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AN OVERVIEW OF THE ROLE OF DATA-DRIVEN MODELING AND BIG DATA ANALYTICS IN BUILDING A RESILIENT SUPPLY CHAIN DIGITAL TWIN

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ABSTRACT

Data-driven analysis and model-based methods represent a vision of future decision support systems (DSS) in risk management of supply chain disruptions. Data-driven disruption modeling provides a basis for the proactive and resilient design of the supply chain in predicting disruptions and parametric-structural adaptation in the event of a disruption. This modeling is a combination of simulation, optimization, and data analytics to create a digital supply chain twin and thereby manage the risks of disruptions. In this article, we examine the role of data-driven modeling based on the simultaneous use of simulation and optimization, i.e., the supply chain digital twin, as well as the role of big data analytics in resilient supply chains. We will have an overview of some previous researches in the literature to examine the effect of big data analytics in creating disruption scenarios, preventing disruptions, and building recovery policies in the event of a disruption, which leads to supply chain risk management and creating a resilient supply chain. We will also review the role of the supply chain digital twin in supply chain risk analysis and creating a resilient supply chain that enables the simulation of the dynamic behavior of the supply chain and supports model-based decision-making. Finally, the features of anyLogistix software, which provides the possibility of modeling the supply chain digital twin, will be examined.

Keywords: Supply Chain Resilience, Supply Chain Digital Twin, Big Data analytics, data-driven analysis, Supply Chain Risk Management.

1. INTRODUCTION

Due to globalization and digital technologies, big data analytics has developed a new capability to create value from a large amount of data and create a competitive advantage for enterprises (Chen, Chiang, & Storey, 2012; Spotfire, 2016). Big data can be referred to as data characterized by the high volume of data (amount of data), variety (number of types), and velocity (speed) of data (Hazen et al., 2016). Therefore, big data analytics refers to the ability of a business to gain business insights from big data by using statistical tools, algorithms, simulations, and optimizations (Wamba et al., 2015).

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Researchers classify macro-analysis into three categories: descriptive, predictive, and prescriptive (Slone, 2004; Trkman et al., 2010; Demirkan & Delen, 2013). While descriptive analytics is used to identify issues and opportunities through existing processes such as On-Line Analytical Processing (OLAP), predictive analytics aims to discover explanatory or predictive patterns using data mining, text mining, and web mining thus trying to portray future trends (Demirkan & Delen, 2013; Hazen et al., 2016). On the other hand, prescriptive analytics involves using data and mathematical algorithms to determine and evaluate alternative decisions to improve business performance (Hazen et al., 2016; Wang et al., 2016).

According to Mishra et al. (2018), the application of big data analytics in supply chain management and forecasting has become important during the last decade. Supply chain professionals have seriously considered the use of big data analytics in their supply chain to gain strategic advantages (Mani et al., 2017). For example, Accenture research revealed that many managers have already started using big data knowledge in their supply chain decisions (Accenture, 2014).

Big data analytics system reports provide managers with insight that enables them to better understand the market and industry changes, make informed and timely decisions during times of disruption, and respond more effectively. In today's data-driven markets and the world, investing in big data analytics technology to increase resilience and innovation may be a prudent choice (Bahrami, Shokouhyar, and Seifian, 2022).

Ivanov et al. (2018) stated that in the future, competition will not occur between supply chains, but between information services and the analytical algorithms behind supply chains. This is also true for risk management of supply chain disruptions. Examples of applications of supply chain risk analysis and operations include logistics and supply chain control with real-time data, inventory control and management using measurement data, dynamic allocation of resources, improvement of recovery prediction models using big data, supply chain visibility, and risk control, optimization of systems based on predictive information and the combination of optimization algorithms and machine learning (Ivanov et al., 2018).

Supply chain management faces serious challenges such as delays in shipments, inefficiencies, accidents, increase in fuel costs, and increase in customer expectations that potentially harm supply chain efficiency (Barnaghi, Sheth & Henson, 2013). In the operation-planning phase of the supply chain, big data analytics has been widely used in solving problems related to purchasing, inventory, and logistics (Wang et al., 2016). Others have pointed out how big data analytics helps the efficiency of design, manufacturing, intelligence, and service processes used in Product Life Cycle Management (PLM) (Li et al., 2015).

For example, Xia et al. (2012) used a big data system to avoid stock-outs and maintain high replenishment rates that enable more accurate sales forecasting. Shen and Chen (2017) investigated demand forecasting and supply forecasting using big data analytics. Similarly, Hofmann (2017) showed how big data can be used to prevent and reduce the bullwhip effect in supply chain operations.

Increasing use of the Internet and traditional Enterprise Resource Planning (ERP) systems has helped companies share real-time information to reduce transaction time, inaccuracy, and redundancy (LaLonde, 2004; Lee, 2002; Lee, 2004; Narayanan & Raman, 2004). However, due to network complexity, consumer diversification, and supply chain efficiency, it is difficult to predict and manage such risks in real-time (Mani et al., 2017). Although big data analytics can not only be used to predict and avoid risks, it can also be used to create sources of innovation that can provide competitive advantage and sustainability (Mani et al., 2017).

Resilient supply chain design is an extension of traditional supply chain approaches, which is integrated with redundancies such as support facilities, inventory, and capacity flexibility. These redundancies are created in the proactive planning stage, which creates flexibility in the reactive control stage in the face of disruptions in the supply chain structure to recover the performance of the system and operational processes (Ivanov & Dolgui, 2019).

At the proactive level, where the probability of disruption can be estimated, simulation and optimization models create valuable insights for managers. On the other hand, big data analytics and advanced tracking and tracing systems may help predict disruptions and provide more accurate data to create complex disruption scenarios for resilient supply chain design analysis. At the proactive level, according to risk mitigation strategies and identifying the effect of disruption on financial and operational performance, digital technologies can be widely used to obtain real-time information about the scope and scale of disruptions, their propagation in the supply chain, and simulate possible recovery strategies (Ivanov & Dolgui, 2019).

We need modeling approaches and decision-making patterns to take full advantage of real-time data and adapt to the changing environment (Wang et al., 2022). Simulation models combined with digital technologies can improve the tools that are currently used in developing supply chain agility and visibility due to the speed of disruption (Ivanov & Dolgui, 2019).

A combination of simulation, optimization, and data analytics is a foundational technology that helps create a fairly accurate model of the real supply chain—its digital twin. The idea behind creating a digital twin comes from managing risks in supply chains, thus making the supply chain more reliable and sustainable in the event of a failure. The purpose of using data analytics in supply chain network design is to embed disruption data in real-time in a reactive simulation model to simulate and optimize the recovery policy. Data analytics can also be used to create a data-driven learning system in the proactive phase and help create adequate disruption scenarios for resilient supply chain design and planning.

Organizations seek to transform data and information into knowledge and value by using the supply chain digital twin. To mitigate risks and increase agility, new issues related to predictive analytics for intelligent supply chains should be explored (Wang et al., 2022).

The main contribution of our study is a literature review in the field of big data analytics and data-driven models in supply chain resilience. Among these data-driven models, the supply chain digital twin model can predict disruption risks and provides recovery policies both on proactive and reactive levels, and as a result, leads to creating a resilient twin of the digital supply chain. By introducing the features of anyLogistix software in the field of data-driven modeling, data analysis, risk analysis, and digital modeling of the supply chain, we investigate a state-of-the-art approach in the field of supply chain resilience based on cutting-edge technology.

This article is organized as follows. In section 2, we examine the role of big data analytics in supply chain risk management and building resilient supply chains. Section 3 is devoted to the review of data-driven models based on the simultaneous use of simulation and optimization in building a resilient supply chain digital twin. Finally, the article ends in section 4 with the conclusion.

2. THE ROLE OF BIG DATA ANALYTICS IN SUPPLY CHAIN RISK MANAGEMENT AND BUILDING RESILIENT SUPPLY CHAINS

2.1. Supply chain resilience

Unpredictable situations and settings today exacerbate supply chain disruption (Christopher and Peek, 2004; Ambulkar et al., 2015). Disruption is defined as an internal or external threat that disrupts the flow of products and services in the supply chain (Jüttner and Maklan, 2011; Craighead et al., 2007).

Supply chain disruptions have a serious effect on the supply chain (Bahrami, Shokouhyar, and Seifian, 2022). Because these disruptions disrupt the flow of information, materials, and money and prevent the normal activities of supply chains, which leads to nothing but reduced efficiency and competitiveness (Ramezankhani et al., 2018). In such situations, a quick and efficient supply chain response to disruptions is critical (Ponomarov and Holcomb, 2009).

With the increasing intensity and frequency of supply chain disruptions, the issue of resilience has attracted new attention in supply chain management as a critical need (Craighead et al., 2007; Pettit et al., 2013; Sabahi and Parast, 2020). The negative effect of supply chain disruptions can be avoided through resilience, and it also helps to recover to a desired level of performance in a favorable time after the impact of an event (Wieland and Wallenburg, 2013).

Holling (1973), as a pioneer in resilience research, defines resilience as the system's ability to absorb changes. According to Brandon-Jones et al. (2014), supply chain resilience refers to the ability of the supply chain to resume normal operations at a reasonable time after a disruption. Supply chain resilience has three stages: 1) prediction (proactive thinking and planning), 2) resistance (maintaining structure and function), and 3) recovery and response (quick and efficient responses) (Kamalahmadi and Parast, 2016).

Supply chain resilience creates a competitive advantage through advanced planning and continuity of operations (Bag et al., 2021a) and provides a balanced situation between risk and vulnerability (Giannakis and Papadopoulos, 2016; Mandal et al., 2016). By improving flexibility, speed, and visibility, supply chain resilience creates a margin to minimize various types of risk and vulnerability to avoid and absorb changes and achieve optimal performance (Bag et al., 2021b; Belhadi et al., 2021). Evaluating the types and nodes of risk, the probability of their occurrence, and the severity of the risk is a prerequisite for building supply chain resilience (Dubey et al., 2017).

Many supply chain professionals have tried to manage supply chain risks, which can disrupt the supply chain in several ways. Strategies to reduce such risks and prevent disruptions are key topics for supply chain professionals (Mani et al., 2017). According to Tang and Musa (2011), risk can be considered as an event with a low probability, but it may occur suddenly. These events have negative consequences for the system.

Adobor and McMullen (2018) argued that disruptions in supply chains have significant economic effects. Hence, risk and vulnerability management related to supply chains has attracted increasing attention among experts and policymakers (Dubey et al., 2021). Resilience as the capacity of a system to adapt to changes and face sudden events along with maintaining the functionality and basic structure of the system (Holling, 1973) has evolved as an important aspect of risk management and supply chain vulnerability (Ponomarov and Holcomb, 2009; Pettit, Croxton, and Fiskel, 2013; Adobor and McMullen, 2018).

Resilience is an interdisciplinary concept (Chowdhury and Quaddus, 2017). Ates and Bititci (2011) argued that organizational resilience is an organizational capability to survive in a turbulent environment. In response to the increasing disruptions that arise from unpredictable events, resilience has become increasingly important in supply chain perspectives (Ambulkar, Blackhurst, and Grawe, 2015; Kim, Chen, and Linderman, 2015; Purvis et al., 2016; Jain et al. ., 2017; Dolgui, Ivanov and Sokolov, 2018; Chowdhury and Quaddus, 2017; Ivanov, Dolgui, and Sokolov 2018, 2019).

Ponomarov and Holcomb (2009) argued that resilient firms are less vulnerable to supply chain disruptions and have a greater ability to absorb more shocks that result from supply chain disruptions. Supply chain resilience allows organizations to continue delivering their products and services to customers (Ambulkar, Blackhurst, and Grawe, 2015). Existing literature recognizes resilience as an interdisciplinary concept (Ponomarov and Holcomb, 2009; Chowdhury and Quaddus, 2017).

Following Holling's (1973) work, several researchers conceptualized the term supply chain resilience as the ability of supply chains to survive, adapt, and grow in the face of disruptive changes. Simply put, how quickly a supply chain can return to its original or initial state or move to a new, more favorable state after a disruption (Christopher and Peck, 2004; Blackhurst, Dunn and Craighead, 2011; Bhamra, Dani, and Burnard, 2011; Pettit, Croxton and Fiksel, 2013; Chopra and Sodhi, 2014; Brandon-Jones et al., 2014; Gunasekaran, Subramanian, and Rahman, 2015; Ali, Nagalingam, and Gurd, 2017; Jain et al., 2017).

Datta (2017) noted that based on a systematic literature review, supply chain literature has grown exponentially since Christopher and Peck's (2004) study but research focusing on how to develop resilience in organizations is still limited.

Based on the existing literature review, we point out that in an unexpected event, cooperation among supply chain partners is critical to building resilience by reducing the risk of disruption through communication, trust, sourcing decisions, and information sharing. Second, under complexity, information sharing regarding supply chain risk is necessary to build resilience by reducing disruption risks, improving response time, and creating new business opportunities (Ambulkar, Blackhurst, and Grawe, 2015; Kamalahmadi and Mellat Parast, 2016; Chowdhury and Quaddus, 2017; Datta, 2017).

2.2. Big data analytics and supply chain risk management

Many supply chain professionals try to manage supply chain risks, which can disrupt the supply chain in many ways. Strategies to reduce this risk and avoid disruption are key agendas for supply chain professionals (Mani et al., 2017). According to Tang and Musa (2011), risk refers to an event that occurs with low probability but unexpectedly and suddenly, these events bring negative consequences to the system. In addition, Tang and Musa (2011) classify the potential risks associated with the supply chain into material flow, cash flow, and information flow risks.

Mason-Jones and Towill (2015) identified five overlapping sources of risk for supply chains: demand, supply, environment, process, and control. The sources of environmental risk are any external uncertainty, from political issues (such as the fuel crisis); to natural (such as fire and earthquake), and social (such as terrorist attacks and strikes). Others discuss natural disasters, terrorist attacks, labor strikes, and incidents that can disrupt supply chains (Berger, Gerstenfeld, and Zeng, 2004; Christopher and Lee, 2004; LaLonde, 2004; Norrman and Jansson, 2004; Quinn, 2006; Tang, 2006). These disruptions halt operations, and without precautions and preparations, more time is needed to recover the affected system (Hendricks and Singhal, 2005; Sheffi and Rice, 2005).

With the expansion of supply chain risk studies, it is argued that such risks determine the degree of supply chain vulnerability, which is defined as: "being exposed to disruptions caused by supply chain risks and affecting the ability of the supply chain to provide effective services to end customer market" (Jüttner, 2005). To be sustainable, these risks must be anticipated and avoided. On the other hand, Choi et al. (2017) stated that big data is a powerful tool that can be used to effectively solve issues related to operational and supply chain risks. Others have acknowledged that there is a similar need for big data applications in risk management and operations in industrial applications (Choi, Chan & Yue, 2017).

Big Data Analytics (BDA) is based on extracting knowledge from a large amount of data and facilitates data-driven decisions. The more data is recorded from the actual production process, the more important the evaluation of this volume of data with big data analytics applications becomes(Ivanov, Dolgui, and Sokolov, 2019). Since data analytics affects supply chains and supply chains are affected by disruption risks, it makes sense that there is a connection between data-driven technology and supply chain disruption risk management.

Big data analytics (BDA) and artificial intelligence (AI) create entirely new potential benefits for data-driven supply chain risk management (Ivanov, Dolgui, and Sokolov, 2019). Big data is characterized by the five V's in the literature. volume, variety, velocity, veracity, and value (Wamba et al., 2015, 2017).

The concept of resilience is an unavoidable necessity in the supply chain to survive in a highly competitive environment (Bahrami, Shokouhyar, and Seifian, 2022). It also has an undeniable role in supply chain performance (Ramezankhani et al., 2018). Achieving supply chain resilience requires long-term strategic investment (Papadopoulos et al., 2018).

According to Dubey et al. (2019), visibility and analysis capabilities are complementary and support each other. In summary, investing in the development of organizational analytical capabilities leads to improvements in visibility, which in turn leads to increased supply chain resilience (Brandon-Jones et al., 2014; Sabahi and Parast, 2020). By using big data analytics technology, a new feature of proactive planning is provided for risk management infrastructure and it improves the ability to reconfigure resources in a recovery phase (Ivanov et al., 2019).

Big data analytics capabilities help identify and manage supply chain risks through their tangible sources (Singh, N.P. and Singh, S., 2019). Human capabilities (from big data analytics capabilities) can also improve the ability to respond to disruptions (Mandal, 2018). In addition, previous research evidence supports the hypotheses that express a positive relationship between big data analytics capabilities and supply chain resilience. Dubey et al. (2021) explained how data analytics capability improves supply chain resilience through the moderating effects of organizational resilience. In addition, Papadopoulos et al. (2017) developed a theoretical framework for supply chain network resilience using big data analytics.

According to Mandal (2018), the key factors that provide supply chain agility include big data analytics business knowledge, big data analytics technology management knowledge, and big data analytics relationship knowledge. Singh and Singh (2019) showed that by applying big data analytics capabilities to organizations, they will be able to effectively use existing knowledge and improve supply chain resilience. Mandal (2019) pointed out that big data analytics management capabilities are important enabling factors of supply chain readiness, supply chain awareness, and supply chain agility. However, he believed that the important role of big data analytics in developing supply chain resilience is not clearly understood. Niesen et al. (2016) and Papadopoulos et al. (2017) observed that big data analytics can help improve supply chain risk management and disaster resilience.

Choi and Lambert (2017) and Choi, Chan & Yue (2017) presented evidence on how data analytics can be used to improve the resilience of supply chain operations by leveraging corporate databases and large volumes of data to predict risks, assess vulnerability, and improve supply chains. Ivanov et al. (2018) showed that data analytics can be used in the planning phase to identify the risks that the supplier is exposed to and can help to monitor and identify disruptions in the reactive phase. They proposed a framework of physical integrated supply chain simulation and optimization and related this framework to system cybernetics principles. Their results mirror those of Choi's (2018) study, which presents a new practical perspective on how big data technologies can be used for global supply chains with an SOS (system of systems) mindset.

2.3. *Applications of big data analytics in supply chain resilience*

The use of big data analytics to predict business trends is gaining momentum among professionals. At the same time, attention to supply chain risk management is important for experts because it briefly includes methods through which companies can reduce the severity of internal and external threats. Anticipating and addressing the risks that social issues create in the supply chain is of the highest importance in sustainable enterprises (Mani et al., 2017).

Mani et al. (2017) explore the application of big data analytics in reducing supply chain social risk and demonstrate how such reduction can help achieve environmental, economic, and social sustainability. The method presented by them is an expert panel and identification and validation of social issues in the supply chain in the study, and they have used a case study to show the application of big data analytics in identifying and reducing the risk of social issues in the supply chain. Their study will contribute to the literature by integrating big data analytics with sustainability to describe how to reduce supply chain risk.

The main purpose of the study of Bahrami, Shokouhyar, and Seifian, (2022) is to understand how big data analytics capabilities can affect supply chain performance through supply chain resilience and supply chain innovation. They proved that big data analytics capabilities have a positive effect on supply chain resilience. Their research results show that big data analytics capabilities improve supply chain performance through supply chain resilience and innovation. Their study contributes to the existing literature by proving the mediating role of supply chain resilience and supply chain innovation between big data analytics capabilities and supply chain performance (Bahrami, Shokouhyar, and Seifian, 2022).

Srinivasan and Swink (2018) argued that organizations that can build demand and supply chain visibility are in a better position to develop and deploy systems and processes that support data analytics capabilities. Jüttner and Maklan (2011) argued that supply chain visibility is a desirable capability that may mitigate the negative effects of supply chain disruption.

Dubey et al. (2019) proved the hypothesis that data analytics has a positive effect on supply chain resilience. Hence, they argued that those organizations that invest in developing analytics capability are more likely to invest in visibility as well because visibility provides the raw data upon which analytics systems process and act.

This is in line with Srinivasan and Swink's (2018) arguments that visualization and analytics capabilities are complementary in that they support each other. The literature provides ample empirical evidence that improving supply chain visibility may reduce both the likelihood and impact of supply chain disruption (Christopher and

Lee, 2004) and subsequently lead to enhanced supply chain resilience (Jüttner and Maklan, 2011; Brandon-Jones et al., 2014; Ivanov et al., 2017).

Kleindorfer and Saad (2005) have argued that the need for a supply chain risk process is to have visibility of vulnerabilities in all parts of a supply chain. Hence, the use of data technology can help managers identify potential threats or sources of disruption so they can develop business continuity plans that may help speed up the recovery that is necessary when a disruption occurs (Dubey et al., 2021).

The purpose of the study of Gani, Yoshi, and Rahman (2022) is to investigate the effect of a firm's supply chain capabilities on supply chain resilience and the impact of supply chain resilience on sustainable supply chain performance in a data-driven business environment. Their study has been conducted to discover the function of supply chain resilience in adjusting the relationships between a company's supply chain capability and sustainable supply chain performance. Table 1 reviews some recent studies which addressed the role of big data analytics in supply chain resilience.

Table1- Literature review on the applications of big data analytics in supply chain resilience

Authors	Research Title	Research Methodology
Papadopoulos et al. (2017)	The role of Big Data in explaining disaster resilience in supply chains for sustainability	Structured and Unstructured Data Analyses
Mani et al. (2017)	Mitigating supply chain risk via sustainability using big data analytics: Evidence from the manufacturing supply chain	Exploratory Approach
Dubey et al. (2019)	Empirical investigation of data analytics capability and organizational flexibility as complements to supply chain resilience	Variance-based Structural Equation Modelling
Ivanov et al. (2019)	Digital supply chain twins: Managing the Ripple effect, resilience and disruption risks by data-driven optimization, simulation, and visibility	Conceptual Framework
Singh, N.P. and Singh, S. (2019)	Building supply chain risk resilience: role of big data analytics in supply chain disruption mitigation	Covariance-based Structural Equation Modeling
Bag et al. (2021a)	How big data analytics can help manufacturing companies strengthen supply chain resilience in the context of the COVID-19 pandemic	Partial Least Squares Structural Equation Modeling (PLS-SEM)
Bag et al. (2021b)	Roles of innovation leadership on using big data analytics to establish resilient healthcare supply chains to combat the COVID-19 pandemic: a multimethodological study	Variance-based SEM, Semi-Structured Qualitative Questionnaires, and Thematic Analysis
Gani, Yoshi, and Rahman (2022)	Optimizing firm's supply chain resilience in data-driven business environment	Partial Least Squares Structural Equation Modeling (PLS-SEM)
Bahrami, Shokouhyar, and Seifian, (2022)	Big data analytics capability and supply chain performance: the mediating roles of supply chain resilience and innovation	Partial Least Squares (PLS)
Schumacher, Tsolakis, and Kumar (2022)	Distributed R&D networks and healthcare crises: data-driven supply chain design for resilience	Resource-Based View and Network Governance Theory

3. THE ROLE OF BIG DATA ANALYTICS IN SUPPLY CHAIN RISK MANAGEMENT AND BUILDING A RESILIENT SUPPLY CHAIN

3.1. Supply chain digital twin

According to Gartner's definition, a digital twin is a digital representation of an entity or system in the real world. The supply chain's digital twin is a detailed simulation model of a real supply chain that leverages real-world real-time data/images to predict supply chain dynamics. From this point of view, analysts can understand the behavior of a supply chain (understanding), predict abnormal conditions (learning), and formulate an action plan (reasoning) (see Fig. 1).

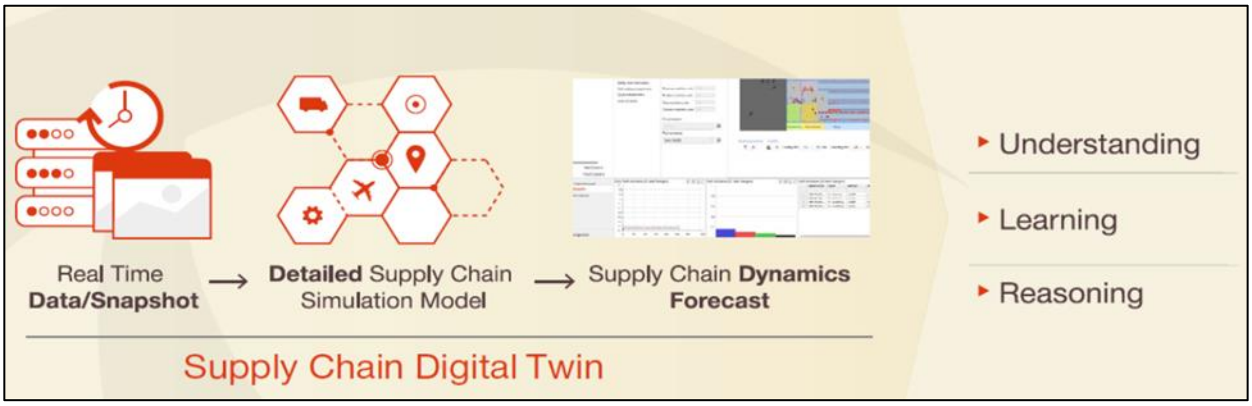

Fig.1: Defining the supply chain digital twin

The real value of the supply chain's digital twin is to help organizations make better short- and medium-term decisions. Mid-term decisions are often related to how a supply chain works and include design, optimization, and master planning. Digital twin helps to review and improve the supply chain and all processes, resources, and logic under it. These tasks may require simulating operations for several months. Short-term decisions are often related to identifying potential problems and analyzing solutions (for example, transportation planning or quantifying the bullwhip effect of external disruption). Typically, these types of decisions will only require a few weeks or days of simulation.

The supply chain digital twin enables building an accurate and timely representation of the state of the supply chain (Wang et al., 2022). Considering the analytical transferability and that data access may be limited, relative, or difficult, simplified assumptions about demand, supply, and risks are used in supply chain modeling instead of accurately describing reality (Wang et al., 2022). Considering the ability of the supply chain digital twin to reflect the dynamics, the assumptions that were generally used in the past need to be revised and a structural and theoretical analysis is necessary (Wang et al., 2022).

The combination of simulation and optimization with data analytics forms a new level of technology to create a supply chain digital twin - a model that always shows the current state of the network. Digital twins provide analysts with the opportunity to test and experience computerized prototypes of the supply chain and allow them to test "what if" scenarios and quantify the effects of changes.

Digital twins use physical supply chain data in real-time—including information from online risk databases, IoT sensors, Track and Trace (T&T) systems, and RFID. These monitoring technologies make it possible to identify sensitive and critical points and send alerts in near real-time about incidents that could disrupt the supply chain. This real-time disruption data can then be fed into a simulation model, along with third-party real-time data on natural, financial, or political risks. Machine learning algorithms are used to reduce noise levels and identify disruption information.

In summary, optimization, artificial intelligence, or other advanced analytical tools can be part of an efficient supply chain digital twin. A digital twin can use optimization, artificial intelligence, or other analytical tools to predict and even implement decision-making. For example, an inventory policy can use artificial intelligence to decide how many products to order and when to order them. At the same time, optimization can help create a master plan, and simulation can determine the best tool for transportation.

3.2. Digital twin and supply chain risk analysis

Success in supply chain competition is becoming increasingly dependent on analytical algorithms combined with optimization and simulation modeling. Originally the goal was process automation, now business analytics techniques disrupt markets and business models and have a significant impact on supply chain development where supply chains are understood not as hard physical systems with the fixed and static allocation of some processes to some companies (Ivanov and Dolgui, 2019). Instead, different physical companies will offer services such as supply, manufacturing, logistics, and sales, which will lead to a dynamic allocation of processes and dynamic supply chain structures (Ivanov et al., 2018).

With optimization and simulation approaches, the current research generates new knowledge about the effect of disruption propagation on supply chain output performance by considering the location, time, and disruption propagation and recovery policies. New digital technologies create new challenges for the application of quantitative analysis techniques to analyze the supply chain ripple effect and open new methods and expressions for these applications (Ivanov and Dolgui, 2019).

The modeling phase is dedicated to predictive simulation and prescriptive optimization. Disruption scenario simulation, supply chain design optimization, and recovery optimization belong to the main decisions to be supported at this level. The structural dynamics control approach can be used in combination with mathematical optimization. The field of real-time control includes real-time control of supply flow, disruption detection, and real-time performance control and recovery. Feedback control can be used with modifications in this domain (Ivanov and Dolgui, 2019).

It is commonly known that feedback control in social or organizational systems is different from technical systems where feedback can be implemented almost in real-time. Likewise, differences in system states can be observed between the system state at the moment of starting to prepare corrective decisions based on feedback information and the system state at the moment of implementing the decision. In other words, delayed feedback occurs due to the inertia of the system. Corrective (adaptive) decisions require implementation in an object or system that is different from the object or system intended to plan the reconfiguration decision (Ivanov and Dolgui, 2019).

Finally, the learning phase consists of risk reduction learning, disruption recovery learning, and disruption pattern identification. A combination of control algorithms and artificial intelligence can provide new insights into this specific field (Ivanov and Dolgui, 2019).

Similarly, a new generation of simulation and optimization models can be seen to develop decision support systems towards Decision Analysis, Modeling, Control, and Learning Systems (DAMCLS) in the form of digital supply chain twins. The combination of simulation, optimization, and data analytics leads to a whole set of technologies to create a digital supply chain twin. A model that always presents the network status in real-time. At any point in time, a digital twin provides the physical supply chain along with real-time transportation, inventory, demand, and capacity data (Ivanov and Dolgui, 2019). The DAMCLS system for supply chain risk analysis seeks proactive and resilient supply chain design to predict disruptions and structural-parametric adaptation in the case of disruptions. The decision support system is based on the concept of combining simulation, optimization, and data analytics (Ivanov and Dolgui, 2019).

The simulation-optimization part of the system aims to provide proactive and resilient optimization of the supply chain and to simulate the dynamic behavior of the supply chain in the face of disruptions or disruption scenarios. In addition, it supports reactive and predictive simulation of the impact of disruption on supply chain performance and recovery policies that are subsequently optimized in a prescriptive manner using an analytical model (Ivanov and Dolgui, 2019). The data analytics part of the system is used for real-time fault detection using process feedback data such as sensors and RFID. In addition, it aims to automatically input disruption data into the reactive simulation model to simulate and optimize the recovery policy. Finally, data analytics is used as a data-driven learning system in the proactive step, which helps to generate sufficient disruption scenarios for resilient supply chain design and planning (Ivanov and Dolgui, 2019).

3.3. Big data analytics and supply chain resilience

Digital innovations and data availability highlight the critical role of data-driven decision-making in operations management and especially during crises to inform effective and timely responses for supply chain continuity and community resilience (Schumacher, Tsolakis, and Kumar, 2022). Despite the capacity and resources of multinational companies to leverage data and improve their supply chain design, there are few studies on the application of data-driven decision-making in community-based organizations. However, this process is temporary since there are no governance frameworks for data-driven supply chain design in the context of innovation activities.

In this context, Schumacher, Tsolakis, and Kumar (2022) proposed a conceptual framework of data-driven supply chain design to help create a more resilient and responsive supply chain in the context of innovation activities with the limitation of disruptive events and limited operations related to health. Their study is one of the first to further elucidate the parameters associated with data-driven supply chain design that occurs in the context of collaborative research and development in a distributed manufacturing environment under a health crisis (Schumacher, Tsolakis, and Kumar, 2022).

Adaptation of the model to real-time data requires future research (Wang et al., 2022). Supply chains today face a changing environment. Simulation models in a supply chain digital twin are a promising way to manage the complexity and uncertainty of reality (Tohamy, 2014).

Rajagopal et al. (2017) addressed using optimization methods that consider supply chain disruptions and risks in a multi-period environment, in supply chain network design and risk propagation analysis (Wu et al., 2012; Bueno-Solano and Cedillo-Campos, 2014; Chen et al. al., 2015), facility location and inventory management (Colicchia et al., 2010; Schmitt and Singh, 2012; Sarkar and Kumar, 2015). Despite these advances, it still requires new approaches for adaptive modeling, which means the ability to continuously learn from the real-time situation and constantly update the models (Wang et al., 2022).

Ma et al. (2020) introduced a framework for data-driven sustainable intelligent manufacturing that combines demand forecasting, machine learning, and simulation-based optimization of operational planning for adaptive synchronization of supply and demand in omnichannel retail supply chains. Despite advances in data-driven methods, leveraging real-time data to update simulation models in a changing environment remains an unsolved problem (Hong and Jiang, 2019).

With the advancement of existing decision support tools with the help of data analytics, the digital supply chain twin was introduced as a computer model of the digital supply chain that shows the status of the network for every moment in real-time and complete end-to-end visibility of the supply chain direction. It improves the resilience and testing of possible designs – it can be created. The digital twin represents the physical supply chain based on real-time transportation, inventory, demand, and capacity data and can therefore be used for real-time planning and control decisions. Supply chain risk managers use tools including data analytics using emerging monitoring systems and real-time data, predicting future impacts and reactions, optimizing local strategic and logistic decisions for efficient implementation of contingency plans, and building corporate control towers (Battarra, Balcik & Xu, 2018; Salman & Yücel, 2015).

3.4. Risk analysis and supply chain digital twin modeling with anyLogistix software

anyLogistix software is a tool that can be used to develop digital twins and integrate them with the organization's IT environment. This software tool includes the following capabilities for data-driven supply chain modeling:

- Detailed supply chain simulation model

With anyLogistix software, logic, and detailed behavior can be added to supply chain models. For example, it is possible to accurately record the company's inventory policies or model the inside of the four walls of the facility to evaluate the internal performance of the factory or warehouse.

- The initial state for simulation of supply chain behavior

It automatically collects data from the initial state of the supply chain and uses it to parameterize the supply chain model with data including financial accounts, warehouse inventories, and vehicle locations.

- Notifications and alerts

Create notifications to notify users of possible critical situations that may occur in the future, such as reduced service levels, low inventory, increased lead times, etc.

- Triggers

Actions can be defined when certain events occur in the system. For example, when an inventory policy is changed, it will cause the key performance indicator of a customer's delivery service level to be lost.

- Development and testing of action plans

Tests provided by anyLogistix can be used to create and test an action plan (e.g., optimization, risk analysis, safety stock estimation, transportation optimization, etc.). It is possible to receive feedback on ideas and test proposed changes in the form of several scenarios using performance prediction.

The risk analysis part of anyLogistix software provides the following capabilities for users:

- The test allows users to analyze and experience risks and uncertainties that include lead times, demand fluctuations, resource availability, and other variable parameters.
- It reveals how changing the value of a parameter can affect the scenario of a supply chain. Instead of creating multiple scenarios for different values of parameters, users can use test changes to automatically change values and run a simulation for each one.
- It helps to anticipate and plan for diverse supply chain uncertainties. The test measures the impact of operational risks and disruptions and determines the time required to recover from them. It helps to test the reliability of logistics networks and determines the metrics needed to increase the robustness of the supply chain.
- With this test, it is possible to understand how variability affects the supply chain: ALX simulation models consider probabilities related to operation schedules and parameter values (such as stochastic variable demand).

4. Conclusion

Variability creates complexity in supply chains. Supply chain managers must predict how these issues will affect the operational performance of their company as a whole and decide how to manage them. They should understand the consequences of every decision they make and calculate the impact of their actions on key performance indicators. Only after thorough analysis should these decisions be implemented.

This complex task is further compounded by the fact that the most commonly used tool, spreadsheet-based modeling, cannot often handle complex, interdependent, and time-related systems such as supply chains.

Apart from the spreadsheet-based approach, some solutions can empower supply chain professionals with a complete set of tools for global and detailed network analysis, supply chain design, and optimization, including analytical optimization and dynamic simulation modeling. With these two methods, a digital prototype is created to model the existing supply chain in the real world. The criteria or success factors of the supply chain, logistics design, and processes are considered. As these methods are different in nature and the technology used, they are used to solve different types of problems.

In the supply chain digital twin, model-based decision-making support enables the simulation of the dynamic behavior of the supply chain in the event of a disruption. Furthermore, before a disruption occurs, potential impacts on supply chain performance can be assessed and recovery policies can then be optimized.

Data analytics in the proactive phase is used to create realistic disruption scenarios based on risk data obtained from historical disruptions and other data (e.g., supplier reliability data from ERP systems) in the supply chain design phase. In the reactive phase, data analytics is used to identify the disruption in real-time using process feedback data, for example from sensors, T&T, and RFID. The purpose of using data analytics in this way is to embed disruption data in real time in a reactive simulation model to simulate and optimize the recovery policy.

Data analytics can also be used to create a data-driven learning system in the proactive phase, helping to create adequate disruption scenarios for resilient supply chain design and planning. In addition, the native data analytics element of the digital supply chain enables observation and monitoring to integrate supply chain disruption management and close the "plan-monitor-adjust-control" loop.

In summary, to take full advantage of real-time information and data in a supply chain digital twin, we need new methods to accurately capture supply, demand, and risks in supply chain modeling. To manage the changing environment, increasing the adaptability of the model remains an important issue for future research.

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