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From Supply Chain Risk to Systemwide Disruptions: Research Opportunities in Forecasting, Risk Management, and Product Design

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Keywords: Resilience, forecasting, prediction for resilience, supply chain risk management, systemwide disruptions.

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Structured Abstract

Purpose: Supply chains must rebuild for resilience to respond to challenges posed by systemwide disruptions. Unlike past disruptions that were narrow in impact and short-term in duration, the Covid pandemic presented a systemic disruption and revealed shortcomings in responses. This study outlines an approach to rebuilding supply chains for resilience, integrating innovation in areas critical to supply chain management.

Design/methodology/approach: The study is based on extensive debates among the authors and their peers. We focus on three areas deemed foundational to supply chain resilience: (1) *forecasting*, the starting point of supply chain planning, (2) the practices of supply chain *risk management*, and (3) *product design*, the starting point of supply chain design. We debated and pooled our viewpoints to outline key changes to these areas in response to systemwide disruptions, supported by a narrative literature review of the evolving research, to identify research opportunities.

Findings: All three areas have evolved in response to the changed perspective on supply chain risk instigated by the pandemic and resulting in systemwide disruptions. Forecasting, or prediction generally, is evolving from statistical and time-series methods to human-augmented forecasting supplemented with visual analytics. Risk management has transitioned from enterprise to supply chain risk management to tackling systemic risk. Finally, product design principles have evolved from design-for-manufacturability to design-for-adaptability. All three approaches must work together.

Originality: We outline the evolution in research directions for forecasting, risk management, and product design and present innovative research opportunities for building supply chain resilience against systemwide disruptions.

Keywords: Resilience, forecasting, prediction for resilience, supply chain risk management, systemwide disruptions.

Paper Type: Viewpoint

1. Introduction

The 2020s have underscored that global supply chains must prepare against the risks of systemwide disruptions. Although supply chain management during crises has been studied extensively in the literature, the primary focus has been on supply-chain-specific disruptions (e.g., Chopra and Sodhi, 2014; Azadegan et al., 2021; Drozdibob et al., 2022). The literature has not looked at broad and systemic disruptions that simultaneously impact multiple industries across the globe (Shen et al., 2021), as witnessed by the impact of the Covid-19 pandemic, the microchip shortage that continues to bedevil the auto industry (Ramani et al., 2022), and the inflation in Europe and the US. Companies across all industry sectors have struggled to develop resilience in their supply chains against such challenges. While there have been past disasters, the potential for economic damage from disruptions now—and in the future—is considerably higher because of tightly connected global supply chains (Azadegan et al., 2020; Faruquee et al., 2021). The critical question facing supply chain scholars and managers is: *How can organisations build resilience to systemwide disruptions without sacrificing cost-effectiveness?*

To provide an answer, we conceptualise resilience tied to the phenomenon of interest, namely systemwide disruptions, through debate, advocacy, and refutation (MacInnis, 2011). As such, we debate the changes needed in developing supply chain resilience as Covid-19 forced us to rethink resilience from individual supply chain disruptions to systemwide disruptions that affect most supply chains. We chose three key domains of research on supply chains: (1) *forecasting*, the starting point of supply chain planning and production planning, (2) the practices in supply chain *risk management*, the very reason for this article, and (3) *product design*, the starting point of supply chain design. The need to create better ways to forecast under increasing uncertainty is self-evident. Likewise, moving from enterprise or supply chain risk management to tackle systemic risk is necessary for environments bearing the risk of systemwide disruptions. Product design underlies both, in addition to the design of the supply chain itself. Next, we compare supply chain management in the pre- and post-2020 periods to see how supply chain practice and research are already changing in response to systemwide disruptions. Given the sheer size of the existing literature, which prohibits a comprehensive, structured review, we conduct a narrative review. Finally, we outline research opportunities in all three domains and their integration.

The rest of the paper is structured as follows: Sections 2, 3, and 4 present the changing focus of forecasting, risk management, and design, respectively, each comparing pre-2020 with the 2020s. Finally, section 5 concludes with opportunities for research on resilient operations and supply chains, including integrating the three approaches.

2. Changes in Forecasting and Demand Prediction

Forecasting seeks to predict future events based on data and is at the heart of an enterprise's ability to respond to its environment. Forecasts drive entire supply chains and enterprise resource planning (ERP) systems; all enterprise decisions are driven by projections of the future and associated risk assessments at various levels: long-term and highly aggregated strategic planning at one extreme and short-term disaggregated forecasts at the other.

2.1 Quantitative and Judgmental Forecasting pre-2020

The long history of forecasting research pre-2020 had primarily looked at the accuracy and selection of methods given the availability of data. Forecasting methods can be broadly categorised into four groups, the first three being quantitative—i.e., statistical, artificial intelligence (AI), and simulation/optimisation)—and the fourth qualitative, based on human judgment. The literature has historically been divided on the relative value of judgmental (qualitative) versus quantitative methods, with several authors warning of judgment's high subjectivity (e.g., Klayman 1988; Bazerman, 1998). Many studies have pointed to the shortcomings inherent in judgmental forecasting due to limitations of human cognition, and biases inherent in judgmental forecasting can create significant and volatile swings of forecast errors, which can seriously impact decisions such as those for supply chain planning. Other authors, however, have provided conceptual or empirical support for using judgment in forecasting (e.g., Edmundson et al., 1988; Lawrence et al., 1985; Arvan et al., 2019; Khosrowabadi et al., 2022). The primary reason for supporting qualitative forecasting is that judgment is privy to the latest information on environmental changes, which managers can rapidly incorporate into their forecasts. Furthermore, judgmental methods offer users a sense of "ownership" that cannot be discounted, as these users are often responsible for implementing plans to respond to forecasts (Lawrence et al., 2006; Goodwin et al., 2007). Their trust in the forecast is essential for implementation.

Quantitative methods are based on mathematical modelling and algorithms. These methods are objective and consistent, capable of handling large amounts of data and uncovering complex relationships. Moreover, given good data, quantitative methods are generally more accurate than judgmental methods (Lawrence et al., 2006). Statistical and AI methods have attracted attention in many applications in recent years with the increasing availability of "big" data, which has fuelled implementation and enabled more robust quantitative models. In general, statistical models dominated before 2010 but were overtaken by AI models in the literature for a short period before a resurgence after 2014. Makridakis et al. (2020)

compared AI models with classical statistical models to evaluate their performance across multiple forecasting horizons using a large subset of monthly time series from the M4 Competition (International Institute of Forecasters). After comparing the post-sample accuracies of popular AI methods with eight traditional statistical ones, they found that the performance of statistical methods dominated AI methods across all accuracy measures and forecasting horizons. Moreover, the computational requirements for AI models were considerably higher than those of statistical methods. These findings are further supported by other studies that looked at forecasting methods in practice.

2.2 Combining Methods in the 2020s

Simple statistical models, such as exponential smoothing, dominated the pre-2020 period, particularly in manufacturing contexts. However, as environments have become highly dynamic and volatile since 2020, these methods are no longer adequate. Implementing good forecasting processes and achieving desirable forecast accuracy in these contexts can be seen as a "wicked problem" that is practically impossible to solve (Churchman, 1967; Rittel and Webber, 1973) due to its complexity and incomplete and changing data requirements. As a result, actionable risk assessments appear almost impossible to obtain, as highlighted by the disruptions over the recent past. Initially, the Covid-19 pandemic resulted in widespread shortages and stockouts of all items, from food to computers and automobiles. Although supply chain disruptions were partly to blame, a fundamental problem was the inability of companies to forecast how a new work-from-home lifestyle would impact consumer buying patterns. Subsequently, most retailers—from Target to Walmart—found themselves holding mountains of excess inventory. There were too many wrong items, and not enough of those consumers wanted. As a result, items ordered by retailers that were popular during the days of the pandemic are now pouring in—only to be met with customers whose preferences and shopping habits have changed again. Similarly, airlines—from American Airlines to Southwest—did a dismal job in forecasting, with a continued inability to meet consumer demand for travel. Collectively these examples illustrate the inadequacy of old forecasting methods and the need for different approaches (Estrin et al., 2020). We must not forget that forecasts provide an anchor or baseline for planning (and design) for resilience, which is more cost-effective than just responding to disruption.

Why were old forecasting approaches inadequate after the first wave of Covid-19? Although quantitative methods are objective and consistent, they require quantifiable data to generate forecasts. Moreover, data should be representative, which becomes an issue under change conditions and for scarce events with low probability. Current quantitative forecasting models are often based on sophisticated machine-learning methods. Despite tremendous advancements in analytics and AI and the availability of vast data, these technologies are still too narrow in what they can achieve. In addition to depending upon the quality of data, the output of these algorithms can also get trapped in "local optima." For example, an algorithm may find better solutions than those nearby in the search process but not see that there are better solutions that are dissimilar to current solutions for a complex problem, which require understanding context and employing creativity.

By contrast, humans can interpret data sets of limited size and detect non-trivial patterns across various datasets. This capability requires context awareness, experience, intuition, and domain-specific knowledge. Although humans can only process small data sets, lack consistency, and often bring biases to decision-making, they can also develop novel solutions (Peysakhovich and Karmarkar, 2016). An excellent example of the difference in "intelligence" between humans and analytical algorithms is offered by (Brooks, 2017, Section 3):

> Suppose a person tells us that a particular photo shows people playing Frisbee in the park. Do we naturally assume that this person can answer questions like *What is the shape of a Frisbee? Roughly how far can a person throw a Frisbee? Can a person eat a Frisbee? Approximately how many people play Frisbee at once? Can a three-month-old person play Frisbee? Is today's weather suitable for playing Frisbee?*

This example illustrates the kinds of contextual connections humans make that are not offered by analytical algorithms but are needed for forecasting in highly dynamic environments to recognise unknowns. Judgmental or qualitative methods also have the advantage of incorporating last-minute 'inside' or 'soft' information, such as short notice of a competitor's advertising campaign, a snowstorm delaying a shipment, or a heat wave increasing ice cream sales. In November of 2021, for example, Walmart announced that they were overriding their algorithm-based forecasts for holiday sales, as historical data were based on a pre-Covid-19 environment.

Most researchers agree that human judgment and analytics have unique, opposite strengths and weaknesses (Sanders and Ritzman, 2001; Sanders, 2000; 2017; Fildes and Goodwin, 2008; Moritz et al., 2014); this is called "Moravec's Paradox" (Brynjolfsson and Mitchell, 2017; Sanders and Wood, 2022). An ideal forecasting methodology is therefore based on the "collective intelligence" of both judgmental and statistical forecasting approaches, augmenting analytics with human judgment (Sanders and Wood, 2022; Taylor-Phillips and Freeman, 2022). Table 1 illustrates the complementary strengths of these methods (Sanders, 2017).

Table 1: Complementarity of statistical forecasting and judgment methods (Sanders, 2017)

	Statistical methods		**Human judgement**
Strengths	- Process large data sets - Precision and accuracy - Flexibility and scaling - Speed	**Complementarity**	- Connect unrelated areas - Creative and innovative - Explain decisions - Empathy and emotion
Weaknesses	- Only as good as the data - Lack creativity and innovation - Cannot explain the decision - Lack empathy and emotion		- Processing limitations - Subject to cognitive biases - Inconsistent - Physical limitations

3. Changes in Supply Chain Risk Management

Managers are accustomed to developing risk management strategies in ordered domains characterised by known risks. Over time, researchers have proposed different approaches to tackle the effects on supply chains of notable disruptive events such as the Fukushima tsunami in Japan in 2011 and 9/11 (Chopra and Sodhi, 2014). However, these approaches are not adequate to contain the prolonged effects of disruptions caused by the 2008-09 financial crisis and Covid-19. Therefore, risk management needs to be extended from variability to building resilience in environments with systemwide disruptions.

3.1 Risk Management pre-2020

The supply chain risk literature looks at risks in two broad categories, *variability* (e.g., demand fluctuations or delays) and *disruptions* (e.g., El Baz and Ruel, 2021; Ivanov, 2020a; Ivanov, 2020b). All companies are subject to variations that impact operations. Since the beginning of the 20th century, scientific management, Fordism, just-in-time (JIT), and lean production have helped companies become more efficient through, for example, *heijunka* (Hüttmeir et al., 2009) and Six Sigma (Kumar et al., 2008). Variability is included in calculations to manage inventory buffers, while many tools exist to identify root causes and thus improve performance (Berman et al., 2011).

Since the beginning of the 21st century, the focus has shifted from delays (variability) to disruptions (Chopra and Sodhi, 2004). These disruptions are low-likelihood events with potentially significant impacts. Unlike variability, which can typically be quantified with probability distributions informed by historical data, sparse events cannot empirically inform the construction of probability distributions (and hence our anticipation of such events in the future) other than assigning such labels as "low" likelihood and "high" impact.

The literature suggests that, like variability, disruptions—even those with massive impacts like the Fukushima disaster of 2011—can be contained with operational countermeasures such as inventory, redundant capacity, and reduced geographic concentration (Chopra and Sodhi, 2004). Other measures are supply chain segmentation and regionalisation (Chopra and Sodhi, 2014).

3.2 Risk Management in the 2020s

Since 2020, however, we have experienced a prolonged and *systemic* propagation of disruptions, with each triggering disruptions in other sectors. Supply chains have more tightly interconnected material and information flows spread over larger geographical areas than in earlier decades. Tighter coupling (interconnectivity) among firms via their supply chains increases network complexity (Simon, 1962) and uncertainty, including unknown unknowns (Ramasesh & Browning, 2014). The interconnectedness within and across global supply chains means that disruptions propagate faster and are more widespread than before. Issues with controllable variability remain, but organisations must now consider unordered environments characterised by low-probability events with unknown or unforeseen causes (Browning and Ramasesh, 2015; Alexander et al., 2018).

Such prolonged disruptions can be widespread geographically. They can be considered 'correlated' (common mode failures) in that distant locations could be affected simultaneously, as with Covid-19. The correlation makes risk management approaches like supplier diversification less effective than they would be with uncorrelated risks since risk pooling effects disappear. The risk of such systemic disruptions increases with the degree of interconnectivity (coupling) in the system—with global supply chains from different sectors being linked through shared suppliers or customers.

Thus, the significant change in the 2020s is the awareness of disruptions becoming systemic, affecting not just the supply chains of a few companies but entire sectors*.* Several researchers have highlighted the phenomenon of systemic risk. Ivanov (2020a) discussed the distinctive features of disruption risks characterised by long-term existence, uncertainty, and propagation, emphasising a *systemic* view of such (super) disruptions. Scheibe and Blackhurst (2018) discussed systemic risk in a supply chain, albeit focused primarily on propagation within the supply chain. Dolgui et al. (2020) noted the 'ripple effect' of such a disruption and described the downstream propagation of the downscaled demand fulfilment in the supply chain. Ivanov (2020a) and Ivanov and Dolgui (2020) studied the ripple effect of pandemic-related disruptions. Furthermore, Haren and Simchi-Levi (2020) provided two examples of Covid-19-induced ripple effects in the supply chains of Fiat Chrysler Automobiles (now Stellantis) and Hyundai, while Ramani et al. (2022) showed that the disruptions caused by the microchip shortage in the auto industry could spill over into other sectors in ways that even an omniscient central planner cannot anticipate or manage.

Other papers have proposed approaches to tackle systemic risk in the wake of Covid-19 or for preparing against future pandemics. Queiroz et al. (2022) reviewed the literature tied to epidemics and proposed a framework to study operational issues—adaptation, digitalisation, preparedness, recovery, ripple effect, and sustainability—and suggested that the traditional supply chain models may not yield solutions to long-term, global, pandemic-driven disruptions. Chowdhury et al. (2021) identified key research themes: the impact of the Covid-19 pandemic, resilience strategies for managing impact and delivery, the role of technology in implementing resilience strategies, and supply chain sustainability in the context of the pandemic. Among the issues studied, the key focus areas were: demand spikes for essential goods and services (Chowdhury et al., 2021; Ivanov and Dolgui, 2021; Queiroz et al., 2022), shortages of essential products (Hobbs, 2020), on-time delivery failures (Ivanov and Das, 2020), supply disruptions and scarcity of parts, increased backlog due to production disruptions and labour shortages (Ivanov and Das, 2020; Mehrotra et al., 2020), and transportation delays and disruption in distribution channels (Choi, 2020; Ivanov and Dolgui, 2020). Finally, Ivanov and Dolgui (2021) also discussed the need to adapt supply chains to better prepare against future pandemics to make supply chains more viable in the long term (Ivanov and Dolgui, 2020).

Recent disruptions have only increased the emphasis on resilience in supply chains. Resilience signifies the ability to resist the impact and, if impacted, recover to reach a (possibly new) steady state to continue to satisfy consumer demand (e.g., Chopra et al., 2021; Wieland and Durach, 2021). Inventory reservation, backup and emergency inventory at the distribution centre, backup capacity and standby capability (Sodhi and Tang, 2021a), and multi-level commons (Chopra et al., 2021) have all been suggested as strategies for systemwide disruptions in the recent Covid-19-motivated supply chain literature.

4. Changes in Design for *x*

Products, manufacturing processes, and supply chains are all complex systems that require careful design. These systems typically emerge from simpler, nearly decomposable ones, simplifying the description of their behaviour and increasing their resilience to disturbances, as in Simon’s (1962) classic example of the watchmakers, Tempus and Hora. Decomposable systems are modular, where subgroups of elements communicate with other subgroups through standardised interfaces in a standardised architecture (Baldwin and Clark, 2000; Langlois, 2002). Modularity underlies the concepts of *design for manufacturability*, characteristic of the pre-2020 period seeking manufacturing and supply-chain efficiency, and *design for adaptability* (DFA), which has become more critical in the post-2020 period. Below, we discuss some aspects of "design for *x*," where *x* has come to represent an increasingly larger set of concerns over the years.

4.1 Design for *x* before 2020

The 1980s brought to the literature an explicit acknowledgement of the importance of early design decisions on later production, sourcing, and other product lifecycle implications (e.g., Whitney, 1988). Efforts around this time focused on design for manufacturability (DFM) or design for manufacture and assembly (DFMA—e.g., Boothroyd et al., 1994), both of which entail designing components with early considerations of their producibility as well as their functionality (Anderson, 2020). As production became globally distributed, the methods of DFM needed an extension for global supply chains. These methods required the operationalisation of any product's *architecture* as a key decision variable for supply chain managers and product designers (e.g., Fixson, 2005). Accordingly, decisions about the design of the product, production process, and supply chain—and the trade-offs among these—had to be made early, during a product's design stage, with inputs from not only designers but also production and supply chain experts (Fine, 1998; Fine et al., 2005), and information from forecasting and risk management. However, the prolific research stream on DFM has not focused on the ability to adapt and quickly recover from disruptive events when designing such systems.

4.2 Design for *x* in the 2020s

Carrying the ideas of ex-ante "design for *x*" even further, *design for adaptability* (DFA) seeks to increase a system's lifetime value by planning appropriate modularity early in its lifecycle, during its design stage, to be more readily redesigned or upgraded to meet unknown future requirements. DFA research to date has focused on product development. For instance, according to Engel et al., (2017, p.877), designers purposefully make a product's design more adaptable by endowing it with "degrees of freedom that enable the addition of new capabilities and the improvement of existing capabilities through economies of substitution (Garud and Kumaraswamy 1995)." These degrees of freedom result from designers' decisions about a product's components, interfaces, and modules.

Decoupling a system's components (i.e., making the system more modular) enables various modules to evolve at different rates without compromising the system's overall functionality. In contrast, changes to an integral (non-modular) system require redesigning and retesting the entire system when making any change. Thus, modular products can be redesigned more easily (as product variants or upgrades). Such changes are more complex and expensive in less-modular products because the entire product must be redesigned instead of only particular (often the most dynamic) modules. Hence, DFA increases the resilience of a product line or platform and potentially upgradable products. However, more modularity is not always cost-effective. Modularity may be characterised as a portfolio of options whose value depends on the technological and market conditions at some future time (de Neufville, 2001; Baldwin and Clark, 2002; Engel et al., 2017). Increasing the number of modules in a system provides more options to change some modules but not others. However, more modules result in more inter-module interfaces and higher transaction, coordination, and standardisation costs. Thus, some of these module options may not be worth the investment.

Furthermore, the value of the module options depends not only on the *amount* of modularity but also on *how* the modularity is achieved (which components reside in which modules and which component interfaces span the modules versus being encapsulated by them), as well as on all projected futures. Engel et al. (2017) offered a conceptual framework grounded in the theories of modularity, options, and interface costs to measure a product's *architecture adaptability value* (AAV). Weighing the specific benefits of increased modularity (the forecasted value of the options created) against its specific coordination and transaction costs indicates the modular architecture that maximises AAV. They made several observations from their case studies of DFA in real products:

- The amount of modularity generally has a concave, ∩-shaped relationship with AAV, as both too little and too much modularity are problematic.
- The amount of modularity alone does not determine overall AAV, because which components are assigned to which modules matters as much as the number of modules.
- Components exhibiting fast rates of technological change should not reside in the same module with components that evolve slowly, allowing the former to be more easily replaced in the next version of the product without having to redesign the stable components.

- Products containing components with heterogeneous rates of technological change should have greater modularity than products composed of components with homogenous rates of technological change.

Of course, product components and modules might need to change for other reasons besides technology evolution, such as the need for alternative sources of nearly compatible substitutes. Hence, these insights are highly likely to apply to supply chain resilience considerations, as we will discuss below.

5. Discussion

Many disruptive events are low probability and nearly impossible to anticipate individually but essentially inevitable collectively. Consequently, most of the means to build resilience presented in the literature focus on limiting the impact and propagation of disruptions. These approaches include decoupling inventories and capacity, increasing supply chain visibility (i.e., the "ability to see from one end of the pipeline to the other" - Christopher and Peck, 2004), developing multiple options for sourcing (redundant suppliers), and improving the management of supplier relationships to reduce the likelihood of a firm being affected by disruptions propagating through those connections (Bode and Wagner, 2015; Han and Shin, 2016; Scholten et al., 2020; van Hoek, 2020). Such approaches take a pre-2020 perspective and are mainly concerned with controlling variability, even when dealing with disruptions.

While studies of supply chain disruptions post-2020 are emerging, there is significant scope for research to improve our understanding of systemic disruptions that affect entire industries and economies. Moreover, means developed can require additional or redundant resources that incur costs, even if a disruption does not occur within the decision horizon. As with insurance, an inherent tension exists between cost-effectiveness and resilience against massive disruptions affecting multiple sectors. This is how we arrived at the question that motivated us: *How can organisations build resilience against systemwide disruptions without sacrificing cost-effectiveness?* As an answer, we explore some research opportunities for each of the three areas discussed in this study and then consider how to integrate them.

5.1 Forecasting for Environments with Systemwide Disruptions

To extend the combined methods described in Section 2, we note two basic, complementary strategies to extract intelligence from data. The first is a *human augmentation of quantitative forecasting methods*. The second is *visual analytics*, the interdisciplinary science of analytical reasoning supported by graphical interfaces (Chung and Thomas, 2004; Winkenbach, 2017). Visual analytics provides tools that enable humans to view the data's information better and communicate it to stakeholders (Aigner et al., 2008). Visual analytics enhances automation's human augmentation and enables better intelligence extraction from big data. For instance, the maintenance team at a major middle-eastern airport uses visual analytics to predict the health of the baggage handling system (Koenig et al., 2021). Through 'marrying' visual analytics with human augmentation of quantitative forecasting models, we can develop—and keep updating—helpful forecasts that will contribute to improved resilience in supply chains. Both approaches offer research opportunities, as they are still nascent.

Meanwhile, computers also encounter problems predicting irrational and nonrational behaviour that underlies mass phenomena such as panic and fake news. In these settings, human judgement may help or harm. Recent disruptions highlight an emotional dimension (in addition to behaviour and ethics) that remains widely disregarded in the supply chain literature. Finally, social capital matters (Polyviou et al., 2020). Human augmentation relies on competent people who care—hence, a need to upskill and reskill the workforce—and research is needed on how to do that. This is vital to improving the accuracy of human forecasting and early detection of weak signals of disruption in supply chains.

5.2 Risk Management for Environments with Systemwide Disruptions

According to normal accident theory (NAT), supply chain disruptions may be viewed as "normal" system accidents in the sense that they are unavoidable in highly complex systems that outpace human capabilities for modelling and control (Perrow, 1999; Hopkins, 1999). "Normal" here includes both variability and disruptions in the sense mentioned above. Thus, NAT implies that we need to reduce complexity or enhance the capacity to cope with it (Shrivastava et al., 2009). Considering that the complexity of supply chains as systems is expected to grow in the foreseeable future, further research on containing or mitigating the disruptions becomes essential.

Super disruptions (Rozhkov et al.,2022) require *extreme supply chain management* with massive unforeseen changes in demand, supply, or both (Sodhi and Tang, 2021a). One way is to create *commons* – or shared resources – for multiple companies or product lines within the same company to use as needed (Chopra et al., 2021). "Ad hoc" supply chains (Müller et al., 2022) may need to be created, for instance, in response to a global pandemic (Srinivasan et al., 2022), such as building ventilators in the US and the UK with the help of auto companies (Sodhi and Tang, 2021b). Having capacity in addition to inventory—and, more importantly, capability—can help design such supply chains rapidly in disaster situations (Li et al., 2022). Humanitarian supply chains in the wake of a major disaster are also ad hoc.

Scenario planning to identify *plausible* risks and their impact can be helpful, especially where the decision horizon is far into the future (Sodhi, 2003).

We must also develop ways to use the increasingly available data and digital technologies to estimate the impact and other cascading disruptions. The use of data can help build digital twins of connected supply chains to understand the implications of unfolding events, compute thousands of what-if scenarios, and build 'nonlinear' supply chain models, thereby facilitating managers to make accurate and informed decisions for lower cost (Tozanli and Saénz, 2022) or sustainability (Apte and Spanos, 2021). With fast-paced information changes, managers' behaviour and decision-making may differ from stable environments. So, behavioural models would also be helpful.

We must also devise ways for managers to understand trade-offs as the shift toward supply chain resilience (Tukamuhabwa et al., 2015; Hendry et al., 2018; de Sá et al., 2019; Faruquee et al., 2021) can appear to conflict with pre-2020 efficiency practices such as sole suppliers, 'zero' inventory, and even risk management. However, Chopra and Sodhi (2014) argued that win-win solutions could reduce both risk exposure and costs rather than only force trade-offs. Each organisation faces different types of risk that require different types of risk management (Table 2). Even in systemwide disruptions, the need for dealing with day-to-day variability continues, requiring inventory management and managing the risk of disruptions with supply chain segmentation and regionalisation (Chopra and Sodhi, 2014). Risk management will be most effective if we consider approaches that span the rows of Table 2. The research opportunity is how to design and operate supply chains that can perform even in highly disruptive environments because of their resilience to systemic risk.

Table 2: Overarching view of risk management approaches before 2020 and in the 2020s

	Variability in Operations	**Prevention and response efforts**	**Risk assessment modelling**
Before 2020	**Some regular variability**	- Preventing variability from entering or leaving any subsystem with upstream and downstream buffers outside the subsystem	- Probabilistic models (normal distribution) for the probability and impact of unsatisfactory outcomes such as unmet demand
	Disruptions	- Supply chain design to contain impact in case of a risk incident with regionalization and segmentation - Reactive efforts to respond to disruptions (Toyota brakes; Aisin fire) and seeking to return to the original state	- Probabilistic models with right-skewed distributions (e.g., log-normal). Identification of plausible risks and responses through scenario planning

2020 and later	**Systemic risk with multiple, interacting disruptions**	- Adapt to post-disruption reality aiming for a new state rather than the original one, anticipating further disruptions - Change business or operating model (online or omnichannel retail) - Multiple disruptions create chaos, further risks generated by the responses taken - Seek the establishment of industry commons from government and cooperation with competitors and companies from other sectors	- Use data to estimate the impact and other disruptions. - Identification of plausible risks and responses through scenario planning - Digital twins of connected supply chains to understand the implications of unfolding events. - Behavioural modelling for decision making.

5.3 Design for Environments with Systemwide Disruptions

The prolific research streams on "design for *x*" have not yet focused on the ability of supply chains to adapt and quickly recover from disruptive events. As production is now more interconnected and globally distributed, it is essential to extend such methods to supply chains, which requires the operationalisation of a product's *architecture* as a key decision variable for operations and supply chain managers and product designers. The concept of DFA should be extended from products to production processes and even entire supply chains (Tozanli and Saénz, 2022) with an eye for *design for resilience* (DFR), which applies DFA to supply chain configuration (e.g., Fixson, 2005; Huang et al., 2005)—the generation of the optimal design of the products, manufacturing processes, and supply sources to enable an effective, efficient, and resilient supply chain. DFR applies to a product and its supply chain because the product design determines the complexity and size of the process that produces and sources it. For example, with the use of additive manufacturing (e.g., 3D printing) technologies, oil and gas giant Shell managed to maintain its digital warehouse during the Covid-19 pandemic for supplying replacement parts locally by commissioning the job to a local manufacturer for 3D printing the parts, allowing the company to reduce part replacement times from 16 to two weeks (Shell Global, 2021). However, not all parts can be sourced this way unless designed initially with a view toward 3D printing. Operationalisation and decision models such as AAV can help managers prioritise which parts merit such emphasis.

Although Engel et al.'s (2017) observations listed earlier pertain to product design (and warrant further research even in that domain), their insights nevertheless suggest fruitful avenues for manufacturing systems and supply chains to increase resilience:

- Should highly dynamic nodes in the network of supplier firms – those with higher uncertainty or risk – be decoupled from more stable ones? Should the decoupling occur by grouping high-risk components (or flows) and providing appropriate redundancy or inventory?
- Should components with higher (supply chain) risks be modularised for easy substitution with minimal impact on the product's performance, such as when electronic devices are designed to use any of several different types of microchips instead of only one that might become unavailable?

Questions like these portend new research areas to explore how DFA can further enable DFR in operations and supply chains.

5.4 Taking an Integrated Approach

Table 3 summarises the main research issues for each area discussed above. Forecasting provides inputs to risk management, which entails identifying risks and riskiness (risk awareness), risk attitudes, and risk reduction. Design—whether for the product, manufacturing system, or supply chain—focuses on creating means to absorb and reduce the impact of adverse events when focused on resilience. It provides the means to manage risks. We thus argue that we need to advance the tools for forecasting, risk management, and design individually but also find ways to integrate them to enable supply chain resilience in environments with systemwide disruptions. For instance, a modular product design with a low lead time for assembling modules greatly simplifies demand forecasting versus individual modules, especially if the respective demands are weakly correlated. Likewise, product design can ensure the commonality and substitutability of parts across product lines, affording less expensive ways of creating redundancy among suppliers and warehouses, which are vital for containing supply chain risk.

Table 3: Research issues for forecasting, risk management, and design for resilience

Domain	Research opportunity
Forecasting	• How can we develop a standardised process to ensure forecasting data are clean and reliable?
	• How can we use scenario planning effectively in complex environments prone to disruptions?
	• How can we combine expert judgment with algorithms in forecasting?

	• How can we enhance human judgment and decision making through data visualisation techniques?
	• What influence have emotions?
Risk management	• How can we manage the risk-shift phenomenon, where attempts to reduce risk in one area or for one stakeholder do not actually reduce a risk but rather just shift it elsewhere?
	• What are the behavioural aspects of risk attitudes and preferences? How can a resilient supply network include a mixture of aggressive and conservative agents or firms?
	• How can we improve the identification and analysis of risks?
Design of products (and their production processes and supply chains)	• How should product, production process, and supply chain architectures be modularized to increase resilience?
	• How should product components, production activities, and supply chain members be designed and chosen to improve resilience with minimal effects on efficiency and effectiveness?
	• How should interfaces among system nodes (product components, production activities, and supply chain members) be managed to increase resilience?
	• What are the best ways to predict the option values of product components, production activities, and suppliers?
	• How to design products, processes, and supply chains to manage risk economically?

The need for integration across these areas is urgent. It is meaningless to worry about risk management if the forecast, or rather, prediction, which provides the input, is wrong or if the means built into the system's design are too limited. For example, Lorentz *et al*. (2021) found that management attention should focus on supply risk sources and the recoverability of the network simultaneously. Thus, an integrated approach provides a rich source of research opportunities:

1. *Conceptual foundation*: Human augmentation of quantitative forecasting methods can be subdivided according to risk type, focusing quantitative forecasting on variability aspects and human augmentation on low probability events. These predictions can be used to calculate and evaluate different risks and guide product and supply chain decisions, such as the location and size of buffers for resilience. Conceptual research is needed to further disentangle the relationships between risk type, supply risk sources and means to build resilience, and their impact on forecasts. A language common to computers and humans needs to be developed and standards introduced, as currently, there is no standard language for risk, resilience, or recovery.
2. *Rapid supply chain configuration*: Further research is needed to understand the configuration and performance outcomes of *ad hoc* supply chains (Müller et al., 2022) set up in response to a specific, acute need (e.g., disruptions such as Covid-19). Such supply chains are the norm in

disaster responses. Research possibilities include how the 'ad-hoc supply chain' concept could be used to design future supply chains. Moreover, adopting a particular set of standards and rules may enable self-organising, complex-adaptive supply chains to emerge faster (cf., Levardy and Browning, 2009). Counterintuitively, would the increased standardisation of supply chain nodes enable greater agility and adaptability (Browning, 2014), e.g. through interoperability?

3. *Procurement*: Another area that can benefit from innovating its process based on the DFR concept is the procurement function. Procurement includes setting up long-term contracts with suppliers and transport service providers, especially in industries like auto or electronics. Reviewing the traditional procurement model suited for the ordered domain to include more flexible, digitally enabled models for unordered domains provides another exciting avenue for future research when combined with the principles of adaptability and resilience.
4. *New methods for planning and control*: The design of a product often precedes that of its production and supply chain, and it predetermines many of the risks that a producing firm and its supply chain will face. The product (with its modules) determines the supply chain's design and vice versa. Similar, demand planning (including forecasting) occurs early in operational planning, followed by supply chain planning and production planning as sequential modules. This heuristic simplifies the planning tasks by modularising them. Such modularisation of planning may have been adequate in the pre-2020 years, but now it should be fundamentally questioned, such as in the context of advanced planning and scheduling. Systemic disruptions require a continual and rapid plan adjustment towards the "new normal". Planning parametrizes the capabilities build into a supply chain, e.g., through DFR. Planning and control must therefore be systematically revised, using the lessons learned from disruptive events as inputs.
5. *Impact of supply chain design on forecasting and risk management*: New ways of operating supply chains also affect forecasting and risk management, highlighting the problem's circularity and that new means must be developed that consider future developments and opportunities. Including counterfactual analysis and models can help close the loop within DFR by incorporating different 'what-if' situations. The application of Digital Twin has, for example, helped DHL and Airbus to model their industrial system, industrial constraints, inventories, and assets against different 'what-if' scenarios and gave them capabilities to visualise hidden suppliers in the long chain, optimise material flows, and expose previously invisible interdependencies.
6. *Understanding and communicating the negative impact of resilience efforts*: Some systemic disruptions could be caused by misguided efforts to create resilience. For example, increasing

inventory levels or the supplier base increases resilience for the buying firm but could cause a capacity shortage at the supplying firm, leading to more disruptions. Similarly, while supply chain visibility is helpful, it also significantly increases system nervousness, the potential for opportunism, and the risk of propagation. There is a need to formalise these trade-offs and develop the means to communicate them to managers.

7. *Resilience of information flows*: While our focus is primarily on physical supply chains, disruptions may also occur in the software maintaining resilience. This aspect of cybersecurity needs more attention. There has been a significant movement towards design science and the pragmatic validity of artefacts. More research is required to focus on resilience against internal and external (e.g., cyber-attack) disturbances.
8. *Design and geographical span*: Finally, geopolitical tensions not only exacerbate uncertainties but also directly impact supply chain design (Roscoe et al., 2022; Sodhi and Tang, 2022)—e.g., cobalt mining or microchips could also be connected to DFA with alternative materials for such products as car batteries or electronic chips. We need to revisit supply chain network design in light of such tensions and uncertainty on the one hand and adaptability on the other.

In summary, we can only achieve the grand challenge of supply chain resilience by building it into the design of the products, processes, and information systems they depend on, from raw materials to finished products and all affected stakeholders. The supply chain management literature must increase its scope and breadth to make a meaningful contribution in the years ahead.

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