



Healthcare network resilience analysis under equipment failure and patients' preferences

Claudia Piffari, Alexandra Lagorio & Roberto Pinto

To cite this article: Claudia Piffari, Alexandra Lagorio & Roberto Pinto (01 Jun 2026): Healthcare network resilience analysis under equipment failure and patients' preferences, International Journal of Production Research, DOI: [10.1080/00207543.2026.2680583](https://doi.org/10.1080/00207543.2026.2680583)

To link to this article: <https://doi.org/10.1080/00207543.2026.2680583>



© 2026 The Author(s). Published by Informa UK Limited, trading as Taylor & Francis Group.



Published online: 01 Jun 2026.



Submit your article to this journal [↗](#)



Article views: 30



View related articles [↗](#)



View Crossmark data [↗](#)

Healthcare network resilience analysis under equipment failure and patients' preferences

Claudia Piffari , Alexandra Lagorio  and Roberto Pinto 

Department of Management, Information and Production Engineering, University of Bergamo, Dalmine, Italy

ABSTRACT

We propose a resilience analysis framework to assess the resilience of an elective healthcare network subject to low-impact-high-frequency (LIHF) disruptions, thereby identifying the most critical facility, considering both the impact of disturbances and the probability of their occurrence. The proposed framework combines agent-based simulation with design of experiment (DOE) and patient behaviour modelling. The framework has been tested with data from a real case, demonstrating its usefulness for conducting resilience analyses and prioritising resilience-enhancing actions to improve network performance. Two resilience-enhancing actions with different characteristics have been tested. The distinctive feature of the framework is the consideration of patient preferences in the simulation, allowing patients to be considered as active actors who can influence the behaviour of the system during a disturbance.

ARTICLE HISTORY

Received 30 September 2025
Accepted 20 May 2026

KEYWORDS

Resilience analysis; supply chain stress test; healthcare network; resilience indicators; resilience actions; patient preferences

1. Introduction

The dependability of healthcare resource networks – including facilities, workforce, and equipment – has always been essential for delivering timely, continuous care to the population, and it has become even more critical today: ageing population, rise of chronic diseases, natural disasters, and even pandemics, increase the pressure on healthcare systems, which must guarantee service continuity and maintain acceptable standards of performance amid contingent challenges that may lead to service disturbances. These disturbances can arise from different types of events, generally categorised as *high-impact-low-frequency* (HILF) – typically linked to man-made or natural disasters – or *low-impact-high-frequency* (LIHF) – usually resulting from inadequate or failed processes, people, and systems (Bhattacharyya, Datta, and Offodile 2010; Chen, Sohal, and Prajogo 2013; Lockamy III and McCormack 2010). Although the former are considerably more evident, the latter may also substantially affect the performance of a healthcare system. For example, failures of medical devices (i.e. the health technologies and equipment needed for prevention, diagnosis, treatment, monitoring, and palliation) due to a lack of maintenance culture, competency, or a tendency to focus on corrective rather than preventative maintenance (Kwaku Kutor, Agede, and Haruna Ali 2017) can cause service degradation for patients seeking treatment.

This, in turn, may impact patients' health if it leads to the abandonment of therapy, medication errors, delays, cancellations, or changes in required treatment. Although HILF events usually attract more attention due to their scale and visibility, the recurrence and cumulative consequences of LIHF events can erode system performance in ways that are less dramatic but equally important. For this reason, this paper concentrates on LIHF events.

A *resilience analysis framework* is required to systematically assess a system's capability to maintain the desired functionality level in the event of disturbances (Geng and Liu 2025) and to support decision-making in resource allocation. Such an assessment can be conducted through *stress tests* (Alikhani et al. 2023), which allow understanding the behaviour and performance of systems under disturbances, allowing for targeted implementation of *resilience-enhancing actions* (Ivanov 2025).

To the best of our knowledge, only a few studies have been conducted on measuring healthcare network resilience, and a gap appears to exist in applying resilience analysis to real-world case studies to inform actions that strengthen resilience (Bruckler et al. 2024).

The limited focus on healthcare resilience may stem from its peculiarity: indeed, unlike other sectors, it cannot be fully understood without considering patient behaviour. Patients often choose healthcare providers based on factors such as proximity, accessibility, wait

CONTACT Claudia Piffari  claudia.piffari@guest.unibg.it  Department of Management, Information and Production Engineering, University of Bergamo, Viale Marconi 5, 24044 Dalmine, Italy

© 2026 The Author(s). Published by Informa UK Limited, trading as Taylor & Francis Group.

This is an Open Access article distributed under the terms of the Creative Commons Attribution License (<http://creativecommons.org/licenses/by/4.0/>), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited. The terms on which this article has been published allow the posting of the Accepted Manuscript in a repository by the author(s) or with their consent.

times, and the quality of service. These choices – shaped by socio-demographic factors such as age, income, health status, and past experiences (Piffari, Lagorio, and Pinto 2024) – can interact with the disturbances to influence the overall performance. For example, during a medical device failure that can last several days, unpredictable patient choices (such as delaying visits or clustering demand at specific facilities) may compound the direct effects of that initial disturbance. Thus, resilience frameworks for the healthcare sector should integrate behavioural components, superimposing patient choices onto classic resilience metrics – such as service availability, waiting time, and recovery time – to better capture system performance.

This paper proposes a resilience analysis framework for elective healthcare networks, based on a real case that accounts for patients' behaviour, that can be used to assess the system's resilience and prioritise resilience-enhancing actions, thus ensuring operational continuity of the network.

The structure of the paper is as follows: Section 2 provides a comprehensive overview of the theoretical background concerning healthcare network resilience analysis and resilience indicators. Section 3 outlines the methodology. Section 4 presents the case test, and Section 5 presents the results. Finally, Section 6 reports the discussion and implications, and Section 7 concludes.

2. Background

This section provides an overview of the theoretical background required to frame our analysis, establishing the groundwork for the methodological and empirical contributions that follow.

2.1. Healthcare network resilience analysis

Designing a resilient healthcare network is a challenging issue that has gained attention in the literature (Sabouhi, Pishvaei, and Jabalameli 2018). Healthcare networks must contend with disturbances of varying frequency and impact (Ho et al. 2015; Ivanov 2020; Ivanov et al. 2017; Tang 2006). HILF events, such as natural disasters, pandemics, or terrorism, are rare but can cause widespread disruption (Moosavi and Hosseini 2021). In contrast, LIHF disturbances, such as everyday medical device malfunctions, minor outages, or process inefficiencies, occur regularly and can cumulatively affect network performance (Bhattacharyya, Datta, and Offodile 2010; Chen, Sohal, and Prajogo 2013; Roh et al. 2022). Regardless of their type, the effect of disturbances mainly depends on two factors: the *duration* of the disturbance (i.e. the time between the initial disturbance and the resumption at

a steady level of performance) and its *severity* (i.e. the magnitude of adverse performance impact) (Burkhart and Bode 2024). In this context, *resilience* refers to a system's ability to prepare for, and respond to, disturbances of varying severity and duration (Foroughi et al. 2022), thereby maintaining the continuity of operations at the desired level (Mandal 2017). In the healthcare context, resilience is essential, as failure to provide timely treatment and services to patients can have fatal effects (Aldrighetti et al. 2019).

An effective way to measure and analyse how healthcare networks respond to disturbances is through *resilience analysis*. In the literature, a few examples of resilience analysis applied to the healthcare sector exist. For instance, Moosavi and Hosseini (2021) proposed a method to deduce quantitative resilience assessment from simulation during the COVID-19 pandemic. Nayeri, Sazvar, and Heydari (2022) proposed a multi-objective mathematical model to maximise, among other things, the resilience and responsiveness of the global medical devices supply chain following an increased demand caused by the COVID-19 pandemic. Nevertheless, in such cases, the emphasis was placed on a single hospital, or the resilience analysis was not utilised to guide resilience improvements directly, applying resilience-enhancing action to all facilities in the network. This approach may not always be sustainable (James et al. 2024).

Extant literature on healthcare resilience has largely focused on disturbances that increase demand (particularly for emergency services), especially during crises such as pandemics or earthquakes (Moosavi and Hosseini 2021). In contrast, less attention has been given to resilience under internal capacity reductions arising from, for example, everyday malfunctions or shortages. Medical device failures, for example, can significantly undermine the ability to provide timely and high-quality care to patients, sometimes forcing facilities to ration scarce resources based on patient characteristics and clinical evidence, potentially leading to difficult ethical decisions (National Academies of Sciences, Engineering, and Medicine 2022).

Resilience analysis can be applied to healthcare networks affected by medical device unavailability, such as that resulting from technological malfunctions (Kwaku Kutor, Agedo, and Haruna Ali 2017). Analysing resilience in this context can inform performance-based resource allocations, reducing the discrepancy between targeted and actual performance, thereby minimising vulnerability not only at the affected facility but across the entire network. Insights from such analyses can also inform businesses and policymakers (Ivanov 2025).

2.2. Resilience indicators

While resilience indicators are commonly studied in industrial contexts, the healthcare sector is relatively new to this research area. Resilience indicators in this sector should consider population health outcomes and the quality of healthcare network performance. They should also serve as a benchmark for resilience across different resilience-enhancing actions, providing information for decision-makers to enhance medical responses (Tippong, Petrovic, and Akbari 2021). Among the metrics used to assess healthcare network resilience, *patient waiting time* is the most common and reflects the system's capacity to deliver care (McIntyre and Chow 2020). Waiting times in the healthcare sector can reflect multiple dimensions. For example, waiting times arise in the emergency department, in access to specialist appointments, or in waiting rooms before the initiation of the healthcare service. Other quality measures, such as service level, can be used for resilience analysis (Poulin and Kane 2021). The *service level* metric can be based on technical metrics such as availability and throughput, as well as domain-specific process performance metrics. In healthcare, one measure used to assess the service level is the percentage of patients waiting longer or shorter than a relevant threshold (OECD 2020). The selected metrics must represent the performance of interest. Analysts, designers, and stakeholders should carefully select performance measures, as different measures can yield significantly different recommendations. For a detailed review of how to select the appropriate performance measure to evaluate the resilience of a system of interest, we refer the reader to Poulin and Kane (2021). In the healthcare sector, in particular for elective procedures, waiting time and service level are crucial as they indicate a healthcare network's ability to deliver timely treatment to patients' needs; therefore, these two metrics have been selected to be used in our research.

The performance of interest is monitored and used for resilience analysis through resilience curves. A resilience curve illustrates changes over time for a selected measure within a specific scenario (Poulin and Kane 2021) and was first introduced by Bruneau et al. (2003). A curve typically begins at a nominal level, changes level due to a disturbance and then recovers to its original level (naturally or, more generally, as the consequence of implemented recovery actions). Resilience indicators are derived from the resilience curve; they formally describe the curve and thereby serve as an indicator of a system's resilience in the face of disturbance. These include *time-based indicators*, *integral-based indicators*, and *rate-based indicators* (Bruckler et al. 2024). A well-known time-based measure is Time-To-Recovery (TTR), defined as the time it

takes for a system (e.g. a network of hospitals) to fully recover after being disrupted (Behzadi, O'Sullivan, and Olsen 2020). Time-based indicators are preferable when performance data is only available for specific points in time or when assessing single characteristics of the curve (Bruckler et al. 2024). Integral-based indicators assess the metric of interest following an organisation's time path after a disturbance. For example, the resilience triangle, introduced by Bruneau et al. (2003), measures the loss of system performance following a disturbance. Other authors have expanded on this using the resilience triangle as a quantitative resilience indicator (Reed, Kapur, and Christie 2009; Spiegler, Naim, and Wikner 2012; Zobel 2014). Another relevant example is the time-dependent Annual Resilience (AR) metric, as the mean ratio of the area between the real performance curve $P(t)$ and the time axis to the area between the target performance curve $TP(t)$ and the time axis during a year (Tang et al. 2023; Yang et al. 2023), reported in Equation 1.

$$AR = \frac{\int_0^T P(t)dt}{\int_0^T TP(t)dt} \cdot 100 \quad (1)$$

$P(t)$ is the performance of interest being monitored over time, for example, waiting time, service level or others (Caputo, Donati, and Salini 2023). $TP(t)$ is the target or desired performance. The use of a yearly time interval as the time scale ensures the measure is comparable. Furthermore, using an annual time period eliminates the issue of precisely determining when the disturbance started and ended, which can be challenging (Ivanov 2022). The annual resilience optimal value is 100%, meaning the actual performance equals the target performance. Finally, rate-based indicators assess resilience through the slope of the performance curve. For example, the failure rate F is defined as the slope of the performance curve immediately following the disturbance (Equation 2), whereas the recovery rate R is defined as the slope of the performance curve during the recovery (Equation 3) (Bruckler et al. 2024; Nan and Sansavini 2017).

$$F = \frac{P(t_{DEG}^{END}) - P(t_{DEG}^{START})}{t_{DEG}^{END} - t_{DEG}^{START}} \quad (2)$$

$$R = \frac{P(t_{REC}^{END}) - P(t_{REC}^{START})}{t_{REC}^{END} - t_{REC}^{START}} \quad (3)$$

where t_{DEG}^{END} is the end of performance degradation, t_{DEG}^{START} is the beginning of performance degradation, t_{REC}^{START} is the beginning of system recovery, and t_{REC}^{END} is the completion of system recovery.

The use of all three types of indicators (time-based, integral-based, and rate-based) allows for a comprehensive analysis of system resilience.

3. Problem statement and methodology

This chapter presents the methodological framework developed to assess the resilience of a healthcare service network in the event of resource disturbances. Building upon the conceptual foundations introduced in Section 2, the proposed approach integrates patient-behavioural modelling with stress testing to evaluate how disturbances impact overall network performance.

3.1. Problem description

Let us consider a set M of facilities and care centres (referred to as *facilities* in the remainder) located in a geographical region. Each facility provides a healthcare service S (or set of services) that requires a specific medical device (e.g. computed tomography, magnetic resonance, ultrasound, angiograph). Let H_m denote the set of medical devices in the facility $m \in M$. This set determines the number of appointment slots available in m for the considered set of services, which we define as the facility's *capacity* $c_m = \gamma_m \cdot |H_m|$ where γ_m is the average number of daily slots provided by each unit in H_m , and $|H_m|$ is the cardinality of the set.

In this study, we consider a homogeneous set of medical devices (i.e. all the devices in H_m are of the same type), although the extension to a heterogeneous set is possible.

A heterogeneous population of patients seeks available slots for service S across the network of facilities, with each patient requiring exactly one slot at a time. In this process, patients exhibit different preferences: some prioritise shorter travel distances, regardless of waiting times (i.e. the time to the first available slot for receiving the required service), while others prefer earlier appointments, even if this requires travelling longer distances. In this study, distance is utilised as a surrogate for accessibility, with the premise that increased distance results in decreased accessibility. While it is acknowledged that other factors may also affect accessibility (Piffari, Lagorio, and Pinto 2024), distance is the sole factor considered for the purposes of this study.

Patients' choices are influenced primarily by their age and health status, parameters that dictate their willingness to travel and wait. For example, younger patients might be less sensitive to distance, prioritising other factors, while patients with severe health conditions are more willing to travel for timely, essential medical care (Burge et al. 2004; Exworthy and Peckham 2006; Miller and May 2006; Welch, Larson, and Welch 1993). While additional factors may influence these preferences, we limit our concern to these two, as they are clearly defined, relatively easy to collect, and have already been addressed in the literature.

The medical devices are subject to random failures (i.e. disturbances), the severity of which determines a temporary reduction in the capacity c_m of a facility. During this period, the reduction in capacity may be reflected in longer waiting times, which persist until the capacity is eventually restored to its original value (i.e. the machine is repaired or replaced), and the patient queues are cleared. Increased waiting times may affect patients' choices of facility, causing shifts in demand among available facilities and potentially leading to congestion elsewhere in the network. Stress testing of the healthcare network is performed by simulating disturbances to a single facility at a time. This design choice is essential for identifying which facility is most critical, i.e. whose disruption most significantly affects overall network resilience. This approach is in line with previous literature, in which risk analysis is performed by removing one supply chain node at a time (Simchi-Levi et al. 2015, 2014).

3.2. Problem modelling and methodology framework

The resilience analysis framework proposed to address the problem, described in Section 3.1, is depicted in Figure 1 and discussed in the remainder of this section.

3.2.1. Patients' behaviour modelling

The first step in the framework involves modelling patients' preferences regarding choice factors such as distance and wait time, enabling the simulation of their decision-making process.

Each individual in the simulation is represented by a perfectly rational (or nearly so) agent that contacts the healthcare facilities to obtain data about the closest appointment (assuming that the cost of the service is uniform across all contacted facilities). Once the information has been obtained, the selection of the facility in which booking a slot works as follows (see the formulation developed in Piffari, Lagorio, and Pinto 2024): a utility v_{im} is computed for the i -th individual with respect to the m -th facility by considering the distance d_{im} of the agent i from the facility m , and the waiting time w_{im} , plus a random term ε capturing random (unobservable) factors that affect the utility. The utility is then used to compute the probabilities p_{im} that agent $i \in I$ would select facility $m \in M$. Under some general assumption regarding the random term ε , we can express these probabilities as (McFadden 1973; Train 2009):

$$p_{im} = \frac{e^{(v_{im} + \varepsilon)}}{\sum_{n \in M} e^{(v_{in} + \varepsilon)}} \forall m \in M, i \in I \quad (4)$$



3.2.2. Healthcare network stress testing

Indeed, ABM allows for accounting for the dynamic complexity of the system (Marshall et al. 2015), and captures the emergence of system resilience from individual interactions and feedback across different levels of a network (Egli et al. 2019). Using AMB to capture healthcare network resilience supports evidence-based practices in redesigning healthcare delivery systems and improving

To perform a resilience analysis based on stress testing, a disturbance is simulated. This disturbance replicates a medical device failure, modelled as a random event causing resource unavailability and a reduction of the capacity of the facility. We iterate over each facility $m \in M$, disrupting it for different disturbance scenarios of duration τ and severity σ (Figure 1). In this way, we defer the need to estimate the probability associated with the disturbance (Simchi-Levi et al. 2015). The severity σ allows evaluation of multiple simultaneous medical device failures within the same facility. For instance, a severity of 100% results in the concurrent unavailability of all devices present in the considered facility.

In response to the simulated disturbance, the average waiting time WT_t and the average service level SL_t are

monitored for $t = 1, \dots, T$. The *waiting time* represents the average number of days patients must wait between the onset of a need and their appointment. The *service level* is computed as the ratio of the number of patients who require a service and find an appointment within a time threshold l to the total number of patients who require a service. The time threshold l is defined based on the waiting time recorded in the scenario without disturbance and on the actual waiting time data for service S considered. Although both indicators are time-related, they capture different aspects of performance: waiting time is a continuous measure of delay intensity, whereas service level is a threshold-based indicator that reflects compliance with a maximum acceptable waiting time. These performances are used to compute the Resilience Indicators (RI) discussed in Section 2.2. Thus, we define the annual resilience AR^p , the time-to-recover TTR^p , the failure rate F^p and the recovery rate R^p , where p represents the performance considered (either WT for waiting time or SL for service level). Although disturbances originate at a single facility, all resilience indicators are computed at the network level in order to capture the propagation of effects across the healthcare system.

The resilience indicators enable the identification of facilities that consistently contribute to the most significant decrease in network resilience when affected by a medical device failure. To this end, a design of experiment (DOE) approach, in accordance with the guidelines set out by Lorscheid, Heine, and Meyer (2012), has been adopted, allowing for valid and objective conclusions to be drawn effectively and efficiently (Antony 2012), thereby fostering transparency and rigour in the simulation process (Lorscheid, Heine, and Meyer 2012). The first step involves identifying the response variables used to measure the experimental outcomes (also referred to as *dependent variables*) and the factors that are systematically varied during the simulation (*independent variables*). For each factor, appropriate quantitative or qualitative levels must be defined within some ranges. Table 1 presents the classification of response variables and factors, along with their corresponding level ranges.

To structure the experiment and simplify the analysis, a cascaded Design-Of-Experiments (DOE) is applied (Lorscheid, Heine, and Meyer 2012). A cascaded DOE comprises one top-level DOE and several sub-DOEs (see Figure 2). The top-level-DOE aims to achieve the overall objective, namely, to conduct a resilience analysis of a healthcare network. Then, $|M|$ sub-DOE, one for each network facility $m \in M$, are performed (Figure 2). In these sub-DOEs, each facility in the network undergoes a medical device failure of varying duration and severity, and, as an output, resilience indicators are collected. The resilience indicators obtained from each sub-DOE

are compared in the top-level DOE to identify the most vulnerable facility m .

For each sub-DOE, a full factorial design is adopted with three levels (defined within the factors' level ranges) for each factor, in accordance with the guidelines on DOE (Montgomery 2017). They are structured in a design matrix illustrated in detail in Appendix Table A1. To ensure statistical robustness, we ran 20 replications for each design point. The number has been determined from preliminary simulations, which estimated the experimental error variance (Table A2) to stabilise the coefficient of variation. Results were tested using one-way ANOVA to assess significant differences in network resilience when different facilities are impacted. When ANOVA was significant, a Tukey HSD (Honestly Significant Difference) test was conducted to identify which facilities differ significantly in resilience performance (Abdi and Williams 2010).

3.2.3. Reliability model

A reliability model is implemented to identify the facility with the highest likelihood of disturbance. Let θ_{mk} be the probability of failure of the k -th medical device in facility $m \in M$ (with, $k \in H_m$) over the period T . We can thus write the probability ϕ of at least one failure in facility m as:

$$\phi_m = 1 - \prod_{k \in H_m} (1 - \theta_{mk}) \forall m \in M \quad (5)$$

We can now compute a *criticality index* χ for each facility m and for each performance p :

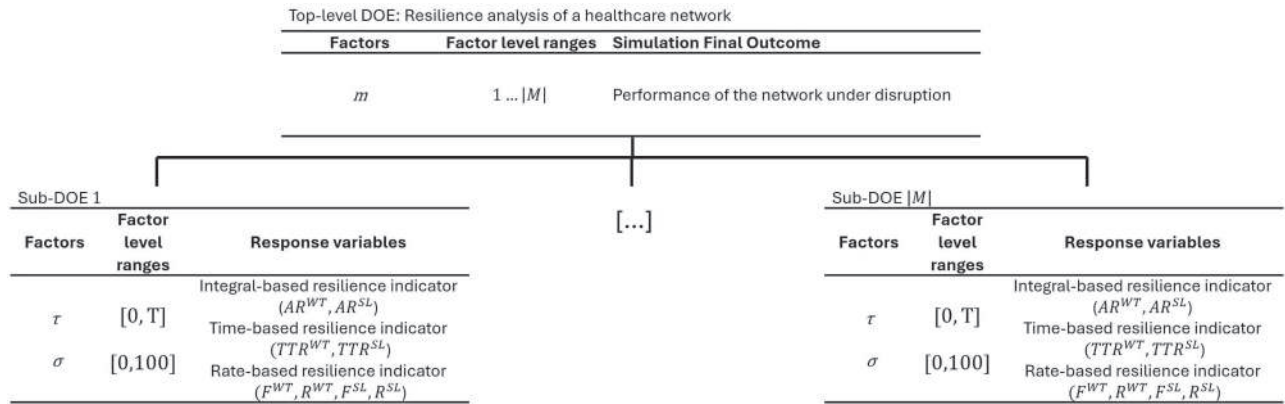
$$\chi_m^p = \phi_m \cdot \Delta RI_m^p \forall m \in M \quad (6)$$

where ΔRI_m^p is the impact of the disturbance on m on the resilience indicator related to performance p . The selection of the *RI*, for instance, between *AR*, *TTR*, failure rate or recovery rate, is contingent on the decision maker and the information they wish to utilise. For example, *TTR* may be selected when focusing on recovery time, whereas *AR* is preferred when considering both recovery time and impact intensity.

The aggregate resilience indicator ΔRI_m^p across different disturbance scenarios can also be tailored to the decision maker's preferences. Depending on risk attitude and strategic priorities, it may be calculated as the average across scenarios, the worst-case value, or another representative statistic. This ensures that the criticality assessment captures both the observed system dynamics and the specific perspective from which resilience is evaluated. Importantly, the choice of resilience indicators and aggregation method does not influence the overall effectiveness of the proposed framework.

Table 1. Response variables, factors and factors level.

		Factors' level ranges	Motivation
Factors	Disturbance duration τ	[0, T]	Covers both short-, medium- and long-term disturbances within the simulation horizon
	Disturbance severity σ	[0, 100] %	The range from 0 to 100% allows for the simulation of all possible severity levels, from normal operation (0%) to complete facility shutdown (100%).
	Affected facility m	$1 \dots M $	Each facility in the network is assessed in terms of its vulnerability to medical device shortages
Response variable	Integral-based resilience indicator	AR^{WT}	AR^{WT}
	Time-based resilience indicator	TTR^{SL}	TTR^{WT}
	Rate-based resilience indicator	R^{WT} F^{SL} R^{SL}	F^{WT}

**Figure 2.** Cascaded DOE.

The criticality index χ allows identifying the most critical facility $\hat{m}^p$ in the set with respect to performance p , considering the impact of the disturbance and the likelihood of occurrence.

$$\hat{m}^p = \arg \max_{m \in M} \chi_m^p \forall p \in \{WT, SL\} \quad (7)$$

3.2.4. Actions assessment and prioritisation

Once the most critical facility has been identified, resilience-enhancing actions can be tested to reduce the vulnerability of the facility under consideration, thereby improving the resilience of the network. To counter the effect of disturbances, different types of resilience-enhancing actions can be implemented: some can be oriented to improve the *absorptive capability* of the system (improving the system's ability to resist or absorb disturbances), while others may be more suitable for

enhancing the system's *adaptation* (improving its ability to reorganise itself to offset disturbances) (Bruckler et al. 2024). In line with this distinction, for the purposes of this study, we tested two resilience-enhancing actions: capacity backup, such as reserving devices for emergencies, as an absorptive-oriented measure, and collaboration between facilities as an adaptivity-oriented measure.

For the absorptive-oriented action (capacity backup), we assume that a capacity reserve can be activated at the critical facility $\hat{m}$: this reserve can be in the form of a standby device not employed under regular operating conditions, or various organisational measures (e.g. overtime or task compression) that temporarily increase the throughput using existing resources upon device failure. During a disturbance, the capacity reserve temporarily increases the effective capacity $c_{\hat{m}}$, thereby mitigating the impact of the disruption without activating inter-facility

reallocation. For the adaptivity-oriented action (collaboration between facilities), when a disturbance reduces the effective capacity $c_{\hat{m}}$ of the disrupted facility $\hat{m}$, a portion of the demand that cannot be accommodated is reallocated across the remaining open facilities: for each candidate facility $n \in M \setminus \{\hat{m}\}$, the earliest available appointment day is identified by searching the first time period in which residual capacity is available, given the current booking schedule and daily capacity c_n . Among the facilities with available capacity, the receiving facility is selected by prioritising the earliest available appointment and, in case of comparable availability, the shortest distance from the requesting individual. In case of ties, one facility is selected randomly among those available. Once the destination facility n^* is selected, the individual is assigned to the earliest available appointment slot, and the corresponding capacity is updated.

The identified actions are then reassessed via ABM simulation to update resilience indicators (as indicated in Figure 1). The updated indicators are finally utilised for prioritising actions, ensuring systematic improvement in the system's resilience and reliability.

4. Test case

We tested the framework for resilience analysis using a real case in Italy, specifically the ultrasound services provided by the eastern district of Bergamo province, for which we had access to both population and healthcare network information from the territorial health authority's websites. The data required for the simulation and analysis include demographic information and details of the public healthcare networks (such as the number of ultrasound scans, capacity, and location of facilities). The distribution of the agents in the area accounts for the heterogeneity of the territory and, consequently, the presence of densely and sparsely populated areas (National Institute of Statistics *n.d.*, www.istat.it). The relative importance assigned to distance and waiting times (parameter α_i in Piffari, Lagorio, and Pinto 2024) is determined using a simplified look-up table based on age (ranging from 18 to 99+ years) and health status. The age and health status data were obtained from the Italian National Institute of Statistics. As empirical estimates of individual preference weights are not available, values are specified to reflect plausible behavioural patterns reported in the literature: older patients tend to place greater importance on distance, while poorer health conditions are associated with a lower willingness to wait for an appointment. The resulting behavioural specification provides a realistic baseline configuration for testing the framework rather than a fully calibrated prediction

Table 2. Facilities' ultrasound scans and daily capacity.

Facility	Number of ultrasound scans	Daily capacity c_m [slots/day]
1	1	1
2	3	33
3	1	5
4	1	9
5	2	17
6	2	13
7	1	6
TOTAL	11	84

model. For brevity, the detailed formulation of the look-up table and utility function v_{im} is not reproduced here; the present work employs the formulation developed in Piffari, Lagorio, and Pinto (2024).

The estimate of demand for ultrasound scans was based on data on access to specialist outpatient services in the Italian national health system (AGENAS 2025). This showed that access to ultrasound scans in the general population occurs on average once every five years. Seven public facilities are operating in the Eastern District of the Bergamo province (ASST BG EST 2025). The characteristics of these facilities, in terms of geographical location, number of ultrasound scans and capacity, have been obtained from the provincial and regional health authorities. For simplicity, they were not separated by medical specialty but were kept aggregated (Regione Lombardia 2025). The data indicate a total daily capacity of 84 ultrasound scans within the healthcare network, distributed among the facilities as shown in Table 2. Some facilities show a low number of daily slots because, being smaller facilities, ultrasound sessions are not offered every day but are concentrated on specific days of the week. Moreover, the number of slots can vary even with the same number of machines, depending on operating hours, staff availability, and the complexity of the exams performed. In the simulated horizon, no intra-week, holiday, or seasonal variations were considered: the baseline demand was assumed to be uniform over time. Although this assumption simplifies reality, it was adopted for the sake of model tractability.

The results from the baseline simulation scenario (i.e. in the absence of disturbances) demonstrated an average waiting time of 53 days. Therefore, a 60-day threshold l was established to evaluate service level, as highlighted in Section 3.2.2. This value represents an empirically based threshold that is also of normative significance. This threshold aligns with the Italian national healthcare classification of deferrable services, which requires delivery within 60 days for instrumental diagnostic procedures. The 60-day threshold, therefore, acts as a compromise that balances acceptable access times with sensitivity to service disturbances.

5. Results

This section presents the simulation results in three parts: the AS-IS baseline scenario (Section 5.1), the absorptive improvement scenario (Section 5.2), and the adaptive improvement scenario (Section 5.3). As explained in Section 3.2.2 and shown in Table 1, each of the seven facilities in the network is subjected to a disturbance (i.e. medical device failure) with three different levels of severity σ and duration τ , as indicated in Table A1. This is repeated for the base case, absorptive improvement, and adaptive improvement.

5.1. AS-IS

The analysis of the AS-IS configuration enabled the assessment of the resilience metrics for each facility following a disruption. The results of all sub-DOEs were merged into a single chart (Figure 3), illustrating time-based (TTR) and integral-based (AR) metrics computed on waiting time and service level resilience curves across disturbance scenarios of varying severity and duration.

In scenarios where the network is affected by disturbances of short duration and low to medium severity (scenarios 1-1 and 2-1), resilience remains high across all facilities, with negligible TTR, and AR values close to 100%. These results suggest that the network can absorb minor disturbances regardless of which facility is disrupted. The same conclusions can be drawn for scenarios with low severity and medium or high duration (scenarios 1-2, 1-3), when the performance used to measure the indicator is the service level. On the other hand, the indicators based on waiting time reveal opportunities for resilience improvement, even in scenarios with low severity and medium to high duration, particularly when the affected facility is Facility 2.

As the severity or duration of the disturbance increases, differences in resilience performance emerge when different facilities are affected. In Scenario 3-3, which represents high severity and high duration, Facility 2 exhibits a TTR computed based on waiting time of nearly 30 days and based on service level exceeding 275 days, significantly higher than those measured when other facilities are affected. Similarly, in the corresponding AR plot for Scenario 3-3, Facility 2 also exhibits the lowest annual resilience, dropping below 85% for waiting time and below 80% for service level, while the same indicator for other facilities stays above 90%. Similar trends are visible in Scenario 3-1 and 3-2 (high severity and low, medium duration), though the contrasts are less extreme.

Some intermediate scenarios, such as 2-2 and 2-3, exhibit partial divergence. Facility 2 begins to emerge as more vulnerable, but the difference with other facilities

is less pronounced. In particular, AR based on both waiting time and service level consistently shows lower values for Facility 2, indicating a reduced ability to maintain performance throughout the disturbance. Additionally, the TTR based on service level exhibits higher values for this facility, indicating that it is less resilient to disturbances, even of moderate intensity. Despite this, in the intermediate scenarios, the TTR based on waiting time exhibits high variability and lacks a consistent pattern. This discrepancy can be attributed to the greater volatility of waiting time as a metric. Since it is a continuous variable, it captures even minor fluctuations in performance, making it harder to define a clear recovery point. Minor changes in waiting time, even if they do not significantly affect access, may result in extended recovery times or no recovery being detected at all. By contrast, service level is a threshold-based metric that changes when the proportion of patients waiting less than 60 days varies. As a result, the service level tends to be more stable, and its TTR is less sensitive to fluctuations that remain entirely above or below the threshold. This behaviour in the annual resilience is overcome by the fact that it is not necessary to identify the point of return to the pre-disturbance state. These results suggest that in intermediate scenarios of severity and duration, integral-based indicators and threshold-based metrics may provide a clearer picture of resilience. In contrast, time-based indicators computed from continuous metrics, such as waiting time, may be too noisy and difficult to evaluate. This unreliability is not present in extreme scenarios (high severity and duration or low severity and duration), in which the TTR computed on the WT is also more stable.

Furthermore, it is possible to observe consistency between TTR and AR computed using the same performance metric. Facilities with high TTR also tend to show lower AR values. For example, in Facility 2, TTR and AR calculated on the service level are both significantly worse in almost all scenarios with high severity or duration, highlighting an apparent vulnerability. However, in intermediate scenarios (e.g. 2-2 and 2-3), partial discrepancies may emerge. Some facilities exhibit high TTR, but AR is still close to 100%, or vice versa. These differences arise from the distinct nature of the indicators. Even minor fluctuations influence TTR, whereas AR captures the overall effect of disturbance across the entire simulated period. This observation reinforces the value of an approach combining multiple indicator types.

In conclusion, the findings indicate that the healthcare network demonstrates resilience to short-term disturbances but exhibits vulnerability to prolonged and severe disturbances. Further analysis of the graphs suggests that Facility 2 is the most vulnerable, meaning it is the one that

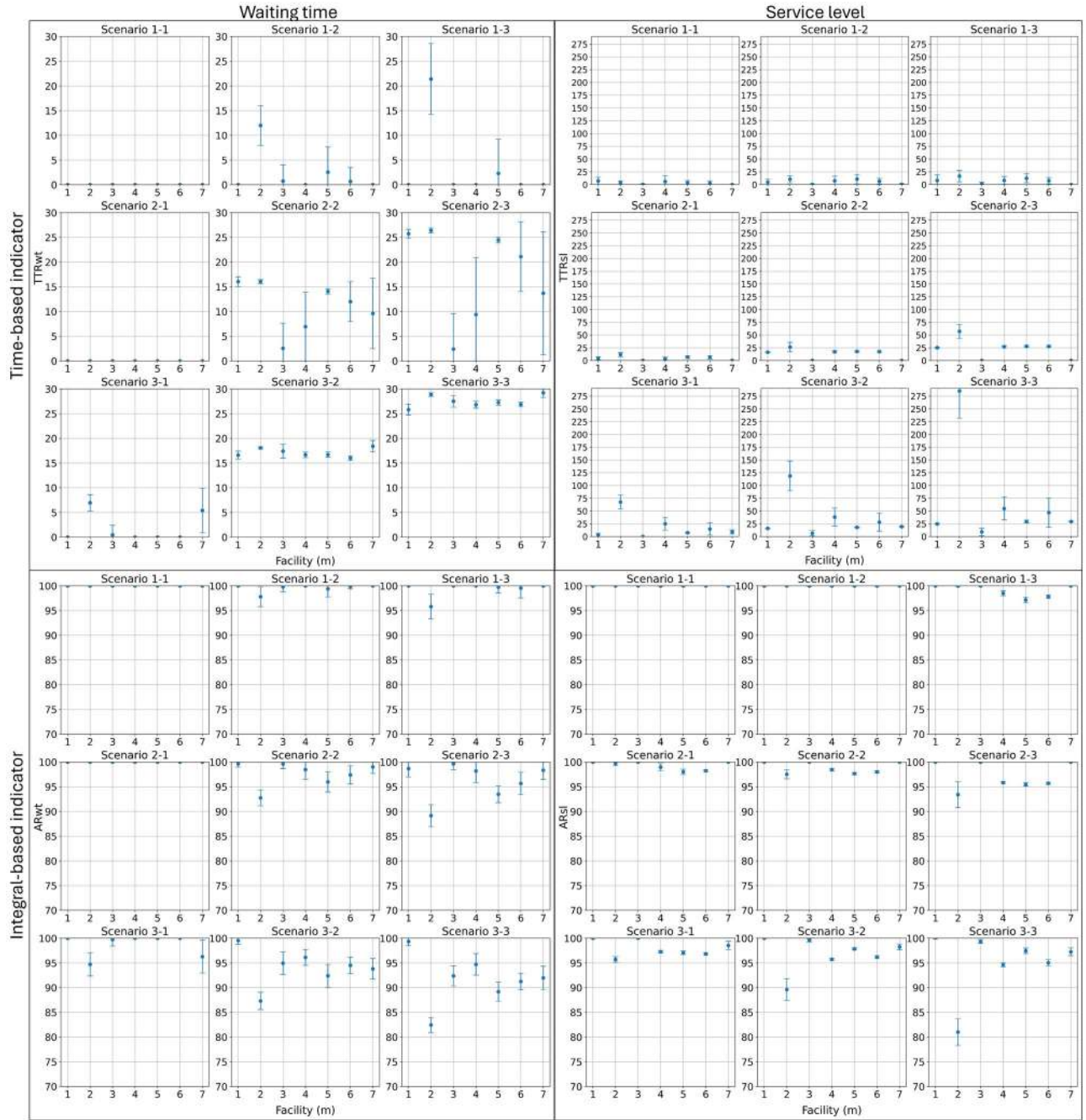


Figure 3. Integral-based and time-based resilience indicators for the AS-IS configuration. Scenarios are identified as $\sigma-\tau$, with σ representing disturbance severity (low, medium, high) and τ representing disturbance duration (low, medium, high).

causes the higher decrease in performance when affected by a disturbance.

To validate these findings, a study of variance and a post-hoc analysis were conducted. For each scenario and resilience indicator, we perform a one-way ANOVA, which yields two key insights. First, the R^2 value quantifies the share of variance in network resilience explained by the affected facility, as opposed to unexplained variance from other simulation factors (Callahan, Hubbard, and Bacoski 2006; Lorscheid, Heine, and Meyer

2012). Second, the ANOVA assesses whether differences between facilities are statistically significant, allowing us to determine if some facilities are more vulnerable than others. The complete results of ANOVA and post-hoc are available upon request, and an extract is available in the appendix Table A3. The experimental procedure confirmed that Facility 2 is the most vulnerable if affected by a disturbance. It is important to note that the indicators – and the resulting effects – measured in this section refer to the overall network. The local effects on individual

facilities or on the population surrounding the affected facility are not analysed in this paper. This is because the current approach is based on a systemic perspective that considers the entire network (and its resilience), since, in this context, the mobility between facilities means the entire system is impacted.

The resilience indicators thus computed must be complemented with medical device reliability models (see Figure 1) to identify the facility on which to concentrate resilience-enhancing actions. In fact, from the impact perspective, Facility 2 appears most critical, as its disruption causes the greatest network performance degradation. However, this assessment ignores the likelihood of disturbances. Facility 2 could, for example, be the facility with the lowest likelihood of medical device failure. Integrating the reliability model enables the identification of the facility on which to focus improvement actions, considering both impact and probability. However, the failure probabilities of the medical devices in the network considered are not available for computing the criticality index χ_m^p . As a consequence, a quantitative integration of disturbance impact and disturbance probability is not available for this test case. To demonstrate the proposed framework, we proceed under the assumption that Facility 2 also has a higher failure probability, thus maintaining it as the most critical facility (i.e. $\hat{m}^p = 2$ in Equation 7). Although this assumption is hypothetical, it helps to demonstrate the application of the framework and does not impact the generalisability of the methodology. Specifically, the assumption that Facility 2 has a higher failure probability is a conservative scenario designed to examine the implications of a disturbance at the node causing the most significant performance degradation if it were to be impacted by a disturbance.

Following the identification of the most critical facility, the absolute values of the failure rate and recovery rate indicators were measured on the resilience curves of waiting time and service level obtained when Facility 2 was affected, as well as for all scenarios presented (Table 3). Unlike the time-based and integral-based indicators presented earlier, rate-based indicators capture the speed of performance loss and recovery. Rate-based indicators are measured only for the most critical facility (Facility 2), identified as the most vulnerable in the previous analysis. This choice is motivated by the fact that rate-based indicators are particularly informative in characterising the dynamics of performance degradation and recovery, and Facility 2 provides the most representative case.

Also rate-based indicators suggest that the disturbance has a limited impact on network resilience in the scenario with lower severity and duration. Furthermore, it is evident that as the severity of the disturbance increases, so does the failure rate. This indicates that the rate of

Table 3. Failure rate and recovery rate for waiting time and service level resilience curves when Facility 2 is affected.

SCENARIO $\sigma - \tau$	F^{WT} [waiting days/day]	R^{WT} [waiting days/day]	F^{SL} [%/day]	R^{SL} [%/day]
1-1	0.00	0.00	0.00	0.00
1-2	0.35	0.47	0.10	0.04
1-3	0.31	0.49	0.04	0.08
2-1	2.74	3.40	7.14	5.45
2-2	1.29	3.83	5.05	9.18
2-3	0.90	4.06	4.56	8.42
3-1	4.45	5.91	28.83	7.85
3-2	2.22	6.33	28.86	7.79
3-3	1.77	7.03	29.00	7.98

performance degradation increases with higher severity. Conversely, as the duration increases, the failure rate decreases. This observation does not necessarily imply a more desirable situation. For instance, in scenarios characterised by high disturbance duration, the failure rate is reduced; however, performance values are worse than in shorter-duration scenarios. In scenario 3-3, the maximum waiting time is 98 days, whereas in scenario 3-2 it is 72 days. The aforementioned considerations also apply to the values measured in terms of service level.

The AS-IS failure rate and recovery rate will be used as a baseline to evaluate the system's performance following the implementation of the improvement actions. As anticipated, one absorptive action (capacity backup) and one adaptive action (collaboration between facilities) were tested to align with two complementary dimensions of resilience.

5.2. Absorptive improvement

The absorptive action is implemented by maintaining reserve capacity that can be activated in case of machine failure. This is consistent with general recommendations on supply chain resilience, such as those outlined by the OECD (2024), which underline the importance of maintaining adequate strategic reserves to address unexpected disturbances and ensure continuity of healthcare services. Such a reserve can be implemented in different ways, such as holding older, albeit functional equipment for emergency use, extending working hours for operating the equipment, or shortening the duration of each appointment slot. Manufacturers, distributors, and healthcare systems all maintain inventories of drugs and devices as a precaution against normal fluctuations in supply and demand (National Academies of Sciences, Engineering, and Medicine 2022). In this case, for illustrative purposes, we assume a capacity reserve equivalent to one ultrasound machine in Facility 2. This value is arbitrary and does not affect the general validity of the proposed approach, as other choices would be

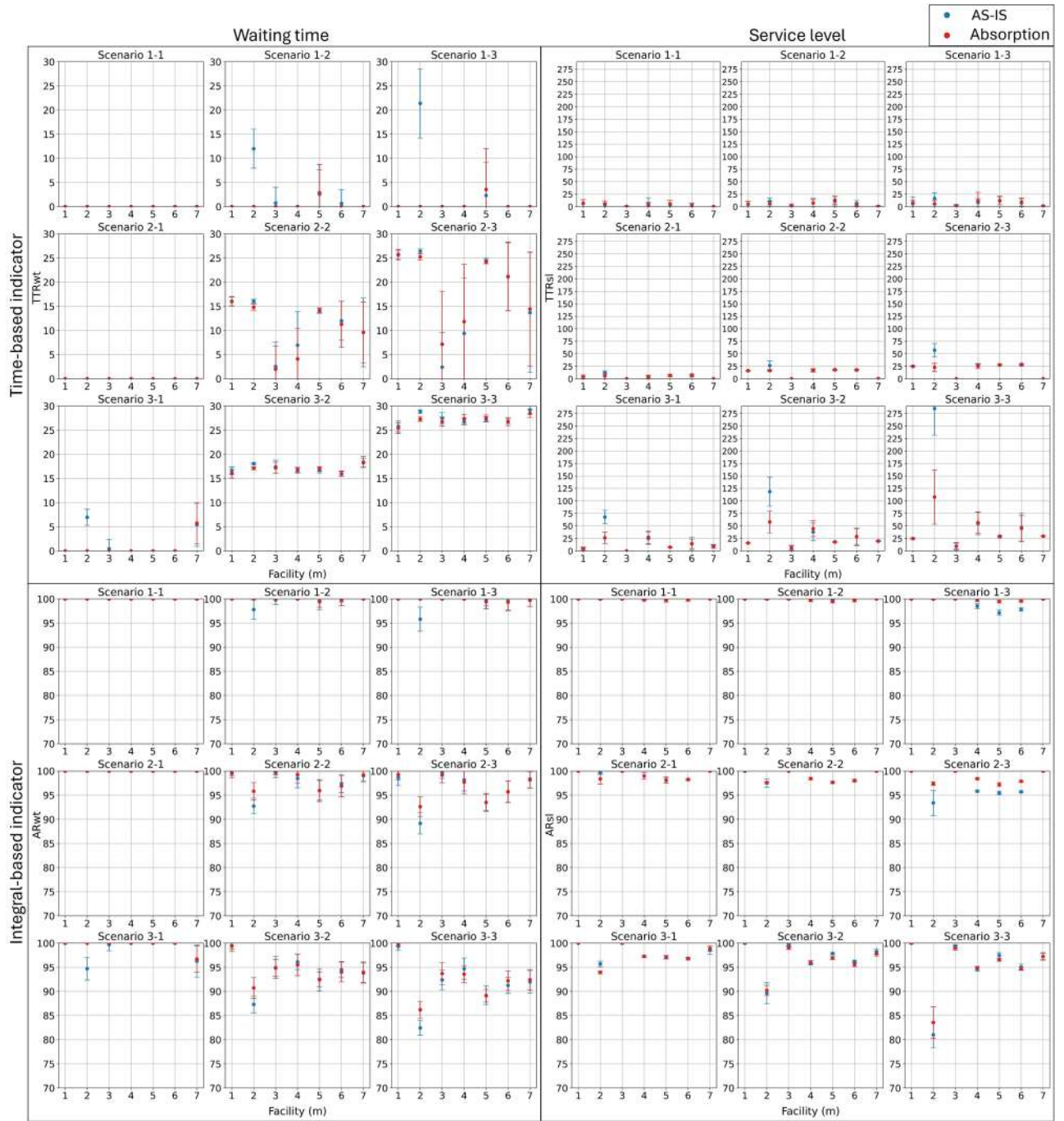


Figure 4. Integral-based and time-based resilience indicator after the introduction of the absorptive improvement. Scenarios are identified as $\sigma - \tau$, with σ representing disturbance severity (low, medium, high) and τ representing disturbance duration (low, medium, high).

equally suitable. Figure 4 illustrates the resilience indicators (time-based and integral-based) for waiting time and service level resulting from the applied absorptive improvement, compared to the AS-IS.

As shown in Figure 4, Facility 2's vulnerability decreased compared to the AS-IS, with lower TTR and higher AR indicators. Focusing on scenarios where criticalities emerged in the AS-IS, resilience improved for

service-level indicators under severe disturbances (3-1, 3-2, 3-3), although Facility 2 remains the most vulnerable. Similar improvements appear in waiting time-based indicators under high and medium severity and duration (2-2, 2-3, 3-2, 3-3). In contrast, in low-severity scenarios (1-2, 1-3) and in the low-severity, high-severity scenario (3-1), waiting time indicators show Facility 2 performing comparably to the other facilities. In intermediate

Table 4. Failure rate for waiting time and service level resilience curves after absorptive improvement when Facility 2 is affected.

SCENARIO $\sigma - \tau$	F^{WT} [waiting days/day]	ΔF^{WT} [waiting days/day]	F^{SL} [%/day]	ΔF^{SL} [%/day]
1-1	0.00	/	0.00	/
1-2	0.09	-0.27	0.03	-0.07
1-3	0.03	-0.28	0.04	/
2-1	1.76	-0.98	1.52	-5.62
2-2	0.75	-0.54	0.27	-4.78
2-3	0.56	-0.34	0.19	-4.37
3-1	2.87	-1.58	16.31	-12.52
3-2	1.50	-0.72	27.60	-1.26
3-3	1.13	-0.65	27.20	-1.80

scenarios (2-2, 2-3), service-level results and subsequent ANOVA and post-hoc tests confirm that Facility 2 is no longer more vulnerable than the others. As in the AS-IS, TTR based on waiting time is unstable in intermediate scenarios, where its variability (standard deviation) is highest.

In almost all scenarios, resilience indicators improved, confirmed by the failure rate analysis from service level and waiting time curves when Facility 2 faces disturbance (Table 4). Only the failure rate is reported, as absorptive actions improve the system's ability to resist or absorb disturbance. Higher absorptive capacity due to resilience actions could lead to a shallower slope and, therefore, a lower failure rate (Bruckler et al. 2024). The difference between the AS-IS failure rate and the absorptive failure rate was also computed, which quantifies the improvement achieved.

The failure rate is useful to quantify the effect of resilience actions. The introduction of a backup device to compensate for failures improves the failure rate in all scenarios, contributing to a more controlled decrease in performance in the event of a disturbance.

5.3. Adaptive improvement

The adaptive improvement introduces a collaborative approach in the simulation as follows: when a facility experiences equipment failure, the capacity of other facilities is used to offset the lost slots. In practice, this means redistributing patients from the affected facility to others. Indeed, collaborating with nearby partners can ensure the successful delivery of critical products or services on time (Nze-Ekpebie and Udealor 2023). The implementation of a collaborative approach has yielded improvements not only for the most critical Facility 2, as in the absorptive improvement, but for all facilities in the network. In particular, performance improvements are observed for all scenarios and all facilities, as can be seen in Figure 5. More specifically, time-based indicators show an improvement in all scenarios. For low severity (i.e.

Table 5. Recovery rate for waiting time and service level resilience curves after adaptive improvement when Facility 2 is affected.

SCENARIO $\sigma - \tau$	R^{WT} [waiting days/day]	ΔR^{WT} [waiting days/day]	R^{SL} [%/day]	ΔR^{SL} [%/day]
1-1	0.00	/	0.00	/
1-2	0.41	0.47	0.00	/
1-3	0.51	1.47	0.00	/
2-1	3.87	-0.05	10.91	5.49
2-2	4.47	0.65	11.11	1.93
2-3	5.12	1.87	14.29	5.87
3-1	7.38	0.03	11.11	3.26
3-2	8.20	1.05	10.00	2.21
3-3	8.87	1.85	12.50	4.52

1-1, 1-2, 1-3) and short duration (i.e. 2-1, 3-1) scenarios, the network appeared to be perfectly resilient, with TTR based on service level and waiting time equal to zero, demonstrating its ability to cope with the disturbance and maintain operational continuity. For scenarios of intermediate and high severity and duration (i.e. 2-2, 2-3, 3-2, 3-3), there is still a clear improvement for many of the network facilities. As regards integral-based resilience indicators, the same considerations can be made for low-severity and/or duration scenarios, in which all facilities prove to be perfectly resilient. In medium/high severity and duration scenarios, the improvements detected are more modest than for time-based indicators. It can be concluded that, in general, resilience enhancement through adaptive improvement has been demonstrated to reduce the vulnerability of the most critical facility (Facility 2) while positively impacting all other facilities within the network.

In Table 5, the recovery rate is reported, computed from the service level and waiting time resilience curves for Facility 2. Only the recovery rate is reported as adaptive resilience actions lead to a steeper slope, thereby resulting in a higher recovery rate (Bruckler et al. 2024). On the other hand, the impact of this action on the failure rate is negligible. Table 5 also shows the difference in recovery rates between AS-IS and adaptive improvement. An increase in the recovery rate is observed in several scenarios, demonstrating an improvement of the Facility 2 to adapt during a disturbance and promptly recover an acceptable level of performance. This is particularly true for the recovery rate calculated on the service level.

6. Discussion and implications

The results presented herein highlight several key considerations along several dimensions.

With respect to *performance indicators*, it is of paramount importance to select the most appropriate

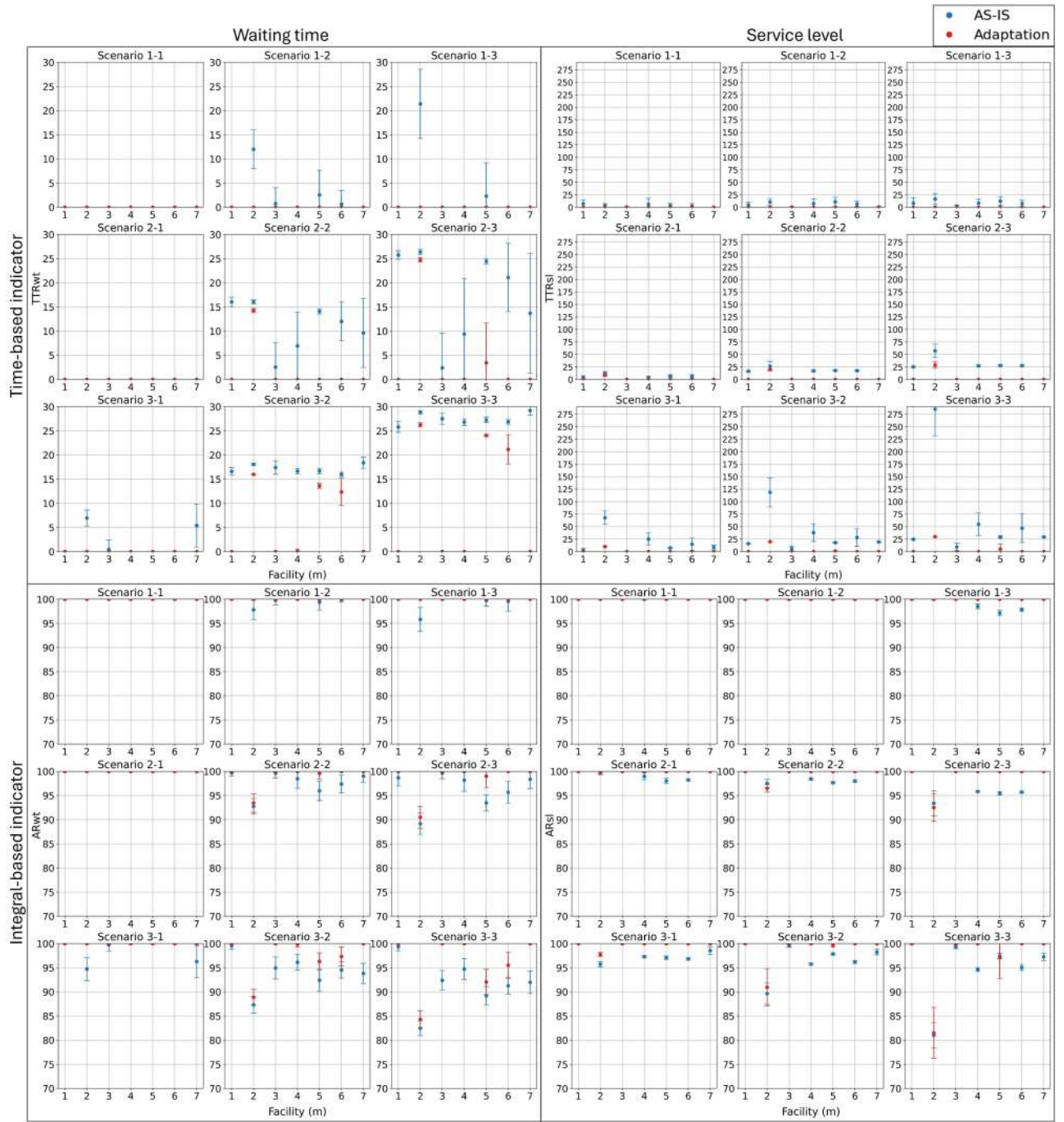


Figure 5. Integral-based and time-based resilience indicator after the introduction of the adaptive improvement. Scenarios are identified as $\sigma-\tau$, with σ representing disturbance severity (low, medium, high) and τ representing disturbance duration (low, medium, high).

ones, as different measures can yield divergent conclusions about network resilience. Service level proved more stable, particularly under mild disturbances, while waiting time was more variable. This difference arises from their definition: how the service level is defined and calculated. It is determined by dividing the number of patients seen within 60 days by the total number of patients. On the other hand, waiting time is a continuous metric that is very sensitive to minor disruptions,

particularly if these disruptions persist over time. This sensitivity renders the TTR derived from waiting time unreliable when assessing resilience in intermediate scenarios, where minor changes can lead to long recovery times. This behaviour in the annual resilience is overcome by the fact that it is not necessary to identify the point of return to the pre-disturbance state. Stakeholders performing resilience analyses should take into account the heterogeneous behaviours and sensitivities of

performance indicators under disturbances (Poulin and Kane 2021).

With respect to *resilience metrics*, they assess resilience in different ways. Annual resilience is especially useful because it is clearly defined within a 0-100 range, making it intuitive and straightforward to interpret. In contrast, TTR lacks specific bounds: although lower TTR values signify a faster recovery and better resilience, its unbounded nature makes it harder to establish a direct, absolute evaluation. The findings also suggest that failure and recovery rates provide useful insights into system behaviour but may sometimes misrepresent resilience; for instance, long disturbances may show low failure rates despite worse overall outcomes. These metrics are useful for evaluating the success of specific interventions and help policymakers assess whether changes made to the system result in meaningful, measurable improvements in network resilience. Each metric captures only part of the picture: TTR focuses on recovery duration, failure and recovery rates on the extent of change, while annual resilience integrates both impact magnitude and recovery time. However, the underlying causes of low resilience remain ambiguous, as it is not possible to determine whether the cause is high impact, prolonged duration, or a combination of both. Therefore, selecting the appropriate indicator is crucial, as each conveys distinct information. In addition, the resilience indicators adopted in this study primarily capture system performance from a patient-centred perspective, focusing on service accessibility and continuity of care. However, resilience is inherently multidimensional (e.g. organisational resilience (Duchek 2020), economic resilience (Khan et al. 2024)). These dimensions are not explicitly modelled in the present framework due to the study's specific focus, but they represent important complementary perspectives for future research.

The resilience analysis demonstrated that it is essential for policymakers to define the *desired level of resilience*. The scenario analysis revealed that the AS-IS network was already fairly resilient to the short-lived disturbances (scenarios 1-1 and 2-1). Adaptive and absorptive improvements enhanced the network's resilience for scenarios of low and intermediate severity (scenarios 1-2, 1-3, 2-2, 2-3) and improved performance in the most severe scenario. These findings suggest that, rather than always designing for the worst-case scenario, policymakers must define the acceptable resilience level of the healthcare network by balancing efficiency with resilience and considering the potential impact on population health (Almeida 2024).

Another essential point to note is related to the two different actions tested. As mentioned above, these

actions align with two complementary dimensions of resilience: absorption and adaptivity. Absorptive actions, implemented through backup capacity, reduced the vulnerability of Facility 2 and improved its ability to absorb shocks, as shown by lower failure rates. However, its benefits were limited to that facility. Adaptivity, implemented through inter-facility collaboration, improved recovery rates and enhanced resilience across the entire network without requiring additional capacity. Yet, this approach may reduce patient satisfaction if patients are redirected to less preferred or more distant facilities. While both actions have a positive effect on resilience, it is important to consider these other implications when policymakers decide which to implement.

Finally, the distinctive feature of this resilience analysis framework is the integration of patient behaviour. Since patients actively shape demand through their choices, simulating their responses to disruption effects, such as changes in waiting time, is essential to capture amplifying or mitigating effects. Incorporating patient behaviour provides a more realistic view of system performance, particularly in elective care, where preferences strongly influence demand patterns. While this study only considers a few elements influencing preferences, it demonstrates the value of including patient behaviour dynamics in resilience analysis and marks a key contribution of this work. In the long term, this could translate into healthcare systems that are more responsive to patients' needs and more resilient to everyday disturbances, thereby impacting public health.

Summarising, as far as managerial implications are concerned, the resilience analysis framework presented in this paper can be used by policymakers and healthcare network managers to make strategic decisions on improving network resilience. The proposed approach facilitates the consideration of patient preferences, thereby ensuring that patient needs are prioritised in strategic decision-making. This dual perspective enables policymakers to analyse and plan improvement actions that address the disturbances affecting today's healthcare networks, all the while maintaining a focus on patients and their needs. In addition, the analyses presented and the use of various key performance indicators have provided a useful overview of potential approaches to operationalising resilience. This allows policymakers to choose the indicator that best suits their needs, whether that be absolute monitoring of resilience or comparing the effect of improvement actions. Furthermore, the framework enables the comparison of different improvement options, supporting a systematic evaluation of their relative contributions to resilience and guiding the prioritisation of interventions that deliver the greatest operational and patient-centred benefits. The framework not

only enables strategic decision-making and priority setting in the implementation of improvement actions, but also supports scalable implementation of these actions, taking into account both the impact of a possible disturbance and the probability of its occurrence. In this way, it is possible to assess which improvement is most suitable, considering the desired and achievable level of resilience, also taking into account the available resources.

From a theoretical perspective, this research contributes to the discourse on operationalising resilience. Although the concept of resilience has been the subject of study for a considerable length of time, the notion itself is often theoretical and challenging to translate into objective indicators. This study utilised established resilience indicators derived from extant literature to conduct a resilience assessment of a real-world healthcare network. Moreover, this research contributes to the analysis of resilience-enhancing actions within the healthcare context by identifying and conceptualising the mechanisms through which organisations can strengthen their absorptive and adaptive capacities in the face of disturbances. This contribution enriches existing frameworks on organisational resilience, offering new insights that can inform both future empirical studies and the development of strategic interventions in healthcare settings. The empirical implementation of these two actions in simulated scenarios has facilitated the evaluation of their effectiveness under different disturbance scenarios. This approach makes a significant theoretical contribution, as it enables a transition from theoretical resilience discussion to a more operational and practical perspective, which is useful for guiding both future research and policy decisions. The theoretical framework improves understanding of the concept of resilience, bridging the gap between resilience theory and practice and reconnecting it to patient-centred care, offering a new operational approach that integrates strategic metrics and individual preferences.

7. Conclusion

This paper introduces a framework for analysing healthcare network resilience that integrates patient preferences to identify vulnerabilities and prioritise resilience-enhancing actions. The framework was applied to a medical device failures case, a typical example of a low-impact-high-frequency event, using data from a real healthcare network. By pinpointing vulnerable facilities and supporting the prioritisation of actions based on their impact on resilience indicators, it helps bridge the gap between targeted and actual performance, thereby reducing the network's overall vulnerability.

This study has some limitations. First, it is limited to medical device failures within a single facility during the simulated period. Another limitation of this study is the exclusion of economic factors in evaluating absorptive and adaptive improvements. While this choice allowed us to focus on the methodological development of the framework, it did not allow to capture the trade-offs between efficiency and resilience or support more informed decision-making.

Future research may delve deeper into the analysis of the two actions tested. The actions have been analysed under limited operational constraints to ensure a comparison with the as-is situation, e.g. no overtime and fixed capacity. Future research could relax these constraints by analysing the effects of the actions in conjunction with different management policies to assist in responding to disturbances. Another promising avenue of research is to extend the framework to account for sequential failures of devices within the same facility. Such an extension would allow investigation of the impact of sequential failures on network resilience, including interactions between failures during recovery phases. This would provide a more comprehensive assessment of systemic vulnerabilities in healthcare networks, particularly under complex disturbance scenarios. Future work should examine other LIHF disturbances, including demand surges and recurrent high-frequency events, as well as simultaneous failures across multiple facilities and heterogeneous devices. Finally, future research should extend the proposed framework through empirical application in real healthcare decision-making contexts. This includes collecting operational data on disturbances, performance, and organisational responses, as well as implementing and evaluating resilience-enhancing actions in practice. The expansion of the modelling scope to incorporate integrated care pathways and interdependent service trajectories, thereby capturing coordination effects across departments and clinical processes, represents a final direction for improvement.

Author contributions

CRedit: **Claudia Piffari**: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Writing – original draft, Writing – review & editing; **Alexandra Lago-rio**: Conceptualization, Formal analysis, Methodology, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing; **Roberto Pinto**: Conceptualization, Formal analysis, Methodology, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing

Disclosure statement

No potential conflict of interest was reported by the author(s).

Notes on contributors



Alexandra Lagorio is an Associate Professor at the Department of Management, Information and Production Engineering of the University of Bergamo. She received a PhD in Economics and Management of Technology in July 2018 from the University of Pavia and Bergamo. Her expertise includes optimisation and simulations. Her major areas of teaching and research include urban freight distribution, last-mile logistics, logistics 4.0, digital supply chain management and healthcare logistics management. She's a member of the IFAC TC 5.2 (Management and Control in Manufacturing and Logistics) and Co-leader of the IFIP Special Interest Group 'Smart and Sustainable Supply Chain Management'



Roberto Pinto is Full Professor of Logistics and Supply Chain Management at the Department of Management, Information and Production Engineering, University of Bergamo. He holds a PhD in the Design and Management of Logistics and Production Systems from the University of Brescia, awarded in 2010. He is a member of the IFAC Technical Committee 5.2 – Management and Control in Manufacturing and Logistics. His research interests include warehouse management and optimisation, supply chain operations, supply chain network design, and the design and application of decision support systems for planning, managing, and optimising logistics and supply chain processes.



Claudia Piffari is a post-doctoral researcher at the University of Bergamo. She received a PhD in Technology, Innovation and Management in 2025, after obtaining a Master's Degree in Engineering and Management for Health. Her expertise includes quantitative modelling approaches such as agent-based simulation, optimisation, and system dynamics. Her research focuses on healthcare logistics, supply chain resilience, and complex socio-technical systems, with increasing attention to human-centered and sustainable design in line with Healthcare 5.0 and Industry 5.0. She is involved in research activities at the SLIM Lab on smart and human-centered manufacturing systems.

Data availability statement

The authors confirm that the data supporting the findings of this study are available within the article or from the corresponding author.

ORCID

Claudia Piffari <http://orcid.org/0000-0002-6182-6258>

Alexandra Lagorio <http://orcid.org/0000-0003-1489-0625>

Roberto Pinto <http://orcid.org/0000-0002-4370-4011>

References

- Abdi, H., and L. Williams. 2010. *Turkey's Honestly Significant Difference (HSD) Test*. *Encyclopedia of Research Design*, 1–5. Thousand Oaks: Sage.
- AGENAS. 2025. "Specialistica ambulatoriale." Portale statistico AGENAS. Accessed 2.12.25. <https://app.powerbi.com/view?r=eyJrIjoiOGE2MTY4NjctZjQ5NS00NTNkLWJjOGMtOTNjMjNjZThmYTlYliwidCI6IjY2ODc0Y2QwLWlOTEtNDliYS1hMTUwLTQwNzI3OTdhNTM5NyIsImMiOiJ9>.
- Aldrighetti, R., I. Zennaro, S. Finco, and D. Battini. 2019. "Healthcare Supply Chain Simulation with Disruption Considerations: A Case Study from Northern Italy." *Global Journal of Flexible Systems Management* 20:81–102. <https://doi.org/10.1007/s40171-019-00223-8>.
- Alikhani, R., A. Ranjbar, A. Jamali, S. A. Torabi, and C. W. Zobel. 2023. "Towards Increasing Synergistic Effects of Resilience Strategies in Supply Chain Network Design." *Omega* 116: 102819. <https://doi.org/10.1016/j.omega.2022.102819>.
- Almeida, A. 2024. "The Trade-Off between Health System Resiliency and Efficiency: Evidence from COVID-19 in European Regions." *The European Journal of Health Economics* 25:31–47. <https://doi.org/10.1007/s10198-023-01567-w>.
- Antony, J. 2012. *Design of Experiments for Engineers and Scientists SECOND EDITION*. Amsterdam: Butterworth-Heinemann.
- ASST BG EST. 2025. "Sedi. Regione Lombardia." Accessed 2.12.25. <https://www.asst-bergamoest.it/it/sedi>.
- Behzadi, G., M. J. O'Sullivan, and T. L. Olsen. 2020. "On Metrics for Supply Chain Resilience." *European Journal of Operational Research* 287:145–158. <https://doi.org/10.1016/j.ejor.2020.04.040>.
- Bhattacharyya, K., P. Datta, and O. F. Offodile. 2010. "The Contribution of Third-Party Indices in Assessing Global Operational Risks." *Journal of Supply Chain Management* 46:25–43. <https://doi.org/10.1111/j.1745-493X.2010.03204.x>.
- Bruckler, M., L. Wietschel, L. Messmann, A. Thorenz, and A. Tuma. 2024. "Review of Metrics to Assess Resilience Capacities and Actions for Supply Chain Resilience." *Computers & Industrial Engineering* 192:110176. <https://doi.org/10.1016/j.cie.2024.110176>.
- Bruneau, M., S. E. Chang, R. T. Eguchi, G. C. Lee, T. D. O'Rourke, A. M. Reinhorn, M. Shinozuka, K. Tierney, W. A. Wallace, and D. Von Winterfeldt. 2003. "A Framework to Quantitatively Assess and Enhance the Seismic Resilience of Communities." *Earthquake Spectra* 19:733–752. <https://doi.org/10.1193/1.1623497>.
- Burge, P., N. Devlin, J. Appleby, C. Rohr, and J. Grant. 2004. "Do Patients Always Prefer Quicker Treatment? A Discrete Choice Analysis of Patients Stated Preferences in the London Patient Choice Project." *Applied Health Economics and Health Policy* 3:183–194. <https://doi.org/10.2165/00148365-200403040-00002>.
- Burkhart, D., and C. Bode. 2024. "On Supplier Resilience: How Supplier Performance, Disruption Frequency, and Disruption Duration Are Interrelated." *Journal of Purchasing and Supply Management* 30:100921. <https://doi.org/10.1016/j.pursup.2024.100921>.
- Cabrera, E., M. Taboada, M. L. Iglesias, F. Epelde, and E. Luque. 2011. "Optimization of Healthcare Emergency Departments

- by Agent-Based Simulation.” In *Procedia Computer Science, Proceedings of the International Conference on Computational Science, ICCS 2011 4*, 1880–1889. <https://doi.org/10.1016/j.procs.2011.04.204>.
- Callahan, R. N., K. M. Hubbard, and N. M. Bacoski. 2006. “The Use of Simulation Modeling and Factorial Analysis as a Method for Process Flow Improvement.” *The International Journal of Advanced Manufacturing Technology* 29:202–208. <https://doi.org/10.1007/s00170-004-2497-5>.
- Caputo, A. C., L. Donati, and P. Salini. 2023. “Estimating Resilience of Manufacturing Plants to Physical Disruptions: Model and Application.” *International Journal of Production Economics* 266:109037. <https://doi.org/10.1016/j.ijpe.2023.109037>.
- Chen, J., A. S. Sohal, and D. I. Prajogo. 2013. “Supply Chain Operational Risk Mitigation: A Collaborative Approach.” *International Journal of Production Research* 51:2186–2199. <https://doi.org/10.1080/00207543.2012.727490>.
- Duchek, S. 2020. “Organizational Resilience: A Capability-Based Conceptualization.” *Business Research* 13:215–246. <https://doi.org/10.1007/s40685-019-0085-7>.
- Egli, L., H. Weise, V. Radchuk, R. Seppelt, and V. Grimm. 2019. “Exploring Resilience with Agent-Based Models: State of the Art, Knowledge Gaps and Recommendations for Coping with Multidimensionality.” *Ecological Complexity* 40: 100718. <https://doi.org/10.1016/j.ecocom.2018.06.008>.
- Exworthy, M., and S. Peckham. 2006. “Access, Choice and Travel: Implications for Health Policy.” *Social Policy & Administration* 40:267–287. <https://doi.org/10.1111/j.1467-9515.2006.00489.x>.
- Foroughi, Z., P. Ebrahimi, A. Aryankhesal, M. Maleki, and S. Yazdani. 2022. “Toward a Theory-Led Meta-framework for Implementing Health System Resilience Analysis Studies: A Systematic Review and Critical Interpretive Synthesis.” *BMC Public Health* 22:287. <https://doi.org/10.1186/s12889-022-12496-3>.
- Geng, S., and S. Liu. 2025. “An Agent-Based Framework for Resilience Analysis of Service Networks.” *Reliability Engineering & System Safety* 253:110523. <https://doi.org/10.1016/j.res.2024.110523>.
- Ho, W., T. Zheng, H. Yildiz, and S. Talluri. 2015. “Supply Chain Risk Management: A Literature Review.” *International Journal of Production Research* 53 (16): 5031–5069. <https://doi.org/10.1080/00207543.2015.1030467>.
- Ivanov, D. 2020. “Predicting the Impacts of Epidemic Outbreaks on Global Supply Chains: A Simulation-Based Analysis on the Coronavirus Outbreak (COVID-19/SARS-CoV-2) Case.” *Transportation Research Part E: Logistics and Transportation Review* 136:101922. <https://doi.org/10.1016/j.tre.2020.101922>.
- Ivanov, D. 2022. “Probability, Adaptability, and Time: Some Research-Practice Paradoxes in Supply Chain Resilience and Viability Modeling.” *International Journal of Integrated Supply Management* 15 (4): 454–465. <https://doi.org/10.1504/IJISM.2022.125995>.
- Ivanov, D. 2025. *Literature Review on the Stress Tests Developed and Applied in Non-Food Supply Chains*. Luxembourg: Publications Office of the European Union. <https://doi.org/10.2760/9174136>.
- Ivanov, D., A. Dolgui, B. Sokolov, and M. Ivanova. 2017. “Literature Review on Disruption Recovery in the Supply Chain.” *International Journal of Production Research* 55:6158–6174. <https://doi.org/10.1080/00207543.2017.1330572>.
- James, C., F. Colombo, D. Morgan, and C. Vammalle. 2024. “Finance and Health Dialogue Needed to Build Resilient Health Systems.” *Bulletin of the World Health Organization* 102:368–369. <https://doi.org/10.2471/BLT.24.291539>.
- Khan, W., M. S. Islam, N. Ullah Ibne Hossain, and S. Fazio. 2024. “Measuring Economic Resilience of Manufacturing Organization Leveraging Integrated Data Envelopment Analysis (DEA)-Machine Learning Approach.” *International Journal of Management Science and Engineering Management* 19:228–238. <https://doi.org/10.1080/17509653.2023.2267505>.
- Kutor, J. K., P. Agede, and R. H. Ali. 2017. “Maintenance Practice, Causes of Failure and Risk Assessment of Diagnostic Medical Equipment.” *Journal of Biomedical Engineering and Medical Devices* 2 (1): 123. <https://doi.org/10.4172/2475-7586.1000123>.
- Lockamy III, A., and K. McCormack. 2010. “Analysing Risks in Supply Networks to Facilitate Outsourcing Decisions.” *International Journal of Production Research* 48:593–611. <https://doi.org/10.1080/00207540903175152>.
- Lorscheid, I., B.-O. Heine, and M. Meyer. 2012. “Opening the ‘Black Box’ of Simulations: Increased Transparency and Effective Communication through the Systematic Design of Experiments.” *Computational and Mathematical Organization Theory* 18:22–62. <https://doi.org/10.1007/s10588-011-9097-3>.
- Mandal, S. 2017. “The Influence of Organizational Culture on Healthcare Supply Chain Resilience: Moderating Role of Technology Orientation.” *Journal of Business & Industrial Marketing* 32:1021–1037. <https://doi.org/10.1108/JBIM-08-2016-0187>.
- Marshall, D. A., L. Burgos-Liz, M. J. IJerman, N. D. Osgood, W. V. Padula, M. K. Higashi, P. K. Wong, K. S. Pasupathy, and W. Crown. 2015. “Applying Dynamic Simulation Modeling Methods in Health Care Delivery Research—The SIMULATE Checklist: Report of the ISPOR Simulation Modeling Emerging Good Practices Task Force.” *Value in Health* 18:5–16. <https://doi.org/10.1016/j.jval.2014.12.001>.
- McFadden, D. 1973. “Conditional Logit Analysis of Qualitative Choice Behavior.”
- McIntyre, D., and C. K. Chow. 2020. “Waiting Time as an Indicator for Health Services under Strain: A Narrative Review.” *Inquiry* 57:0046958020910305. <https://doi.org/10.1177/0046958020910305>.
- Miller, L., and D. May. 2006. “Patient Choice in the NHS: How Critical are Facilities Services in Influencing Patient Choice?” *Facilities* 24:354–364. <https://doi.org/10.1108/02632770610677637>.
- Montgomery, D. C. 2017. *Design and Analysis of Experiments*. New York: John Wiley & Sons.
- Moosavi, J., and S. Hosseini. 2021. “Simulation-Based Assessment of Supply Chain Resilience with Consideration of Recovery Strategies in the COVID-19 Pandemic Context.” *Computers & Industrial Engineering* 160:107593. <https://doi.org/10.1016/j.cie.2021.107593>.
- Nan, C., and G. Sansavini. 2017. “A Quantitative Method for Assessing Resilience of Interdependent Infrastructures.” *Reliability Engineering & System Safety* 157:35–53. <https://doi.org/10.1016/j.res.2016.08.013>.

- National Academies of Sciences, Engineering, and Medicine. 2022. *Building Resilience into the Nation's Medical Product Supply Chains*. Washington (DC): National Academies Press (US).
- National Institute of Statistics. Istat Popolazione Residente al 1 Gennaio. n.d. Accessed August 3, 2025. http://dati.istat.it/Index.aspx?DataSetCode=DCIS_POPRES1.
- Nayeri, S., Z. Sazvar, and J. Heydari. 2022. "A Global-Responsive Supply Chain considering Sustainability and Resiliency: Application in the Medical Devices Industry." *Socio-Economic Planning Sciences* 82:101303. <https://doi.org/10.1016/j.seps.2022.101303>.
- Nze-Ekpebie, R. 2023. "Global Supply Chain Effects on Medical Devices." *Journal of Health Care Communications* 8 (4): 170–182. <https://doi.org/10.36846/2472-1654-8.4.8038>.
- OECD. 2020. *Waiting Times for Health Services: Next in Line, OECD Health Policy Studies*. OECD Publishing. <https://doi.org/10.1787/242e3c8c-en>.
- OECD. 2024. *Policies for Enhancing Supply Chain Security Routinely*. OECD. Accessed 4.30.25. https://www.oecd.org/en/publications/securing-medical-supply-chains-in-a-post-pandemic-world_119c59d9-en/full-report/component-5.html.
- Piffari, C., A. Lagorio, and R. Pinto. 2024. "The Role of Information Visibility on Healthcare Resource Network Performance: An Agent-Based Simulation Approach." *Journal of the Operational Research Society* 76 (5): 1019–1033. <https://doi.org/10.1080/01605682.2024.2407454>.
- Poulin, C., and M. B. Kane. 2021. "Infrastructure Resilience Curves: Performance Measures and Summary Metrics." *Reliability Engineering & System Safety* 216:107926. <https://doi.org/10.1016/j.res.2021.107926>.
- Reed, D., K. Kapur, and R. Christie. 2009. "Methodology for Assessing the Resilience of Networked Infrastructure." *IEEE Systems Journal* 3:174–180. <https://doi.org/10.1109/JSYST.2009.2017396>.
- Regione Lombardia. 2025. "Volumi Prestazioni Specialistica Ambulatoriale. Regione Lombardia - Open Data." Accessed 2.12.25. https://www.dati.lombardia.it/dataset/Volumi-Prestazioni-Specialistica-Ambulatoriale-in-/hdbq-kes5/data_preview.
- Roh, J., T. Tokar, M. Swink, and B. Williams. 2022. "Supply Chain Resilience to Low-/High-Impact Disruptions: The Influence of Absorptive Capacity." *The International Journal of Logistics Management* 33:214–238. <https://doi.org/10.1108/IJLM-12-2020-0497>.
- Sabouhi, F., M. S. Pishvaei, and M. S. Jabalameli. 2018. "Resilient Supply Chain Design under Operational and Disruption Risks considering Quantity Discount: A Case Study of Pharmaceutical Supply Chain." *Computers & Industrial Engineering* 126:657–672. <https://doi.org/10.1016/j.cie.2018.10.001>.
- Simchi-Levi, D., W. Schmidt, and Y. Wei. 2014. "From Superstorms to Factory Fires: Managing Unpredictable Supply-Chain Disruptions." *Harvard Business Review* 92 (1/2): 96–101.
- Simchi-Levi, D., W. Schmidt, Y. Wei, P. Y. Zhang, K. Combs, Y. Ge, O. Gusikhin, M. Sanders, and D. Zhang. 2015. "Identifying Risks and Mitigating Disruptions in the Automotive Supply Chain." *Interfaces* 45:375–390. <https://doi.org/10.1287/inte.2015.0804>.
- Spiegler, V. L. M., M. M. Naim, and J. Wikner. 2012. "A Control Engineering Approach to the Assessment of Supply Chain Resilience." *International Journal of Production Research* 50:6162–6187. <https://doi.org/10.1080/00207543.2012.710764>.
- Tang, C. S. 2006. "Perspectives in Supply Chain Risk Management." *International Journal of Production Economics* 103:451–488. <https://doi.org/10.1016/j.ijpe.2005.12.006>.
- Tang, J., S. Han, J. Wang, B. He, and J. Peng. 2023. "A Comparative Analysis of Performance-Based Resilience Metrics via a Quantitative-Qualitative Combined Approach: Are We Measuring the Same Thing?" *International Journal of Disaster Risk Science* 14:736–750. <https://doi.org/10.1007/s13753-023-00519-5>.
- Tippong, D., S. Petrovic, and V. Akbari. 2021. "A Review of Applications of Operational Research in Healthcare Coordination in Disaster Management." *European Journal of Operational Research* 301 (1): 1–17. <https://doi.org/10.1016/j.ejor.2021.10.048>.
- Train, K. 2009. *Discrete Choice Methods with Simulation* (Cambridge Books). Cambridge: Cambridge University Press.
- Welch, H. G., E. B. Larson, and W. P. Welch. 1993. "Could Distance Be a Proxy for Severity-of-Illness? A Comparison of Hospital Costs in Distant and Local Patients." *Health Services Research* 28:441–458.
- Yang, Z., H. Su, X. Du, E. Zio, Q. Xiang, S. Peng, L. Fan, M. H. Faber, and J. Zhang. 2023. "Supply Resilience Assessment of Natural gas Pipeline Network Systems." *Journal of Cleaner Production* 385:135654. <https://doi.org/10.1016/j.jclepro.2022.135654>.
- Zobel, C. W. 2014. "Quantitatively Representing Nonlinear Disaster Recovery." *Decision Sciences* 45:1053–1082. <https://doi.org/10.1111/deci.12103>.

Appendix

Table A1. Full factorial design for each sub-DOE.

Design points	Factors	
	σ	τ
1	Low (1)	Low (1)
2	Low (1)	Medium (2)
3	Low (1)	High (3)
4	Medium (2)	Low (1)
5	Medium (2)	Medium (2)
6	Medium (2)	High (3)
7	High (3)	Low (1)
8	High (3)	Medium (2)
9	High (3)	High (3)

Table A2. Error variance matrix.

Response variables		Number of runs				
		5	10	15	20	25
Low factor levels						
AR_{wt}	Mean	98.47	98.89	99.29	99.15	98.80
	Coefficient of Variance	0.02	0.01	0.01	0.01	0.01
AR_{sl}	Mean	100.00	99.99	99.99	99.99	100.00
	Coefficient of Variance	0.00	0.00	0.00	0.00	0.00
TTR_{wt}	Mean	43.40	35.50	25.13	25.45	38.80
	Coefficient of Variance	0.72	0.54	0.61	0.50	0.45
TTR_{sl}	Mean	0.00	6.40	4.33	4.00	2.24
	Coefficient of Variance	0.00	0.73	1.13	0.00	0.00
Mean factor levels						
AR_{wt}	Mean	87.37	87.63	88.19	88.44	88.34
	Coefficient of Variance	0.02	0.02	0.02	0.02	0.02
AR_{sl}	Mean	96.52	95.75	95.69	95.96	95.76
	Coefficient of Variance	0.02	0.01	0.01	0.01	0.01
TTR_{wt}	Mean	142.40	134.40	128.07	131.30	131.04
	Coefficient of Variance	0.17	0.13	0.12	0.14	0.14
TTR_{sl}	Mean	54.50	64.70	63.27	63.60	68.12
	Coefficient of Variance	0.48	0.16	0.18	0.18	0.18
High factor levels						
AR_{wt}	Mean	54.27	53.03	53.51	53.45	53.74
	Coefficient of Variance	0.04	0.02	0.02	0.03	0.04
AR_{sl}	Mean	68.82	67.35	68.90	68.53	68.72
	Coefficient of Variance	0.03	0.03	0.03	0.04	0.04
TTR_{wt}	Mean	309.60	316.40	318.93	314.90	312.36
	Coefficient of Variance	0.04	0.02	0.01	0.04	0.04
TTR_{sl}	Mean	206.60	205.20	195.93	202.45	200.36
	Coefficient of Variance	0.09	0.10	0.08	0.10	0.10

Table A3. Tukey post-hoc for AR^{WT} and AR^{SL} in the worst-case scenario (3-3).

Facilities' pairwise comparison		$AR_m^{[WT, SL]} - AR_n^{[WT, SL]}$	HSD
AR^{WT}	2-1	16.89	1.80
	2-3	9.92	
	2-4	12.26	
	2-5	6.71	
	2-6	8.79	
	2-7	9.52	
AR^{SL}	2-1	18.99	1.08
	2-3	18.34	
	2-4	15.61	
	2-5	18.44	
	2-6	16.04	
	2-7	16.25	

The following Table A3 shows an example of the results of the Tukey post-hoc test for AR^{WT} and AR^{SL} in the high duration and severity scenario (scenario 3-3), comparing Facility 2 with the other.