A Holistic View of Adaptive Supply Chain in Retailing Industry

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Completed Research

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Abstract

The retailing industry witnessed a significant shift from conventional retailing to online marketplaces, inducing many challenges on the common practices of supply chain. Supply chains are normally subject to a wide range of disruptions, that are caused by certain events. Still, few organizations are relying on appropriate data streams and required technologies to detect and report on potential disruptions in supply chain. As a result, current supply chains remain marginally adaptive and lack the ability to react to the dynamic nature of markets on strategic as well as operative levels, which leads to loss of optimization potential. Therefore, in this study, we investigate data sources that might be beneficial to develop adaptive supply chain management (A-SCM) practices. This paper presents a holistic view of A-SCM that includes a thorough analysis of the problem domain and nature, often used data sources, employed solution techniques and finally the adopted objective function.

Keywords

Adaptive supply chain, Retail, Data analytic techniques, Optimization techniques, External data sources

Introduction

In the past decade, the retailing industry witnessed a significant shift from conventional retailing to online marketplaces such as Amazon (Grewal et al. 2018). This shift induced many challenges on the common practices of supply chain management in the retailing industry (Alexandrova and Kochieva). In addition, the constant rise of customer expectations, the role of social media platforms and its impact on customer behavior contribute to a steady increase of competition in these markets (Alexandrova and Kochieva), which are in nature inherently dynamic and very complex. Therefore, investigating new innovative concepts and harnessing the capabilities of new IT technologies became not only an important task in information systems research in general, but also a necessity to achieve adaptive practices in supply chain management in particular (Sorescu et al. 2011). Adaptive Supply Chain Management (A-SCM) includes the application of “modern concepts and technologies” to achieve for instance, stability, effectiveness, responsiveness, flexibility, and robustness in SCs (Ivanov and Sokolov 2010). SCs are normally subject to a wide range of disruptions, that are caused by certain events and/or by the volatility of the markets they operate on (Christopher and Holweg 2011; Craighead et al. 2007). For instance, the recent pandemic unfolded severe economic fallouts, which are mainly caused by serious disruptions in SC networks (Elliott 2021; Ongkowijoyo et al. 2020). Mitigating these disruptions requires developing strategic capabilities, which constitute the core concepts of Supply Chain Resilience (SCRES). Briefly, in terms of strategy, the concepts of SCRES can be divided into three main categories: proactive, concurrent, and reactive (Ali et al. 2017). The former is usually the hardest to achieve since proactive strategies require thorough analysis of historical and online data streams to predict possible disruptions and develop appropriate counter measures. Supply Chain Risk Management (SCRM) is the main research field that deals with the development of proactive SCRES approaches. The successful adoption of such approaches is usually based on three building blocks risk identification, assessment, and evaluation (Janjua et al. 2021). A recent study suggests that only half of organizations are relying on appropriate data streams and required technologies to detect and report on potential disruptions in supply chains, which establish the ground to develop suitable measures and precautions to overcome their impact (Elliott 2021). The effectiveness of SCRM approaches heavily depends on data quality and its nature to produce near-real time results (Janjua et al. 2021), which can be employed to support adaptive decision making processes (Chen et al. 2013). As a result, current SCs remain marginally adaptive and lack the ability of detecting major disturbances on strategic as well as on operative levels, leading to a gap of existing A-SCM. Therefore, we investigate potential data sources that might be beneficial to develop A-SCM practices in the digital age. Based on the identified data sources, we present a systematic overview on the nature of common problems, that are addressed in A-SCM, SCRES, and SCRM. We discuss the evolution of solution techniques that are employed to address these problems and elaborate on the usually adopted objectives. Eventually, this paper presents a holistic view of A-SCM that includes a thorough analysis of the problem domain and nature, often used data sources, employed solution techniques, and finally the adopted objective function. The derived overview of A-SCM provides clarity for systematic treatments of A-SCM concerns in the field of information systems and points out research and development gaps. The paper is structured in five sections. After a brief introduction and a motivation of the problem, the second section is dedicated to discussing the research methodology. This section also highlights the investigated research questions and layouts a plan to answering them. In the third section, the results of the systematic literature analysis are presented alongside a thorough analysis of state-of-the-art techniques in the field of A-SCM. Based on the obtained results, the fourth section comprises the holistic view of the A-SCM. The paper is closed with conclusions and future research directions.

Methodology and Research Objectives

We followed a research methodology that starts with an exploration phase to investigate the relevant research fields in the body of the related literature and concludes with a structured literature analysis on a scientific database. In the first phase, the forward and backward literature search method suggested in (Webster and Watson 2002) is followed to investigate state-of-the-art publications in the fields of SC optimization, analytics, early warning systems, and event fundamentals in SC. In this process, a total of 102 relevant publications were identified. This preliminary step contributed to the definition of the following research questions (RQs) and search strings (see Table 1).

RQ 1: Which external data sources are potentially beneficial for adaptive supply chain and supply chain resilience in the retail industry?

RQ 2: What are the most common used data analytics and optimization approaches for addressing event-based retailing concerns?

RQ 3: What are the current approaches to process events and manage risks in the supply chain of the retail industry?

RQ 1	**Title, abstract, keywords:** 1) *(News data OR social media OR big data);* 2) *(Twitter OR Instagram OR Facebook OR Youtube),* 3) *(Google Trends AND Supply Chain)*; **Title:** 1,2) *Supply chain*
RQ 2	**Find articles with these terms:** 1,3) *retailing;* **Title, abstract, keywords:** 1,2) *(Machine Learning OR data science OR analytics),* 3) *(Machine Learning OR data science OR analytics OR external data sources OR retail or retailing OR optimization)*; **Title:** 1) *Supply chain management,* 2) *(Supply chain optimization OR supply chain management),* 3) *(Supply chain optimization OR supply chain management OR adaptive supply chain);* **Year:** 3) *2010-2021*
RQ 3	**Title, abstract, keywords:** 1) *("supply chain risk" OR "supply chain vulnerability" OR "supply chain management issues"),* 2) *("disruption risk" AND "supply chain"),* 4) *("risk assessment" OR "risk identification");* **Find articles with these terms:** 3) *("event processing" AND "supply chain"),* 4) *("supply chain" AND retail)*; **Year:** 4) *2015-2021*

Table 1. Search Queries in ScienceDirect for each RQ

Our focus is on the use of external data sources and online analytics for A-SC in the retailing industry. Accordingly, potentially useful data sources (RQ 1) and commonly used data analytics as well as optimization approaches (RQ 2) need to be identified. Additionally, the current ways of handling events and risks regarding SCs require examination in this context (RQ 3). Therefore, the second phase starts with a structured literature review on ScienceDirect to systematically select relevant articles (Jalali and Wohlin

2012) and collect evidences to answer the presented RQs. Due to the deviating subject of the individual RQs, three different search processes with a separate set of search queries need to be executed. Nevertheless, some of the findings of a respective search process might also be relevant for another RQ. Furthermore, it is possible that some articles are retrieved across multiple different search processes as they fit the narrative of several RQs. Figure 1 graphically summarizes the entire methodological process, starting with the exploration and concluding with the manual selection of articles for each RQ. In the automatic filtering stage, the presented search queries resulted in a total of 1570 articles. The majority of papers was associated with RQ 3. This was expected because of the fact that the included terms "risk" and "event" occur in contexts beyond the scope of this research. Accordingly, we limited the fourth query to the years from 2015-2021 to focus on the recent publications. After reading the title, 327 papers were left. The following examination of the abstract reduced this number to 134. In the end, the final revision of the articles identified a total of 51 publications that were found to provide useful insights with respect to our RQs.

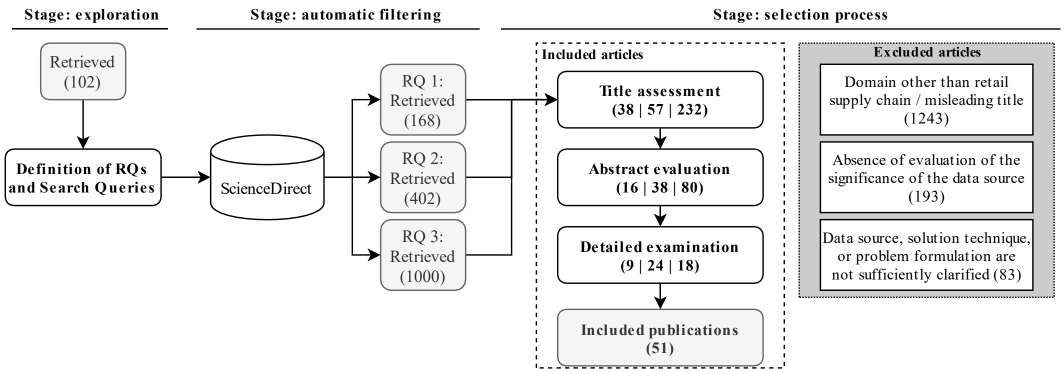

Figure 1. Literature filtering process

Results and Discussions

In this section, we summarize the results of the literature analysis. In alignment with the RQs, this section is divided into three subparts. Eventually, we use the insights of the literature analysis to answer the RQs and derive a holistic view of A-SCM in retail, including conclusions regarding the challenges as well as opportunities (e. g. data sources, methods) in optimizing SC practices.

External Data Sources for Adaptive Supply Chain and Supply Chain Resilience

RQ 1 is related to potentially beneficial external data sources that can help with implementing adaptive SC and SCRES, especially for retail businesses. All in all, most of the retrieved articles discuss the potential and usefulness of social media data like Twitter (Janjua et al. 2021). (Chae 2015) presents a Twitter data analyzing framework to describe potential use and benefits for SCs. Twitter data are the focal point of further included studies. (Sharma et al. 2020) use company tweets to identify SC themes and strategic recommendations after heavy disruptions caused by the COVID-19 pandemic. Similarly, (Papadopoulos et al. 2017) analyze several external data sources (e. g. Twitter, news, Instagram) to help managers (re-)build resilient SCs in the aftermath of disastrous events. (Singh et al. 2018) use tweets to inform SC decision-makers about customer feedback and issues in the flow and quality of food products. (Sakaki et al. 2010) highlight the potential of Twitter for real-time event detection by building an earthquake reporting system. Two additional articles cover the potential of harnessing web and social media data in more general terms. (Pagano and Liotine 2020) view social media as a "mechanism of collective intelligence" in a SC. "Social sentiment" can help in sourcing vendors and suppliers and improve SC processes as well as existing problems through enhanced communication with customers, generated demand, mitigated risk, and reduced operating cost (Pagano and Liotine 2020). According to (Zhan and Tan 2020), web and social media offer wide-ranging information on customer experiences and preferences, behavioral data and opinions, allowing to gain a better understanding about the consumers. Accordingly, applying Machine Learning (ML) on these data sources can improve business performance (Zhan and Tan 2020). However, challenges such as a high data volume and the necessary data integrations pose a certain difficulty in this matter. (Pagano and Liotine 2020) also mention the potential of sensors and telematics, for instance weather and traffic data, to detect repeatable patterns to predict transit times and delays, in turn enabling better decision-making along the SC (Pagano and Liotine 2020). (Zhan and Tan 2020) highlight the benefits of leveraging mobile and sensor data, too. SC management can be made more "efficient and effective" and a greater diversity of consumer behavior and changing dynamics become observable (Zhan and Tan 2020). Additionally, Google Trends, an external data source for web search statistics, shows potential for forecasting demands and consumer trends (Silva et al. 2019; Yuan and Lee 2019). (Yu et al. 2019) use Google Trends to improve the effectiveness of the prediction of oil consumption. Additionally, the possibility of enriching the proposed model with further data sources like online news articles and social network data is outlined. (Nikolopoulos et al. 2021) predict the excess demand for products and services in the COVID-19 pandemic with Google Trends, correctly forecasting the panic buying effect for groceries and electronics. Consequently, in future applications, operational SC decisions can be positively affected and disruptions can be avoided (Nikolopoulos et al. 2021). Nevertheless, (Yu et al. 2019) emphasize that the selection of the adequate search queries related to the topic requires a comprehensive investigation.

Data Analytics and Optimization for Event-based Retailing Concerns

The main goal of this subsection is to present an overview of the findings that are obtained from literature analysis under the second research question (RQ2). To systematically discuss the results, we classified the selected papers into six main categories in terms of adopted solution technique, namely, heuristic, metaheuristic, machine learning, hybrid, and simulation-based techniques. Briefly, heuristic techniques are a simple constructive procedure, in which an algorithm is used to construct a solution for a given problem without any improvement mechanism. The internal design of metaheuristics techniques usually comprises a constructive heuristic technique and an improvement procedure, which systematically modify the initial set of solutions to seek improvements for solving a given problem. Most of such techniques are inspired by some natural phenomena such as Genetic Algorithms (GA) (Holland 1975), which is based on the theory of evolution or Simulated Annealing (SA) (Kirkpatrick et al. 1983), which is motivated by the annealing process of metal. Recently, the popularity of ML techniques and their adoption for solving various optimization problems in SCM field increased. In the general sense, ML techniques are automatic statistical and data analytics methods, that can be employed to identify patterns and extract knowledge from raw data, which can be used for further decision making processes. Artificial intelligence (AI) techniques are a branch of ML techniques that can support a decision making process automatically with minimal human intervention. Under hybrid technique, we classified research efforts that presented solution techniques, which combine the use of heuristic, metaheuristics, or ML techniques for solving a given SCM problem (Nahhas et al. 2021). Finally, our analysis suggests that simulation techniques are often employed to investigate different concerns in SCM. Briefly, a simulation model is a representation of a real system in a digital model with a predefined level of abstraction. Based on a simulation model of a system, simulation experiments are conducted to obtain knowledge that allows investigating the impact of certain events, mimicking, and analyzing the natural development of the modelled system (Borshchev and Filippov 2004). In the following, we will discuss some state-of-the-art papers to highlight aspects related to the problem definition in the context of SCM, the adopted solution techniques and pursued objective function.

Heuristic techniques – (Schildbach and Morari 2016) developed a heuristic approximation technique for optimizing a multi-echelon SC taking into account multiple scenarios and incorporating a predictive control mechanism. The model uses internal sales data. Similarly, in (Zhang et al. 2016) a heuristic optimization model is presented to develop an ordering strategy considering stochastic factors in a global SC with the goal of minimize costs. Also in (Wei et al. 2013), a heuristic model based on a fairly standard product price–demand formula is presented to maximize revenue. Rather a more sophisticated problem is addressed in (Wan et al. 2018) to investigate joint profit maximization between manufacturers and retailers in a SC network using a polymorphic equilibrium model. Rather uncommon, (Le et al. 2013) present a heuristic method to avoid risks in retail SC collaboration by removing sensitive knowledge.

Metaheuristic techniques –In (Khalifehzadeh et al. 2019), the authors address a production distribution network problem, which includes multiple suppliers, producers, distribution hubs, and retailers. The problem is solved with objective to maximise profit in the SC and minimize the total delivery lead time. The authors reported improvements by relying on a heuristic method compared to the ranking GA. (Masoud and Mason 2016) adopted a hybrid simulated annealing with an effective encoding-decoding technique to address a two-stage SC cost optimization problem including production and delivery to customers in the field of automotive industry. As for inventory management, (Sadeghi et al. 2014) propose a bi-objective inventory model optimization employing a metaheuristic algorithm. Similarly, material procurement and distribution scheduling problems are addressed using GA in (Yimer and Demirli 2010).

To efficiently tackle multistage-based SC issues, (Yun et al. 2009) provide a GA approach with an adaptive local search method. (Yao 2010) offer a mathematics optimization model and an improved ant colony optimization to enhance SC resource integration decision optimization.
ML techniques – In (Pereira and Frazzon 2021) and (Pereira et al. 2018), the authors present a ML-based demand forecasting technique using historical sales data and operational planning simulation-based optimization to adaptively synchronize demand and supply in omni-channel retail SCs. For improving inventory management and cost reduction of SC processes, (Praveen et al. 2019) utilize historical sales data to build an AI-based time series forecasting with artificial neural network modelling. The search process also resulted in a couple of papers that discuss the application of analytics on external data sources for SC activities. For instance, (Chu et al. 2020) present a global SC risk management framework based on text mining techniques like sentiment analysis of online news articles. The approach of (Nguyen et al. 2021) relies on both external and internal data sources. The authors provide two data-driven methodologies for better SC management decisions, including a Long Short Term Memory (LSTM) Autoencoder network-based technique for forecasting multivariate time series data.
Hybrid techniques – (Medina-González et al. 2020) present a data-driven decision-making framework using ML and optimization techniques to handle centralized multi-objective SC planning being hampered by raw material uncertainty. (Resat and Unsal 2019) propose a two-stage hybrid solution method based on Analytic Hierarchy Process (AHP) and a heuristic multi-objective mathematical model for solving the supplier selection problem, taking into account different efficiency measures. (Rostamzadeh et al. 2015) suggest a hybrid GA to optimize material routing in SC. In (Keyvanshokooh et al. 2016), the authors provide a profit maximization model for closed-loop SC network design to cover the proportions of demand met and returns. (Wu et al. 2013) describe a stochastic fuzzy multi-objective programming model based on utility theory for SC outsourcing risk management. (Shafiei Kisomi et al. 2016) present a set-based robust optimization approach using a mixed-integer linear programming model including a closed-loop SC network and a supplier selection problem. Relying on supplier data and market demand, (Xanthopoulos et al. 2012) present a general single period inventory model for describing the trade-off between inventory policies and disruption risks in a dual-sourcing SC network.
Simulation techniques – In a further publication, (Schmitt et al. 2017) present a simulation model based on adaptive ordering that mimics a realistic SC composition to prevent disruptions.

Approaches for Event Processing and Risk Management in Supply Chain of Retail

The third RQ comprises the identification of approaches for risk management and event processing to prevent SC disruptions. Only the minority of the results rely on external data like Social Media.
Heuristic techniques – A multi-stage stochastic integer programming model, solved using a progressive hedging algorithm, is proposed by (Ghorashi Khalilabadi et al. 2020) to mitigate SC risks via product substitution. The model is based on the processes and contracts of the respective firm.
Metaheuristic techniques – To relieve disruption impacts on SC's resilience and robustness due to COVID-19, (El Baz and Ruel 2021) introduce a multi-objective optimization model with three metaheuristics to minimize travel time, makespan and picking overlap, using survey data.
ML techniques – (Singh et al. 2018) utilize text analysis on tweets to detect SC management issues. (Chu et al. 2020) apply text-based approaches such as sentiment analysis on online news articles to recognize risk patterns. (Er Kara et al. 2020) propose a data mining-based framework for the identification, assessment and mitigation of different SC risks to improve decision-making. The authors use data from internal SC information systems (e. g. ERP, CRM) and external databases such as government agencies and real-time natural disaster data, weather conditions, and social media. The approach proposed by (Baryannis et al. 2019) uses both internal (e. g. sales and production records) and external data (e. g. social media, weather reports) for a SC risk prediction framework that implements data-driven AI techniques such as support vector machines (SVM) and decision trees. (Vera-Baquero et al. 2016) introduce real-time business activity monitoring and analysis of process performance to respond fast to continuously changing business environments, relying on collected data from enterprise systems.
Hybrid techniques – (Farahani et al. 2017) aim to mitigate disruption risk for substitutable inventories with the help of internal data sources and a hybrid algorithm including Tabu and Variable Neighborhood Search. (Lam et al. 2015) design a knowledge-based logistics operation planning system that supports planning and controlling warehouse operations and mitigate risk in warehouse order fulfillment using AHP and case-based reasoning. Therefore, a data collection module gets warehouse data using radio-frequency identification while risks are identified via case study and interviews. (Giannakis and Louis 2011) introduce

a multi agent-based framework for the design of a decision support system that facilitates collaborative risk management in manufacturing SCs. Risks are identified with various key performance indicators related to the SC partners. (Oke and Gopalakrishnan 2009) present a conceptual framework to investigate the type and management of risks for retailing. The risk categories result from interviews conducted with retailer representatives. (Neiger et al. 2009) highlight a value-focused process engineering methodology for process-based SC risk identification from high-level modeling. (Venkatesh et al. 2015) establishes interdependencies between various risks across diverse apparel retail SC functions with the help of expert opinions using the Delphi technique, interpretative structural modeling, and Fuzzy Matriced' Impacts Cruoses Multiplication Applique a un Classment (MICMAC) analysis.
Simulation techniques – (Ivanov 2019) performed a study of product-ordering behavior in SCs with disruption risk in recover and post-disruption periods with discrete-event simulation. Moreover, the influence of “disruption tails”, contingency policies, and revival policies is examined. (Adhitya et al.) designed a structured methodology for risk identification and consequence analysis through dynamic simulation. Risks are detected by systematically generating deviations in different SC parameters and identifying their possible cause, consequences, safeguards, and mitigating actions.
Multi-Criteria Decision Making – (Mital et al. 2018) identify and assess SC risks across multiple product categories with cognitive maps and AHP based on SC risk ranking of 20 respondents from the retail sector. (Majumdar et al. 2021) use Fuzzy Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) to weight and rank risk mitigation strategies for sustainable clothing SCs. In preparation, 12 risks and 13 mitigation strategies are identified through literature review and expert opinion. (Bradley 2014) presents a risk measurement and prioritization method to account for characteristics of rare risk and analyzes the differences to frequent risks based on internal data sources such as ERP systems.

A Holistic View of the State of the Art in Adaptive Supply Chain

Based on the conducted structured literature review and a thorough analysis of the selected papers, a holistic view of the adaptive supply chain management is derived and presented in Figure 2. The holistic view is used to mainly answer the RQs. We viewed the selected articles taking into account four main aspects: Problem domain in the context of SCM, problem nature and objectives, the often-used data sources and finally adopted and/or developed solution techniques to solve these problems. Problem domain relates to the nature of common issues, that are addressed in the fields of A-SCM, SCRES and SCRM, according to our literature analysis. These are risk and resilience management, for example discussed in (Papadopoulos et al. 2017) and (Oke and Gopalakrishnan 2009), inventory management, strategic production management and supplier management (e. g. supplier selection). Under data sources, we differentiate between internal and external. Amongst the analyzed literature, internal data sources such as sales and production data from ERP and CRM systems were presented as the foundation for most solution techniques. However, because of **RQ 1**, we particularly focused on external data streams. Our findings point out social media as the predominantly highlighted external data source for A-SC in the literature. Social networks like Twitter offer a plethora of possibilities in this regard. First of all, these platforms can be used for communication, networking and hiring (Chae 2015). Furthermore, tweets can serve as a tool to shape demand and sense markets. Wide-ranging information on customers (e. g. experiences, preferences, and opinions) can be derived (Zhan and Tan 2020). Thus, risk management and event monitoring is enabled, even in real-time (Chae 2015). Google Trends is presented as another promising tool. The analysis of web search statistics allows to mitigate uncertainties by increasing the accuracy in demand prediction (Nikolopoulos et al. 2021; Yu et al. 2019). Further external data sources such as sensor, online news, and weather data were also marginally discussed in terms of building adaptive and resilient SCs. Problem nature and objectives describes the set of potential goals of an approach, categorized into strategic, tactical and operative. Strategic encompasses SC risk minimization and SC resilience maximization and is therefore directly related to the above-mentioned problem domain of risk and resilience management. Tactical comprises inventory level optimization like in (Sadeghi et al. 2014), material routing optimization such as proposed in (Rostamzadeh et al. 2015), and replenishment optimization, discussed e. g. in (Resat and Unsal 2019). On the operative side, we identified production efficiency optimization like in (Masoud and Mason 2016), anomaly detection such as proposed in (Nguyen et al. 2021), and demand forecasting, introduced e. g. in (Pereira and Frazzon 2021), in the reviewed literature. The final branch of the holistic view depicts different kinds of solution technique applied for the discussed SC issues. We separate between heuristic techniques, metaheuristic techniques (e. g. GA), ML techniques such as SVM and text mining, hybrid techniques, multi-criteria decision making (MCDM) procedures like AHP, and simulation techniques. The identification of such techniques is the particular focus of two RQs. In terms of approaches for event-based retailing concerns **RQ 2**, the included literature showed an enormous diversity in the applied approaches for various problems across the SC. Only MCDM procedures could not be identified in this context.

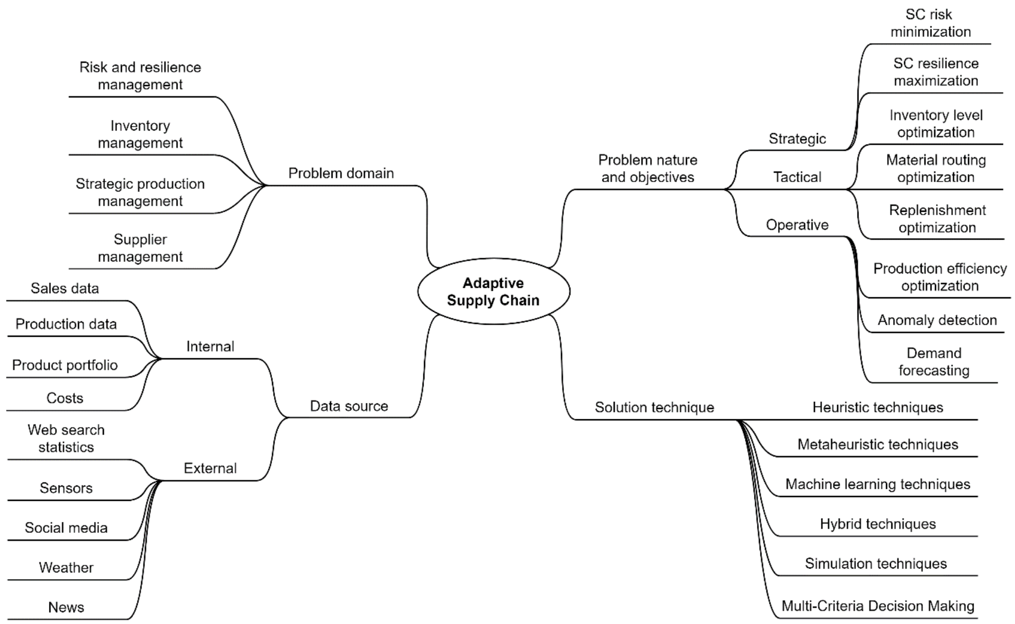

Figure 2. A Holistic View of Adaptive Supply Chain in Event-Based Retailing

Additionally, only one approach was assigned under simulation technique. However, the rest of the solution technique categories was equally present for RQ 2. Furthermore, the majority of the solutions utilizes internal data sources and is almost exclusively of tactical and operative problem nature. Here, the adoption of an external data source was merely found for ML techniques like in (Chu et al. 2020). On the other hand, **RQ 3** asks for approaches for event processing to react to possible disruptions and for risk management in general. First of all, all six types of solutions techniques are present for this purpose, including MCDM approaches like AHP and Fuzzy TOPSIS which can be applied for weighting and ranking risks and mitigation strategies. Nevertheless, metaheuristic techniques were just sparsely identified in this area. Contrary to RQ 2, the presented problems are mostly either of operative (event processing) or strategic (risk management) nature whereas the strategic branch was more dominant. For both fields, external as well as internal data sources are used. However, the latter is more prevalent.

Conclusion and Future Research Directions

In this paper, we performed a systematic literature analysis in the context of A-SCM to i) identify beneficial external data sources that can help with SCRES, ii) report on most common data analytics and optimization approaches that are used to address SCM in retailing industry, and iii) to get an overview of the appropriate solution techniques for event processing and SCRM in the retailing industry. Although the literature review is limited to ScienceDirect, the database offered a broad set of insights that can serve as the basis for further studies and prototypical implementations in the field of A-SCM, SCRES and SCRM. Our findings suggest that the majority of research conducted in the field of SCM heavily relies on internal data sources. This implies that extensive research and development efforts are necessary to investigate the integration and use of external data sources to support decision making processes. The findings also highlight the lack of adopting cloud computing technologies, which are powerful enablers to support near-real time data processing and optimization for A-SCM. Among the analyzed papers only a couple of contributions as in (Vera-Baquero et al. 2016) presented solutions that relied on cloud computing technologies. In fact, the integration of external data sources necessitates relying on cloud technologies that allow rapid development of fully integrated ML and optimization pipelines to present digital innovations in the field of A-SCM. For instance, our upcoming research effort will be concentrated on integrating ML techniques to analyze external sources such as news headlines and Google Trends to construct risk and trend models using cloud technologies. These models will be then integrated to develop optimization models to adaptively adjust strategic inventory management and production planning. The optimization models will be constructed taking into account the dynamics of demands and possible bottlenecks in supply chain.

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