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Review

A Systematic Investigation of the Integration of Machine Learning into Supply Chain Risk Management

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Abstract: The main objective of the paper is to analyze and synthesize existing scientific literature related to supply chain areas where machine learning (ML) has already been implemented within the supply chain risk management (SCRM) field, both in theory and in practice. Furthermore, we analyzed which risks were addressed in the use cases as well as how ML might shape SCRM. For this purpose, we conducted a systematic literature review. The results showed that the applied examples relate primarily to the early identification of production, transport, and supply risks in order to counteract potential supply chain problems quickly. Through the analyzed case studies, we were able to identify the added value that ML integration can bring to the SCRM (e.g., the integration of new data sources such as social media or weather data). From the systematic literature analysis results, we developed four propositions, which can be used as motivation for further research.

Keywords: supply chain risk management; machine learning; cases; propositions; supply chain

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1. Introduction

Different results in recent years have shown how vulnerable supply chains can be [1,2]. Due to the domino effect, individual actors in the supply chain are often not the only ones affected by an interruption but rather the entire network [3–6]. The tsunami in Japan in 2004, hurricane Katrina in the US in 2005, the volcanic eruption in Iceland in 2010, and the current COVID-19 pandemic are good examples demonstrating how numerous networks and even entire industries can be impacted by the negative effects of certain events (e.g., [7,8]).

In order to prevent disturbances, companies should apply Supply Chain Risk Management (SCRM) [4,5,9,10]. Supply Chain Risk Management is 'a part of Supply Chain Management which contains all strategies and measures, all knowledge, all institutions, all processes, and all technologies, which can be used on the technical, personal, and organizational level to reduce supply chain risk' [11] (p. 157). The aim is to increase the transparency and robustness of value-added processes in order to counteract any supply chain interruptions or even avoid them altogether [12–14]. Here, a distinction must be made between reactive and proactive SCRM. Reactive SCRM refers to all activities that are carried out after the occurrence of a supply chain risk in order to keep the extent of damage as low as possible [15]. In contrast, proactive SCRM includes all activities carried out prior to the risk occurring in order to proactively protect the company from supply chain risks [10].

Many companies do not focus on supply chain risks. In addition to a lack of time and personnel resources, the reasons often given are a lack of standards with regards to system compatibility and data consistency, as well as technical difficulties in integrating risk management software into existing information and communication systems [16]. One of the greatest challenges is to receive information about deviations from the planned process at an early stage in order to ensure timeliness of logistics processes within the supply chain [17].

The early identification of different supply chain risks is crucial for the timely introduction of countermeasures in order to avoid supply chain disruptions [4,11]. SCRM must predict potential causes of these process disruptions and analyze interruptions that have occurred in the past in order to minimize financial losses and process failures throughout the supply chain. Here, machine learning (ML) can help to detect risks early on [18–23].

Machine Learning can broadly be defined as an algorithm that generates outputs based on available data without first programming the respective learning outcome [24]. Instead, the ML algorithm 'learns' and iteratively assimilates its perception to the underlying real-world phenomena represented in the input data.

The current hype regarding ML is based on an amalgamation of several trends, which reinforce each other, making ML a powerful tool in an array of fields and practical use-cases. First, the availability of vast amounts of digital data is a necessary condition for the application of most ML algorithms—particularly for Deep Learning approaches [25], which utilize multi-layered Artificial Neural Networks to enable the most sophisticated, modern use-cases (e.g., the state-of-the-art Natural Language Processing system GPT-3) [26].

In general, the increased availability of data in previous years has been able to empower the application of ML. Supply chain networks generate over 1.6 billion new data points each month, supplying a number of data streams that can be used as inputs in an ML system [27,28]. Second, computational power has proven to be a major driver of progress in AI. Major breakthroughs were enabled through significant improvements in computational performance [29]. Third, algorithmic advances play a relevant role in enabling efficient and scalable applications. Though many of the applied algorithmic foundations (such as backpropagation) were conceived long ago, modern innovations (such as batch normalization [30] and dropout [31]) were crucial in facilitating recent developments [32].

Supplementary factors, such as the increased use of Cloud Computing (and thus easier access to powerful computing), software libraries which make it easier to execute ML projects despite the limited number of available skilled ML engineers, and the Internet of Things which provides more data-generating sensors [33], support the trends outlined above [34].

The increasing digital transformation in companies and supply chains and the associated greater availability of evaluable real-time data open up new potential for a proactive SCRM [21,35,36]. ML approaches can leverage a vast amount of supply chain data and generate solutions that represent improvements over traditional methods [37]. Although the integration of ML into the SCRM can be useful, this topic has rarely been considered scientifically.

For this reason, in this paper, special attention is paid to ML which is intended to improve SCRM. The aim of the paper is, therefore, to investigate how ML can be incorporated into SCRM. By showing which areas ML have already been taken into account for the implementation in SCRM, we would like to offer decision-makers an easier start for implementation. We will answer the following research questions:

- In which supply chain areas has ML already been considered for implementation in SCRM—both in literature and practice?
- Which are primary risks considered in the use-cases?
- How might ML shape and improve SCRM?

Furthermore, we will develop a set of four propositions based on the literature analysis which can be used as an impetus for further research.

The paper is organized as follows: In Section 2, we explain the methodological procedure using a systematic literature analysis, which was subsequently extended by a multi-vocal literature review. We then evaluate the results and describe the identified use cases. In Section 3, we discuss the findings from our analysis regarding ML added value in SCRM. We also derive propositions from the results of the literature analysis, which could be used in future research. The article closes in Section 4 with summary and limitations.

2. Methodology and Findings

2.1. Systematic Literature Review

An overview of current contributions where ML is applied for SCRM should be created, using a systematic literature review (SLR). In order to use the results of the literature review to answer the research questions, the evaluation of the contributions considered the following:

- What examples of ML application in SCRM have already been described in literature?
- Which risks could be influenced by the integration of ML into SCRM?

The literature analysis was carried out in two parts, with the first part being based on Tranfield et al. [38]. In the first part of the analysis, an SLR was conducted in the scientific database, SCOPUS, for publications (up until December 2020) using a search for titles and abstracts which include 'supply chain' AND 'crisis' OR risk* OR vulnerability* OR uncertainty* OR disruption* OR disaster* OR disturbance* OR catastrophe OR peril OR hazard OR resilience OR robustness OR safety OR flexibility OR agility AND 'machine learning' OR 'artificial intelligence' OR 'predictive analytics'. The search string was previously matched with search terms used in relevant SLRs in SCRM and ML [9,12–14,39–42].

The combination resulted in 533 hits. In the subsequent title screening, the authors found that only in a few cases did the titles indicate that the subject areas SCRM and ML were treated, so that a selection based on a title screening was not considered to be appropriate. Instead, the authors linked title screening directly to abstract screening and thus considered 109 articles to be relevant. Most of the rejected contributions were publications that were not relevant to the research project. Some of the publications contained the keywords, but the content did not refer to supply chains. Other journal articles did not meet the scientific standards and were, therefore, not included in the analysis. A further condition for contributions to be considered was that they were written in English.

The last step in the SLR included a complete review and analysis of the remaining articles. Publications that deal with general mathematical optimization models or whose topic is too far away from the focus of this paper were not included in the analysis. The final selection of relevant papers included 23 publications, which the authors identified as relevant for the research project.

The results of the SLR showed a research gap; only a few examples of ML applied in SCRM have thus far been considered in the scientific literature. This is mainly due to the fact that although ML has been used in supply chain management for some time, its integration into SCRM is still a very young research field.

In addition, the few examples described in the scientific literature contain a low level of detail, such that it was barely possible to extract meaningful answers to the above research questions. For this reason, the authors extended the scope of the literature analysis.

After these initial assessments, the literature analysis focused on the scientific consideration of the field, ML in SCRM, and the second section on the analysis of applied examples in existing business practices. For this purpose, the additional information on the previously identified examples was sought in practical journals and the internet to increase the level of detail. To structure this approach, a multi-vocal literature review (MLR) was employed. The method initially appears in an educational context [43]. The authors at that time focused on case study research, but, in 1991, Patton had already emphasized that this constraint limitation should be expanded [44]. Accordingly, the method has recently been adopted to a diverse field of primarily technologically focused research areas, among them blockchain [45], cloud computing [46], cloud data migration [47], and many studies in software development (e.g., [48], and especially [49] as a secondary study).

We thus used the method to generate a more holistic research scope from the beginning: "Multivocal literatures [...] are comprised of all accessible writings on a common, often contemporary topic" [43]. This additional search was executed via the search engine Google, based on the search query as described above. The most relevant use cases will be discussed in Section 2.3.

Our primary goal was to "clos[e] the gap between academic research and professional practice." [50] (p. 296) To avoid primary drawbacks such as the mixing of higher quality, rigorous 'white' literature, and 'grey' literature (GL) we clearly differentiated among these sources in Sections 2.2 and 2.3. We generally followed the guidelines set out by Garousi et al. [51]. Of particular importance is the quality assessment. In our case we decided to execute follow-up interviews on some examples from the GL to ensure that our quality criteria such as objectivity (despite vested interests of company perspectives) were met and to enhance the information base of the presented GL studies [52]. These expert interviews are included in the information laid out in Section 2.3.

2.2. Current Status of ML Application in SCRM in Scientific Literature

The results of the systematic literature analysis have shown that the link between ML and SCRM has been increasingly investigated over the last ten years. The initial focus has been on individual risks associated with computational intelligence, swarm intelligence, and simulations [53,54]. Only by beginning research on neural networks, such as the developed AlexNet architecture [55], will the number of scientific contributions increase significantly (see Figure 1). In the last two years in particular, there has been an increase in the number of published contributions as ML has become more widely integrated in companies [56–59]. Figure 1 shows the number of published articles using the search string described in Section 2.1.

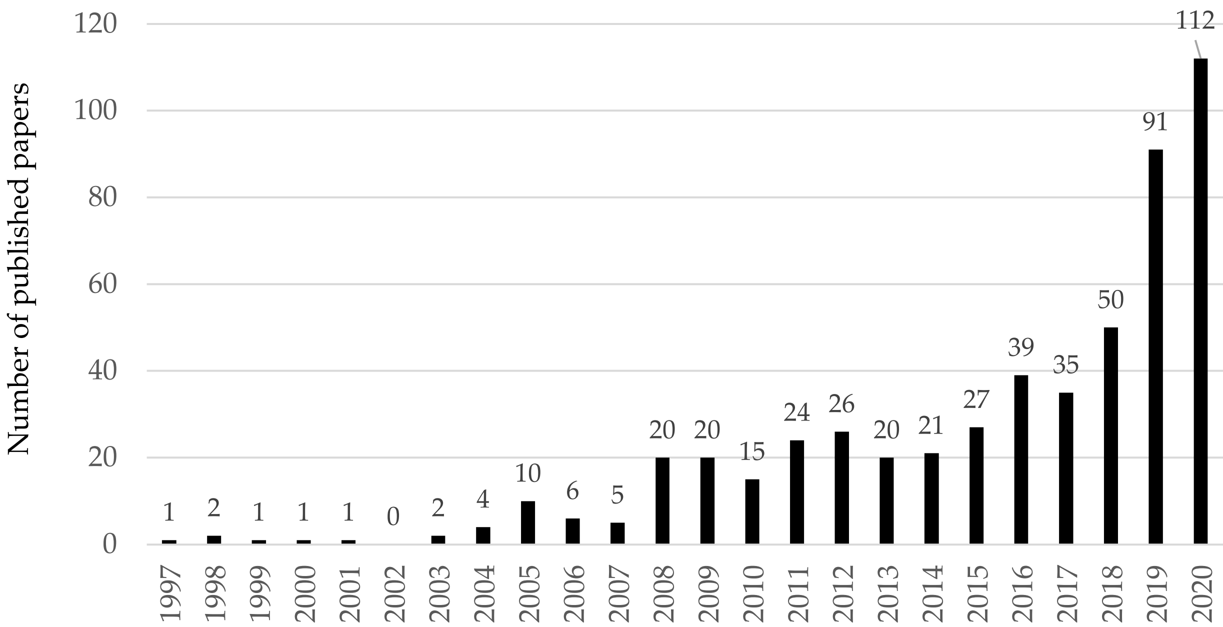

Figure 1. Historical series of published papers on ML in SCRM.

A total of 533 articles were found, consisting of 49% conference proceedings, 44% journal articles, 3% books or chapters within books, and 4% others (e.g., editorials). A more detailed examination of the journal articles has shown that no journal to date has dealt with the topic in a comprehensive manner (see Figure 2). Instead, the relevant articles are scattered across different journals, ranked primarily in B.

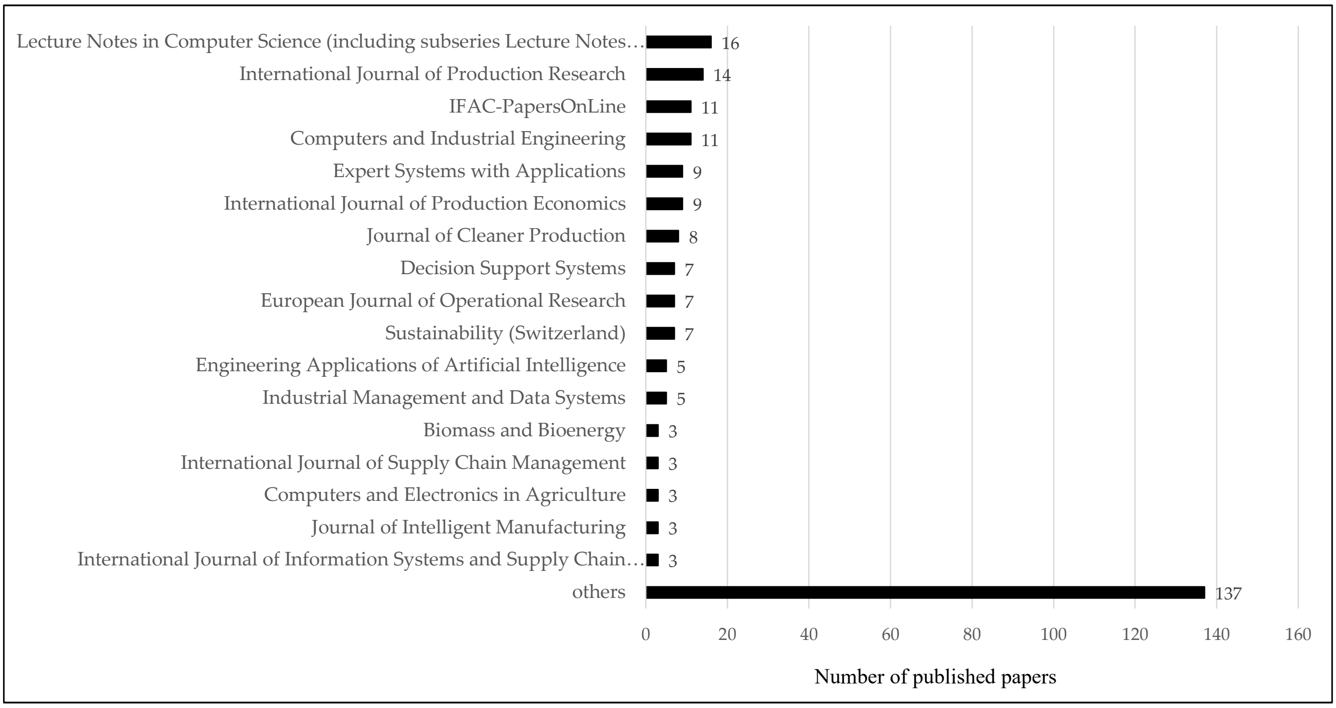

Figure 2. Journals that have published papers concerning ML in SCRM.

As described in Section 2.1, after careful selection, 23 articles were considered relevant. The contributions were analyzed in detail and evaluated with respect to their focus and the risks considered. The results showed that the authors in the articles rarely consciously make a connection to SCRM. For this reason, the link concerning ML and SCRM is often only made indirectly. For example, Alfian et al. [60] use an ML based forecasting model to predict future temperature for perishable food supply chain to minimize food quality and safety risks during transport. To do so, Alfian et al. [56] use ML to detect the direction of passive RFID tags so that products entering or leaving a gate can be correctly identified. The aim is to improve the efficiency of RFID-based product traceability, thereby reducing transport risks. Baryannis et al. [18] are currently developing a framework that uses data-driven artificial intelligence (AI) techniques to predict delivery delays in a multi-level manufacturing supply chain, using the example of a multi-stage supply chain in aerospace. Benjaoran and Dawood [61], on the other hand, present an integrated, comprehensive planning system (Artificial Intelligence Planner), which uses AI techniques to improve data analysis and decision support for production planning, and thus reduce production risks. The case study was conducted in a concrete construction company in the UK.

Blackburn et al. [62] present a time series model (exponential smoothing with covariates) that takes into account both historical data and environmental business information to develop robust demand forecasts to reduce production risks. The model was tested at the chemical company BASF. Bouzembrak and Marvin [63] use climatic, agricultural, and economic data as well as an ML algorithm to construct a Bayesian Network which can be used to optimize specific hazard categories for food safety, thereby avoiding food quality and transport risks. The authors use the Rapid Alert System for Food and Feed for the data. Brintrup et al. [57] use historical data available to an Original Equipment Manufacturer for ML application and prediction, thereby avoiding supply disruptions. Cavalcante et al. [58] combine simulations and ML to explore applications for data-driven decision support in the selection of robust suppliers. The use of ML algorithms supports supplier selection and thus leads to a reduction of supplier risks.

Constante-Nicolalde et al. [64] use ML techniques to predict fraud in an intelligent supply chain. They enable an assessment and classification of whether a transaction can be classified as normal or fraudulent to reduce product quality risks. Fu and Chien [65] present a data-driven analysis framework that integrates ML technologies and temporal aggregation mechanisms to predict the requirements of intermittent electronic components and, thereby, to reduce supply risks. The empirical study was conducted in a distribution company for electronic components. Hassan [19] has designed a conceptual model in which ML is used to identify delivery risks using text documents. Lau et al. [66] present a knowledge-based infrastructure system to collect information on procurement and on the selection of supplier network partners with the help of both ML and neural networks to reduce information risks. The prototype developed by the authors was tested in the Chinese company GPP Limited, which manufactures plastic toys and exports its products to customers in the USA, Europe, and Japan. Layouni et. al. [20] provide an overview of ML techniques and describe how they can be used to reduce transportation risks by assessing the safety of oil and gas pipelines.

Pereira et al. [67] present a conceptual method for a predictive and adaptive omni-channel supply chain management for the retail industry. ML and simulation-based optimization are applied to minimize uncertainty and incompatibility between supply and demand. Rodriguez-Aguilar et al. [22] use ML to model disruptive events and their impact on the supply chain to identify potential risks in a timely manner. Wichmann et al. [59] discuss whether and to what extent supply chain maps can be automatically generated by evaluating unstructured texts in natural language, such as news reports or blog posts, in order to reduce supplier risks. Yong et al. [23] present a vaccine blockchain system as well as ML technologies, which are based on blockchain, to enable vaccine traceability and prevent vaccine record fraud, thereby reducing supply risks.

However, the contributions of Baryannis [42], Sharma et al. [41], and Hamdi et al. [68] which provide a systematic literature analysis do not provide practical examples. Nychas et al. [69] describe the potential of internet technologies for dealing with perishable products, while the Smith publication [70] discusses the potential added value that AI can bring to agriculture in the next decade; both also fail to provide concrete examples of possible applications. Finally, Paul et al. [71] discuss the application of AI adoptions in the field of SCRM. Based on a qualitative study in India they propose a research model on the implementation of AI in SCRM at an organizational level. These latter publications are therefore not listed in Table 1.

Table 1. List of publications with an ML SCRM application example.

Authors	Study Type	Scope of Application	Considered Risks	SCRM Focus
Alfian et al. [56]	Conceptual work	transport	transport risks	indirect
Alfian et al. [60]	Conceptual work	transport	transport risks	indirect
Baryannis, Dani, Antoniou [18]	Conceptual work	production	supplier risks	direct
Benjaoran and Dawood [61]	Case Study	production	production risks	indirect
Blackburn et al. [62]	Conceptual work & use case	production	production risks	indirect
Bouzembrak and Marvin [63]	Conceptual work	transport	food quality/transport risks	indirect
Brintrup et al. [57]	Case study	transport	supplier risks	direct
Cavalcante et al. [58]	Conceptual work	transport	supplier risks	direct
Constante-Nicolalde et al. [64]	Conceptual work	supply chain	quality risks	indirect
Fu and Chien [65]	Conceptual work	production	supply risks	indirect
Hassan [19]	Conceptual work	supply chain	supply risks	direct
Lau et al. [66]	Conceptual work	procurement	information risks	indirect
Layouni et al. [20]	Survey	production	transport risks	indirect
Pereira et al. [67]	Conceptual work	supply chain	sales risks	indirect
Rodriguez-Aguilar et al. [22]	Conceptual work	supply chain	supply risks	direct
Wichmann et al. [59]	Conceptual work	supply chain	supplier risks	direct
Yong et al. [23]	Conceptual work	supply chain	supply risks	direct

The results of the systematic literature analysis clearly show that only a few examples of ML in SCRM have been described in any meaningful detail within the scientific literature to date [18,57,61,62,65]. The existing few examples focus on supply chain areas of production [18,20,61,62,65], transport [56–58,63], and the entire supply chain [19,22,23,59,64,67]. This is not surprising for production divisions, where automation and built-in sensor technology for data acquisition has already been implemented for years and is, therefore, more mature than other areas of the supply chain. Also, the technological development of retrofittable sensors, which can be attached to transport containers enables the collection of extensive data from the entire supply chain, so that the identified practical examples reflect this technological trend [56,72]. The examples described provide a rather low level of detail and, with few exceptions, do not allow any conclusions to be drawn about the company or the characteristics associated with it (e.g., [57,61]).

Furthermore, it can be seen from the analyzed contributions that ML is used in SCRM primarily to improve risk identification. Different data is used, which can be of either an internal company origin—such as order date, supply time delta, contracted supply time, supplier ID, etc.—or an external origin, such as GPS data, weather data, or entries in social media. Here, too, the analysis shows that the contributions rarely mention which data sources were actually used in the analysis [18,56,57,62,63].

In the contributions, the application of ML is primarily aimed at identifying production, transport, and supply and suppliers risks in order to be able to quickly counteract potential supply chain problems (see Table 1). In addition, ML is used in these examples to quickly identify the risks associated with suppliers [18,58,59]. Sales and quality risks, on the other hand, are hardly ever examined in any of these scientific contributions [63].

2.3. Analysis of Identified Practical Use Cases

As described in Section 2.1, examples of real-world ML supply chains were researched in a multi-vocal literature review. For the analysis, only practical examples with usable information were considered. Figure 3 shows the identified practical use cases. In the following, selected practical examples are described in more detail.

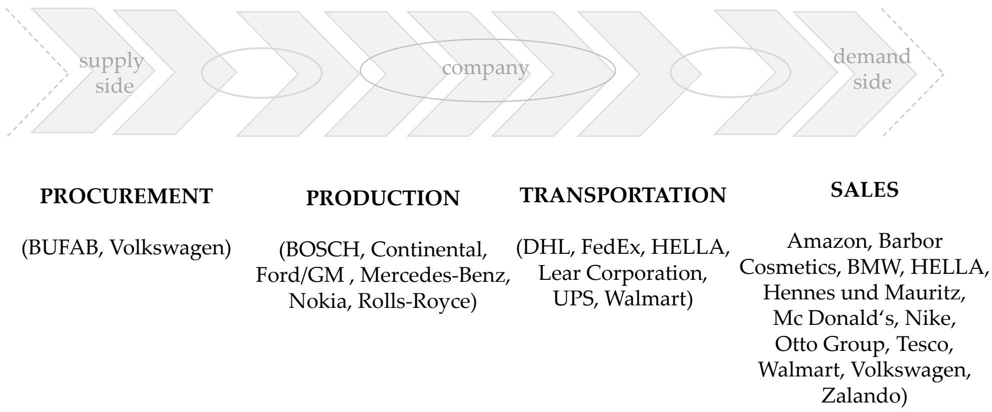

Figure 3. Practical examples of ML in SCRM.

The trading company BUFAB Sweden AB offers its customers a full-service solution for sourcing and logistics for C-Parts (https://www.bufab.com, accessed on 21 May 2021). If the company receives an order from a customer, the purchasing staff then seeks to obtain offers from potential suppliers. The search and contacting of these suppliers as well as the waiting periods during communication takes approx. 40% of the available work time; whereby, a hit rate of only 7–10% is reached [73]. By using relevant data, such as product price, delivery compliance/performance, product quality/reliability, lead-time, or the stable delivery of goods, BUFAB excludes non-qualified suppliers from bid solicitation and thus supply risks can be proactively reduced or even eliminated completely [58,68,73]. Consequently, requests for quotes are only sent to suppliers who have also filled out purchase requisitions. Recommendations for improved supplier efficiency and performance can be made, considering not only price, product quality, product quantity, and service, but also risk factors regarding uncertainty, vulnerability, and possible supply disruptions [68]. According to Hassan [19], an extension of this approach would be to use ML for risk identification when evaluating text documents, such as news articles, in order to make as realistic assessments of supplier situations as possible.

The car manufacturer Volkswagen has also developed a so-called bidder list generator, which uses ML to precisely determine possible suppliers. In this way, delays and risks in purchasing can be reduced (www.volkswagen.com, accessed on 21 May 2021; interview with expert from procurement). According to Rao [74] and Qu et al. [75] ML could also be used in procurement in the context of contract management as well as in the determination of optimal prices.

The automotive supplier HELLA, one of the largest trade organizations for vehicle parts and accessories in Europe, develops and manufactures lighting technology and electronic products for the automotive industry (www.hella.com, accessed on 21 May 2021). HELLA transfers material planning to internal and external suppliers within 24 months. Until now, delivery performance has been evaluated retroactively according to predefined criteria in supplier logistics. In order to be able to predict the reliability of deliveries, HELLA has tested the use of ML techniques. Here, call-off history, incoming goods history, advanced shipping notification history, purchasing and supplier data, as well as supplier and material master data were used in ML to forecast the reliability of delivery quantities for a single supplier-material-plant relationship for a defined period of 30 days. The results have shown that the reliability of critical supply quantities can be correctly predicted with an accuracy between 75% and 80%. Therefore, the use of ML in SCRM can reduce supply chain interruptions [76] (interview with expert from SCRM).

In addition to the interface consideration to suppliers, practical examples for the use of ML could be found, which aim at a reduction of transportation risks. For example, the courier—express and parcel (CEP) service providers—such as Fedex, DHL, or UPS, use ML techniques to optimize transport processes. They improve the transparency of their supply chain with the ML-based systems, composed of IoT and scanning devices used to generate a huge data pool. Together with up-to-date information on weather forecasts, traffic scenarios, and other important factors, which can have a direct or indirect influence on transport, the systems provide real-time insight into the supply chain. This allows delivery delays to be predicted and modified routes to be developed if necessary [77]. The ML-based 'Supply Watch' system, used by DHL, also monitors more than 140 different risk categories, including financial, environmental, and social factors—e.g., risks due to crime, labour violations, quality defects—and dangers within the supply chain such as general bottlenecks, capacity bottlenecks, and delays [78]. If a disruption is predicted, proactive measures can be taken, and customers can be informed about changes earlier on.

Walmart Inc., a US retail group, uses ML to process orders from approximately 2000 stores (www.walmart.com, accessed on 21 May 2021). Delivery is optimized considering order quantities, staffing levels, available delivery vehicle types, and the estimated distance between stores and homes [79,80].

In addition, ML is used especially in the sales area to better predict customer behavior. McDonald's, which suggests further additional sales to the customer during the purchase transaction, processes information using ML and considers weather data, times of day, local traffic, events in the vicinity, and historical sales data [81].

By addressing supply and demand imbalances and triggering automated responses using ML applications, companies cannot only improve the customer experience, but also limit sales risks. They can also reduce costs through better forecasting of freight and warehouse processes and improve collaboration with logistics service providers [82].

In addition, examples of ML applications in the production area could also be found. Robert Bosch GmbH, a manufacturer of industrial technology and consumer goods, uses ML to test components on the test bench and to recognize error patterns based on collected data, thus distinguishing relevant from non-relevant error messages. As a result, risks regarding product quality and delays in the process flow can be reduced [83].

Figure 4 summarizes the risks that are addressed in the practical examples when integrating ML into the SCRM. While the examples from the production area mainly refer to internal risks, the purchasing, transport, and sales areas show a focus on supply chain-wide risks.

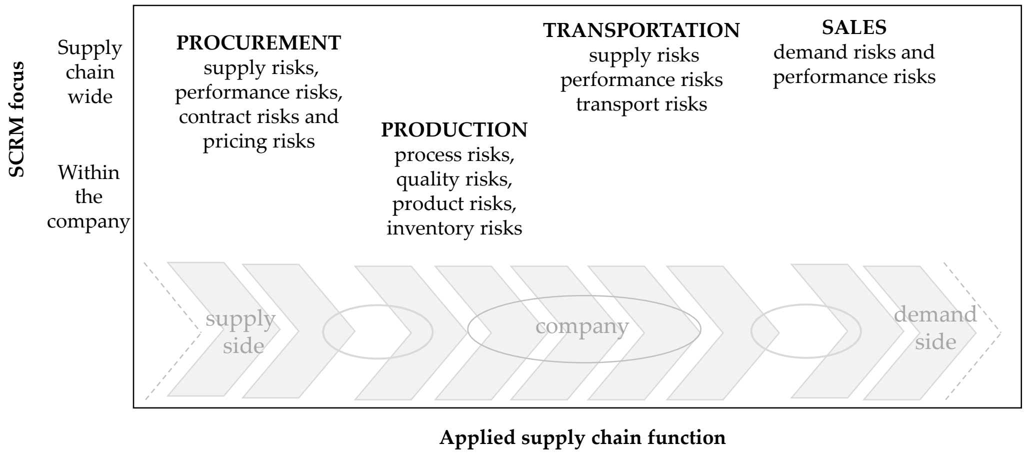

Figure 4. Focused risks in the ML in SCRM practical application examples.

3. Discussion

As described previously, ML is already generating value for SCRM in practical use-cases. The results of the literature analysis demonstrate that ML in SCRM enables different approaches for using and integrating data. ML is able to consider multiple, complex data sets, an array of strategic choices, and various scenarios [84]. Building complex models was also possible previously, but increasingly data volumes are becoming too large to be processed with traditional technology [85]. Additionally, ML approaches are able to process structured data, unstructured data, and a combination of both as shown in Wichmann et al. ([59], see also [86]). This is particularly valuable as the quantity and frequency of unstructured digital data is experiencing tremendous growth, and as such, only extracting data from structured sources would, therefore, severely limit SCRM's potential. For instance, data sources, such as social media, are promising origins for analyses [87]. To develop such cases, the availability of data is crucial. This is also becoming easier, as digitized business processes and the application of data-generating sensors has been normalized across industries [72]. We should not, however, omit the challenges inherent in collecting this data—ensuring adequate data quality is a necessary precondition. Establishing a governance structure and incorporating data quality measures are thus critical success factors for big data analytics in general and ML in SCRM in particular [88].

The continuous evaluation of unstructured data cannot be accomplished using IT tools alone; it also requires the support of experts (i.e., data scientists) who perform the technical data analyses and provide decision support. This includes both the manual cleansing of raw data in order to improve data quality as well as the programming of algorithms to automatically utilize real-time data. Therefore, companies need to hire qualified people to maintain AI-Risk-Management Systems [85]. As two areas of responsibility, Data Science and SCRM are merged, and their competencies and responsibilities must be redefined and clearly assigned in order to avoid errors in data preparation, provision, and evaluation.

In addition, one of the risk manager's core tasks in the future will be to consider the results of data analyses as a forecasting aid in management decision—as shown in the BUFAB und Volkswagen examples. The focus of the tasks will consequently progress towards stronger data-based decision-making, i.e., drawing the right conclusions from the results of ML integration. Consequently, the requirements on the qualifications of the supply chain risk manager do vary, as this individual should also have an understanding of mathematical methods of analysis [89]. Drawing from the above discussion, we propose:

Proposition 1. *The integration of ML into SCRM leads to changes in the qualification requirements of supply chain risk managers.*

It has been demonstrated that humans have more trust in their own capabilities than in the capabilities of AI [90], and, as such, humans tend to make decisions without the help of AI [90]. Consequently, stronger control mechanisms should be built into ML-based decisions. At the same time, the decision-making process should be systematically and analytically prepared, as shown in the BUFAB example, in order to make the derivations comprehensible and, thus, promote acceptance among employees.

In addition, the automated research and evaluation of real-time information leads to a reduction in the manual activities of the supply chain risk manager. This leaves them more time for analytical and strategic tasks (i.e., their focus shifts from an operations-centered view towards medium to long-term strategies with an SCRM orientation, as shown in the HELLA example) [76].

Furthermore, utilizing ML approaches in SCRM catalyzes a trend towards a more proactive mentality. The potential to include real-time data makes quicker reactions possible [6] and bridges the path towards prescriptive decisions while considering risks in advance [5]. This improvement in flexibility and response time [6] can lead to reduced time demands on data analysis and initiate necessary actions, culminating in the identification of fraud and hazards in real time [84]. The collection of real-time data within the enterprise, and especially within the supply chain, as shown in the FedEx example, means that companies need to pay more attention to risk avoidance strategies as their response time to risk will increase. The perspective of risk assessment as well as the associated risk avoidance measures shift from a reactive SCRM approach to a more proactive approach due to the inclusion of ML. Consequently, the integration of ML also requires the introduction of new assessment standards which include the integration of proactive measures. These measures should consider: to what extent is it economically sensible to avoid risks? For example, when does the effort involved in avoidance exceed the follow-up costs caused by a risk that has occurred?

The traditional assessment criteria, "probability of occurrence" and "extent of damage", are not sufficient here as a basis for decision-making. Threshold values for deviations from the normal state should be defined, starting from when the intervention of an employee is required (though there are challenges in doing so, see e.g., [91,92]). Drawing from the above discussion, we propose:

Proposition 2. *The integration of ML into SCRM requires new evaluation standards.*

Additionally, the quality of SCRM decisions can be improved. Using traditional approaches, which involve multiple points of human-supply chain contact, intuition and feelings are often used as decision making tools, increasing the risk of planning fallacies or other biases entering the equation [93]. Relying more on algorithmic decision-making or incorporating data-driven requirements into the judgement process of the SCRM professional reduces this risk, resulting in higher reliability and precision [85]. This precision can be improved further by utilizing algorithms to sort potential risks based on their priority [87].

One should not, however, be blind to the fact that algorithmic bias is an issue and must be considered, particularly in the black-box nature of ML algorithms such as Artificial Neural Nets—despite recent advances in Explainable AI (XAI)-research [94]. Assuming objectivity in decision making because an algorithm was used, falls short of this aim, and as such implementing transparency measures to ensure algorithmic accountability is necessary [95]. Companies must expand their monitoring and data-mining techniques for SCRM in order to ensure high quality data and efficient control measures have been taken [96].

Having implemented these and other necessary prerequisites for data security and privacy concerns, the automatization of decisions and processes is the tantalizing promise of ML in SCRM [84]. The FedEx use case touched on above manages this by automatically rerouting packages due to changing external circumstances in real-time. Similarly, ML is able to identify customers with a high-risk profile, automatically engaging various checks and responses, reviewing only a subset of cases manually [97].

These benefits provide tangible value to companies, leading to a more efficient and effective use of resources along the supply chain [36]. However, the results of the literature analysis have clearly highlighted a research gap. Since few application examples are available, companies need more guidance on how to integrate ML into SCRM. What are the first steps they need to take? What approach should they follow? Should existing data be analyzed to determine which risks can be reduced, or should risks be the starting point, and data for problem solving purposes be generated afterwards? What level of maturity should the SCRM have reached before ML can be integrated? Science should provide appropriate recommendations for implementation and action.

In order to sensitize managers to the topic, more publications of use cases from both science and real-world applications are required. As a starting point for further research, existing examples of ML in supply chain management could be analyzed and evaluated against the background of SCRM in order to illustrate the cross-functional added value of ML applications. Another starting point for future research is an empirical review of the improvement of SCRM by ML, which is still pending. Drawing from the above discussion, we propose:

Proposition 3. *Companies need more guidance on how to integrate ML into SCRM.*

Several supply chain areas can benefit simultaneously from the results of the ML deployment. The use cases of the CEP companies in Section 2.3. show that the integration of ML not only reduces transport and delivery risks, but also intensifies the customer relationship through an improved information supply. By integrating ML into SCRM, the company can strengthen its position vis-à-vis the customer, since it knows its strengths and weaknesses better. Thus, the cooperation between the individual actors in the supply chain can be improved at the same time. The integration of ML into SCRM can also be an important lever in price negotiations with customers or insurance companies. It can also help to set oneself apart from competitors [4].

ML-based results can help communicating supply risks with organizational decision-makers. Informing decision-makers early on about supply chain risk levels has implications for manager cognition and how they adapt decision-making strategies based on risk knowledge [98]. According to Pournader et al. [99], this is an important component of behavioral SCRM. ML consequently supports decision-making and mitigates problems related to managers' cognition and potential biases. From these findings we derive the following proposition:

Proposition 4. *The integration of ML into SCRM can have a positive effect on other supply chain functions and business units.*

Finally, it should be noted that the integration of ML into the SCRM also requires a critical examination. For example, it must be considered that ML-based risk management systems require high initial investments [85]. In addition to the IT infrastructure, the storage of data (capacity) and the tracing of failure-causes are expensive [28]. There are also legal concerns about the massive collection or use of data for risk management [72]. Thus, new legal regulations for the use of AI/Big Data could follow in the future, which have to be considered in the process phases of risk management.

4. Conclusions

In this paper, we answered the research questions about which supply chain areas ML has already been considered for implementation to improve SCRM, about what the primary risks considered in the use-cases are, and how ML might shape SCRM. For this purpose, the existing scientific literature was analyzed and synthesized to investigate how ML can be incorporated into SCRM, and which risks can be addressed with it. We have followed a two-step approach consisting of a systematic literature review and a multi-vocal literature review to generate a more holistic view of our research field. We selected 533 contributions in this topic area with the help of the systematic literature review and analyzed a total of 23 publications in-depth. The results of the systematic literature review clearly showed that only a few examples of ML in SCRM have been described in any meaningful detail within the scientific literature to date and that the existing examples focus on supply chain areas of production, transport, and the entire supply chain.

The results also showed that the application examples are primarily related to the early identification of production, transport, and supply risks in order to be able to counteract potential supply chain problems quickly. At the same time, the evaluation has shown that, to-date, few examples of ML exist which contain a sufficient level of detail to allow for more in-depth analysis. The very manageable number of scientific contributions clearly reflects the research gap of integrated ML in the SCRM.

Nevertheless, through the case studies analyzed, we were able to identify the added value that the integration of ML in SCRM can provide such as increased flexibility and response time, the integration of new data sources (e.g., social media or weather data), or higher reliability and precision compared to conventional analysis technologies.

From the results of the systematic literature analysis, a set of four propositions have been developed to show how ML might shape and improve SCRM. Among them is the need to develop new assessment standards and to change the qualification requirements for supply chain risk managers associated with the use of ML; this can be used as impetus for further research. In order to better understand the positive impact of ML on SCRM, we advocate the further publication of detailed use cases. More use cases are needed to better demonstrate the benefits of using ML in SCRM to decision makers. Companies should therefore be encouraged to publish their approaches and share experiences with researchers. They should also enable researchers to conduct empirical studies in which the positive impact on different supply chain risks is verified. Only through an intensive exchange of knowledge for better solution finding can progress be made in this field, from which both practitioners and researchers can benefit.

We also note that reliance on good database search and retrieval is essential for a systematic literature review. The results of this research are limited by the search engines, whose volume of contributions change regularly. The use of alternate terminology as well as the lack of precision of the search term can be listed as further deficiency. Sometimes authors use different definitions to define the same things [100].

Another limitation is the limited number of available use cases. The number of case studies should be continuously updated and evaluated. Furthermore, not all use cases could be discussed with company representatives in order to obtain additional information. To deepen the analysis, further interviews should be conducted in the future.

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