three primary tasks: supervised learning, unsupervised learning, and reinforcement learning. Supervised learning utilizes labeled data to construct a predictive model, with the aim of establishing a mapping between input and output variables [11, 12]. Techniques such as random forests, decision trees, Bayesian networks, and regression analysis fall under this category. Unsupervised learning operates on unlabeled datasets, seeking to uncover hidden patterns within the data [11]. This approach is primarily used for data reduction and exploratory analysis and encompasses techniques such as artificial neural networks (ANN), genetic algorithms, instance-based learning models, deep learning, and clustering. Reinforcement learning combines training and testing datasets to enable the learner to interact with the environment while gathering information [11].

Significant advancements in machine learning algorithms and computational power have propelled its transition from a laboratory curiosity to a practical technology with widespread commercial adoption across various industries [13].

The application of machine learning techniques in supply chain management has been extensively investigated by several researchers, starting with Estelles-Lopez et al. [14]. These studies have explored a range of approaches, including decision trees, random forests (RF), logistic regression (LR) [15], support vector machines (SVM) [16], and neural networks [17]. However, Ni et al [5] reported that, despite its potential, machine learning remains under-utilized in practical supply chain operations. Indeed, Sasaki and Sakata [18] have examined the adoption of machine learning in supply chain research up until 2018 and identified key reasons for its limited implementation, including a lack of understanding regarding its practical applications, insufficient integration into company culture, and difficulties in obtaining relevant and suitable data. Addressing these challenges, Štrumbelj and Kononenko [19] have sought to overcome the interpretability issues associated with machine learning models, particularly in risk-sensitive domains like finance and medicine. The need for increased confidence in utilizing machine learning models is significant, even when their interpretation is challenging, especially in critical application areas. Ensuring the reliability, transparency and accountability of these complex models is crucial when they are deployed in high-stakes domains. Developing robust techniques for model explanation and validation can help build trust and facilitate the responsible use of machine learning [19].

B. Supply Chain Performance

Performance measurement underpins effective planning, control, and decision-making by providing essential insights [20, 21]. Bititci et al. [22] argue that the context in which performance measurement is used is constantly evolving. They question whether current performance measurement practices are equipped to handle emerging trends and identify gaps in our understanding. The authors propose a holistic, systems-based approach to performance measurement research, recognizing the interconnected nature of challenges faced by practitioners and the field.

Lemghari et al. [23] argue that performance measurement is crucial for companies to evaluate their supply chain effectiveness and efficiency, especially in the highly competitive automotive industry. They emphasize the importance of having a structured approach and adequate methodological tools, such as the SCOR® model, to identify appropriate performance indicators and guide continuous improvement initiatives. They highlight the need for a comprehensive framework that covers the entire global automotive supply chain, encompassing different actors and business typologies, to ensure a holistic understanding of performance and enable effective benchmarking.

Supply chain performance is a complex and widely studied topic within the supply chain management literature [20, 24]. Najmi and Makui [25] have evaluated supply chain performance by examining factors such as reliability, flexibility, quality, responsiveness, and asset management. Similarly, Bourlakis et al. [26] have considered performance indicators related to flexibility, efficiency, responsiveness, and quality. Balfaqih et al. [27] and Reddy et al. [28] have categorized articles based on different approaches and techniques concerning supply chain performance. Dreyer et al. [29] offer another perspective, measuring performance improvement in terms of innovation, variety, price, time, and availability. Effective information exchange is recognized as a crucial element in supply chain relationships management and enhancing supply chain performance [30, 31]. Companies invest in technological innovation to facilitate efficient collaborative mechanisms and communication channels, thereby improving supply chain performance by sharing more information [32, 33].

In order to facilitate efficient information exchange and seamless end-to-end business processes, Supply Chain Integration (SCI) plays a crucial role [2, 34]. SCI encompasses both external and internal integration [35]. External integration (EI) involves establishing connections between a company's logistics operations and its customers and suppliers beyond organizational boundaries [36]. On the other hand, internal integration (II) pertains to the sharing of information among different functions within the supply chain, promoting strategic cross-functional cooperation and collaboration [37]. Enhanced integration has the potential to enhance performance indicators such as quality, variety, cost, and service level [38]. Collaboration and integration throughout the supply chain also contribute to Collaboration and integration throughout the supply chain also contribute to an enhanced level of flexibility, which in turn positively impacts supply chain performance [39]. Effective information sharing and collaboration, as discussed earlier, result in operational improvements in terms of flexibility and responsiveness [40]. The agility and resilience of the supply chain are also crucial factors influencing supply chain performance, as they enable effective management of supply chain risks [41]. Operational performance is expected to be significantly improved by increasing visibility and transparency across the supply chain [42].

III. Methodology

This research is classified as theoretical due to its technical approach, involving structured content analysis that draws on data and findings directly from existing literature on the topic [43]. The research objectives can be classified as both explorative and descriptive in nature. The aim of this research is to gather specific information and characteristics related to the subject matter in question [44]. To construct a comprehensive literature review, a structured approach utilizing bibliometric analysis was employed. The ProKnow-C (Constructivist Knowledge Development) approach suggested by Ensslin et al. [44] was utilized for the selection of a bibliographic analysis. This method is divided into four distinct stages [44] (see Fig. 1):

a) Initial selection: In this phase of the process, it is necessary to select appropriate keywords, identify relevant databases, search for articles and verify the accuracy of the keywords in use [44].

b) Database filtering: This stage filters the raw database elements for redundancy and removes elements that are not repeated by title matching [44].

c) Article database filtering: This stage determines the scientific recognition of the articles and identifies the authors [44].

d) Full article relevance filtering: This stage covers the full text of the articles, ensuring relevance to the research topic [44].

Firstly, in April 2024, we began by defining the keywords "Supply chain*", "Performance", and "Machine learning". These keywords were selected as primary terms to guide our research focus. To ensure comprehensive coverage, we opted to utilize the Scopus and Web of Science databases. These databases were chosen for their multidisciplinary nature and their inclusion of highly cited journals within various fields. Notably, the Scopus and Web of Science databases comprise a vast collection of resources, encompassing approximately 265 million Web pages, over 15000 periodicals, 18 million patents, and other relevant documents [45].

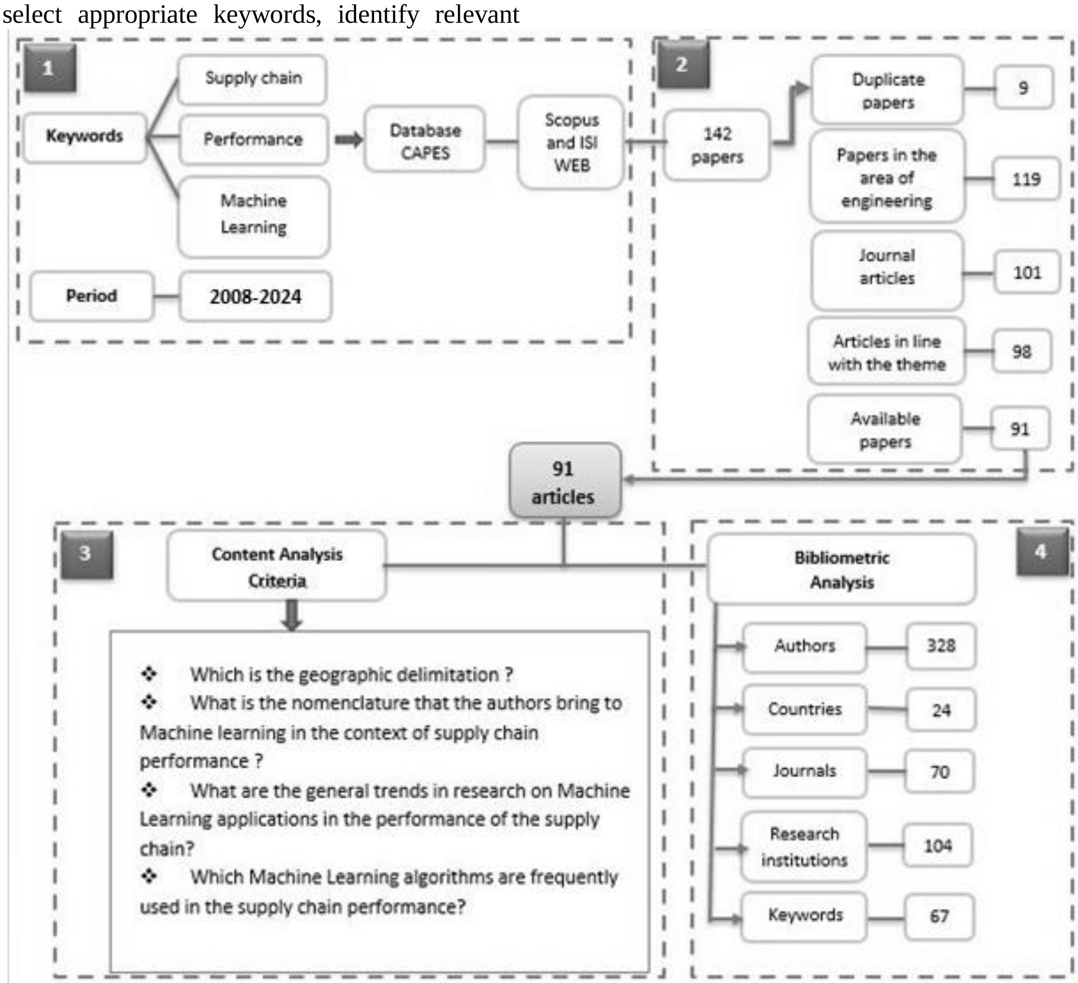

Fig. 1. Bibliometric analysis workflow.

Conducting our search using these defined keywords and databases, we obtained a total of 186 relevant articles about the subject of our study. These articles were published within the past 14 years and served as valuable sources for our research. To further analyze the literature, we classified the articles according to their respective research areas, as illustrated in Fig. 2. Engineering accounted for the highest proportion, representing 32% of the articles, followed by computer science (10%), physics and astronomy (12%), environmental sciences (13%), and materials science (7%). Given the considerable number of articles and our expertise, we concentrated our study within the field of engineering.

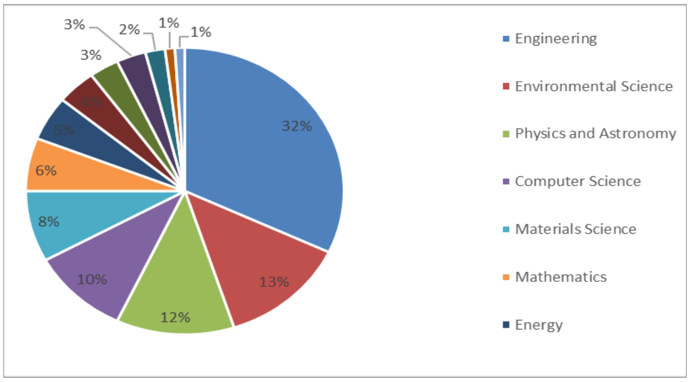

Fig. 2. Item domains found in scopus.

We applied consecutive filters to narrow down the initial set of articles to a more refined result aligned with our research objectives. The purpose of these filters was to eliminate unwanted articles and enhance the search process. The filtering method involved considering various features: (i) identification and removal of duplicate articles (1 article in total); (ii) relevance to the field of engineering (119 articles); (iii) publication in reputable journals (116 articles); (iv) alignment of article titles and abstracts with the research scope (98 articles); and (v) accessibility of full-text articles (91 articles).

Bibliometric analysis is a method used to map key authors, journals, and keywords within a specific research area [43]. Vanalle and Santos [46] explain that these methods depend on a methodologically recognized theoretical-methodological foundation, which allows the use of statistical and mathematical techniques to analyze information from bibliographic databases. In this study, content analysis was carried out following the criteria established by Bardin [47] to organize the analysis, encode data, categorize information, draw inferences, and identify research gaps related to machine learning and supply chain performance.

As shown in Fig. 1, the authors established certain criteria. Two software applications were used to manage and compile the collected data: (i) Mendeley [48] and (ii) VosViewer [43].

Mendeley is an online reference management software developed by Mendeley Ltd [48]. It facilitates research and scholarly work by collecting references from online databases, importing their metadata, and grouping them according to various methods [43]. In this study, Mendeley was used to perform quantitative analyses of authors, keywords, journals, research centers, citations and countries [43].

VosViewer, on the other hand, is a software used to construct bibliometric networks based on data obtained from bibliographic databases such as Web of Science and Scopus [43]. This software allows the user to choose between total and fractional counting methods [49]. In the current study, VosViewer was used to perform co-author and co-occurrence analyses of keywords [45].

IV. Findings

The literature review serves as the initial step for researchers to delve into a study and acquire knowledge within a specific context [50]. It offers an introductory perspective on enhancing research projects and examines the existing body of scientific knowledge in the field [50]. Additionally, it enables researchers to familiarize themselves with the subject matter, gaining exposure to new concepts and definitions [50]. Creswell [51] has highlighted the multiple purposes of a literature review, including sharing the findings of related studies with readers, fostering dialogue around the research, contributing to the existing body of knowledge, addressing research gaps, and extending prior studies.

In this study, we analyzed 91 articles authored by 331 individuals or collaborations, which were published in 70 journals over a 14-year period. These articles collectively cited 4148 references and generated 67 keywords. Contributions were made by researchers from 24 countries, including Japan, United States, India, France, and Netherlands, affiliated with 75 institutions or research centers.

Fig. 3 displays the chronological distribution of the 91 articles analyzed in this study. The earliest identified article on the subject was published in 2007, titled "Machine learning-based demand forecasting in supply chains" by Carbonneau et al. [52]. This paper aimed to compare the performance of novel predictive techniques based on machine learning (ML) with more conventional methods. The authors utilized data from various sources, including a chocolate manufacturer, a toner cartridges manufacturer, and the Statistics Canada manufacturing survey, to conduct their analysis.

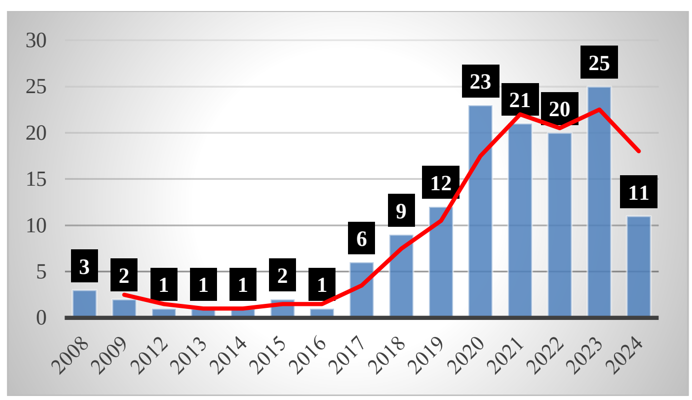

Fig. 3. Publications per year.

Concerning the authors of articles, we identified 331 authors and co-authors for 91 selected articles. The most productive authors are V. Kumar, S.P. Singh, Y. Liu, R. Carbonneau, G.J. Wang, E.M. Frazzon, K. Laframboise, A. Gunasekaran, S.

Punia, B. Jin, R. Vahidov, B. Karimi, C. Xie, Y. Zhu, and J. Kim, with two articles each.

Fig. 4 depicts the co-authorship network of the authors involved in the study, comprising 331 individuals. The network consists of 20 distinct groups connected by 98 links. The visualization suggests that authors within the "Machine Learning and supply chain performance" domain tend to work in isolation, with only a limited number of collaborations observed.

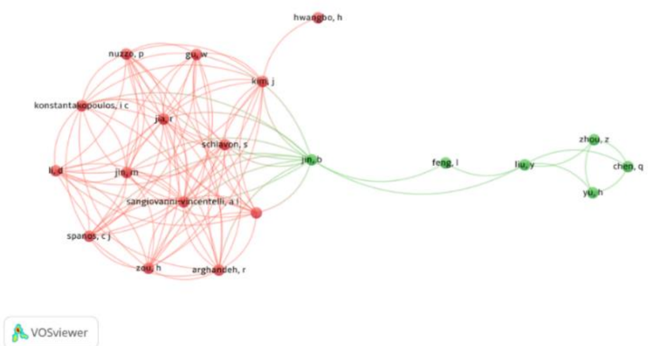

Fig. 4. Co-authorship of authors.

Fig. 5 portrays the co-occurrence of 67 keywords, with 16 items forming four distinct clusters. Notably, the visualization highlights two main themes associated with the keywords "Performance*", "Supply chain," and "Machine learning". The first theme revolves around "Machine learning," while the second theme centers around "Supply chain management". These clusters represent the prominent topics that emerge when exploring the interconnections between performance, supply chain, and machine learning in the literature.

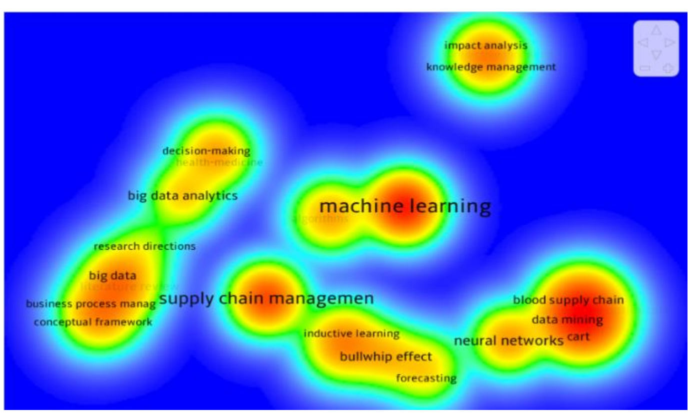

Fig. 5. Keyword co-occurrence.

At least one citation was found in the Scopus database for 59 of the 91 articles selected for this study. There are two main ways of checking citations, as explained by Mingers and Leydesdorff [53]. The first is to use the Web of Science or Scopus databases, which require subscriptions and offer different levels of access based on payment plans, allowing researchers to access resources accordingly. The second option is to use Google Scholar, which is more easily accessible and offers in general free access to resources. Since our laboratory has access to the Scopus database through the IMIST platform [43], we have also chosen to use it in this study. Articles with more than 10 citations are shown in Fig. 6.

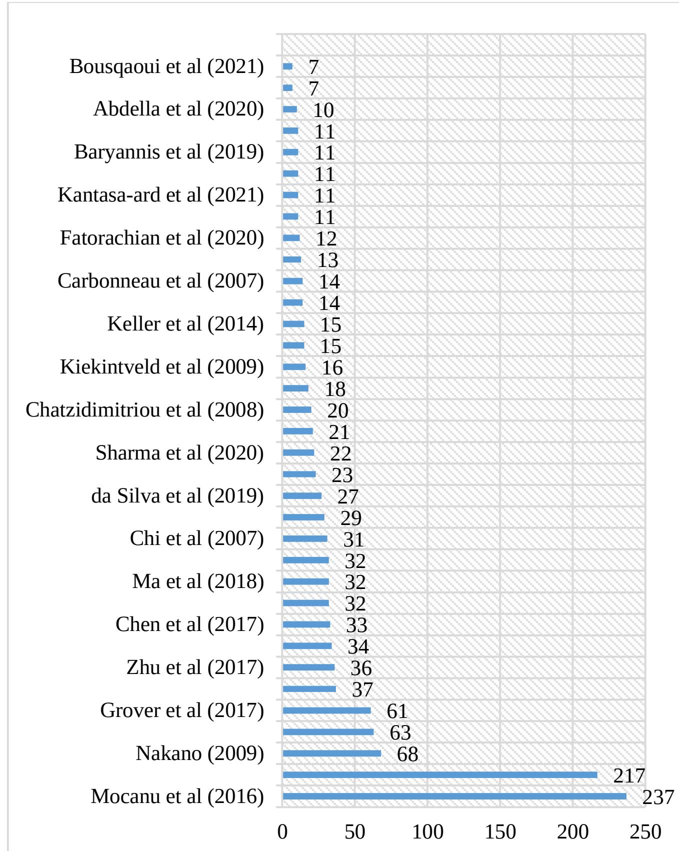

Fig. 6. Most cited articles.

V. Discussion

The authors have verified that among the 91 selected articles, 51% are empirical, 24% theoretical and 25% are a mixture of both, knowing that the publications were made between 2008 and 2024. It should be noted that our investigation has identified only one article corresponding to the considered subject for each of the four following years: 2012, 2013, 2014, and 2016. The distribution of articles by theoretical and empirical nature, and the mix of both, is shown in Fig. 7.

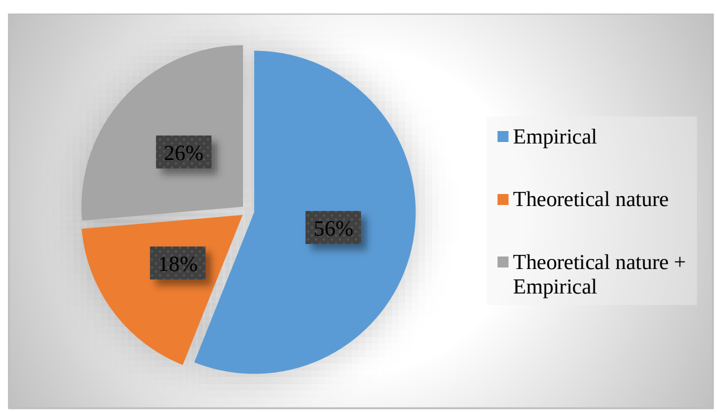

Fig. 7. Item breakdown by nature.

Furthermore, Fig. 8 presents the research methodologies used in the 91 articles. Indeed, we can state that 36% of the articles are experimental studies, such as the research conducted by Zhou et al. [54] that deals with information collaboration on supply chain management and the Internet of Things (IoT). In addition, Dubey et al. [3] have investigated artificial intelligence (AI) and Big Data Analytics (BDA) in production companies.

On the other hand, 24% of the studies were theoretical, distributed as follows: 10% systematic literature reviews, 18% theoretical frameworks, 7% conceptual models, and 3% classical literature reviews. Finally, 25% are mixed research between theoretical and empirical study, such as the research presented by Pereira and Frazzon [55] which proposes a conceptual model and validates it through a practical case study.

In the following Table I, we will present the synthesis of articles by category.

This table provides a summary of key findings and contributions for each considered article. It is not exhaustive and does not cover all aspects of each study. For detailed information, please refer to the original publications.

That is, the final section of this paper will give some conclusions from the above analysis as well as possible perspectives for future research in the same field.

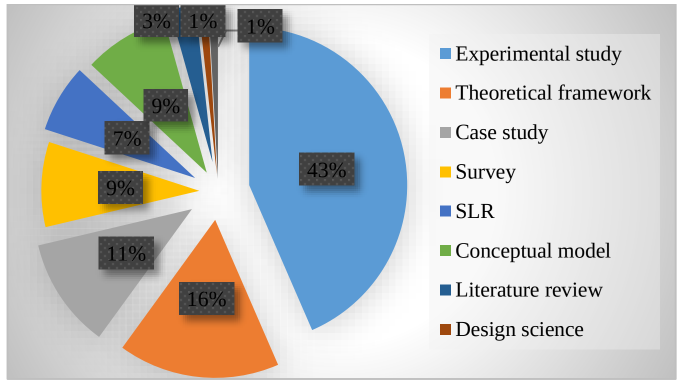

Fig. 8. Distribution of articles according to their methodologies.

TABLE I. MACHINE LEARNING APPLICATIONS IN SUPPLY CHAIN PERFORMANCE

Category	Study	Methodology	Key Findings/Contributions
Case Studies	Gonçalves et al. (2021)	Multivariate approach	Predicting component manufacturers' demand across multiple forecast horizons using leading demand change indicators.
	Brintrup et al. (2020)	Data analytics	Predicting first-level supply chain disruptions using historical OEM data.
	Abbasi et al. (2020)	Machine learning	Solving large stochastic operational optimization problems.
	Kim et al. (2018)	Stochastic control and optimization	Solving mathematical problems related to initial fashion product distribution using real data.
	Pereira et al. (2021)	Machine learning demand forecasting and simulation-based optimization	Synchronizing demand and supply in omnichannel retail supply chains.
	Leung et al. (2020)	Adaptive neuro-fuzzy inference system	Developing a novel predictive methodology by integrating data time series features.
	Priore et al. (2019)	Inductive learning algorithm	Defining appropriate replenishment policies in response to environmental changes.
	Baryannis et al. (2019)	Data-driven AI techniques	Developing a framework for predicting supply chain risks, balancing prediction performance with interpretability.
	Fu and Chien (2019)	UNISON analytical framework	Predicting intermittent electronic component demands using machine learning and temporal aggregation mechanisms.
	Gabellini et al. (2024)	Deep learning (LSTM) model trained on preprocessed data including macroeconomic indicators	Predicting supply chain delivery delay risk using deep learning and macroeconomic indicators. Deep learning approach outperforms benchmarks, highlighting the importance of macroeconomic indicators for accurate predictions
Theoretical Frameworks	Galetsi et al. (2020)	Systematic literature review	Mapping the scientific field of machine learning in supply chain management using a resource-based theory framework.
	Hatamlah et al. (2023)	Conceptual model development, literature review	Develops a conceptual model that outlines how AI can be leveraged to enhance supply chain risk management, focusing on areas like early warning systems, predictive analytics, and scenario planning.
	Sharma et al. (2020)	Systematic literature review	Reviewing machine learning applications in agricultural supply chains and highlighting their contribution to sustainability.
	Dhamija and Bag (2020)	Systematic literature review	Analyzing prominent research on artificial intelligence in supply chain management.
	Fatorachian et al. (2020)	Systems theory	Studying the impact of Industry 4.0 on supply chain performance and developing an operational framework.
	Ni et al. (2020)	Overview	Providing an overview of machine learning applications in supply chain management and offering future research directions.
	Aryal et al. (2018)	Exploration of disruptive technologies	Examining how research approaches differ when managing disruptive change, particularly with massive data analytics and IoT.
	Nguyen et al. (2017)	Classification framework	Proposing a classification framework for big data analytics applications in supply chain management.
	Grover and Kar (2017)	Investigation	Studying the primary use of big data analytics in various industries, investigating its role in resource utilization and sustainability.
	Abdella et al. (2020)	New method	Presenting a new method for assessing and modeling the sustainable impacts of food consumption.

	Bahaghighat et al. (2019)	Machine-learning vision	Using machine-learning vision to monitor and control drug packaging in pharmaceutical product lines.
	Bucur et al. (2019)	Multi-view tuning	Proposing merging information sources and considering tuning as a multi-view problem.
	Kim et al. (2008)	Supplier selection	Focusing on supplier selection in a manufacturing company, allowing suppliers to compete for purchase.
	Souza et al. (2019)	Literature review	Identifying different approaches for assessing sustainable performance.
	da Silva et al. (2019)	Contextualization	Contextualizing technology transfer in the supply chain of Industry 4.0, focusing on supply, manufacturing, and consumer stages.
	Wu et al. (2020)	Conceptual model	Proposing a conceptual multi-partner classification model for partner qualification and classification.
	Brinch (2018)	Structured content review	Addressing the poor understanding of massive data's value in supply chain management from a business process perspective.
Investigation Methods	Mishra et al. (2023)	Survey-based research, statistical analysis	Examines the adoption of digital technologies in supply chains within the manufacturing sector, identifying key trends, challenges, and best practices.
	Benzidia et al. (2021)	Survey	Investigating the impact of massive data analysis and artificial intelligence on green supply chain processes.
	El-Khchine et al. (2018)	Exploration	Exploring the application of social metadata networks and their analysis in supply chain management.
	Keller et al. (2014)	Study	Studying the use of data mining techniques for filtering and aggregating raw RFID data.
Experimental Studies	Zhou et al. (2021)	Demonstration	Demonstrating that logistics cooperation based on supply chain management reduces costs and improves services.
	Islam and Amin (2020)	Exploration	Exploring the use of machine learning models for predicting backorders to enhance decision-making.
	Yan et al. (2020)	Proposal	Proposing a distributed anti-collision algorithm for RFID systems incorporating machine learning.
	Feizabadi (2020)	Development	Developing hybrid demand forecasting methods based on machine learning.
	Tamy et al. (2020)	Description	Describing a machine learning approach to build an efficient and accurate network intrusion detection system.
	Liu et al. (2020)	Presentation	Presenting a surrogate mechanism using supervised learning, where sets of decision trees are trained on historical data.
	Liu Y. et al. (2020)	Proposal	Proposing a new model, F-TADA, derived from trend alignment with recurrent multi-task dual attention neural networks.
	Tosida et al. (2020)	Optimization	Optimizing an assistance classification model for Indonesian telematics SMEs using deep learning.
	Cavalcante et al. (2019)	Presentation	Presenting a new approach to resilient supplier selection using data analytics.
	Zhu et al. (2019)	Proposal	Proposing an improved hybrid ensemble machine learning approach for SME credit risk prediction.
	Shankar et al. (2019)	Prediction	Aiming to predict container throughput using deep learning methods.
	Lau et al. (2018)	Design	Designing a novel big data analytics methodology based on a parallel aspect-oriented sentiment analysis algorithm.
	Ma et al. (2018)	Proposal	Proposing a method to determine false positives in RFID systems using machine learning algorithms.
	Gyulai et al. (2018)	Analysis and comparison	Analyzing and comparing analytical and machine learning prediction techniques.
	Çimen et al. (2017)	Proposal	Proposing an Approximate Dynamic Programming (ADP) methodology to overcome computational challenges.
	Mocanu et al. (2016)	Study	Studying two stochastic models for energy consumption time series prediction.
	Hogenboom et al. (2015)	Proposal	Proposing a two-level machine learning approach for computing tactical pricing decisions.
	Kandananond (2012)	Development	Developing two machine learning methods (ANN and SVM) and a traditional approach (ARIMA) for predicting consumer product demand.
	Kiekintveld et al. (2009)	Documentation	Documenting successful approaches for price forecasting, emphasizing the exploitation of information sources.
	Carbonneau et al. (2008)	Investigation	Investigating the applicability of advanced machine learning techniques to predict demand distortion.
	Chatzidimitriou et al. (2008)	Presentation	Presenting Mertacor, an SCM agent using heuristic techniques and statistical modeling.
	Chen Yu (2024)	Exploration	The study examines the revolutionary potential of artificial intelligence (AI) and machine learning (ML) in contemporary supply chain management, and their effects on supply chain performance.
	Chi et al. (2007)	Demonstration	Demonstrating the feasibility of applying computational intelligence (machine learning) and evolutionary algorithms to optimize data-rich environments.

VI. Conclusion

This research delves into the burgeoning landscape of Machine Learning (ML) applications within supply chain management, analyzing a comprehensive collection of literature from 2008 to 2024. Through a rigorous bibliometric and content analysis approach, utilizing the ProKnow-C method and data from Scopus and Web of Science databases, this study unveils key trends, advancements, and future research directions within this dynamic field.

Our analysis reveals a clear trajectory of increasing sophistication in ML applications for supply chain management. Demand forecasting, a cornerstone of effective supply chain operations, stands out as a domain where ML has achieved significant maturity, with well-defined performance measurement and evaluation methods. However, the reach of ML extends far beyond demand prediction, encompassing a diverse range of applications that address critical challenges within the supply chain ecosystem.

The study highlights the transformative potential of ML in tackling complex issues such as disruption prediction, inventory optimization, risk management, and the integration of disruptive technologies like Big Data Analytics (BDA) and the Internet of Things (IoT). Furthermore, ML is proving instrumental in enhancing supply chain resilience through the development of robust supplier selection methodologies, leveraging data analytics to assess disruption likelihood and predict performance impacts.

The integration of ML into partner qualification and classification processes, employing ensemble learning and fuzzy set theory, demonstrates its ability to optimize collaboration and strategic partnerships within the supply chain. ML's capacity to predict consumer product demand, exemplified by the development of methods like Artificial Neural Networks (ANN) and Support Vector Machines (SVM), underscores its role in driving informed decision-making and enhancing market responsiveness.

The study also underscores the growing awareness of ML's environmental impact. The significant influence of BDA and AI on the integration of environmental processes necessitates the development of adaptive replenishment policies, leveraging inductive learning algorithms to respond effectively to environmental changes.

Looking ahead, this research identifies several promising avenues for future research. A case study focusing on the application of ML methods to enhance the performance of automotive supply chains would provide valuable insights into industry-specific applications. Additionally, experimental analysis of integrating ML models into the best practices outlined by the SCOR model would contribute to a deeper understanding of ML's practical implementation within established frameworks.

Finally, the exploration of conceptual frameworks and empirical evidence that examine the influence of adopting ML algorithms on supply chain performance is crucial. This endeavor would aim to quantify the extent to which manufacturing firms can leverage ML algorithms to achieve tangible improvements in supply chain efficiency, resilience, and sustainability.

In conclusion, this research underscores the transformative potential of ML in revolutionizing supply chain management. The diverse applications, ongoing research efforts, and emerging trends suggest a promising future for ML in optimizing performance, enhancing resilience, and fostering sustainability within the complex and dynamic landscape of global supply chains.

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