Predictive Intelligence in Supply Network Dynamics: A Data-Driven Approach to Operational Analytics and Disruption Forecasting

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1. Introduction

In an effort to streamline logistics and support functions, industries are leaning heavily towards supply chain analytics. The installation of sensor-based systems, RFID tagging, IoT, etc., augments the tracking of products and intensifies available historical data. In this connected era, the application of AI decouples the traditional methodology of managing the supply chain. The classic demand and supply chain theory was a push-based system, whereas the proliferation of AI can lead to pull-based systems that would preempt the urgency of decision-making. The integration of heterogeneous sensor data produces value creation through a variety of services, which is based on the automatic adoption of contextual and predictive data analytics in real time. New data-driven businesses broach the traditional supply chains, regardless of the industry sector. Industries desire advanced technologies that would handle big data, data analytics, data-driven decision strategies, integration with business analytics, and enterprise analytics. Various industries face different challenges, but the amplitude of industrial challenges accentuates the necessity of techno-commercial innovation for academics and practitioners. The new research dimensions offer solutions for managing the seamless data flow to maintain real-time decision-making in dynamic environments. This work will be useful for data, system, and business analytics professionals, as they provide techno-commercial insights, industry 4.0 business scenarios, and their real-time data management demands. This research work discusses in particular how suitable technologies can be and are applied in supply chain analytics to address increasing complexity and to enhance supply chain performance.

1.1. Background and Significance

Supply chain analytics has a long history of development. As early as the 1940s, DuPont fixed the minimum goal of the management activity to maximize production efficiency by developing three mathematical models. As the importance of logistics and supply chain has been recognized by scholars and practitioners, more and more innovative operational strategies, theoretical research, and models have emerged, such as the discount transportation model and endogenous parameter model. An increasing number of online and brick-and-mortar companies started to apply big data technologies to their decision-making to manipulate supply mass customization, supported by big data and cloud computing services. The increasing significance of supply chain cost because of globalization and the pressure of social responsibility has been emphasized. The organizational environment has become more complicated, so timely and reliable information is significant to both top managers and general managers for making operational strategies and aligning supply chain operations with organizations' strategic goals.

The informative decisions of supply chain executives can lead to enormous savings in both time and money. Linking decision actions to profits absorbs management's attention. There is evidence demonstrating that the application of big data, business intelligence, and analytics technologies makes business terms more complex, but adopting technologies is vital to remain competitive in today's business environment, especially in supply chain management. Efficient supply chain analytics appears as a fundamental aspect of shortening delivery times, decreasing inventory levels, and overall logistics costs. Since enterprises cannot afford to be less efficient than their rivals, all these issues can directly contribute to companies' success. Several studies have analyzed the role of different analytics in supply chain, such as predictive modeling, risk modeling, outlier detection techniques, and business rule analysis for retail sales. Furthermore, supply chain analytics has shown to be an attention-drawer for commercial industries. Many firms have currently established their analytical teams. Domain-specific analytics in supply chain have turned out to be a topic of interest for both practitioners and researchers. In addition to the improved field application of supply chain analytics, large-scale IT systems continue to collect and generate massive data sets over time. The size of one of these data sets can often be hundreds of gigabytes or more, and they must be managed in a distributed way and treated with an analytics computing model in real time. Further investigations can also focus on data streams. On this basis, recent attention is on different directions. In one direction, researchers are increasingly aggregating analytical and computational power to perform real-time analytics that drive supply chain decisions. Such analytics is essential because it can greatly improve the value created by supply chains and provide the engineering knowledge to support advanced decision analytics. Hence, these analytics can enhance supply chain performance. In another direction, researchers are fine-grained and perfect the attributes of data to improve the application performance of the model. In supply chain, advanced control and analytic systems are applied to modeling, design, and synchronization of local agents comprising the supply network. Recent large-scale optimization work has appeared at the intersection of supply chain optimization and analytical systems.

1.2. Objective and Scope

This report presents a study whose objective is to investigate the concept, importance, and managerial relevance of the integration of artificial intelligence technologies in shaping the future of data analytics-based supply chain management. Although the application of AI technologies, such as machine learning, in supply chain analytics and management has rapidly expanded, the frontier research that focuses directly on understanding the role of AI and its current and future impact on supply chain analytics is timely and relevant. The scope of this study includes the application of AI technologies in driving better supply chain analytics. We direct our attention to four aspects, as follows. Firstly, the scope of data to be mined. That is, how AI and its technologies could be used to analyze new and growing types of unstructured and non-structured data in a supply chain context. Secondly, the type of methods that practitioners and scholars could use to enable AI-driven analytics. This aspect limits our inquiry to methods to be used for analytics in-house or in facilities. Thirdly, how AI-driven analytics could offer new ways for companies to perform performance measurement and benchmarking. Fourthly and finally, we are interested in the impact of companies, from the point of view of companies that provide solutions for claims management that spin off into various sectors targeting different types of clients. The outcomes of this study are intended for multinational companies, mainly those in consumer packaged goods and its sectors which have large manufacturing, distribution, or logistics operations. Furthermore, artificial intelligence has the potential to dramatically enhance analytics capabilities in all sectors and industries, not just supply chain management.

2. Fundamentals of Supply Chain Analytics

Supply chain analytics, in simple terms, refers to the application of analytic tools and techniques for improving decision-making and performance within a supply chain. A supply chain is a network of organizations that collectively converts raw materials into finished products, distributing these products to the end market, and finally delivering them to the ultimate consumers. Supply chain systems may involve a range of actors such as suppliers, manufacturers, distributors, retailers, and third-party service providers. The exchange of information and funds between these organizations and the physical movement of the product is made possible. In any given time and location, these processes work simultaneously or concurrently.

In the realm of supply chain management, decision-making is becoming more complicated because of increasing demand uncertainty, shorter lifecycles, greater reliance on supply chain partners, increasing global competition, and complex product architectures. Analytics are important for data-driven, fact-based decision-making, and most of today's supply chain strategies are built upon better information visibility and responsive decision-making results from good supply chain analytics. Analytics can be used to answer questions concerning what has happened, what might happen, what should be done, and how to adapt future behaviors. Indeed, increasing volumes of data combined with advances in computing power and algorithmic capabilities are driving a growing demand for the use of tables, charts, graphs, dashboards, and alerting systems covering various supply chain domains in meaningful ways.

There are at least six analytics philosophies and techniques that bring both advanced and breakthrough thinking to real distribution, multinational, reverse, and other practice-based supply chain systems. These techniques include statistical and correlation analysis, pattern recognition, process mined model development, predictive modeling, optimization, and simulation systems. These techniques can be used separately or can be utilized differently in phases of hypothesis, model, and concept development and experimentation. There is no argument for the use of one approach over another; varying the level of accuracy and breadth are the major differences. Ultimately, depending upon the downstream and upstream needs of the firm and the level of strategic or tactical decision being supported will be the real determinant as to which type of tool or philosophy to use. The time it takes to go through the modeling process and the associated cost are also key limitations. Many will have only a single chance to get it right, as a result.

2.1. Key Concepts and Definitions

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Supply chains have been studied for many years, leading to a comprehensive language that is used within the different sectors and scientific areas to describe various concepts and phenomena. This sub-section provides an overview of the most relevant terms, and the definitions will be used in the remainder of the paper.

Forecasts: Forecasts are estimations of future events or conditions obtained through the analysis of existing data. They can be used in various forms, such as point forecasts, probabilistic forecasts, distributions, etc. In the context of supply chain analytics, forecasts are frequently used to estimate demand, lead times, or service levels, as well as to serve as inputs for other analytics processes.

Inventory Management: Inventory management includes all the internal procedures related to a company's stock. Overall, we can speak about raw material inventory, work-in-progress inventory, and final product inventory. Each of these inventory types has different purposes and, consequently, different management strategies.

Process Optimization: The continuously improving process can have a range of characteristics and takes many forms. The industrial engineering paradigm of work study focuses on repetitive production in both manufacturing and service sectors. Optimal control in industrial processes covers a wide area of applications. The Lean and Green concept consists of continuous improvement with the objective of reducing buy-in. Best practices in the supply chain dictate an optimal control application that can be enacted through the use of policy standardization and protocol development such as collaborative planning, forecasting, and replenishment, vendor-managed inventory, and sales and operations planning.

Data Quality and Governance in Analytics: One of the most critical assets of a company is data. The quality of the decisions made at operational and strategic levels of a company is heavily influenced by data. The impact of data-driven decision-making can be substantial. Constantly challenging and overseeing data quality reduces the probability of making negligible decisions. In the case of analytics, forecasting or optimization methods are “fed” with a set of data, from which a model extracts regularities or relationships.

Stakeholders: There are different stakeholders with different objectives in a company. For instance, in the case of demand planning, forecasting procedures and methods performed by the operational department will be primarily utilized by inventory managers and production planners. The top management, on the other hand, will be interested in the expected return of operating-off-balancing activities, usually correlated to the service level. While the recommended stock level will primarily rely on forecasts and expected value forecasts, the optimization of the economic order quantity will be elaborated from a probabilistic forecast.

3. Machine Learning in Supply Chain Management

The use of machine learning promises to transform the way business is conducted by improving the speed and accuracy of supply chain data analytics. Machine learning comprises a set of techniques for computation and data analytics that is based on the formation of analytical models through data. In the supply chain context, such analytical models are then used to quantify future sales demand or lead times. Generally, machine learning can be used in classification or regression problems on both structural and unstructured data. Altogether, employing machine learning offers many advantages such as being less data biased than methods based on expert systems; it can offer a higher degree of automation, completion, and accuracy, and it can digest large amounts of data and information, thus offering a more timely and accurate supply chain decision-making.

Machine learning can have multiple applications in the supply chain domain, supporting the optimization of different business processes. Specifically, in the case of time series demand prediction modeling, deep learning structural models prove to provide greater accuracy in predicting future trends for FMCGs than linear models. They are also able to handle complex demand patterns, unknown inputs, and can 'fill in the gaps' when the database is not complete, overall proving to be powerful demand forecasting techniques. In the case of logistics, machine learning models have also been applied to reverse logistics for return supply operations. In this study, a custom-developed backtracking AI model that applies machine learning to predict the routing probabilities of returns from both consumers and dealers was proposed and integrated with a forward-to-reverse logistics sourcing optimization model. Results showed substantial cost reductions and lead time improvements when compared to current practice, returning substantial business value to the company and, consequently, to the consumers and dealers. In particular, 20% of the cost can be saved if the optimization model is fed by real-time data.

3.1. Applications and Benefits

Projects analyzing machine learning applications in supply chain management mostly categorize the areas of application. Six use-case groupings include demand forecasting, inventory and production management, procurement, logistics and transportation management, warehousing, and supply chain risk management. AI in logistics operations and risk management is also considered, along with demand forecasting and risk management. Differentiations include demand forecasting and multitrader-based options, with a more complex set of high-road clusters including demand forecasting and sales analytics, production planning, logistics and transportation, inventory management and control, workforce management, order fulfillment and customer service, financial management, sustainability, risk management and resiliency, and transient supply chain business networks.

Machine learning is expected to optimize supply networks, improve customer satisfaction, and optimize costs of production. Supply chain analytics based on AI leads to informed improved decision-making and enhanced supply chain planning. Moreover, AI mechanisms could improve agility and responsiveness in supply chain operations. For instance, real-time sales and logistics performance data from numerous stores were integrated into the company's already high-performance infrastructure of traditional intelligence. Process mining and analytics platforms were applied for employees to be alerted in real time if sales patterns are shifting in a given store. Besides trends going upwards or downwards for the purpose of restocking or maintaining an internal product's display, pricing strategies can also be optimized in real time across different stores. When prices come down, demand increases and so do customer visits. Resolving demand and supply leads to optimized desirability to the customer. The above-given example is only one of the possible and successful real-time applications in practice.

4. Data Collection and Preprocessing

In any analytical project, arguably the most comprehensive (and ill-posed) part is data collection and preprocessing. Every step that follows derives from the quality of the data we are able to collect, their relevance to the problem, and their positional precision. The quality of the data, in turn, relies on the process of collecting, preprocessing, storing, and updating the data according to the needs it is intended to serve. This section will briefly discuss the sources from which data can be collected, the steps to follow once data are collected, and the pitfalls and troubles that one should be prepared to encounter.

There are two broad streams of data sources one can consider when thinking about supply chain-related data: internal and external. The former are those directly collected by an organization from their operations and inside their stores; the latter are those acquired from third-party companies and service providers. External data can include news and weather forecasts, data aggregated and labeled by vertical-market software suites, social media posts and market trends, data from publicly available government reports and filings, among others. Regardless of the complexity of machine learning techniques employed or the accuracy of the algorithms that fit on the data, the result of any analytic project is only as accurate and valuable as the quality and relevance of the data it uses.

Data cleaning, data transformation, and data normalization are activities that continue the path from garbage data to finished product. The use of these techniques ranges from exploratory searches to information extractions: systematically manipulating and altering data to understand it better, knowing it sits in a spreadsheet or for use with some algorithms, are crucial parts of the data processing experience that are also critical to data exploration. Data cleaning is generally a manual step where the user scans a set of data for anomalies or errors and either no longer considers such data for demonstration, marks information as missing, or deletes the cause of a problem if it originates from just one misinformed entry. Data transformation and normalization are also important parts of the model preparation phase. Data normalization and transformation must be applied prior to fitting their models when the requirements do not adequately match the model or cannot be modeled directly by complex algorithms.

Data cleansing, transformation, and normalization are intended to ensure that data can be used to answer the correct question; they maintain those messages unaltered through surgically detected patterns and ensure individuals are no longer capable of being traced back through the data to which they once contributed. These data processing efforts ensure that all data used by a finished product are relevant, and all data unfavorable to a particular social group or confidential information, particularly through natural language processing, is removed.

4.1. Data Sources and Types

To effectively manage and govern supply chain activities, organizations have started to leverage big data analytics that help them turn raw data into valuable information. The data collected from various sources and used to optimize supply chain activities consist of two types: structurally predefined structured data and unstructured data like individual file notes, voice data, etc. The data of these two types are collected, combined, cleaned, processed, and analyzed. These sources are summarized as below:

Structured Data Sources: - ERP Systems - Warehouse Management Systems - Transportation Management Systems - Inventory movement - Point of Sale / Sales and Operations data - Security scans / X-rays / Video streaming and others - Utility payment systems - Cell phone tower systems - E-commerce platforms

Unstructured Data Sources: - Social media - Radio dispatch - Traffic radio broadcasts - Email - Video conferencing - Documents - Excel files, and - More.

The logistics and supply chain share a lot of unstructured data sources, which are usually more descriptive in nature, primarily due to their lack of application integration. With real-time pervasive devices in hand today, a wide variety of expensive technology and labor can assist us in forecasting, tracking, assessing, and reporting KPIs and supporting optimization of supply chains. Data has to be collected from within the supply chain as well as from a vast number of databases and external sources in such supported applications. A diverse range of data points represent the source of supply chain data. Physical and information data will include purchase details, storage details, sourcing, route details, pick and pack details, ship and deliver details, and order status and compliance details. Data will also include human-related performance details as relevant. Data (structured and unstructured) has to be integrated from diverse databases and sources to support end-to-end process analytics; it can include: GPS tracking devices, RFID devices, security mantraps, utilities – power, communications, and gas, contract personnel, and more. The data collected should include human attendance records, system event logs, automated compliance and scheduling confirmations, inbound and outbound physical world data, as well as a host of email, lab, video, and other content documents. Examples of data sources, enterprise databases, and third-party integrated data sources where KPI and process analytics can be supported are presented as follows:

5. Performance Evaluation and Improvement

To identify areas of supply chains that would benefit from advanced analytics, it can help to be aware of how supply chains are evaluated and how performance can be improved. Performance measures or performance metrics indicate whether an organization, department, or coordination of departments, such as a supply chain, is achieving its goals. At the top level, such goals can be expressed in a vision and mission statement. Performance objectives or criteria that describe how mission and vision are achieved can be constructed to provide guidance on achieving the goal while preserving the company's values. This construct includes performance measures which are then detailed into performance metrics such as key performance indicators and warning indicators that monitor the success of key activities and resource investments.

In a more specific supply chain context, there is a list of specific activities or processes in the supply chain, along with accompanying KPIs to allow the assessment of how efficiently and effectively each particular activity contributes to overall success. This list of KPIs includes the following activities, among others: 1) Procurement 2) Production 3) Inventory Management 4) Transport 5) Warehousing 6) Order Processing 7) Information Technology Management 8) Product Development (only as a result measure for product innovation) 9) Customer Service Management. There are various evaluation frameworks available that help not just in finding the right performance metrics to monitor, but also in regarding the organization as part of a larger system – industry clusters, for instance – and encouraging continual improvement. However, many companies today spend a great deal of time and effort collecting data without using it. Hence, this section will dispense with one-off descriptions of supply chain analytics use in practice and instead provide a look at potential uses of supply chain analytics. Help for the subsequent section's discussion is available in a framework that should still be useful as a starting point.

5.1. Metrics and KPIs

Supply chain analytics are intended to help managers measure and make informed decisions about the supply chain. The actual metrics used in supply chain analytics are known as key performance indicators (KPIs). Typically, KPIs refer to targets or objective metrics that "should be measured and analyzed, and expected to have a critical impact" when they fall short or exceed expected values. In recent years, KPIs have begun appearing in the context of supply chain performance management, strategy, integration, and a wide variety of other issues, and no single definition has emerged to cover all of them. There are many different KPIs because many different metrics might be important and might mean different things in different contexts.

Typically, KPIs are used to benchmark and measure performance in terms of efficiency and effectiveness. Efficiency measures reflect the ratio of input to output, such as total cost to produce output or inventory investment to sales, and are often related to financial or cost-effectiveness issues. Effectiveness refers to how well output matches the firm's objectives, such as customer satisfaction with quality, speed, reliability, agility, or innovation. In making measurements and setting objectives, leaders must support and balance short-term KPIs that drive behavior and decision-making and long-term KPIs that reflect the organization's strategic objectives. KPIs are useful in a variety of management contexts across a number of industries, enabling companies to make operational improvements in areas that matter most and to measure those improvements over time. Identifying the best metrics to use is difficult. Often, large numbers of metrics could be decomposed into specific, detailed metrics that managers have always felt in their gut to be important, such as days of supply inventory, profit margin, customer satisfaction, and so forth.

6. Future Direction

Considerable advancements in the field of AI and machine learning continue to be made, especially in the development of unsupervised and reinforced machine learning, as well as automatically generated machine learning models. Their influence on automated and autonomous systems is arguably even more substantial. Such technologies are expected to not only enable a more advanced forecasting and prediction capability, enhancing our knowledge of the likely future and what the best actions to take are, but also enable us to automate many of the day-to-day processes that are currently performed manually within our supply chains. We anticipate that such innovations will drive many of the future discussions and research performed in both academia and the industry. An important next step lies in how blockchain technology will further enable our supply chain operations. It is inevitable that more and more of our processes will benefit from the significant levels of security that can be afforded through the immutable and transparent nature of blockchain, and the integration into AI is likely to bring significant cost and performance benefits.

In this respect, many future applications of AI-driven supply chain analytics will focus on enhancing predictive analytics and, of course, the subsequent automated decision-making for process and service optimizations. New improved decision support systems will span not only inventory management and transportation models, but will provide end-to-end optimization capabilities at increasingly strategic levels. However, one of the larger challenges these advancements bring is the ability of our workforce to adapt to new ways of working with intelligent machines, and it will require a large amount of upskilling to ensure the technology is adopted effectively to best serve the industry. As well as the technical challenges, there is a very large component of ethical and legal considerations that need to be wrestled with. Overcoming these barriers will be crucial in shaping our future within the industry. Given this rapidly evolving landscape, it would be difficult to produce a description of stable practices; indeed, to some extent, supply chain analytics is by definition about continuously reconfiguring practices in response to circumstances. The main contribution that can be made to such thinkers is to give pointers in choosing a direction.

7. Conclusion

The success of any organization critically depends on its ability to manage its upstream and downstream supply chain. Advances in information systems have yielded a valuable opportunity for insight into supply chain operations. AI-driven analytics can transform these vast amounts of data into valuable insights to inform strategic and operational decision making. The insights revealed suggest that organizations are struggling to manage supply chain complexity and uncertainty and must adopt the advanced analytics tools required to address these challenges. Further, the conclusions have revealed a gap in the literature for tools to aim to mitigate the downside risks of ventures into Big Data Analytics.

An objective for this essay was to summarize both the challenges and opportunities that the adoption of AI-driven analytics presents in a supply chain context. The literature review therefore identified these challenges and opportunities and sought to integrate them with our insights in order to complete our essay objective. Indeed, in light of these challenges, the compelling opportunities of this research should encourage organizations to invest in their capabilities to use AI-driven supply chain analytics effectively. The interplay between AI technology and business operations will continue to sustain the development of innovative and disruptive technologies and reframe the nature of operations and associated managerial challenges. Over the next four years, the increasing adoption of AI and Big Data Analytics in supply chain management will continue to change strategic paradigms. Accordingly, a proactive approach is needed in the management of supply chains, as opposed to reactive-based solutions to market dynamics - a necessity that is particularly relevant amidst changing global markets. Our insights support this proactive approach, revealing the potential avenues for investment into AI-driven analytic solutions that could mitigate supply chain related risks. The front-end treatment in our insights reveals that there is a lack of existing published research for mitigating the downside risks of venturing into Big Data Analytics strategies, which can form as a key focus or antecedent of future research in this field of study.