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Data Analytics in Supply Chain Management: A State-of-the-Art Literature Review

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ABSTRACT

In recent years, there has been a growing surge of interest in the application of data analytics (DA) within the realm of supply chain management (SCM), attracting attention from both practitioners and researchers. This paper presents a comprehensive examination of recent implementations of DA in SCM. Employing a systematic literature review (SLR), we conducted a meticulous analysis of over 354 papers. Building upon a prior SLR conducted in 2018, we identify contemporary areas where DA has been applied across various functions within the supply chain and scrutinize the DA models and techniques that have been employed. A comparison between past findings and the current literature reveals a notable upsurge in the utilization of DA across most SCM functions, with a particular emphasis on the prevalence of predictive analytics models in contemporary SCM applications. The findings of this paper offer a detailed insight into the specific DA models and techniques currently in use across various SCM functions. Additionally, a discernible increase in the adoption of mixed or hybrid DA models is observed. However, several research gaps persist, including the need for more attention to real-time DA in SCM, the integration of publicly available data, and the application of DA to mitigate uncertainty in SCM. To address these areas and guide future research endeavors, the paper concludes by delineating six concrete research directions. These directions offer valuable avenues for further exploration in the field.

Keywords: *data analytics, descriptive analytics, predictive analytics, prescriptive analytics, supply chain management, systematic literature review*

1. INTRODUCTION

Supply Chain Management (SCM) represents the backbone of our economy. Regardless of sectors or industries, supply chains (SC) are the preferred form of value creation in manufacturing and distributing products and services and ultimately in delivering value to customers. In recent years, SC have become increasingly complex, multi-echelon networks of companies. Once stable relationships and reliable partnerships have become unpredictable and customer demands are increasingly volatile. Against the background of global pandemics, natural disasters and conflicts becomes obvious that modern SC are very different from SC of even just a few years ago (Brandtner, 2023; Riahi *et al*., 2021).

Especially over the last two decades, SC complexity and uncertainty has increased significantly. First, due the adoption of lean management and the just-in-time philosophy, that left SC vulnerable to adverse events with only little room for error or change. Second, the increased global and less vertical integration in SC exposed SCM to much higher risks than before. And third, numerous disruptive events disturbed global SC (Baryannis *et al*., 2019; Khuan *et al*. 2023).

Faced with a multitude of challenges and high degrees of uncertainty, SCM is forced to adopt new approaches to handle and manage complex SC networks. At the same time, increasing amounts of data are generated and exchanged along the SC and across the activities and tasks of SCM. However, unlike capital, data per se has no value without appropriate ways of analysis (Dubey *et al*., 2020) and the field of Data Analytics (DA) is increasingly becoming popular in SCM research (Aamer *et al*. 2020). Various publications have analysed the maturity and scope of DA applications and their SCM specifics. Especially in the previous years, new approaches to data analytics have been proposed by research, encompassing a wide variety of tasks and issues (I. Lee & Mangalaraj, 2022; Nguyen *et al*., 2018; Stefanovic, 2021).

The amount of empirical evidence demonstrating the successful application of DA in SCM on a theoretical level is high and encompasses a variety of application settings and technical specifications (I. Lee & Mangalaraj, 2022; Aamer *et al*. 2020). Benefits include reduced costs, increased availability, higher sustainability, better SC agility and increased customer satisfaction (Nguyen *et al*., 2018). DA can be considered a game-changer in SCM and the need for identifying proven use-cases along SCM tasks and technical details of models used is growing (Fawcett & Waller, 2014). However, in SCM practice, the adoption DA is still in its infancy and literature reviews dealing with actual applications are often limited to certain SCM tasks and operational functions (Gonçalves *et al*., 2021; Mageto, 2021; Tirkolaee *et al*., 2021).

One of the few papers providing a comprehensive overview of actual practical applications of DA in SCM was published by Nguyen *et al.* (2018). They provide a well-structured and comprehensive overview of various application potentials of big data analytics (BDA) in SCM on the level of i) specific SCM areas, ii) DA levels, iii) DA model type and iv) specific DA techniques. They applied a systematic literature review (SLR) and analysed over 88 papers published between 2011 and 2017 in detail. Their results showed yearly increased numbers of publications and strong upward trends at all levels of analytics (Nguyen *et al.*, 2018). Maheswari *et al.* (2020) conducted a SLR to analyze current applications of DA in SCM, focusing on 2015 to 2019 (Maheshwari *et al.*, 2021). Their results also indicate an increasing number of publications and a growing relevance of DA across various SCM tasks. However, they did not provide details on the level of DA models and specific DA techniques. Similarly, Aryal *et al.* (2020) conducted a SLR to analyse the impact of disruptive technologies like DA and the Internet of Things (IoT) on SCM. Their analyses encompassed literature from 2008 to 2017. They did not provide details on the level of specific DA models and techniques (Aryal *et al.*, 2018). Chebh-Gamoura *et al.* (2020) published a SLR focusing on the application of DA based on the elements of the supply chain operations reference model (SCOR). Their results cover literature between 2001 and 2017 (Chehbi-Gamoura *et al.*, 2020).

More recent articles either focus on benefits of DA in SCM and challenges occurred in the course of its actual application only (Lee and Mangalaraj 2022), did not take into consideration published papers from 2021 (Pawar & Paluri, 2022), or did not focus on actual applications but theoretical potential only. For example, the SLR study provided by Lee and Mangalaraj (2022) showed similar results to Nguyen *et al.* (2018) for the time span of 2013-2021, however, they focused on prior literature reviews only. Literature reviews regarding the current status (i.e., in the years of 2020 and 2021) of actual applications of DA and their model- and technique-related aspects in different tasks of SCM are missing. In contrast to the papers stated above, our paper addresses this research gap and - building on the previous work by Nguyen *et al.* (2018) - focuses on actual DA application studies in SCM between 2020 and 2021. To close the gap between their study and the current state of research, we follow the proven methodology presented in Nguyen *et al.* (2018) and analyze 354 papers in detail. Following their methodology, we define the following research questions for our paper, allowing for a detailed comparison of their results from the analysis timeframe of 2011 to 2017 and current research on DA application in SCM from 2020 to 2021:

(1) In what areas of SCM is DA being applied?
(2) At what level of analytics is DA used in these SCM areas?
(3) What types of DA models are used in SCM?
(4) What are DA techniques employed to develop these models?

The remainder of the paper is structured as follows. Section 2 provides the details of the review methodology (i.e., our SLR procedure) for literature search delimitation, and analysis. Section 3 presents the results of the SLR. Section 4 discusses the findings of our study against the background of Nguyen *et al.* (2018) and additional literature sources. Section 5 provides an overview of possible future research directions and section 6 concludes the paper and states research limitations.

2. REVIEW METHODOLOGY

Following the methodological approach applied in Nguyen *et al.* (2018), the structure of our review methodology is based on (Nguyen *et al.*, 2018) and on the acknowledged content analysis approach by Mayring (Mayring, 2022). The basic steps of this approach comprise four sequential activities, which were used to systematically conduct our literature review:

(1) Step 1 – Material collection: Systematic and reproducible process of article search and delimitation.
(2) Step 2 – Descriptive analysis: Provision of general characteristics of articles.
(3) Step 3 – Category selection: Construction of a framework of analytical dimensions and categories to classify articles.
(4) Step 4 – Material evaluation: Analysis of articles based on the dimensions and categories of the classification framework and interpretation of results.

Subsequently, the first three steps and their results are described in sections 2.1., 2.2, and 2.3, followed by a detailed provision and interpretation of the main results of step 4 in section 3.

2.1 Material Collection

The first step of material collection consists of defining an effective set of search keywords. Nguyen *et al*. (2018) defined two groups of keywords related to “BDA” and “SCM”. They argued that their keywords classification (cf. **Table 1**) allows for capturing literature at the intersection of BDA, DA and SCM (Nguyen *et al*., 2018). To encompass recent advancements and guarantee the inclusion of pertinent works that could be overlooked when employing more general terms such as "machine learning," we've introduced three additional keywords to the DA group: "deep learning", "neural networks", and "reinforcement learning." Following their proposed material selection approach combined with three new keywords, we started with searching for possible pairs (90 pairs) between these groups in selected popular databases such as Scopus, Science Direct, EBSCO, and Emerald. As the aim of the current paper is to explore latest developments in the context of BDA, DA and SCM, we focused on articles published between 2020 and 2021. Since we are following the exact review approach of Nguyen *et al.* (2018), we are in a second step able to compare trends based on our results with theirs for the time span of 2011 to 2017. Table 1 presents the keywords used.

The initial search resulted in 37.387 articles, eliminating duplicated papers reduced the list to 24.055 papers. We subsequently checked for papers without "BDA" and "SCM"-related keywords as defined in **Table 1** in title or abstract. The next step comprised filtering based on language and publication type. Our analysis was focused on English articles that have been published in academic journals. Therefore, by excluding non-English conference papers, news, or thesis results, 5.701 papers were further selected for the next filtering step. We intended to have a list of articles that actually implemented "BDA" to solve "SCM" problems. Nguyen *et al.* (2018) excluded irrelevant papers by carefully reading the introduction and discussion part. Due to large number of resulted papers, we needed to split this step into two phases of a first, quick skimming of title and abstract and a second, careful analysis of introduction and discussion section. This exclusion reduced our list to 354 papers, which have been further selected for a full paper review. **Figure 1** illustrates this material collection and article delimitation process.

Table 1 Keywords defined in the two keyword groups

Group 1 - DA	Group 2 - SCM
Big data	Supply chain
Data analytics	Purchasing
Data mining	Procurement
Machine learning	Manufacturing
Descriptive analytics	Inventory
Predictive analytics	Storage assignment
Prescriptive analytics	Order picking
Deep learning	Logistics/ transportation
Neural network	Transport
Reinforcement learning	

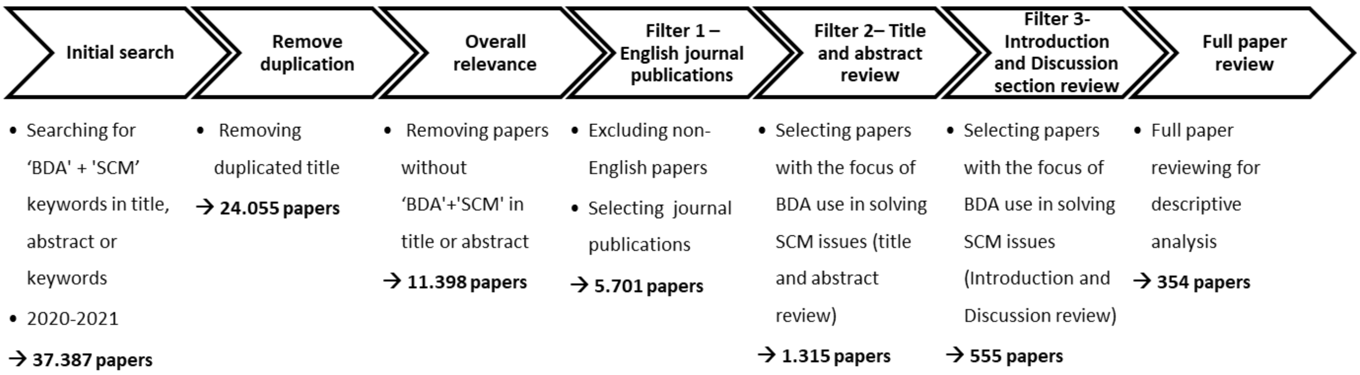


Figure 1 Material collection process

Figure 1: Flow-based figure of the material collection process steps done to filter relevant research papers from initially 37.387 results to ultimately 354 selected papers.

2.2 *Descriptive Analysis*

Figure 2 provides a comparison of the number of publications in 2020 and 2021, contrasted to the results of the reference paper published by Nguyen *et al.* (2018) for 2011 to 2017. The graph indicates that the number of articles published in this context has increased radically in recent years, i.e., to 154 in 2020 and 200 in 2021.

Figure 2: Bar-chart figure showing the development of relevant articles based on the defined keywords from 2011 to 2021, including 154 in 2020 and 200 in 2021.

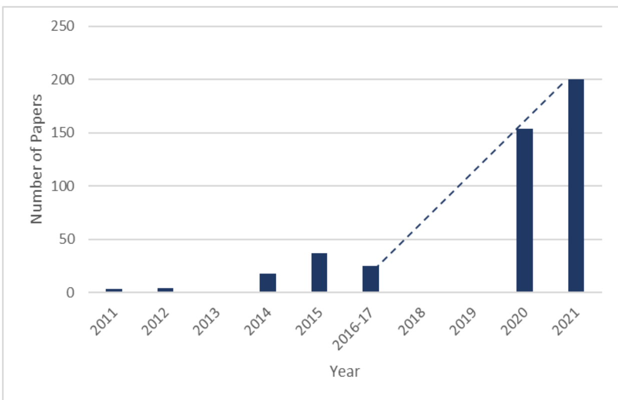


Figure 2 Comparison of the number of relevant articles published between 2011 and 2021

The 354 papers that are selected have been published in 204 different journals. In the reference study of Nguyen *et al.* (2018), this list was limited to 46 journals. The number of journals publishing application-oriented papers at the intersection of DA and SCM has hence more than tripled in our recent study. Out of the 204 journals examined, 49 of them were found to have multiple repetitions, amounting to a total of 200 papers (as shown in **Figure 3**). We proceeded to investigate these journals based on their respective subject areas using Scimagojr websites, and then compared the results with the journals that were most frequently repeated in a previous study conducted by Nguyen *et al.* (2018). A detailed comparison of the top 10 subject areas among the most repeated journals in both studies is presented in **Figure 4**. From the figure, it becomes evident that new areas, such as material science, mathematics, chemical engineering, and physics and astronomy, have surfaced. This clearly indicates a broader spectrum of interest and a wider audience for the research field under examination.

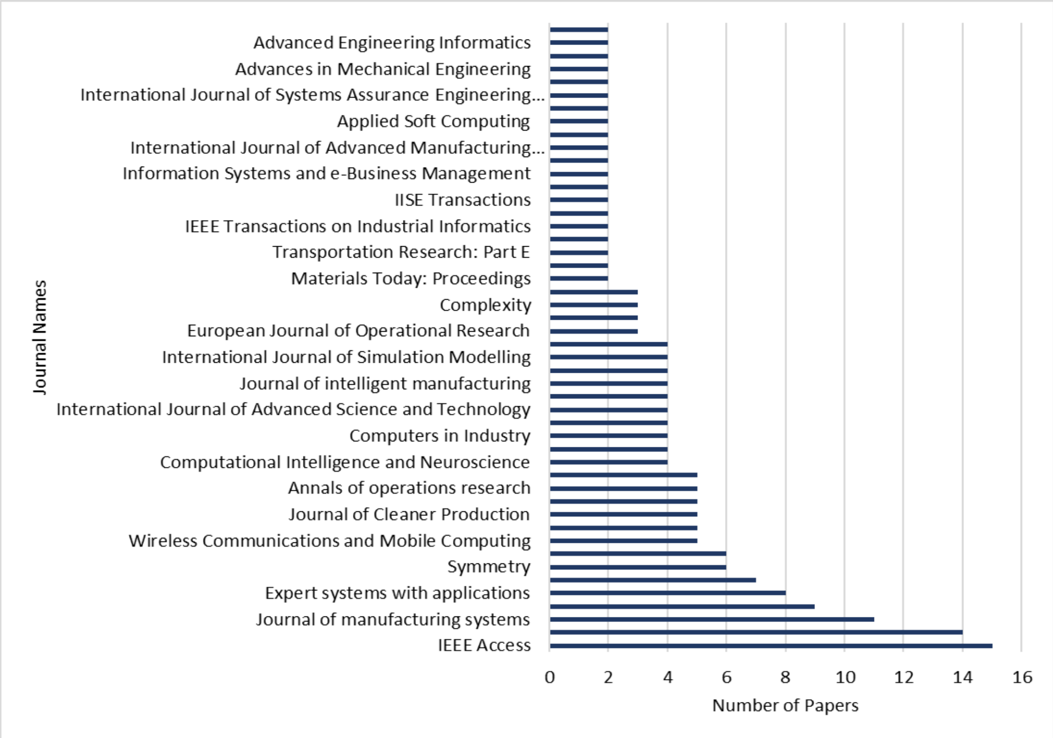


Figure 3 Distribution of papers amongst most frequent journals

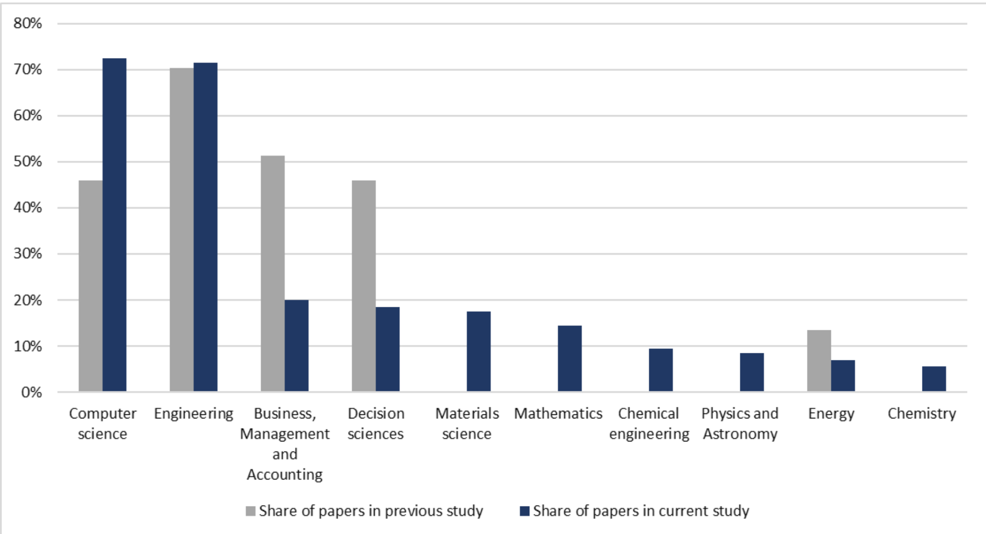


Figure 4 Share of most frequent papers among top 10 subject area

Figure 3: Bar charts of the distribution of relevant articles among journals, most articles were published in IEEE access, IJPR and JMS. **Figure 4** : Visual representation of the share of most frequent papers amongst top 10 subject areas, the top 3 being (1) computer science, (2) engineering and (3) business, management, and accounting.

For analyzing connections between SCM functions and DA levels and models, the classification scheme proposed by Nguyen *et al.* (2018) and depicted in **Figure 5** was applied in the current study. In total, we defined four main analysis dimensions, i.e., i) SCM function, ii) DA level, iii) DA models and the respective DA techniques, and iv) industry of application. All 354 selected papers were critically read in full and mapped to 17 analytic categories across these dimensions.

The first dimensional layer is related to the DA level of each article. This categorization is defined based on what the respective study focused on. Data analytics comprises three categories: descriptive analytics, predictive analytics, and prescriptive analytics. In a SCM context, descriptive analytics refers to the type of data analytics that typically applies statistics to summarize what has happened or is currently happening in the SC of a company. It produces valuable hindsight about events in the SC, identifies factors and correlations, detects exceptional events, and enables the analysis of the impact of identified events on other elements of the SC. Usually, descriptive analytics represents the basis for SCM reports, which are used to carry findings from DA to management (Tyagi, 2021). Predictive analytics (PA) refers to the type of DA that makes predictions about yet unknown, hence uncertain, events. PA typically applies advanced analytics models. By examining past data trends and patterns in the data, PA seeks to discover the causes of events as well as to predict possible future events respectively to fill in data or information that does not yet exist but can be generated based on existing data (Brandtner, 2023). Prescriptive analytics extends beyond all previous three types of DA and recommends actions for decision making (Tyagi, 2021). The focal question of prescriptive analytics is "what should I do" and its results typically include recommendations through multi-criteria decision-making (MCDM) techniques, simulation, and optimization (Riahi *et al.*, 2021). Hence, if the application study only describes past, predicts future or prescribes action measurements for decision making processes, it is accordingly mapped to descriptive, predictive, or prescriptive analytics, respectively. Besides these three categories, some sources also introduce diagnostic analytics, which involves a more thorough examination of the analyzed data to uncover and comprehend the underlying reasons for events and their influence on supply chain behavior (Maheshwari *et al*., 2021). Nevertheless, it's worth noting that diagnostic analysis can, to some extent, be encompassed within the descriptive and predictive analytics (PA) classification (Riahi *et al*., 2021).

The second dimensional layer represents the main functions of SCM addressed in each paper. In case the SCM function of a paper is not applicable to any of the proposed dimensions, it will be regarded to as "General SCM"-related work. The selected literature is subsequently categorized into levels of key activities for each SCM function. The activities are defined as follows, each comprising a set of sub-tasks:

- Procurement: Supplier selection, sourcing cost improvement, sourcing risk management
- Manufacturing: Product research and development (R&D), production planning and control, quality management, maintenance, and diagnosis
- Warehousing: Storage assignment, order picking, inventory control
- Logistics/ Transportation: Intelligent transportation system, logistics planning and in-transit inventory management
- Demand management: Demand forecasting, demand sensing, demand shaping

The third analytical dimension represents the specific models that are used in DA. Each model may include one or several DA techniques. Popular examples include e.g., K-means clustering, association rule mining, linear or logistic regression, neural networks, decision trees, support vector machines (SVM), statistics, heuristic and metaheuristic approaches, naïve bayes, time series forecasting, text mining, anomaly detection, sentiment analysis, fuzzy logic, feature selection and, etc.

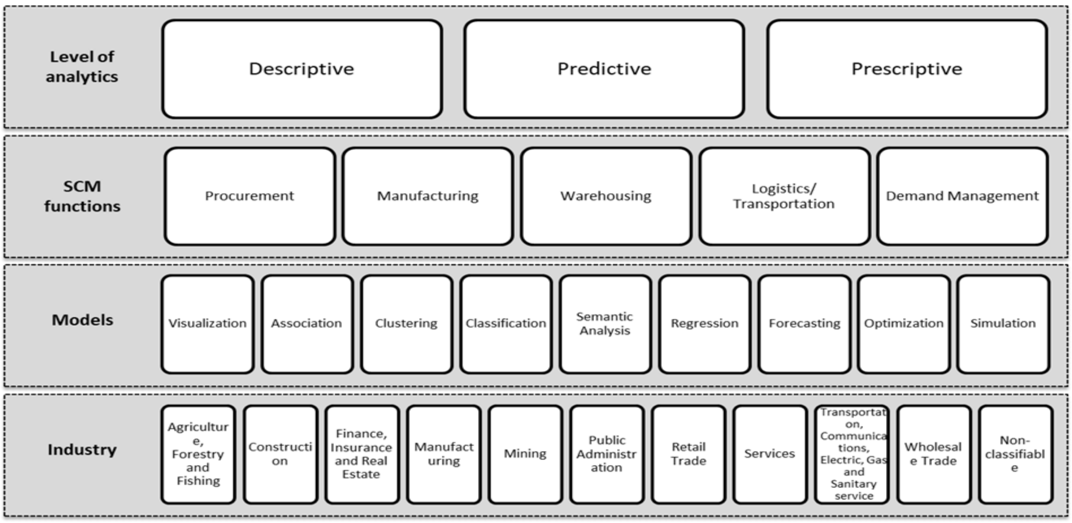


Figure 5 Classification of analysis dimensions and categories

Figure 5 Alt Text: Figure with the four levels of analysis dimensions of the literature review, including the level of analytics, the SCM functions, the models used and the industry it was applied in.

In addition to the classification scheme developed in (Nguyen *et al*., 2018), we analysed the relevant industry in which the application study took place. To this end, we used the categories defined in the standard industrial classification (SICCODE, 2023):

- Agriculture, Forestry and Fishing
- Construction
- Finance, Insurance and Real Estate
- Manufacturing
- Mining
- Public administration
- Retail trade
- Services
- Transportation, Communications, Electric, Gas and Sanitary service
- Wholesale trade
- Non-classifiable

3. MATERIAL EVALUATION

In this section, the detailed results of the systematic literature review conducted in accordance with the approach presented in section 2 are provided.

3.1 Review Results by SC Functions

The selected literature can be classified based on SC function and key activities as follows (cf. **Table 2**).

Table 2 Classification of literature based on SC functions and key activities

SC functions	Key activities	Papers
Demand management	Demand forecasting	Kharfan *et al*. (2021), Wang *et al*. (2020b), Anglou *et al*. (2021), Xiao *et al*. (2021), Amalnick *et al.* (2019), Spiliotis *et al.* (2020), Abolghasemi et al. (2020), Lalou et al. (2020), Nikolopoulos *et al.* (2021), Gustriansyah *et al.* (2020), Feizabadi (2020), He and Yin (2021), Inedi et al. (2020), Bajaj *et al.* (2020), Weng *et al.* (2019), Matthew & Abdullah (2021), Garrido-Labrador *et al.* (2020), van Belle *et al.* (2021), Meng (2021), Li and Kockelman (2022), Croce *et al.* (2021 Massaro *et al.* (2021), Yu *et al.* (2021e), Cho (2020), Dou *et al.* (2021), Zhang and Mu (2021), Chen *et al*. (2020b), Aktepe *et al.* (2021), Jiang *et al.* (2021a), Xu *et al.* (2021a), Li *et al.* (2021c), Chandriah and Naraganahalli (2021), Liu *et al.* (2021), Ye *et al.* (2020).
	Demand sensing	Sathyan *et al.* (2021), Pereira and Frazzon (2021), Martínez *et al.* (2020), Grzybowska *et al.* (2020), Bhutada *et al.* (2020), van Steenbergen and Mes (2020), Jain and Kumar (2020), Li *et al.* (2021a), Bilgic *et al.* (2021), Taghikhah *et al.* (2021), Türk *et al.* (2021), Shokouhyar *et al.* (2021), Barnes *et al.* (2021), Wu *et al*. (2021), García-Barrios *et al.* (2021), Anglou *et al*. (2021), Wei *et al.* (2020), Migdał-Najman *et al*. (2020)
	Demand shaping	Safara (2020), Verma *et al*. (2020), Lam *et al.* (2021), Lisnawati and Sinaga (2020), Xu *et al*. (2021b), Song and Xue (2021), Kalinin *et al.* (2020), Iftikhar and Khan (2020), Shahbazi *et al*. (2020), Yang *et al.* (2021c), Li *et al*. (2021b)
	Other	Konishi *et al.* (2021), Jo and Lee (2021), Brandtner *et al.* (2021), Vijayaragavan *et al.* (2020), Alqwadri *et al*. (2021)

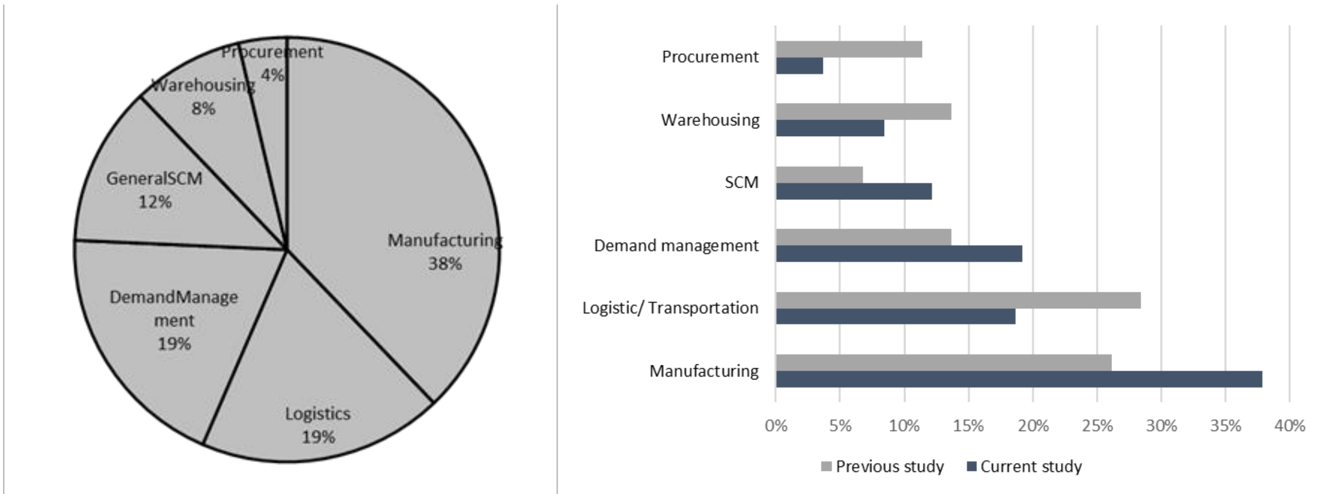
Table 2 Classification of literature based on SC functions and key activities (Con't)

SC functions	Key activities	Papers
General SCM		Kara *et al.* (2020, Melançon *et al.* (2021), Gholizadeh *et al.* (2020), Bifulco *et al.* (2021), Yu *et al.* (2021b), Jiang *et al.* (2021b), Song *et al.* (2021), Ma *et al.* (2021a), Li and Mao (2020), Deng *et al.* (2020), Bertsimas and Kallus (2020), Goodarzian *et al.* (2021), Chakraborty and Das (2021), Ali *et al.* (2021a), Moghimi and Beheshtinia (2021), Dai and Liu (2020), Li *et al.* (2020c), Abdella *et al.* (2020), Wong *et al.* (2021), Kuo *et al.* (2021), Narwane *et al.* (2021), Zhou and Guo (2021), Salamai *et al.* (2021), Park (2021), Wu *et al.* (2022), Asghari *et al.* (2021), Fang and Su (2021), Gumte *et al.* (2021), Yeboah-Ofori *et al.* (2021), Wan (2021), Ping Zhang *et al.* (2021), Chen and Huang (2021), Guillermo Muñoz *et al.* (2020), Lunardi and Lima Junior (2021), Xiang (2020), Khan *et al.* (2020), Sang (2021), Jianying *et al.* (2021), Abdelsamad *et al.* (2021), Nezamoddini *et al.* (2020), Abdelaziz *et al.* (2020), Yang *et al.* (2021d), Akbarian-Saravi *et al.* (2020), Chen *et al.* (2021a)
Logistics	Intelligent transportation system	Dimokas *et al.* (2020), Ibrahim *et al.* (2020), Chen *et al.* (2021b), Hwang (2021), Lorenc *et al.* (2021), Wiegmans *et al.* (2020), Mouammine *et al.*(2020), Zanin *et al.* (2020), Cerquitelli *et al.* (2020), TASHEV *et al.* (2020), Zhang *et al.* (2020b), Kinra *et al.* (2020), George and Santra (2020), Gupta *et al.* (2020), Chen (2020), Ding (2020), Kosowska-Stamirowska (2020), Harrison *et al.* (2020), Chen *et al.* (2021c), Han *et al.* (2021a), Sarabia-Jácome *et al.* (2019), Lock *et al.* (2021), Tsolakis *et al.* (2021), Jurdana *et al.* (2020), Oucheikh *et al.* (2021), Lee and Jeong (2021), Adi *et al.* (2020), Ren *et al.* (2020), Nadi *et al.* (2021)
	In-transit inventory management	Li *et al.* (2020b), Sun *et al.* (2020b), Yi and Ma (2020), Li and He (2021), Kim *et al.* (2020a), Molaris *et al.* (2021)
	Logistics planning	Moscoso-López *et al.* (2021), Balster *et al.* (2020), Liang and Wang (2021), Mangina *et al.* (2020), Cheng and Pan (2021), Choi (2020), Yue *et al.* (2021), Monteil *et al.* (2021), Vorkapić *et al.* (2021), Hathikal *et al.* (2020), Wang and Yin (2020), Govindan and Gholizadeh (2021), Ahmadi *et al.* (2020), Gocer and Sener (2022), Han *et al.* (2021a), Ruan *et al.* (2021), Yuan *et al.* (2021), Kemmar *et al.* (2021), Min and Kang (2021), Yu *et al.* (2021a), Puskás *et al.* (2020), Chargui *et al.* (2021), Maity *et al.* (2020), Issaoui *et al.* (2021), Abosuliman and Almagrabi (2021), Liu (2021a), Yuan *et al.* (2021), Phiboonbanakit *et al.* (2021), Zhang *et al.* (2020a), Teng (2021), Adi *et al.* (2021), Nagendra *et al.* (2020)
Manufacturing	Maintenance & diagnosis	Arjomandi *et al.* (2021), Oleghe (2020), Kang *et al.* (2020a), Yu *et al.* (2021d), Li *et al.* (2021d), Frumosu *et al.* (2020), Feng *et al.* (2018), Kaparthi and Bumblauskas (2020), Jun (2021), Sánchez *et al.* (2020), Malawade *et al.* (2021), Li *et al.* (2020a), Kapp *et al.* (2020), Vasavi *et al.* (2021), Eirinakis *et al.* (2021), Cao *et al.* (2020), Stietencron *et al.* (2021), He *et al.* (2021a), Ayvaz and Alpay (2021), Dierkes *et al.* (2021), Acernese *et al.* (2020), Chang *et al.* (2021), Kim *et al.* (2021), Han *et al.* (2021b), Sang *et al.* (2021), Al-Shayea *et al.* (2022), Liu *et al.* (2020b), Lv *et al.* (2021), Tanuska *et al.* (2021), Benatia *et al.* (2020)
	Product R&D	Huma *et al.* (2021), Corney *et al.* (2020), Ghahramani *et al.* (2020), Zhang *et al.* (2021), Pahwa and Starly (2020), Oh *et al.* (2021), Wang *et al.* (2021d), Ning *et al.* (2020), Bhatnagar *et al.* (2020), Wang *et al.* (2020c)
	Production planning & control	Subramaniyan *et al.* (2020), González Rodríguez *et al.* (2020), Shin (2020), Oberdorf *et al.* (2021), Tamás and Koltai (2020), Zhao and Zhang (2021), Fang *et al.* (2020), Tang and Ge (2021), Ma *et al.* (2020), Yamashiro and Nonaka (2021), Qiao *et al.* (2020), Tayal *et al.* (2020), Tayal *et al.* (2020), Mahmoudi *et al.* (2021), Li *et al.* (2020d), Morariu *et al.* (2020), Morin *et al.* (2020), Goettsch *et al.* (2020), Lucht *et al.* (2021), He *et al.* (2021b), Lee *et al.* (2020a), Tong *et al.* (2021), Tassel *et al.* (2021), Yang *et al.* (2021a), Ribeiro *et al.* (2020), Sun *et al.* (2020a), Mishra *et al.* (2021), Jomthanachai *et al.* (2020), Lin *et al.* (2020), Fang *et al.* (2021), Bouzary *et al.* (2021), Wang *et al.* (2021a), Lan and Chen (2021), Rehman *et al.* (2021), Kazi *et al.* (2021), Kuhnle *et al.* (2021), Lee and Gao (2021), Chen *et al.* (2020a), Wang (2021), Han and Yang (2020), Wang *et al.* (2021c), Liang (2020), Pooya *et al.* (2021), Lai *et al.* (2020), Ghoushchi and Abbasi (2021), Yu *et al.* (2021c), Hu *et al.* (2020), Kim *et al.* (2020b), Golmohammadi *et al.* (2021), Seidgar *et al.* (2020), Sadiq *et al.* (2020), Alnahhal *et al.* (2021), Berges *et al.* (2021), Feldkamp *et al.* (2020), Guo *et al.* (2020), Wang *et al.* (2021g)

Table 2 Classification of literature based on SC functions and key activities (Con't)

SC functions	Key activities	Papers
	Quality management	Khayyati and Tan (2021), Liu and Duan (2020), Wang *et al.* (2021e), Abdelrahman and Keikhosrokiani (2020), Wenzlick *et al.* (2021), Sun *et al.* (2021b), Sanchez-Marquez *et al.* (2020), Ali *et al.* (2021b), Papananias *et al*. (2020), Fathy *et al.* (2020), San-Payo *et al*. (2020), Niccolai *et al.* (2021), Teniwut *et al*. (2020), Kappelman and Sinha (2021), Rousopoulou *et al.* (2020), Schmitt *et al.* (2020), Ismail *et al.* (2021), Jun *et al.* (2020), Oh *et al.* (2021), Sun and Braatz (2021), Xin-chun *et al*. (2021), Sariyer *et al*. (2021), Zaman and Hassan (2021), Detzner and Eigner (2021), Wang *et al.* (2021h), Stauder and Kühl (2022), Liu (2021b), Wen *et al.* (2020), Chaikine and Gates (2021), Ma *et al*. (2021b), Kafunah *et al*. (2021), Lee *et al.* (2020b), Kang *et al.* (2020b), Pu *et al.* (2020), Nagata *et al*. (2021), Noor *et al*. (2020), Konovalenko and Ludwig (2021)
Procurement	Sourcing risk management	Fayyaz *et al.* (2020), Wang *et al*. (2020a), Brintrup *et al.* (2020), Niu *et al.* (2021), Chitikela *et al.* (2021), Rabe *et al.* (2021)
	Supplier selection	Alavi *et al*. (2021), Liu *et al.* (2020a), Liou *et al.* (2021), Wilson *et al.* (2020), Islam *et al.* (2021), Gegovska *et al.* (2020)
Warehousing	Inventory control	Hajek and Abedin (2020), Arumsari and Aamer (2021), Punia *et al*. (2020), Wang *et al*. (2021b), Luchko *et al*. (2019), Galli *et al*. (2020), Agarwal, Mohit, Anurag Wadhwa, Kartik Batra, and Senthil Kumar. (2020), Galli *et al.* (2021), Andaur *et al.* (2021), Kalaiarasi *et al.* (2021), Ntakolia *et al.* (2021), Cui *et al.* (2021b), Dittrich and Fohlmeister (2021), Abu Zwaida *et al.* (2021), Yang *et al.* (2021b), Wang *et al*. (2021f), Sharifnia *et al.* (2021), Deng and Liu (2021)
	Order picking	Li *et al.* (2021e), Granillo-Macías (2020), Zhou *et al.* (2020), Villarreal-Zapata *et al.* (2020), Dunke and Nickel (2020), Ardjmand *et al.* (2020)
	Storage assignment	Saleet (2020), Aylak *et al.* (2021), Sun *et al.* (2021a), Cui *et al.* (2021a)

Figure 6 illustrates the share of each SC functions amongst the reviewed articles. As it is shown in the part A of **Figure 6** in most publications (38%), researchers addressed manufacturing related issues in SCM. Demand management (19%), logistics respectively transportation (19%) and general SCM (12%) also were amongst the most popular topics of applied research at the intersection of DA and SCM. When comparing these results with those of the previous study (Nguyen *et al*., 2018) (cf. part B of **Figure 6**), we can see, that the proportion of applications of DA in procurement, warehousing and logistics respectively transport has reduced, whereas for general SCM, demand management and manufacturing it has increased in recent literature.



A: Recent distribution | B: Comparison of recent results and (Nguyen *et al*., 2018)

Figure 6 Distribution of analysed papers by SC function (A) and comparison to previous study (B)

Figure 6: Distribution of analysed papers amongst SC function in a pie chart on the left side and a bar charts-based comparison of our results with the previous paper from Nguyen *et al*. (2018)

As illustrated in **Figure 7**, production planning & control (56 papers) and quality management (38 papers) in the manufacturing function, logistics planning (31 papers) in the logistics/transportation function and demand forecasting (34 papers) in the demand management function were the most focused areas for researchers in recent years. In the field of warehousing, inventory control (20 papers) and in the field of procurement, supplier selection and sourcing risk management (6 papers for each) are the most repeated topics recently.

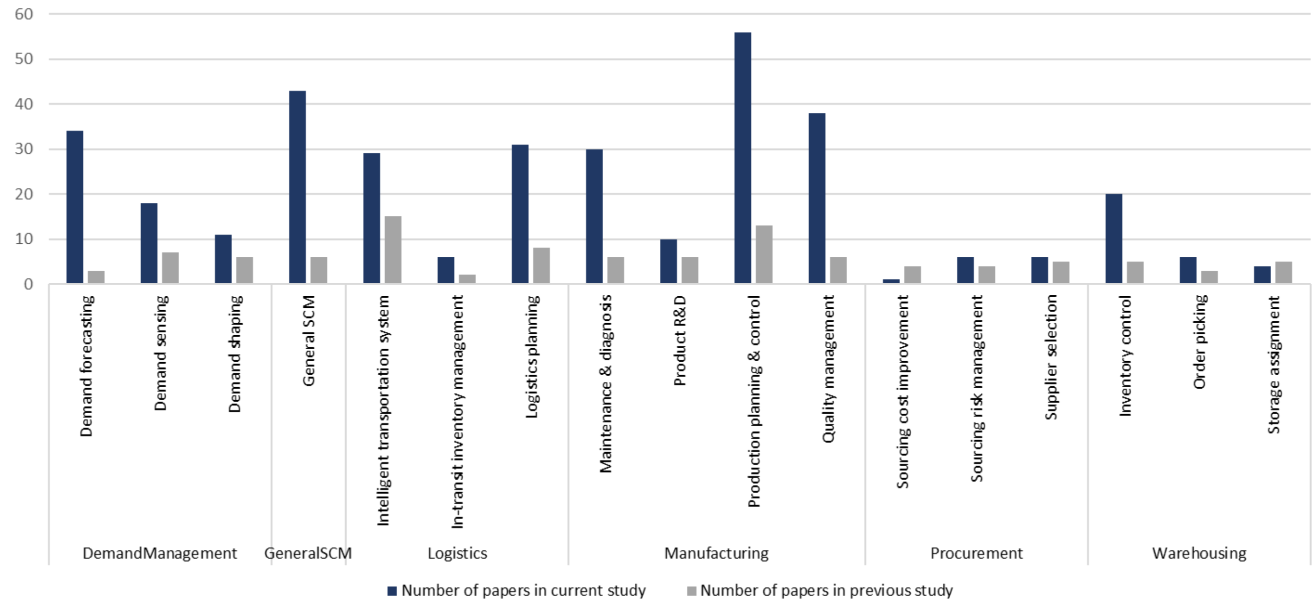


Figure 7 Comparison of article distribution by SC function and activity between recent study and (Nguyen *et al*., 2018)

Figure 7: Figure showing several bar charts comparing the number of analysed papers in the different SCMs functions in the current and the past SLR by Nguyen *et al.* (2018).

There are 43 papers which are not dealing with a specific SC function. These papers have been categorized under the group of "general SCM" and focus on different areas. Due to the significant increase in the number of papers within this field in recent years (cf. **Figure 8**) and for a more detailed analysis, we have broken down this general category into 7 sub-catgories. Based on this categorization, more than half of the articles within the "general SCM" function are in the area of risk management (12 papers) and sustainable supply chain management (11 papers).

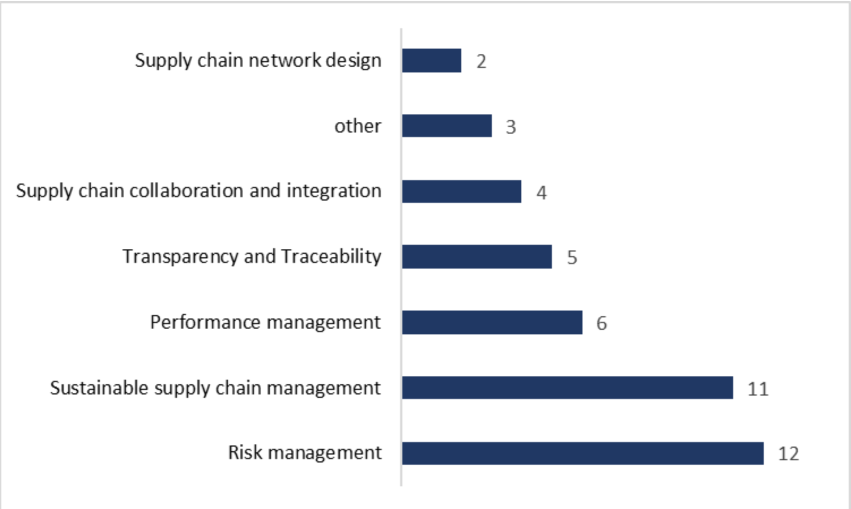


Figure 8 Distribution of analysed papers with "General SCM" function by Analytic categories

Figure 8: Figure showing the distribution of topics in the field of general SCM. The top three sub-categories include risk management, sustainable SCM and performance management.

3.2 Review Results by Level of Analytics

Figure 9 provides an overview of latest trends across the three analytics levels in publications compared to previous years. In contrast to the previous study, which depicted the dominance of prescriptive analytics, the current literature review identifies an increased focus on predictive analytics, becoming the most common analytics type applied in the analysed articles. All three levels of analytics experienced a significant increase compared to the previous study, however, for descriptive analytics, a decrease in 2021 compared to 2020 could be shown.

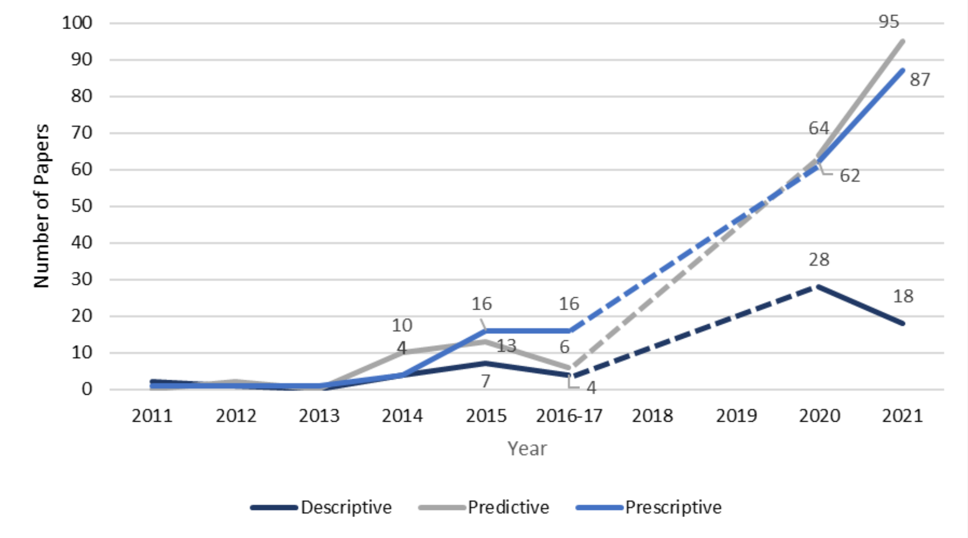
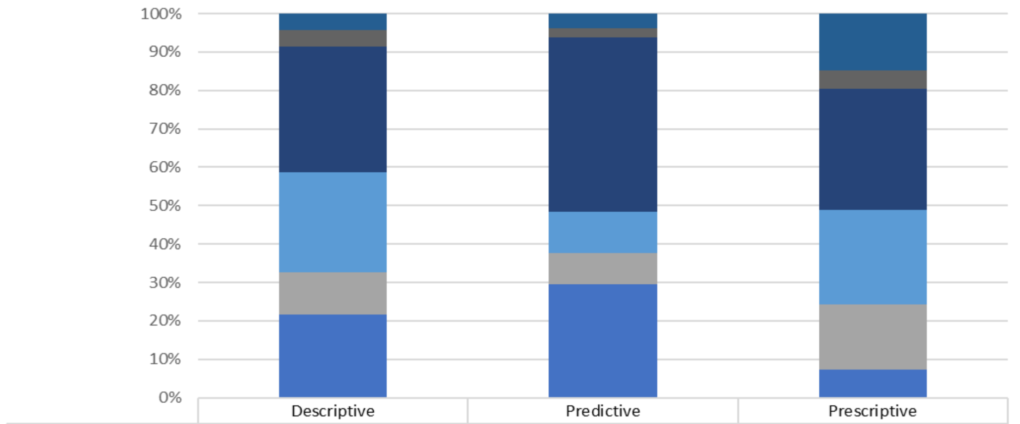


Figure 9 Number of papers by year and level of analytics

Figure 9: A trendline showing the development relevant papers in the three levels of descriptive, predictive, and prescriptive analytics.

Next, the share of SC functions in each analytics type is provided in **Figure 10**. The results show that - apart from general SCM - solving manufacturing issues is the most popular topic at all analytics levels. For descriptive analytics, the second most specific SC function after manufacturing is logistics, followed by demand management. For predictive analytics, the second most popular topic is demand management, followed by logistics. For prescriptive analytics, the second most dealt with application area is logistics, followed by warehousing (besides general SCM).



	Descriptive	Predictive	Prescriptive
Warehousing	2	6	22
Procurement	2	4	7
Manufacturing	15	72	47
Logistics	12	17	37
GeneralSCM	5	13	25
DemandManagement	10	47	11

Figure 10 Distribution of papers by SC functions and level of analytics

Figure 10: Three stacked bar-charts – one per levels of analytics - showing the numbers of papers in the different SC functions.

3.3 Review Results by Type of DA Model

Figure 11 depicts the distribution of papers based on DA models applied in Nguyen *et al.* (2018) and in comparison to the current study. Same as previous study, most articles applied optimization models (92 out of 354, 26%). Their share has slightly increased in recent publications compared to the analysis of Nguyen *et al.* (2018). Popular route and location optimization models have been widely used in this context to support decision makers in solving supply chain issues. The next popular model categories are mixed or hybrid models (19%) and forecasting approaches (19%). As visualized in **Figure 12**, these models are mostly used for manufacturing and demand management issues. Next is classification models (16%), which are mostly applied in solving manufacturing and warehousing problems.

For simulation, association, regression, and semantic analysis, we noticed a downturn compared to the past. Clustering models are the next most repeated model type in the current analysis. Manufacturing and demand management represent the dominating SC functions for such models.

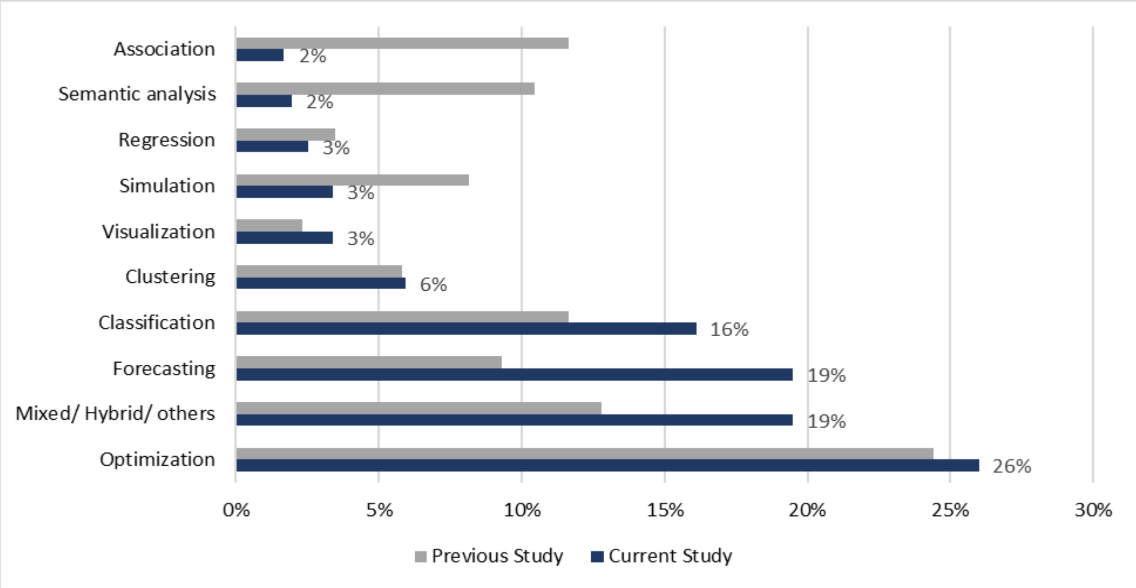
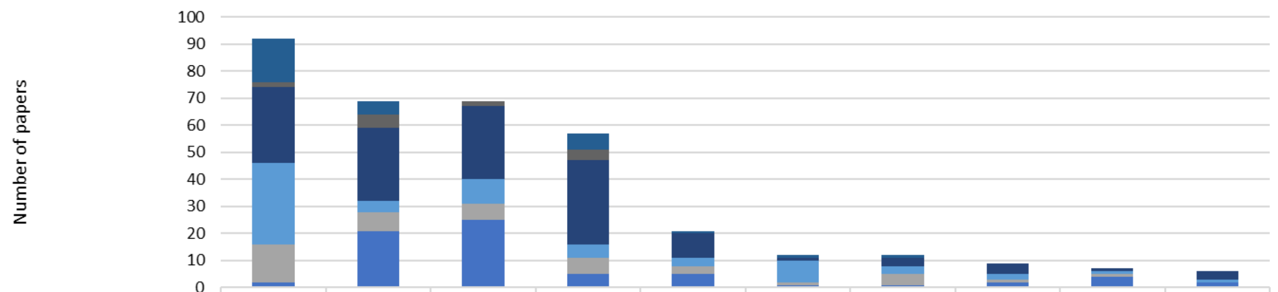


Figure 11 Compression of past and recent distribution of papers by model



	Optimization	Mixed/ Hybrid/ others	Forecasting	Classification	Clustering	Visualization	Simulation	Regression	Semantic analysis	Association
Warehousing	16	5	0	6	1	1	1	0	0	0
Procurement	2	5	2	4	0	0	0	0	0	0
Manufacturing	28	27	27	31	9	1	3	4	1	3
Logistics/ Transportation	30	4	9	5	3	8	3	2	1	1
General SCM	14	7	6	6	3	1	4	1	1	0
Demand management	2	21	25	5	5	1	1	2	4	2

Figure 12 Distribution of papers by SC functions and models

Figure 11: Horizontal bar-charts comparing the number of papers dealing with the different DA models in the current and past SLR.

Figure 12: Several stacked bar-charts – one per DA model type - showing the numbers of papers in the different SC functions.

As mentioned, hybrid, mixed or other types of approaches that use more than one DA model are widely used in recent publications. 19% of recently published papers in the scope of our analysis apply a combination of more than one model to address SCM issues. Hence, it is worthy taking a closer look at these. **Table 3** and **Figure 13** provide an overview of the distribution of papers applying model combinations by analytics level and specific DA models used. For instance, as indicated in **Table 3**, **11** papers in the area of prescriptive analytics employed a mixed/hybrid approach, incorporating both classification and optimization models. Out of 69 articles, 40 (58%) are in the context of prescriptive analytics, 24 (34%) focus on predictive analytics and the rest (5 papers) is related to descriptive analytics. Classification (24%), optimization (22%) forecasting (18%) and clustering (15%) respectively are the most repeated models. To put it another way, DA models that seemed to be fading out when comparing recent publications to past applications are now combined and empowered with other models in the form of hybrid and mixed approaches.

Table 3 Distribution of papers with mixed/hybrid/others models by analytics level and DA models

Number of articles			Association	Classification	Clustering	Forecasting	Optimization	Regression	Semantic	Simulation	Visualization
Descriptive	Predictive	Prescriptive									
0	0	11		*			*				
0	6	0		*		*					
0	0	6				*	*				
0	0	5			*		*				
1	2	1		*	*						
0	3	0		*	*	*					
0	3	0		*		*		*			
0	2	1				*		*			
0	3	0			*	*					
0	0	2	*				*				
0	0	2		*			*	*			
1	0	1	*		*						
0	1	1		*					*		
0	0	2					*	*			
0	2	0		*				*			
0	1	0	*			*					
0	0	1			*	*	*				
0	0	1					*			*	
1	0	0			*				*		
1	0	0		*	*				*		
0	0	1				*			*		
0	0	1	*	*	*		*				
0	1	0	*							*	
1	0	0			*						*
0	0	1					*		*		
0	0	1	*		*					*	
0	0	1		*			*		*		
0	0	1								*	

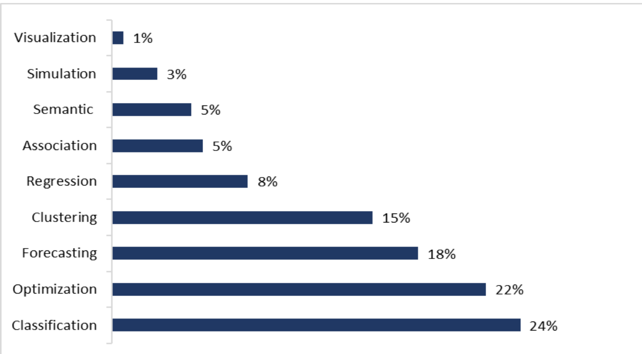


Figure 13 Frequency of individual models in hybrid or mixed model approaches

Figure 13: A bar-charts showing the numbers of different model types applied in hybrid or mixed model approaches. The top three include classification, optimization and forecasting approaches.

3.4 Review Results by DA Techniques

Table 4 and **Figure 14** provide a detailed overview of most repeated DA techniques and models. Mixed or hybrid techniques are the most repeated approaches in recent publications (139 papers). After that, statistics/heuristic approaches are the most popular techniques (49 papers), which are mostly applied in optimization models. Similarly, neural networks in forecasting (24 papers), reinforcement learning in optimization (15) and decision trees in classification models (14 papers) prevail. Unlike the previous study, association rule mining (ARM), support vector machines (SVM), and sentiment analysis are less discussed in recent literature while approaches such as metaheuristic and mixed techniques are addressed more frequently. We have categorized techniques that are used only once in the papers as others.

Table 4 Distribution of papers by DA techniques and models

	Association	Classification	Clustering	Forecasting	mixed	Optimization	Regression	Semantic analysis	Simulation	Visualization	Grand Total
Mixed	1	19	1	25	69	21			3		139
Statistics/heuristic		1	1	6		33	3	1	3	1	49
Neural network		6		24		10		1	2		43
Reinforcement learning				1		15			4		20
Decision tree		14		2							16
Other clustering algorithms			14					1			15
Visualization										11	11
Linear regression				3			6				9
Metaheuristic approach				1		7					8
Other classifications		7									7
Support vector machines		4		2							6
Decision making		2				4					6
Other		2		2		2					6
Association rule mining	5										5
K-means clustering			4								4
Text mining			1	1				2			4
Annomaly detection		1		1							2
Naïve bayes		1		1							2
Sentiment analysis								2			2

To conduct a more detailed analysis of mixed or hybrid techniques, we have provided a closer look at the individual techniques used in these approaches. As shown in the figure, statistics/heuristics, neural networks, and support vector machine techniques are the most frequently used in mixed/hybrid approaches, which have been enhanced by combining them with other techniques in recent publications.

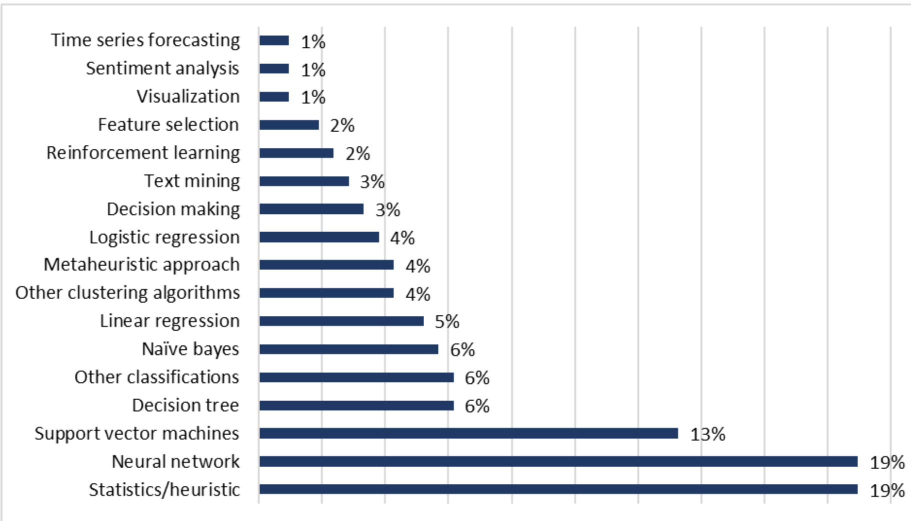


Figure 14 Frequency of individual techniques in hybrid or mixed technique approaches

3.5 *Review Results by Industry*

In **Table 5**, the distribution of articles in each industry of the standard industrial classification (SIC) framework as well as the corresponding level of analytics is provided. As shown, manufacturing problems prevail in literature. After that, "transportation, communications, electric, gas and sanitary service" and "retail trade" are the most focused industries. Predictive analytics is mostly applied in manufacturing and retail trade industries for failure and demand forecasting, respectively. Descriptive and prescriptive analytics are more applied for DA use cases in manufacturing and transportation industries.

Table 5 Distribution of papers by industry and level of analytics

Industry	Descriptive	Predictive	Prescriptive	Total
Manufacturing	22	85	70	177
Transportation, Communications, Electric, Gas and Sanitary service	11	20	36	67
Retail trade	6	29	17	52
Nonclassifiable	2	14	12	28
Services	2	3	5	10
Finance, Insurance and Real Estate	1	2	4	7
Agriculture, Forestry and Fishing	2	2	2	6
Mining		1	2	3
Wholesale trade		2		2
Sanitary service			1	1

4. RESULTS AND DISCUSSION

In this section, a discussion of the main changes in each SC function and activity as well as on the analytics type, the DA model and the DA techniques level is provided by comparing the results and the selected papers of our literature review with those of the reference study provided by Nguyen *et al*. (2018).

4.1 In What Areas of SCM is DA being Applied?

The distribution of recent papers in different fields of the manufacturing area has not changed significantly. Manufacturing area in recent years is still amongst the most impacted fields by advances of DA and digital transformation, which resulted in huge expansion of data availability (Tamás & Koltai, 2020). Production planning and control are the dominant topics for applying DA in this context (Lucht *et al*., 2021). The results of the current literature review are in line with the previous one and we also confirmed that most papers in the manufacturing area address production planning and control issues. Quality management is the next frequent topic in the manufacturing area which has been more discussed in manufacturing literature. High quality products or services are vital and desired by both customers and companies. While quality management was often performed by humans in the past, nowadays DA and machine learning techniques can be employed in solving many quality management tasks (San-Payo *et al.*, 2020). Increasingly, the generation of data and information because of implementation of internet of things (IoT) and particularly radio frequency identification (RFID) technologies have enabled companies to implement real-time traceability of their production systems (Feng *et al.*, 2018; Sánchez *et al.*, 2020). This leads manufacturing areas into implementing DA for empowering early detection systems and increase their responsiveness to disruptions (Eirinakis *et al.*, 2021). However, selecting appropriate data and applying machine learning techniques in real-time maintenance and diagnostics field is a challenging issue discussed in a plethora of articles (Feng *et al.*, 2018; Yifu Li *et al.*, 2021).

Although in the previous study the dominant topic in the field of logistics and transportation were intelligent transportation systems (ITS), in recent years, logistics planning has gained slightly more prominence. Routing optimization (Dimokas *et al*., 2020; Y. Zhang *et al*., 2020; Chen, 2020; Han *et al*., 2021; Wiegmans *et al*., 2020) and traffic monitoring (Ibrahim *et al*., 2020; Hwang, 2021; George & Santra, 2020; Y.-T. Chen *et al*., 2021) prevail in the ITS domain. In addition, process traceability (Yineng Chen *et al*., 2021; Harrison *et al*., 2020) is a newly emerged topic in literature in this context. Applying DA techniques in logistics planning is more practical todays. Location-allocation optimization (Cheng & Pan, 2021), reverse logistics planning (Govindan & Gholizadeh, 2021; Ahmadi *et al*., 2020), production logistics scheduling (Yue *et al.*, 2021), smart logistics planning (Liang & Wang, 2021), improved transport prediction models (Monteil *et al*., 2021; Balster *et al.*, 2020; Hathikal *et al*., 2020; Moscoso-López *et al.*, 2021) and sustainability focused planning (Mangina *et al.*, 2020; Vorkapić *et al*., 2021) are amongst the most repeated topics.

Demand management is a topic of growing interest recently. Forecasting daily demand of products in the retail sector (Amalnick *et al*., 2019; Spiliotis *et al*., 2020; Abolghasemi *et al.*, 2020; Lalou *et al*., 2020; Massaro *et al.*, 2021), predicting potential customer demand (Wang *et al.*, 2020) or newly launched products (Kharfan *et al.*, 2021) are amongst the most repeated topic in “demand forecasting” area. Moreover, there are lots of contributions in context of demand shaping (Safara, 2020; Verma *et al*., 2020; Lam *et al*., 2021; J.-S. Song & Xue, 2021; Kalinin *et al*., 2020) and demand sensing (Sathyan *et al*., 2021; Grzybowska *et al*., 2020; Jain & Kumar, 2020; Taghikhah *et al*., 2021; Türk *et al.*, 2021; Shokouhyar *et al*., 2021) in recent publications.

Benefiting from DA in warehousing operations is not as frequent as manufacturing and logistics in literature. Though, the popularity of this issue in recent years has decreased by half. However still, expansion of data availability and uncertainty draws researchers’ attention towards application of big data (BD) and machine learning to improve decision making in the field of warehousing and stock management (Luchko *et al*., 2019; Galli *et al*., 2020). In this area, the focused field is inventory control (Hajek & Abedin, 2020), which is the most repeated problem both in past and current literature review. Compared to the previous study, real-time DA and process and inventory monitoring in smart warehouses (Arumsari & Aamer, 2021) as well as more advanced classification and optimization methods with heuristic approaches have more been applied in smart retail, drug and perishable products segments (Wang *et al.,* 2021; Ahmadi *et al*., 2020; Galli *et al*., 2020). Order picking is an undeniable part of warehousing specially in distribution centers (DC) (Yue Li *et al*., 2021) as improving in this sector can reduce logistics costs (Granillo-Macías, 2020). Increasing the efficiency of order picking activities by optimizing storage location is popular in recent papers (Zhou *et al*., 2020; Yue Li *et al.*, 2021).

Regarding DA applications in the procurement area, recent publications showed increased applications in risk management and supplier selection. Benefiting from predictive and prescriptive analytics to improve supplier risk management has become a more mature topic compared to the past. Outsourcing and dealing with uncertain demand information (Niu *et al.,* 2021) and predicting supply disruptions (Brintrup *et al.,* 2020) are amongst the most repeated topics in this field. In the area of supplier selection, nowadays environmental concerns in companies have increased and as a result, sustainable supplier selection has been widely adopted in literature (Alavi *et al.,* 2021; Liou *et al*., 2021). Moreover, same as in the previous study, ML methods have been utilized to improve the speed and reliability of supplier selection (Wilson *et al*., 2020 Islam *et al*., 2021) as well as improving SC visibility (J. Liu *et al.*, 2020).

The last part is dedicated to general SCM, related to the whole SC or a combination of several activities. As mentioned before, this area has attracted researchers' attention and new issues have been addressed in the selected articles. In addition to the former topics of risk management (Kara *et al*., 2020; Melançon *et al*., 2021; Dai & Liu, 2020; Salamai *et al*., 2021; Jing Wu *et al*., 2022), sustainability and green supply chain (Gholizadeh *et al*., 2020; D. Ma *et al*., 2021; Wong *et al*., 2021; Abdella *et al*., 2020; Goodarzian *et al*., 2021; Moghimi & Beheshtinia, 2021; Nagendra *et al*., 2020; Kuo *et al.,* 2021; Park, 2021), and performance management (Jiang *et al.* 2021b; Chakraborty and Das, 2021; Li *et al.* 2020c; Lunardi and Lima Junior, 2021; Abdelsamad *et al.*, 2021). Supply chain collaboration and integration (Ali *et al*., 2021a; Gumte *et al*., 2021; Guillermo Muñoz *et al*., 2020; Xiang, 2020), supply chain network design (Zhou and Guo, 2021; Yang *et al.,* 2021d) and transparency and traceability (Wong *et al*., 2021; Ping Zhang *et al*., 2021; Khan *et al*., 2020) have been discussed in recent DA publications.

4.2 At What Level of Analytics is DA Used in These SCM Areas?

As mentioned earlier, the distribution of predictive and prescriptive analytics has fluctuated widely over the years. In the early years of the emergence of DA, predictive analytics was superior to prescriptive analytics, though from 2015 onwards, articles in the field of prescriptive analytics prevailed. Then again, predictive analytics has been the most frequent approach of 2020 and 2021 articles.

In terms of application of each analytical level in SC areas, the results are close to the previous analysis of (Nguyen *et al*., 2018), however, in that study "logistics/ transportation" was dominant in the prescriptive analytics. In recent years "manufacturing" received more attention. In addition, "Demand management" has attracted considerable attention in all analytics level. In contrast, "Warehousing" seems to be disappearing in predictive analytics. Moreover, previously, all SC areas were discussed almost uniformly in descriptive analytics papers (between 2 to 4 papers), while now the distribution is more diversified. To exemplify, "procurement" issues are less discussed with descriptive analytics and more addressed with optimization and prediction. Though, newly emerged problems in other SC topics are widely noticed in descriptive analytics.

4.3 What Types of DA Models are Used in SCM?

As provided in **Figure** 11, optimization methods prevail in our selected papers of application of DA in SCM. Same as before, manufacturing and logistics and transportation are the most focused areas in this context. However, as stated by Nguyen *et al*. (2018), smart logistics and warehousing solutions for routing or location optimization, also based on real-time data, have become more mature recently. Especially against the background of Industry 4.0, the application of real-time DA to enable timely decisions in SCM represent an area of growing importance in research and practice (Ahmad & Sanjog, 2023). Digital transformation and intelligent systems enabled sustainable developments in different fields of SCM (Ma *et al.*, 2020). Therefore, optimizing sustainability and energy consumption is another issue that has attracted the attention of researchers in recent years.

The second most repeated approaches are hybrid or mixed methods as well as forecasting. Hybrid or mixed methods are mostly applied in prescriptive analytics, especially in manufacturing and demand management. Semantic analysis, association and other methods that used to be common in literature previously, are now mostly combined or mixed with other models to build more advanced DA models and improve reliability and accuracy analysis. For forecasting models, the main applications are predicting customer demand (Abolghasemi *et al*., 2020; Lalou *et al*., 2020; Spiliotis *et al*., 2020), in demand management or early detection (Malawade *et al*., 2021; Li *et al*., 2020a) or in resource consumption in the manufacturing area (Ribeiro *et al*., 2020; Tong *et al*., 2021). Such methods have also been applied in flow time prediction in the field of logistics especially perishable products transportation (Moscoso-López *et al.*, 2021).

Despite the frequency of semantic analysis and association models in previous study, classification approaches are the fourth most common element in the current literature review. It has been applied mostly on predictive analytics and specially manufacturing problems. Though, current directions of articles are now in the area of quality management as well as failure detection and prediction (Jun *et al*., 2020; Niccolai *et al.*, 2021; Niccolai *et al*., 2021; Frumosu *et al*., 2020). In the field of logistics and transportation, classification methods have been applied to deal with lead time and delay prediction (Zanin *et al*., 2020; Hathikal *et al*., 2020). Also, such approaches have been used to categorize products and predict new product demand (van Steenbergen & Mes, 2020).

Finally, clustering models have been applied in more than 6% of selected papers. They are more frequent in descriptive and predictive analytics and less common in prescriptive modeling. Cluster based approaches were mostly noticed in manufacturing area for quality management and production planning and control. They have little insight in sustainability (Abdella *et al*., 2020) and risk management (Kara *et al*., 2020) problems in general SCM.

4.4 What are DA Techniques Employed to Develop These Models?

In addition to the prevalent mixed/hybrid techniques found in most approaches, like what was mentioned previously, certain techniques take precedence in specific models. For instance, neural networks are frequently employed in forecasting, while tree-based techniques are predominant in classification models. In contrast to prior literature reviews on optimization models, alongside heuristics and statistical approaches, reinforcement learning methods have become increasingly common.

Due to diversity of BD, in recent articles, the tendency towards mixing or combining different techniques to solve SCM issues has increased. Some former common methods that are not prevalent in the new study have been mixed with other techniques. For example, association rule mining used to be widely adopted in descriptive and predictive analytics. However, in the current study, often prescriptive analytics have been improved by combining ARM with other techniques, especially clustering and statistics/heuristic approaches (Yue Li *et al*., 2021; Mangina *et al*., 2020; Feng *et al*., 2018; Kappelman & Sinha, 2021; Bilgic *et al*., 2021; Zhou *et al*., 2020). Same status is recorded for SVM technique. This method is mostly applied as a single classification approach in recent literature, though it has been widely combined with neural networks (Safara, 2020; Kharfan *et al*., 2021; Kuo *et al.*, 2021), regression (Ismail *et al*., 2021; Taghikhah *et al*., 2021), clustering (Rousopoulou *et al*., 2020; Vijayaragavan *et al*., 2020) and other techniques to improve predictive and prescriptive analyses.

The evolution from traditional models to hybrid and mixed DA models represents a leap in operational efficiency and decision-making accuracy. Hybrid models, integrating both qualitative and quantitative data, offer a more holistic approach to SCM problems. For instance, a study by Min *et al*. (2021) demonstrated that hybrid models incorporating machine learning algorithms with traditional forecasting methods significantly improved demand prediction accuracy compared to conventional models alone. Furthermore, mixed DA models, which blend various analytical techniques, have shown considerable promise. Research by Kumar and Singh (2022) revealed that mixed models, combining predictive analytics with real-time data processing, enhanced supply chain responsiveness and reduced costs by up to 20%. These advancements underscore the practical implications for SCM professionals: by embracing these innovative approaches, they can achieve a more robust, agile, and data-driven supply chain, leading to improved operational performance and competitive advantage. Such a transition, however, requires an upskilling of the workforce and investment in new technologies, as emphasized by Lee and Kang (2023), to fully exploit the potential of these advanced analytical models in SCM.

5. FUTURE RESEARCH DIRECTIONS

Nguyen *et al.* (2018) put forth a range of potential research paths for future studies. Several of these have since been explored in recent publications, including the extension of research into the application of data analytics (DA) in areas like reverse logistics, quality control, and demand forecasting within the supply chain. Nonetheless, certain research gaps identified by Nguyen *et al.* (2018) remain unaddressed. Moreover, the current paper's findings introduce several fresh and inventive opportunities for future research that bridges the realms of data analytics and supply chain management (SCM). Consequently, this paper outlines six illustrative directions for future research in this domain.

5.1 Further Research on DA Applications in Specific SC Functions

Although the application of DA has significantly increased across most SC functions, there are still considerably limited areas like in-transit inventory management, order picking, demand shaping and procurement. Similar results of previous research also state a high benefit of DA in these areas and confirm the need for additional studies (I. Lee & Mangalaraj, 2022; Raut *et al*., 2021). Future research could focus on these still little researched areas and contribute new knowledge and application results to these SC functions. Especially in the context of sourcing cost improvement, sourcing risk management, supplier selection, order picking and storage assignment the amount application studies is low. Further areas that have already been dealt with but could also benefit from additional application-oriented studies include product R&D and demand shaping.

5.2 Focusing on Cross-functional and Internally Aligned DA in SCM

Investigating cross functional issues in SCM and adaption of DA in integrated SC functions is another research gap identified by (Nguyen *et al*., 2018). Unfortunately, also the current literature review for 2020 and 2021 did only reveal few articles considering cross functional activities in SC. It still seems to be the dominant practice to conduct DA projects on the level of single SC functions. This results was also confirmed in recent literature, which also identified missing knowledge and data sharing along the company-internal SC as the source for silo-based DA application in SCM (Brandtner, Udokwu *et al*., 2021a). Future research in this regard should especially focus on company-internal SC and their cross-linking within and outside the organization. Fostering internal transparency and enabling DA that is linked throughout the organization represents a promising research field. Especially against the background of organisational silos and difficulties in establishing transparency with indirect suppliers and customer (i.e., tier-2 and above), internally aligned DA initiatives could provide significant benefits without the need for gathering new data from company external sources. Their focus would hence rather be on data and knowledge identification and data exploitation.

5.3 Combining Different DA Models across DA Levels

In terms of analytics level of the analyzed studies, we have noticed a close share of predictive and prescriptive analytics in publications, while descriptive and diagnostic analytics are still neglected in many cases. This is in line with current research (I. Lee & Mangalaraj, 2022). More precisely, predictive analytics prevails in current literature, especially to forecast customer demand, production failures or transportation delay. Partial reasons for a reduction in descriptive and diagnostic analytics might be due to the fact, that they are often part of predictive and prescriptive analytics. Still, we deem it important to further analyze the potential of descriptive and diagnostic approaches in SCM to extract important factors and features from the data. Related to the stages of a DA project, it might especially be useful for the earlier tasks of business and data understanding (Brandtner, Udokwu *et al.*, 2021b). Future research might especially focus on the combination of different DA models across the levels of descriptive, predictive, and prescriptive analytics, as e.g. done in (Amellal *et al.* 2023), where CNN and LSTM models were combined. This need has also already been stated by Nguyen *et al.* (2018) as a foreseen perspective.

5.4 Enabling Real-time DA in SCM

Cloud systems and intelligent information systems have provided the opportunity of accessing huge amounts of data. Many researchers have investigated methods of how to deal with big data and extract knowledge and information so far (Ghahramani *et al.*, 2020), (Feldkamp *et al.*, 2020). However, selecting, processing, monitoring, and applying DA models on real-time data is still a challenging issue in SCM. It can be beneficial for future studies to provide real-time analysis with applying streaming data in their DA models in smart SC, especially for routing and allocation as well as for sustainability problems (Oleghe, 2020). This research gap is also identified in current literature, which also emphasizes the need for real-time, cloud-based data sharing and storage as well as respective DA models to enable real-time DA in SCM (Udokwu *et al*., 2022).

5.5 Applying DA in SC Uncertainty Reduction

The appearance of the COVID-19 pandemic as one of the biggest disruptive events in the last two years (Brandtner, Darbanian *et al*., 2021), has an overlap with the timespan of our literature review. The pandemic has encouraged many researchers to exploit the advantages of DA models on SC resilience problems. Therefore, improving the reliability of DA models with stochastic approaches to overcome SC uncertainties is another potential topic for future studies. Our results in this context are in line with other current literature, which also states that the application of DA in SC risk management and SC uncertainty reduction is still in its infancy (Brandtner, 2023). Future research in SCM could also try to build on existing application knowledge in the context of reducing strategic uncertainty in innovation management and strategic foresight (Brandtner & Mates, 2021; Capurro *et al.*, 2021; Pietronudo *et al.*, 2022). Promising research has already investigated the application of stochastic models to SC uncertainty reduction and SC resilience, still, the need for further research is also stated in current literature (Sawik, 2022).

5.6 Consideration of Publicly Available Data

Considering additional internal factors such as pricing and promotional activities has proven to enhance prediction accuracy, a practice that has gained widespread acceptance in recent academic literature. Nevertheless, there remains a promising avenue for future research, as highlighted by Song *et al.* (2021), which involves identifying influential elements within publicly accessible data and incorporating them into predictive models.

Prior research has already ventured into this territory, with studies focusing on the collection and analysis of publicly available data, such as web reviews, to assess the impact of factors like COVID-19 on retail supply chains (Brandtner *et al*., 2021; Udokwu *et al*., 2020). Consequently, an exciting and expansive prospect for future research at the intersection of data analytics (DA) and supply chain management (SCM) lies in the methodical and structured integration of publicly accessible data into the domain of supply chain analytics. This observation aligns with the current literature on artificial intelligence in SCM, which underscores the significance of publicly available data in making informed supply chain decisions (Bechtsis *et al*., 2022).

A potential application lies in connection with the forthcoming supply chain due diligence directive. Classification and clustering models could be employed to identify patterns of unethical practices, for instance, at the level of source countries, suppliers, or categories of raw materials, and assess the acceptability of future network partners. Data for this purpose could be collected, particularly through web and social media scraping or text mining, or derived from investment baskets, and linked with internal data. This would enable companies to act with confidence and prepare for compliance with the supply chain law.

6. CONCLUSION AND LIMITATIONS

Utilizing the qualitative content analysis approach introduced by Mayring (2022) and building upon the groundwork established in the previous study by Nguyen *et al.* (2018), this paper conducted a comprehensive examination of 354 papers through a systematic literature review. By comparing our findings with prior literature, we gained valuable insights into recent applications of data analytics (DA) in supply chain management (SCM), facilitating an in-depth discussion of research trends and developments spanning the past decade. Our analysis, spanning six SCM functions and 17 sub-activities, revealed a significant upsurge in the importance of DA in SCM. Across all three types of analytics—descriptive, predictive, and prescriptive—there was a noticeable increase in application-oriented articles, particularly within the realm of predictive analytics.

It's essential to acknowledge the potential limitations of this study. One such limitation is the subjectivity inherent in authors' categorization within the applied classification framework. While the QCA approach by Mayring ensures a degree of objectivity, subjectivity bias remains a possible constraint. Another limitation lies in the selected time frame, which covers the years 2020 and 2021. Given that the reference study encompassed the period between 2011 and 2016, no data was available for the years 2017-2019, necessitating interpolation. Nevertheless, the ample number of articles analyzed in this study (354) compared to the smaller dataset of Nguyen *et al.* (88) affords a broad scope for deriving meaningful insights.

The practical contributions of this paper are manifested in the form of an overview of SCM tasks, sub-activities, and applicable DA models and techniques. For practitioners seeking to implement DA within their organizations, this paper offers valuable starting points and references to expedite the specification of use cases and model requirements. In terms of theoretical contributions, our paper furnishes a comprehensive overview of recent application studies at the intersection of DA and SCM. Furthermore, it provides a springboard for future research, offering detailed exploration of six exemplary research directions. These directions span various aspects, from the necessity for research within specific SCM functions, such as procurement, to the facilitation of real-time DA and the integration of DA to mitigate uncertainty in SCM.

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DATA AVAILABILITY STATEMENT

The authors confirm that the data supporting the findings of this study are available within the article and its supplementary materials.

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