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Literature review on the stress tests developed and applied in non-food supply chains

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Contents

Abstract

This report presents the results of a literature review on stress tests developed and applied in non-food supply chains. The primary focus of the project is on quantitative and qualitative methodologies applied in the literature for stress testing non-food supply chains, their advantages and disadvantages, data used, and identification of stress test typologies applied in different methodologies. We also identify methodological gaps in the literature, especially those related to real-world applications of stress testing. The focus of the literature review is on identifying generalisations, categorizations, and patterns rather than on the specific description of individual papers. We analyze the progress of stress testing methodologies and their applications using 61 papers identified through a SCOPUS search performed in May 2024. We identify objectives of stress tests, disruptions/shocks used in stress tests, different methodological approaches used for stress tests, design and typologies of disruption scenarios used for stress tests, data used for stress tests, and indicators used to analyse impacts/responses to different stress factors. Likewise, we analyse managerial recommendations resulting from stress tests and evaluate the advantages and disadvantages of different methodologies developed and applied for stress tests.

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Executive summary

Supply chains are exposed to a multitude of stressors stemming from different internal and external disruptions. COVID-19 pandemic, geopolitical tensions, and natural hazards have clearly shown the importance of developing and maintaining resilience and viability capabilities for business continuity. A **stress test** is an analysis or simulation designed to determine the ability of a supply chain to withstand disruptions and recover. Stress tests are performed to understand behavior and performance of supply chains under disruptions in order to analyse the existing and suggest improved protection and recovery plans. Stress tests can be based on either quantitative (e.g., computer simulation of disruption scenarios) or qualitative (e.g., social, expert-based simulation of crisis scenarios) methods.

Our main findings are as follows. The main **objectives** of supply chain stress tests have been to investigate the ripple effect, predict disruptions and disruption scenarios, examine interlinkages between supplier performance and resilience, analyse resilience strategies, performance impact of disruptions, and COVID-19 pandemic impacts, identify hidden suppliers and links, and analyse viability and role of trust and collaboration.

Most typical **shocks** considered in the stress tests have been supplier, production, logistics, cash-flow, and ripple effect risks. A special stream of literature is the COVID-19 pandemic studies which are characterized by long-term crisis context and specific shocks such as lockdowns, shutdowns, panic buying, virus propagation, and workforce fluctuations.

Quantitative **methodologies** such as discrete-event simulation, Bayesian networks, stochastic and robust optimization, network theory, machine learning and artificial intelligence (AI), and optimal control dominate the stress test domain. Qualitative research has contributed to understanding of empirical and expert context of supply chain exposure to disruptions using organizational theories, social simulations, and regression analyses. Our analysis encompasses a large variety of industry sectors and countries used in the case-studies, numerical examples and data samples.

Data used for stress tests have a multitude of sources. Company, transactional, panel, business (e.g., MarkLines, Bloomberg, and Mergent Horizon), synthetic, secondary, and social media data have been used.

The commonly utilized **indicators** for supply chain stress tests have been service level, time-to-recover, delivery reliability, network connectivity and centrality, total costs and revenue, cash conversion cycle, demand satisfaction, and different types of resilience and vulnerability indexes.

The most typical **managerial recommendations** based on the stress tests include building network redundancy (e.g., backup suppliers and risk mitigation inventory), flexibility and adaptability (e.g., multiple sourcing and omnichannel), necessity to recognize early signals for disruptions, identification of critical suppliers and logistics channels prone to disruptions, and use of AI (artificial intelligence) and digital twins for visibility and real-time control of disruptions. We generalize these practices toward integrated stress testing schemes for different methodologies offering a generalized framework of supply chain stress testing for managers and policy makers.

Novel and **future topics** in supply chain stress tests are digital twins, Metaverse and supply chain visibility, supply chain viability and Industry 5.0, intertwined supply networks and cross-industry ripple effect, financial ripple effect, ripple effect in the presence of hyper-disruptions like COVID-19 pandemic and global trade system disruptions, ripple effects in closed loop supply chains and circular economy, combination of simulation and AI, and combination of quantitative and empirical methods. The existing methodological gaps are mainly related to the fragmented and isolated application of different methods leading to the gaps between research problems and real life needs. A promising practical approach to supply chain stress testing is a combination of qualitative (e.g., a social simulation) and quantitative (e.g., computer simulation) methods. One practical trade-off in

building stress test scenarios is between network complexity and data availability. In addition, a connection between network and process levels should be established.

Keywords: Supply chain, stress test, disruption, resilience, viability, simulation, optimization, analytics

1. Introduction

Supply chain resilience has gained increasing importance over the past two decades, particularly triggered by the COVID-19 pandemic and post-pandemic global and regional vulnerabilities (Simchi-Levi et al. 2015, Yan et al. 2015, Ivanov 2020b, Dolgui et al. 2024, Ergun et al. 2023, Namdar et al. 2024). Supply chains have proven to be unprepared for the unprecedented scale of disruptions cascading through their networks. Even though such ripple effects (i.e., disruption propagations) have been studied and mitigation strategies have been proposed (Mizgier et al. 2013, Sokolov et al. 2016, Ivanov 2017, Ojha et al. 2018), most of the supply chains became prone to long-term disruptions and crises suffering from destabilized operations and decreased performance. Some supply chains collapsed while others only barely survived.

The COVID-19 crisis followed by post-pandemic economic instabilities, geopolitical conflicts, semiconductor and container shortages and natural hazards unveiled the necessity for supply chain stress testing. Stress testing techniques have been used in various disciplines including medicine (Nalesso et al. 2024), material science (Winzer et al. 2008), financial sectors (Rhee and Dogra 2024), and psychology (Mattlin et al. 1990) to study the behavior of complex systems under extreme conditions. Across different fields, the main goal stays the same: to assess the resilience and strength of a structure or system (or its components) by exposing them to crisis situations, often involving multiple shocks.

During the COVID-19 pandemic, Simchi-Levi and Simchi-Levi (2020) first introduced the term "stress test" to the supply chain management discipline by publishing a seminal paper entitled 'We Need a Stress Test for Critical Supply Chains'. They emphasized the intricacies involved in the analyses of critical supply chain networks during a hyper disruption. Ivanov and Dolgui (2021) analysed methods available in the literature for the ripple effect stress testing. They also extended the analysis toward supply ecosystems. Altay and Pan (2023) noted an analogy between the coping theory in psychology and supply chain resilience presenting a framework of coping in supply chain management.

Stress tests are performed to understand behavior and performance of supply chains under disruptions in order to analyse the existing and suggest improved protection and recovery plans (Ivanov and Dolgui 2022). Stress tests can also inform decision makers about resilience capabilities to be developed (Burkhart and Bode 2024). Although several studies have mentioned the term "stress test" and considered it in their analysis, we are not aware of any published research, which systematically analyzes the evolution, context, methods and technologies of stress testing in supply chain management field. Having this research gap and urgent practical need to develop stress tests for both individual supply chains and the whole industry sectors and even cross-industry ecosystems (i.e., intertwined supply networks (Ivanov and Dolgui 2020) in mind, we conducted this study to address the following four research questions.

***RQ1**: What is the meaning and objectives of stress tests in supply chain management?*

***RQ2**: How can the stress tests be conducted and what are the major stress testing methods and scenarios?*

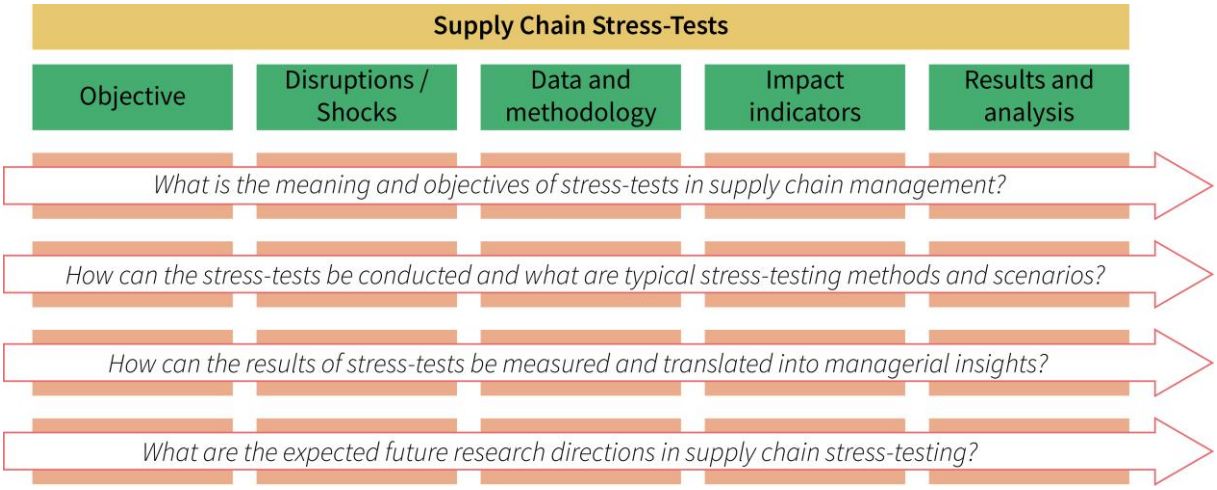
***RQ3**: How can the results of stress tests be measured and translated into managerial insights and policy recommendations?*

***RQ4**: What are the expected future research directions in supply chain stress testing?*

In this report, we analyze quantitative and qualitative stress testing methodologies and their applications using 61 papers identified through a SCOPUS search performed in May 2024. We identify the objectives of stress tests, disruptions/shocks used in stress tests, different methodological approaches used for stress tests, design and typologies of disruption scenarios used

for stress tests, data used for stress tests, and indicators used to analyse impacts/responses to different stress factors. We analyse managerial recommendations resulting from stress tests and evaluate the advantages and disadvantages of different methodologies developed and applied for stress tests. The conceptual design of our study is summarized in Fig. 1.

Figure 1. Conceptual design of our study



Source: Author's own compilation.

The remainder of the report is organized as follows. In Section 2, we discuss bibliometric methodology. Section 3 is dedicated to elaborate on the findings of the literature analysis. Section 4 discusses novel topics and future research areas. Section 5 is devoted to a conclusion. Appendixes provide a summary of the statistics and papers analysed.

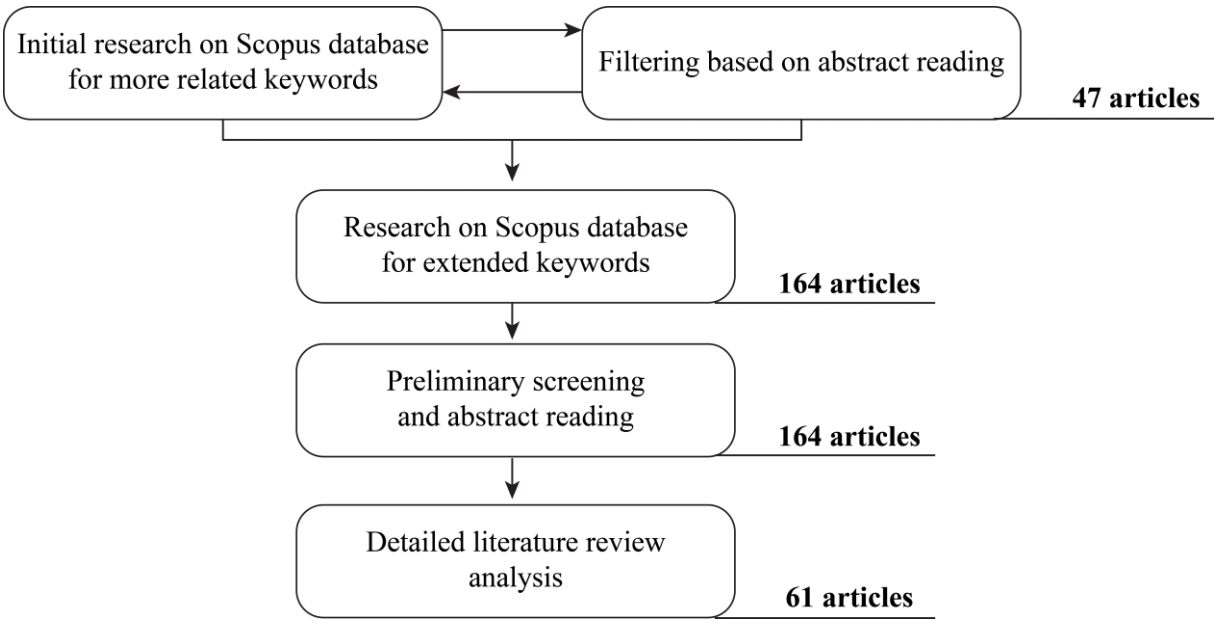
2. Methodology

Literature review methodology has been used in different disciplines. Literature review is an efficient technique integrated with a set of common guidelines to study and summarize the existing knowledge and generate new research directions (Queiroz et al. 2022). In this paper, we employed the literature review approach to understand the current knowledge related to stress testing techniques. An iterative process of selecting and defining relevant keywords, filtering the results to get a reasonable sample, analyzing the literature, summarizing the results and generating the new research directions is used in this review.

Even though supply chain resilience has a large and well-developed body of literature, the stress test is relatively a new term. Since our report is the first academic literature review about supply chain stress tests, there is no reference point in literature regarding the keywords to be used in analysis. To identify a variety of related keywords that have been paired with stress test, we started the analysis with a simple search string (i.e. ("supply chain" OR "supply network") AND ("stress test*" OR "stress test*")) and limited the subject areas to Engineering, Business, Management and Accounting, Computer Science and Decision Science.

Proofing our assumption on the emerging nature of stress test literature, 47 works were found in this initial search as illustrated in Fig. 2. Through analysis of abstracts, running the VOS Viewer analysis and an expert analysis, the list of keywords has been extended (Fig. 3). Primarily we noted out that common keywords in the initially found papers were related to the resilience, disruptions, ripple effect, prediction, and performance. Accordingly, we formed our extended search string as shown in Annex 1.

Figure 2. The flowchart of the literature review methodology

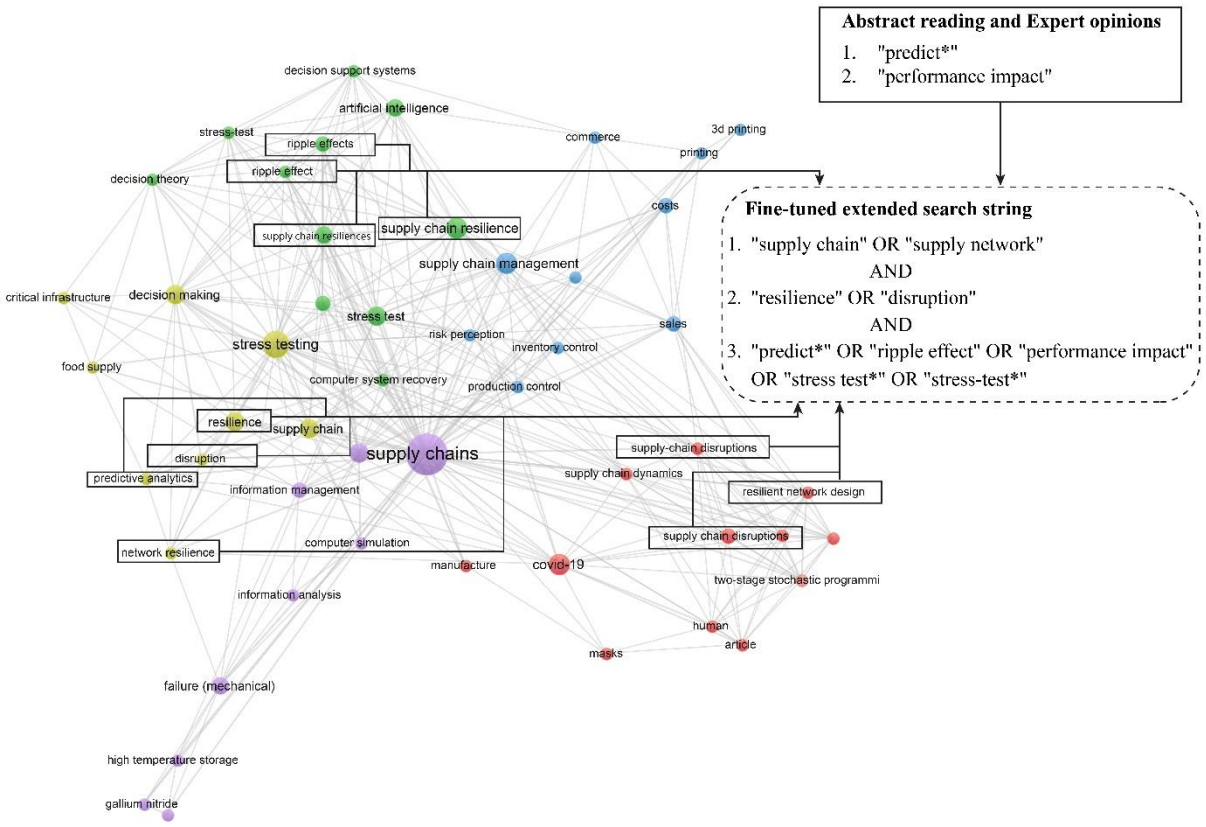


Source: Author's own compilation.

The SCOPUS search was conducted on May 23, 2024 and the rational of the extended SCOPUS search string is as follows. Our search string has been limited to journals with the highest number of publications about resilience and ripple effect identified in the initial search. According to the initial research, it is evident that “resilience” and “disruption” are the most discussed areas in supply chain stress testing (see Fig. 2). While limiting our study to the supply chain area, we used those two keywords connecting them with the help of the Boolean operator “AND”. Additionally, "predict*",

"ripple effect", "performance impact", "stress test*", "stress test*" have been added as the third search group according to the VOS viewer analysis, abstract reading, and expert opinion. Separating the third group of keywords from the second group provided a reasonable amount of journal articles (i.e. 164 articles) for further analysis. Finally, based on the paper screening and abstract reading, 61 journal papers have been selected for a detailed literature review.

Figure 3. The extended literature review research process



Source: Author's own compilation.

When selecting the sample, the German VHB rankings of logistics, operations research, and production management areas are considered. Considering only A+, A, and B category journals (i.e. the highest quality ranks) journals ensures the quality of the selected sample by filtering the most relevant articles for our further analysis.

3. Results

In this section, we explain stress test approaches, identify the objectives of stress tests, disruptions/shocks used in stress tests, design and typologies of disruption scenarios used for stress tests, data used for stress tests, indicators used to analyse impacts/responses to different stress factors. We also analyse managerial recommendations resulting from stress tests and evaluate the advantages and disadvantages of different methodologies developed and applied for stress tests.

3.1 Stress test definitions in different disciplines

Irrespective of the origin of the concept, stress test is considered as a technique to measure the variations by stressing a system. Table 1 summarizes several stress test definitions found in literature across different disciplines.

A simple search in the SCOPUS database using the string 'stress test*' OR 'stress test*' reveals that out of 25,775 articles, 15,728—approximately 61%—are published in the medicine field. For instance, Nalesso et al. (2024) explain that stress testing techniques such as protein loading and pharmacological stimuli can be used to assess the renal functional reserve variations in living kidney donors. Supply chain resilience can borrow a variety of ideas for stress testing from medicine and biological sciences, e.g., replicating immune system responses as shown in (Ivanov 2024b).

According to social science stress theories, stress can arise as a reaction (i.e. physique), as a stimulus, or as a transaction (i.e. psyche) to external changes (Céline and Peter 2023). The insights from the stress and coping theories in *psychology* have been found relevant for supply chain resilience by Altay and Pan (2023).

The stress test has become a key tool in the *financial* sector, especially during the global financial crises in 2007-2009. Rhee and Dogra (2024) mention that stress test is a method that can restore the confidence of the financial system by analyzing associated risks during a crisis and can provide credible predictions. However, they argue that such tests cannot provide information with perfect accuracy as they inevitably ignore some risk sources, which can change the system completely. In general, in finance stress tests are used to examine how robust a financial instrument, a bank, or financial networks are with regards to systemic risks and crashes using scenario analysis (Gandy and Veraart 2016, Glasserman and Li 2024).

Following the successful utilization during the financial crises to prepare the system for future collapses (Simchi-Levi and Simchi-Levi 2020), stress test techniques have been used in supply chain management stream to assess the supply chain resilience and viability particularly during and after the COVID-19 pandemic (Delasay et al. 2022, Graves et al. 2022, Jackson and Ivanov 2023). Going beyond the crises-related analysis, stress tests can be employed to explore any bottlenecks occurring in the supply chain since disruptive risks are often hidden and difficult to uncover (Chen et al. 2022, Li et al. 2023).

Despite the rapid development of supply chain stress test literature, this research stream is still at its infancy. Alikhani et al. (2023) define stress testing as a simulation technique that can analyze the behavior of the supply chain facilities during disruption events. In our paper, we provide the following definition:

> *A stress test is a resilience analysis through a computer or social simulation designed to determine the supply chain ability to withstand disruptions and recover in different crisis scenarios.*

Table 1. Stress test definitions in different disciplines

Discipline	Definition	Reference
Medicine	Exercise stress testing is a non-invasive, safe and affordable screening test for coronary artery disease, provided there is careful patient selection for better predictive value.	Kharabsheh et al. (2006)
Material science	Accelerated stress tests is a test to simulate different materials/component degradation mechanism(s) experienced within the membrane electrode assembly of a Polymer electrolyte membrane fuel cell during operation.	Stariha et al. (2018), Mukundan et al. (2018)
	Stress test is a development tool addressing many issues related to automated vehicle guidance, such as velocity control in automatic emergency braking (AEB), lane keeping assist (LKA) and automated lane change but also more complex issues such as time delays, actuator failures, and network attacks.	Nalic et al. (2020)
Finance and banks	Stress tests help assess the resilience of financial systems in economies and underpin policy advice to preserve or restore financial stability.	Adrian et al. (2020)
	Stress test is a tool that can restore the confidence of the financial system by analyzing associated risks during a crisis and can provide credible predictions.	Rhee and Dogra (2024)
Psychology	Trier social stress test is an experimental paradigm used as a tool in investigating the psychobiological stress response in laboratory settings, as it activates the hypothalamic-pituitary-adrenal axis.	Montero-López et al. (2015)
Computers	Stress testing is exercising the system under strenuous conditions (i.e. the system is more susceptible to errors or performance degradation when much resource is being used)	Zhang et al. (1999)
	Executing a system under test in conditions that are different from the ones expected during the system design.	Mandrioli et al. (2023)
	Evaluating the performance of processors under specific load on the computer.	Schöne et al. (2021)
Environmental engineering	A tool to manage the risk induced by low-frequency high-consequence events and can be adopted for managing flood risks.	He et al. (2021)
	Stress tests is a tool to evaluate the risks and impacts of disruptive climatic conditions, which involves a more narrow and targeted focus on a discrete event or set of extreme conditions under which a system of interest breaks or fails.	Albano et al. (2021)
Business management	Business model stress testing is a systematic analysis of the robustness (i.e., long-term viability as well as feasibility) of business model components - such as a value proposition, revenues or cost structure – based on different future conditions (or uncertainties).	Bouwman et al. (2018)

Source: Author's own compilation.

3.2 Objectives of and disruptions/shocks used in stress tests

3.2.1 Objectives of stress tests

Analysis of the literature sample allows categorizing nine main objectives of supply chain stress tests (Table 2).

Table 2. Objectives of stress tests

Objective	Number of papers	Indicative references
Ripple effect analysis	17	Dolgui et al. (2020), Habibi et al. (2023), Li et al. (2021), Rozhkov (2022).
Performance impact of disruptions	12	Badakhsan and Ball (2023), Hosseini and Ivanov (2022b), Ren et al. (2024)
COVID-19 pandemic impacts	9	Brusset et al. (2023b), El Baz et al. (2023), Ivanov (2020b)
Prediction of disruptions and disruption scenarios	8	Brintrup et al. (2020), Jauhar et al. (2023), Pavlov et al. (2022)
Role of trust and collaboration	4	Giannoccaro and Iftikhar (2020), De Vries et al. (2022)
Interlinkages between supplier performance and resilience	3	Corsini et al. (2024), Zheng et al. (2023)
Analysis of resilience strategies	3	Alikhani et al. (2023), Aldrighetti et l. (2024)
Viability analysis	3	Liu et al. (2024), Ivanov (2024b)
Identification of hidden suppliers and links	2	Mizgier et al. (2013), Kosasih and Brintrup (2022)

Source: Author's own compilation.

The most popular objectives for supply chain stress tests have been the ripple effect, performance impact of disruptions, COVID-19 pandemic, and prediction of disruptions (Table 2). The ripple effect stream analyses how prone the supply chains are against disruption propagation. Performance impact of disruptions has usually been tested by providing some singular shocks (e.g., a supplier disruption) and observing the performance reaction to this shock (e.g., on-time delivery decrease). COVID-19 pandemic context for stress testing is distinctively characterized by long-term disruptions, simultaneous disruptions at different supply chain echelons, and recovery in the presence of disruptions.Prediction of disruptions and disruption scenarios along with identification of interlinkages between supplier performance and resilience as well as identification of hidden suppliers and links represent another type of stress tests which aim at foreseeing disruptions in advance rather than focusing on ad-hoc reactions. This is an important observation since it allows to uncover a combination of prediction-based (i.e., proactive) and reaction-based (i.e., reactive) approaches to stress testing and supply chain resilience. Finally, analysis of resilience and viability strategies (e.g., sourcing diversification and inventory pooling) has been a subject of stress tests.

We note that some papers analysed might have multiple objectives of stress tests (e.g., ripple effect during the COVID-19 pandemic). In these cases, we selected the main focus and counted each paper exactly one time in Table 2.

3.2.2 Disruptions/shocks analysed in stress tests

In the majority of papers, it can be seen that the stress test is used to examine supply chain behavior and performance under disruptions. Shocks such as supplier disruptions (Bodendorf et al. 2023, Hosseini et al. 2020), demand disruptions (Badakhshan and Ball 2023), and disruption propagation (Ojha et al. 2018, Brusset et al. 2023a) have been analysed.

The most typical disruptions and shocks used for stress tests can be classified into four groups depending on the types of uncertainty considered, i.e., known-known uncertainty in material flows, known-known uncertainty in non-material flows, unknown disruption reasons, and long-term supply chain crises. We organise our analysis accordingly.

Group 1: Known, material flow-driven reasons for disruptions and the ripple effect

- supply disruptions (e.g., failure of a supplier and associated performance impact) (Li and Zobel 2020, Pavlov et al. 2022, Yang and Peng 2023)
- production disruptions (Li et al. 2021, Moosavi and Hosseini 2021, Liu and Ren 2024)
- workforce fluctuations (e.g., sudden high volatility of workforce) (Brusset et al. 2023b)
- demand disruptions (Badakhsan and Ball 2023, Nguyen et al. 2023)

Group 2: Known, non-material flow-driven reasons for disruptions and the ripple effect

- energy shocks (e.g., blackouts or energy shortages) (Ivanov 2022)
- financial shocks (Proselkov et al. 2024, Ivanov 2024c)

Group 3: Reasons of disruptions and the ripple effect are unknown

- search for reasons / origins of disruptions the ripple effects (e.g., a hidden supplier) (Chauhan et al. 2021, Kosasih and Brintrup 2022)
- detection of disrupted buyer-supplier relations and sub-networks (Pavlov et al. 2022)

Group 4: Long-term supply chain crises

- systemic risks/ripple effect of long-term durations (e.g. semiconductor shortage) (Ren et al. 2024, Ivanov 2024a, Ivanov and Dolgui 2021, Park et al. 2022, Sawik 2022)
- crisis conditions (Sawik 2023a)

In Table 3, we summarize the disruption reasons in the literature sample analysed.

Table 3. Analysis of disruption reasons

Reference	Disruption type									
	S	M&P	DC	MF	D	L	F	W	NF	LT
Alam et al. (2024)		√					√			
Aldrighetti et al. (2024)	√	√	√	√						
Alikhani et al. (2023)	√	√	√	√					√	
Aljuneidi et al. (2024)	√			√						√
Badakhshan and Ball (2023)		√			√		√			

Reference	Disruption type									
	S	M&P	DC	MF	D	L	F	W	NF	LT
Bodendorf et al. (2023)	√							√		
Brintrup et al. (2020)	√			√						
Brusset et al. (2023a)								√		√
Brusset et al. (2023b)								√		√
Burkhart and Bode (2024)	√									
Chauhan et al. (2021)	√									
Chen et al. (2022)						√				
Choudhary et al. (2021)	√			√						√
Corsini et al. (2024)	√	√								
Cuong et al. (2022)						√				√
De Vries et al. (2022)	√	√								
Dolgui et al. (2020)	√			√						
Dreyfus and Nair (2022)	√									
El Baz et al. (2023)				√						√
Ghadge et al. (2021)	√			√	√	√				
Giannoccaro and Iftikhar (2020)				√						
Habibi et al. (2023)	√			√						
Hosseini and Ivanov (2022a)	√	√			√		√	√		√
Hosseini and Ivanov (2022b)	√									
Hosseini et al. (2020)	√									
Ivanov (2017)		√								
Ivanov (2020a)		√						√		
Ivanov (2020b)				√						√
Ivanov (2022)	√				√	√				
Ivanov (2023)	√	√			√					
Ivanov (2024a)				√						
Ivanov (2024b)				√						
Ivanov (2024c)	√						√			
Ivanov (2024d)		√			√					√
Ivanov and Dolgui (2021)				√						√
Jauhar et al. (2023)					√					
Kinra et al. (2020)	√									
Kosasih and Brintrup (2022)	√									
Liu et al. (2024)	√									
Liu et al. (2021)	√									
Liu and Ren (2024)		√						√		
Li and Zobel (2020)	√	√								
Li et al. (2021)	√	√								
Lopez and Ishizaka (2019)										√
Mariappan et al. (2022)				√						√
Mizgier et al. (2013)	√									
Moosavi and Hosseini (2021)		√								√
Nguyen et al. (2023)					√					√
Ojha et al. (2018)	√									
Park et al. (2022)				√						
Pavlov et al. (2022)	√									
Queiroz et al. (2022)										√
Ren et al. (2024)										√
Rozhkov (2022)				√						
Sawik (2022)				√						√
Sawik (2023a)				√						
Sawik (2023b)				√						

Reference	Disruption type									
	S	M&P	DC	MF	D	L	F	W	NF	LT
Shi et al. (2022)				√						
Yang and Peng (2023)	√									
Zhang et al. (2024)	√									
Zheng et al. (2023)	√									
TOTAL	**32**	**15**	**2**	**21**	**8**	**4**	**4**	**6**	**1**	**16**

Heading: "S"= Supplier; "M&P"= Manufacturing and Production; "DC"= Distribution Center / Warehouse; "MF"= Multi-Facilities; "D"= Demand; "L"= Logistics; "F"= Financial; "W"= Workforce; "NF" = non-material flows (e.g., energy, cash-flows, information); "LT"= Long-Term Crises

Source: Author's own compilation.

While the interest in supplier disruptions, manufacturing and production disruptions, and demand disruptions has been trending in literature, other types of shocks such as logistics and warehouse disruptions as well as non-material flow-related disruptions (e.g., financial, energy, and information disruptions) have been less prioritized. Multi-facility disruptions, where disruption propagation is considered, showed a significant increase during the pandemic, along with studies focusing on long-term crisis contexts.

Summary: The main objectives of supply chain stress tests have been investigation of the ripple effect, prediction of disruptions and disruption scenarios, interlinkages between supplier performance and resilience, analysis of resilience strategies, identification of hidden suppliers and links, COVID-19 pandemic impacts, viability, analysis, and role of trust and collaboration. Most typical shocks analysed in the stress tests are supplier, production, logistics, cash-flow, and ripple effect risks. A special stream of the literature is the COVID-19 pandemic studies which are characterized as long-term crisis and specific shocks such as lockdowns/shutdowns, panic buying, virus propagation, and workforce fluctuations.

3.3 Methodologies of supply chain stress testing

Both theoretical and empirical (qualitative) methodologies have been used for stress testing, with theoretical modeling research being more prevalent (Table 4).

Table 4. Methodologies of supply chain stress testing

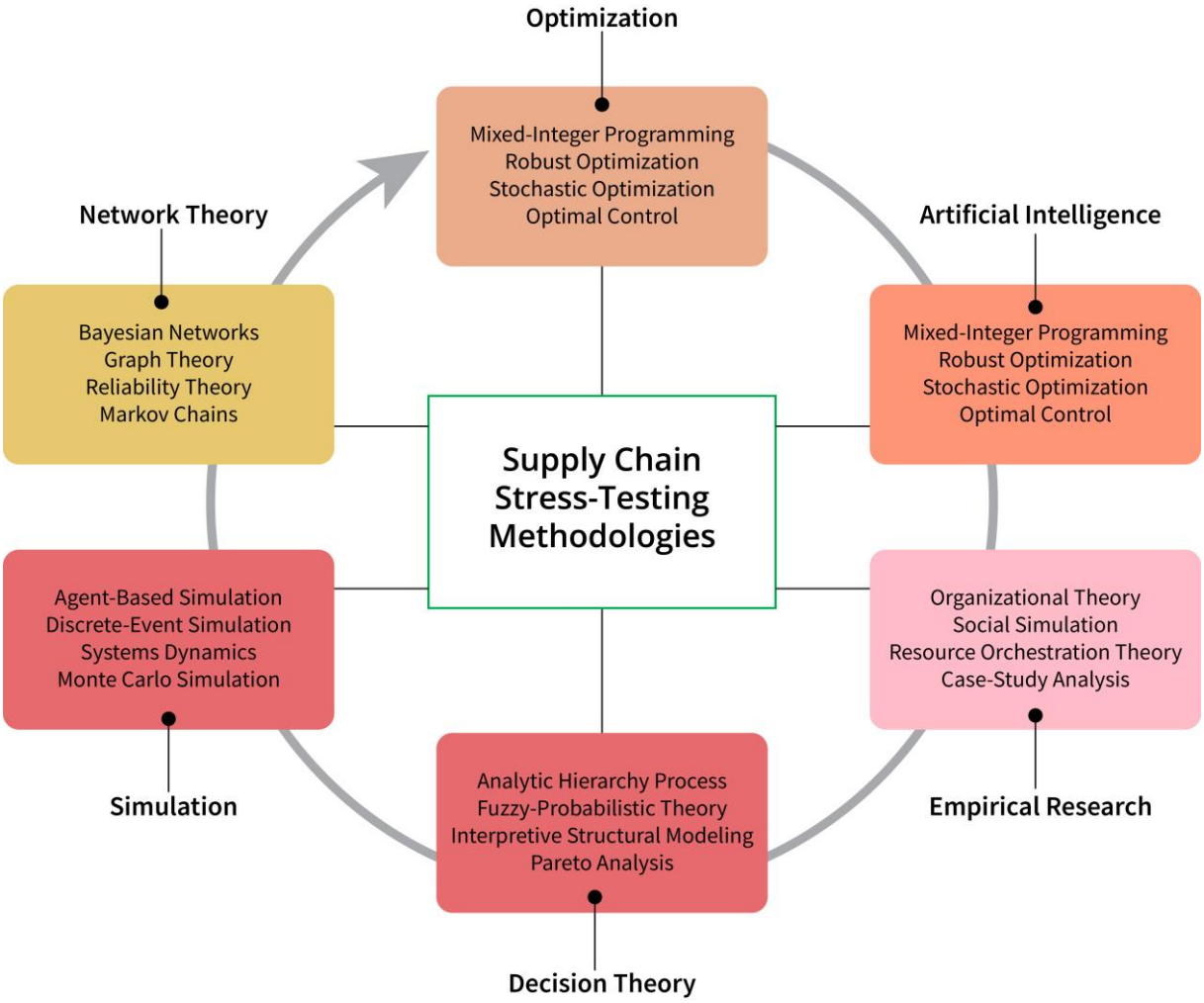
Methodology	Number of papers	Indicative references
Simulation	17	Dolgui et al. (2020), Ivanov (2020b), Park et al. (2022)
Network theory	13	Chen et al. (2022), Hosseini and Ivanov (2022a), Li and Zobel (2020)
Optimization	11	Alikhani et al. (2023), Sawik (2022)
Artificial intelligence	9	Brintrup et al. (2020), Jauhar et al. (2023)
Empirical research	6	Burkhart and Bode (2024), El Baz et al. (2023)
Decision science	4	Alam et al. (2024), De Vries et al. (2022)
Mixed-methods	11	Liu et al. (2021), Bodendorf et al. (2023)

Source: Author's own compilation.

It can be observed that simulation has been the most popular methodology used followed by optimization, network science and AI. Empirical research and decision science studies represent in total about 15% of all studies considered. Combining results in Tables 3 and 4, Table 5 summarizes

how frequent different types of disruptions have been addressed by different methodologies. Fig. 4 classifies and categorizes the main methodologies used for supply chain stress testing.

Figure 4. Taxonomy of the main methodologies used for supply chain stress testing



Source: Author's own compilation.

Table 5. A combined view of methodologies of supply chain stress testing and disruption types

	Disruption type									
	S	**M&P**	**DC**	**MF**	**D**	**L**	**F**	**W**	**NF**	**LT**
Simulation	9	5		11	3	2	1	1		7
Network theory	7	3		2	1	1	1	1		2
Optimization	6	3	2	7				2	2	4
Artificial intelligence	4	2		2	3	1	1			3
Empirical research	4	2						1		1
Decision science	2	1					1			1

Heading: "S"= Supplier; "M&P"= Manufacturing and Production; "DC"= Distribution Center / Warehouse; "MF"= Multi-Facilities; "D"= Demand; "L"= Logistics; "F"= Financial; "W"= Workforce; "NF" = non-material flows (e.g., energy, cash-flows, information); "LT"= Long-Term Crises

Source: Author's own compilation.

Table 5 indicates both the most popular disruption types used for stress testing in different methodologies and reveals some research gaps. The numbers in Table 5 are the number of papers using a specific methodology and a specific type of disruption (e.g., 9 simulation papers analysed supplier disruptions).

3.3.1 Simulation and artificial intelligence / predictive analytics

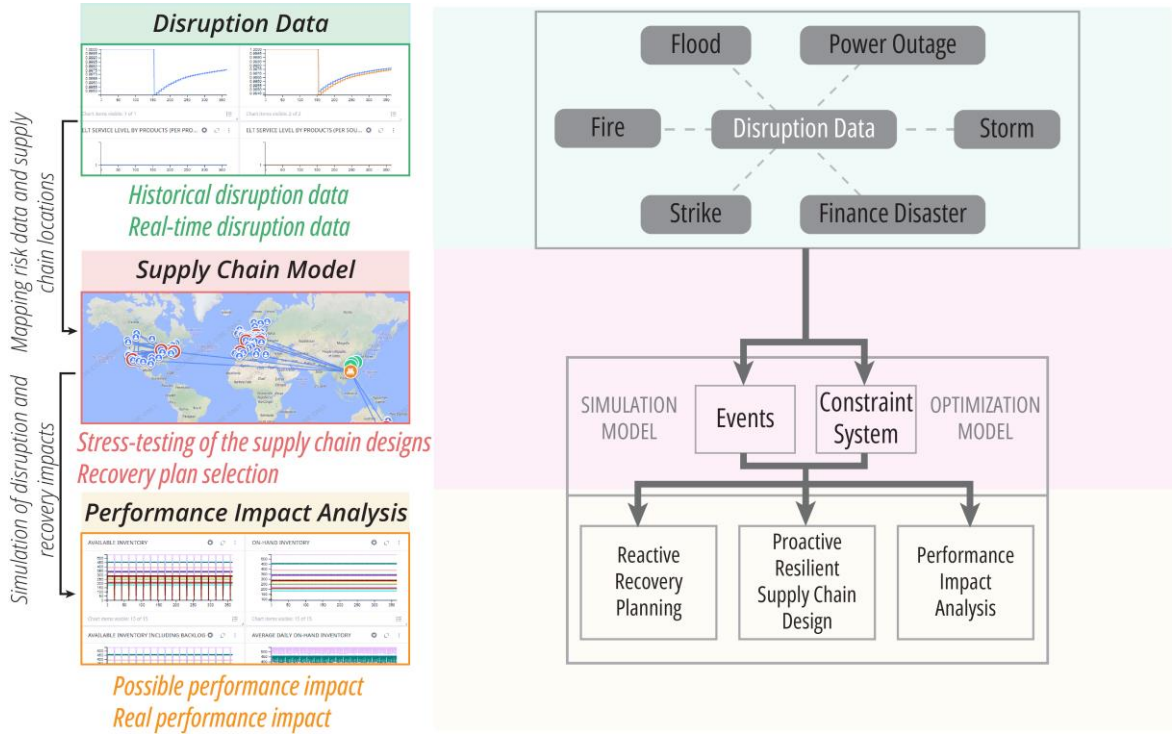
Computer simulation methodologies include discrete-event simulation (DES) (Ivanov 2020b), system dynamics (Ghadge et al. 2021), agent-based simulation (Choudhary et al. 2021), and Monte Carlo simulation (Mizgier et al. 2013). Simulation methods in general have the capability of handling randomness. In particular, DES – the most frequently used simulation method for stress testing can be employed to understand how a system reacts over time and compare its performance impacts under different disruption scenarios (Dolgui et al. 2020, Ivanov 2020a, Moosavi and Hosseini 2021).

Agent-based simulation – frequently combined with machine learning and other AI techniques allows modeling behaviors of customers and supply chain partners when stress testing the supply chain. Monte Carlo simulation is based on random generation of disruptions while system dynamics methods allow modeling causal relationships between parameters influencing supply chain resilience and performance impact (Cuong et al. 2022).

AI techniques such as machine learning, federated learning, and neural networks have been used for identification of hidden links and suppliers (Kosasih and Brintrup 2022) and prediction of disruptions using big data sets, e.g., supply disruptions based supplier performance (Brintrup et al. 2020, Zheng et al. 2023) and inventory disruptions based on demand shocks (Jauhar et al. 2023).

The principal schema of supply chain stress testing by computer simulation is shown in Fig. 5. In the first step, the supply chain risk data are mapped with the supply chain model. In the second step, optimization and simulation models are executed for given disruption scenarios. They provide performance impact assessment and visualization of the disruption impacts on supply chain operations.

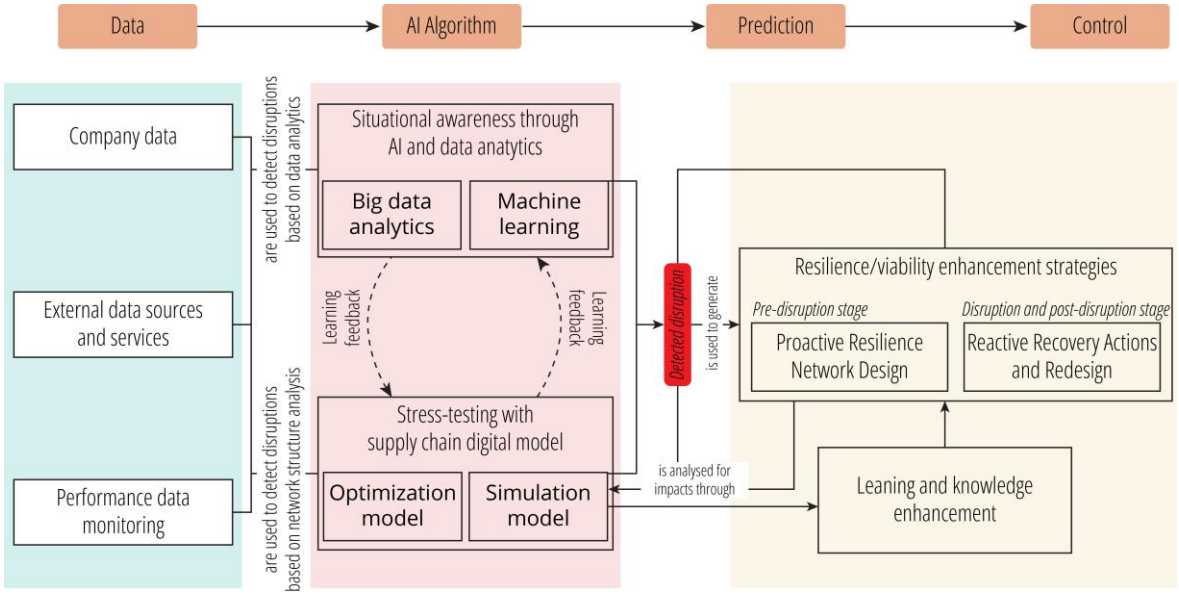
Figure 5. Principal schema of supply chain stress testing using simulation and optimization



Source: Author's own compilation.

When combined to the AI, the following stress test schema can be generalized (Fig. 6).

Figure 6. Supply chain stress testing based on simulation and AI combination



Source: Author's own compilation.

Advantages of a combined simulation and AI methodology are as follows:

— Dynamic analysis of disruption propagation and impacts triggered by disruptions

— Predicted performance impacts in supply chains for different disruption scenarios

— Methodology which can be used in real life

— Revealing bottlenecks

— Identification of hidden links and suppliers in networks

— Accurate modeling of time to recover and time to survive

— Visualization of supply chain processes and disruption impacts

Disadvantages of simulation and AI methods are seen first of all in the general issues with computer simulation studies such as possible gaps between the digital model and physical supply chains due to high complexity and a lack of visibility, difficulties to obtain all the data required to correctly represent a physical supply chain in computer simulation, model and result validation as well as criticism about the generalization of results since most of the insights are valid within a particular context and logical rules used for simulation model development.

If the trade-off between model complexity and comprehensiveness versus feasibility, data completeness, and coherence is successfully resolved, computer simulation becomes a preferable and valuable tool for supply chain stress tests.

3.3.2 Optimization / prescriptive analytics

Stochastic, robust and linear/mixed-integer optimization have been used for stress testing. Stochastic methods presume an availability of information about disruption probabilities (Alikhani et al. 2023, Sawik 2022). Once in place, such models can help find resilient network designs and/or production-sourcing-distribution plans under different stress conditions modelled through disruption scenarios (Sawik 2023b). In some cases stochastic models are combined with fuzzy optimization to relax requirements on known disruption probabilities (Pavlov et al. 2022). Such fuzzy-probabilistic models can be used for disruption scenario predictions and recovery planning.

Robust optimization methods do not presume detailed information to build probability distribution function but data are known to belong to uncertainty sets (Liu et al. 2021). The primary objective is to make a decision that is feasible for constraints belonging to the uncertainty set. Specifically, the optimal decision holds true for the worst-case objective function. Considering the latter fact, robust optimization methods tend to deliver quite pessimistic recommendations on resilient network designs (Liu et al. 2024).

Mixed-integer programming (MIP) is a deterministic form of modeling supply chains under disruptions where the uncertainty is considered in another model, e.g., demand forecasting (Aljuneidi et al. 2024). This is a favorable method when modeling of the large variety of uncertainty factors is difficult within one model (Yang and Peng 2023). Optimal control methods belong to dynamic optimization and describe supply chain dynamics as control execution trajectories (Brusset et al. 2023a). Optimal control methods are frequently combined with epidemiological models to integrate internal (i.e., optimal control model) and external (i.e., epidemiological model) dynamics, e.g., in COVID-19 scenarios (Brusset et al. 2023b).

Advantages of optimization methods for supply chain stress testing are as follows:

— Rigor methodology with an advanced algorithmic knowledge

— Selection of the best action plans from multiple resilience strategies

— Resilient network designs for given stress scenarios

— Possibility to work with different types of data and uncertainty

— Possibility to acquire the robust performance of risk estimation

Disadvantages of optimization methods for supply chain stress testing are seen in high complexity of the models, many unrealistic assumptions and simplifications of reality to obtain feasible solutions, and possible unavailability of data in companies required for running optimization models.

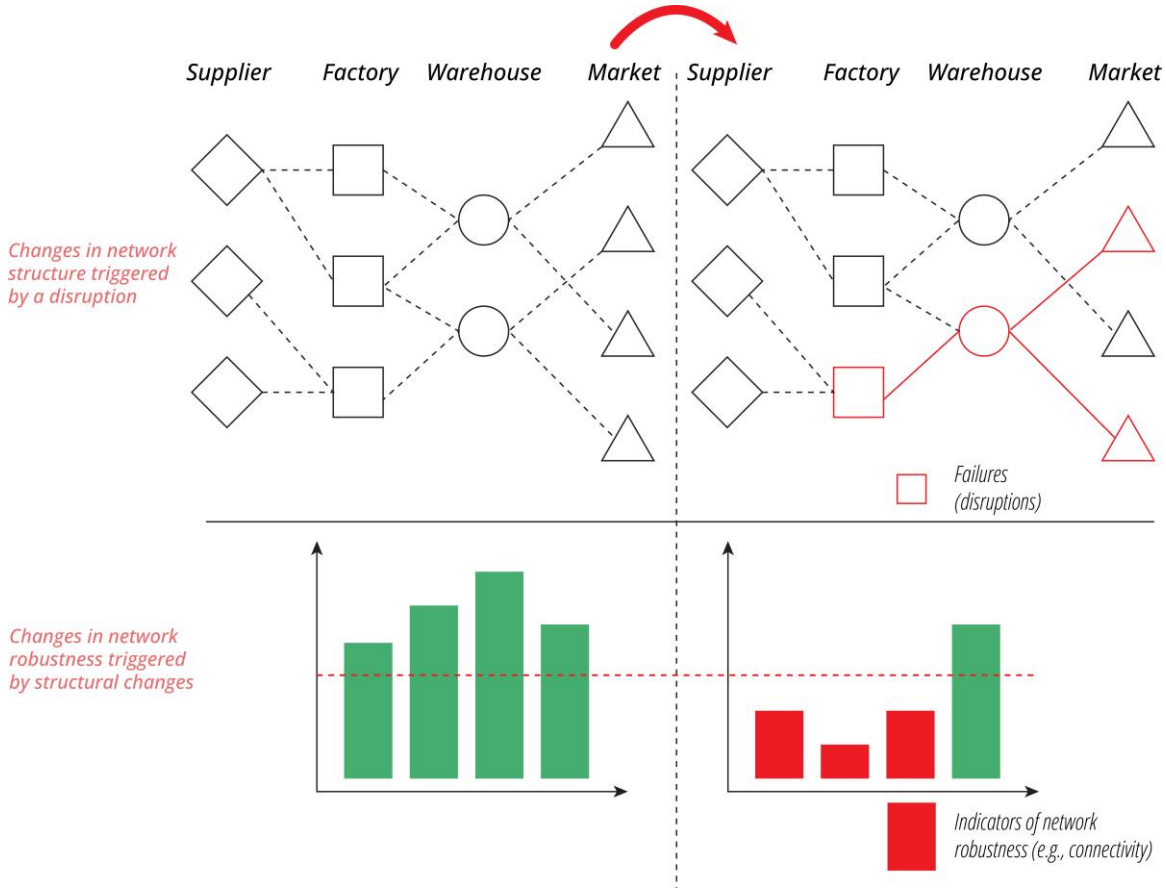
Optimization models are suitable for resilient supply chain design but less useful for dynamic stress testing. In combination with other methods, they can assist in stress testing to enhance simulation and AI.

3.3.3 Network theory

Network theory studies are centered around stress testing of supply chain network structural connectivity and robustness (Li and Zobel 2020, Zhang et al. 2024). In contrast to simulation and optimization methods, network-theoretical studies do not consider processes and material flow dynamics mostly restricting the scope of the analysis to the network (i.e., structure) level (Li et al. 2021, Shi et al. 2022). In essence, a network is constructed and then some nodes and links are removed to observe the extent to which the network would maintain its main characteristics such as connectivity, reachability, and structural robustness, following principles of reliability theory (Fig. 7).

Going beyond mere structural assessments, Bayesian Networks have become a popular method, particularly among researchers studying disruption propagation in complex networks, due to their ability to connect disruption events, triggers, and consequences (Fig. 8). The Bayes theorem explicitly represents the conditional probability dependencies between different variables through feedback (Hosseini and Ivanov 2022a). Bayesian networks are frequently combined with Markov chains (to model state dynamics, see e.g., Hosseini et al. 2020) and robust optimization (Liu et al. 2024). Another specific feature of Bayesian networks is consideration of expert assessments making them suitable for use in mixed-method approaches when empirical and modelling analyses are combined.

Figure 7. Principal schema of supply chain stress testing through graph-theoretical studies



Source: Author's own compilation.

The advantages of network theory applications to supply chain stress testing are as follows:

— Rigor methodology and well-developed theoretical apparatus

— Easy-to-use computational analysis

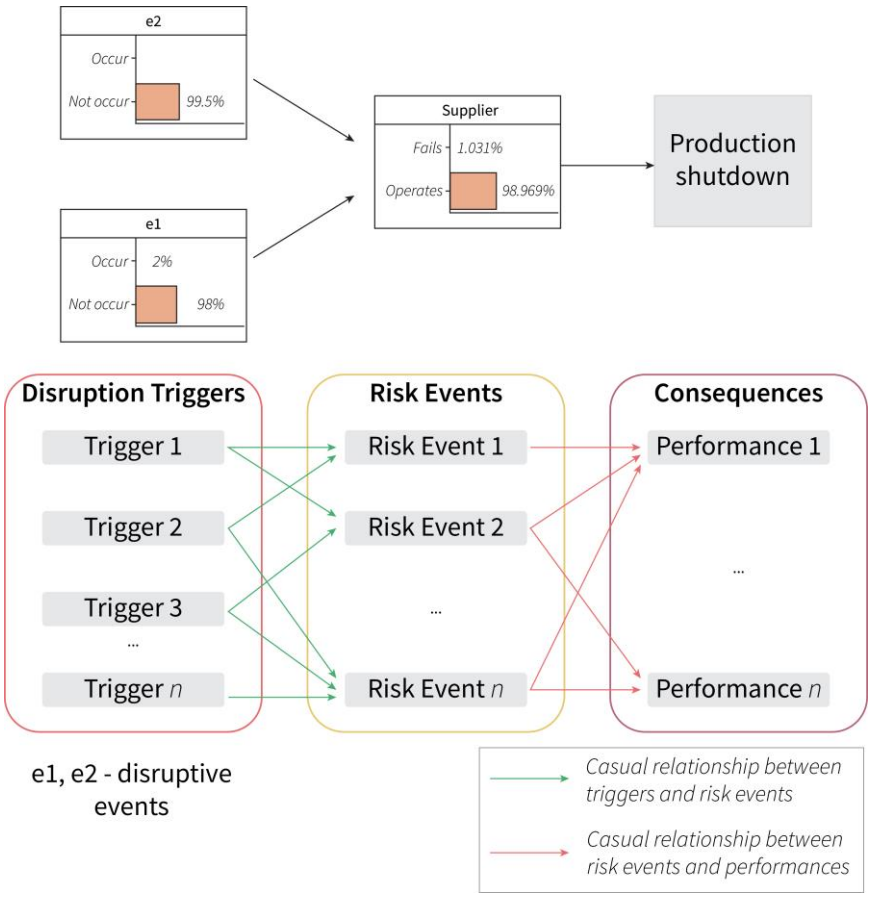
— Analysis of structural robustness to disruptions

— Exploring cascading (ripple) effects in networks

Disadvantages of applying network theory to supply chain stress testing include the limited complexity of networks that can be analyzed (especially in multi-echelon structures), the focus on structural aspects only (excluding material flows), and a static view of the supply chain, which may overlook dynamic changes. Another practical challenge is constructing networks for analysis. Even advanced companies often lack comprehensive data about their supply networks. Extracting such data from commonly used business databases can encounter issues with accuracy and completeness, necessitating validation by company experts.

To become a practically useful tool for stress testing, network theory-based methods should include both structure and process-product dynamics being integrated with material flows. Bayesian networks in combination with qualitative methods (e.g., panels and social simulation) can add some value to supply chain stress tests quantifying and validating qualitative assessments and opinions of experts.

Figure 8. Principal schema of Bayesian networks applications to supply chain stress testing



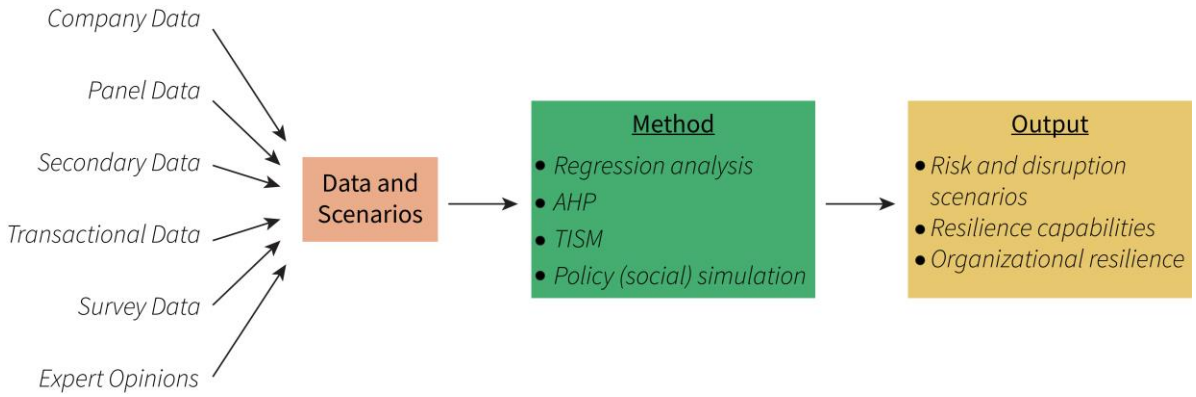
Source: Author's own compilation.

3.3.4 Qualitative research: empirical methods and decision theory

Empirical methods have been used for supply chain stress testing with a lower frequency compared to modeling, theoretical studies. Our search identified empirical studies in the areas of ripple effect analysis (Alam et al. 2024), predicting supply disruptions based on supplier performance data (Bodendorf et al. 2023, Burkhart and Bode 2024), policy (social) simulation based on reaction of cross-functional teams to supply disruption warnings (De Vries et al. 2022), and predicting the effects of disruptions on performance (El Baz et al. 2023).

Common quality of empirical studies is data collection and their subsequent analysis using statistical regression and decision theory methods (e.g., AHP – Analytic Hierarchy Process, FCM – Fuzzy Cognitive Maps, MICMAC – matrice d'impacts croisés multiplication appliquée à un classement, and TISM – total interpretive structural modeling). Interestingly, some studies combine empirical and modeling methods, i.e., using empirically-grounded analytics (Mariappan et al. 2022, Bodendorf et al. 2023). The principal schema of empirical studies on supply chain stress testing is illustrated in Fig. 9.

Figure 9. Principal schema of empirical studies on supply chain stress testing



Source: Author's own compilation.

For practical use, policy (social) simulation based on interactive, participatory activities of supply chain experts confronting with some crisis scenarios can be very important. They can result in the identification of risks and disruptions scenarios and their qualitative assessment, which can be transferred to computer simulation for detailed quantitative analysis.

In Table 6, we summarize main application areas, advantages and disadvantages of different methodologies for supply chain stress testing.

Table 6. Main application areas, advantages and disadvantages of different methodologies for supply chain stress testing

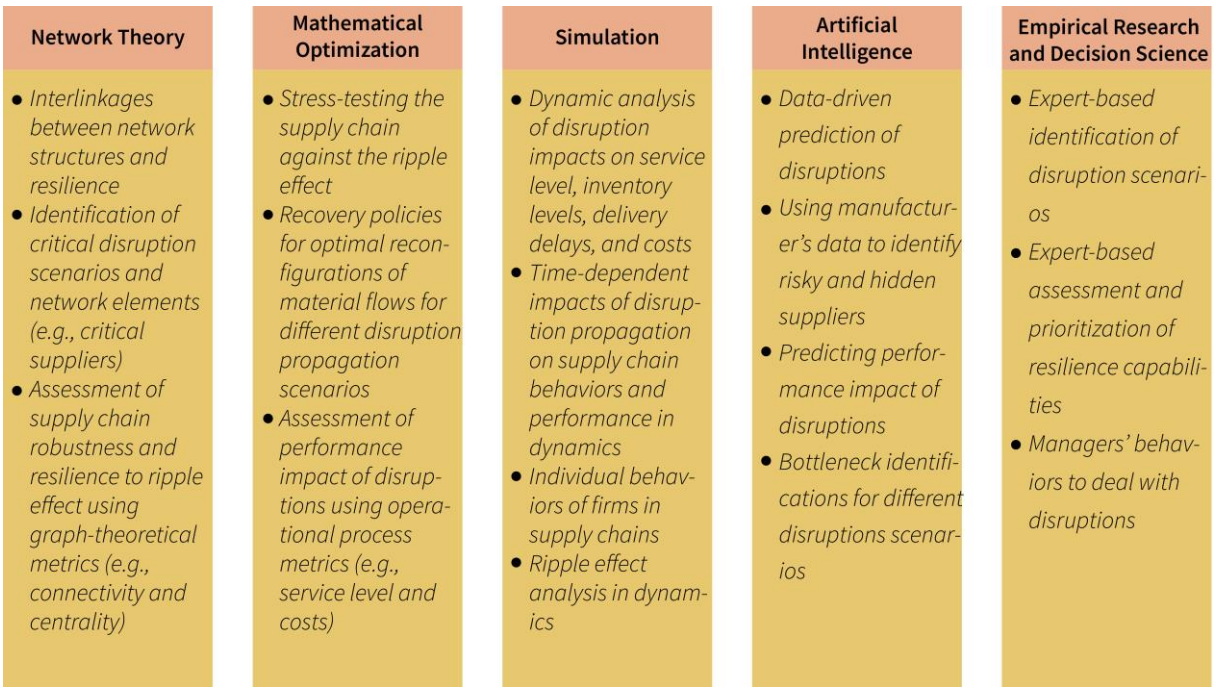
Methodology	Application areas	Advantages	Disadvantages
Simulation and AI	Dynamic stress testing the supply chain against the ripple effect; Prediction of performance impacts in supply chains for different disruption scenarios; Dynamic analysis of disruption impacts on service level, inventory levels, delivery delays, and costs; Individual behaviors of firms in supply chains; Data-driven identification of disruptions, hidden suppliers and links	Methodology which can be used in real life; Accurate modeling of time to recover and time to survive; Visualization of supply chain processes and disruption impacts	Trade-offs between model complexity, feasibility, and data visibility; Model and result validation; Criticism about the generalization of results and their contextual scope
Optimization	Resilient network designs for given stress scenarios; Recovery policies for optimal reconfigurations of material flows for different disruption propagation scenarios; Assessment of performance impact of disruptions using operational process metrics	Rigor methodology with an advanced algorithmic knowledge; Possibility to work with different types of data and uncertainty; Possibility to acquire the robust performance of risk estimation;	High complexity of the models; Unrealistic assumptions and simplifications of reality to obtain feasible solutions; Unavailability of data in companies required for running optimization models.

Methodology	Application areas	Advantages	Disadvantages
Network theory	Stress test of supply chain networks against node/link failures; Analysis of structural robustness to disruptions; Exploring cascading (ripple) effects in networks; Identification of hidden suppliers and links; Interlinkages between network structures and resilience	Rigor methodology and well-developed theoretical apparatus; Easy-to-use computational analysis	Limited level of network complexity (especially multi-echelon structures); consideration of structural level only (without material flows); static view on the supply chain (missing consideration of dynamics); Construction of networks can be biased because of inaccurate and incomplete data
Empirical research and decision theory	Expert-based identification of disruption scenarios; Expert-based assessment and prioritization of resilience capabilities; Managers' behaviors to deal with disruptions	Real-life context and data; Consideration of management knowledge and experience	Subjective nature of datasets; Some methods can be too difficult to use for large-scale problems

Source: Author's own compilation.

Fig. 10 summarizes the main applications of methodologies for supply chain stress testing.

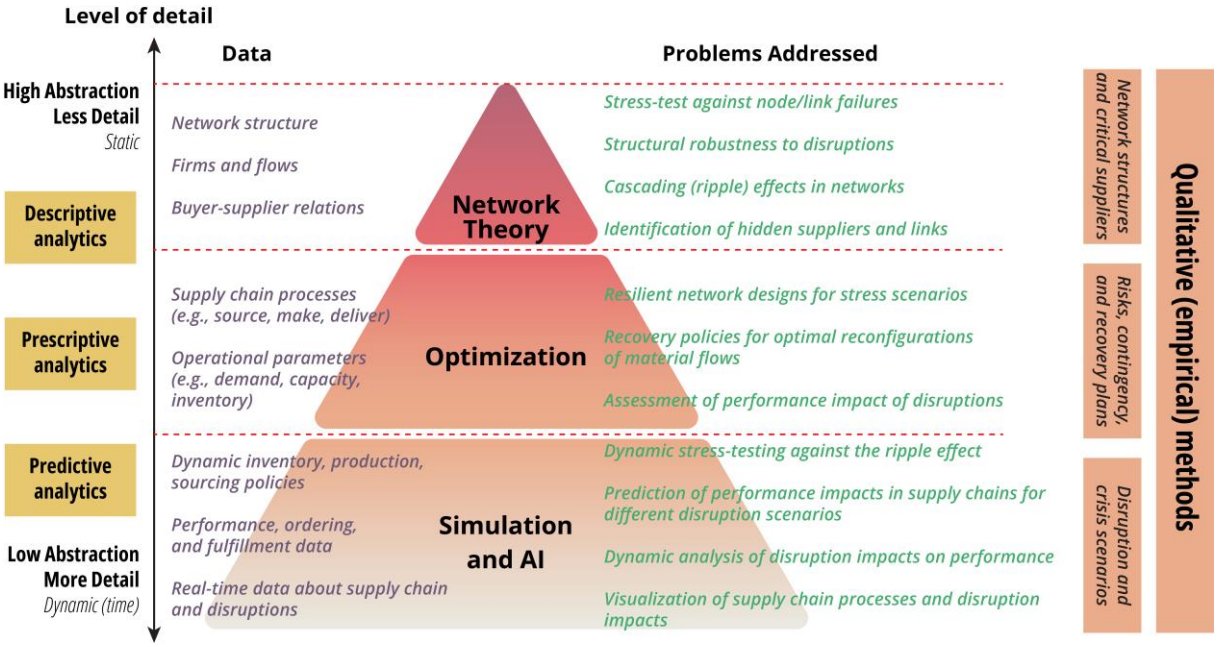
Figure 10. Taxonomy of the main applications of methodologies for supply chain stress testing



Source: Author's own compilation.

Finally, we propose a 3-level methodological taxonomy for supply chain stress testing combining insights about different methodologies discussed above (Fig. 11).

Figure 11. 3-level methodological taxonomy for supply chain stress testing



Source: Author's own compilation.

The taxonomy in Fig. 11 shows that the simplest stress tests can be conducted using network science with just a few data points (e.g., firms and buyer-supplier relationships). However, the insights obtained from purely network-theoretical modeling would be quite limited. The second level involves optimization, which builds upon network analysis by incorporating material flows and operational parameters such as demand, capacities, and inventory. The third level is the most detailed—and the most computationally complex and data-intensive—namely, simulation. With an increase in computational and data complexity, more complex and detailed problems can be addressed. Finally, qualitative methods such as policy (social) simulation and empirical analysis enable expert-based assessment of risks, identification of potential disruptions and crisis scenarios, and the development of resilience capabilities.

Summary: Quantitative methodologies such as discrete-event simulation, Bayesian networks, stochastic and robust optimization, network theory, machine learning and AI, and optimal control dominate the stress testing domain. Qualitative research has contributed to understanding supply chain exposure to disruptions through policy simulation, organizational theories, and regression analyses, even though qualitative studies represent only 10% of the papers analyzed. Combining qualitative and quantitative methods is beneficial at all three levels of the proposed methodological taxonomy.

3.4 Data and indicators

3.4.1 Data sources

Data used for stress testing differ across methodologies but share some common patterns. In empirical studies, data are usually collected through interviews and multi-respondent surveys (Dreyfus and Nair 2022, El Baz et al. 2023, Alam et al. 2024). Some studies have utilized Enterprise resource planning (ERP) data (Bodendorf et al. 2023) and supplier panel data (Burkhart and Bode 2024). De Vries et al. (2022) obtained data for their study of how cross-functional teams react to disruption warnings through a management simulation based on "Fresh Connection" game.

Mariappan et al. (2022) used organic data of over 5.9 million records of therapeutic shipments to predict shipment times during COVID-19 pandemic shock.

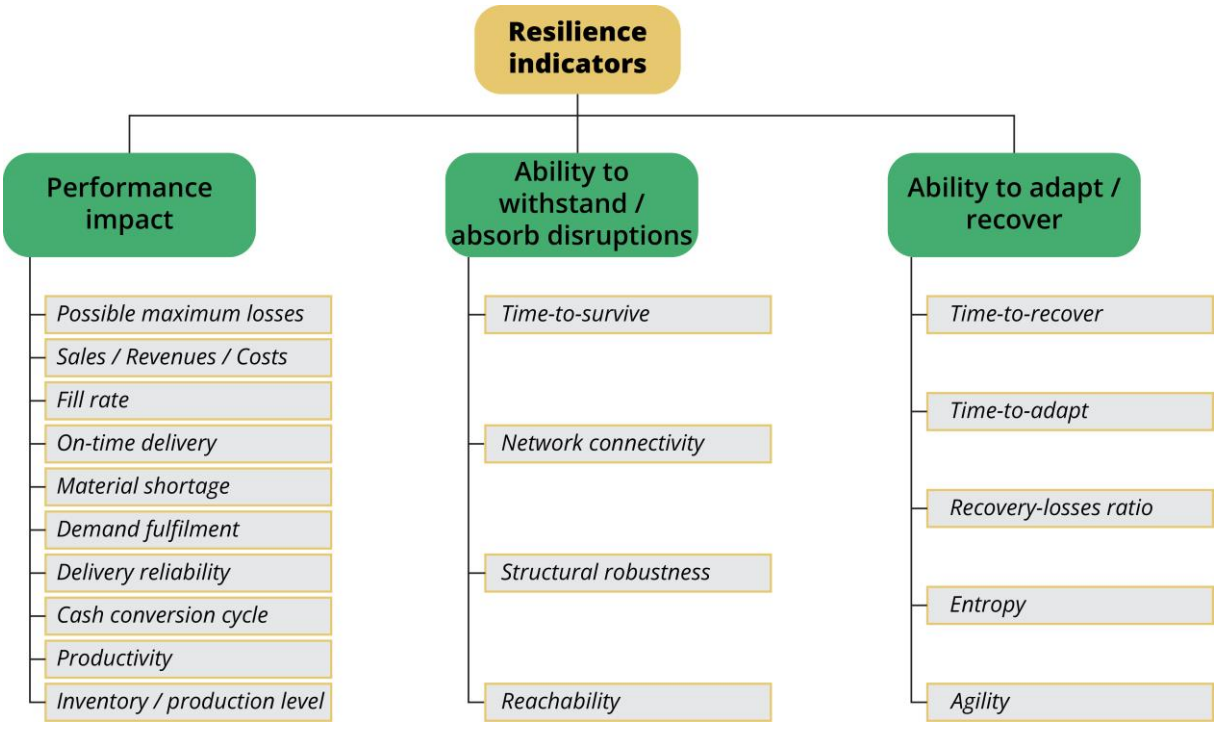
In modeling studies, the data sources include company data to predict supply chain responses to disruptions (Yand and Peng 2023), supply risks (Zheng et al. 2023), inventory disruptions (Jauhar et al. 2023), and recovery of port operations after COVID-19 pandemic (Cuong et al. 2022). Twitter data were used for demand volatility prediction during shocks (Nguyen et al. 2023).

In the network-theoretical studies, the usual procedure is to use business databases such Bloomberg, Marklines, and MergentHorizon to replicate networks of real companies like Apple, Honda, and Boeing for stress testing and revealing some generalized recommendations and patterns (Park et al. 2022, Li et al. 2021, Chauchan et al. 2021). Despite the visible trend toward primary data in optimization and simulation studies, many of them used secondary or artificial data. In AI-based studies, company ERP data (e.g., supplier performance and sales) and data from business databases have been used (Chauchan et al. 2021, Kosasih and Brintrup 2022).

3.4.2 Performance indicators

By definition, resilience is "*the firm's capability to withstand, adapt, and recover from disruptions to meet customer demand, ensure target performance, and maintain operations in vulnerable environments*" (Hosseini et al. 2019). This definition shows three major dimensions forming the resilience notion, namely a *performance* impact of disruptions, the ability to withstand/absorb disruptions, and the ability to adapt / recover after disruptions. As such, there are three groups of resilience indicators used in stress tests (Fig. 12).

Figure 12. A taxonomy of metrics used in supply chain stress tests



Source: Author's own compilation.

The *first* group of indicators used in stress tests aims at measuring the impact of disruptions on supply chain performance. Disruption impact on supply chain performance has been frequently measured by three major service level indicators, i.e., on-time delivery, fill rate, and demand fulfillment (Aldrighetti et al. 2024, Badakhsan et al. 2023, Nguyen et al. 2023). Assuming that a

disruption translates in late deliveries at customers, reduction in on-time delivery was associated with resilience decrease (Dolgui et al. 2020). While the on-time delivery and demand fulfilment indicators helps to detect a disruption in the supply chain from the customer perspective, fill rate allows identifying a disruption from the operational perspective (Moosavi and Hosseini 2021, Ivanov 2024d). For example, fill rate immediately informs about a disruption based on missing inventory in a warehouse while on-time delivery is measured at the customer and so indicated a disruption with some time delay because of some inventory pipeline and system inertia (Ivanov 2020a). Especially simulation studies performed with the use of anyLogistix software focused on a multi-indicator analysis covering service levels, costs, lead time, production and inventory levels, and demand fulfilment (Ivanov 2022, Ivanov 2024c).

Brusset et al. (2023a) proposed productivity as a measure of impacts of the COVID-19 pandemic on supply chains. Another important perspective of performance impact-based indicators is the financial one, for which such indicators as annual revenues, costs and sales have been used in extant literature (Alikhani et al. 2023, Ivanov 2017). Badakhsan and Ball (2023) and Ivanov (2024c) used cash conversion cycle as a metric for stress testing against financial flow disruptions. The concept of possible maximum losses has been used by Kinra et al. (2020) for quantifying the ripple effect in supply chains. This method is based on a monetary quantification of possible losses in sales and revenue due to disruptions upstream and associated material / component shortages which translate in the sales losses. Interestingly, indicators of supplier performance such as delivery reliability and delivery delays have been frequently applied in disruption predictions using AI methods (Bodendorf et al. 2023, Zheng et al. 2023).

The *second* group of indicators characterizes the ability to withstand / absorb disruptions. Network theory has been frequently applied using such metrics like spatial complexity, network density, degree and betweenness centrality, connectivity, reachability, and structural robustness to analyse structural integrity (Choudhary et al. 2021, Li and Zobel 2020, Habibi et al. 2023). Network indicators focus on quantifying the ability of a supply chain to maintain its structural connectivity and adaptability (Pavlov et al. 2022). When using network metrics, the focus is on a structure connectivity rather than a disruption impact. For example, a supplier disruption can result in some temporary discontinuity of a network. However, if a recovery is deployed effectively, the disruption can be mitigated and not seen at the performance level. This separation of network and process levels is one of the shortcomings to use graph-theoretical metrics for practical stress tests.

The *third* group of indicators focuses on the ability to recover. Here, two major approaches exist. The first one is based on measuring time. Simchi-Levi et al. (2015) introduced TTR (time-to-recover) indicator which measures the period between a disruption-driven capacity shutdown and the recovery of original capacity or its substitution by a back-up source. TTR has been used in stress tests against delivery time variability at suppliers by Ojha et al. (2018) and Corsini et al. (2024). The second approach is based on a ratio of disruptions and recovery efforts. Focusing on TTR and the time a supply chain is able to cope with shortages, Simchi-Levi et al. (2015) measured resilience as a relation of TTR and time-to-survive (TTS). TTS shows how long a supply chain can operate without its disrupted capacity (e.g., using some pre-positioned inventory). In short, if TTS is longer than TTR, a supply chain is considered resilient. However, there is no explicit quantification of resilience in this method. Burkhart and Bode (2024) used disruption intensity (disruption frequency × disruption duration) to investigate the relationship between supplier performance and supply chain disruptions.

Some studies focused on measuring the intensity of performance loss and recovery where resilience or vulnerability indicators are bounded between 0 and 1 (Ghadge et al. 2021Ren et al. 2024, Shi et al. 2022). Ojha et al. (2018) and Hosseini and Ivanov (2022b) quantified resilience using Bayesian networks. Resilience is calculated by 1 minus fraction of loss, so both metrics are bounded between 0 and 1. The main idea of their metric is to quantify resilience as a ratio of recovery and losses levels associated with a performance indicator (e.g., service level). As long as the recovery level is lower than the losses level, resilience is less than 1. Brintrup et al. (2020) used machine learning for predicting supplier disruptions based on agility metric understood as a

capability of suppliers to handle the highest monthly order variations as a proxy of the supplier's flexibility. For the COVID-19 pandemic-driven supply chain re-purposing, Dolgui et al. (2024) proposed a time-to-adapt (TTA) metric which measures time between disruption recognition and begin of adaptation deployment. Dolgui et al. (2024) show that an accurate determination of the TTA is crucial for an effective adaptation and shortage avoidance. In summary, our literature analysis allows identifying three major groups of indicators used for supply chain stress testing. In their integrity, these indicators can help recognise, predict, and analyse disruptions in the supply chain.

3.5 Managerial and policy implications

In this section, we analyse managerial and policy recommendations stemming from supply chain stress testing. Our analysis is based on both the set of papers used for the structured literature review and an additional set of references related to supply chain resilience research (see Annex 4).

In general, there are four groups of resilience capabilities related to preparedness and two groups related to recovery (Fig. 13).

Figure 13. Supply chain resilience capabilities

Supply Chain Resilience and Viability Capabilities					
Preparedness				**Recovery**	
Redundancy	Flexibility	Visibility	Learning	Network	Process
• *Risk mitigation inventory* • *Capacity buffers (warehouse, manufacturing, transport)* • *Backup suppliers and facilities* • *Facility fortification* • *Information system backup* • *Financial reserves*	• *Resilient and agile suppliers* • *Flexible / reconfigurable manufacturing systems* • *Additive manufacturing* • *Manufacturing agility (postponement, product variety, volume flexibility)* • *Multiple sourcing* • *Supplier diversification* • *Omnichannel and agile distribution and transport* • *Shared warehouses* • *Energy supply flexibility* • *Financial flexibility*	• *Digital twins* • *Industry 4.0* • *Blockchain* • *Data spaces* • *Collaborative supplier portals* • *Early warning systems*	• *Human-AI collaboration* • *AI and Generative AI* • *Social crisis simulations* • *Emergence trainings with suppliers* • *Resilience knowledge management* • *Contingency plans* • *Supply chain resilience management organization* • *Internet-of-Behaviors*	• *Cross-industry intertwining* • *Network reconfiguration (material, information, financial, energy)*	• *Capacity scalability* • *Process reconfiguration* • *Product substitution* • *Re-purposing* • *Third-party financing*

Source: Author's own compilation.

Preparedness builds a fundamental pillar of supply chain resilience and is composed of four major areas, i.e.:

— Redundancy

— Flexibility

— Visibility and

— Learning.

Redundancy is essentially related to using extra inventory (Li et al. 2023, Sawik and Sawik 2024), capacity expansion (Singh et al. 2021), and backups in material, financial, and information flows (Simchi-Levi et al. 2015, Zobel et al. 2021). Redundant assets are typically not used in everyday operations waiting for an emergency case. This approach can be costly and reduces efficiency (Ivanov 2022b).

Flexibility means organizing sourcing, manufacturing, warehousing, and transport operations based on principles of structural variety and process agility (Kim et al. 2015, Ivanov 2022a, Birge et al. 2023). Typical flexibility practices include selection of resilient and agile suppliers (Simchi-Levi et al. 2015, Torabi et al. 2015, Brintrup et al. 2020), supplier diversification and multiple sourcing (Li et al. 2020), manufacturing flexibility through reconfigurable technology equipment, postponement, product variety and process flexibility (Park et al. 2022, Lamorgese et al. 2024), distribution and transport flexibility (e.g., omnichannel and shared warehouses) (Li et al. 2023, Echefaj et al. 2024). A special part of flexibility is related to non-material flows, e.g., energy supply flexibility (Ivanov 2022) and financial flexibility (Badakhsan and Ball 2023). In contrast to redundancy, flexibility capability are not just waiting for an emergency case but can be actively used in everyday operations for improving efficiency and effectiveness (Aldrighetti et al. 2023). As such, additional investments in resilience can be avoided since systems with some degree of adaptability in their "normal" operations are presumed to behave resilient in a crisis scenario (Ivanov 2024d).

Visibility is a so-called 'soft resilience' capability that nonetheless plays a vital role in both supply chain stress testing and the development of managerial and policy recommendations. End-to-end visibility is crucial for both identification of disruptions and deployment of recovery policies (Nguyen et al. 2023, Jiang et al. 2024). Visibility can be designed using supply chain mapping and digital twins, Industry 4.0, blockchain, data spaces and collaborative supplier portals, as well as early warning systems (Duong and Chong 2020, MacCarthy and Ivanov 2022, Dolgui and Ivanov 2023, Zamani et al. 2023, Li et al. 2024, Smyth et al. 2024). Building digital twins of supply chains consists of two major parts: network discovery and process visibility.

Learning is another soft capability the importance of which has been growing with the development of data analytics capabilities and AI (Baghersad et al. 2022, Jackson et al. 2024b). Learning capabilities are strongly connected to knowledge management. On the one hand, systemic knowledge about disruption management is important for effective reactions to disruptions based on previous experiences (Baghersad et al. 2022, Shi et al. 2022). Social crisis simulations, emergence trainings with suppliers, resilience knowledge management, contingency plans, and supply chain resilience management organization are recommendations for development of learning capabilities. On the other hand, human-AI collaboration and generative AI along with Internet-of-Behaviors offer new technologies for both collecting, integrating and replicating human knowledge in AI but also for generating new knowledge and learnings using, e.g., intelligent digital twins (Ivanov 2023).

Turning the discussion toward *recovery* policies, we note that specific reactive capabilities can be related to network and process levels. The recovery at the network level can be performed using cross-industry intertwining (Dolgui et al. 2024) and network reconfiguration (material, information, financial, energy) through using other factories or change of suppliers (Ergun et al. 2023, Xu et al. 2024). Process recovery options are capacity scalability (e.g., increase of production capacity), process reconfiguration (e.g., logistics re-routing (Birge et al. 2023)), product substitution, re-purposing, and use of third-party financing (Badakhsan and Ball 2023). It should be noted that efficiency and effectiveness of reactive actions strongly depend on the scale and scope of preparedness.

Results of supply chain stress testing and the outcomes of scenario modeling can yield some useful recommendations not only for businesses but also for *policy makers*. For the context of long-term crises (e.g., COVID-19 pandemic or global semiconductor shortage), traditional, recovery-based resilience capabilities should be extended by supply chain viability (Ivanov and Dolgui 2020, Ivanov 2022) which aims at performance persistence and survivability ensuring business continuity in the presence of disruptions. Moreover, the notion of viability emphasizes the importance of considering not only the business aspects of resilience but also looking beyond the financial losses of individual firms. Viability suggests an ecosystem perspective and consideration of the whole intertwined supply networks responsible for provision of society with good and services (e.g., mobility, communication, agriculture, and healthcare ecosystem viability).

Dolgui et al. (2024) conclude that an appropriate collaboration of governmental agencies, healthcare, and industry is crucial for a prompt capacity conversion in case of a crisis such as a pandemic. Echoed by Li et al. (2023), concrete implementation ways are end-to-end visibility, standby inventory, cross-industry inventory monitoring for critical products and materials, technology backup plans, and repurposing contingency plans at the preparedness stage. At the response stage, a correct adaptation start time determines success. As such policy makers can provide incentives for businesses to develop technological and managerial plans for supply chain re-purposing and a cross-industry adaptation.

Summary: Our analysis shows a large variety of industry sectors and countries used in case-studies, numerical examples, and data samples. Data used for stress testing have a multitude of sources. Company, transactional, panel, business (e.g., MarkLines, Bloomberg, and Mergent Horizon), synthetic, secondary, expert, and social media data have been used. The commonly utilized indicators for supply chain stress tests have been service level, time-to-recover, delivery reliability, network connectivity and centrality, total costs and revenue, cash conversion cycle, demand satisfaction, and different types of resilience and vulnerability indexes. The most common managerial recommendations based on stress tests include identifying supply chain risks and crisis scenarios, building network redundancy (e.g., backup suppliers and risk mitigation inventory), enhancing flexibility and adaptability (e.g., multiple sourcing and omnichannel strategies), recognizing early signals of disruptions, identifying critical suppliers and logistics channels vulnerable to disruptions, optimizing contingency and recovery plans, and utilizing AI and digital twins for visibility and real-time disruption control. The recommendations for building more resilient supply chains include design of structurally adaptable and flexibly reconfigurable networks along with development of coordination mechanisms for cross-industry ecosystem viability based on a collaboration of governmental agencies and industry.

4. Methodological gaps, novel topics and future research directions

The existing methodological gaps are concerned with the fragmented and isolated application of different methods, which creates a disconnect between research problems and real-life needs. Practical industry applications of supply chain stress testing should be based on multi-method approaches. On the one hand, this can be achieved by integrating qualitative and quantitative methods. For instance, a policy (social) simulation can help uncover risks and crisis scenarios. These scenarios can then be examined using discrete-event simulation to quantify performance impacts, observe the ripple effect, and propose recovery strategies. On the other hand, different quantitative methods can be combined to enhance each other, such as integrating AI with simulation. Regardless of the method used, a crucial trade-off exists between the complexity of the supply chain for stress testing and its observability (visibility) to obtain all the data required for analysis.

While the interest in supplier disruptions, manufacturing and production disruptions, and demand disruptions has been trending in literature, other types of shocks such as logistics and warehouse disruptions as well as non-material flow-related disruptions (e.g., financial, energy, and information disruptions) have been less prioritized. Multi-facility disruptions where disruption propagation is considered show a significant increase during the pandemic along with the studies considering long-term crisis context. In future, stress testing should include crisis scenarios of different length and severity going beyond single, temporary disruptions.

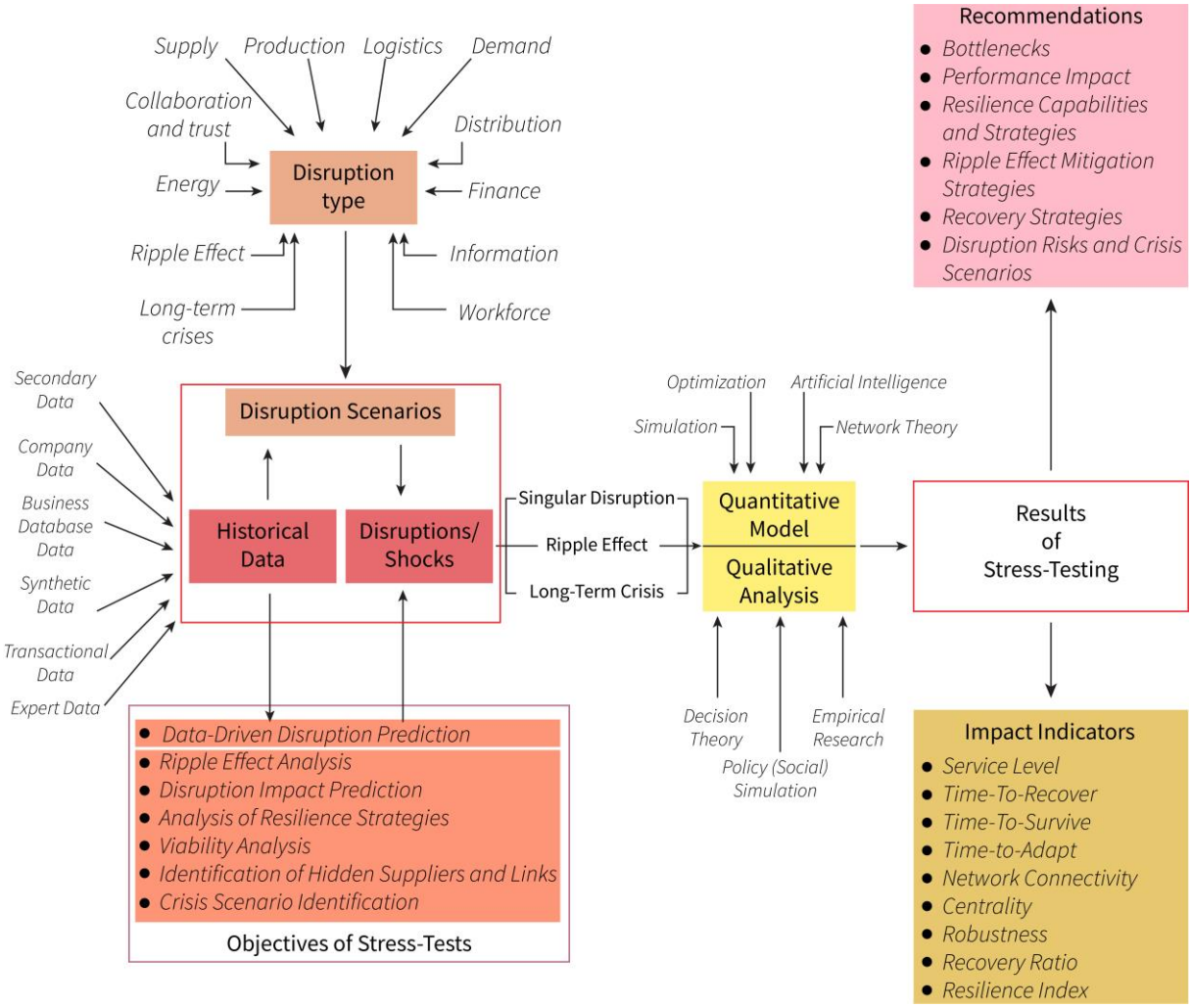
Novel and future topics in supply chain stress tests are digital twins, Metaverse and supply chain visibility, supply chain viability and Industry 5.0, intertwined supply networks and cross-industry ripple effect, financial ripple effect, ripple effect in the presence of hyper-disruptions like COVID-19 pandemic and global trade system disruptions, ripple effects in closed loop supply chains and circular economy, combination of simulation and AI, and combination of quantitative and empirical methods. Stress test studies should provide more decision-making support regarding investments in resilience. The fundamental question is, what is return-on-investments when considering resilience? Literature is silent about methodologies to quantify the impact of resilience investments. Finally, supply chain economics topics should be considered. The recently developed supply chain viability theory (Ivanov and Dolgui 2020, Ivanov 2022, Ivanov et al. 2023, Ivanov and Keskin 2023, Ruel et al. 2024) offers some foundations for stress-testing in the industry and even cross-industry context going beyond merely business objectives of individual supply chains and combining business, society, and ecological dimensions. The macroeconomics elements such as demand and supply elasticity, market equilibrium, purchasing behaviors, price dynamics, and financial ripple effect are important for viability analysis.

5. Conclusions

This report presented the results of a literature review on stress tests developed and applied in non-food supply chains. In Fig. 14, we summarize the main topics considered in this report in the form of a generalized framework for supply chain stress testing.

Supply chains are exposed to a multitude of stressors stemming from different internal and external disruptions. COVID-19 pandemic, geopolitical tensions, and natural hazards have clearly shown the importance of developing and maintaining resilience and viability capabilities for business continuity. A stress test is an analysis or simulation designed to determine the ability of a supply chain to withstand disruptions and recover. Stress tests are performed to understand behavior and performance of supply chains under disruptions in order to analyse the existing and suggest improved protection and recovery plans.

Figure 14. Generalized framework of supply chain stress testing



Source: Author's own compilation.

In this report, we analyzed the progress in stress testing methodologies and their applications using papers identified through a SCOPUS search performed in May 2024. We applied the bibliometric analysis approach to identify the objectives of stress tests, disruptions/shocks used in stress tests, different methodological approaches used for stress tests, design and typologies of disruption scenarios used for stress tests, data used for stress tests, and indicators used to analyse impacts/responses to different stress factors. We also analysed managerial recommendations

resulting from stress tests and evaluated the advantages and disadvantages of different methodologies developed and applied for stress testing.

Our main findings are as follows. The main objectives of supply chain stress tests have been to investigate the ripple effect, predict disruptions and disruption scenarios, examine interlinkages between supplier performance and resilience, analyse resilience strategies, performance impact of disruptions, and COVID-19 pandemic impacts, identify hidden suppliers and links, and analyse viability and role of trust and collaboration. Most typical shocks considered in the stress tests have been supplier, production, logistics, cash flow, and ripple effect risks. A special stream of literature is the COVID-19 pandemic studies, which are characterized by long-term crisis context and specific shocks such as lockdowns, shutdowns, panic buying, virus propagation, and workforce fluctuations.

Quantitative methodologies such as discrete-event simulation, Bayesian networks, stochastic and robust optimization, network theory, machine learning and AI, and optimal control dominate the stress test domain. Qualitative research has contributed to understanding of empirical and expert context of supply chain exposure to disruptions using organizational theories, social simulations, and regression analyses.

Our analysis shows a large variety of industry sectors and countries used in the case-studies, numerical examples and data samples. Data used for stress tests have a multitude of sources. Company, transactional, panel, business (e.g., MarkLines, Bloomberg, and Mergent Horizon), synthetic, secondary, and social media data have been used. For practical stress tests, network (i.e., buyer-supplier relations), process and product (i.e., capacity, inventory, demand, and bill-of-materials), and financial data are required.

The commonly utilized indicators for supply chain stress tests have been service level, time-to-recover, delivery reliability, network connectivity and centrality, total costs and revenue, cash conversion cycle, demand satisfaction, and different types of resilience and vulnerability indexes.

The most typical managerial recommendations based on the stress tests include building network redundancy (e.g., backup suppliers and risk mitigation inventory), flexibility and adaptability (e.g., multiple sourcing and omnichannel), necessity to recognize early signals for disruptions, identification of critical suppliers and logistics channels prone to disruptions, and use of AI and digital twins for visibility and real-time control of disruptions. We proposed generalized stress testing schemes for different methodologies as well as a generalized framework of supply chain stress testing.

The insights of our analysis allow for generalizing some relevant policy recommendations for supply chain stress testing. First, it is essential to define two major components, i.e., a supply chain model and crisis/disruption scenarios. The more complex the crisis scenarios, the more comprehensive model and data of high granularity degree might be needed. Second, the outcomes of stress testing depend on the type of uncertainty considered. For scenarios with known-known uncertainty (i.e., known risks and their probabilities), it is typically sufficient to hedge against disruptions using inventory pooling, multiple sourcing, and capacity redundancy principles. In case of unknown-unknown scenarios, the focus should be shifted from predictions to reactions. As such, one useful policy recommendations is in favor of designing supply chain adaptability through structural variety and process flexibility. Third, supply chains of different industries are intersecting building so called intertwined supply networks and ecosystems. For this type of system, the focus shifts from resilience of individual supply chains to stress testing viability of the whole ecosystems (e.g., mobility, communication, and healthcare).

The existing methodological gaps are mainly related to the fragmented and isolated application of different methods leading to the gaps between research problems and real life needs. A promising practical approach to supply chain stress testing is a combination of qualitative (e.g., a social simulation) and quantitative (e.g., computer simulation) methods. One practical trade-off in building stress test scenarios is between network complexity and data availability. In addition, a connection

between network and process levels should be established. Novel and future topics in supply chain stress tests are digital twins, Metaverse and supply chain visibility, supply chain viability and Industry 5.0, intertwined supply networks and cross-industry ripple effect, financial ripple effect, ripple effect in the presence of hyper-disruptions like COVID-19 pandemic and global trade system disruptions, ripple effects in closed loop supply chains and circular economy, combination of simulation and AI, and combination of quantitative and empirical methods.

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List of abbreviations and definitions

Abbreviations	Definitions
AI	Artificial Intelligence
AEB	Automatic Emergency Braking
LKA	Lane Keeping Assist
DES	Discrete-Event Simulation
MIP	Mixed-Integer Programming
AHP	Analytic Hierarchy Process
FCM	Fuzzy Cognitive Maps
MICMAC	Matrice d'Impacts Croisés Multiplication Appliquée à un Classement
TISM	Total Interpretive Structural Modeling
ERP	Enterprise Resource Planning
TTR	Time-To-Recover
TTS	Time-To-Survive
TTA	Time-To-Adapt

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Annexes

Annex 1. SCOPUS search string

((TITLE-ABS-KEY ("supply chain") OR TITLE-ABS-KEY ("supply network") AND TITLE-ABS-KEY ("resilience") OR TITLE-ABS-KEY ("disruption") AND TITLE-ABS-KEY ("predict*") OR TITLE-ABS-KEY ("ripple effect") OR TITLE-ABS-KEY ("performance impact") OR TITLE-ABS-KEY ("stress test*") OR TITLE-ABS-KEY ("stress test*"))) AND (LIMIT-TO (EXACTSRCTITLE,"International Journal Of Production Research") OR LIMIT-TO (EXACTSRCTITLE,"Computers And Industrial Engineering") OR LIMIT-TO (EXACTSRCTITLE,"International Journal Of Production Economics") OR LIMIT-TO (EXACTSRCTITLE,"Annals Of Operations Research") OR LIMIT-TO (EXACTSRCTITLE,"Transportation Research Part E Logistics And Transportation Review") OR LIMIT-TO (EXACTSRCTITLE,"International Journal Of Operations And Production Management") OR LIMIT-TO (EXACTSRCTITLE,"IEEE Transactions On Engineering Management") OR LIMIT-TO (EXACTSRCTITLE,"Production And Operations Management") OR LIMIT-TO (EXACTSRCTITLE,"European Journal Of Operational Research") OR LIMIT-TO (EXACTSRCTITLE,"International Journal Of Physical Distribution And Logistics Management") OR LIMIT-TO (EXACTSRCTITLE,"Journal Of Supply Chain Management") OR LIMIT-TO (EXACTSRCTITLE,"Journal Of Business Logistics") OR LIMIT-TO (EXACTSRCTITLE,"Journal Of Operations Management") OR LIMIT-TO (EXACTSRCTITLE,"Journal Of Purchasing And Supply Management") OR LIMIT-TO (EXACTSRCTITLE,"Journal Of Business Research") OR LIMIT-TO (EXACTSRCTITLE,"Computers And Operations Research") OR LIMIT-TO (EXACTSRCTITLE,"Manufacturing And Service Operations Management") OR LIMIT-TO (EXACTSRCTITLE,"Transportation Research Part B Methodological") OR LIMIT-TO (EXACTSRCTITLE,"Decision Sciences") OR LIMIT-TO (EXACTSRCTITLE,"Management Science") OR LIMIT-TO (EXACTSRCTITLE,"IISE Transactions") OR LIMIT-TO (EXACTSRCTITLE,"Journal Of The Operational Research Society") OR LIMIT-TO (EXACTSRCTITLE,"Operations Research") OR LIMIT-TO (EXACTSRCTITLE,"Decision Support Systems") OR LIMIT-TO (EXACTSRCTITLE,"Omega United Kingdom") OR LIMIT-TO (EXACTSRCTITLE,"International Journal Of Logistics Management") OR LIMIT-TO (EXACTSRCTITLE,"International Journal Of Integrated Supply Management")) AND (LIMIT-TO (SUBJAREA,"BUSI") OR LIMIT-TO (SUBJAREA,"DECI") OR LIMIT-TO (SUBJAREA,"ENGI") OR LIMIT-TO (SUBJAREA,"COMP")) AND (LIMIT-TO (DOCTYPE,"ar"))

Annex 2. Detailed literature review analysis

Study	Objective / main context of stress testing	Study type: empirical/ theoretical	Method	Sector	Stage of the chain covered	Country/region covered	Type of data used	Advantages	Limitations	Impact indicators	Identified risks and vulnerabilities	Identified recommendations
Alam et al. (2024)	Ripple effect in the supply chain	Empirical	A multi-method approach: Pareto analysis, TISM, and MICMAC	Food grain SC	customer, retailer, wholesaler, and manufacturer production, suppliers	Bangladesh	Primary data collected in interviews	Real-life context, primary data	Subjective opinions of experts	N/a	Grain production risks, panic buying risks, liquidity crisis	Sourcing diversification, governing cash flow to avoid the liquidity crisis, and supplier clustering according to disruptive risks are the most significant enablers of resilience
Aldrighetti et al. (2024)	Supply chain stress testing framework	Theoretical	Optimization and simulation	Mechanical manufacturing	Customer, distribution, production, suppliers	Italy	Primary and synthetic	A decision-support system for stress testing is proposed	Focus on industry sector only	Service level, costs	Supplier disruption, production disruption, warehouse disruption; combined disruptions	Stress testing framework should consist of three major steps: data collection, model, and validation mechanism
Alikhani et al. (2023)	Choosing the right resilience strategies given different types of stressors	Theoretical	Stochastic programming	Retail	Customer, retailer, wholesaler, and manufacturer production, suppliers	Iran	Primary and synthetic	Real-life context, primary data, multiple resilience strategies, optimization methodology	Single-objective optimization, single product model; limited managerial insights	Total SC cost, unmet demand	Earthquake-triggered supplier, production, and retail disruptions; widespread disruption (i.e., the COVID-19 pandemic); a cyber disruption	Importance of considering synergistic effects among resilience strategies under budget limitations for supply chain resilience, e.g., multiple sourcing, omnichannel, production and retail diversification
Aljuneidi et al. (2024)	Stress testing a supply chain for disruptions during COVID-19	Theoretical	Time-series forecasting and MIP	Meat supply chain	Farms, processing centers, and retailers	USA / California	Primary data	Real-life context, primary data, optimization methodology, combination of predictive and prescriptive analytics	Cost-oriented optimization; limitations in terms of products and geographical scope	SC costs	COVID-19 pandemic and associated supply capacity disruptions due to lockdowns	Model to forecast the available capacity of meat processing centers during a pandemic; accurate demand and supply forecasting, and the recourse to rolling horizon planning approach, allow for satisfying the demand and maintaining the SC profit during disruptions

Study	Objective / main context of stress testing	Study type: empirical/ theoretical	Method	Sector	Stage of the chain covered	Country/region covered	Type of data used	Advantages	Limitations	Impact indicators	Identified risks and vulnerabilities	Identified recommendations
Badakhshan and Ball 2023	To examine the impact of disruptions in physical and financial flows on SC performance.	Theoretical	ML and DES	N/a	customer, retailer, wholesaler, and manufacturer production	N/a	Synthetic	The model can be integrated with ML algorithms, which could establish a set of decision rules for setting inventory and cash replenishment policies to minimize the impact of disruptions.	The decision tree algorithm might recommend different inventory strategies for SC members in presence of other inventory ordering policies; single-objective model focusing on the manufacturer; centralized approach without collaboration elements	Service level; cash conversion cycle; inventory level	Demand increase, capacity reduction, and credit purchase increase	Inventory and cash replenishment policies that minimise the impact of the disruptions on SC performance; noticeable reduction in the cash conversion cycle for upstream members of the SCs; cash conversion cycle for the upstream SC members is greatly impacted by the inventory policy employed by their immediate downstream members.
Bodendorf et al. (2023)	Predict supply disruptions based on external and internal data and quantify causal effects on delivery reliability.	Mixed (empirically-grounded analytics)	Causal inference and deep learning	Automotive	Tier 1 supplier and manufacturer	N/a	Supplier's ERP system, the Global Economy platform, Visual Crossing's climatic data	Real-life context, primary data, identification of causal relationships between supplier characteristics and the expected delivery performance	The method can be used for creating scenarios for stress tests but does not propose a methodic for stress tests themselves	Delivery reliability	Sourcing disruptions, vulnerabilities in buyer-supplier relationships	The model can learn causalities from observed data and analyze interventions effecting supply disruptions, identification of causal relationships offers the potential to identify lacking supplier relationships and consequently bundle supply chain risk management activities.
Brintrup et al. (2020)	Predicting Tier1 supplier disruptions using historical data available at a manufacturer	Theoretical	ML	Manufacturing of complex engineering assets	Tier 1 supplier and manufacturer	N/a	Manufacturer's ERP system data about supplier delivery performance	Real-life context, primary data, quantification of agility as a measure to predict supplier exposure to disruptions	Only one prediction approach is considered, no comparison with other approaches; data set from only one single case-study	Agility: capability of suppliers to handle the highest monthly order variations as a proxy of the supplier's flexibility.	Supplier disruptions	The method can be used for creating scenarios for stress tests and predicting supplier proneness to disruptions based on manufacturer data
Brusset et al. (2023a)	Stress test of a supply chain against the ripple effect	Theoretical	Optimal control and epidemiological models	N/a	Supplier, manufacturer, warehouse, customer	Europe	Synthetic data	The model enables prospective analyses to be performed in what-if scenarios to simulate the	Unclear if the model can handle complexity of real-life supply chains; limited number of performance	SC productivitiy	Workforce variability under pandemic conditions	The model can help analyse the impact and spread of a pandemic in a particular region on supply chain productivity. It can also help examine the ability of a supply network to overcome

Study	Objective / main context of stress testing	Study type: empirical/ theoretical	Method	Sector	Stage of the chain covered	Country/region covered	Type of data used	Advantages	Limitations	Impact indicators	Identified risks and vulnerabilities	Identified recommendations
								impact on the workforce in each node.	indicators in the analysis			the ripple effect under long-term disruptions.
Brusset et al. (2023b)	Production stress test for pandemic-triggered restrictions and spread of infections	Theoretical	Optimal control and epidemiological models	Meat processing plant	Production and retail	Europe	COVID-19 data, secondary data	The models help understand and measure the impact of an infection on production and the corresponding cost. It can help examine the ripple effect as suppliers affected by the pandemic are unable to fulfill the processing plant requirements and so the retailer's orders.	Unclear if the model can handle complexity of real-life supply chains; some hard assumptions which can be difficult to fulfil in real-life	Protection effort, demand satisfaction, costs	Workforce variability under pandemic conditions	Decision support models for a plant manager to help in deciding on (a) the level of protection of the workforce against the spread of the virus in the absence of regional protection measures, (b) on the duration of the protection, and (c) the level of protection of the workforce with regional protection measures enforced by health authorities.
Burkhart and Bode (2024)	To investigate the relationship between supplier performance and supply chain disruptions.	Empirical	Regression analysis	Large industrial machinery	Production and suppliers	Germany (manufacturer), worldwide (suppliers)	Supplier panel data	Empirical evidence of relationship between a supplier's overall performance and the frequency and duration of supply chain disruptions	Contextual findings which might be difficult to generalize	Disruption intensity (disruption frequency × disruption duration)	Disruptions notably affect supplier quality; poorly performing suppliers are associated with more frequent and longer disruptions.	For purchasing practice, this study suggests that supplier performance is a proxy for supplier resilience; supplier performance is an important predictor for the occurrence of disruptions
Chauhan et al. (2021)	The relationship between nested patterns and the ripple effect	Theoretical	Network science / graph theory	Automotive	Multi-echelon supply chain	Global	Marklines database	A cascade model by bringing together the product-supplier-buyer structure	Secondary data, missing flow considerations (only network)	Robustness	Upstream disruptions	Nested organisational structures are significantly more robust to random disruptions but vulnerable to hub disruptions under cascade conditions.
Chen et al. (2022)	Stress testing of a logistics network resilience against node failures	Theoretical	Network science / graph theory	Express delivery industry	Logistics	China	Data provided by ZTO express (a leading express delivery company in China)	Impacts of the node/nodes failure to resilience of logistics network are analysed.	Disruptions only at nodes (no consideration of edges), unclear if the model can tackle real-life complexity	A resilience metric based on the criticality of nodes in a network	Disruptions in the logistics networks can lead to the ripple effect	Strategies for resilience improving yields of different investments and nodes involved, By improving the tolerance ability of the nodes, the criticality of each node and each node pair can be suppressed and the

Study	Objective / main context of stress testing	Study type: empirical/ theoretical	Method	Sector	Stage of the chain covered	Country/region covered	Type of data used	Advantages	Limitations	Impact indicators	Identified risks and vulnerabilities	Identified recommendations
												resilience of the express logistics network can be improved.
Choudhary et al. (2021)	Stress testing of a SC during COVID-19 pandemic	Theoretical	Network science / Agent-based simulation	Electronics	Customers, a manufacturer, Tier 1 and Tier 2 suppliers)	US / worldwide	Network of Apple constructed	Complex network, sound methodology	Unclear if the model can tackle real-life complexity; only network indicators in the analysis, no process indicators	Spatial complexity, degree centrality, betweenness centrality, and closeness centrality	The disruptions experienced by firms depend on the stringency of measures taken to curb the pandemic in their respective countries and the severity of disruptions experienced by suppliers in a specific region.	At the network level, average degree and spatial complexity significantly influence resilience. At the firm-level, powerful firms within the network influence resilience based on their betweenness centrality and closeness Centrality.
Corsini et al. (2024)	Stress testing the supply chain against delivery time variability at suppliers	Theoretical	Simulation, ML and metaheuristics	Semiconductor industry	Manufacturer and supplier	N/a	Synthetic data	Combination of data analytics, simulation modeling, ML, and a metaheuristic	Only two-stage supply chain is considered; origin of data is not clearly explained at times	Time-to-recover and Time-to-survive	Delivery time disruptions at suppliers result in manufacturing disruptions	The approach helps improve the manufacturer's performance through adaptation of inventory replenishment policies under critical and unexpected peak loads, in particular in terms of time-to-recover and time-to-survive
Cuong et al. (2022)	Predicting recovery of seaport operations after a pandemic	Theoretical	Four-dimensional fractional Lotka-Volterra competition model, fractional calculus, and system dynamics, and neural networks	Maritime logistics	Seaport	Vietnam	Primary data	Real-life context and data, consideration of a post-recovery stage, multi-method analysis	No resilience-related indicators in the analysis, too complex method for real-life applications	Growth rate of a seaport throughput	COVID-19 pandemic and maritime disruptions	Control strategies with neural network forecasting can help managers obtain timely and cost-effective decision-making policy for port resilience considering disruption impacts on global supply chains related to COVID-19 pandemic.
De Vries et al. (2022)	To examine how cross-functional teams react to supply chain disruption warnings	Empirical	SC management simulation	N/a	N/a	N/a	Data from "The Fresh Connection" (TFC) simulation	Real-life context and data, consideration of cross-functional teams	Contextual data obtained in a management simulation; no clear blueprint for managers to organise the process of	N/a	Disruptions in supply and capacities	The cross-functional team is an effective solution for firms dealing with increased information-processing demands due to several SC disruption warnings.

Study	Objective / main context of stress testing	Study type: empirical/ theoretical	Method	Sector	Stage of the chain covered	Country/region covered	Type of data used	Advantages	Limitations	Impact indicators	Identified risks and vulnerabilities	Identified recommendations
									processing disruption warnings			
Dolgui et al. (2020)	To stress test the SC against both ripple and bullwhip effects	Theoretical	DES / anyLogistix	N/a	Customers, warehouses, manufacturer	N/a	Synthetic data	Combination of disruption and operational risks, methodology which can be used in real life	Limited data set, secondary data	Service level, costs	Increased risk of both the ripple and bullwhip effects if supply quantities decrease and demand increases during a disruption	To avoid amplification of the ripple and bullwhip effects, it is recommended to avoid backlog accumulation during the disruption period and so called disruption tails, i.e. the transition of the accumulated backlog into the post-disruption period resulting in further destabilizations in inventory and production control even in the case of full capacity restoration.
Dreyfus and Nair (2022)	To examine the impact of magnitude and likelihood of disruptions on surgical procedure performance.	Empirical	Normal accident and high-reliability organizational theories	Healtcare	Hospitals	USA	Multi-respondent survey	Service supply chain context (healthcare), strong theoretical concept	Insights explain what should be done, but the analysis does not provide a clear blueprint on how the proposed measures should be implemented	N/a	Operational disruptions	Information exchange and risk management infrastructure play moderating role in mitigating the negative effect of disruptions on performance.
El Baz et al. (2023)	Predicting the effects of supply chain resilience and robustness on COVID-19 impacts and performance	Empirical	Resources orchestration theory and structural equation modeling analysis	Cross-industry	N/a	France	Multi-respondent survey	Real-life context and data, consideration of cross-industry perspective	Perceptual data were collected at the beginning of the pandemic crisis in Europe, and objective data relate to the year 2020. Thus, the results of this study could change over time.	N/a	COVID-19 pandemic disruptions	Managers should understand their key role in orchestrating the resources and capabilities linked to SC resilience and robustness in order to maintain the firm's performance in a 'super-disruption' situation.
Ghadge et al. (2021)	Stress testing the supply chain against the ripple effect	Theoretical	Systems dynamics simulation	N/a	Retailers, manufacturers, suppliers	N/a	Secondary data	Dynamic analysis of the ripple effect	No real-life data	Vulnerability index (between 0 and 1) that measures risk exposure and is calculated by combining quantitative weighted	The ripple effect subject to supply, demand, and logistics disruptions as well as a combined, simultaneous disruption of supply,	The model can help practitioners visualise and recognise the ripple effect cascading across the SC network

Study	Objective / main context of stress testing	Study type: empirical/ theoretical	Method	Sector	Stage of the chain covered	Country/region covered	Type of data used	Advantages	Limitations	Impact indicators	Identified risks and vulnerabilities	Identified recommendations
										risk scores into a cumulative value.	demand and logistics	
Giannoccaro and Iftikhar (2020)	Role of trust and network topology for resilience	Theoretical	NK simulation	N/a	Retailers, distributors, manufacturers	N/a	Secondary data	Dynamic analysis of the ripple effect	No real-life data	N/a	The ripple effect in supply chains	Trust positively affects supply network resilience; however, across the different topologies, the beneficial effect of trust varies. In particular, trust is most beneficial for the following topologies: local, small-world, block-diagonal, and random.
Habibi et al. (2023)	Stress testing the supply chain against the ripple effect	Theoretical	Simulation	N/a	N/a	N/a	Synthetic data	Six metrics to assess the absorptive, adaptive, and restorative capacities of resilience.	No real-life data; only network level of analysis (no analysis of processes and flows)	Network density, graph energy	The ripple effect in supply chains	Networks exhibiting scale-free structure offer enhanced reliability, responsiveness, persistence, and shorter recovery time.
Hosseini and Ivanov (2022a)	Stress testing the supply chain during COVID-19 pandemic	Theoretical	Bayesian network (BN)	Meat industry	Retailers, distributors, manufacturers	USA	Survey-based data	The unique features of BN, such as forward and backward propagation analysis, are utilised to simulate and measure the impact of different triggers on SC financial performance and business continuity.	Methodology would need some adjustments when dealing with real-life complexities.	Lost sales	Demand shocks, labor shortage, logistics disruptions, price surge, production disruption, supply drop	An approach to stress test SCs under pandemic with consideration of expert assessments
Hosseini and Ivanov (2022b)	Stress testing the supply chain for disruptions	Theoretical	Bayesian network (BN)	Automotive	Manufacturer and suppliers	Iran	Secondary data	Stress testing the supply chain with consideration of both disruptions and recovery	Methodology would need some adjustments when dealing with real-life complexities.	A resilience metric representing a ratio of recovery to ratio of loss (bounded 0; 1)	Supplier disruptions propagating to the manufacturer	The approach can be used by managers to identify the disruption profiles in the supply base and associated SC performance degradation caused by the ripple effect. The method explicitly allows uncovering latent, high-risk suppliers which make the SC prone to the ripple effect.
Hosseini et al. (2020)	Stress testing the supply	Theoretical	Bayesian network (BN) and	N/a	Manufacturer and suppliers	N/a	Synthetic data	It proposes a metric that quantifies the	Methodology would need some adjustments	Service level, utility of a	Supplier disruptions propagating to	The model can be used for uncovering latent high-risk paths in the SC, analysing

Study	Objective / main context of stress testing	Study type: empirical/ theoretical	Method	Sector	Stage of the chain covered	Country/region covered	Type of data used	Advantages	Limitations	Impact indicators	Identified risks and vulnerabilities	Identified recommendations
	chain for the ripple effect		Markov Chains					ripple effect of supplier disruption on manufacturers in terms of total expected utility and service level.	when dealing with real-life complexities.	manufacturer	the manufacturer	the performance impact of both disruptions and their propagations, and prioritising contingency and recovery policies.
Ivanov (2017)	Stress testing the supply chain for the ripple effect	Theoretical	DES / anyLogistix	N/a	Customers, distributors, manufacturers	N/a	Synthetic data	Dynamic analysis of disruption propagation	No real data, only downstream part of the SC is considered	Total sales, revenue, costs	Capacity disruption at manufacturer and its propagation downstream	The simulation model can be used to observe SC behaviour and associated ripple effects in case of an upstream disruption
Ivanov (2020a)	Stress testing the supply chain for production capacity disruptions	Theoretical	DES / anyLogistix	Retail	Customers, distributors, manufacturers	N/a	Synthetic data	Notions of disruption overlays and disruption tails are defined; dynamic analysis of disruption impacts on performance	No real data, only downstream part of the SC is considered	Service level, backlog	Capacity disruptions at factories	Capacity disruptions at factories can be mitigated by back-up sourcing, risk mitigation inventory, and subcontracting
Ivanov (2020b)	Stress testing the supply chain against COVID-19 pandemic	Theoretical	DES / anyLogistix	FMCG	Customers, distributors, manufacturers, suppliers	Global	Synthetic data	The first simulation paper that predicted pandemic impacts on global supply chains; this paper put foundations on supply chain simulation stress test methods	No real data since the research was done before the pandemic	Service level, lead time, inventory level, revenue, costs	Ripple effect caused by lockdowns and shutdowns during the COVID-19 pandemic	It predicted that the timing of the closing and opening of the facilities at different echelons will become a major factor that determines the epidemic outbreak impact on the SC performance. Other important factors are lead-time, speed of epidemic propagation, and the disruption durations. It offered a methodology of supply chain stress testing using simulation.
Ivanov (2022)	Stress testing the supply chain against power outage and blackout	Theoretical	DES / anyLogistix	FMCG	Customers, distributors, manufacturers	N/a	Synthetic data	The first simulation paper that dealt with a stress test for a blackout proposing a methodology for this specific type of disruptions	No real data	Service level	Dynamics of the power loss propagation across different regions, simultaneous unavailability of supply and logistics along with the	Blackout is determined as a special case of SC risks which is distinctively characterized by a simultaneous shutdown of several SC processes, disruption propagations (i.e., the ripple effect), and a danger of viability losses for entire ecosystems. The model can be used to predict the operative and

Study	Objective / main context of stress testing	Study type: empirical/ theoretical	Method	Sector	Stage of the chain covered	Country/region covered	Type of data used	Advantages	Limitations	Impact indicators	Identified risks and vulnerabilities	Identified recommendations
											unpredictable customer behaviour because of the blackouts	long-term impacts of blackouts on the SCs and viability and develop mitigation and recovery strategies
Ivanov (2023)	To develop a general methodology of SC stress testing using digital twins	Theoretical	DES / anyLogistix / AI	N/a	N/a	N/a	N/a	Introduction of intelligent digital twin concept using human-AI collaboration for SC stress testing	The framework is developed but its application in practice is described only conceptually	N/a	Supply, demand, capacity risks	A notion of an intelligent digital twin for SC stress testing was introduced - a human–AI system which visualizes physical SCs in digital form, collects and processes data for modelling using analytics methods, mimics human decision-making rules, and creates new knowledge and decision-making algorithms through human–AI collaboration.
Ivanov (2024a)	Literature review about trends in supply chain resilience and stress testing	Conceptual	N/a	N/a	N/a	N/a	N/a	The first paper analysing transformation of supply chain resilience research through the COVID-19 pandemic.	No modelling examples	N/a	Pandemic risks	Observation of a major shift from preparedness and disruption predictions in the pre-pandemic literature towards recovery and proactive adaptation in the pandemic and post-pandemic research. New topics are digital technology, supply chain viability, the cross-industry ripple effect, and intertwined networks.
Ivanov (2024b)	Immune system-based model for supply chain resilience analysis	Theoretical	N/a	N/a	N/a	N/a	N/a	The first paper proposing a methodology to stress test SCs using immune system analogy	Only a generalized model, no numerical modelling examples	N/a	N/a	An immune system-inspired mechanism for supply chain resilience is proposed using a combination of innate and adaptive responses and complemented by the principles of diversity and redundancy.
Ivanov (2024c)	Stress testing the supply chain cash-flows against supplier disruptions	Theoretical	DES / anyLogistix	Retail	Customers, distributors, suppliers	China, South Korea, Japan	Synthetic data	The paper proposes recommendations for payment terms adjustment across the supply chain in case of	Contextual analysis based on a single data set	Cash conversion cycle, accounts payable, accounts receivable	Supplier disruptions can lead to cash-flow disruptions	A collaborative adjustment of payment terms is an effective strategy to cope with supplier disruptions. Ad hoc adjustments and immediate returns to pre-disruption payment schemes

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								disruptions at suppliers				do not yield visible improvements. Positive effects on cash and loans are observed if an adjustment of payment terms occurs proactively and in a coordinated manner, especially when expediting payments downstream and payment slowing down upstream.
Ivanov (2024d)	Stress testing the supply chain against disruption tails when recovering after the COVID-19 pandemic	Theoretical	DES / anyLogistix	Brewery	Customers, distributors, factory	Europe	Synthetic data	The paper proposes recommendations for adapting inventory-production-ordering policies when recovering after a long-term disruption to avoid disruption tails	Contextual analysis based on a single data set	Service level, demand backlog, inventory level	Demand and capacity shocks; supply chains with postponed demand and shutdown capacity during the COVID-19 pandemic are particularly prone to disruption tails.	The model can be used guide the selection of post-pandemic recovery strategies. A conjunction of recovery and supply chain coordination mitigates the impact of disruption tails by demand smoothing over time in the post-disruption period. A gradual capacity ramp-up prior to expected peaks of postponed demand is an effective strategy for disruption tail control.
Ivanov and Dolgui (2021)	Literature review about supply chain stress testing against the ripple effect	Conceptual	N/a	N/a	N/a	N/a	N/a	The first paper analysing OR methodologies for the ripple effect analysis	No modelling examples	N/a	COVID-19 pandemic	Adaptation capabilities play the most crucial role in managing the SCs under pandemic disruptions
Jauhar et al. (2023)	Predicting inventory disruption in case of demand shocks	Theoretical	No Code AI and ML	N/a	Retail and warehouse	N/a	Two years' sales data	AI-based method for disruption predictions	Contextual analysis based on a single data set	Inventory level	Demand shocks cause inventory destabilization	No Code Artificial Intelligence (NCAI) approach is proposed enabling non-technical companies to build machine learning models based on production quantity and inventory replenishment.
Kinra et al. (2020)	Quantifying the ripple effect exposure	Theoretical	Possible maximum loss method	Retail, contract manufacturing	Customer, warehouse, supplier	Germany	Company data	Monetary quantification of the ripple effect exposure; The ripple effect quantification is validated with simulations using	Contextual analysis based on a single data set	Ripple effect exposure and supplier risk exposure	Supplier disruptions lead to the ripple effect and associated financial losses	The model can be used to reveal latent high-risk supplier relations and prioritise risk mitigation efforts when probability estimations are difficult. The performance indicators proposed can be used by

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								actual company data.				managers to analyse disruption propagation impact and to identify the set of most critical suppliers to be included in the disruption risk analysis.
Kosasih and Brintrup (2022)	Predicting hidden links in supply chain	Theoretical	ML, graph neural networks	Automotive	Multi-stage supply chain	Global	Marklines database	The model is suitable for supply chain practitioners who only have limited local information about their companies' suppliers and buyers	Secondary data, focus on technical part rather than managerial insights	N/a	Supplier disruptions	A data-driven method to identify hidden links in supply chains
Liu et al. (2024)	Stress testing supply chain resilience and viability against the ripple effect	Theoretical	Robust optimization and BN	N/a	Suppliers and factory	N/a	Randomly generated a data	Focus on both resilience and viability	The method can need adjustments to be used in real-life	Costs	Risks of supply chain disruptions triggered by supplier failures can be mitigated by governmental interventions	The limited budget and data scarcity are considered for government intervention.
Liu et al. (2021)	Stress testing supply chain resilience against the ripple effect	Theoretical	Robust optimization and BN	N/a	Suppliers and factory	N/a	Secondary data	Possibility to acquire the robust performance of risk estimation, measured by the worst-case probability in the disrupted state for the manufacturer.	The method can need adjustments to be used in real-life complexities	Recovery measure	Supplier disruption risks	Supplier disruptions lead to the ripple effect
Liu and Ren (2024)	Impact of production disruptions on customers, supply chain, and society	Theoretical	Game theory	N/a	Manufacturer and retailers	N/a	N/a	Both business and societal components of resilience are considered	The method can be difficult to use for large-scale problems	Profit	Production disruptions leading to profit risks in the supply chain	The model allows examining the profit risk in a supply chain facing production disruptions and also the impacts on consumer surplus and society
Li and Zobel (2020)	Stress testing supply chain resilience against the ripple effect	Theoretical	Network theory	Automotive	Multi-echelon supply chain	Japan	Bloomberg SPLC database for Honda and Toyota	Systematic analysis of the factors contributing to SC resilience; a comprehensive analysis of how	Secondary data, the level of SC complexity for computation of different indicators is unclear	Robustness, recovery time, average functionality	Supplier and production disruptions	A multi-dimensional framework that enables a better characterization of the complexity of resilience, and thus that it provides support for more informed managerial decision-making

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								network structure and node risk capacity influence resilience and the ripple effect				about investing in improving resilience.
Li et al. (2021)	Stress testing supply chain resilience against the ripple effect	Theoretical	Network theory	Automotive	Multi-echelon supply chain	Japan	Bloomberg SPLC database for Honda and Toyota	Multi-level quantitative analysis to explore the effects of forward and backward disruption propagation, moderated by network structure, network-level health and node-level vulnerability.	Secondary data, the level of SC complexity for computation of different indicators is unclear	Network health, propagation period, centrality, in- and out-degrees	Supplier and production disruptions	Forward disruption propagation generally can be mitigated by substitute and backup supply and has greater impact on firms serving the assembly role and on the sup-ply/assembly networks, whereas backward disruption propagation is normally mitigated by flexible operations and distribution and has bigger impact on firms serving the distribution role and on distribution networks.
Lopez and Ishizaka (2019)	To predict the impacts of offshore outsourcing location decisions on SC resilience.	Theoretical	Fuzzy Cognitive Maps (FCM) and Analytic Hierarchy Process (AHP)	Drinks	Multi-echelon supply chain	Global	Expert information	Practical tool and real life content	Subjective nature of data	N/a	N/a	Locations criteria and their influence on the supply chain resilience capabilities.
Mariappan et al. (2022)	Predicting shipment times of therapeutics in e-pharmacy supply chains	Empirical / Theoretical	ML	E-pharmacy	Multi-echelon supply chain	Global	Organic data of over 5.9 million records of therapeutic shipments	Practical tool and real life content	Subjective nature of data	N/a	COVID-19 pandemic	A novel ML-based framework for predicting the shipment times of therapeutics, diagnostics and vaccines
Mizgier et al. (2013)	How to identify firms that induce high losses at the focal firm and the entire supply chain?	Theoretical	Monte Carlo simulation	N/a	Multi-echelon supply chain	N/a	N/a	Production disruptions on the firm level are modelled with stochastic point processes, and a mechanism for the propagation of losses through the network is defined	No real data, the level of SC complexity for computation of different indicators is unclear	Costs	Production disruptions	The model can be used as an efficient tool for the quantification of losses caused by supply chain disruptions, both in isolation and when embedded in the network structure.

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Moosavi and Hosseini (2021)	Stress testing the supply chain against disruption tails when recovering after the COVID-19 pandemic	Theoretical	DES / anyLogistix	LED manufacturing	Supplier, factory, customers	China, Iran	Primary data	Dynamic analysis, real-life context	Contextual findings based on a single data set	Costs, demand fulfilment, lost sales	Production disruptions during COVID-19	Supply chain disruptions can be mitigated by back-up sourcing and inventory pre-positioning
Nguyen et al. (2023)	To predict demand volatility during shocks	Theoretical	Deep-learning-based sentiment analysis model	Pharmaceuticals	Multi-echelon supply chain	France	Twitter	A framework allowing for combining extracted information from unstructured data with structured data of medicines demand was defined	Contextual findings based on a limited data set	Demand fullfilment	Demand shocks during COVID-19 pandemic	An approach combining efficient artificial intelligence techniques with existing forecasting models is proposed to enhance demand forecasting in times of disruption.
Ojha et al. (2018)	Stress testing the supply chain against the ripple effect	Theoretical	BN	N/a	Supplier, factory, retailer, customers	N/a	N/a	Model to stress test the supply chain considering disruption propagations	No real data, the level of SC complexity for application of the proposed approach is unclear	Time-to-recover, lost sales, service level, fragility, resilience index	Supplier disruptions propagating through the network	The ripple effect of node disruption is evaluated using metrics like fragility, service level, inventory cost and lost sales. Developed risk exposure and resilience indices support in assessing the vulnerability and adaptability of nodes in the supply chain.
Park et al. (2022)	Stress testing the supply chain against the ripple effect considering circular flows	Theoretical	Simulation	Aerospace	Multi-echelon supply chain	Global	Boeing supply chain structure extracted from the Mergent Horizon database	The model can be applied when a Tier 2 supplier is also a Tier 3 (or higher) supplier in the supply chain network. Additionally, it can be used when a supplier is also a customer in the same network.	Secondary data, small-scale numerical example	Production level, demand satisfaction, inventory level	Ripple effect in the supply chain with circular flows	The model can be used to examine the effect of circular flows on the ripple effect and identify how this influences the supply chain's resilience to disruptions.
Pavlov et al. (2022)	Identification of the disruption scenarios, ripple effect dispersal, and recovery paths	Theoretical	Fuzzy-probabilistic method	N/a	Supplier, retailer, customers	N/a	N/a	New methodical approach to the detection of disruption scenarios, ripple effect dispersal and recovery paths in supply	No real-life data, too complex approach for real-life applications	Structural robustness	Upstream disruptions leading to the ripple effect.	The method can be used to compare different supply chain structural designs regarding the robustness and to identify disruption scenarios that interrupt the supply chain operations to different extents. The

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								chains on the basis of structural genomes.				scenario detection can be further used for identifying optimal reconfiguration paths to deploy proactive contingency and reactive recovery policies.
Queiroz et al. (2022)	Literature review on impacts of epidemic outbreaks on supply chains	Conceptual	N/a	N/a	N/a	N/a	N/a	Major elements of scenarios for pandemic disruptions	Paper was written in the spring of 2020, insights from the COVID-19 pandemic are not considered	N/a	N/a	Research agenda for pandemic-triggered stress testing
Ren et al. (2024)	Stress testing the supply chain against geopolitical disruptions	Theoretical	Simulation	Electric vehicle lithium-ion battery production	Multi-stage supply chain	Global	Mergent Online, iFinD financial data terminal	A meso-level supply chain network was constructed based on real data; a geopolitical disruption diffusion model has been developed to simulate the disruption propagation in two distinct scenarios, i.e., single-region blockade and inter-region blockade.	Contextual data, single-industry focus	Vulnerability index	Geopolitical disruptions	The approach can be used for the evaluation of both direct and indirect impacts of geopolitical disruptions
Rozhkov (2022)	Stress testing the supply chain against the ripple effect	Theoretical	Simulation	FMCG, perishable products	Multi-stage supply chain	N/a	N/a	Dynamic analysis, focus on perishable products	Contextual findings, limited data set	Service level, costs	Ripple effect risks	The model can be used for industries with perishable products
Sawik (2022)	Supply chain resilience under ripple effect	Theoretical	Stochastic programming	Hi-tech industry	Customer, retailer, distribution, manufacturer suppliers	EU, USA Asia	Primary and synthetic	A multi-portfolio decision framework for computationally efficient optimization of supply chain resilience under pandemic crises	Focus on COVID-19 pandemic crisis	Total SC cost, customer service, unmet demand	Multi-regional pandemic disruption risks and ripple effect	Resilient measures commonly used to mitigate the impacts of region-specific disruptions can also be successfully applied to mitigate the impacts of multi-regional pandemic disruptions and the ripple effect.

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Sawik (2023a)	Supply chain viability under ripple effect	Theoretical	Stochastic programming	Hi-tech industry	Customer, retailer, distribution, manufacturer suppliers	EU, USA, Asia	Primary and synthetic	A multi-portfolio decision framework for computationally efficient optimization of supply chain viability under ripple effect	Focus on smartphone manufacturing under pandemic crisis	Total SC cost, customer service, lost sales	Multi-regional pandemic disruption risks and ripple effect	Instead of a viability kernel commonly used in the viability theory, the boundaries on acceptable supply chain states are established. Within the boundaries, the supply chain can continue to exist under the ripple effect and avoid severe losses.
Sawik (2023b)	Supply chain reshoring under ripple effect	Theoretical	Stochastic programming	Hi-tech industry	Customer, retailer, distribution, manufacturer, suppliers	EU, USA, Asia,	Primary and synthetic	A decision framework for computationally efficient optimization of supply chain reshoring under ripple effect	Focus on tier-one suppliers and tier-zero manufacturers in a multi-tier smartphone supply chain.	Total SC cost, reshoring cost, government subsidy, customer service, lost sales	Multi-regional pandemic disruption risks and ripple effect	Reshoring decisions are strongly dependent on the level of government subsidy for capital expenditure. For risk-neutral reshoring, a portfolio of supply chain nodes with positive expected net savings can be considered only.
Shi et al. (2022)	Ripple effect with collaboration	Theoretical	Network science	N/a	Suppliers and manufacturers	Global	N/a	Collaboration is included in the analysis	The approach might be too complex for implementation	Resilience index	Ripple effect risks	The model can be used to examine the impact of collaboration in networks on the ripple effect
Yang and Peng (2023)	Prediction of supply chain recovery strategies	Theoretical	Demand forecasting and MIP	Electronics	Customer, distribution, manufacturer, suppliers	China	Company data (Dongsheng Electronics Co., Ltd)	A data-based demand predictive method with feedback errors; selection of the supply portfolio incorporating product change.	The approach might be too complex for implementation	Product costs, service level	Supplier disruption risks	The proposed disruption recovery strategy can reduce the unit product cost and improve the service level
Zhang et al. (2024)	Stress testing the supply chain against the ripple effect	Theoretical	Network theory	N/a	Multi-stage supply chain	N/a	Synthetic and real-life data	A three-dimensional quantitative framework to evaluate network resilience by conducting case studies on synthetic and real-life supply chain networks.	The approach might be too complex for implementation	Resilience metric	Supplier disruptions	The more uniform the role distribution of firms, the more resilient the network is.
Zheng et al. (2023)	Collective supply risk prediction	Theoretical	Federated ML	Maritime complex enginee	Suppliers and manufacturer	UK	Primary and synthetic data	Federated learning can help predict supply risk effectively, especially for	Can be challenging to use for large-scale networks	Delivery delays	Supply risks	It proposes a federated learning approach for collective risk prediction without the risk of data exposure.

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				ring assets				buyers with limited datasets.				

AHP – Analytic Hierarchy Process

BN – Bayesian Network

DES – discrete-event simulation

FCM – Fuzzy Cognitive Maps

MICMAC – matrice d'impacts croisés multiplication appliquée à un classement

MIP – mixed integer programming

ML – machines learning

TISM – total interpretive structural modelling

Source: Author's own compilation.

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