Risk Indicators and Data Analytics in Supply Chain Risk Monitoring

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Abstract. This paper seeks to complement the supply chain risk monitoring literature by identifying analytics methods and the risk indicators being monitored for this purpose. This includes the underlying supply chain data used for short-term or even real-time monitoring of risks in supply chain risk management. A systematic literature review is carried out in order to identify risk types and underlying factors considered in the context of risk monitoring. Furthermore, the monitored risk indicators and the data analytics methods applied in their generation, monitoring or prediction, as well as the underlying risk data are examined. The identified works focus mainly on micro risks, where supply and transport risks are the most prevalent. A variety of risk indicators is found to be used including both, qualitative and quantitative, which are often used jointly. Identified data sources range from operational databases to IoT and sensor networks. Moreover, first approaches utilizing predictive analytics methods to anticipate risks are identified. The findings are used to derive promising research topics to further explore this largely underrepresented field within supply chain risk management and pave the way for data-driven risk monitoring.

1 Introduction

Compared to the supply chain risk management (SCRM) phases of risk identification, assessment and mitigation, risk monitoring has received only little attention in research (Fan and Stevenson 2018; Ho et al. 2015) and few address IT-support for risk monitoring (Fischer-Preßler et al. 2020). This is despite the fact that in practice, several examples of advanced monitoring systems exist and have existed for years (e.g. Intel, Cisco, DHLResilience, Ericsson, Blackhurst et al. 2008). Still, even among practitioners less than half utilize some sort of technology to record, monitor, measure and predict supply chain disruptions (BCI 2019). The incorporation of automatically collected data for monitoring and early warning-systems has the potential for a significant time advantage as opposed to relying solely on traditional risk assessment techniques. These usually depend on qualitative data collected in time-consuming processes involving many experts (Marhavilas et al. 2011). To capture the level of risks in supply chains, the choice of relevant risk indicators is of utmost importance in order to monitor and predict changes in risk-relevant conditions (Scarlat and Bradea 2011; Schlüter et al. 2017). These may rely on a multitude of data from different sources and aid in the monitoring of different types of risks and underlying factors which are relevant for the supply chain, ranging from

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demand, to transport and supply risks (Baryannis et al. 2019a; Diedrich and Klingebiel 2020; Zhang et al. 2020), and therefore constitute a valuable risk management tool. The potential of supplementing advanced monitoring with real-time business intelligence capabilities to discover or predict risks has been pointed out (Schlüter et al. 2017) and therefore raises the question of how data analytics methods can utilized for this purpose.

With proceeding digitalization and technological advancements, a greater data basis than ever before is available for supply chain decision-makers (Rozados and Tjahjono 2014). This in conjunction with data analytics tools allows for new risk indicators to be calculated and underlying data to be gathered at a higher speed; however, data-driven approaches are still rarely reported in the SCRM literature (Baryannis et al. 2019b). These approaches carry great potential for automated risk identification, improved risk assessment and advanced warning-systems (Schlüter et al. 2017). Data-based approaches are regarded as more suitable for real-time application (Poschmann et al. 2019) as opposed to relying solely on survey-based risk assessment, disregarding the advantages of a model-based risk score derived from the supply chain database (Li et al. 2016). So far, the literature has approached this topic mostly conceptually (Fu and Chien 2019; He et al. 2014; Radanliev et al. 2020), indicating the need for a more application and method-focused research approach.

The utilization of real-time data thus enables short-term, even live risk monitoring in supply chain operations, which this work seeks to explore. Despite the numerous studies (Ho et al. 2015; Rao and Goldsby 2009; Tummala et al. 2011) examining different types of risk, e.g. demand risk, and their underlying factors such as inaccurate forecasts, at the time of writing, to the best of the authors' knowledge, no dedicated synthesis of risk monitoring and prediction, and the considered risk indicators in the SCRM-phase of risk monitoring exists. By carrying out a systematic literature review, this work seeks to address this issue by answering the following three research questions:

1. Which risk types and factors are considered in supply chain risk monitoring?
2. What are suitable risk indicators to monitor these risk factors?
3. How can data analytics methods and supply chain data be used in the analysis, prediction and monitoring of these risk indicators?

The remainder of this work is organized as follows: First, a background on supply chain risks and their measurement is given and previous works on the potential of supply chain risk monitoring are reviewed. Next, the methodology for the systematic literature review is laid out. Afterwards, the results are presented and discussed. Promising research topics are presented to conclude the work.

2 Theoretical Background on Risk Factors, Indicators and Data Analytics in Supply Chain Risk Management

In the SCRM literature a distinction is generally made between risk types and risk factors. Risks types can be categorized in many ways. Ho et al. (2015) divide them into macro- and micro-risks where macro risks can be natural or man-made and micro-risks, which can refer to supply, demand, manufacturing, and infrastructure risks. The latter can be further divided into information, transportation and financial risks. Risk factors on the other hand comprise “events and situations that drive a specific risk type” (Ho et al. 2015, 7), and are therefore very case-specific and will also influence the possibility of monitoring and predicting the occurrence of different types of risks. Monitoring performance indicators and risks themselves is made possible thanks to real-time data from a variety of internal (sensors, IT systems) and external (SC partners, web) sources and enables warning-systems that not only provide information the moment a risk is manifested but may even predict this ahead of time (Schlüter et al. 2017). To monitor supply chains, indicators are used which may be considered “key” if they describe particularly relevant properties. While key performance indicators (KPIs) are used to evaluate a supply chain’s performance and tend to rely on lagging indicators, key risk indicators (KRIs) show the level of risk and rely on forward-looking indicators (Chadha and Rodriguez 2016). Similarly, key control indicators (KCIs) are used to monitor the controls applied in the risk treatment phase (Chadha and Rodriguez 2016). As the focus of this work lies on the risk monitoring phase, KRIs are of primary interest. The relationship between data, risk indicators and key risk indicators can thus be structured as follows (Chadha and Rodriguez 2016):

- SCRM data: all available internal and external data relevant to SCRM including risks
- Risk indicator: SCRM-relevant data or calculated value from SCRM-relevant data that indicates level of risk on a regular, short-term basis
- Key risk indicator (KRI): chosen risk indicator to be “key” to risk management

Technological advances driven by Industry 4.0 surrounding advanced sensor networks, cloud computing or cyber physical systems have led to greater data availability, potentially in real-time (Schroeder et al. 2014). Also, the potential and challenges of utilizing big data and advanced analytics in supply chain management (Rozados and Tjahjono 2014; Waller and Fawcett 2013) and later SCRM (Choi et al. 2017; Kache and Seuring 2017; Schlüter et al. 2017) have been a subject in the scientific literature for some years now. He et al. (2014) developed a conceptual framework on the monitoring of supply risks and proposed the usage of a variety of data sources ranging from traditional data regarding supplier capability, deliver history, and quality and new, external data sources including weather and social media. An example for dealing with demand-side risks is a data-driven demand forecast framework proposed by Fu and Chien (2019) that includes several methods such as time series and machine learning. Radanliev et al. (2020) evaluate the potential of artificial intelligence and machine learning to combat cyber risks, which can be positioned in information risks. These works approach monitoring of risks in supply chain management primarily conceptually. A synthesis of concrete applications, utilized risk indicators and analytics methods is yet missing. Thus, the work at hand seeks to fill this gap by complementing the existing body of research by identifying monitored risk factors, utilized risk indicators, concrete analytics methods and data that enable short-term or even real-time risk monitoring.

3 Research Approach

Risk analysis methods and risk indicators used for monitoring and prediction in SCRM are identified through a systematic literature review. The methodology relies on the five-step approach of Vom Brocke et al. (2009). The goal of the review is to identify which risk types and factors are considered in risk monitoring, to identify suitable risk indicators and how data analytics methods can be used to support risk monitoring. The search string consists of "supply chain" as a central term and then "risk", which is combined with various expressions often used synonymous with "indicator". Additionally, "risk" is combined with "analytics", "monitoring" and "prediction", motivated by a greater availability of supply chain data as an enabling factor. Given the focus on applications and the scope of the research questions, the literature is expected to include most if not all information relevant to answer all three research questions and is therefore searched using a single query. Works identified in the initial scoping review are included, too. To explore this sub-field of SCRM, a representative sample typifying similar works must be analyzed (Cooper 1988). Scopus and Web of Science were seen fit for this purpose due to their size and range of publications.

Search string (title-abstract-keyword):

> "supply chain" AND ("risk index" OR "risk score" OR "risk indicator" OR "risk value" OR "risk analytics" OR "risk monitoring" OR "risk prediction")

Similar to how key performance indicators can be selected from all available performance indicators (Neely et al. 1995), such a relationship between key risk indicators and regular risk indicators can be assumed, which is generally not mentioned explicitly in the literature. It is instead documented if a central risk indicator is constructed from several risk indicators. The identified works are then classified according to risk types, which are determined using the framework by Ho et al. (2015) encompassing different types of risks within the categories of macro and micro risks. This ensures statements about the coverage of risk types and factors in the literature can be made regarding research question one. Furthermore, risk indicators are identified to answer research question two and utilized data and analytics methods are documented to answer research question three.

In order to be included, a work must utilize some sort of risk indicator capable of monitoring on the short term or even in real-time, or some sort of data analytics method for (near) real-time risk monitoring in order to follow the indication of potential of such approached pointed out in the previous chapter (Choi et al. 2017; Kache and Seuring 2017; Schlüter et al. 2017). In order to determine if a work complies with the inclusion criterion concerning data analytics methods, a taxonomy of big data analytics in SCM is used encompassing data discovery, reduction, deduction, quantification and visualization, as well as predictive, event-oriented and statistical-inference methods (Chehbi-Gamoura et al. 2019), where the latter four are expected to be most suitable for the purpose of risk monitoring on the short-term. As the focus of this paper lies on methods and actual applications in contrast to the various existing theoretical approaches, purely conceptual works are excluded, and the results are limited to journal and conference articles. Furthermore, the work must deal with managing risks in the supply chain context and not solely rely on qualitative risk assessment methods to quantify the probability and likelihood in a way not suited for regular monitoring and quick responses, e.g. via annual expert interviews which take weeks to complete.

From the 259 results, 239 were articles and conference papers from which 52 duplicates were removed. Of the remaining 187, 101 works have been selected through title and abstract reading and were then filtered further through content screening. The remaining eleven papers were used for forward and backward search which yielded an additional seven papers, which combined with the three found in the initial scoping review make for a final set of 21 papers.

4 Risk Indicators and Data Analytics in Supply Chain Risk Monitoring

Many of the works in the query result rely solely on data gathered from interviews, surveys etc., which are then used in conjunction with traditional analytic hierarchy process (AHP), analytic network process (ANP), fuzzy logic for risk identification, assessment and prioritization. Due to the limited suitability of this type of data collection for monitoring, these works were therefore discarded unless they elaborate on how exactly the results can be used for monitoring at regular intervals. Through title and abstract reading, 63 works and through full text reading further 56 were discarded due to limited monitoring suitability. The finally selected works are the few that either implicitly – through their use of methods and data – or explicitly state how their respective models and methods can be used on a regular basis to monitor supply chain risks. Many of them go into surprising detail when it comes to analytics methods and data, in theory, their application or both.

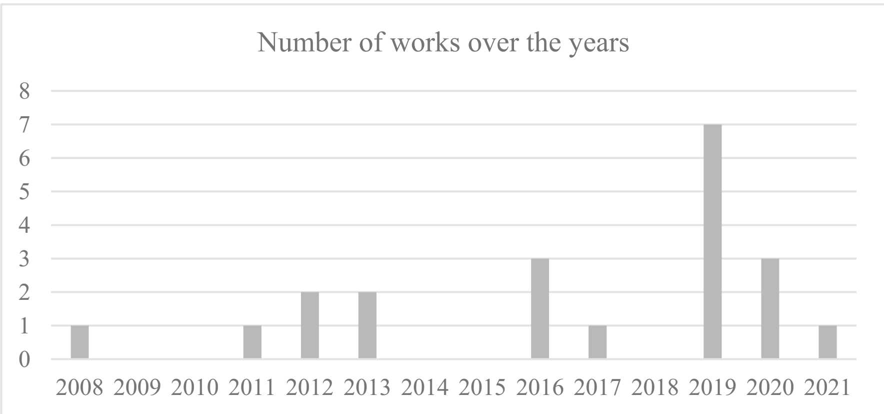

Fig. 1. Distribution across time of analyzed papers

Most of the works were published during the last 5 years which may be an indicator of progressing supply chain digitalization, increased interest in data-driven methods and corresponding research revealing the necessity of developing risk early-warning capabilities (see Fig. 1). In the following, the result set is thematically analyzed in accordance with the research objectives of this paper.

4.1 Risk Factors and Indicators

The risk factors and indicators considered in the literature are categorized according to their associated risk type in Table 1 using the framework by Ho et al. (2015). The occurrence of all risk types encountered in the result set are shown in Fig. 2. The most prominent risk types are transportation risks considered in five works (Bains et al. 2016; Kim et al. 2016; Poschmann et al. 2019; Shin et al. 2012; Zhang et al. 2020) and supply risks in five (Baryannis et al. 2019a; Blackhurst et al. 2008; Er Kara et al. 2020; Hosseini and Khaled 2019; Li et al. 2016). This might be due to the data availability of transport data, which can be collected easily, both, for the actual transport itself and the transported goods, using localization technology like GPS and various types of sensors. Similarly, data on suppliers might be collected from publicly available sources and complemented by company experts working together with the suppliers. There are only two works considering demand risks (Beheshti-Kashi et al. 2019; Diedrich and Klingebiel 2020) and one work considering social (man-made) risks (Mani et al. 2017). Further five works consider multiple risks where one regards different risks according to different performance attributes (Curbelo et al. 2019) and the other focusses on enabling supply chain risk visualization capabilities and therefore does not make any restrictions in terms of risk types (Goh et al. 2013).

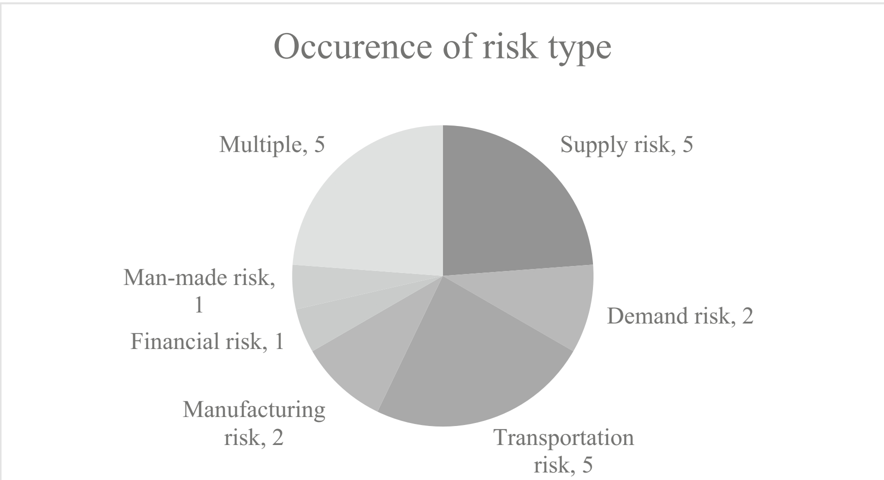

Fig. 2. Occurrence of risk types in analyzed papers

Apart from the rather focused consideration of risk types, different industries ranging from manufacturing in automotive, aero-space, steel and telecommunication to fashion and dairy produce are present. Modes of transportation include road, air, railway and maritime, showing that transportation risks are deemed highly relevant irrespective of the mode of transportation, and also that transportation data for all of them are available.

Almost half of the works utilize a risk indicator directly based on SCRM data to monitor risks while the other half calculates and, in some cases, predicts a key risk indicator in order to support the risk managers with one central value. For example, supply chain data such as the temperature and humidity of products in transport are used directly in cold chain scenarios (Kim et al. 2016; Lam et al. 2013) while various technological and biological indicators can be aggregated into a central transportation risk indicator (Zhang et al. 2020). Even within one risk type, there is a great variety of indicators that can be utilized for specific risks. This is illustrated for example with supply risk. Here, choices for indicators are supply quality and disruption-related ones such as labor availability and disputes (Blackhurst et al. 2008), whether deliveries are delayed or on time (Baryannis et al. 2019a), rather traditional indicators such as cost, quality and time (Hosseini and Khaled 2019) or the questions if a product will stop being produced as indicated by its price, lead time, cycle time and throughput, as well as further secondary indicators (Li et al. 2016). It can be observed that not just data associated with supply chain risks, but the likelihood of risk events can be utilized as an indicator (Baryannis et al. 2019a). The choice of risk indicators is generally described in great detail, which emphasizes the importance of understanding the organization's specific context and risks which threaten it. However, which supply chain member should use which indicators is not explained further. In summary, it is not entirely possible to answer the question of which risk factors and indicators can be used in supply chain risk monitoring since the identified factors and indicators vary greatly with different industries and risk types. However, this can be seen as a great indication of the need for guidance when establishing risk monitoring beyond specific use cases as is the case for the studies analyzed here.

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Table 1. Risk factors and indicators identified in the literature

Author	Risk factors	Key risk indicators and indicators
Supply risks		
Blackhurst et al. (2008)	Supply risk (different risks per supplier and per part in automotive industry)	Risk indicator based on different quality and disruption-based indicators for part and supplier
Li et al. (2016)	Supply risk (end-of-supply risk for a maintenance and repair organization (MRO))	Risk indicators calculated from data – price, lead time, cycle time, throughput – summed up in survival probability of respective part as central indicator
Baryannis et al. (2019)	Supply risk (order fulfilment and late delivery in multi-tier aerospace manufacturing supply chain)	Risk classification whether delivery in time or too late
Hosseini and Khaled (2019)	Supply risks (supplier risk in sewage pipe manufacturing)	Supplier resilience value as central index, primary indicators cost, quality, lead time, response rate and several secondary indicators
Er Kara et al. (2020)	Supply risks (supplier risk)	Numerous qualitative and quantitative indicators of supplier risks used in final selection
Demand risks		
Beheshti-Kashi et al. (2019)	Demand risk (forecasting risk in fashion industry)	Use correlation between textual and sales data as indicator for forecasting risk
Diedrich and Klingebiel (2020)	Demand risk (inaccurate demand planning of automobile manufacturer)	Theory: Early warning risk indicator Case: spread of risk, risk impact on the KPI for the security of supply of the OEM
Transportation risks		
Shin et al. (2012)	Transportation risk	Use cost of transportation and costs caused by machine malfunctioning and delay of manufacturing or delivery as indicators

(*continued*)

Table 1. (*continued*)

Author	Risk factors	Key risk indicators and indicators
Bains et al. (2016)	Transportation risk (global airline logistics)	Risk indicator based on weighted ubiquity score per part and geopolitical score per supplier to determine high-risk supply chain nodes
Kim et al. (2016)	Transportation risk (cold supply chain)	Risk indicator given specific rules and contexts, e.g. temperature and humidity
Poschmann et al. (2019)	Transportation risk (maritime supply chain)	Expected time of arrival as central risk indicator
Zhang et al. (2020)	Transportation risk (cold supply chain, case of strawberry supply chain)	Aggregated transportation risk indicator based on various indicators ranging from technological to biological (hypothetical case)
Manufacturing risks		
Zhang et al. (2011)	Production risks (food supply chain, case of pork industry)	Three level indicator system considering water, pig farms and pork quality (physical and chemical)
Lam et al. (2013)	Storage risks (food supply chain, case of wine industry	Storage temperature and humidity range, fluctuation
Financial risks		
Lyu and Zhao (2019)	Financial risks (internet supply chain finance)	Indicators referring to solvency, profitability, operations and products, network technology and environment, among others
Man-made risks		
Mani et al. (2017)	Man-made risks (social risks in milk production and 3PL provider)	Monitor drivers and vehicles for personal safety, unethical or illegal behavior and environmental concerns
Multiple risks		
Zhang and Lu 2012	Multiple (supply chain risk level in steel industry w.r.t finances, business processes, customer service, development)	E.g. net sales and growth, supply chain response time, on-time delivery and order fulfilment, market share

(*continued*)

Table 1. (*continued*)

Author	Risk factors	Key risk indicators and indicators
Goh et al. (2013)	Multiple (supply chain risk level)	Logistics-related, inventory, order-related indicators
Curbelo et al. (2019)	Multiple (supply chain risk level w.r.t different performance attributes, case in telecommunications industry)	Aggregated risk indicators for different objectives
Yang and Xie (2019)	Multiple (supply, technology, docking and external risks in agricultural supply chain)	E.g. unfulfilled demand, overproduction, delivery delay, organizational efficiency, public opinion, severe weather, among others
Han and Zhang (2020)	Multiple (supply chain risk level, case of food producing company)	Three-level indicator system, including suppliers, demand and consumers, logistics costs and processes, technology and information sharing, environmental indicators, among others

the identified factors and indicators vary greatly with different industries and risk types. However, this can be seen as a great indication of the need for guidance when establishing risk monitoring beyond specific use cases as is the case for the studies analyzed here.

4.2 Methods and SCRM Data

Analysis methods and data related to the various risk indicators used in each work are summarized in Table 2. Different machine learning methods are utilized to predict future risk levels and approximate experts' estimates. For example, support vector machines (SVMs) are compared with decisions trees in order to illustrate how the choice of methods can impact the risk manager's ability to interpret the prediction result when using delayed deliveries as an indicator (Baryannis et al. 2019a). SVMs are also utilized to predict an aggregated risk indicator for transportation risks in the case of cold chains (Zhang et al. 2020). Another tool utilized is supply chain visualization which is realized using dashboards (Goh et al. 2013), to include geopolitical risk indicators (Bains et al. 2016) or drivers' routes and associated vehicle activities as risk indicators (Mani et al. 2017). Er Kara et al. (2020) suggest the creation of a risk data warehouse and further utilize k-means clustering to cluster suppliers into groups. The risk level within each cluster varies given different risk indicators related to sales performance (e.g. failure rate), production planning and control (e.g. number of delayed orders) or logistics (e.g. inaccurate deliveries). Bayesian Belief Networks are used to model interdependencies between risks and their associated location along the supply chain and thus go beyond monitoring single KRIs on their own (Shin et al. 2012; Yang and Xie 2019). Also, artificial neural networks find their uses when trained based on experts' judgements of risk levels, thus enabling ongoing, automated risk level estimations (Han and Zhang 2020; Zhang et al. 2011; Zhang and Lu 2012).

Hosseini and Khaled (2019) combine several methods such as decisions trees and artificial neural networks with an ensemble approach to predict the supplier risk using indicators such as cost, quality, lead time, response rate and qualitative resilience criteria. This illustrates how predictive methods can be used in conjunction with an AHP approach based on data generated from questionnaires. Curbelo et al. (2019) and Lyu and Zhao (2019) show how approaches relying on qualitative data can be extended with quantitative data to warrant monitoring at regular intervals. Quantitative and qualitative data can thus be used jointly, the latter mostly with expert involvement where the bounds of the risk levels of different indicators are initially determined through forms or interviews. Furthermore, the range of different methods and underlying data illustrate how various approaches could be incorporated into one integrated approach. Apart from the potential of integrating internal and external data, which only few of the works incorporate, the approaches range from the acquisition of quantitative and qualitative risk data, their integration into risk databases, their processing and preparation for further analysis, the application of analysis methods with the goals of monitoring risk levels associated with supply chain members, actors or products, or their classification or clustering into different groups, each associated with different risks, as well as modelling their interdependencies. Finally, automatic handling of minor exceptions might be implemented, based directly on the data and method outputs used for monitoring.

Some of the works even give details on how they introduced their specific approach in the case company. One work (Diedrich and Klingebiel 2020) relied on a proven methodology in the form of CRISP-DM. Others describe the creation of risk management tool (Li et al. 2016), integration into existing risk management tools or prototype development (Poschmann et al. 2019), while many did not reflect upon the integration into any system. This also means that the supply chain perspective has not been elaborated on in detail. Not only discrepancies in function and location of supply chain members, but also those regarding the definition and sharing of data may result in problems (Zhang et al. 2011). It may be necessary to involve all members in order to collect the necessary data and understand each supply chain actor's role (Poschmann et al. 2019), as well as involving experts with different backgrounds, including risk management, domain, IT and those with knowledge in the applied methods (Er Kara et al. 2020). In most of the identified cases, the data was collected with a certain goal determined beforehand, indicating that different monitoring goals come with different data requirements. Also, it has been pointed out that data availability and the communication between experts in supply chain risks and data-driven methods largely influence the success of such efforts (Baryannis et al. 2019a). All of this might indicate certain specifics in the application and introduction of data analytics and monitoring systems in supply chain risk management and the need for a more detailed analysis on how to conduct and introduce data-driven risk monitoring in organizations.

In summary, as for research question three, identified approaches include data visualization, discovery, deduction and quantification, mostly predictive machine learning

Table 2. Analytics methods and SCRM data identified in the literature

Author	Methods	SCRM data
Bains et al. (2016)	Dashboard with geographic display	Component data of airplane models, geopolitical information
Blackhurst et al. (2008)	Define maximum percentage change in risk and control limits for risk score and monitor trends	Quantitative data for calculated measures (e.g. defects per million) supplemented by qualitative ratings
Baryannis et al. (2019)	Support-vector machine (grid search for parameters), decision tree with and without limited number of leaves	Around 500.000 product deliveries from tier 2 to the tier 1 supplier over six-year period (2011–2016), two sets of around 30 features in two models based on product-, order- and delivery-related data
Beheshti-Kashi et al. (2019)	Natural language processing	Textual data from blogs relevant to the industry, sales data
Curbelo et al. (2019)	Mathematical model with fuzzy inference system	Define list of control objects for different risk events with different data each
Diedrich and Klingebiel (2020)	Several machine learning methods	Over seven million values, over 90 calculated for each part number and demand date
Er Kara et al. (2020)	Risk data warehouse, k-means to group suppliers, best-worst for weights	Quantitative and qualitative data associated with the indicators, not further specified
Goh et al. (2013)	Dashboard with geographic display, risk alerts, determine vulnerabity using optimization and simulation	Internal operational data (logistics, inventory, order fulfilment, …) and external (public map services, OSINT, twitter)
Han and Zhang (2020)	Artificial neural network	Data gathered via questionnaires from enterprises and universities to determine risk levels
Hosseini and Khaled (2019)	Logistic regression, decision tree (CART), artificial neural network in ensemble	Data for primary criteria, qualitative data for resilience-related attributes, complemented by web-data

(*continued*)

Table 2. (*continued*)

Author	Methods	SCRM data
Kim et al. 2016	Ontology and dynamic rule creation engine for risk detection & response	RFID data (temperature, humidity, …) and other sensors
Lam et al. 2013	Statistical analysis, genetic algorithm for case handling	RFID data (temperature, humidity) and product data (quantity, value…)
Li et al. (2016)	Proportional hazard model (PHM)	MRO's purchase history (date, part, price, quantity, supplier, delivery)
Lyu and Zhao (2019)	Big Data-drive gray assessment	Financial risk scored by group of experts from case company, financial statement data
Mani et al. (2017)	Dashboard with geographic displays for vehicles, routes	Quantitative logistics data from 3PL provider (fleet-management, live-tracking, IoT sensors) with millions of data points combined with qualitative data from interviews
Poschmann et al. (2019)	Estimation of importance and maturity of available information, propose array of artificial intelligence methods	Transport data (planned and actual times, disruption information)
Shin et al. (2012)	Bayesian belief networks	Not specified
Yang and Xie (2019)	Bayesian belief networks	Probabilities gathered from field research and questionnaires
Zhang et al. (2011)	Artificial neural network and statistical analysis for anomaly detection	Pre-warning rules defined by the case company's experts, integrated data from supply chain members
Zhang and Lu (2012)	Artificial neural network	Integrated historic and surveyed data over two years corresponding to the various indicators

(*continued*)

Table 2. (*continued*)

Author	Methods	SCRM data
Zhang et al. (2020)	Support-vector machine	350 values across 30 different features surrounding logistics and fresh-keeping technology, product, packaging, equipment effectiveness, biological, sustainability, environmental and emergency

methods for regression and classification as well as clustering, and furthermore data management itself, which means almost all categories as defined by Chehbi-Gamoura et al. (2019) could be identified by this study.

5 Future Research for Data-Driven Supply Chain Risk Monitoring

The analyzed works reveal several promising topics for future research. As we learn from research question one, for instance, the analysis of risk factors must go beyond hierarchical relationships and instead incorporate risk agents and their interaction (Curbelo et al. 2019). The progressing digitalization is mentioned as a further driver for the expansion to more supply chain risks (Diedrich and Klingebiel 2020). Another common topic is the application of the respective methodologies and methods in different industries, e.g. the manufacturing of different vehicles (Bains et al. 2016), different OEMs (Diedrich and Klingebiel 2020) or just generally more case studies for validation purposes and to advance theory (Curbelo et al. 2019; Er Kara et al. 2020; Mani et al. 2017; Shin et al. 2012). Monitoring different products and extending proposed methodologies from e.g. transportation to storage and production are proposed as well (Zhang et al. 2020). This resonates with the highly heterogenous set of application areas identified in this paper, indicating the need for an evaluation of methods across different domains.

In terms of risk indicators considered in research question two, apart from using supply chain data as a risk indicator or to calculate one, the duration of risk events may be an important indicator (Curbelo et al. 2019), just as the dynamics of disruptions themselves (Hosseini and Khaled 2019). In the case of supplier risks, their resilience level could be used as an indicator to determine the risk level of the entire supply chain (Hosseini and Khaled 2019). Most of the works analyzed in this paper focus on micro-risks and consequently primarily internal data sources are used, with a few exceptions. This raises the question of how to determine suitable macro risk indicators and their underlying data.

As for research question three, a common theme is the application of more data, both in volume and variety (Curbelo et al. 2019) and period of storage (Diedrich and Klingebiel 2020), as well as extending risk monitoring to the entire supply chain in order to support the decision making for exceptional case management (Kim et al. 2016). This holds the potential for more accurately portrayed risks and additional risk indicators (Bains et al. 2016) and to improve prediction performance by adding more features (Baryannis et al. 2019a). On the side of data analytics methods, the application of a larger set of machine learning techniques (Curbelo et al. 2019; Kim et al. 2016), also for risk prediction (Baryannis et al. 2019a), as well as combining data-driven and knowledge-based artificial intelligence approaches (Baryannis et al. 2019a; Diedrich and Klingebiel 2020) are mentioned. This indicates that future research may be required, eliciting concrete data and IT-infrastructure requirements to enable data-driven risk monitoring. A transfer of general big data analytics literature in the context of supply chain management as a whole may constitute a first step in such an endeavor. Finally, integrating data-driven and knowledge-based approaches makes for a promising topic for future research, in particular in the area of artificial intelligence.

The impact and integration of the identified methods into SCRM phases, specifically risk monitoring processes, may reveal interesting results. Here, the development of data-driven risk monitoring methodologies may be supported by examining the willingness of stakeholders to adopt them (Blackhurst et al. 2008). Also, the implications for other phases such as risk mitigation with regard to assisting in decisions making and automation are mentioned (Diedrich and Klingebiel 2020), just like the usage for risk identification (Goh et al. 2013) and integration of further assessment methods (Li et al. 2016). This raises the question of what barriers there are to introducing risk monitoring into organizations and how to overcome them, as well as methodologies for the creation of risk monitoring systems and continuous control of the adequacy of chosen risk indicators in a specific context.

6 Conclusions and Outlook

In this work, risk factors, monitored risk indicators and the usage of data analytics to generate, monitor and predict risk in the field of supply chain risk monitoring were explored through a systematic literature review. The results where synthesized along the dimensions of risk types, and corresponding application of risk indicators. Analytics methods and data were identified, revealing foci and gaps in the literature. The findings were discussed and potential reasons for them outlined. Following the discussion, propositions for future research were derived. A trend towards more data-driven monitoring approaches and analytics methods was revealed, yet there are still many more risk types and factors that need to be explored in future research. Also, the introduction of supply chain risk monitoring with its wide array of potential data sources and analytics methods into organizations requires particular attention.

The main limitations for this work result from the choice of databases and keywords. Even though the small result set may be explained by the current lack of research in supply chain risk monitoring, the discussion and implications for future research were based on a limited set of results and are therefore insufficient to provide the full picture. Second, the focus lies on KRIs as opposed to KPIs or KCIs, which may warrant research of their own, but may require an entirely different research approach. As a lesson from the current effects of the Covid-19 pandemic onto global supply chains and their ever-increasing complexity as well as changing environments, the need for advanced monitoring capabilities will continue to rise. This paper established the first overview of supply chain risk monitoring and derived future research topics, giving both researchers and practitioners a starting point for further exploration and investigation in this endeavor.

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