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Reconfiguring healthcare in crisis: Relational mechanisms of network resilience in regional hospital systems

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A R T I C L E I N F O

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A B S T R A C T

Background: Organisational resilience in healthcare systems under stress remains poorly understood, particularly in relation to the role of inter-organisational networks. This study investigates how a regional hospital network in Italy responded to the 2009 L'Aquila earthquake, with a focus on the relational mechanisms enabling system-level stability despite the sudden collapse of a key hospital.
Methods: We analyse complete inter-hospital patient transfer data (N = 33 hospitals) over four time periods (one pre-shock and three post-shock). Using stochastic actor-oriented models (SAOMs), we assess how hospitals reconfigured their patient referral ties and whether relational mechanisms such as reciprocity, transitivity, and cyclicality changed over time. We also incorporate measures of geographical, institutional, organisational, and cognitive proximity.
Findings: Despite the collapse, the overall healthcare system functionality remained stable overall. Immediately following the shock, hospitals adapted their collaborative structure by relying on generalised and anti-hierarchical exchange patterns—particularly reciprocity and transitivity. Over time, these mechanisms declined, giving way to more hierarchical, stratified referral structures. Geographical and social proximity significantly shaped tie formation, highlighting uneven responses across the network.
Interpretation: Our findings suggest that relational mechanisms underpinning social capital are critical for healthcare network resilience. In contexts of high uncertainty, collaborative agility and flexible relational structures allow hospital networks to absorb shocks while preserving functionality. These results offer theoretical contributions to resilience, healthcare management, and network theory, and have practical implications for health system design and disaster preparedness.

Introduction

Healthcare systems are increasingly exposed to shocks, ranging from technological failures and regulatory changes to natural disasters and pandemics (Kruk et al., 2015). In this context, resilience—understood as the capacity to absorb, adapt to, and recover from disruptions while maintaining essential functions—has become a crucial concept in both policy and academic debates (Haldane et al., 2021; Kruk et al., 2015; Turenne et al., 2019). Traditionally, resilience has been explored as an internal organisational capability, drawing from psychological (Luthar et al., 2000), ecological (Holling, 1996), and engineering perspectives (Limnios et al., 2012). These studies privilege intra-organisational antecedents—such as leadership, resource slack, and learning culture (Cavalieri et al., 2025; Kantur, Iseri-Say, 2012; Ortiz-de-Mandojana and Bansal, 2016)—while neglecting the inter-organisational dynamics that enable health systems to respond collectively to crises.

Yet, healthcare delivery is inherently networked: hospitals, providers, and public institutions rely on tightly interwoven collaboration to manage patient flows, coordinate resources, and ensure continuity of care (Mascia et al., 2015; Veinot et al., 2012). In this view, resilience

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depends not only on the robustness of individual nodes, but on the adaptability and coherence of the relational structures connecting them (Lengnick-Hall et al., 2011; van der Vegt et al., 2015). More recent work has in fact highlighted the systemic and relational nature of resilience in health systems, pointing to the importance of coordination, connectivity, and distributed adaptation (Fridell et al., 2020; Blanchet et al., 2017; Barasa et al., 2018). While inter-organisational networks have been widely recognised as a key mechanism of systemic recovery in response to natural disasters or epidemics (Kapucu and Garayev, 2013; Van Den Oord et al., 2020), studies in this area focus mainly on new organisational arrangements arising from exogenous shocks. Instead, extant literature is less equipped to explain how *existing* networks in the public domain cope with such shocks to maintain public service levels. As a result, current understanding is still limited on how healthcare systems adapt their relational structure to enact resilience, particularly as a response to sudden shocks.

To address this gap, this study conceptualises resilience as a relational phenomenon grounded in the structure and dynamics of inter-organisational ties. We draw on social capital theory (Gulati and Gargiulo, 1999; Coleman, 1988) to examine how hospitals reorganise their referral relationships following a major exogenous shock, the 2009 L'Aquila earthquake, a catastrophic event that led to the immediate collapse of one of the largest hospitals in Italy's Abruzzo region. In particular, we focus on patient transfer networks as observable manifestations of interdependence, where decisions to create, maintain or dissolve ties are driven by both practical constraints and embedded collaborative routines (Mascia et al., 2015; Iwashyna et al., 2009a, 2009b).

We contribute to current debate in three main ways. First, we advance a relational perspective on health systems resilience, showing how organisational adaptation is shaped by network position and prior relational embeddedness. Second, we provide empirical evidence on how specific network mechanisms—such as reciprocity and transitivity—support the reconfiguration of ties in the face of uncertainty. Third, we contribute to network theory by tracing the dynamic interplay between exogenous shock and endogenous structural responses in a high-reliability, decentralised system. By focusing on the evolution of inter-hospital ties in a real-world disruption scenario, this study enriches current understanding of how relational infrastructures sustain resilience in complex health systems. It also offers actionable insights for policymakers and administrators seeking to enhance health systems' adaptive capacity through network-based interventions.

Theoretical background

Resilience in healthcare

Resilience is a multifaceted concept that has been explored across various disciplines. In psychology, it is typically understood as an individual trait that enables people to withstand adverse events and maintain a positive outlook (Luthar et al., 2000; Masten and Monn, 2015). In ecology, it refers to the flexibility and integrity of systems that allow them to absorb shocks without compromising their functionality (Holling, 1996). In engineering, resilience is defined as a system's capacity to return to a single equilibrium state following a disturbance (Limnios et al., 2012). Similarly, in crisis and disaster management, resilience is conceived as the ability of organisations or systems to "bounce back" after major shocks (van der Vegt et al., 2015). Across these perspectives, two key components emerge: *robustness*—the ability to absorb and withstand disturbances while continuing to function—and *rebound*—the ability to return to pre-crisis performance levels (Bakker et al., 2012; Linnenluecke and Griffiths, 2010). More recent work expands on this view, by proposing that resilience may also entail transformation, whereby systems adapt and improve as a result of disruption—"bouncing forward" rather than merely bouncing back to a pre-existing state (Weick et al., 1999; Kahn et al., 2013; Ortiz-de-Mandojana and Bansal, 2016).

On the same line, resilience in healthcare systems is often conceptualised as the ability to absorb, adapt to, and recover from disruptions while continuing to deliver essential services (Ortiz-de-Mandojana and Bansal, 2016; van der Vegt et al., 2015; Kruk et al., 2015). Traditional accounts have emphasised resilience as structural robustness or a return to equilibrium. More recent perspectives, however, conceive resilience as a dynamic process that involves behavioural adaptation, organisational improvisation, and relational reconfiguration (Weick et al., 1999; Kantur and Iseri-Say, 2012). A recent scoping review by Turenne et al. (2019) systematically examined how resilience has been applied within health systems research. Their analysis demonstrates the diversity of definitions and methodological approaches adopted, while also highlighting a predominant focus on system-level resilience, typically understood as the capacity to maintain or restore service provision in the face of shocks. Critically, their review shows that resilience in healthcare is conceptualised less as a fixed trait and more as a dynamic, processual feature that emerges from interactions between governance structures, organisational routines, and inter-organisational relationships. In this view, resilience is not solely located within individual organisations but shaped by the embeddedness of actors within broader institutional and relational frameworks. This perspective is further developed by Paschoalotto et al. (2023), who investigate how expert conceptions of health system resilience evolved during the COVID−19 pandemic. They argue that existing frameworks were insufficient to capture the complexity of real-world responses and propose a revised model incorporating four adaptive stages (preparedness, alert, impact, and recovery), emphasising the importance of decentralised decision-making, community engagement, and multilevel governance.

Despite the richness of these conceptual contributions, empirical research has predominantly focused on intra-organisational antecedents of resilience—such as perceptual stance, resourcefulness, and learning orientation (Pal et al., 2014; Kantur and Iseri-Say, 2012; Barbash and Kahn, 2021; Cavalieri et al., 2025). In contrast, the inter-organisational dimension—particularly relevant in decentralised healthcare systems—remains underexplored. Yet, the capacity of health systems to absorb and adapt to shocks frequently depends on patterns of collaboration among hospitals and other care providers. From this perspective, inter-organisational social capital—the structure of ties through which organisations exchange information, form trust, and build support—may constitute a key but underexamined mechanism of both organisational and systemic resilience (Al Asfoor et al., 2024; Haldane et al., 2021).

A relational perspective on healthcare resilience

Healthcare systems are inherently interdependent. They rely on networks of collaboration among hospitals, providers, and public agencies to coordinate patient flows, manage resources, and maintain continuity of care (Pal et al., 2014; Veinot et al., 2012; Mascia et al., 2017). These inter-organisational ties—such as patient transfers, logistical coordination, and information exchange—are not merely technical arrangements. They are embedded in relational histories shaped by trust, familiarity, and repeated interaction (Gulati and Gargiulo, 1999). In crisis situations, such ties may function as informal coordination mechanisms that enable the system to absorb strain, redistribute demand, and continue functioning without requiring centralised command.

From this relational viewpoint, resilience is not simply institutional robustness but also network elasticity—the capacity of inter-organisational ties to reconfigure under pressure while maintaining coherence and mutual understanding. This conceptualisation resonates with social exchange theory, which frames organisational relationships as transactions based on reciprocity, interdependence, and the exchange of both material and symbolic resources (Emerson, 1972; Molm, 2003). In healthcare networks, these relational dynamics are often visible through patient transfer patterns, which reflect both clinical needs and embedded collaborative routines.

In decentralised systems, where formal coordination mechanisms may be limited, these relational structures become even more critical. Without hierarchical control, adaptation must emerge from the bottom-up, through the activation and reshaping of existing relationships. Prior relational embeddedness—manifested in referral patterns, informal trust, or previous collaborations—can facilitate more agile and context-sensitive responses to systemic shocks. Mechanisms such as reciprocity, familiarity, and mutual recognition thus play a central role in shaping how healthcare networks reorganise in the wake of disruption.

Hypotheses development

In normal circumstances, hospital referrals often follow hierarchical or status-based patterns, whereby smaller or peripheral hospitals refer patients to larger, better-equipped hubs (Elrod and Fortenberry, 2017). Under conditions of acute uncertainty and disrupted infrastructure, however, such hierarchies may become obsolete. Instead, organisations will rely on social capital mechanisms—such as reciprocity, trust, and familiarity—to guide collaborative action when knowledge about resources and capabilities of other organizations within the networks becomes outdated or risks being inaccurate because of the changes brought about by the exogenous shock. This shift aligns with social exchange theory, which posits that when formal structures and information channels are insufficient, actors turn to established relational ties to manage interdependence and access resources (Hall et al., 2023; Molm et al., 2007; Agneessens and Wittek, 2012).

We formulate four hypotheses to test how such mechanisms shape the restructuring of healthcare referral networks in the aftermath of an exogenous shock, and thereby underpin network elasticity and ultimately resilience.

We expect hospitals to rely more heavily on reciprocity—returning referrals from other hospitals—as a mechanism to reduce uncertainty and reinforce coordination under disrupted conditions. In the aftermath of a shock, established referral pathways are destabilized and information about partners' capacities and resources becomes incomplete or unreliable. Under these conditions, reciprocity provides a low-risk coordination strategy: by favoring partners who have already demonstrated willingness to exchange patients, hospitals can rely on prior interactions as a proxy for trustworthiness and capability.

From a social capital perspective, reciprocal exchanges reinforce relational trust and facilitate mutual access to critical resources (Burt, 2000; Agneessens and Wittek, 2012). At the same time, reciprocity functions as a decentralized governance mechanism, helping stabilize exchange relationships when formal coordination is weakened or temporarily unavailable. By creating mutual obligations and reinforcing expectations of continued interaction, reciprocal transfers reduce the risk of opportunistic behavior and support more predictable patterns of coordination.

More formally:

Hypothesis 1. Following the earthquake, the likelihood of reciprocal patient transfers between hospitals will increase, reflecting greater reliance on trusted partners to stabilize exchange relationships under uncertainty. Therefore, we expect that if hospital A sends patients to hospital B, then hospital B will be more likely to send patients to hospital A.

Beyond direct reciprocity, we anticipate the activation of triadic mechanisms—particularly transitivity—whereby hospitals draw on their partners' partners to infer new referral possibilities. This mechanism enables decision-making based on indirect reputational knowledge and helps reduce uncertainty in a disrupted environment. Transitivity promotes the flow of trust and information through indirect ties (Granovetter, 1983; Savage and Bergstrand, 2013) and may be particularly useful when direct knowledge of potential partners is unavailable. More formally:

Hypothesis 2. Following the earthquake, the likelihood of transitive patient transfers between hospitals will increase, reflecting greater reliance on trusted partners' partners to stabilize exchange relationships under uncertainty. Therefore, we expect that, if hospital A sends patients to hospital B and B sends patients to hospital C, then A will be more likely to send patients to C.

We also expect to observe cyclical exchange patterns, where indirect reciprocity unfolds within triads and favours clustering of trusted partners: hospitals benefit not directly from the partner they help, but from a third party within the network. Such configurations indicate generalised trust and solidarity, particularly useful in decentralised systems. This kind of anti-hierarchical exchange supports the resilience of decentralised systems by diffusing expectations of reciprocity across a broader structure. It reflects a move from transactional to generalised exchange (Molm et al., 2009) and enables adaptation in the absence of centralised command. More formally:

Hypothesis 3. Following the earthquake, the likelihood of cyclical patient transfers between hospitals will increase, reflecting greater tendency to engage in generalized exchange that promotes clusters of partners under conditions of uncertainty. Therefore, we expect that if hospital A sends patients to B and B sends patients to C, then hospital C will be more likely to send patients to A.

Finally, we hypothesize that the prevalence of key relational mechanisms—reciprocity, transitivity, and cyclicality—will decrease over time. As uncertainty subsides and hospitals regain knowledge about others' post-shock capacities, coordination is expected to progressively shift toward more stratified and hierarchical referral patterns. This reflects a temporal view of network resilience in which relational mechanisms dominate in the immediate aftermath of disruption but are gradually replaced by hierarchical structures and role differentiation (Gulati and Gargiulo, 1999). More formally:

Hypothesis 4. The tendency of patient transfers to exhibit reciprocity and cyclicality will decline over time as the network progressively shifts toward more hierarchical structures.

Together, these hypotheses conceptualise resilience in healthcare as an emergent property of inter-organisational networks, shaped not only by formal capabilities but also by relational mechanisms. The shift from hierarchical to relational coordination—and back again—highlights the adaptability of healthcare systems under stress and the critical role of network dynamics in enabling recovery.

Methods

Empirical setting

The Abruzzo region comprises approximately 1.3 million inhabitants and hosts 33 hospitals (22 public and 11 private), including two University hospitals. Public hospitals are responsible for the delivery of specialised care and emergency services, while private facilities offer hospitalisation and diagnostic services, operating partially under public funding. The organisational structure of the regional health system is characterised by a decentralised model without a single coordinating authority.

On 6 April 2009, a 6.3-magnitude earthquake struck the Abruzzo region in central Italy, causing over 300 deaths, 2000 injuries, and displacing more than 70,000 people. The epicentre was located near L'Aquila, the regional capital, where the main public hospital, San Salvatore, sustained substantial damage and was forced to cease operations. Medical services were relocated to a makeshift field hospital, while emergency coordination was managed by a temporary control centre. When the San Salvatore hospital was declared unfit to admit patients, a field hospital was set up as a short-term triage center eligible to treat only urgent and not-transferable patients. After stabilization, patients were transferred to other, more appropriate hospitals. The San Salvatore maintained its network of relationships until the relocation of all the patients. Despite these disruptions, the regional health system continued to provide essential services.

The unexpected collapse of San Salvatore—one of the region's largest and most central hospitals—created a natural experiment that enables to investigate how a decentralised hospital network adapts under acute systemic disruption. As shown in Figs. 1a and 1b, system-level indicators such as total discharges and average length of stay remained stable in the months following the earthquake. A Mann–Kendall trend test revealed no significant variation in discharges ($\tau = -0.262$; $p = 0.064$) or average length of stay ($\tau = 0.133$; $p = 0.362$), suggesting that the network was able to maintain overall operational capacity and volumes of service delivery.

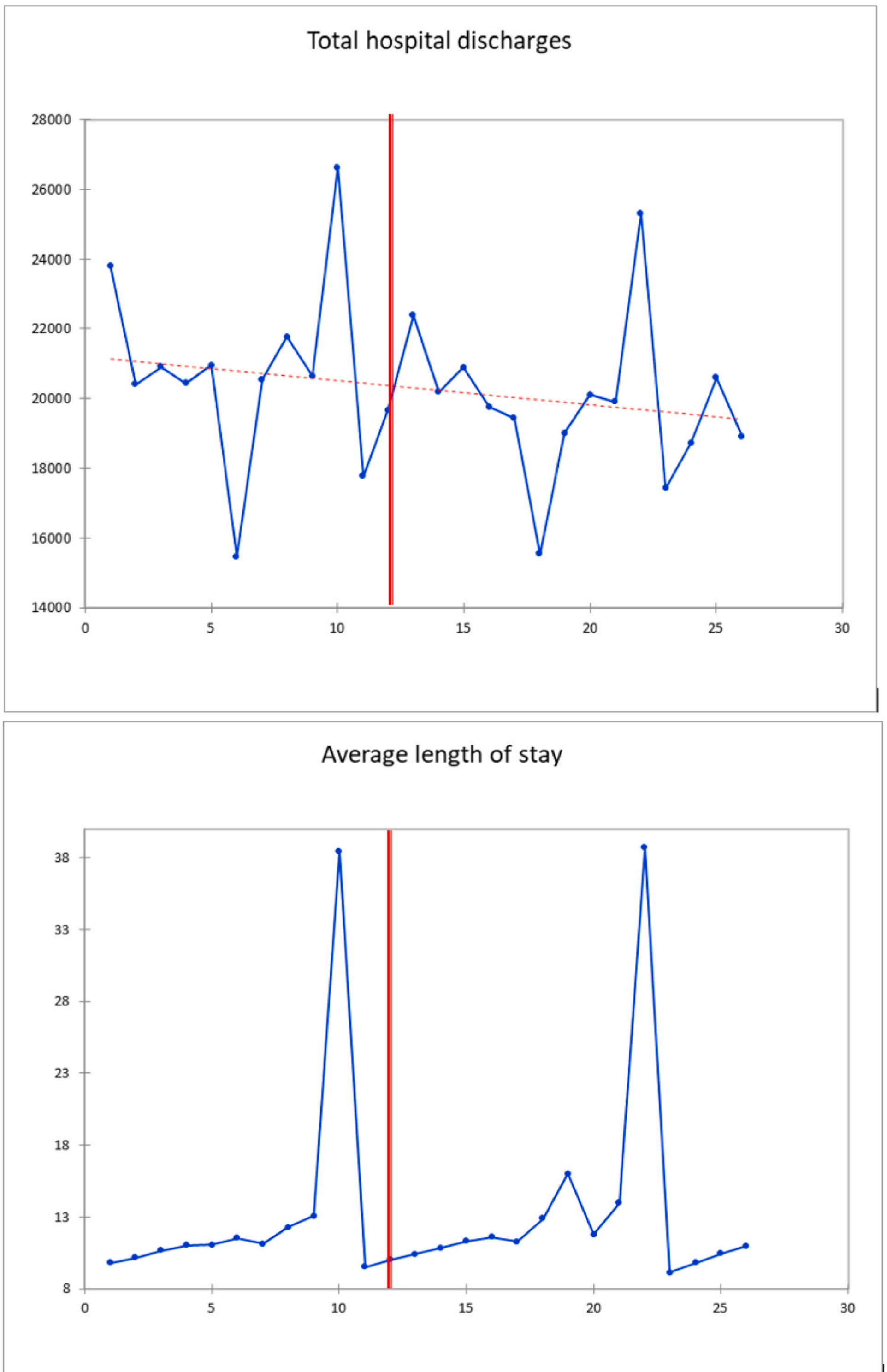


Fig. 1. a−1b: The time series of total hospital discharges and average length of stay.

Data and measures

We used administrative data from the Abruzzo Agency of Public Health, which collects hospital discharge information for planning, monitoring, and reimbursement purposes. The dataset includes detailed information on patient characteristics, transfers, hospital attributes, and service provision. Our primary focus was on patient transfers—a form of inter-organisational coordination in which patients are discharged from one hospital and directly admitted to another. Prior research identifies patient transfers as a key mechanism of operational collaboration in healthcare systems (Berta et al., 2022, Cohen et al., 2011; Iwashyna et al., 2009a; Mascia et al., 2015).

We analysed data from all 33 hospitals in the region using a longitudinal network panel design consisting of four time periods: T1 (12 months before the earthquake), T2 (first 3 months after the earthquake), T3 (6 months after the earthquake), T4 (12 months after the earthquake). This design allowed for the observation of both short- and medium-term adaptations in the referral network. The choice of the time intervals is rooted in the authors' contextual knowledge and informed by fieldwork in this setting at the time of the earthquake. This highlighted that the critical phase after the earthquake lasted for about 3 months, followed by 6 months of progressive recovery. Twelve months after the earthquake was considered as the chronological milestone when routinary activity had fully resumed and all hospital wards had been re-opened. Based on these intervals, we therefore considered 12 months after the earthquake as endline and accordingly 12 months before as baseline.

For each time wave, we constructed an adjacency matrix in which cell (i, j) records the number of patients transferred from hospital i to hospital j. To focus on substantive relationships and reduce noise, we dichotomised the matrices using a > 1 threshold to indicate the presence of a referral tie. Fig. 2 illustrates the network structure over time.

Table 1 presents summary statistics for the dichotomised networks.

Table 1
Descriptive network statistics.

Observation Time	N Nodes /N Dyads	N Total ties	N Reciprocal ties	Network density	Average Degree
T1 (before earthquake)	33 / 1056	149	76	14.0%	4.51
T2 (3 months after earthquake)	33/ 1056	98	38	9.3%	2.97
T3 (6 months after earthquake)	33/ 1056	122	54	11.6%	3.70
T4 (12 months after earthquake)	33/ 1056	164	84	15.5%	4.97

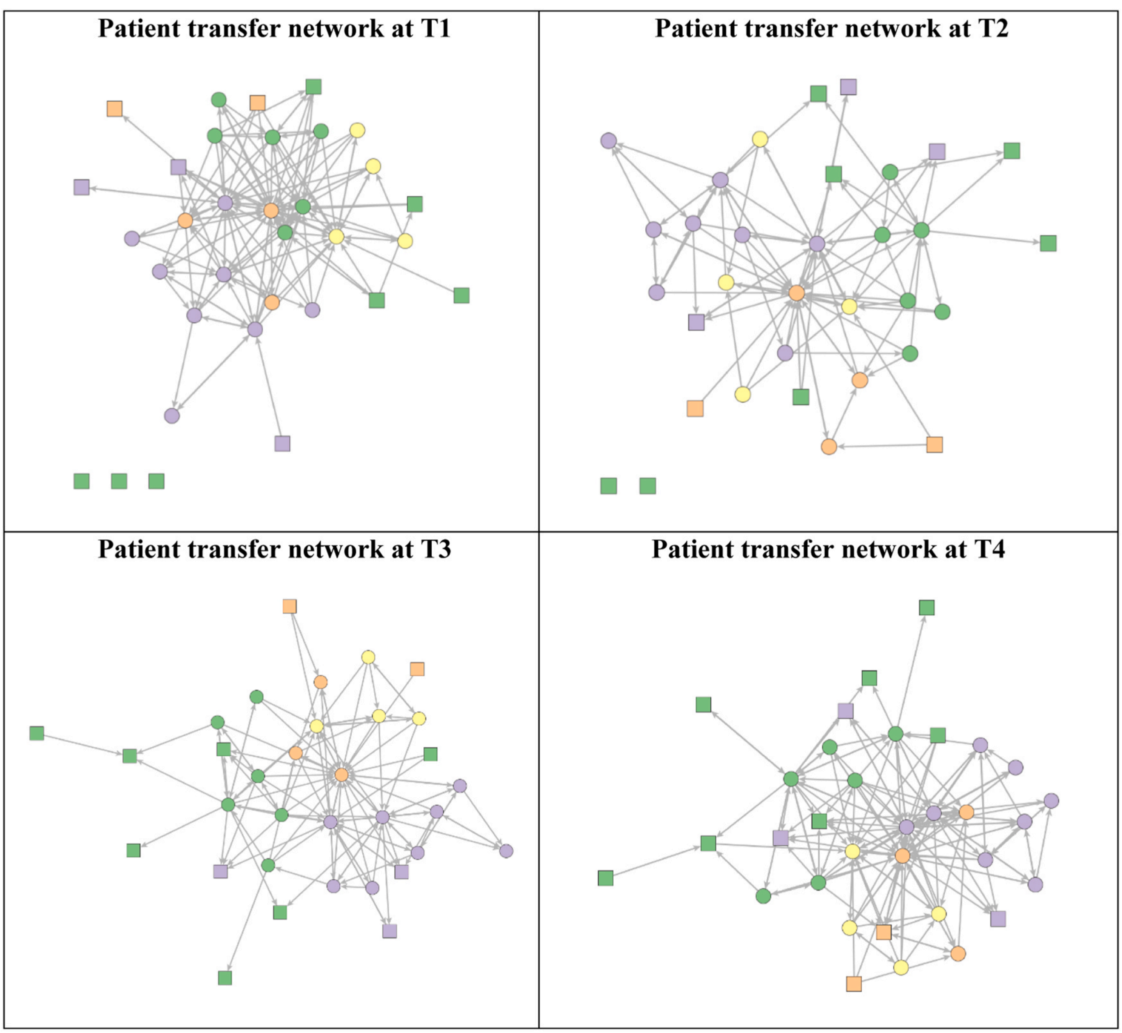


Fig. 2. Graphical illustration of the network dynamics between regional hospitals. Note: Circle nodes represent private hospitals, while rectangular nodes are public hospitals. The color of nodes indicate the Local Health units (LHUs) which hospitals belong to.

The sharp decline in ties in T2 reflects the closure of San Salvatore Hospital. From T3 onward, the total number of ties increased, reflecting the emergence of new referral pathways. On average, each hospital maintained four referral ties (mean degree = 4.038) across the observation period, with notable variation between T2 and T3.

Table 2 details network tie changes. The "0→1" and "1→0" columns indicate newly formed and dissolved ties, respectively, while "0→0" and "1→1" represent absent and stable ties. A total of 93 new ties and 78 dissolved ties were recorded across the four waves.

To assess network stability, we computed Jaccard similarity coefficient between consecutive network waves. Values above 0.3 are considered indicative of sufficient longitudinal stability for meaningful structural comparisons (Snijders et al., 2010; Ripley et al., 2023). The Jaccard coefficients were as follows: T1 → T2: 0.403 (moderate stability); T2 → T3: 0.803 (high stability); T3 → T4: 0.800 (high stability). These results suggest that the network rapidly reorganised after the disruption and then stabilised over time. Table 3 compares the pre- and post-shock networks (T1 vs. T4) and reveals a 9.9% increase in total referral ties (from 222 to 244), indicating that structural adaptation occurred despite the loss of a major hospital.

Our analytical approach investigates how patterns of inter-hospital patient sharing were affected over time by the earthquake. Specifically, we estimated the probability that a regional hospital *i* transfers patients to another hospital *j* across different time points. To model tie formation while accounting for both organizational attributes and endogenous network effects, we employed Stochastic Actor-Oriented Models (SAOMs). This methodology overcomes the limitations of traditional regression techniques, which often fail to consider the dependency structures inherent in network data (e.g., Kim et al. 2016).

Network variables. We capture social capital mechanisms through a set of endogenous network effects that reflect how collaborative relations are embedded in broader relational structures. Drawing on embeddedness theory, we understand that economic and organisational exchanges are not atomistic but are shaped by social context and historical ties (Granovetter, 1985; Uzzi, 1996). In this study, we interpret these structures as proxies for relational resilience, reflecting how hospitals rely on trusted and reciprocal partnerships to maintain functionality under uncertainty. To operationalise social capital as an enabler of resilience, we focus on dyadic and triadic social mechanisms that are consistent with our theoretical argument and hypotheses. At the dyadic level, we include *reciprocity*, capturing the tendency of hospitals that receive patients from others to reciprocate by transferring patients back (Balland, Boschma, and Frenken, 2015). This mechanism reflects mutual trust and equity and is a core feature of resilient, non-hierarchical collaboration (Molm et al., 2007; Agneessens and Wittek, 2012). At the triadic level, we include *three-cycles*, which capture the formation of indirect reciprocity patterns—i.e., A sends to B, B to C, and C to A. These ties express a logic of generalised exchange, which has been linked to social solidarity and collective adaptation under stress (Yamagishi and Cook, 1993; Molm et al., 2009). In parallel, *transitivity* captures closure mechanisms where actors prefer to collaborate with partners of their partners (Mirc and Parker, 2020). In the context of uncertainty, such configurations reduce information asymmetry and serve as relational heuristics for reliable exchange. Together, these network mechanisms represent relational strategies that hospitals may adopt to reduce uncertainty, restore operational stability, and reconstruct informational pathways after disruption—thereby facilitating systemic and organisational resilience.

Table 2
Collaborative ties change over time.

	0 = > 0	0 = > 1	1 = > 0	1 = > 1	Jaccard coefficient
T1 = => T2	880	27	78	71	.403
T2 = => T3	934	24	0	98	.803
T3 = => T4	892	42	0	122	.744

Table 3
Summary of changes overtime.

w	$T_n$size	T_{n+1}size	NewTies	LostTies	KeptTies
T1 = => T2	222	158	42	106	116
T2 = => T3	158	190	32	0	158
T3 = => T4	190	244	54	0	190

Note: TnSize = Number of ties at Time period n; T2Size = Number of ties at time period n + 1; NewTies = Number of NEW ties added at T2; LostTies = Number of LOST ties that were present at T1 and not at T2; KeptTies = Number of ties present at both time periods; NeverTies = Number of ABSENT at both time periods.

Network controls. To account for general structural tendencies in network evolution, we included controls for density, reflecting overall propensity to form ties (measured as out-degree), and out-degree popularity, capturing whether hospitals with many outgoing ties are more likely to form additional ones (Ripley et al., 2023).

Interaction with time dummies. To capture how network dynamics evolved across different time intervals (T1–T2, T2–T3, and T3–T4), we created interaction terms between time dummies and the key network effects of reciprocity, three-cycle, and transitivity. This strategy, grounded in prior work (Corbo et al. 2016; Mirc and Parker, 2020), enabled us to test whether and how the influence of network mechanisms changed over time. Table 4 presents the network effects included in our empirical model.

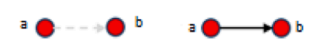
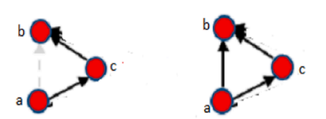
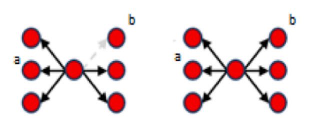
Control variables (dyadic attributes). Hospitals are embedded in complex institutional, social, and geographical environments (Hollway et al. 2017). Accordingly, we controlled for multiple forms of proximity: geographical, institutional, organisational, and cognitive (Balland et al. 2015; Boschma, 2005). (i) *Geographical proximity* is measured as the absolute distance in kilometers between hospitals, with an expected negative effect (i.e., greater distance implies lower likelihood of collaboration); (ii) *Institutional proximity* is based on whether hospitals belong to the same Local Health Authority, which fosters shared administrative and operational norms: (iii) *Organisational proximity* refers to similarity in ownership type (public vs private). Literature suggests that similarity in governance may both facilitate and inhibit collaboration (Iwashyna et al. 2009a, 2009b; Lee et al. 2011); (iv) *Cognitive proximity* is measured using Euclidean distance in service offerings between hospitals. Greater complementarities in services are hypothesised to promote collaboration, as cognitive proximity supports mutual understanding and reduces conflict (Wuyts et al. 2005; Knoben and Oerlemans, 2006; Inkpen and Tsang, 2005). These covariates entered the model as similarity effects, indicating a higher likelihood of collaboration between hospitals sharing specific attributes. Table 5 provides the relevant definitions, while Table 6 reports descriptive statistics of the control variables included in the model specification.

Analyses and results

To investigate the dynamics of patient transfer networks following an exogenous shock, we employed Stochastic Actor-Oriented Models (SAOMs) (Snijders, 1996; Steglich et al., 2010; Jung et al., 2019). These models allow us to model network evolution over time under the assumption that changes result from micro-level decisions by individual actors concerning the formation, maintenance, or dissolution of ties. SAOMs are particularly appropriate in our context, as they account for structural interdependencies and feedback effects in longitudinal networks—elements that are central when analysing relational adaptations under conditions of systemic disruption.

All analyses were conducted using the RSiena software package (Ripley et al., 2023). Table 7 presents the results from a series of progressively complex models. Model 1 includes only network controls and organisational covariates. Model 2 adds the theoretically relevant structural mechanisms—reciprocity, transitivity, and three-cycles.

Table 4
Main network effects used in the empirical model specifications.

NETWORK EFFECT	PATTERN T_I T_{I+1}	DESCRIPTION
Density (outdegree)		The tendency of hospitals to send outgoing ties
Reciprocity		The tendency of hospitals to reciprocate ties
Generalized exchange (3-cycle)		The general tendency of hospitals to create ties with partners in close cyclic way
Transitivity		The general tendency of hospitals to create ties with partners of partners
Outdegree activity (sqrt)		The tendency of active hospitals to become more active (sending out more ties)

Note: Red nodes represent hospitals, solid lines indicate existing ties, dashed lines indicate predicted p ties.

Table 5
Description of the organizational attributes used in the analysis.

VARIABLE	DEFINITION	TYPE	CONSTRUCT
Geographical distance (*dyadic*)	Distance (in kilometers) between every pair of hospitals	Real	Geographical proximity
LHU membership (*monadic*)	Membership to local health units (LHUs)	Categorical	Institutional proximity
Organizational profile (*monadic*)	Type of ownership-governance structure	Binary	Organizational proximity
Service complementarity (*dyadic*)	Complementarity in the range of services measured as Euclidean distance on the hospitals (n) by (m) specialties matrix	Real	Cognitive proximity

Table 6
Descriptives statistics of attributive variables of hospitals.

Descriptive statistics ***Characteristics of attributive variables of hospitals (N = 33)***	
Geographical distance, mean SD (range)	91.56 15.52 (65–120)
Service complementarity, mean SD (range)	3.34.52 (3–5)
Organizational profile, n (%)	
Private	21 (63.63%)
Public	12 (36.36%)
Membership to LHUs, n (%)	
LHU 1	13 (39.39%)
LHU 2	11 (33.33%)
LHU 3	5 (15.15%)
LHU 4	4 (12.12%)

Model 3 incorporates interactions between these structural mechanisms and time dummies, allowing us to test whether the effects vary across the different post-earthquake periods. Convergence diagnostics for all models meet established standards, with t-ratios below 0.1 and the overall maximum convergence ratio remaining under 0.19 (Ripley et al., 2023).

Turning to the control variables and covariates, across all models, the density parameter is negative and statistically significant, suggesting that the formation of new referral ties is constrained by coordination and information exchange costs. At the same time, the positive and significant out-degree popularity effect reflects a tendency toward preferential attachment, whereby hospitals that already transfer many patients are more likely to further expand their referral activity. Among organisational-level covariates, geographical proximity negatively predicts tie formation, indicating that hospitals tend to refer patients to nearby facilities. Organisational proximity, defined by shared ownership type, displays a strong positive association with tie formation, consistent with the idea that governance similarity fosters collaboration. Similarly, cognitive proximity—measured via complementarities in service offerings—has a significant positive effect. By contrast, institutional proximity (shared local health authority) does not appear to influence referral behaviour significantly.

The rate parameters suggest that most of the network restructuring occurred immediately after the earthquake. The highest change rate is observed between T1 and T2 (6.206), followed by a marked decrease

Table 7
Stochastic Actor-Oriented Models estimates.

Variables	Model 1	Model 2	Model 3
Rate function			
Rate 1	6.206	7.037	6.558
	(.863)	(.995)	(.973)
Rate 2	.927	.981	1.204
	(.191)	(.199)	(.247)
Rate 3	1.605	1.708	1.288
	(.247)	(.259)	(.197)
Control variables (Attributes)			
Geographical proximity	-.017***	-.014***	-.015***
	(.003)	(.003)	(.003)
Cognitive proximity	.630**	.608***	.630***
	(.110)	(.123)	(.151)
Institutional proximity	.335	.200	.138
	(.221)	(.215)	(.245)
Organizational proximity	.945***	.760***	.822***
	(.213)	(.212)	(.263)
Control variables (Network)			
Outdegree (Density)	−3.711***	−3.705***	−3.687***
	(.477)	(.437)	(.699)
Out-degree popularity (sqr)	.415*	-.087	-.028
	(.201)	(.223)	(.313)
Network Variables of theoretical interest			
Reciprocity		.772**	1.188**
		(.250)	(.363)
Transitivity		1.270**	1.682***
		(.264)	(.498)
3-Cycle		-.021	.114
		(.132)	(.264)
Interaction effects			
Time dummy T2-T3 x Reciprocity			1.101
			(.794)
Time dummy T3-T4 x Reciprocity			.717
			(.795)
Time dummy T2-T3 x Transitivity			-.209
			(.805)
Time dummy T3-T4 x Transitivity			1.094
			(1.370)
Time dummy T2-T3 x 3-Cycle			1.301*
			(.558)
Time dummy T3-T4 x 3-Cycle			.277
			(.496)
Time dummy T2-T3 x Out-degree popularity (sqr)			-.954
			(.813)
Time dummy T3-T4 x Out-degree popularity (sqr)			.867
			(.611)

Note: Standard erros in parantheses; *** p < .001, ** p < .01, * p < .05.

between T2 and T3 (0.927), and a modest rebound between T3 and T4 (1.605). These patterns underscore the shock's immediate disruptive impact and the ensuing need for rapid adaptation, consistent with resilience theory.

Model 2 examines the core relational mechanisms theorised in the hypotheses. Reciprocity emerges as a positive and significant predictor of tie formation, supporting the hypothesis that hospitals tend to reciprocate patient transfers in the wake of disruption (Hypothesis 1). This finding reflects relational cohesion and trust, in line with social capital theory. Transitivity also shows a positive and significant effect, indicating that hospitals are more likely to form ties with partners of their partners—a strategy that helps reduce uncertainty and build on known collaborative paths (Hypothesis 2). Three-cycle structures, on the other hand, do not reach statistical significance, offering no support for the hypothesis that hospitals engage in triadic generalised exchange as a stable coordination strategy (Hypothesis 3).

In Model 3, we assess whether these mechanisms change over time, in line with our Hypothesis 4. Reciprocity remains statistically stable across all time periods, as indicated by the non-significant interaction terms. This contradicts the expectation that reciprocal behaviour would fade as uncertainty diminishes and instead suggests that reciprocity constitutes a persistent principle of inter-organisational coordination in crisis. For three-cycles, however, we observe a significant positive interaction during the T2–T3 period, followed by a non-significant effect in T3–T4. This pattern indicates that generalised exchange emerged as a short-term relational response to uncertainty, which gradually dissipated as the network stabilised—supporting the hypothesis that such mechanisms are temporally bounded. Transitivity does not show significant temporal variation, suggesting that its effect is consistently present over time.

To assess overall model fit, we examined violin plots of in-degree, out-degree, and triad census distributions for Model 3, presented in Fig. 3. In all cases, observed values fall well within the expected range of the simulated distributions, confirming model adequacy (Ripley et al., 2023). These results are further validated by associated p-values. Finally, to explore whether structural adaptation occurred at a broader level, we compared the pre-earthquake referral network (T1) with the one observed 12 months post-earthquake (T4). Despite the collapse of one of the most central hospitals in the region, the number of active ties increased from 222 to 244, representing a 9.9% rise. This growth, arising through decentralised relational adaptations, is a clear signal of the systemic resilience exhibited by the hospital referral network.

Discussion and conclusion

This study set out to examine how system resilience is influenced by inter-organisational collaboration within a regional hospital network and how this evolves in response to a major exogenous shock. Specifically, we asked: how do hospitals reorganise their patient transfer relationships following a sudden, system-wide disruption such as a natural disaster? To address this question, we analysed the case of the 2009 L'Aquila earthquake, which severely impacted the Abruzzo region in Italy, including the collapse of one of its largest hospitals. Using longitudinal social network data covering 33 hospitals over a period of one year before and after the earthquake, we employed Stochastic Actor-Oriented Models (SAOMs) to investigate how referral ties were dissolved, maintained, or newly formed over time.

Our analysis reveals that although the overall functionality of the hospital network—measured by patient discharges and average length of stay—remained stable throughout the observation period, this apparent systemic resilience masked significant relational adaptations. In particular, the ego-network of the collapsed hospital underwent marked transformation, and proximity—both geographic and social—played a pivotal role in shaping the relational shifts experienced by other hospitals. Our dynamic modelling further shows that, in the immediate aftermath of the disaster, hospitals relied on anti-hierarchical patterns of collaboration—such as reciprocity and transitivity—to rebuild trust and continuity of care. Over time, the network gradually reverted to more hierarchical and stratified configurations as uncertainty subsided.

Theoretical contributions and practical implications

This study contributes to existing literature on at least three key fronts: it advances a relational understanding of organisational resilience, offers novel insights for healthcare management in times of crisis, and extends network theory by modelling dynamic responses to exogenous shocks.

The first contribution is to the literature on resilience. Our findings support the view that resilience is not only a system-level outcome, but also an emergent property rooted in the relational behaviours of individual organisations. While aggregate system functionality remained stable, this was sustained through localised adaptations in relational structures—particularly among hospitals most proximate to the collapsed node. These findings align with a relational and distributed view of resilience (Lengnick-Hall et al., 2011; Sutcliffe and Vogus, 2003; van der Vegt et al., 2015), in which organisations navigate crises by

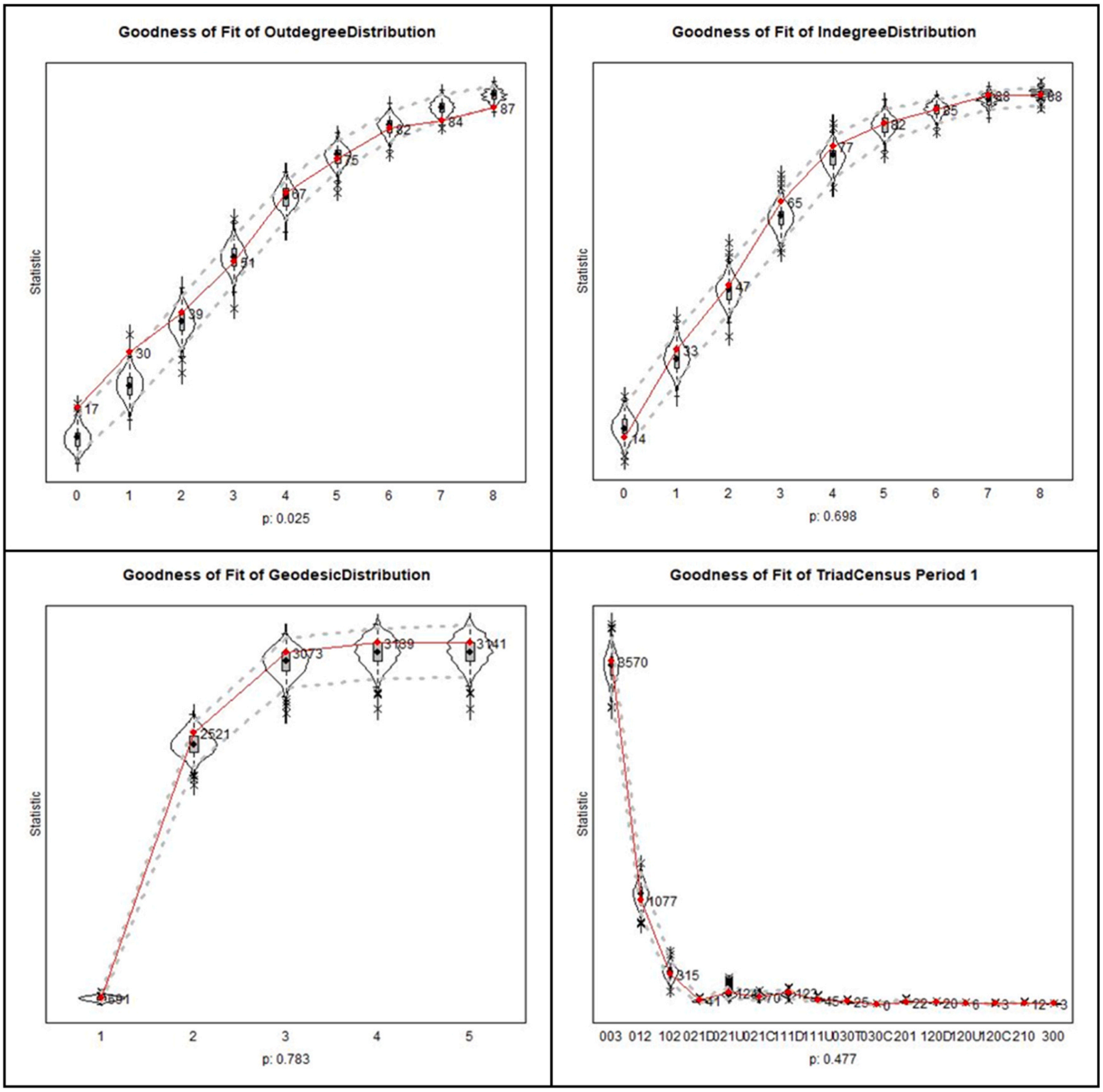


Fig. 3. Goodness of Fit (Violin plots for Model 3).

leveraging trusted partners and social capital. This perspective is further reinforced by recent work by de Graaff and colleagues (2023), which conceptualises resilience as rooted in the "connections we've made with each other"—emphasising collaboration, mutual adjustment, and trust as essential components of governance under stress. Their notion of "resilience-in-practice" underscores the importance of informal, relational mechanisms in sustaining healthcare delivery when formal structures falter. At the same time, this work is complementary to the studies offered by Kapucu and colleagues (Kapucu and Garayev, 2013, Kapucu et al., 2013) in the context of natural disasters, which shed critical light on how agencies structure situated collective action to respond to emergencies but falls short to explain whether and how organisations reconfigure existing relationships as a form of adaptation to an exogenous shock.

Second, we contribute to healthcare management research by showing how hospitals' capacity to maintain service delivery in high-uncertainty conditions depends on their ability to flexibly reconfigure referral ties and governance arrangements (Haldane et al., 2021; Kruk et al., 2015; Turenne et al., 2019). The case of San Salvatore Hospital—whose ego-network shifted rapidly to absorb and redistribute patients—illustrates how inter-hospital collaboration can act as a functional buffer against disruption. Our findings highlight relational mechanisms such as mutual adjustment, distributed knowledge sharing, and trust as key levers of adaptive response (Peeters et al., 2023). For healthcare managers, this points to the value of fostering collaborative cultures that support reciprocity and flexibility, especially in decentralised systems without clear central authority.

Third, we contribute to network theory by examining how structural features respond dynamically to exogenous shocks. Whereas much of the extant literature adopts a static lens, our longitudinal analysis reveals the temporal evolution of network mechanisms. We find that reciprocity and transitivity guide tie formation in the post-disaster period, consistent with theories of social capital under uncertainty. At the same time, the temporary surge and subsequent decline of cyclicality suggest a shift from generalised exchange to more hierarchical patterns as the system stabilises. These findings contribute to ongoing debates about network adaptation in turbulent environments (e.g., Corbo et al., 2016; Mirc and Parker, 2020) and show how endogenous mechanisms interact with organisational proximity dimensions—social, geographical, institutional, cognitive—to shape micro-level adaptation.

Our findings also bear important implications for practice. In high-reliability systems like healthcare, maintaining service continuity during crises requires more than formal emergency planning—it demands relational adaptability. Hospital administrators should proactively support inter-organisational collaboration by nurturing trust-based, decentralised relationships that enable responsive, flexible behaviours.

As de Graaff et al. (2023) argue, resilience-in-practice emerges from ongoing relational work, not just contingency plans. Policymakers and health authorities, therefore, should recognise that resilience is not a top-down outcome of central design, but rather an emergent property of mutual interdependence. Investments in shared infrastructure, interoperable data systems, and enabling protocols can support the spontaneous reconfiguration of networks more effectively than rigid centralisation.

Limitations and directions for future research

Despite its contributions, this study has some limitations. Our data covers only one-year post-shock; longer-term dynamics could reveal further phases of network transformation. In a similar vein, the indicators that we report to document health system functionality–average length of stay and number of discharges–are short-term metrics and cannot reflect long-term effects on health outcomes of unobserved changes in admission, triaging and discharge patterns that hospitals might have implemented in the immediate aftermath of the earthquake. The findings are also grounded in a single regional healthcare system in Italy, potentially limiting generalisability. More specifically, the Abruzzo case reflects a relatively decentralized institutional setting, characterized by the absence of a single central authority coordinating patient transfers during the emergency. This feature makes bottom-up and endogenous relational adaptation particularly visible, as hospitals may rely more heavily on pre-existing ties, mutual adjustment, and locally grounded responses to cope with unexpected disruption. At the same time, our study does not allow us to determine whether, or how, the same mechanisms operate in more centralized and formalized institutional contexts, where coordination may be shaped more directly by hierarchical arrangements and stricter emergency protocols. This issue is especially relevant in light of the organizational and regulatory changes introduced after the COVID−19 pandemic, which have made emergency preparedness and response protocols more structured in many healthcare systems. Future research should therefore examine these dynamics comparatively across healthcare systems characterized by different degrees of centralization, formalization, and emergency governance. Finally, while our focus was on inter-hospital ties, future work might examine cross-sectoral linkages—such as those with emergency services, NGOs, and civil protection agencies—to better understand how healthcare systems embed within wider institutional networks during crises.

In conclusion, this study deepens our understanding of how healthcare networks recover from major disruptions, highlighting the critical role of relational dynamics and network elasticity in shaping resilience. By linking organisational resilience, healthcare management, and network evolution, this work opens promising new pathways for theory and practice in managing uncertainty in complex, interdependent systems.

CRediT authorship contribution statement

Valentina Iacopino: Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **Fausto Di Vincenzo:** Writing – review & editing, Writing – original draft, Methodology, Data curation, Conceptualization. **Anna Piazza:** Writing – review & editing, Visualization, Formal analysis, Data curation, Methodology. **Daniele Mascia:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **Federica Angeli:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization.

Declaration of Competing Interest

All authors declare no competing interests.

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