AI-Powered Supply Chain Resilience

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1. Introduction

Supply chain processes are complex, global, and unpredictable. Over the past decade, advances in AI technologies have enabled companies to rethink their traditional supply chain strategies and consider paradigms leading to more adaptive and responsive supply chains. As such, many recent works have shown a growing interest in the development of AI-driven supply chains. When it comes to addressing resilience quantitatively, the proposed solution can generally be categorized according to the level of information available to supply chain actors. If historic sales data is available, AI models enable the subjective process to be semi-automated, feedforward, and extrapolated from the training data. The bottom line is that AI reduces uncertainty by increasing business information and supports decision-makers in making more profitable arrangements.

The use of AI can prevent or limit global supply chain disruptions. In this work, we analyze some of the possibilities for using AI in developing resilient supply chains. We discuss the possibilities to build supply chain resilience using AI technologies such as planning and real-time simulation, which potentially enables visibility and flexibility. We also look at the literature on AI-driven supply chains and how AI can actually visualize the supply chain. Moreover, in the following parts of this work, we discuss how AI can enable a more flexible supply chain. Next, we focus on how AI can be implemented in supply chain planning and control to better respond to, and even prevent, uncertainty and risks. Although data-based AI control systems and neural networks are promising, they have not yet proved to be a panacea because they are difficult to understand and can sometimes exhibit unexpected results.

1.1. Overview of Supply Chain Resilience

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Figures and forecasts show that supply chain disruptions remain a critical and increasing risk, thereby calling for the need to enhance supply chain resilience. Resilience is defined as the ability of a supply chain to anticipate, prepare for, respond to, and recover from disruptions with a minimum of disruption to time, a minimum of loss of function, and a minimum of increased expenditure. Critical points of view that are presented in this definition are the anticipation and disaster preparedness.

Some of the factors contributing to supply chain vulnerability include market attractiveness, industrial and economic pollution, market fluctuations, product life cycles, organizational dynamics, globalization, business relationships, natural events, communication and supply chain support infrastructure, human factors, process design and documentation, changing regulatory requirements, and supply net fragmentation. Resilience is defined differently based on operation, organization, and supply chain. Furthermore, operational resilience is one step of an overall supply chain resilience framework that shows how the operations of a supply net impact the overall net resilience. Operational resilience is the ability of an operation to achieve or regain its fundamental purpose or function or the ability to maintain, or return an operation to, previously determined levels of performance so that the goals of the operation can be met again. The continuation of operational performance, even in anticipation or during operational adverse events, has become very important.

Operating in a dynamic environment, including rapid technological developments, societal changes, and the increased occurrence of weather-related events, most of which have global impacts, makes the use of long-term planning uncertain and leads to immediate demand for operational resilience. The measures to quantify and maintain the resilience of the operation are becoming ever more critical, with resilience engineering capabilities and limitations rapidly developing. Operational resilience is based on three main areas, including timing flexibility, process flexibility, and recovery capability. A framework based on integrated resilience consisting of three dimensions of an operation, a partnership, and a supply chain has been introduced. Strategically, resilience is always higher than an operation and a partnership for integrated resilience, but the three are interrelated. The increase in these performances respectively enhances the resilience of the overall supply chain. Two tools were also proposed: SupplyNet Resilience Assessment and Extended Resource Availability Analyses.

An alternative approach is to take the collaboration around measures such as lean and agile supply chains and extend this further to look at the possibility of an adaptive and therefore resilient supply chain strategy as it moves closer in its conceptual model towards a truly collaborative supply chain. Resilience approaches have been considered, particularly in the context of regional and global supply chains. Standard resilience, which focuses on engineering and some operational aspects, is not easily transferable to supply chains. However, though supply chain resilience is a constant topic of concern during the last decade, examining less new research presents practical steps that can help to ensure supply chain resilience.

The creation of adaptive network architectures in which data, cash, and information flows around a network means that, historically, supply chains and indeed networks of all types across political, economic, technological, and social spheres, and regardless of their business, economic, and/or political aims, have, since commercial activity began following war, uncertainty, natural disasters, and sudden political change.

2. The Role of AI in Supply Chain Resilience

Given the uncertainty and disruption seen over the past couple of years, resilience has risen to the heart of how enterprises manage their supply chains. A new wave of thinking is looking to leverage powerful artificial intelligence to bolster these efforts. At its core, AI can better enable predictive or reactive interventions based on detailed and historical data patterns. In particular, there are three key aspects of AI that have relevance in driving supply chain resilience: Inductive intelligence: Uses machine learning and predictive analytics to uncover insights and optimize models from past and current data to discover where the best leverage is present in the end-to-end supply chain. Directed intelligence: Automates real-time decisions at crucial intervention points. Coalescence intelligence: Similar to directed intelligence, but identifies synergistic models of intervention that, when executed together, produce a more favorable result. Indeed, multiple applications of AI are being developed and deployed to enhance supply chain resilience by augmenting decision-making and reducing the impact of disruptions. One of the area priorities in the face of disruptive events can be improved visibility into existing or potential bottlenecks and their potential consequences along the supply chain, to establish scenario planning and contingency policing. AI can also be used in the management of potential responses – be these financial hedging, holding extra inventory, having a well-practiced approach to demand shaping, or leveraging multiple modes of transport – that can improve resilience to supply or demand risks. AI can improve predictive delivery estimates and/or order-to-shipment feasibility by automating real-time track and trace and aligning delivery plans to machine and process schedules. While globally many industries are leveraging AI-driven supply chain resilience tools more actively, given that the advantages will vary by industry and organization, critical operations need to handcraft resilience strategies based on their business model and market dynamics plus profit versus cost of protecting profit.

2.1. Applications of AI in Supply Chain Management

AI technologies have wide-ranging applications in supply chain management. Inventory management, order processing, and logistics are three key areas within supply chain management in which AI tools are used in combination with other digital technologies. AI-based predictive analytics tools can help companies forecast demand and mitigate the risks associated with unpredictable dynamics in the supply chain environment. AI can also be used to automate tasks like planning, optimizing, monitoring, and controlling to improve the efficiency of operations. In this case, AI is used as a supportive technology, such as robotics, to perform repetitive and dangerous tasks for operational efficiency. The application of AI in supply chain management has delivered significant business value to companies. Integrating AI and machine learning into supply chain strategies brings about advanced technologies and capabilities, which enable organizations to optimize their supply chain using near-real-time data, mitigate supply chain risk, and improve forecasting accuracy and speed, among other benefits. Challenges facing organizations looking to deploy AI and machine learning in their supply chains include integration with legacy systems, data that lacks standardization or sufficient quality, strategic adoption concerns, and risks associated with AI-generated output.

Most of the applications of AI in supply chain center on improving the efficiency of supply chain functions by performing those functions with improved accuracy and/or speed. This allows organizations to improve inventory turns, leading to the reduction of inventory costs, reduce stockouts, thereby improving service levels to customers, and/or reduce logistics costs. In this section, we describe the technology, how it applies to a supply chain function, the benefits and challenges of employing the technology, and provide a short industry or company example.

3. Machine Learning Techniques for Resilience

Supply chain resilience argues the importance of AI techniques for enabling data-driven approaches leading to predictive insights driving proactive decision-making. Table I lists various machine learning techniques that are used to achieve the goal of supply chain resilience. Each row outlines the machine learning technique or model, the strength of a successful application, a scenario in which the machine learning method is applied in the supply chain context.

3.1 Predictive techniques for resilience A number of predictive modeling techniques can be used together with classification models to predict the resilience of a supply chain. Many supply chain performance measures are, in fact, continuous rather than binary, and can best be predicted using regression models. Model pollution is also an important issue for supply chain resilience to be ensured by clustering historical data, effectively identifying potential penalties or adverse events. The resilience of supply chains can be improved through enhanced risk assessment, reducing both the likelihood and impact of disruptions. Marketers can also gain from improved revenue predictions. Trend and seasonality identification improve predictions by allowing algorithms to use different approaches for different points in time, such as the amount of data one customer buys over time.

In contrast, trend and seasonality do not influence direct cash flow predictions. However, they do guide the analysis of the vast majority of classified suppliers. Most techniques were shown to perform well in practice. There are some barriers to broader commercial adoption of machine learning. There are algorithmic fairness and interpretability aspects that may limit the usefulness of the approaches. Concerns have been raised about algorithm bias, difficulty in predicting the effect of new policies on systems, and issues of model transparency, data privacy, and security when analyzing and using the resulting predictive outcomes.

3.1. Supervised Learning for Demand Forecasting

Supply Chain Digital Resilience Monthly prevalence of COVID-19 in India 3. Methodology 3.1. Supervised Learning for Demand Forecasting One of the earliest and most impactful applications of AI in supply chains is demand forecasting, which is the process of using historical data and known exogenous influencing factors to make better predictions of the quantities and timing of future demand. The history of sales data is often used for this purpose. Demand forecasting traditionally involves the use of statistical tools and time series methods. Classical time series methods assume a lack of any further relationships for time series data beyond those that have been directly measured over time. Statistical models like causal models are employed to capture the influence of exogenous factors or predictors on the demand. Models in statistical algorithms are built from the data rather than any underlying knowledge and heuristics. The statistical model leverages the underlying statistical behavior of demand data to identify patterns or groups of customers, which can help improve forecasts. Learning from data is an application of AI that requires a learning dataset to capture the relationships between input and output variables. Suppose a dataset of the historical sales is available to train the model to forecast future sales; supervised learning algorithms such as linear regression, decision trees, and their ensemble models can capture underlying patterns to improve demand forecasting accuracy. Some commonly used demand forecasting models include ARIMA, Exponential Smoothing, Causal Models, Gradient Boosting Machines, Single Exponential Smoothing, and the regression models based on supervised learning. Each model has its own strengths and limitations. Such models assume that historical orders provide insights into future orders in a stationary state and do not capture factors leading to changes in consumer behaviors, market trends, and other influences that consistently change the underlying demand, which may challenge the integrity of planning results. Model-based approaches may also be suboptimal in coping with larger spatiotemporal dimensions. As a result, companies have recognized the added value of improved demand forecasts by supplementing existing forecasting software with machine learning algorithms that can bolster their traditional forecasting accuracy. In this case, the selection of algorithms to improve the demand forecast depends on the time horizons defined, the organization of data, and the challenges encountered. Given the variety of approaches and datasets used in research, both classic statistical and modern machine learning algorithms are applied. The results can vary significantly based on data quality, granularity, and length of the available dataset. It is important to mention that with an increased number of external factors influencing the demand, traditional approaches were not able to keep up, hence leading to a spike in the use of predictive models using machine learning algorithms to predict the demand, with the increasing popularity of including artificial neural networks in order to improve the results, which is considered a future point of research. In order to improve results, the multiple response metal shrinker approach can be used to include model ensembles significantly. Therefore, using external parameters and machine learning in research is consistent with achieving the research objective.

4. Case Studies in AI-Driven Supply Chain Resilience

This collection of AI-driven strategies to achieve supply chain resilience features four case studies from a diverse range of industries, including pharmaceuticals, automotive, retail, and MLCC parts. The studies in this section illustrate the broad range of sectors in which AI can offer business process enhancements and underscore the importance of using AI to enable continuous learning and adaptability for an ever-changing world. In each study, we detail the challenges the company was facing prior to deploying AI, outline the integrated supply chain and risk management strategy, partition our AI tools and technologies, and summarize the outcomes and impacts. Each case study in this section also includes our reflections and lessons derived from integrating AI in the supply chain space. Throughout this special issue, there are examples of the use of AI to improve insights and achieve resilience in supply chains faced with change, risk, and disasters, from pharmaceuticals to MLCC production. Here, we provide four stories from the field. One company runs an immunization supply chain documenting the difficulty of protecting vaccines from temperature excursions. Another company makes cars and has numerous tiers of suppliers. They worry about how to restart their operations during COVID-19 after pausing production and sorting out their suppliers from bankruptcy. A retailer is facing large demand variation across stores. Another company delivers electronic components for white goods, cars, industrial products, and defense systems. They cannot predict demand changes in time to avoid delivery failure, so they prioritize orders. In these examples, we focus on the following questions: What was the company doing before AI was used? What did they do about COVID-19? What were the outcomes and impacts?

4.1. Lessons Learned from Real-World Implementations

The two in-depth case studies highlight a number of themes and insights for others wishing to implement AI in their own supply chain and logistics contexts. These studies revealed a comprehensive set of advice and lessons for executives, project managers, and other leaders in charge of implementing AI-powered supply chain resilience solutions. One important point is the high relevance and significance of data infrastructures and data acquisition, which is challenging in several different ways, including the need for garage-based methods. Furthermore, this case study showed other issues and difficulties, in particular the necessity of remaining patient, the insights from the suspected leaders, the strategies concerning the team's dynamics, the documents that the team is working on, and obstacles. Moreover, this case shows the potential role for public ethical guidelines, the management attention required, and the necessity of spending time on cost-benefit evaluations.

Starting from the executive summary and continuing through the case studies, a number of recurring themes, lessons, and managerial implications become apparent. In general, many of the difficulties are deeply embedded in organizations, such as a resistance to technological change, the need for strong and centralized leadership, the importance of strong incentives for employees, and the need to focus on recruiting or developing AI talent through ongoing training and professional development, based in local, regional, and/or internal AI research hubs. Moreover, the unprecedented advancements in AI require a strongly iterative adoption, not a big-bang approach, but a trial-and-error; a learning-by-doing approach. The in-depth case studies invite ongoing members of workshops and other audiences to develop their own tools to evaluate the operational, strategic, control, decisional, or any decision of the ROI impacts, in order to enable the assessment of the developed AI decision-making methods. The in-depth case studies also elaborate on some of the principal challenges and solutions applicable in installing and evaluating the AI solution in e-Science.

5. Future Directions and Emerging Trends

Some new and advanced data sources combined with advanced analytics such as AI and the Internet of Things could also have added new dimensions to enhance supply chain performance. The integration of AI with other technological advancements could indeed accelerate data-driven and trust-based supply chain initiatives. While the AI-focused study of supply chain resilience has been relatively unexplored, it is expected that increasing emphasis on ethical responsibility and sustainable practices across industries would also translate to the AI-powered supply chain. AI sustainability models could be used to evaluate the environmental impact of various supply chain strategies. Of course, multiple challenges could emerge in the future of the AI-focused supply chain. The increasing complexity of supply chain structures and interconnectivity necessitates data handling that respects consumer privacy and meets high standards of security. Along similar lines, the advent of more rules and regulations pertaining to AI could impede design innovation. Strong data protection laws in certain countries could prevent thorough supply chain visibility, which is a compelling instance of the ethical and legal friction associated with the AI-powered supply chain. Amidst these challenges, it is important to consider directions for the future of the AI-powered supply chain in organizations as they design, develop, and deliver resilient supply chains. As has been the case in the past, organizations will invariably have to adapt to new, unforeseen, and unexpected disruptions as well as the changing face of the consumer. Creating an innovative and resilient mindset in an organization will enable them to be adaptable when facing the market and other disruptions, and a commitment to technology and innovation could deliver an advantage in empowering organizational cultures to anticipate and circumvent future challenges. Exploiting and investing in emerging technologies like AI shows that an organization is strategically positioned and focused on the future, as these technological innovations can be used to maintain a customer-oriented focus as part of the broader people-process-technology strategy. Furthermore, with the AI market showing substantial potential, continuous investment in AI systems will be necessary, as these systems ensure competitive advantage is sustained and reinforced.

5.1. Ethical Considerations in AI-Driven Supply Chain Management

While AI and related technologies have the potential to greatly improve companies' operations and unlock unexplored opportunities in the end-to-end supply chain spectrum, a number of ethical considerations need to be taken into account in light of the particular roles of supply chain activities. Some of these considerations are addressed through basic principles set forth by general guidelines on AI use and development, yet several issues arise after considering AI in the context of supply chain management.

Bias in AI is a well-known set of problems related to imbalances in volume and type of the data used to train algorithms, especially when data is not representative of the general population. In supply chain management and logistics, this can lead to unbalanced predictions, which in turn can make firms' decisions unfair. Thus, algorithms used to manage the supply chain should be implemented with data that are consistent and representative across the operating contexts. In this light, transparency and accountability of the data should be key for implementing ethical AI-driven solutions. In addition, other hidden biases can affect managerial control when implementing AI tools in supply chain management. For example, the use of AI solutions for surveillance via supply chain visibility tools and delivery vehicles for real-time monitoring of operations can create tensions with employees' expectations of privacy, particularly if personalized data is collected.

Finally, the appropriate balance of automated and human-controlled processes needs to be managed in order to avoid unemployment. In some cases, in fact, AI-driven systems for worker monitoring can be less risky than existing solutions and can explicitly be developed to be less damaging. This requires the development of standardized and statistically significant data collection about the effects of the technology on employment. In addition, AI solutions for human resources should respect the possibility of human decision-making intervention. A step towards fairness is the inclusion of a human-in-the-loop system that can help avoid incorrect interpretation of the data and results. Solutions developed on the basis of this approach, allowing for business ethics considerations, can achieve dual objectives, making operations more efficient and ensuring a fairer treatment of all stakeholders. Fairness in AI needs to be addressed at two levels: at the application level and at the entry point. In this respect, it is urgent to develop guidelines and frameworks for ethical AI in the context of supply chain management and logistics, with specific attention to the fairness aspect.

6. Conclusion

This essay discusses several insights on AI-powered supply chain resilience as follows. Given the increasing complexity and fast-changing dynamics of supply chain management, AI plays a critical role in transforming the design and operation of resilient supply chains. Forward-looking companies should make adaptive strategies the mainstream to prevent and hedge against future crises, which require utilizing the potential of related emerging technologies. They should invest strongly in technologies and big data but should not overlook the increasing ethical considerations. For academic research or enterprise tactics, one critical point is to go beyond the current review and disclose those emerging ethical, social, and environmental questions about the storage, sharing, use, and repurposing of big data and related technologies in designing supply chain resilience.

In summary, recent advances in AI have transformed different industries, including supply chain management. As the international business environment becomes even more complex and volatile, organizations are expected to further explore AI's transformative potential in supply chains. Furthermore, the post-COVID-19 recovery process is seen as a phase that allows companies to invest in adaptive strategies to foster an even faster recovery process. To do so, organizations, regardless of the size or sector they are part of, are expected to invest in different types of technologies and AI-driven mechanisms to create resilient supply chains. AI technologies such as machine learning and other emerging technologies will be crucial components of being ready to adapt and become more competitive in the market. Thus, new research opportunities are expected to emerge related to AI-powered adaptive strategies for supply chain recovery processes. We encourage authors to systematically explore this field in the future since only a few studies have analyzed adaptive strategies for futuristic supply chains or those that shed light on developing nations. Given the interconnected nature of technology and supply chain management, such an investigation will definitely attract interest from academic communities and business practitioners alike.

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