Automated Supply Chain Risk Management with AI

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1. Introduction

Supply chains are increasingly complex systems within a rapidly changing environment. As a result, organizations are vulnerable to a myriad of risks, from geopolitical and economic to social and environmental risks, and many others. Organizations today are, therefore, presented with a constantly expanding list of threats that pose a danger to the achievement of their strategic goals. The development and practice of risk management strategies are of paramount importance to any company that is susceptible to the negative impacts of a potential disruption. Disruptions are now more frequent and severe than in the past and are capable of creating long-term damage. Therefore, the potential benefits for a company due to an improved understanding of its supply chain risks lead to operational resilience.

Automated SCRM is the next phase in the evolution of risk management approaches and is based on the deployment of advanced technology. AI can have a wide array of uses in SCRM, from additional predictive capabilities to automated decision support for the risk management team. Since supply chain risks can have a direct impact on the performance and successful operations of a company, understanding them can lead to prevention or, at the very least, early responses. This essay is structured in five subsequent chapters. In the second part, we will define SCRM, discuss the implications of potential disruptions, as well as provide and discuss a simplified SCRM procedure. This logical flow describes the 'cause and effect' of not treating supply chain risks as a disruptor of business operations. This chapter is finished by providing an overview of the key methodologies typically used when researching SCRM.

1.1. Background and Importance of Supply Chain Risk Management

Organizations have been subject to supply chain risks for as long as the concept of complex trading networks has existed. However, the number of drivers of modern supply chain risks and disturbances is continually expanding, and markets have grown ever scarcer. This trend has created significant challenges and has sparked a renewed interest in developing and adopting innovative and adaptive supply chain risk management strategies. Research also reports that superior supply chain management practices lead to greater organizational resilience, competitive and financial performance, customer satisfaction, and working behavior among members of the supply chain. Today's businesses are beset by a growing number of risks, from disruption, quality, and procurement threats to longer-term strategic and disruptive threats such as human capital shortages, market evolution, or industry commoditization. Each company faces its own unique set of obstacles that weigh on profitability and further exacerbate industry instability.

In late 2020, the COVID-19 pandemic unfolded, illustrating the massive impact of supply chain disturbances on business continuity for companies across the board and industries. In response, a significant percentage of the businesses over the last two years drastically adjusted their supply chain processes. Such supply chain disturbances can have disastrous effects on organizations that lack adequate supply chain risk management methods in place. A majority of organizations do not have the in-house capacity to remain knowledgeable about business, economic, and supply chain risks, which makes strategic planning to avert such issues nearly implausible. Recent studies highlight how the losses as a result of certain supply chain disruptions amount to various billions. In addition, inadequate management of threats could lead to loss of brand elevation, customer confidence, and adversely affect the reasonable expectations investors, customers, and the stock market have of a corporation.

1.2. Role of AI and Machine Learning in Supply Chain Risk Management

AI, particularly machine learning, can improve and even transform organizations' supply chain risk management practices. An advanced AI system powered by ML technology can foresee disruptions in global supply services, compute the risk of these disruptions, and recommend relevant proactive behavior. There is some debate in the emerging literature concerning AI in organizations. Some may argue that it will soon be vital to possess AI capabilities if an organization wishes to remain competitive, while others believe that cultural and economic barriers to AI investment need to be overcome in order to prevent AI from becoming merely a nice-to-have option for risk management. In either situation, worldwide SCM is altering.

One of the most revolutionary prospects is integrating AI solutions into a risk management framework. This is particularly intriguing in the field of supply chain risk management owing to AI's capacity to process vast quantities of data. By combining new datasets and processing data in new ways, AI can enhance the ability of firms to predict potential disruptions and dynamically assess risks. AI technologies such as computer vision-based analytics can mine and manage unstructured data to aid with early-stage risk detection. ML algorithms learn to distinguish between risky and clean channels by successfully identifying patterns and building distinct profiles that help in risk assessment through a variety of mathematical calculations. AI tools for supply management can update users in real time, offering significant predictive benefits over workspace options in terms of decision-making reliability.

2. Key Concepts in Supply Chain Risk Management

A supply chain is a network of organizations that receive inputs, add value to them, and deliver them to the next link in the chain or, ultimately, to the final customer. Generally, risk reflects the potential to gain or lose something of value. Risk can be categorized into global, local, internal, and external, and can involve different dimensions. In the context of supply chains, there is a substantial amount of research that discusses the potential risks and uncertainties this can generate. Risk to a supply chain can have operational, financial, and reputational effects.

It is expedient for the supply chain risk management tools to leverage the availability of vast data and computational infrastructure. As such, through data and process mining, areas of potential risk or disruptions can be identified and acted upon accordingly. Further, with cumulative data, data-driven forecasts can be accurately made. This would enable the co-design of a novel and proactive risk management tool for supply chains, which can reduce the level of risks within the supply chain. In the past year, the idea to develop closer integration between supply chain risk management and IT risk management was suggested in a direction of what is currently defined as an AI- and IT-enabled.

2.1. Types of Risks in Supply Chains

There are several risks that can emerge along supply chains. The following five main types of risks are proposed: operational, supply, physical, location, and demand. There is substantial disagreement in SCRM research about what types of risks to categorically define and discuss. Other definitions include four types of SCRM risks: natural disasters, like earthquakes, floods, and tsunamis; loss of supply; logistics and transportation; and global sourcing risks, like regulatory changes.

Natural disasters like tsunamis and earthquakes can be catastrophic, with lingering socioeconomic implications for the specific supplier area or location. Loss of supply, especially when the supply is critical, can halt production. Such occurrences are often covered in mainstream news. Logistics and transportation-related problems can lead to supply chain breakdowns or friction, like the expensive and immediate weather-related supply chain disruptions on perishables, causing lengthy shipping delays and increasing transaction costs for warehoused product distribution. Regulatory changes are the last of the four types of SCRM risk mentioned. Such changes can alter, sometimes irrevocably, the original basis for the selection and use of suppliers. For example, a regulatory change in the European Union could suddenly interfere with the migration of products across the area or increase transaction costs by leading to heightened security checks and onerous verification of product certifications. Such a change could potentially destabilize a cost-driven roof tile company operating in Spain that exports to Western Europe. Together, the types of risks in the SCRM spectrum enhance the complexity of SCRM. Different types of risks call for specific responses. It is intellectually stimulating to conceptualize the various responses for the benefit of supply chain managers in this field. Such exercises should help them focus appropriate resources or management interventions in order to mitigate these risks.

2.2. Traditional Approaches vs. AI-based Approaches

Supply chain disruptions pose a great challenge nowadays. Many firms still rely on their past experience to manage potential risks. Traditional approaches in supply chain risk management often use historical data combined with heuristic models to assess the probability of occurring disruptions and then develop a responsive plan. Often, they are pushed into working under constant pressure, and because of the urgency of the situation, hurried decisions are made. Hence, sufficient time for careful decision-making and for a structured empirical validation is not available. It has been observed that, due to the sudden and deep impact of disruptions, the controllability and adaptability of large parts of a supply chain are reduced, so the handling of the situation becomes more a matter of damage control. Therefore, it would be better to look at those who manage crisis processes and especially modeling crisis management, such as the police and army.

A strong shift is present in the concept. While traditional approaches in supply chain risk management can be described as reactive risk management, the trends suggest a need for more proactive approaches that reduce the probability, the impact, and the costs of disruptions in supply chains. Artificial intelligence approaches using predictive analytics and real-time data would help organizations in proactively managing supply chain risks. Therefore, the shift in the approach towards risk management is considered. The final output of the AI-based approaches would provide an opportunity to evaluate the additional benefits that could be achieved by implementing an AI-based approach. Although both traditional and AI-based approaches in supply chain risk management aim to improve decision-making, services, and business processes, AI-based approaches have added benefits. By using real-time data, AI can react promptly and synchronously with an increased supply chain risk situation. Hence, AI-based approaches are also focused on enhancing supply chain risk management and increasing the agility across the supply network.

3. Machine Learning Techniques for Risk Identification

Machine learning empowers AI systems to extract knowledge, i.e., to systematically identify the data that is needed for certain tasks and unravel the patterns indicating that the task is running into some effects related to risks occurring, such as the bankruptcy of a supplier due to a financial crisis, a cyber attack, customs regulations, political risks, and the like. ML algorithms are able to identify patterns or trends that explain or are associated with specific outcomes. Their ability to learn from data is suitable for the systematic analysis of vast data volumes and unprecedented volumes of interactions, as they can take account of complex, often non-linear interactions of regular and irregular disturbances, making it feasible for systems to operate smoothly in reliable and scarce mode. The various machine learning techniques are particularly able to handle risks of being misled by various disruptions emitting complex signals, often unforeseeable in detail and extent but compliant with systems' dynamics. Practically, machine learning already combines and selects various input signals to find evidence for threats forming part of high levels of disruption, asset failure, or characteristics of actors that become disruptions. The combination of evidence is possible across various types of input that lie in different types of domains that are now mashed together. Basically, machine learning works based on the consumption of data in large quantities and crowd-sourced data. This approach can be best exemplified by trust-based forms of crowd-sourcing. It is regarded as a techno-social vehicle by which combined actors could aggregate information through methods such as cryptography and sharing information. The learning techniques are numerous but can be categorized into three different methodological categories: supervised, unsupervised, and reinforcement learning. The first category, supervised learning, requires labeled data. The data is labeled when it is known which predictions, results, or outcomes should be associated with the data. In case the aim is to spot risks that may be indicated by low-frequency supplier bankruptcy cases, many bankruptcy cases need to be included in the labeled set. The techniques seek this class of examples and apply them to predict labels for new data entries. In contrast, the counterpart, unsupervised learning, works with non-labeled data. It recognizes that data naturally segregates instances, grouped according to subject distributions. Essentially, the techniques use statistical clustering techniques that search for subsets or classes, data belonging to which share some mutual characteristics. The third category, reinforcement learning, uses a very different learning approach employing interactions with the environment and waiting for this interaction to provide the monitor task's success or failure. This method is particularly relevant for organizations that operate in high or uncertain risk, where organizations must learn through the adaptation, assessment, and management of risks and their possible errors and learn from them. Reinforcement learning is especially important as the foundation for risk management given the expansion of dynamic risks. In seeking to manage current and uncover unforeseen future risks, organizations must learn to assess and adapt to risks dynamically. It is mainly for dynamic risk scenarios. In the following subsections, we discuss the various machine learning techniques already used.

3.1. Supervised Learning Algorithms

Supply chain risk identification is one of the main tasks in supply chain risk management. It addresses the probability of potential risks and disruptions occurring and the severity of their impact. One group of AI-ML algorithms with significant modeling capabilities focuses on identifying highly volatile signals and risks in supply chains with labeled data; thus, they are referred to as supervised learning techniques. Depending on the nature of the data to be modeled as well as the type of the outcome (or risk), different supervised AI-ML algorithms can be used for modeling. The goal of such models is to provide us with data-driven models or data patterns, based on which we can make predictions about future outcomes (or risk) by using several models and tools such as linear regression, logistic regression, neural networks, decision trees, support vector machines, etc.

The above algorithms have their own strengths against various kinds of data. For instance, logistic regression builds more reliable (as opposed to actionable) risk prediction models when the probability of the outcome belonging to a certain category is needed. Decision trees usually require less tuning of their parameters against data compared to neural networks and support vector machines; they can perform easily against categorical and binary outcomes. Neural networks have been successfully used for incorporating historical data and in identifying unknown and hidden patterns. One of the main advantages of neural networks over other models is that they do not rely on strong parametric and distributional assumptions of the outcome (or the risk). The basic tenet when building a decision tree model is to take continuous data or data with a large number of levels and then try to find a small number of nodes (hypotheses) that will model the data well. For incoming data, these nodes will be used to make a prediction. Logistic regression models are also widely used, especially when the outcome of the risk is categorical, e.g., binary or multinomial. Thus, the choice of model, for the most part, relies closely on the outcome as well as the presence (or absence) of historical (or labeled or past) data. By combining these tools, different models may jointly capture the symptoms leading to a more accurate assessment of the risk level compared to the employment of a single model. A higher accuracy can be achieved in risk assessments by fine-tuning the parameters and inputs such as features, outcomes, and subsets to achieve better prediction performance. When supervised learning models are used with historical data collected from a supply chain, potential risks can be identified faster with high accuracy. Although a great number of supervised learning techniques can be used for supply chain risk forecasting, the logistic regression model was chosen for the case study due to the availability of historical data, the binary classification of risks, and the good representation of patterns and relationships held by the variables. The case study findings identified that E. coli, salmonella, and dioxins were the predominant microbiological, biological, and chemical contamination hazards within the Brazilian agri-food supply chains.

One of the crucial limitations of supervised learning models is overfitting when they try to model the noise within data, which mitigates the generalization capability of the model on new, unseen data. The better the quality of data, the higher the efficiency of the model.

3.2. Unsupervised Learning Algorithms

Another way of risk identification is to use unsupervised learning algorithms, which do not require labeled data. They analyze a set of unlabeled inputs and classify them as per their features. There are some techniques of unsupervised learning such as clustering, anomaly detection, and dimensionality reduction, which are used in AI for supply chain risk management. These techniques help in the analysis of data without particular risk being defined. Previously, some of these risks may have been known as manageable but were neglected, leading to disruption if they occurred. By analyzing all data, it may be possible to identify the risks that are not generally seen. The current literature is reviewed to determine the effectiveness of using these unsupervised machine learning techniques for identifying risk in the supply chain. Two case studies are reviewed where machine learning has identified potential supply chain risks by examining patterns in real-time data. The aim is to reduce the impact of supply chain disruption from unforeseen risks by enhancing supply chain risk management, rather than mitigating all disruption, which is generally measured in terms of costs to rectify disruption after it has occurred. Due to an increased amount of data available through the growth in digitization, there is increasing interest in the use of unsupervised machine learning, particularly in the use of Big Data analytics in industrial applications, to assist manufacturers and other supply chain professionals in identifying unforeseen risks in the supply chain through data analysis. Many current studies focus on supervised learning algorithms that are trained on data pre-classified by risk to 'learn' to identify the risk. However, it is proposed to identify risks where there is currently no or low suspicion, rather than identifying risks currently known to be present. This research will concentrate on unsupervised learning, where potential risks have not been previously specified. The use of unsupervised learning for risk identification will be explored in detail in subsequent sections.

3.3. Reinforcement Learning

Reinforcement learning (RL) is a rather new approach in the supply chain risk management literature, yet a prominent approach in AI enabling supply chain decision-making. It optimizes a decision-making strategy by interacting with its environment and through trial and error learning. If a given action does not result in the intended state, then the agent receives feedback in the form of a reward and will adjust its actions to hopefully make the correct prediction. The RL agent executes required activities to appropriately react to sudden supply chain incidents. As a result, such real-time risk assessment can aid supply chain managers in making changes or executing contingency plans in case of actual incidents, leading to inhibiting or mitigating the risk. RL has been used in various supply chain applications such as warehouse management, production and inventory systems, supply contracts, supply chain design, demand planning, and supply allocation and transportation coordination.

Reinforcement learning can take into account the changes in the states or some of the new information about the rewards in an adaptive manner. Few attempts to apply these potential advantages of reinforcement learning for supply chain risk management have been reported. However, a major challenge is the scalability of the RL agent in an interconnected, large, and complex supply chain due to the combinatorial explosion of its state space and actions, while acquiring enough experience can be challenging given the scarcity of real incident data. The amount of data required and the complexity of models are among such major issues, whereas the adaptive nature of orders deserves attention to plan the response during and adapt the plans to the changing dynamics of the supply chain network. The integration of reinforcement learning is meant to enable real-time risk assessment by learning in an interactive environment and gathering information until it can make decisions or take actions. It can thus be leveraged as a complementary solution to fuzzy modeling and other machine learning approaches for risk assessment, risk prediction, and supporting decisions.

4. Case Studies and Applications

Georgiadou et al. offer a case study of how Enel, a multinational power company, utilizes blockchain technologies to support the transition to distributed generation for renewable energy. Blockchain and AI technologies reduce the time to respond to risk events and support the reconstruction of the operational behavior of the company’s supply chain. Manzi and

Caputo present a case study to demonstrate AI application in risk monitoring in the EPC industry. An AI-based risk management system featured decision-making support tools that four large EPCs developed to address a lack of resources for urgent risk management and reduce the quality and accuracy of risk assessments, which created a need to improve the EPC companies' resources for risk management.

Manzi and Caputo discuss the relevance of AI for natural events and the inclusion of topic analysis in risk evaluation. Marasco et al. present a case study application of the DPS supplementary approach for Automated Supply Chain Risk Management system development by considering one industrial and three multi-industrial Italian companies. The case is decomposed using the supply chain characteristics. Furthermore, the paper discusses the main challenges of the four companies—associated with the COVID-19 outbreak—that enforced the innovation of their SCRM strategy and procedures, showing the commercial benefits linked with a correct risk analysis and demonstrating the financial implications of adopting preventative measures in the supply chain. Yang et al. present an industry response to the SCRM module, Risk Management. The module focused on current risk management issues and solutions after the COVID-19 pandemic, recruiting an external speaker. In this case study, Dr. Castro presented a business model in Italy and the main supply chain risks of perishable products. The students were given the opportunity to compare their newly acquired knowledge in SCRM from the course with the direct experience during the pandemic.

4.1. Real-world Examples of AI in Supply Chain Risk Management

Organizations across the world use AI to manage supply chain risk and improve performance. The following examples are fractured across different industries and mostly come from the US and China. What these cases have in common is that they take on a stance of operational resilience, where organizations embrace the fact that any supply chain will occasionally run into trouble and put in the effort to prepare for it. This preparation involves identifying vulnerable points in the network and investing in increased responsiveness to avoid and recover from disruptions. AI is a crucial tool in this fight due to its ability to separately identify and predict various types of risks in an adaptive manner. Moreover, these examples show that, for organizations to adopt AI, the real challenge often lies in aligning organizational culture and business processes. Deciding on which outcome to optimize for is less of a problem when the AI solution suggests adjusting the available set of decisions rather than making the decisions themselves.

Much of the US's supply chain for manufactured goods, as well as for retail, runs through transoceanic container ships. If an electronics company exports its products to be sold abroad, chances are they will travel through the ports of LA and Long Beach in Southern California. These ports work constantly in a mesmerizing, 365-days-a-year revolving dance of dozens of ships carrying cargo from Europe, South America, and Asia that upload and download their containers with the swiftness of an assembly line. The efficiency and astounding level of coordination required to keep trading moving at an almost 24/7 pace can mask the complexity and vulnerability of these ports. When the precise velocity or sequence of some part of the complex system fails, the cogs of the whole operation grind to a halt and set off a ripple effect in trading across the US. As it turns out, this ease of disruptions has been causing the US ports to be some of the worst in the world for logistics performance, with an estimated cost per hour of unexpected delay. In order to circumvent this problem, sea ports are better off quickly prioritizing recoveries from disruptions to mitigate the impact of unexpected stoppages. To do so, a port authority teamed up with a local university to find out what kind of disruptions hurt the ports the most and on what kind of response they should best focus. By continuously documenting events over a period, they found that unexpected rail delays, bad weather, and missing truck drivers cost them the most. Based on these results, the port could either rearrange ships to allow the affected rail carriers to play catch-up, send the excess cargo someplace else, and then maximize the amount of time cargo travels by rail out of the port, or review logistics operations.

5. Challenges and Future Directions

A few challenges need to be addressed when AI and automation are leveraged as part of automated supply chain risk management. From an organizational perspective, the collection and sharing of data could lead to data privacy issues. Furthermore, the application of AI in supply chain risk management can lead to algorithmic bias. Moreover, AI requires a sound technological infrastructure for effective implementation. Eventually, AI technique integration in supply chain risk management is also limited by the lack of availability of the right expertise.

To leverage the full potential of AI, more research is needed to understand how AI as an enabler can assist in supply chain risk management in addressing the systemic interconnected environment. Some emerging trends that have not been explored in relation to SCRM, and represent future research directions, include the application of autonomous control to manage supply chains and AI in risk management. Techniques and methods for SCRM to incorporate emerging trends into practice are still in their nascent stage. To address these challenges, the following recommendations can be made: AI-driven SCRM is a function driven by human intervention that ensures that ethical coding and the code of conduct do not compromise the quality of the system. The processes are underpinned by the mechanisms used to develop and capture the knowledge in the system. The opportunities that AI can bring to organizations with its enabling practices have practical significance in shaping their strategy. AI, particularly neural and deep learning, is used in a number of practice-based applications, but to a lesser extent in supply chain risk. Future organizations seeking to apply AI in their management activities should take into account the research strategy for SCRM implications. The concerns of ethics and accountability are of utmost importance, given that AI and automation are gaining popularity in the creation and management of codes and rules. An optimum balance of AI and people is increasingly relevant to organizations as they strive to strike a balance between high adaptive resource allocation or control and the desired outcomes. This indicates a preference for technology infrastructure that supports rapid innovation while also considering responsible technology.

5.1. Ethical and Legal Considerations in AI-driven Supply Chain Risk Management

AI has enormous potential – also in terms of supply chain risk management. However, at the same time, the use of AI always bears certain risks and critical issues. Data privacy and the standards for the processing of personal data must be respected as a minimum; further issues concern the interpretability and explanation of results, the possibility of controlling the AI, and the consequences of discrimination resulting from the use of AI. As companies are using AI solutions for more and more decisions and risk rankings, the question of the ethical correctness of their use becomes all the more pertinent. After all, organizations are ultimately before a judge when something goes wrong. Moreover, a growing share of consumers are encouraging ethical AI by making ethical behavior a part of a purchasing decision.

Regarding AI solutions for supply chain risk management, the black-box character of some approaches, the large number of possible influencing factors, and the related reduction in interpretability make the issue of explaining AI results more pertinent. Bias and fairness should also be a major concern when using AI for supply chain risk management, as decisions based on arbitrary or discriminatory criteria may result in damage to various stakeholders. From a legal point of view, the decision to use an AI solution brings several legal challenges, not only in terms of compliance with data protection and restrictions, but also in terms of civil law. In particular, it raises the question of whether an automated decision with potentially relevant consequences for a company's business is legitimate. Failing to address these issues in advance could lead to significant liability for businesses. To ensure ethical conformance, regulation and compliance are extremely important and have to be evaluated accordingly. Furthermore, in the case of differential treatment and the usage of personal data, ethical considerations are crucial. Compliance with data protection aspects does not automatically confer ethical correctness. Therefore, the legal and ethical aspects of the usage of consumer or partner data will be important.

6. Conclusion

The supply chain environment has become more complicated, not least due to the ongoing pandemic and economic crises, so has supply chain risk management. Traditional supply chain risk management methodologies do not provide an adequate response to today's managerial challenges. Organizations must use their adaptive capacity to increase their resilience and long-term viability, while incidents will continue to emerge. This fosters the case for more advanced methodologies. This essay has introduced the case for employing automated supply chain risk management enabled by AI as a consequence of the growth in outsourced, multi-tiered supply chains and the increased capabilities of AI. Machine learning may be used to identify patterns in the data and automate the system. Although AI may not replace humans, it can significantly assist in the early detection and response to risk.

AI methods, including machine learning, can be used for both pre- and post-event detection of risk events. Although improving pre-event detection in supply chain risk management methodologies, AI and machine learning can have a significant impact on re-establishing post-event supply operations. However, in order to embrace the AI-based approach to increasing supply chain resilience, the system must be functional and relevant. No system can ever perfectly forecast all prospective future threats; therefore, industries need an alternative approach that holds value. Finally, it cannot be emphasized enough that ethical considerations must be at the very heart of developing and employing AI in the supply chain risk management process. Predominantly, these must focus on the importance of privacy and the potential for AI prioritization of short-term financial considerations at the expense of workers. Currently, it is the responsibility of corporations, as well as the governments that regulate them, to critically evaluate these AI-based supply chain risk management methodologies and implement them effectively and responsibly. Failure to do so will not only place further unnecessary pressure on an already over-encumbered system but may also deter future widespread acceptance. We hope this essay provides the foundation for further research and engagement in the expanding area of AI-enabled supply chain risk management.

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