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Review of metrics to assess resilience capacities and actions for supply chain resilience

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ABSTRACT

Efficiency and profitability are the main drivers of globalization and have led to long and complex supply chains. Recent disturbances such as COVID-19 or the Suez Canal obstruction caused severe supply disruptions and thereby unveiled the vulnerability of global trade. Resilient supply chains are characterized by the capacity to absorb, adapt to, and restore after disruptions. Building upon the established concept of the 'resilience curve', this article explores the interplay between resilience capacities, metrics, and actions in the state-of-the-art literature. We first analyze and harmonize the terminology used to describe capacities as well as metrics for quantifying resilience. This results in a set of 17 resilience metrics that describe all characteristics of the resilience curve and can be used as a tool to assess the resilience of a supply chain. Subsequently, we propose how these metrics can be applied to quantify the effect of resilience actions. Finally, we analyze which actions are proposed in the literature and classify those actions according to their relation to traditional supply chain planning tasks. Practitioners such as supply chain decision-makers can implement these actions to strengthen the absorptive, adaptive, and restorative capacities and are provided with mathematical formulations to quantify the strengthening effect of actions. Academic research can, inter alia, integrate the metrics into multi-criteria optimization models for decision-making and explore the interplay between economic efficiency, environmental sustainability, and resilience.

1. Introduction

Supply chains provide products and services to customers and society, and to be competitive, the product or service must be provided cost-efficiently and fast. Companies thus strive to increase their economic performance by increasing revenues (e.g., expansion of product variety), reducing costs (e.g., reduction of the number of suppliers, just-in-time production), and reducing assets (e.g., outsourcing of less profitable divisions), which has led to long and complex global supply chains (Tang, 2006). However, economic efficiency under normal circumstances can come with high costs and even lead to uncompetitive supply chains in case of unexpected disruptions and changing market environments (Lee, 2004). In light of pandemics, politically unstable regions, vulnerable trade routes, and consequences of climate change, the topic of supply chain disruptions is more discussed than in previous decades. For example, the COVID-19 pandemic demonstrated how shortages due to local production stops can propagate through highly specialized, efficient, and global supply chains, leading to disrupted systems and networks (Pujawan & Bah, 2022). Similarly, the obstruction of the Suez Canal by the *Ever Given* in March 2021 blocked 12 % of the daily global trade for six days and caused a total economic loss of between $6 and $10 billion, illustrating the vulnerability of global supply chains (Russon, 2021).

Those two prominent examples demonstrate that a wide variety of causes can compromise the performance of a supply chain. Bruneau et al. (2003) initially presented a conceptual framework for studying a system's resilience by mapping a performance degradation after a disruption over time, which later resulted in the so-called 'resilience curve'. *Resilience metrics* formally describe the curve and are thereby an indicator for the resilience of a system that faces a disruption (Poulin & Kane, 2021). How good or bad a supply chain copes with a disruption depends on its *resilience capacities*, i.e., its capabilities to absorb the disturbance, adapt to the changed conditions, or restore the status quo ante (Biringer et al., 2013; S. Hosseini et al., 2019; Vugrin et al., 2011).

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Resilience actions are precautionary, anticipatory steps that decision-makers can proactively take to strengthen the absorptive (e.g., physical protection of plant), adaptive (e.g., rerouting), and restorative (e.g., repair team) capacities and thereby to improve the resilience metrics (Carvalho et al., 2012; S. Hosseini et al., 2019; Sun et al., 2022).

Several literature reviews on supply chain resilience (SCR) have investigated definitions, quantification methods, and resilience actions. Among existing definitions of SCR, there is little consensus regarding terminologies and the various aspects that 'resilience' may comprise (Y. Han et al., 2020; Hohenstein et al., 2015; Kamalahmadi & Parast, 2016; Poulin & Kane, 2021; Ribeiro & Barbosa-Póvoa, 2018). To fill this gap, some reviews have synthesized existing definitions (e.g., Kamalahmadi & Parast, 2016) or proposed frameworks to analyze existing and standardize new definitions (e.g., Ribeiro & Barbosa-Póvoa, 2018).

Other reviews have focused on existing quantitative SCR assessment methods and their relation to qualitative, theoretical resilience concepts. Han et al. (2020) synthesized the literature on performance metrics of resilience, identified *readiness*, *response*, and *recovery* as the three main resilience capacities, and presented a framework to link capacities to metrics. S. Hosseini et al. (2019) reviewed operations research (OR) models incorporating resilience metrics and categorized actions (i.e., proactive or reactive decisions) to increase SCR according to the absorptive, adaptive, and restorative capacity. Both studies identified a lack of resilience metrics that are developed based on capacities (Y. Han et al., 2020; S. Hosseini et al., 2019). Ribeiro and Barbosa-Póvoa (2018) reviewed quantitative SCR models and concluded that many studies examine drivers of resilience (e.g., connectivity of edges within a network, or robustness of a supply chain) without quantifying resilience per se. Similarly, Sharkey et al. (2021) investigated the relationship between network optimization and resilience theory in articles on physical or cyber-physical systems by classifying networks according to four resilience aspects (robustness, rebound, adaptability, and extensibility). They found that most models focus on the optimization of system robustness and rebound, while the aspects of adaptability and extensibility are rarely represented. As a first attempt to close the gap between quantitative approaches and concepts of resilience theory, Poulin and Kane (2021) addressed previous findings on heterogeneous metrics and terminologies. They introduced a standardized taxonomy and categorized existing metrics according to the characteristics of the resilience curve they describe (Poulin and Kane, 2021).

Other reviews have focused on quantitative methods that aim to increase SCR by actions. Hohenstein et al. (2015) and Behzadi et al. (2020) analyzed existing quantitative methods and categorized actions separately, and Snyder et al. (2016) categorized methods from OR and management science according to their aim (e.g., assessment of disruption effects on supply chains, modeling of decisions on sourcing strategy) and found that most models consider only a single resilience action.

Although the existing reviews contribute to a better understanding of existing SCR definitions and the interrelations between resilience capacities and resilience metrics, as well as between resilience actions and resilience metrics, the following research gaps still exist:

Gap 1: The terminology for resilience capacities is heterogeneous and needs clarification and consolidation. In contrast to existing reviews, we aim to provide an overview of various existing terms and analyze which of the aforementioned capacities established in resilience theory (i.e., absorptive, adaptive, restorative capacity) is addressed.

Gap 2: The relation between the concept of the resilience curve, resilience capacities, and existing quantitative metrics needs to be analyzed. To extend the work of Poulin and Kane (2021), we use their proposed taxonomy to reformulate the heterogeneous mathematical formulation of the various metrics employed in the literature, locate them along the resilience curve, and analyze the differences in the mathematical formulation. Finally, we propose a set of metrics with a unified terminology and synthesized mathematical formulations, with which all characteristics of the resilience curve can be described quantitatively. In addition, we integrate the resilience capacities into the resilience curve to draw the relationship between resilience capacities, resilience metrics, and the resilience curve.

Gap 3: The benefit of resilience actions needs to be quantifiable (Behzadi et al., 2020). We conceptually present how the set of metrics (cf. gap 2) can be used to quantify the positive effect of resilience actions on each characteristic of the resilience curve.

Gap 4: The relation between resilience actions, traditional supply chain planning tasks, and their effect on resilience is underrepresented in SCR literature. Sharkey et al. (2021) state that the contribution of resilience actions to the improvement of the overall resilience of a system is insufficiently investigated. Studies have already classified existing resilience actions according to their type (e.g., Hohenstein et al., 2015), time-horizon (e.g., Ribeiro & Barbosa-Póvoa, 2018), or which capacities they strengthen (e.g., S. Hosseini et al., 2019). However, understanding the interplay between traditional supply chain planning tasks, resilience actions, and the capacities strengthened by these actions is essential for estimating the effect of planning decisions on SCR. Our work categorizes identified resilience actions according to their time-horizon and type of planning task and draws the link to the capacities that are strengthened. Against this background, we investigate the following research questions:

- ***RQ1***: Which terminology does resilience literature use to describe **resilience capacities** (Gap 1)?
- ***RQ2***: Which general mathematical formulations of **resilience metrics** can be derived from literature to describe the resilience curve and to assess the **resilience capacities** (Gap 2)? How can the effect of **resilience actions** be quantified with these metrics (Gap 3)?
- ***RQ3***: Which **resilience actions** for strengthening the SCR are proposed in the literature, and how can they be classified (Gap 4)?

To answer RQ1 and RQ2, we review articles on SCR as well as articles on systems and networks other than supply chains. This is attributed to the rapid development of the field of resilience research, which is why including systems and networks ensures that the state of the art of system resilience theory and resilience quantification is captured. Finally, RQ3 is answered based on the reviewed supply chain literature specifically.

This work adds to the existing literature by investigating the relations between *resilience capacities*, *resilience metrics*, and *resilience actions.* It further contributes to a standardized terminology and, consequently, a common qualitative and quantitative understanding of resilience in the supply chain context based on the concept of the resilience curve. To the best of our knowledge, our work is the first that derives a literature-based set of generalized metrics for assessing the benefit of resilience actions on each characteristic of the resilience curve. This set is proposed as a basis for decision-making to strengthen the resilience of supply chains. Section 2 presents the method to identify, review, and analyze the relevant literature. Section 3 answers the research questions: Subsection 3.1 analyzes the existing types of *performance, i.e.*, the benchmark value against which the resilience of a system is measured. Subsection 3.2 analyzes how resilience capacities are understood in the literature and which terms are used. Subsection 3.3 analyzes existing metrics, their relation to the resilience curve and the capacities, and how they can be used to assess resilience actions. In subsection 3.4, the resilience actions proposed in the supply chain literature are classified into an extended version of the traditional supply chain planning matrix by Fleischmann et al. (2008). Finally, section 4 discusses the limitations of our work and provides an outlook on how our findings can be used by both academia for future research and supply chain decision-makers.

2. Method

Fig. 1 visualizes the research procedure to identify resilience

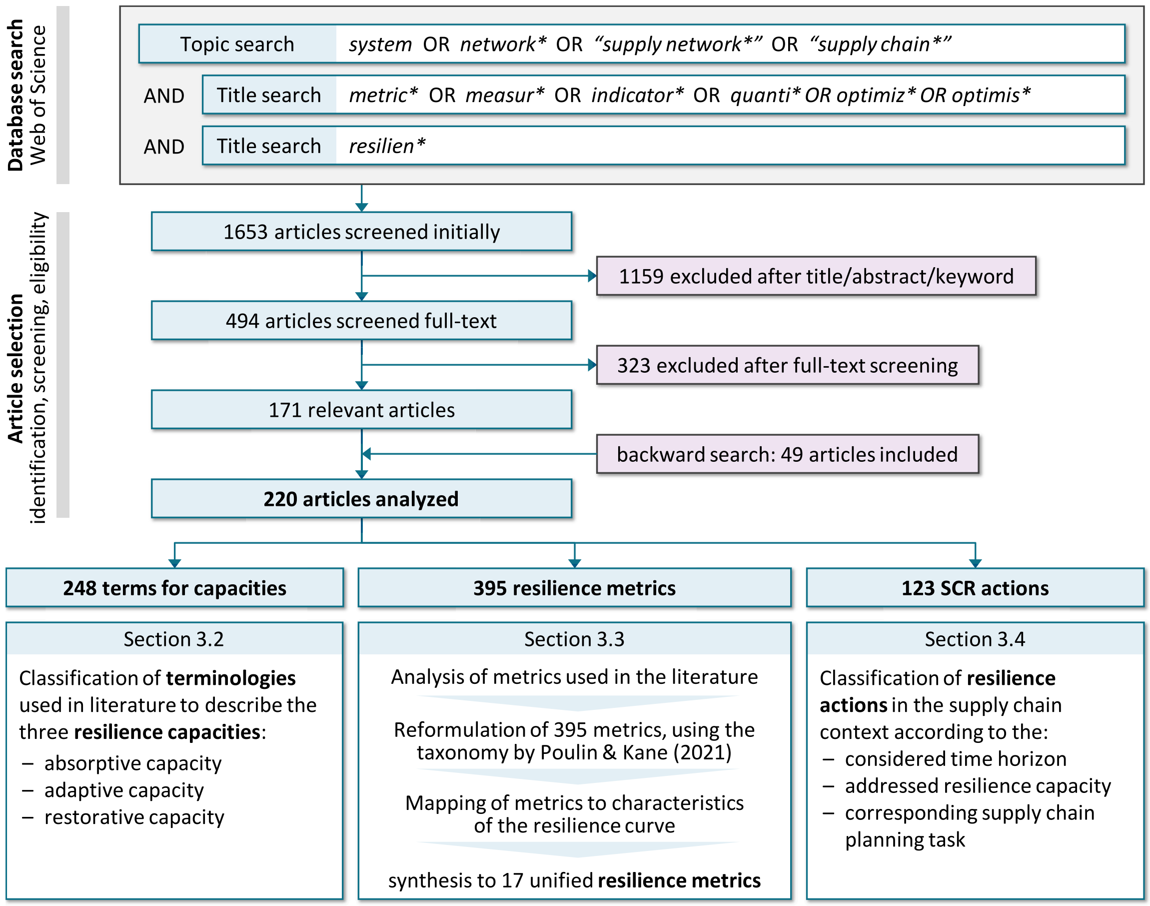

Fig. 1. Literature search and review methodology.

capacities, metrics, and actions from existing literature. Since we focus on articles that explicitly provide a resilience metric, keywords referring to *metrics* and *resilience* are included in a title search. Many quantitative SCR articles have developed optimization models containing metrics as objective functions or constraints to design or improve resilient systems. Consequently, the title search also includes two keywords referring to optimization to cover these articles in our analysis. Furthermore, the applied search string is tailored to detect metrics in the context of systems and networks, and supply chains in particular. Since existing research on resilience theory mainly focuses on systems, with supply chains being one prominent example (S. Hosseini et al., 2016; Poulin and Kane, 2021; Quitana et al., 2020), we extend the search to the literature on resilient systems in general, aiming to transfer insights (e.g., metrics) to supply chains specifically. The terms *system*, *network*, *supply network*, and *supply chain* are therefore searched in title, abstract, and keywords. The terms *capacity* and *actions* are intentionally not included in the search string since existing literature may refer to these concepts with a plethora of different terms. The search for peer-reviewed articles was conducted in August 2023 in the 'Web of Science' database, which was chosen due to its multidisciplinary scope and frequent use within quantitative resilience reviews. We are aware that the applied search string might not identify all articles on resilience optimization models that might be applied in individual OR case studies. However, the search string adequately covers our primary goal to include a broad set of existing metrics that are sufficient to quantify all resilience curve characteristics and the effect of resilience actions. The application of a broader search string, including synonymous of *resilience* (e.g., *disruption* or *risk*) or the keywords *metric* or *optimization* in the topic search, would lead to an unmanageable number of results.

In total, 1653 articles were identified and subsequently screened based on their title, abstract, and keywords. In this step, 1159 articles were excluded when they (1) focus on psychology, livelihood, or human, animal, social, or ecological systems, (2) do not present resilience metrics or a resilience objective function, or (3) cannot be linked to the resilience curve. Consequently, 494 articles were identified as eligible for the full-text analysis as they present a resilience metric in the context of supply chains, systems, or networks and can be linked to the resilience curve or resilience capacities.

After the full-text analysis, 323 articles were excluded when (1) the proposed resilience metric cannot be expressed quantitatively, (2) the resilience metric cannot be linked with the resilience curve, (3) the mathematical formulation of the resilience metric is missing, or (4) the article presents a review of resilience metrics, resulting in 171 relevant articles. Lastly, we conducted a backward search with (previously excluded) SCR reviews and the identified SCR articles, which yielded 49 additional articles. In total, 220 relevant articles (see Appendix A) were analyzed in depth. If possible, three main pieces of information were extracted from these articles: (1) the terminology applied to describe resilience capacities, (2) the resilience metric and its mathematical formulation, and (3) the resilience actions proposed to strengthen the resilience capacities of supply chains.

Section 3.2 assigns the identified terms to describe resilience aspects to the corresponding capacities. Section 3.3 analyzes and consolidates the resilience metrics. First, we identify the mathematical formulations of 395 metrics in the investigated literature. Second, these metrics are reformulated using the taxonomy of Poulin and Kane (2021) to express the mathematical formulations in a standardized language (e.g., $p(t)$ is the performance at any time t). Third, the standardized metrics are mapped to the characteristics of the resilience curve they describe. Fourth, we analyze the variants of the mathematical formulations for each characteristic and ultimately synthesize them into 17 unified metrics. Finally, in section 3.4, the identified resilience actions are assigned to existing supply chain planning tasks and categorized according to the planning horizon and the resilience capacity that is strengthened. All identified actions are located in an extended version of the traditional supply chain planning matrix introduced by Fleischmann et al. (2008).

3. Results

Section 3 analyzes the identified terminologies for capacities, metrics, and actions. It discusses different types of system performances (section 3.1), analyzes and harmonizes terms used to describe resilience capacities and maps them to the resilience curve (section 3.2), compiles a set of 17 metrics to quantify all characteristics of the resilience curve and the benefit of resilience actions (section 3.3), and reviews resilience actions and classifies them into an extended supply chain planning matrix (section 3.4).

3.1. Types of performance

A wide variety of causes can disrupt the performance of supply chains. Observing *performance* over time allows for illustrating the resilience curve of disrupted systems, which builds the foundation for resilience considerations in various studies. Since there is no unambiguous measure of a system's performance, this section examines how 'performance' is interpreted in the literature: It either refers to the *productivity* of a system (economic performance $p_e(t)$, physical output $p_o(t)$), to the *quality* ($p_q(t)$), or to *availability* criteria (availability/number of components $p_n(t)$) (Poulin & Kane, 2021).

The majority (174 of 220) of the reviewed articles present resilience metrics based on output performance. In the context of supply chains specifically, this can refer to the percentage of fulfilled demand (Ojha et al., 2018; Ribeiro & Barbosa-Póvoa, 2022; Sawik, 2017; Schmitt & Singh, 2012; Zavala et al., 2019), the number of products shipped from the manufacturer to the customer (Fattahi et al., 2017; Rajesh, 2016), the number of products not delivered from supplier to the manufacturer (Torabi et al., 2015), or the production capacity (Vugrin et al., 2011). Most of the remaining studies refer to the output performance in terms of the loss in system functionality (e.g., Francis & Bekera, 2014; Ghosh & De, 2022; Henry & Ramirez-Marquez, 2012; Sun et al., 2022). Only 52 of 220 studies present resilience metrics based on economic, quality, or availability criteria. Economic criteria determine the system's performance in 30 studies, especially in the context of SCR. Here, most of the presented metrics are based on the increase in costs associated with a disruption and/or recovery (e.g., Anderson et al., 2018; Arab et al., 2016; Belhadi et al., 2021; Carvalho et al., 2012; Fattahi et al., 2020; Hishamuddin et al., 2013; Maheshwari et al., 2017; Mari et al., 2014; Shahbazi et al., 2021; Smith et al., 2020; Vugrin et al., 2011; H. Zhang et al., 2018, 2019), or to the overall profit or lost profit (e.g., Bao et al., 2019; Behzadi et al., 2020; Shang et al., 2022; W. J. Tan et al., 2020). Ribeiro and Barbosa-Póvoa (2022) propose the cash flow-based expected net present value as part of their resilience metric. 16 studies describe the performance through quality parameters $p_q(t)$ such as the lead time (Carvalho et al., 2012; Spiegler et al., 2012), the ratio of products delivered on-date, the ratio of shipments arriving with no damage (Rajesh, 2016), the reliability of infrastructure (Aghababaei et al., 2021; Bruneau et al., 2003) or individual performance indices (e.g., Y. Bai et al., 2022; Zarghami & Zwikael, 2022). Ten studies refer to the performance based on the availability of components $p_n(t)$ by evaluating the number of failed edges or nodes in power systems (Ouyang et al., 2012; Panteli et al., 2017; Yarveisy et al., 2020; H. Zhang et al., 2018), the number of employed workers (Di Tommaso et al., 2023) or the number of facilities affected by a stockout within a supply chain (Rajesh, 2016).

3.2. Resilience capacities

How a system maintains its performance in case of a disruption depends on the system's *resilience capacities*. Most conceptual resilience literature differentiates between *absorptive*, *adaptive*, and *restorative capacity* (Biringer et al., 2013; S. Hosseini et al., 2019; Vugrin et al., 2011), with some literature separately including a *withstanding capacity* (Ouyang et al., 2012; Shin et al., 2018; Umunnakwe et al., 2021). *Absorptive capacity* is the extent of a system's ability to resist or absorb external impacts and refers to the system's vulnerability (Biringer et al., 2013; Vugrin et al., 2011). A*daptive capacity* is a system's ability to reorganize itself to offset disruptions (Biringer et al., 2013; Vugrin et al., 2011), and *restorative capacity* describes a system's repair efficiency and effectiveness (Biringer et al., 2013; Vugrin et al., 2011); both refer to a system's recoverability. In this chapter, we investigate the terms used in literature to refer to the characteristic of the resilience curve that is addressed by a metric. Consequently, the evaluated terms are assigned to the related resilience capacity. Our procedure aims to categorize heterogeneous terminology on resilience capacities. We thereby contribute to a better understanding of the relation between resilience metrics and absorptive, adaptive, and restorative capacity, as pointed out by Y. Han et al. (2020). In some works, it is noticeable that the terms *capacity* and *capability* have been used interchangeably, with a majority of studies using the term *capacity*. This work only uses *capacity* but understands the two terms as synonyms. In total, 248 terms (81 unique terms) relating to the absorptive, adaptive, or restorative capacity were identified in the literature and are analyzed in detail in the following (cf. Table 1).

95 of the 220 investigated studies refer to the absorptive capacity. Absorptive capacity has the highest impact on a system's performance from the beginning of the disruptive event until the performance is compromised the most (cf. Fig. 2). The term 'absorptive capacity' itself has been used by ten studies (Aghabegloo et al., 2023; Cheng et al., 2020; Francis & Bekera, 2014; Jinyi et al., 2020; Ouyang et al., 2012; Vugrin et al., 2011; Y. Yang et al., 2018; Yarveisy et al., 2020; Zhao et al., 2016, 2017). Eleven studies use the term 'robustness' when referring to absorptive capacity (Ahmadi et al., 2022; Amirioun et al., 2019; Beyza & Yusta, 2021; Cimellaro et al., 2010; Dong et al., 2022; Fang & Zio, 2019; Goldbeck et al., 2019; Y. Li & Zobel, 2020; Reed et al., 2009; Tao et al., 2022; Yao et al., 2023; Z. Zhang et al., 2023). For example, Fang and Zio (2019) propose a resilience metric to quantify the robustness of a system as the functionality right after the disruption. Nine studies use the term 'vulnerability' (Alguacil et al., 2014; Amirioun et al., 2019; Fang et al., 2015; Ghorbani-Renani et al., 2020; Kim & Yeo, 2016; Mari et al., 2014; Niu et al., 2023; Ojha et al., 2018; Z. Zhang et al., 2023) to describe resilience metrics which, e.g., assess the event impact in terms of the immediate performance decline (Amirioun et al., 2019). Six studies use the term 'absorption' (Najarian & Lim, 2019; Roach et al., 2018; Tran et al., 2017; Valenzuela et al., 2018; Veit et al., 2023) for metrics that evaluate, e.g., how well the performance of a system can be retained during a disruption (Najarian & Lim, 2019). Five studies refer to 'responsiveness' to describe the immediate reaction to a disruption (Ahmadian et al., 2020; Ayala-Cabrera et al., 2019; Rajesh, 2016; Schmitt & Singh, 2012). Three studies use the term 'resistance', which is used similarly to 'robustness' (Amirioun et al., 2019; H. Li et al., 2023; H. Zhang et al., 2018). Only three studies use the term 'absorptive capability' (Nan et al., 2016; Nan & Sansavini, 2017; X. Wang et al., 2022), underlining the dominance of the term 'capacity' in quantitative resilience literature. However, some works use terms like 'recovery speed' (Y. Li & Zobel, 2020; Z. Liu & Wang, 2021; Schmitt & Singh, 2012) or 'rapidity' (Huang & Pang, 2014; Ren et al., 2017; X. Wang et al., 2022) which do not explicitly refer to absorptive capacity. Those works aim at quantifying resilience on an aggregated level without differentiation between resilience capacities. In this case, we separated the applied metrics into the components that describe the characteristics of the resilience curve that refer to absorptive capacity (see 3.3). For

Table 1
Heterogeneity in the terminology in the observed literature. The table links the used terms with associated resilience capacities (absorptive, adaptive, and restorative; Vugrin et al., 2011). The number of the respective sources refer to the numbering of the reviewed articles as provided in Appendix A.

Term		Articles
		Absorptive capacity
"robustness"	11	(Ahmadi et al., 2022; Amirioun et al., 2019; Cimellaro et al., 2010; Dong et al., 2022; Fang & Zio, 2019; Goldbeck et al., 2019; Y. Li & Zobel, 2020; Reed et al., 2009; Tao et al., 2022; Yao et al., 2023; Z. Zhang et al., 2023)
"absorptive capacity"	10	(Aghabegloo et al., 2023; Cheng et al., 2020; Francis & Bekera, 2014; Jinyi et al., 2020; Ouyang et al., 2012; Vugrin et al., 2011; Y. Yang et al., 2018; Yarveisy et al., 2020; Zhao et al., 2016, 2017)
"vulnerability"	9	(Alguacil et al., 2014; Amirioun et al., 2019; Fang et al., 2015; Ghorbani-Renani et al., 2020; Kim & Yeo, 2016; Mari et al., 2014; Niu et al., 2023; Ojha et al., 2018; Z. Zhang et al., 2023)
"absorption"	6	(Najarian & Lim, 2019, 2020; Roach et al., 2018; Tran et al., 2017; Valenzuela et al., 2018; Veit et al., 2023)
"responsiveness"	4	(Ayala-Cabrera et al., 2019; Q. Han et al., 2023; Rajesh, 2016; Schmitt & Singh, 2012)
"resistance"	3	(Amirioun et al., 2019; H. Li et al., 2023; H. Zhang et al., 2018)
"absorptive capability"	3	(Nan et al., 2016; Nan & Sansavini, 2017; X. Wang et al., 2022)
"recovery speed"	3	(Y. Li & Zobel, 2020; Z. Liu & Wang, 2021; Schmitt & Singh, 2012)
"sustainability"	3	(Anderson et al., 2018; Cimellaro et al., 2015; C. Zhang et al., 2022)
"rapidity"	3	(Huang & Pang, 2014; Ren et al., 2017; X. Wang et al., 2022)
"redundancy"; "robustness"	2	(Ayyub, 2014; Didier et al., 2018)
"resistant capacity"	2	(Ouyang et al., 2012; Y. Yang et al., 2018)
"response"	2	(Ahmadian et al., 2020; Z. Zhang et al., 2023)
"mitigation"	2	(X. Liu et al., 2021; Lücker & Seifert, 2017)
"resistance ability"	2	(W. J. Tan et al., 2020; Tao et al., 2022)
"withstanding capacity"	2	(Fan et al., 2023; Marasco et al., 2022)
"withstanding capability"	2	(Kwasinski, 2016; Tofani et al., 2018)
"mitigation ability"	2	(Abdin et al., 2019; Gabrielli et al., 2022)
+ 24 other terms	1	
		Adaptive capacity
"adaptive capacity"	7	(Aghabegloo et al., 2023; Francis & Bekera, 2014; Gotangco et al., 2016; Vugrin et al., 2011; Yarveisy et al., 2020; Zhao et al., 2016, 2017)
"adaptive capability"	2	(C. Chen et al., 2021; Nan & Sansavini, 2017)
adaptation	2	(Najarian & Lim, 2019, 2020)
redundancy	2	(Aghababaei et al., 2021; Appasani et al., 2022)
adaptability	1	(Ojha et al., 2018)
		Restorative capacity
"restoration"	20	(Alizadeh et al., 2022; Arab et al., 2016; Baroud et al., 2014; Cavdaroglu et al., 2013; Fang & Sansavini, 2017a, 2019; Heath et al., 2016; Henry & Ramirez-Marquez, 2012; Matisziw et al., 2010; Ni et al., 2018; Niu et al., 2023; Nurre et al., 2012; Nurre & Sharkey, 2018; Pant et al., 2014; Sang et al., 2021; Sharkey et al., 2015; Y. Tan et al., 2018, 2019; Ulusan & Ergun, 2018; Z. Yang & Marti, 2022)
"restorative capacity"	6	(Aghabegloo et al., 2023; Cheng et al., 2020; Ouyang et al., 2012; Vugrin et al., 2011; Y. Yang et al., 2018; Yarveisy et al., 2020)
"restoration efficiency"	2	(Amirioun et al., 2019; H. Zhang et al., 2018)
"restoration economics"	2	(H. Zhang et al., 2018, 2019)
+ 4 other terms	1	
		Adaptive or restorative capacity (allocation ambiguous)

Table 1 (*continued*)

Term		Articles
"recovery"	36	(Abdelmalak et al., 2023; Ahmadi et al., 2021, 2022; Ahmadian et al., 2020; G. Bai et al., 2021; Bao et al., 2019; Beyza & Yusta, 2021; Burton et al., 2017; Carvalho et al., 2022; Di Tommaso et al., 2023; Dui et al., 2023; Fattahi et al., 2020; Hishamuddin et al., 2013; Y. Hosseini et al., 2023; Kwasinski, 2016; Kyriakidis et al., 2018; M. Li et al., 2019; R. Li et al., 2017; X. Liu et al., 2021; Mishra et al., 2022; Munoz & Dunbar, 2015; Najarian & Lim, 2019; Reed et al., 2009; Roach et al., 2018; Senkel et al., 2021; Smith et al., 2020; Spiegler et al., 2012; Tofani et al., 2021; Tran et al., 2017; Veit et al., 2023; J. Zhang et al., 2022; J. Zhang, Li, et al., 2023; J. Zhang, Ren, et al., 2023; M. Zhang et al., 2022; Z. Zhang et al., 2023; Zhao & You, 2019)
"recovery ability"	10	(Galbusera et al., 2016; Hao et al., 2023; Jinyi et al., 2020; H. Li et al., 2023; Nan et al., 2016; Podesta et al., 2021; W. J. Tan et al., 2020; Tao et al., 2022; J. W. Wang et al., 2010; Zhao et al., 2016)
"responsiveness"	8	(Fattahi et al., 2017; Q. Han et al., 2023; Rajesh, 2016; Ribeiro & Barbosa-Póvoa, 2022; Schmitt & Singh, 2012; Watson et al., 2022; H. Zhang et al., 2018, 2019)
"rapidity"	8	(Bruneau et al., 2003; Cimellaro et al., 2010; Goldbeck et al., 2019; Huang & Pang, 2014; Reed et al., 2009; Ren et al., 2017; Q. Zhang et al., 2020; Zhou & Chen, 2020)
"recovery capability"	7	(Baroud et al., 2014; L. Chen & Miller-Hooks, 2012; Fang & Sansavini, 2017b; Q. Han et al., 2023; Miller-Hooks et al., 2012; Nan & Sansavini, 2017; X. Wang et al., 2022)
"recovery capacity"	6	(Fan et al., 2023; Marasco et al., 2022; Song et al., 2022; Yu & Baroud, 2019; Zhao et al., 2016, 2017)
"recovery rapidity"	4	(Arjomandi-Nezhad et al., 2021; Fang & Zio, 2019; Mao et al., 2021; Najarian & Lim, 2020)
"recoverability"	3	(Fang et al., 2016; Francis & Bekera, 2014; Ghorbani-Renani et al., 2020)
"recovery effort"	2	(Chan & Schofer, 2016; Das, 2020)
+ 29 other terms	1	

example, the duration of performance degradation from the start of disruption to the minimum performance describes the absorptive capacity of the system as part of a metric that quantifies the total duration of disruption (e.g., Ren et al., 2017). The remaining identified terms are closely related to absorptive capacity and either refer to the aspect of robustness (i.e., 'redundancy and robustness', 'resistant capacity', 'resistance ability', 'withstanding capacity', 'withstanding capability') or absorption (i.e., 'response', 'mitigation', 'mitigation ability' 'sustainability'). 78 studies do not use a term related to the absorptive capacity, although we conclude that they present a corresponding metric.

The *adaptive capacity* and *restorative capacity* jointly correspond to a system's recoverability (S. Hosseini et al., 2019) after a shock and thus affect the performance from its lowest point to the end of recovery. The *adaptive capacity* is mentioned in eleven studies, of which the majority directly refer to the resilience curve and the differentiation between the three resilience capacities. The majority of studies use the term '*adaptive capacity*' (Aghabegloo et al., 2023; Francis & Bekera, 2014; Gotangco et al., 2016; Vugrin et al., 2011; Yarveisy et al., 2020; Zhao et al., 2016, 2017). These studies aim to assess the extent to which a system can increase its performance to a new equilibrium as a reaction to a disruption. Alternative terms are 'adaptive capability' (C. Chen et al., 2021; Nan & Sansavini, 2017) and 'adaptation' (Najarian & Lim, 2019, 2020), appearing in two studies each, and 'adaptability' (Ojha et al., 2018). The term 'redundancy' is used by two studies to evaluate the extent of performance recovery by using alternative routes within a redundant road network (Aghababaei et al., 2021) or the duration until the redundancy of a network is used for performance recovery of a communication network (Appasani et al., 2022). 33 studies refer with their metrics to *restorative capacity*. Most of them use the term

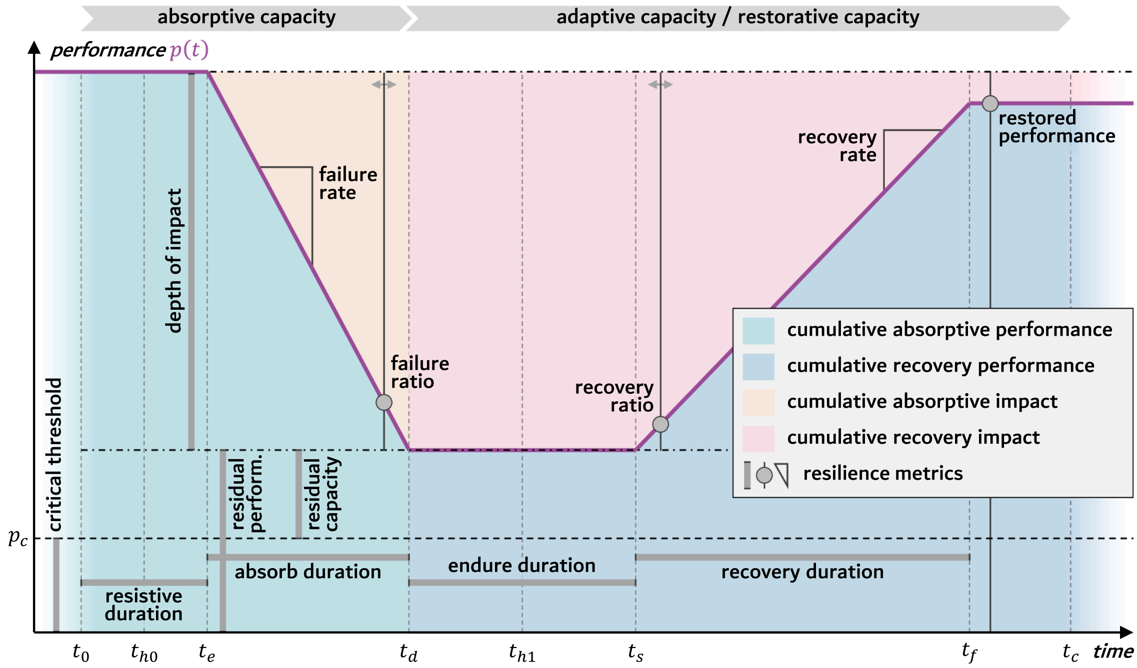

Fig. 2. General resilience curve with resilience metrics identified in the reviewed literature or as summarized by Poulin and Kane (2021). Nomenclature: p_c critical threshold | t_0 beginning of control interval | t_{h0} exposure to hazard | t_e initial system disruption | t_d end of performance degradation | t_s begin of system recovery | t_f completion of system recovery | t_{h1} end of exposure to hazard | t_c end of control interval (see Appendix B).

'restoration' (Alizadeh et al., 2022; Arab et al., 2016; Baroud et al., 2014; Cavdaroglu et al., 2013; Fang & Sansavini, 2017b, 2019; Heath et al., 2016; Henry & Ramirez-Marquez, 2012; Matisziw et al., 2010; Ni et al., 2018; Niu et al., 2023; Nurre et al., 2012; Nurre & Sharkey, 2018; Pant et al., 2014; Sang et al., 2021; Y. Tan et al., 2018, 2019; Ulusan & Ergun, 2018; Z. Yang & Marti, 2022), followed by the term 'restorative capacity' (Aghabegloo et al., 2023; Cheng et al., 2020; Ouyang et al., 2012; Vugrin et al., 2011; Y. Yang et al., 2018; Yarveisy et al., 2020). The majority of these studies present metrics to assess the extent of performance restored from disruptions by repair activities (e.g., Baroud et al., 2014; Henry & Ramirez-Marquez, 2012; Ouyang et al., 2012; Pant et al., 2014; Yarveisy et al., 2020). Similar terms like 'restorative capability' (Nan & Sansavini, 2017), 'restoration ability' (Khayatzadeh et al., 2022), and 'restoration capability' (C. Chen et al., 2021) appear in single studies. Two studies each refer to the terms 'restoration efficiency' to assess the effectiveness (Amirioun et al., 2019; H. Zhang et al., 2018) and 'restoration economy' to evaluate the costs (H. Zhang et al., 2018, 2019) of restoration.

108 studies use terminology that cannot be mapped unambiguously to one of the three capacities. The most common ambiguous term is 'recovery', appearing in 36 studies (e.g., Li et al., 2017), followed by 'recovery ability' in ten studies (Galbusera et al., 2016; Hao et al., 2023; Jinyi et al., 2020; H. Li et al., 2023; Nan et al., 2016; Podesta et al., 2021; W. J. Tan et al., 2020; Tao et al., 2022; J. W. Wang et al., 2010; Zhao et al., 2016) indicating that most of these studies do not build their resilience metrics on the theoretical concept of three distinct capacities. Instead, they differ in the ability of a system to absorb and recover from a disruption (e.g., Galbusera et al., 2016) without clearly indicating if the adaptive or restorative capacity has effected the recovery. In eight studies, the term 'responsiveness' is used to describe the speed and extent of performance recovery attributable to the system's restorative and adaptive capacities (Fattahi et al., 2017; Ribeiro & Barbosa-Póvoa, 2022; Schmitt & Singh, 2012; Watson et al., 2022; H. Zhang et al., 2018). The term 'rapidity' and 'recovery rapidity' is used in eight and four studies and refers to the speed (Goldbeck et al., 2019; Mao et al., 2021; Najarian & Lim, 2020; Ren et al., 2017; Q. Zhang et al., 2020; Zhou & Chen, 2020), the slope of the performance curve (Arjomandi-Nezhad et al., 2021; Cimellaro et al., 2010; Reed et al., 2009), or the ability/inability to recover within a proper time (Arjomandi-Nezhad et al., 2021; Bruneau et al., 2003; Fang & Zio, 2019; Huang & Pang, 2014), which could either be attributed to adaptive or restorative capacity. The terms 'recovery capability', 'recovery capacity', 'recovery effort', and 'recoverability' are also used to describe metrics focusing on the extent of performance recovery and do not explicitly refer to adaptive or restorative capacity. 29 studies use individual terms to describe their resilience metrics. However, 90 studies present resilience metrics, which – according to our understanding – assess adaptive or restorative capacity without using any terminology besides 'resilience'.

3.3. Resilience metrics

Resilience metrics describe the resilience curve and can be used to assess a system's capacities to absorb, adapt, or restore in case of a disruption. In the literature, we identify 395 metrics. As already apparent from the terminology used to describe these metrics (see 3.2), many studies combine different aspects of the resilience curve into one single metric, which we break down into its components for comparability. This procedure results in 523 metrics analyzed in this review (see Supporting Information B). We apply a consistent taxonomy (cf. Appendix B) on these metrics to reformulate the mathematical formulations for a comparative analysis. Finally, they are categorized according to the characteristic elements of the resilience curve they describe and to the related capacity. Thus, we complement and extend the set of resilience metrics introduced by Poulin and Kane (2021). The resulting set of 17 resilience metrics describes all characteristics of the resilience curve. It represents the state of the art of quantifying resilience (i.e., the absorptive, adaptive, and restorative capacities) of systems and networks, specifically supply chains. After describing the resilience curve in Fig. 2, this section analyses the 17 metrics in detail and proposes mathematical formulations to assess the improvement of these metrics by resilience actions.

Fig. 2 displays the idealized performance of a system in case of a disruption, commonly referred to as the *resilience curve*. The performance is generically denoted with $p(t)$ and each characteristic point in time is based on the literature: The observation period starts at t_0 (e.g., Fang & Zio, 2019; Q. Han et al., 2023; Losada et al., 2012; Ouyang et al., 2012; Poulin & Kane, 2021; Spiegler et al., 2012; Touzinsky et al., 2018; Veit et al., 2023), the actual hazard at t_{h0} (e.g., Abdin et al., 2019; Amirioun et al., 2019; Anderson et al., 2018; Poulin & Kane, 2021; Y. Yang et al., 2018), and the disruption at t_e (e.g., Fattahi et al., 2020; R. Li et al., 2017; Munoz & Dunbar, 2015; Vugrin et al., 2011). The hazard then ends at t_{h1} (Senkel et al., 2021; Y. Yang et al., 2018; H. Zhang et al., 2018), the performance stops to degrade at t_d (e.g., Ayyub, 2014; Shen et al., 2023; Valenzuela et al., 2018; Zavala et al., 2019; J. Zhang, Ren, et al., 2023), the recovery starts at t_s (e.g., Nan & Sansavini, 2017; Panteli et al., 2017; Poudel et al., 2020; H. Zhang et al., 2019) and ends at t_f (e.g., Das, 2020; Marasco et al., 2022; Omer et al., 2009; Sun et al., 2022). t_c marks the end of the observation period (e.g., Blagojević et al., 2022; Cimellaro et al., 2010; Nozhati, 2021; Tran et al., 2017). Our work introduces the metrics *absorb duration*, *failure ratio*, *cumulative absorptive performance*, and *cumulative absorptive impact* in addition to the resilience metrics *depth of impact*, *residual performance*, *critical threshold, residual capacity*, *failure rate*, and *resistive duration* (defined by Poulin & Kane, 2021), which can be applied for assessing its absorptive capacity. We further introduce the metrics *cumulative recovery performance*, *cumulative recovery impact*, *endure duration*, and the *recovery duration* in addition to the *recovery rate*, *recovery ratio*, and *restored performance* (defined by Poulin & Kane, 2021), which can be used to determine adaptive and restorative capacity.

Table 2 lists all 17 resilience metrics, separated into metrics affecting the absorptive, adaptive, and restorative capacity, and whether the metric is performance-, time-, rate-, or integral-based. It includes the generic formulation for quantifying each metric (column a). Table 2 further recommends how these metrics can be applied to assess the positive effect of resilience actions (column b) compared to a system without explicit resilience considerations. Except for three relative metrics, the remaining formulations are not normalized to receive absolute values. However, as identified in some studies, normalization can be useful in the case of comparative studies. Fig. 3 displays the performance increase resulting from improved *resilience capacities* by *resilience actions* for systems facing a disruption. The magnitude of the performance increase can be calculated for each metric using the calculation rule of Table 2, column b.

Resistive duration (metric 1a in Table 2) was identified in five studies as the duration from the beginning of the hazardous event, which is chosen as the start of the observation period ($t_0 = t_{h0}$) to the start of performance disruption (t_e) (Amirioun et al., 2019; Anderson et al., 2018; X. Wang et al., 2022; J. Zhang et al., 2022) A single study proposes a normalization by the extreme event duration (t_{h0} to t_d) as part of a resistance metric to assess the absorptive capacity (Kwasinski, 2016). A *resilience action* could lead to a delayed start of performance disruption, which could be quantified as the difference between *resistive duration with* implemented resilience actions and *without* (metric 1b). *Absorb duration* (2a) was defined in our study as the duration from t_e to the end of performance degradation (t_d) in line with five studies (Abdelmalak et al., 2023; Malek et al., 2023; Ren et al., 2017; Roach et al., 2018; X. Wang et al., 2022). The remaining 17 studies refer to the *absorb duration* by assessing the total disruption phase from t_e to t_f (e.g., Losada et al., 2012; W. J. Tan et al., 2020) and thus do not differ between the three capacities. For these studies, we focus in our analysis on the component of the metric representing the *absorb duration* (i.e., t_e to t_d). Six studies propose to normalize this metric, either against the duration of the hazardous event (Senkel et al., 2021), the observation period (Didier et al., 2018), or the disruption duration (Q. Han et al., 2023; Jinyi et al., 2020; Veit et al., 2023). A *resilience action* could lead to, e.g., a delayed drop in performance, and could be quantified analogously to the *resistive duration* (2b).

Depth of impact (3a) was identified in 28 studies and is measured as the difference between the undisrupted performance ($p(t_0)$) and the performance after the end of performance degradation ($p(t_d)$) (e.g., Ahmadian et al., 2020; Shang et al., 2022). Eleven of these studies propose a normalization by dividing by $p(t_0)$ (e.g., Amirioun et al., 2019; Fang et al., 2015). A resilience action mitigates the impact of the disruption on the maximum performance loss. The performance gap with and without adequate resilience action can quantify this benefit (3b).

The resilience metrics *critical threshold* and *residual capacity* are only provided in the framework by Poulin and Kane (2021). *Critical threshold* (4a) defines the minimum level of performance required to prevent a system collapse (Poulin & Kane, 2021). A resilience action could lower this threshold and thus decrease the system's vulnerability (4b). *Residual capacity* (5a) is the distance between the *critical threshold* and the

Table 2
Overview of resilience metrics, their localization along the resilience curve, their quantification (column a), and how they quantify the positive effect of resilience decisions (b).

Resilience metric	Articles	Capacity	Type	(a) Quantification	(b) Positive effect of resilience decisions
(1) *resistive duration*	1	absorptive	time-based	$t_e - t_0$	$(t_{er} - t_0) - (t_e - t_0) = t_{er} - t_e$
(2) *absorb duration*	8	absorptive	time-based	$t_d - t_e$	$(t_{dr} - t_{er}) - (t_d - t_e)$
(3) *depth of impact*	10	absorptive	performance-based	$p(t_d) - p(t_0)$	$(p_r(t_{dr}) - p_r(t_0)) - (p(t_d) - p(t_0))$
(4) *critical threshold*	1	absorptive	performance-based	p_c	$-(p_{cr} - p_c)$
(5) *residual capacity*	1	absorptive	performance-based	$p(t_d) - p_c$	$(p_r(t_{dr}) - p_{cr}) - (p(t_d) - p_c)$
(6) *residual performance*	11	absorptive	performance-based	$p(t_d)$	$p_r(t_{dr}) - p(t_d)$
(7) *failure ratio*	5	absorptive	performance-based	$\frac{p(t) - p(t_d)}{p(t_0) - p(t_d)}$	$\frac{p_r(t) - p_r(t_{dr})}{p_r(t_0) - p_r(t_{dr})} - \frac{p(t) - p(t_d)}{p(t_0) - p(t_d)}$
(8) *failure rate*	2	absorptive	rate	$\frac{p(t_d) - p(t_e)}{t_d - t_e}$	$\frac{p_r(t_{dr}) - p_r(t_{er})}{t_{dr} - t_{er}} - \frac{p(t_d) - p(t_e)}{t_d - t_e}$
(9) *cumulative absorptive performance*	20	absorptive	time integral	$\int_{t_0}^{t_d} p(t)dt$	$\int_{t_0}^{max(t_d,t_{dr})} (p_r(t) - p(t))dt$
(10) *cumulative absorptive impact*	14	absorptive	time integral	$\int_{t_0}^{t_d} (p(t) - p(t_0))dt$	$\int_{t_0}^{max(t_d,t_{dr})} [(p_r(t) - p_r(t_0)) - (p(t) - p(t_0))]dt$
(11) *endure duration*	14	adapt. / restor.	time-based	$t_s - t_d$	$-((t_{sr} - t_{dr}) - (t_s - t_d))$
(12) *recovery duration*	22	adapt. / restor.	time-based	$t_f - t_s$	$-((t_{fr} - t_{sr}) - (t_f - t_s))$ s.
(13) *restored performance*	13	adapt. / restor.	performance-based	$\frac{p(t_f)}{p(t_0)}$	$\frac{p_r(t_{fr})}{p_r(t_0)} - \frac{p(t_f)}{p(t_0)}$
(14) *recovery ratio*	7	adapt. / restor.	performance-based	$\frac{p(t) - p(t_s)}{p(t_0) - p(t_s)}$	$\frac{p_r(t) - p_r(t_{sr})}{p_r(t_0) - p_r(t_{sr})} - \frac{p(t) - p(t_s)}{p(t_0) - p(t_s)}$
(15) *recovery rate*	5	adapt. / restor.	rate	$\frac{p(t_f) - p(t_s)}{t_f - t_s}$	$\frac{p_r(t_{fr}) - p_r(t_{sr})}{t_{fr} - t_{sr}} - \frac{p(t_f) - p(t_s)}{t_f - t_s}$
(16) *cumulative recovery performance*	32	adapt. / restor.	time integral	$\int_{t_d}^{t_c} p(t)dt$	$\int_{max(t_d,t_{dr})}^{t_c} (p_r(t) - p(t))dt$
(17) *cumulative recovery impact*	22	adapt. / restor.	time integral	$\int_{t_d}^{t_c} (p(t) - p(t_0))dt$	$\int_{max(t_d,t_{dr})}^{t_c} [(p_r(t) - p_r(t_0)) - (p(t) - p(t_0))]dt$

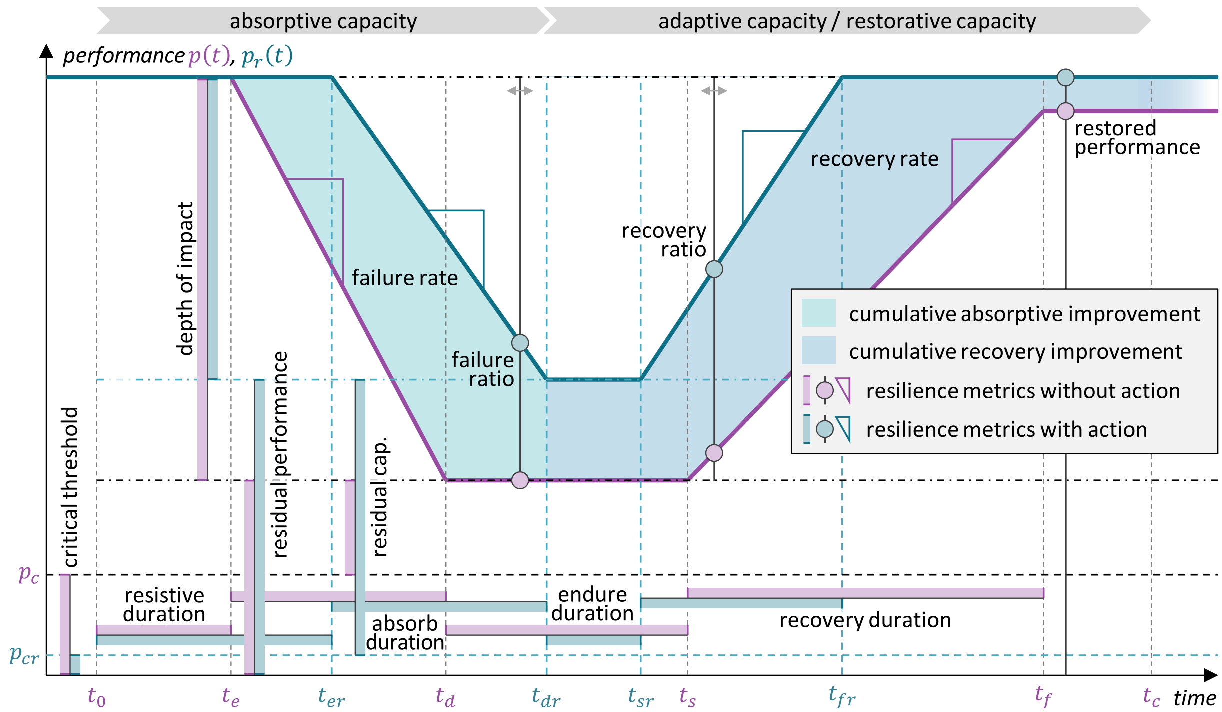

Fig. 3. Application of resilience metrics to determine the effect of resilience decisions on performance. Mathematical formulations for the computation of the positive effect of resilience decisions can be found in Table 2, column b. Nomenclature: p_{cr} lower critical threshold | t_{er} delayed initial system disruption | t_{dr} delayed end of performance degradation | t_{sr} earlier begin of system recovery | t_{fr} earlier completion of system recovery (cf. Figure 2 and Appendix B).

performance at its lowest point $p(t_d)$ (Poulin & Kane, 2021). *Residual performance* (6a) is defined in our work according to the majority of studies (14 out of 25) as the distance between $p(t_d)$ and zero performance (e.g., Cimellaro et al., 2010; Nan & Sansavini, 2017; Badr et al., 2023). Ten of 25 studies normalize the *residual performance* against $p(t_0)$ (e.g., Goldbeck et al., 2019). Both *residual capacity* and *residual performance* can be increased by lowering the critical threshold or reducing the depth of impact by a suited resilience action (5b, 6b).

Failure ratio (7a) is defined in our work as the percentage of performance that, at any time t, has not degraded yet. This is in line with five studies (Azimian et al., 2021; Carvalho et al., 2012; Z. Liu & Wang, 2021; Rajesh, 2016; Schmitt & Singh, 2012), mainly from the supply chain context, which formulate this metric as the current performance during a disruption $p(t)$ normalized by the hypothetical undisrupted performance $p(t_0)$. In contrast, three studies refer to the performance already degraded until time t (Haeri et al., 2020; Hosseini-Motlagh et al., 2020; Zahiri et al., 2017). When this ratio is measured during the *endure* or *recovery duration* instead of the *absorb duration*, it is called the *recovery ratio* (14a; see below). *Failure rate* (8a) is defined as the slope of the performance curve, i.e., the ratio of the total performance loss and the *absorb duration* as identified in six studies (Abdelmalak et al., 2023; Di Tommaso et al., 2023; Nan et al., 2016; Nan & Sansavini, 2017; Panteli et al., 2017; X. Wang et al., 2022). Similar to the *failure ratio*, a higher absorptive capacity due to a resilience action could lead to a shallower slope and, thus, a more controlled, less severe performance degradation. The resulting improvement could be quantified as the difference between the respective metric with and without a resilience action (7b, 8b).

Cumulative absorptive performance is the most common metric identified for measuring absorptive capacity. It represents the area under the performance curve as the time integral of the system's performance until t_d (9a) as identified in 10 studies (e.g., Ayyub, 2014; Cheng et al., 2020; X. Liu et al., 2021; Tao et al., 2022). Another, only rarely employed variant is to calculate the integral between the beginning of the hazard (t_{h0}) and t_e (Anderson et al., 2018) or t_d (Abdin et al., 2019) to assess the ability of a system to completely resist a disruption without performance loss. Most studies propose to normalize the integral of the disrupted against the undisrupted performance. Conversely, *cumulative absorptive impact* represents the time-integrated *performance loss*. It is measured as the area over the resilience curve until t_d (Amirioun et al., 2019; Chan & Schofer, 2016; Nan et al., 2016; Nan & Sansavini, 2017; Shen et al., 2023). Analogously to *disruption duration* as a proposed metric, 71 studies refer to the area above or under the resilience curve and quantify resilience by a single value comprising the absorptive, adaptive, and restorative capacity. Thus, these studies do not refer exclusively to the characteristics of the resilience curve attributed to the absorptive capacity. Their metrics capture the area under the performance curve either during the observation period (from t_0 to t_c) (e.g., Cimellaro et al., 2015; Ghorbani-Renani et al., 2020; Kalinowski et al., 2015; Ouyang et al., 2012; Spiegler et al., 2012; Veit et al., 2023) or the disruption phase (from t_e to t_f) (e.g., Cubillo & Martínez-Codina, 2019; Hong et al., 2021; Panteli et al., 2017; Vugrin et al., 2011; Yao et al., 2023). Especially studies in the optimization context often do not differentiate between resilience capacities but apply area-based metrics as objective functions (e.g., Nozhati, 2021) or just use them to evaluate the resilience of a network (e.g., Lau et al., 2018). When an implemented resilience action has a positive effect on the resilience curve's trajectory (e.g., a longer *resistive duration*, a smaller *failure rate*, or a smaller *depth of impact*), the area below the performance curve increases accordingly. As illustrated in Fig. 3, we propose to measure this *cumulative absorptive improvement* as the difference between the time-integrated performances with and without resilience actions between t_0 and t_d or t_{dr}, depending on which of the two curves reaches the point of lowest performance last (9b, 10b). A selection of cases where the lowest performance is reached earlier with the resilience action not in place is displayed in Appendix C.

Endure duration (11a) covers the disrupted phase from t_d to t_s, as identified in three studies (Malek et al., 2023; Panteli et al., 2017; Ren et al., 2017), only two studies propose a duration from the end of the hazard (t_{h1}) to t_s (H. Zhang et al., 2018, 2019). As for the *absorb duration*, eleven studies propose the total disruption phase (from t_e to t_f) as resilience metric (e.g., Losada et al., 2012; Paseka et al., 2018), which includes the *endure duration* without explicitly referring to its characteristic of the resilience curve or its relation to the capacities. A resilience action could shorten the endure phase by a prolonged *absorb duration* or by an earlier start of recovery activities (11b). *The endure duration* is followed by the *recovery duration* (12a) from t_s to t_f which is in line with 16 studies (e.g., Carvalho et al., 2022; Goldbeck et al., 2019; Munoz & Dunbar, 2015; Pant et al., 2014). Another 16 studies measure it from t_d to t_f or t_c, either assuming that recovery operations starts immediately ($t_d = t_s$, no *endure duration*) (e.g., Francis & Bekera, 2014; Veit et al., 2023) or do not precisely differentiate between *endure* and *recovery duration* (e.g., Ahmadi et al., 2021; Burton et al., 2017; Chan & Schofer, 2016). Simultaneously to the *absorb* and *endure duration*, the *recovery duration* is identified as part of the disruption duration (e.g., Badr et al., 2023; Belhadi et al., 2021). Like for the *endure duration*, a resilience action could have the effect of a shortened *recovery duration* (12b).

Restored performance (13a) and the *recovery ratio* (14a) describe the percentage of performance after full recovery relative to the undisrupted performance $p(t_0)$. *Restored performance* is identified in 27 studies (e.g., Miller-Hooks et al., 2012; Podesta et al., 2021; Zavala et al., 2019) as the metric of the performance after full recovery at t_f. The metric is often used as objective function of models optimizing the SCR (e.g., Dixit et al., 2016; Ribeiro & Barbosa-Póvoa, 2022). Few studies either quantify the extent of recovered performance ($p(t_f) - p(t_d)$ or $p(t_f) - p(t_s)$) (e.g., Q. Han et al., 2023; Jinyi et al., 2020; Zavala et al., 2019; H. Zhang et al., 2018), or the deviation of $p(t_f)$ from $p(t_0)$ (H. Li et al., 2023; Z. Zhang et al., 2023). The *recovery ratio* is applied in five studies (e.g., Carvalho et al., 2012; Schmitt & Singh, 2012) as the metric of recovered performance relative to the undisrupted performance generically for any time t. As already identified for the *failure ratio*, three studies quantify the performance not recovered yet as the difference between the performance at any time $p(t)$ and $p(t_0)$ (Haeri et al., 2020; Hosseini-Motlagh et al., 2020; Zahiri et al., 2017) during the *endure* and *recovery duration*, whereas one study additionally normalized this expression by $p(t_0)$ (Gotangco et al., 2016). Two studies quantify the actual performance restored ($p(t) - p(t_s)$) relative to the performance lost ($p(t_0) - p(t_s)$) (Baroud et al., 2014; Henry & Ramirez-Marquez, 2012), which we adopted for our set of mathematical formulations (14a). The effect of a resilience action can be quantified analogously to the *failure ratio* (13b, 14b; see 7b).

Recovery rate (15a), analogously to *failure rate* (8a), is defined as the slope of the performance curve during the *recovery duration* and appears in seven studies as proposed in our work (e.g., Kwasinski, 2016; Reed et al., 2009). A resilience action that leads to a steeper slope thus strengthens the restorative and/or adaptive capacities of the system (15b).

Similar to *cumulative absorptive performance* during the *resistive* and *absorb duration*, the most common metric to quantify the recoverability is *cumulative recovery performance*, which is identified in 106 studies. 43 of these studies refer to the area under the curve during the complete observation or disruption period as already discussed for *cumulative absorptive performance* and consequently do not propose metrics exclusively assessing the adaptive or restorative capacity. In contrast, 21 studies explicitly correspond to the area under the performance curve from t_d to t_c which is adopted in our formulation (16a) (e.g., Alizadeh et al., 2022; Cavdaroglu et al., 2013; Iloglu & Albert, 2020; Shang et al., 2022) or from t_d to t_f as in 26 studies (e.g., Arjomandi-Nezhad et al., 2021; Ayyub, 2014; Lei et al., 2019). Most of the studies propose a normalization against the area under the undisrupted performance curve. Eight studies subtract the performance at the end of degradation ($p(t_d)$) to only consider the recovered part of the area under the performance curve (e.g., Mishra et al., 2022; Sharkey et al., 2015). Only a few studies refer to the performance integral from t_d to t_s (e.g., Poudel et al., 2020) or from t_s to t_f as in ten studies (e.g., Cheng et al., 2020). Conversely, *cumulative recovery impact* is – similar to *cumulative absorptive impact* – defined as the integral of the performance lost. The most common formulation is the area above the curve during disruption (from t_e to t_f) (e.g., Ghosh & De, 2022) or observation period (t_0 to t_c) (e.g., Huang & Pang, 2014). 13 studies (e.g., Bao et al., 2019; Bruneau et al., 2003; Fang & Sansavini, 2019; Kyriakidis et al., 2018) measure it from t_d to t_f, while four studies integrate from t_d until a defined level of recovery (t_c) (Burton et al., 2017; Munoz & Dunbar, 2015; Y. Tan et al., 2018, 2019) which we choose as most appropriate formula in our work (17a) to additionally consider the performance loss until the end of the observation period when the performance does not return to the initial state. Only four studies integrate from t_s to t_f (Goldbeck et al., 2019; Y. Hosseini et al., 2023; Nan et al., 2016; Nan & Sansavini, 2017). Thirteen studies propose a normalization against the undisrupted performance curve (e.g., Amirioun et al., 2019; Uday & Marais, 2014) or the duration of *endure* and/or *recovery duration* (e.g., Hong et al., 2021; X. Wang et al., 2022). Two studies quantify the area above the curve from t_s until any time t (e.g., G. Bai et al., 2021; Dui et al., 2023) following the idea of the *recovery ratio*. An exemplary resilience action could increase the overall *cumulative recovery performance* and reduce the *cumulative recovery impact* (e.g., through a shorter *endure phase*, a shorter *recovery phase*, a higher *recovery ratio*, a faster *recovery rate*, or a higher *restored performance*). This effect can be quantified analogously to *cumulative absorptive performance* as *cumulative recovery improvement* (16b, 17b; see 9b, 10b), starting at the point (t_d or t_{dr}) at which the latter two end. Heath et al. (2016) propose to assess the benefit of network restoration according to the area between the resilience curve with and without the implementation of a resilience action as proposed in this work.

3.4. Resilience actions

This section reviews the resilience actions identified in the observed literature on SCR in particular. *Resilience actions* are precautionary, anticipatory actions that decision-makers can implement proactively to strengthen the system's absorptive, adaptive, and restorative capacities to cope with disruptions and improve resilience, as visualized in Fig. 3. The observed literature does not apply a consistent terminology for resilience actions, wherefore different studies refer to *management controls* (e.g., Pettit et al., 2010), *resilience* or *mitigation measures* (e.g., C. Chen et al., 2021; L. Chen et al., 2020; Lücker & Seifert, 2017), and *resilience* or *mitigation strategies* (e.g., Carvalho et al., 2012). In quantitative models for SCR planning, the resilience actions are the 'objects of decision', i.e., it needs to be decided which set of different actions is to be implemented, at what time, and to what extent. The type of action varies according to the capacity to be strengthened, the planning horizon (strategical, tactical, operational), the potential disruption, and the industry. Actions take a central role in quantitative decision models (Behzadi et al., 2020; Ribeiro & Barbosa-Póvoa, 2018), which is why an overview and classification of identified actions is given in the following.

Fig. 4 gives an overview of the analyzed systems and the type and frequency of the investigated disruptions. Supply chains are, with 29 studies, most frequently subject to resilience considerations, followed by electric power systems, communities, and production sites. Generic disruptions without further specification and meteorologically caused disruptions (e.g., storms, tornados, blizzards, and drought) are most frequently assumed, followed by geophysical-caused disruptions (e.g., earthquakes) and generic supply disruptions. A few studies assume anthropogenic disruptions such as cyber and terrorist attacks. While studies on multi-echelon supply chains mostly consider generic supply, transportation, or distribution disruptions without further description of causality, studies on electric power systems and communities primarily assume natural disasters (especially meteorological and geophysical).

The supply chain planning matrix is a model for structuring the planning tasks that underlie supply chain decision-making (Fleischmann

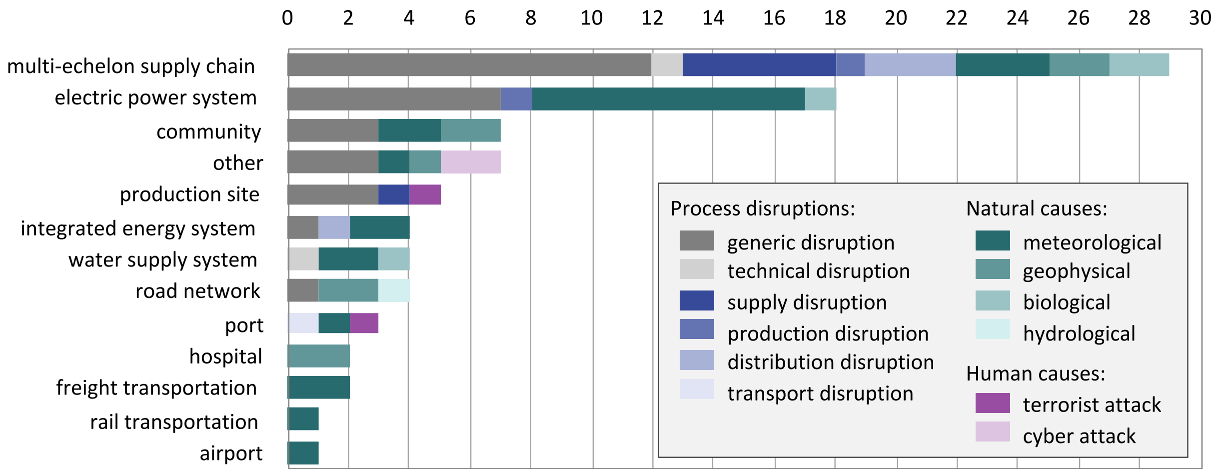

Fig. 4. Frequency of analyzed systems in the identified literature with the assumed type of disruptions.

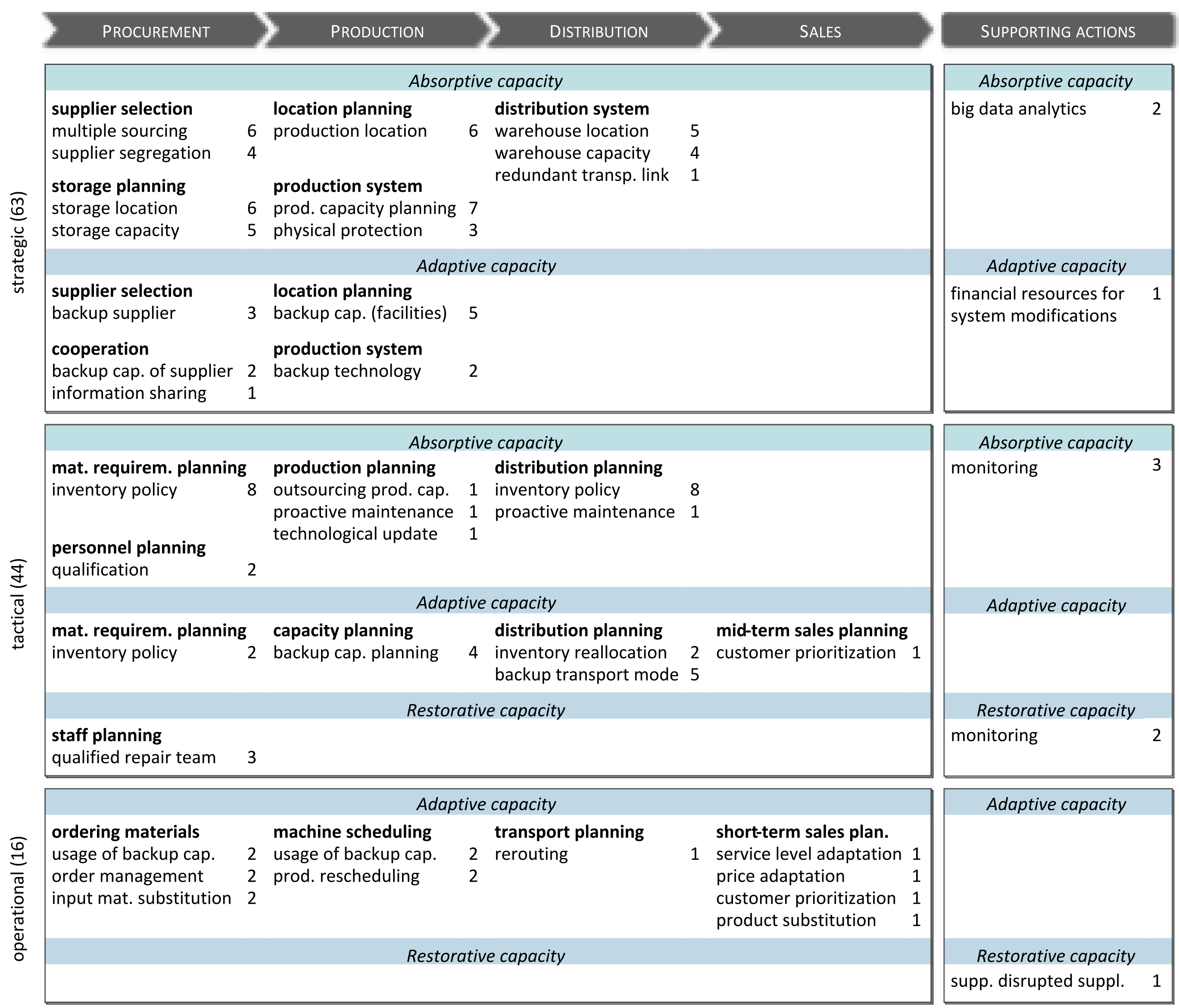

Fig. 5. Supply chain planning matrix (based on (Fleischmann et al., 2008) extended by absorptive, adaptive, and restorative resilience actions and structured by hierarchical decision-level and supply chain process. The number indicates in how many studies the respective measures were found (please find the full table with references in Supporting Information C).

et al., 2008). It hierarchizes the individual decisions in supply chain management by their *planning horizon* into the strategic, tactical, and operational decision levels (Fleischmann et al., 2008). It further subdivides the planning tasks by the *supply chain processes* of procurement, production, distribution, and sales. Fig. 5 gives an overview of all identified resilience actions classified by an extended supply chain planning matrix (Fleischmann et al., 2008) that additionally clusters into absorptive, adaptive, and restorative actions alongside the two regular dimensions. Since some resilience actions cannot be matched with the four existing SC processes, it introduces *supporting actions* as an additional process. To indicate the focus of current research, the figure further shows the number of studies in which a resilience action was mentioned. We identified 63 actions on the strategic level, 44 on the tactical level, and 16 on the operational level. While most actions are identified in the *procurement*, only a few are found for *sales*.

Very few studies classify their proposed resilience actions by resilience capacity, horizon, or process. S. Hosseini et al. (2019) are the only study to classify SCR actions by their hierarchical decision level. To address this literature gap, this work classifies the actions based on the context of the studies they originate from and matches them to the planning tasks and horizons of the original supply chain planning matrix introduced by Fleischmann et al. (2008).

Actions associated with large investments and long-term planning horizons are classified on the *strategic level*, and most identified actions on the strategic level strengthen absorptive capacity. The strategic procurement strengthens absorptive capacity through supplier segregation (rejection of high-risk suppliers) and multiple sourcing (S. Hosseini et al., 2019). *Storage planning* for raw material and intermediates storage location and capacity is suggested by various literature as actions for increasing the absorptive capacity (Ribeiro & Barbosa-Póvoa, 2018). Adaptive capacity is enhanced by the identification of potential backup suppliers, by strategic cooperations with backup suppliers that are used in case of primary supplier disruption (S. Hosseini et al., 2019), and by sharing information that contributes to the recovery process with cooperating supply chain partners (Belhadi et al., 2021). A resilience action of strategic production planning is *location planning* that contributes to absorptive capacity by spatially distributed facilities and warehouses (Fang & Zio, 2019; Senkel et al., 2021). *Production system planning* increases absorptive capacity through resilience-oriented planning of production capacities, which mainly includes the planning of redundant production capacities (Ribeiro & Barbosa-Póvoa, 2018; W. J. Tan et al., 2020). Another action is the physical protection of assets (Vugrin et al., 2011). To strengthen adaptive capacity, backup facilities and technologies can be implemented, which are only activated in the event of disturbances (W. J. Tan et al., 2020). Strategic distribution planning increases absorptive capacity by implementing redundant transportation links (Ribeiro & Barbosa-Póvoa, 2018) and resilience-oriented warehouse location planning (Fattahi et al., 2017; Schmitt & Singh, 2012). A supporting action with a strategic character that increases absorptive capacity is the implementation of big data analytics for the early identification of disruptions (Rajesh, 2016). To strengthen adaptive capacity, financial resources for system modifications can be kept available for urgently required system modifications (Vugrin et al., 2011).

On *tactical level*, procurement strengthens the absorptive capacity through resilience-oriented inventory policies (Spiegler et al., 2012). Qualifying staff can prevent potentially hazardous behavior (Sun et al., 2022) and improve staff's ability to analyze and interpret information on critical system components (Belhadi et al., 2021). Adaptive capacity is strengthened by flexibly adapting inventory policies in the event of disruptions, e.g., by placing orders at backup suppliers (Torabi et al., 2015). Restorative capacity is strengthened by introducing a qualified repair team (C. Chen et al., 2021; Sun et al., 2022; Vugrin et al., 2011). Tactical production planning increases resilience by outsourcing production capacities (Ribeiro & Barbosa-Póvoa, 2018) and proactive maintenance (Sun et al., 2022). Adaptive capacity is strengthened by backup resources such as machinery and personnel (Behzadi et al., 2020; Vugrin et al., 2011). Tactical distribution planning improves absorptive capacity by increasing final product inventories (Ojha et al., 2018) and by proactive maintenance of lifelines (Belhadi et al., 2021). Adaptive capacity is strengthened by keeping backup transportation modes available in case of primary mode disruptions (S. Hosseini et al., 2019). Reallocating final product inventories in case of disruptions increases the adaptive capacity (Fattahi et al., 2017; Zavala et al., 2019). Tactical sales improves adaptive capacity by prioritizing customers (Fattahi et al., 2017). The regular monitoring of critical system components is a supporting action that increases the absorptive capacity (Datta et al., 2007). To strengthen the restorative capacity, resilience management can implement a monitoring system that detects failures and tracks down disruptions efficiently (Vugrin et al., 2011).

On the *operational decision level*, no actions for improving absorptive capacity were identified. Adaptive capacity is determined by the actual realizable quantities of backup suppliers (Torabi et al., 2015; Zhao et al., 2017), the agile adaption of order management (C. Chen et al., 2021; Hishamuddin et al., 2013), and the ability to flexibly substitute input materials (Vugrin et al., 2011). The adaptive capacity of the production is strengthened by the efficient integration of backup production capacities and flexible production rescheduling (Hishamuddin et al., 2013). Distribution planning improves the adaptive capacity by flexible routing abilities (Carvalho et al., 2012). In sales, adjusting prices and flexibly adjusting the pursued service level (e.g., not serving the entire demand) simultaneously increase the supply chain's adaptive capacity (S. Hosseini et al., 2019). Customer prioritization (Fattahi et al., 2017) and the ability to temporarily deliver a product substitute (Carvalho et al., 2022) also improve adaptive capacity. Torabi et al. (2015) suggest to support disrupted suppliers in their recovery efforts to ensure continuous supply, which we ascribe to the supporting actions that increase restorative capacity.

4. Discussion and conclusion

Hardly predictable disturbances can affect the functionality of systems and impair their performance. Depending on how well a system can absorb, adapt to, or restore from a disruption, the performance decline and recovery will turn out differently. Building upon Poulin and Kane (2021), who set the basis for assessing infrastructure resilience by a consistent set of metrics that describe the resilience curve, our work covers the interplay between the curve, capacities, metrics, and actions in a supply chain context (as illustrated in the graphical abstract). First, we extract 395 metrics from the investigated literature and second, harmonize them by the terminology of Poulin and Kane (2021). We then map the standardized metrics to the characteristics of the resilience curve and eventually synthesize them into 17 unified metrics with respective mathematical formulations (i.e., 1a-17a). This set represents the state of the art of quantifying resilience based on the concept of the resilience curve and the absorptive, adaptive, and restorative capacities of systems and networks generally and supply chains specifically. Based on the identified set of metrics, we propose a set of mathematical formulations for those metrics to assess the effect of resilience actions (i.e., 1b-17b).

The applicability is given in science and practice: Research, for example, could apply the set of standardized mathematical formulations (i.e., 1a-17a) in ex-post analyses to compare, e.g., how different systems have coped in the face of disruption and what resilience capacities the system possessed in each case. Companies could apply the metrics for assessing the resilience of their supply chain by simulating hypothetical disruption scenarios to approximate their resilience curve and gain insights into their absorptive, adaptive, and restorative capacities. As an example, an OEM interested in assessing its absorptive capacity could investigate the performance (e.g., in terms of produced units) in the face of a real historical or simulated hypothetical disruption. The resulting curve could then be characterized by the metrics relating to the absorptive capacity (e.g., resistive duration, absorptive duration, depth of impact, failure rate) to draw conclusions on the state of resilience or to deduce if additional actions are required to build up resilience capacities.

Decision-makers aiming to increase resilience (of a system in general, a supply chain, or a specific process) could apply the metrics (i.e., 1b-17b) to compare the efficiency of different potential resilience actions in cost-benefit assessments. These metrics could further be integrated into optimization models to decide on the optimal combination of actions aiming at maximizing economic or resilience objectives. For instance, Iris and Lam (2019) studied the case of berth and quay crane planning in vessel loading by using the concept of *recoverable robustness* to optimally balance the absorption of uncertainties through buffers and the recoverability through efficient rescheduling in case of disruptions. Our concept could be applied in such assessments to quantify the benefit of integrated optimization approaches compared to less elaborate resilience planning approaches.

Furthermore, we classified anticipatory resilience actions identified in literature into the traditional supply chain planning matrix according to their time horizon, similar to Hosseini et al. (2019), and the supply chain stage. In addition, we identified supporting actions for strengthening resilience capacities, extending the traditional supply chain planning tasks. The resulting Fig. 4 gives practitioners and researchers an overview of actions, organized by planning task, time horizon (i.e., short-term, mid-term, long-term), and affected resilience capacity.

Naturally, the conclusions drawn from our results are subject to certain limitations. While applying the proposed metrics works in a synthetic and academic setting, real-life cause-effect chains are often difficult to trace and interpret. Therefore, the applicability of practical case studies and potential adjustments needs further investigation. Consequently, the trajectory of the resilience curve (Fig. 2) and the effect of resilience actions on it (Fig. 3) are only illustrated exemplarily. To show the abundance of possible trajectories, Appendix C presents three alternative examples of how actions could affect the resilience curves and their metrics. The concept of the resilience curve, the proposed set of metrics, and the understanding of 'resilience' in our study are only one attempt to assess resilience in a supply chain context. Without adjustments, it is not universally applicable to other resilience contexts, such as urban or food system resilience. In addition, we only consider metrics that can be located along the resilience curve and exclude formulations that do not fit the resilience curve concept, e.g., metrics that quantify the volatility of performance during recovery (Tran et al., 2017).

As illustrated in Appendix C, resilience actions do not necessarily positively impact all metrics simultaneously. For example, the positive effect of a shorter *endure duration* and an earlier start of recovery could come, in turn, with a decreased *recovery rate* (cf. Appendix C, case IV). Consequently, we advise decision-makers to select resilience metrics according to the supply chain process they want to improve. For instance, in critical infrastructure (e.g., electric grids, hospitals), the time-integrated performance may be less relevant than the ability to ensure a minimum performance level, for which magnitude-based metrics may be more meaningful. It also bears mentioning that the presented resilience metrics are interdependent, meaning that a change in one metric will automatically lead to a change in at least one other metric (e.g., between duration-based and integral-based metrics). Generally, we deem time integral-based resilience metrics like the *cumulative absorptive performance* preferable, as they convey the most information. However, they require a high level of data available to be precise and meaningful. Time-based (e.g., *endure duration*) or performance-based metrics (e.g., *depth of impact*) may be preferable when performance data is only available for certain points in time or when single characteristics of the curve are to be assessed.

The underlying data to describe the resilience curve can either be empirical (real-life data of disruption and following recovery) or be estimated based on simulated disruption scenarios and predictions of the resulting reactions (Poulin & Kane, 2021). While ex-post analyses can yield relevant insights on passed events, conclusions for future system performances are limited since disruptions can occur in a wide variety of different and hardly predictable ways. The decision as to which resilience actions should be implemented requires a prediction of disruption scenarios and an approximation of the resulting change in performance. It must be emphasized that an exact determination of a system's resilience is hardly possible due to uncertainties in predicting the nature, scope, and timing of eventual disruptions. The preciseness of resilience considerations depends on various factors, such as the accuracy of prediction on how an action affects the system or whether a disruption occurs as predicted.

Building upon our findings, future research could focus on the following aspects: (1) application of the proposed metrics and their mathematical formulations in real case studies for a better understanding of resilience curve characteristics and related capacities, (2) application of the metrics to select and assess the effect of actions to strengthen capacities, (3) integration of the proposed metrics as resilience objectives in multi-criteria optimization models to weight the benefit of resilience actions against economic or environmental objectives (e.g., minimizing costs) or by integrating them as constraints. If research introduces new metrics, they should be categorized according to the presented characteristics of the resilience curve and related capacities.

The uncertainty of future disruptions remains the main challenge. Therefore, future studies could assess the effect of actions on the resilience curve by the proposed metrics for various scenarios weighted by their probability of occurrence as a measure of risk. To bring the concepts of 'resilience' and 'risk and uncertainty' together, future studies could also examine the existing literature specifically on risk and uncertainty in the context of resilience. The overview of SCR actions gives an idea about possible resilience-enhancing measures and how actions could be classified in future studies. This study's search string was not pivotally designed to identify resilience actions, wherefore future research could explicitly review feasible actions to be applied to strengthen the absorptive, adaptive, and restorative capacities of supply chains.

CRediT authorship contribution statement

Martin Bruckler: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing – original draft. **Lars Wietschel:** Conceptualization, Validation, Writing – original draft, Writing – review & editing. **Lukas Messmann:** Conceptualization, Validation, Visualization, Writing – review & editing. **Andrea Thorenz:** Supervision, Writing – review & editing. **Axel Tuma:** Supervision, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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Appendix

Appendix A

Overview of the reviewed articles. Nomenclature: SCR supply chain resilience | SR system resilience | SC supply chain.

					Capacities					Metrics			
Authors	**Year**	**Context**	**Application**	**Disruption**	**absorptive**	**adaptive**	**restorative**	**adapt. / restor.**	**original terminology for respective capacities**	**time-based**	**performance-based**	**rate-based**	**integral-based**
Abdelmalak et al.	2023	SR	electric power system	meteorological	x			x	recovery	x	x	x	
Abdin et al.	2019	SR	electric power system	meteorological	x				mitigation ability				x
Aghababaei et al.	2021	SR	road network	geophysical				x	robustness; redundancy				x
Aghabegloo et al.	2023	SR	integr. energy system	generic disruption	x	x	x		absorptive capacity; adaptive capacity; restoration capacity		x		x
Ahmadi et al.	2022	SR	electric power system	meteorological	x			x	robustness; recovery; readjust ability	x	x		x
Ahmadi et al.	2021	SR	electric power system	meteorological	x			x	recovery; readjust ability	x			x
Ahmadian et al.	2020	SR	electric power system	production disruption	x		x	x	responsiveness; restoration; criticality		x		x
Alguacil et al.	2014	SR	electric power system	generic disruption	x				vulnerability		x		
Alizadeh et al.	2022	SR	other	generic disruption			x		restoration				x
Amin et al.	2023	SR	electric power system	generic disruption	x				–		x		
Amirioun et al.	2019	SR	electric power system	meteorological	x			x	robustness; vulnerability; resistance; restoration efficiency	x	x		x
Anderson	2018	SR	electric power system	meteorological	x				sustainability	x			x
Appasani et al.	2022	SR	electric power system	generic disruption				x	redundancy	x			
Arab et al.	2015	SR	electric power system	meteorological				x	–				x
Arab et al.	2016	SR	electric power system	generic disruption			x		restoration				x
Arjomandi-Nezhad et al.	2021	SR	electric power system	meteorological	x			x	recovery rapidity			x	x
Ash et al.	2022	SCR	multi-echelon SC	biological	x			x	–				x
Ayala-Cabrera et al.	2019	SR	water supply system	technical	x				responsiveness		x		
Ayyub et al.	2014	SR	community	generic disruption	x			x	redundancy; robustness; resourcefulness; rapidity				x
Azimian et al.	2021	SR	electric power system	generic disruption	x			x	–		x		
Badr et al.	2023	SR	integr. energy system	generic disruption	x			x	–	x	x		x
G. Bai et al.	2021	SR	electric power system	generic disruption				x	recovery				x
Y. Bai et al.	2022	SR	integr. energy system	technical	x	x	x		degradation; adaption; restoration				x
Bao et al.	2019	SR	production site	terrorist attack				x	recovery				x
Baroud et al.	2014	SR	water supply system	meteorological			x	x	recovery capability; restoration	x	x		
Behzadi et al.	2020	SCR	multi-echelon SC	technical	x			x	–	x			x
Belhadi et al.	2021	SCR	multi-echelon SC	biological	x			x	–	x			
Beyza & Yusta	2021	SR	electric power system	generic disruption	x			x	recovery		x		
Blagojevic et al.	2022	SR	community	generic disruption	x			x	–				x
Borghei & Ghassemi	2020	SR	electric power system	meteorological	x			x	–				x
Bruneau et al.	2003	SR	community	geophysical				x	rapidity				x
Burton et al.	2017	SR	community	geophysical	x			x	recovery	x	x		x
Carvalho et al.	2012	SCR	multi-echelon SC	supply disruption	x			x	–		x		

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Appendix A (*continued*)

					Capacities					Metrics			
Authors	**Year**	**Context**	**Application**	**Disruption**	**absorptive**	**adaptive**	**restorative**	**adapt. / restor.**	**original terminology for respective capacities**	**time-based**	**performance-based**	**rate-based**	**integral-based**
Carvalho et al.	2022	SCR	multi-echelon SC	supply disruption; production disruption	x			x	recovery	x	x		
Castillo et al.	2020	SR	other	technical			x		restorability		x		
Cavdaroglu	2013	SR	electric power system; other	generic disruption			x		restoration				x
Chan & Schofer	2016	SR	rail transportation	meteorological	x			x	preparedness; recovery effort; rebound ability	x			x
Chandrasekaran & Banerjee	2016	SR	other	geophysical				x	–				x
C. Chen et al.	2021	SCR	production site	terrorist attack	x	x	x		resistance capability & mitigation capability; adaptive capability; restoration capability				x
H. Chen et al.	2017	SR	port	terrorist attack				x	redundancy; efficiency		x		
L. Chen & Miller-Hooks	2012	SCR	freight transportation	meteorological				x	recovery ability		x		
Cheng et al.	2020	SR	other	generic disruption	x		x		absorptive capacity; restorative capacity		x		x
Cimellaro et al.	2010	SR	hospital	geophysical	x			x	rapidity; robustness		x	x	x
Cimellaro et al.	2015	SR	integr. energy system	geophysical	x			x	sustainability				x
Confrey et al.	2020	SR	electric power system	meteorological				x	–		x		
Cubillo & Martinez-Codina	2019	SR	water supply system	meteorological	x			x	response capacity				x
Das et al.	2020	SR	road network	hydrological				x	recovery effort				x
Didier et al.	2018	SR	community	generic disruption	x			x	redundancy; robustness; resourcefulness; rapidity	x	x		x
Dixit et al.	2016	SR	freight transportation	meteorological				x	–		x		
Dong et al.	2022	SR	road network	generic disruption	x			x	robustness; adaption; recovery capability				x
Dui et al.	2023	SR	freight transportation	transport disruption				x	recovery				x
Fan et al.	2023	SR	integr. energy system	supply shock	x			x	withstanding capacity; recovery capacity	x	x		
Fang et al.	2016	SR	integr. energy system	meteorological				x	recoverability				x
Fang et al.	2015	SR	electric power system	cyber attack	x				vulnerability		x		
Fang & Sansavini	2019	SR	electric power system	generic disruption			x		restoration				x
Fang & Sansavini	2017b	SR	electric power system	generic disruption			x				x		x
Fang & Sansavini	2017a	SR	electric power system	cyber attack				x	recovery capability		x		
Fang & Zio	2019	SR	electric power system	generic disruption	x			x	robustness; recovery rapidity				x
Fattahi et al.	2017	SCR	multi-echelon SC	distribution disruption				x	responsiveness		x		
Fattahi et al.	2020	SCR	multi-echelon SC	distribution disruption				x	recovery				x
Faturechi et al.	2014	SR	airport	generic disruption				x	–		x		
Feng et al.	2022	SR	other	terrorist attack				x	–				x
Figueroa-Candia	2018	SR	electric power system	meteorological				x	restoration ability				x
Filippi et al.	2019	SR	other	technical	x			x	–				x

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Appendix A (*continued*)

					Capacities					Metrics			
Authors	**Year**	**Context**	**Application**	**Disruption**	**absorptive**	**adaptive**	**restorative**	**adapt. / restor.**	**original terminology for respective capacities**	**time-based**	**performance-based**	**rate-based**	**integral-based**
Francis & Bekera	2014	SR	electric power system	meteorological	x	x		x	absorptive capacity; adaptive capacity; recoverability	x	x		
Gabrielli et al.	2022	SCR	multi-echelon SC	generic disruption	x			x	mitigation ability; recovery possibility				x
Galbusera et al.	2016	SR	other	generic disruption	x			x	recovery ability				x
Garifi et al.	2022	SR	electric power system	meteorological	x			x	–				x
Gerges et al.	2023	SR	community	generic disruption	x			x	–				x
Ghorbani-Renani et al.	2020	SR	integr. energy system	terrorist attack	x			x	vulnerability; recoverability				x
Ghosh & De	2022	SR	electric power system	meteorological	x			x	–				x
Goldbeck et al.	2019	SR	rail transportation; electric power system	meteorological	x			x	robustness; rapidity	x	x		x
Gong & You	2018	SR	production site	generic disruption					–				x
Gotangco et al.	2016	SR	community	meteorological	x	x			adaptive capacity		x		
Haeri et al.	2020	SCR	multi-echelon SC	generic disruption	x			x	–		x		
Q. Han et al.	2023	SR	other	–	x			x	responsiveness; survivability; recovery capability	x	x		x
Hao et al.	2023	SR	rail transportation	generic disruption				x	recovery ability				x
Hashemifar et al.	2022	SR	electric power system	generic disruption	x			x	–				x
Heath et al.	2016	SR	electric power system	meteorological			x		–				x
Henry & Ramirez-Marquez	2012	SR	road network	geophysical			x		restoration		x		
Hishamuddin et al.	2013	SCR	multi-echelon SC	meteorological				x	recovery				x
Hong et al.	2021	SR	community	meteorological	x			x	–				x
Y. Hosseini et al.	2023	SR	road network	geophysical				x	recovery				x
Hosseini-Motlagh et al.	2020	SCR	multi-echelon SC	generic disruption	x			x	–		x		
Y. H. Huang	2021	SR	electric power system	generic disruption	x			x	–				x
Huang & Pang	2014	SCR	multi-echelon SC	meteorological	x			x	rapidity; redundancy		x		x
Hulse et al.	2021	SR	other	generic disruption	x			x	resistance; absorption; restoration; recovery				x
Iloglu & Albert	2020	SR	road network	meteorological				x	–				x
Ivanov	2018	SCR	multi-echelon SC	supply disruption				x	–		x		
Jeong et al.	2006	SR	water supply system	terrorist attack	x				–		x		
Kalinowski et al.	2015	SR	–	generic disruption	x			x	–				x
Khalili et al.	2017	SCR	multi-echelon SC	generic disruption				x	–				x
Khayatzadeh et al.	2022	SR	integr. energy system	generic disruption	x			x	withstanding ability; restoration ability				x
Kim & Yeo	2016	SR	road network	generic disruption	x				vulnerability		x		
Kwasinski	2016	SR	electric power system	generic disruption	x			x	withstanding capability; recovery	x		x	
Kyriakidis et al.	2018	SR	integr. energy system	meteorological				x	recovery	x			x
Ladipo et al.	2019	SR	other	meteorological	x			x	–				x
Lau et al.	2018	SR	electric power system	generic disruption	x			x	–				x
Lei et al.	2019	SR	electric power system	meteorological				x	–				x
H. Li	2023	SR	other	terrorist attack	x			x	resistance; recovery ability		x		x

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Appendix A (*continued*)

					Capacities					Metrics			
Authors	**Year**	**Context**	**Application**	**Disruption**	**absorptive**	**adaptive**	**restorative**	**adapt. / restor.**	**original terminology for respective capacities**	**time-based**	**performance-based**	**rate-based**	**integral-based**
M. Li et al.	2019	SR	rail transportation	generic disruption				x	recovery				x
Li et al.	2017	SCR	multi-echelon SC	generic disruption	x			x	withstand disruption; recovery				x
Y. Li & Zobel	2020	SCR	multi-echelon SC	generic disruption	x		x	x	robustness; restorative capacity; recovery speed	x	x		x
L. Liao & Ji	2020	SR	electric power system	meteorological	x			x	–				x
T. Liao et al.	2018	SR	road network	terrorist attack	x			x	–				x
X. Liu et al.	2021	SR	integr. energy system	generic disruption	x			x	mitigation; recovery				x
Z. Liu & Wang	2021	SR	electric power system	cyber attack	x			x	reliability; recovery speed	x	x		x
Losada et al.	2012	SR	production site	generic disruption	x			x	–	x			
Lücker & Seifert	2017	SCR	multi-echelon SC	production disruption	x			x	mitigation				x
Maheshwari et al.	2017	SCR	multi-echelon SC	meteorological	x			x	–		x		
Malek et al.	2023	SR	electric power system	generic disruption	x			x	–	x	x		x
Mao et al.	2021	SR	road network	meteorological				x	recovery rapidity	x			x
Marasco et al.	2022	SR	community	meteorological	x			x	withstanding capacity; recovery capacity		x		x
Mari et al.	2014	SCR	multi-echelon SC	generic disruption	x			x	vulnerability				x
Matisziw et al.	2010	SR	other	generic disruption	x		x		restoration				x
Miller-Hooks et al.	2012	SR	freight transportation	generic disruption				x	recovery capability		x		
Mishra et al.	2022	SR	electric power system	generic disruption	x			x	coping capacity; recovery				x
Munoz & Dunbar	2015	SCR	–	–	x			x	recovery	x	x		x
Najarian & Lim	2019	SR	electric power system	generic disruption	x	x		x	absorption; adaptation; recovery	x			x
Najarian & Lim	2020	SR	electric power system	generic disruption	x	x	x		absorption; adaptation; rapidity	x			x
Nan & Sansavini	2017	SR	electric power system	meteorological	x	x	x	x	absorptive capability; adaptive capability; restorative capability; recovery capability		x	x	x
Nan et al.	2016	SR	electric power system	meteorological	x	x		x	absorptive capability; adaptive capability; restorative capability; recovery ability		x	x	x
Ni et al.	2018	SR	production site	generic disruption			x		restoration				x
Niu et al.	2023	SR	road network	geophysical	x		x		vulnerability; restoration				x
Nozhati	2021	SR	electric power system	geophysical	x			x	–				
Nurre et al.	2012	SCR	electric power system; other	meteorological			x		restoration				x
Nurre & Sharkey	2018	SR	electric power system	meteorological			x		restoration				x
Ojha et al.	2018	SCR	multi-echelon SC	generic disruption	x	x			vulnerability; adaptability				x
Omer et al.	2009	SR	other	geophysical				x	vulnerability reduction		x		
Omidian & Khaji	2022	SR	other	geophysical				x	sustainability				x
Ouyang et al.	2012	SR	electric power system	biological	x		x		resistant capacity; absorptive capacity; restorative capacity				x
Ouyang & Fang	2017	SR	electric power system	terrorist attack	x			x	–				x

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Appendix A (*continued*)

					Capacities					Metrics			
Authors	**Year**	**Context**	**Application**	**Disruption**	**absorptive**	**adaptive**	**restorative**	**adapt. / restor.**	**original terminology for respective capacities**	**time-based**	**performance-based**	**rate-based**	**integral-based**
Pant et al.	2014	SR	port	transport disruption			x		restoration	x			
Panteli et al.	2017	SR	electric power system	meteorological	x			x	–	x	x	x	x
Paseka et al.	2018	SR	water supply system	meteorological	x			x	–	x			
Podesta et al.	2021	SR	community	meteorological	x			x	recovery capacity		x	x	x
Poudel et al.	2020	SR	electric power system	meteorological	x			x	–				x
Rajesh	2016	SCR	multi-echelon SC	supply disruption	x			x	flexibility; responsiveness		x		
Reed et al.	2009	SR	electric power system	meteorological	x			x	robustness; rapidity; recovery		x	x	x
Ren et al.	2017	SR	other	generic disruption	x			x	rapidity	x			
Ribeiro & Barbosa-Povoa	2022	SCR	multi-echelon SC	supply disruption				x	responsiveness		x		
Roach et al.	2018	SR	water supply system	meteorological	x			x	absorption; recovery	x	x		x
Sabouhi et al.	2021	SCR	multi-echelon SC	generic disruption	x				–		x		
Salehi et al.	2022	SCR	multi-echelon SC	production disruption	x			x	–				x
Salmeron et al.	2009	SR	electric power system	terrorist attack	x				–		x		
Salmeron & Wood	2015	SR	electric power system	terrorist attack				x	–				x
Sanchis et al.	2020	SCR	production site	generic disruption	x				–		x		
Sanci & Daskin	2019	SR	other	transport disruption			x		–				x
Sang et al.	2021	SR	integr. energy system	generic disruption	x			x	restoration				x
Sawik et al.	2017	SCR	production site	supply disruption	x			x	–				x
Schmitt & Singh M.	2012	SCR	multi-echelon SC	supply disruption	x			x	recovery speed; responsiveness	x	x		
Senkel et al.	2021	SR	integr. energy system	distribution disruption	x			x	recovery	x	x		x
Shahbazi et al.	2021	SR	electric power system	meteorological	x			x	–		x		
Shang et al.	2022	SR	hospital	geophysical	x			x	redundancy; resourcefulness	x	x		x
Sharkey et al.	2015	SR	electric power system; water supply system; other	meteorological			x		restoration				x
Shen et al.	2023	SR	electric power system	generic disruption	x			x	recovery response				x
Simonovic & Arunkumar	2016	SR	water supply system	meteorological				x	–				x
P. Singh et al.	2023	SR	other	meteorological	x			x	–				x
Smith et al.	2020	SR	electric power system; water supply system	geophysical				x	recovery				x
Song et al.	2022	SR	water supply system	geophysical				x	recovery capacity	x			x
Soualah et al.	2023	SR	electric power system	generic disruption	x			x	–				x
Spiegler et al.	2012	SCR	multi-echelon SC	supply disruption	x			x	readiness; responsiveness; recovery				x
Sun et al.	2022	SCR	production site	generic disruption	x			x	–				x
J. Sun et al.	2023	SR	other (infrastructure system: road network, electric power system, wastewater system)	meteorological	x			x	–				x

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Appendix A (*continued*)

					Capacities					Metrics			
Authors	**Year**	**Context**	**Application**	**Disruption**	**absorptive**	**adaptive**	**restorative**	**adapt. / restor.**	**original terminology for respective capacities**	**time-based**	**performance-based**	**rate-based**	**integral-based**
W. J. Tan et al.	2020	SCR	multi-echelon SC	generic disruption	x			x	effectiveness; resistance ability; recovery ability	x			x
Y. Tan et al.	2018	SR	electric power system; water supply system	meteorological			x		restoration				x
Y. Tan et al.	2019	SR	electric power system; water supply system	meteorological			x		restoration				x
Tang et al.	2023	SR	other	generic disruption	x			x	–				x
Tang et al.	2021	SR	rail transportation	transport disruption	x			x	–				x
Tao et al.	2022	SR	road network	technical	x			x	resistance ability; recovery ability; robustness		x		x
Tariverdi et al.	2019	SR	hospital	generic disruption				x	–		x		
Tofani et al.	2021	SR	electric power system	generic disruption				x	recovery				x
Tofani et al.	2018	SR	electric power system	generic disruption	x			x	withstanding capability				x
Di Tommaso et al.	2023	SR	other	generic disruption	x			x	recovery		x	x	
Torabi et al.	2015	SCR	multi-echelon SC	geophysical				x	robustness; rapidity				x
Touzinsky et al.	2018	SR	port	meteorological	x			x	preparation; resistance; recovery; adaption				x
Tran et al.	2017	SR	other	meteorological	x			x	absorption; recovery; responsiveness; recovery speed	x	x		
Uday & Marais	2014	SR	airport	generic disruption				x	recoverability importance; disruption importance				x
Ulusan & Erugn	2018	SR	other	geophysical			x		restoration				x
Valenzuela et al.	2018	SCR	–	–	x				absorption		x		
Veit et al.	2023	SR	other	cyber attack	x			x	absorption; recovery; performance capacity	x	x		x
Verleysen et al.	2023	SR	production site	supply disruption	x			x	–				x
Vugrin et al.	2011	SR	multi-echelon SC	meteorological	x	x	x		absorptive capacity; adaptive capacity; restoration efficiency				x
J. Wang & Liu	2019	SR	road network	meteorological	x				absorbing ability				x
J. W. Wang et al.	2010	SR	other	cyber attack				x	recovery ability	x			
X. Wang et al.	2022	SR	airport	meteorological	x	x	x	x	susceptibility; absorptive capability; rapidity; recovery capability; adaptive capability;	x	x	x	x
Y. Wang & Wang	2020	SR	road network	generic disruption				x	recovery effectiveness		x		
Watson et al.	2022	SR	other	generic disruption				x	responsiveness				x
Jinyi et al.	2020	SR	other	cyber attack	x			x	absorptive capacity; recovery ability; stable state capability	x	x		x
Xu et al.	2023	SR	electric power system	meteorological	x			x	–				x
Y. Yang et al.	2018	SR	electric power system	meteorological	x		x		resistant capacity; absorptive capacity; restorative capacity				x
Z. Yang & Marti	2022	SR	electric power system	generic disruption			x		restoration				x

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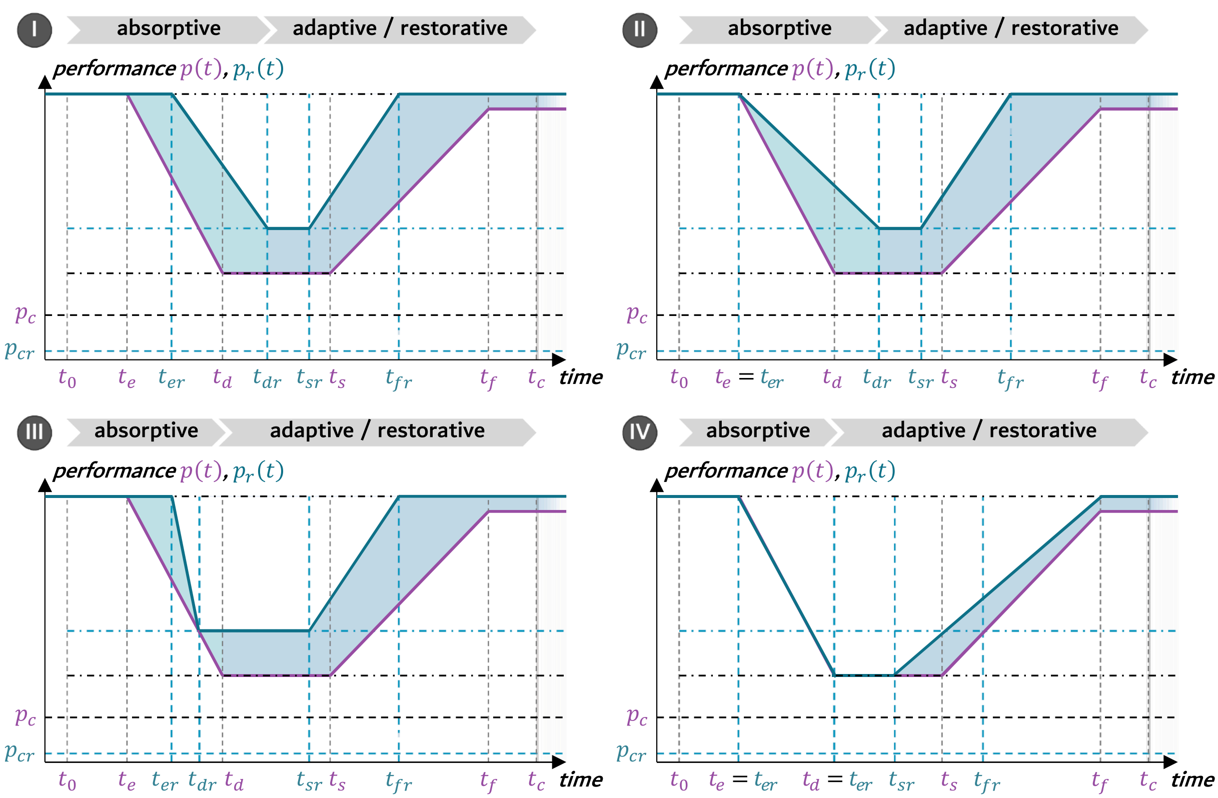
Appendix A (*continued*)

					Capacities					Metrics			
Authors	**Year**	**Context**	**Application**	**Disruption**	**absorptive**	**adaptive**	**restorative**	**adapt. / restor.**	**original terminology for respective capacities**	**time-based**	**performance-based**	**rate-based**	**integral-based**
Yao et al.	2023	SR	electric power system	meteorological	x			x	robustness	x	x		x
Yarveisy et al.	2020	SR	electric power system	generic disruption	x	x	x		absorptive capacity; adaptive capacity; restorative capacity	x	x	x	
Yu & Baroud	2019	SR	community	meteorological				x	recovery capacity		x		
Yuan et al.	2014	SR	electric power system	terrorist attack	x				–		x		
Zahiri et al.	2017	SCR	multi-echelon SC	generic disruption	x			x	–		x		
Zarghami & Zwikael	2022	SR	other	generic disruption	x			x	–				x
Zavala et al.	2019	SCR	multi-echelon SC	distribution disruption				x	capability to recover		x		
C. Zhang et al.	2022	SR	water supply system	technical	x			x	sustainability	x	x		x
H. Zhang et al.	2019	SR	electric power system	meteorological				x	responsiveness; recovery efficiency; restoration economics	x	x		x
H. Zhang et al.	2018	SR	electric power system	meteorological	x			x	toughness; resistance; responsiveness; restoration efficiency; restoration economics	x	x		x
Zhang, Li et al.	2023	SR	community	geophysical	x			x	recovery	x	x		
J. Zhang et al.	2022	SR	rail transportation	technical				x	recovery		x		x
Zhang, Ren et al.	2023	SR	rail transportation	technical				x	recovery				x
J. M. Zhang & T. Wang	2023	SR	other	biological	x			x	–				x
M. Zhang et al.	2022	SR	other	geophysical				x	recovery	x			x
Q. Zhang et al.	2020	SR	water supply system	geophysical				x	rapidity	x			x
X. Zhang et al.	2021	SR	electric power system	meteorological				x	restoration		x		
X. G. Zhang et al.	2022	SR	production site	meteorological				x	–		x		
Z. Zhang et al.	2023	SR	rail transportation	biological	x			x	vulnerability; robustness; response; recovery	x	x		
Zhao et al.	2017	SR	water supply system	biological	x	x		x	adaptive capacity; absorptive capacity; recovery capacity	x	x		x
Zhao et al.	2016	SR	water supply system	biological	x	x		x	absorptive capacity; adaptive capacity; recovey capacity; recovery ability	x	x		x
S. Zhao & You	2019	SCR	multi-echelon SC	generic disruption	x			x	recovery				x
J. X. Zheng & Huang	2023	SR	electric power system	meteorological	x			x	–				x
Zhou et al.	2020	SR	airport	generic disruption	x			x	–				x
Zhou & Chen	2020	SR	airport	meteorological				x	rapidity	x			
Zobel et al.	2021	SR	community	meteorological				x	resistance ability; recovery ability				x
Zong et al.	2022	SR	integr. energy system	geophysical	x			x	–				x
Zukhruf & Frazila	2018	SR	port	technical				x	recovery response		x		

Appendix B
Nomenclature used within this article.

Explanation	Without implementation of resilience actions	With implementation of resilience actions
beginning of control interval	t_0	
exposure to hazard	t_{h0}	
initial system disruption	t_e	t_{er}
end of performance degradation	t_d	t_{dr}
begin of system recovery	t_s	t_{sr}
completion of system recovery	t_f	t_{fr}
end of exposure to hazard	t_{h1}	
end of control interval	t_c	
performance	$p(t)$	$p_r(t)$
performance based on the output	$p_o(t)$	$p_{or}(t)$
performance based on number of system components	$p_n(t)$	$p_{nr}(t)$
performance based on technical system parameters	$p_t(t)$	$p_{tr}(t)$
performance based on economic parameters	$p_e(t)$	$p_{er}(t)$
critical threshold	p_c	p_{cr}



Appendix C. Alternative trajectories of the resilience curve.

(I) Resilience curve as illustrated and described in section 3.3

(II) Alternative case 1: The resilience actions lead to a performance disruption starting at $t_e = t_{er}$ and ending at $t_{dr} > t_d$. As a result, the *resistive duration* is not affected by a resilience action, but i.a., the *absorb duration* has been increased and thus improved (cf. formulations in Table 2), strengthening the absorptive capacity. Likewise, the adaptive and/or restorative capacity have been strengthened by shorter *endure* and *recovery phases* and a higher *restored performance* and *recovery rate*, resulting in a higher cumulative recovery performance.

(III) Alternative case 2: The resilience actions lead to a performance disruption starting at $t_{er} > t_e$ and ending at $t_{dr} < t_d$. As a result, i.e., the *resistive duration, residual performance*, and *depth of impact* are positively affected by the resilience actions, strengthening the absorptive capacity. However, the *absorb duration* has been shortened, and the *failure rate* has increased, offsetting improvement in the *cumulative absorptive performance* to some degree. The adaptive and/or restorative capacities have been strengthened regarding a higher *restored performance, recovery rate,* and *residual performance*, correlating with a higher *cumulative recovery performance*. Some resilience metrics remain almost unchanged (e.g., *endure duration*).

(IV) Alternative case 3: The absorptive capacity remains entirely unchanged by the resilience actions. Only the adaptive and/or restorative capacities are strengthened by a shorter *endure duration*, a higher restored performance, and, consequently, a higher *cumulative recovery performance*.

Appendix D. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cie.2024.110176.

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