A review of post-earthquake hospital functionality simulation methods

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ABSTRACT

The ability of hospitals to maintain functionality after an earthquake is essential for treating injuries, saving lives and ensuring community safety. This paper presents a comprehensive review of current methods for simulating post-earthquake hospital functionality and the frameworks for evaluating hospital seismic resilience. The methods are assessed on their data requirements, dynamic capabilities and interpretability. Amongst the different methods, the review considered Loss and Recovery Function-based Analysis (LRFA), Fault Tree Analysis (FTA), Bayesian Networks (BN), Discrete Event Simulation (DES), System Dynamics (SD), and hybrid models. A key finding is the lack of adaptable, scalable and practical tools for consistent seismic resilience assessment in a healthcare environment that is often complex.

1 INTRODUCTION

Hospitals play a crucial role in providing essential medical service after an earthquake. Yet, they frequently experience service interruptions due to structural and non-structural components damage (Achour et al., 2011; Santarsiero et al., 2019). To ensure the continuity of healthcare services, various national and international organisations have implemented regulations aimed at enhancing emergency management for hospitals (Ministry of Health, 2015; World Health Organization, 2020). However, these regulations offer limited insight into the actual dynamic process of maintaining functionality and the recovery process, which is critical for effective disaster response planning.

The concept of seismic resilience refers to a system's ability to withstand, absorb, and recover from earthquake impacts and can assists in enhancing emergency management across both pre- and post-disaster phases (Bruneau et al., 2003; Bruneau & Reinhorn, 2007).

A hospital is a complex system with many interdependent components to achieve multiple medical services. Although frameworks such as FEMA P-58 (Federal Emergency Management Agency (FEMA), 2018) and REDi (Ibrahim Almufti & Michael Willford, 2013) provide valuable performance metrics—including repair cost, casualties, and repair time—they do not adequately capture the interwoven processes that define hospital functionality. To address this gap, numerous researchers have proposed alternative frameworks and methodologies aimed at more comprehensively simulating hospital functionality and assessing seismic resilience.

The primary goal of this paper is to provide a comprehensive review of these studies, identifying common methods and comparing their strengths and limitations in simulating hospital functionality. This analysis aims to guide the development of more effective tools for assessing and improving hospital seismic resilience.

2 FUNCTIONALITY AND SEISMIC RESILIENCE

System resilience is often presented as a resilience curve which maps the change in system performance as shown in Figure 1. Resilience (R) is defined as the area under the resilience curve mathematically by equation (1), or graphically as the shaded area in Figure 1.

$$R = \int_{t_o}^{t_o+T_C} Q(t)/T_C dt \tag{1}$$

Where $Q(t)$ is the unitless performance indicator for the functionality of system; and T_C is the control time for the resilience assessment exercise.

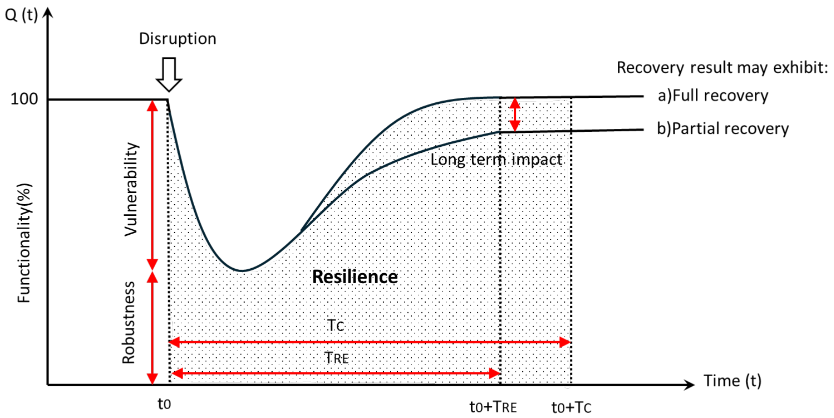

Figure 1 Definition of key parameters in a general resilience curve

The key to assessing seismic resilience and enhancing hospital emergency management lies in accurately simulating hospital functionality, $Q(t)$, after an earthquake and its recovery process. This review includes studies evaluating the post-earthquake hospital functionality and process of calculating the resilience indicators.

3 REVIEW OF THE SIMILATION METHODS

3.1 Loss and recovery function-based analysis (LRFA)

This method quantifies resilience by integrating loss and recovery functions into a single analytical framework (Cimellaro et al., 2010a, 2010b). The loss function translates damage descriptors into a single objective parameter such as equivalent monetary losses or hospitalisation numbers. Losses are categorised into direct (e.g. physical damage) and indirect (e.g. downtime) losses, each further subdivided into economic and casualty-related losses. Detailed descriptions of these loss types are presented in Table 1.

The economic losses, $L_E(I)$, are calculated by equation (2). Where L_i is repair cost ratio of component i, defined as the cost of repairing damaged components back to their original state divided by the cost of completely replacement the same component. $P_{DS_i|I}$ represents the probability that a component in damage state *i* (DS_i) given an earthquake intensity measure *I*. This is commonly derived from the fragility function of the component. Losses related to casualties, $L_C(I)$, are expressed as the ratio of the number of injured or deceased (N_{in}) individuals to the total population (N_{tot}), as given by Equation (3).

$$L_E(I) = \sum_{i=1}^{N} L_i \cdot P_{DS_i|I} \tag{2}$$

$$L_C(I) = \frac{N_{in}}{N_{tot}} \tag{3}$$

In the Cimellaro study, three simplified recovery functions (f_{Rec}), linearly, trigonometrically and exponentially, are proposed to capture the functionality restoration process over time. These functions are selected based on the system's level of preparedness and resourcefulness. Similarly, the recovery functions can also be formulated based on a detailed predetermined repair sequence (Shang et al., 2022).

The overall loss of hospital functionality is modelled as a sum of the direct and indirect losses, as given by Equation (4).

$$L(I, T_{RE}) = L_{D(I)} + \alpha_I L_{I(I,T_{RE})} \tag{4}$$

Where α_I is the weighting factor that adjusts for indirect loss and T_{RE} is the repair time. The hospital functionality $Q(t)$ is then quantified by considering (i) the reduced functionality due to losses, (ii) the timing of the seismic event, and (iii) the chosen recovery function:

$$Q(t) = \underbrace{[1 - L(I, T_{RE})]}_{\text{(i) Reduced functionality}} \times \underbrace{[H(t - t_{OE}) - H(t - (t_{OE} + T_{RE}))]}_{\text{(ii) Event timing}} \times \underbrace{f_{Rec}(t, t_{OE}, T_{RE})}_{\text{(iii) Recovery function}} \tag{5}$$

Where *H()* is the Heaviside step function; $f_{Rec}(t, t_{OE}, T_{RE})$ is the chosen recovery function. Shang et al. (2022) further improved this approach by assigning importance factors to each component, thereby reflecting the varying impacts of different components on the hospital's functionality.

Table 1 Losses considered in hospitals (Cimellaro et al., 2010a)

Category		**Loss**	**Description**
Direct	Economic losses	Structural and non-structural repair cost	Cost for repairing beams, columns, joints, etc. and architectural, electrical and mechanical items.
		Loss of building contents	Cost equivalent to the loss of furniture, equipment, computers, etc.
	Casualty losses	Death and Injury	Number of deaths and seriously injured people
Indirect	Economic losses	Relocation expenses	Cost for temporary space
	Casualty losses	Loss of functionality	Reduced hospital capacity may cause additional human life losses

3.2 Reliability based analysis

Reliability analysis is a systematic methodology for evaluating a system's ability to perform its intended functions, with a focus on quantifying the likelihood of performance under specific conditions. Fault Tree Analysis (FTA) and Bayesian Networks (BN) are two widely applied methods for evaluating hospital post-earthquake functionality.

3.2.1 Fault tree analysis

Fault Tree Analysis (FTA) systematically links a system's top event—the unexpected or target failure—to underlying causes (basic event, e.g., component malfunctions, human errors) in an inverted tree diagram. This method identifies root causes and diagnoses faults for qualitative failure analysis, and it also quantifies a system's failure probability to guide reliability improvements (U.S. Nuclear Regulatory Commission (NRC), 1981).

There are two fundamental logic gates used in fault trees:

i. the AND gate, which allows a path to proceed when all input events are true, and

ii. the OR gate, which is fulfilled if at least one input event is true.

Their probabilities are respectively calculated using equations (6) and (7). The fault tree consists of multiple layers of logic gates, with the output of each layer serving as the input for the next. The top event probability can be recursively calculated using the gate formulas as shown in equation (8). Figure 2 illustrates a sample fault tree for a hospital surgery service.

$$P_{AND} = \prod_{i=1}^{n} P_i \tag{6}$$

$$P_{OR} = 1 - \prod_{i=1}^{n} (1 - P_i) \tag{7}$$

$$P_{TOP} = f\left(P_{Gate_1}, P_{Gate_2}, P_{Gate_3}, \dots, P_{Gate_k} \right) \tag{8}$$

Where n is the number of events connected with a logic gate; P_i is the probability of the event i; k is the number of logic gate; P_{Gate_k} is the probability of the k-th gate output; f is a recursive function that propagates failure probabilities up the fault tree using the AND/OR formulas.

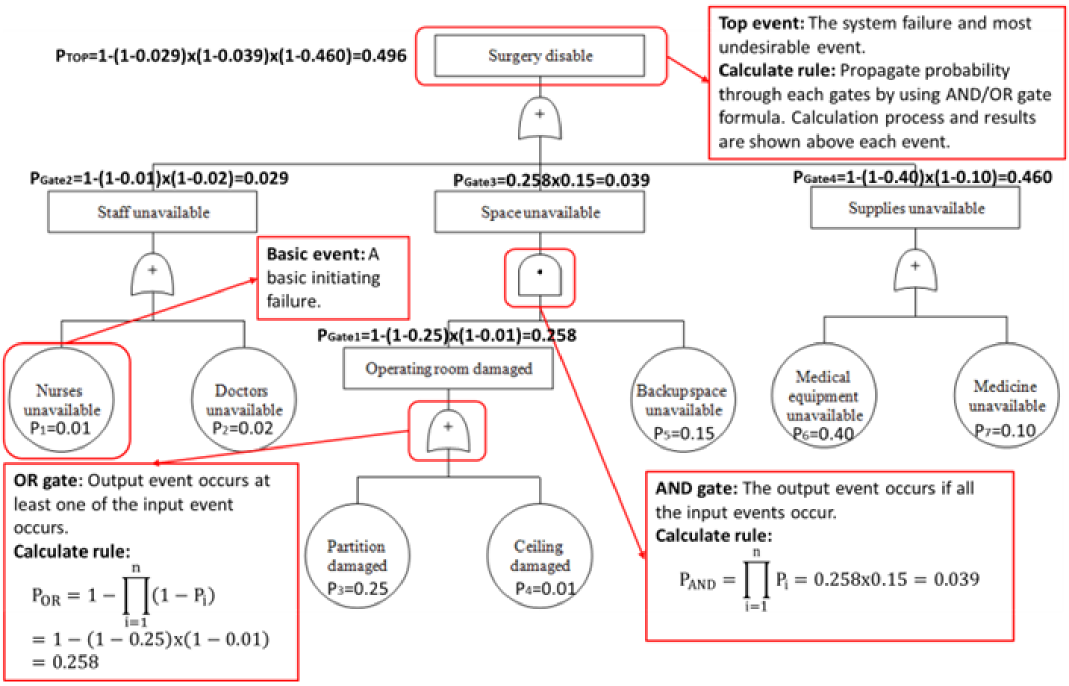

Figure 2: An example fault tree representing the ability for a hospital to conduct surgery

Fault Tree Analysis (FTA) has transformed hospital resilience assessment by revealing complex systemic interdependencies between various components failures and hospital functionality failures. Jacques et al. (2014) demonstrated this in their resilience assessment of the 2011 Canterbury earthquake, showing how FTA integrates diverse data—from building damage to staff and supply shortages—to map cascading service disruptions. By integrating the Engineering Demand Parameters (EDP) from seismic analysis and fragility data from FEMA P-58, researchers can conduct a reliability analysis of hospital functionality (Yu et al., 2019) and make targeted improvements based on key events identified in the critical failure path of the fault tree (Cheng et al., 2024).

An interesting finding is that the structure of fault trees can vary among different researchers due to their inherent adaptability, allowing users customisation based on the events they deem most pertinent. Fault trees straightforward logic and strong visualisation capabilities make them particularly suitable for risk communication with stakeholders from different fields (Boston, 2017). However, the static nature of this method fails to capture the dynamic aspects of real-world systems, and the results and events are binary—either operational or not, making it difficult to reflect partial functionality levels of the hospital.

3.2.2 Bayesian network analysis

Bayesian Network (BN) analysis is a probabilistic modelling technique that uses a directed acyclic graph to represent conditional dependencies among variables. Figure 3 shows an example BN representing an operating room. Each node of the BN denotes a random variable, while edges show dependencies quantified by a Conditional Probability Table (CPT) shown as Table 2. In practice, CPTs are derived from observational data or expert solicitation (Koller & Friedman, 2009). By assigning conditional probability distributions to each node, BN enables systematic updating of likelihood when new evidence is introduced, making them particularly effective for inference, prediction, and decision-making under uncertainty. The joint probability distribution of all nodes in the network can be calculated by Equation (9).

$$P(X_1, X_2, \ldots, X_n) = \prod_{i=1}^{n} P\big(X_i \mid Pa(X_i)\big) \tag{9}$$

Where $P\big(X_i \mid Pa(X_i)\big)$ is conditional probability of the random variable X_i, given its parent nodes $Pa(X_i)$.

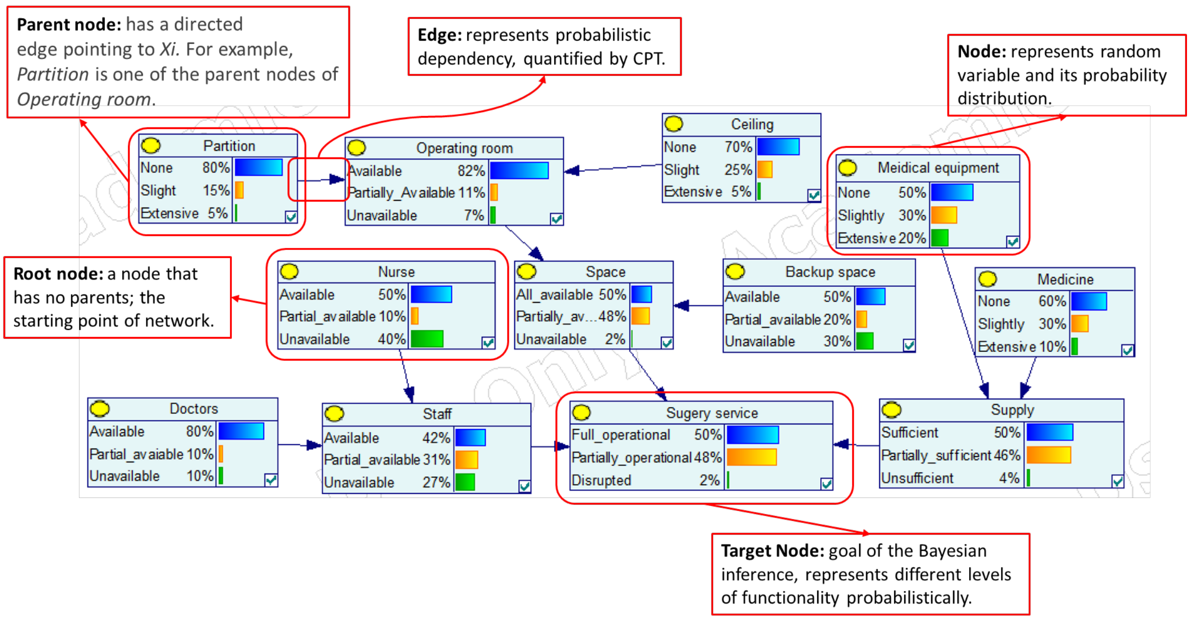

Figure 3 An example of Bayesian network and its analysis results

Although it is widely used to handle uncertainty and perform reasoning in complex systems by combining causal relationships with probabilistic inference (Omoya, 2023; Zhang et al., 2021), only a few researchers have adopted it on hospital seismic resilience.

Liu et al. (2022) proposed a BN for assessing the seismic resilience of hospital by dividing them into multi-level nodes, departments, rooms, and components, where each node may have multiple functional or damage states. The recovery process is guided by sensitivity analysis, prioritizing components for repair based on their impact on hospital function.

Table 2 A Conditional probability table for Operating room node of the example Bayesian network

Partition Ceiling	States	DS0			DS1			DS2		
		DS0	DS1	DS2	DS0	DS1	DS2	DS0	DS1	DS0
Operating room	All available	1	0.8	0.2	0.7	0.4	0.2	0.1	0.05	0
	Partially available	0	0.2	0.3	0.2	0.5	0.3	0.3	0.25	0
	Unavailable	0	0	0.5	0.1	0.1	0.5	0.6	0.7	1

DS0: No damage; DS1: Slightly damage; DS2: Extensive damage

3.3 Simulation-based organisational analysis

Although reliability-based analysis can provide stakeholders with insights into post-earthquake hospital functionality, it is limited to macro explanations of hospital operations and does not provide much insight into detailed hospital's service quality and efficiency. Computer simulations address this by integrating information such as patient arrival rates, resource availability, and staff efficiency to quantify metrics like number of treated patients and patients waiting time. These metrics are normalised into functional performance indices, capturing hospital resilience under seismic disruptions. Common simulation techniques used in hospital seismic resilience evaluation include Discrete Event Simulation (DES) and System Dynamics (SD).

3.3.1 Discrete event simulation

Discrete Event Simulation (DES) models a series of discrete events over a specific period. It is a powerful tool to model the queueing structure thus is widely used in modelling various flow-based process, such as healthcare system, customer service, manufacturing and production, and etc (Scheidegger et al., 2018). Figure 4 illustrates an example of a simple hospital emergency treatment process for different types of injuries. As shown in the figure, a DES model includes entities (patients) with different attributes (types of injuries and arrival time), resources (Triage room and Emergency room), a network of processes, and input/output variables (number of resources, distribution of treatment times / patient waiting time). Entities flow through processes, changing states tracked by attributes. Resources affect entity states, and interactions between entities and resources are modelled in process networks to simulate patient journeys and output the desirable results.

The DES model developed by (Yi et al., 2010) is specific for post-earthquake hospital emergency function which consider the injuries type caused by earthquake. The patient waiting time is adopted as the performance metric. A meta-model for patient waiting time is developed by using parametric regression according to the data derived from simulation. However, the model does not consider hospital damage caused by the earthquake. The application of DES is further expanded to simulate post-earthquake emergency functionality by incorporating earthquake impacts on patient flow and damage on hospital. These are achieved by scaling the historical records of earthquake patient arrival rate and shutting down a portion of emergency rooms or applying penalty factors to reduce organisational capacity. Additionally, a meta-model was developed, offering improvements on accounting for different earthquake intensities and distinguishing between types of injuries (Cimellaro et al., 2011, 2017).

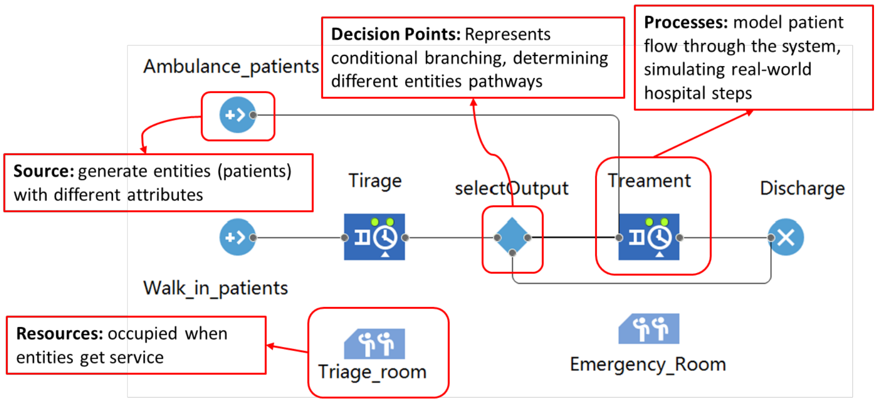

Figure 4: An example DES model of treatment process for different types of patients

Although these models reflect the hospital's losses following an earthquake, the corresponding treatment process flows remain unchanged, which may not align with real-world scenarios. Basaglia et al. (2022) developed two comprehensive DES models to simulate hospital capacity, capturing both pre- and post-earthquake treatment processes. These models were grounded in interviews with hospital staff, ensuring a realistic and accurate depiction of hospital operations across varying conditions.

3.3.2 System dynamics simulation

System dynamics (SD) simulation models how complex systems evolve continuously over time by focusing on stocks, flows, and feedback loops (Scheidegger et al., 2018). As shown in Figure 5, stocks represent accumulations—such as the number of patients in an emergency room—while flows capture the rates of change, like patient arrivals and treatment rates. A powerful feature of SD is its ability to incorporate multiple feedback loops. Different feedback loops can model various out-of-equilibrium behaviours. For example, a reinforcing loop might simulate how an increased patient load amplifies staff fatigue, slowing treatment and further escalating patient accumulation. Conversely, a balancing loop may model how rising patient numbers can trigger shifts in work patterns, ultimately reducing patient accumulation.

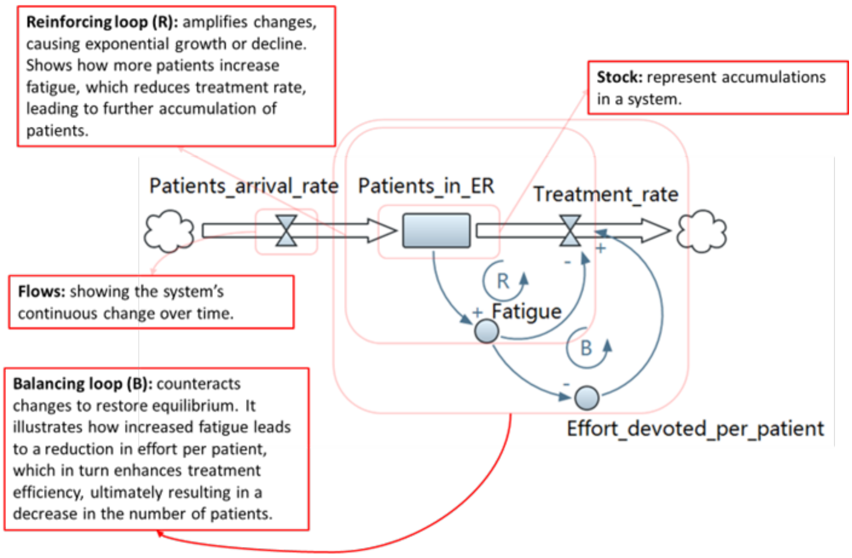

Figure 5: An example System dynamics model of hospital treatment process

In post-earthquake hospital functionality, SD has been applied to capture both operational challenges and recovery dynamics. Arboleda et al. (2007) developed a model that linked patient flow with service areas and critical infrastructure supplies such as water and power, evaluating preparedness strategies like increasing bed capacity. Li et al. (2020) extended this framework by incorporating earthquake-induced injuries, simulating damage to buildings and infrastructure, and modeling recovery processes across physical, social, and cyber domains. Similarly, Khanmohammadi et al. (2018) examined how damage to components—buildings, staff, medicine, technical systems, and equipment—affects hospital service quality, emphasizing recovery driven by monetary resource allocation. These studies demonstrate how SD's nuanced feedback structures enable the modeling of complex, dynamic imbalances and provide strategic insights into both immediate response and long-term recovery.

3.4 Hybrid models

Hybrid models integrate discrete event simulation (DES) with reliability analysis and historical data to provide a systematic assessment of hospital functionality, particularly under post-earthquake conditions. This approach leverages the event-driven precision of DES while using probabilistic methods to estimate resource availability and performance degradation.

A key strength of hybrid models is their ability to determine the availability of hospital service units—the number of functional resources—by combining different analytical tools. For instance, Palomino Romani et al. (2023) used decision trees built on past earthquake data to damage ratios to structural and non-structural components, staff, and utilities. Combinations of these ratios determine four degradation levels for service areas: Fully Functional (0% reduction), Functional (50% reduction), Affected Functionality (75% reduction), and Not Functional (100% reduction).

In another example, Zhai et al. (2022) employed fault tree analysis to equate failure probabilities with the loss ratio of medical rooms. Favier et al. (2019) modeled examination room functionality using a piecewise linear function that correlates the likelihood of operational failure with the percentage of fallen ceilings, while for operating rooms, a fault tree with an OR gate linked failures to moderately damaged walls, doors, and ceilings.

Additionally, Hassan & Mahmoud (2019) combined loss functions with fault tree analysis and simulated recovery using a continuous Markov chain. Their model captured the interdependence among five critical lifelines and incorporated dynamic resource allocation to optimise recovery speed or economic return. These hybrid approaches underscore the power of combining discrete and probabilistic methods to capture both immediate and long-term hospital system dynamics.

4 DISCUSSION

To evaluate the aforementioned approaches, we selected three criteria—data requirements, dynamic capability, and interpretability—based on their critical roles: (1) ensuring feasibility under hospital data constraints, (2) capturing time-dependent system behaviours for the purpose of resilience assessment, and (3) enabling cross-disciplinary understanding and validation to enhance decision-making trust. Each criterion has its own evaluation standards, which are detailed in the following sections.

4.1 Data Requirements

This criterion evaluates the quantity, accessibility, and granularity of input data. Quantity captures both the diversity and volume of the required inputs data, categorised as "Large" or "Small". Accessibility assesses how readily the data can be obtained, classified as "Easy" or "Hard". Granularity indicates the level of detail needed, divided into "High" or "Low".

In terms of quantity, LRFA and FTA require relatively smaller datasets compared to other methods, relying primarily on failure probabilities, repair costs, and recovery times of components. BN, in contrast, demands significantly larger datasets due to its inclusion of multiple damage states for components, various system functionality states, and the need for a comprehensive conditional probability table, which requires substantial data to define accurately. This also contributes to BN being rated as high for accessibility. Simulation-based methods, such as SD and DES, necessitate extensive datasets because of the diverse data types required, as outlined in Table 4. Data for LRFA and FTA are generally more accessible, often sourced from FEMA P-58 databases. Conversely, acquiring input data for SD and DES is more challenging due to the variability of hospital-specific operational processes. While most methods depend on component-level data, SD relies on aggregated data, reflecting its macro-level modelling characteristic.

4.2 Dynamic Capability

Dynamic capability assesses a method's ability to capture the temporal evolution of hospital performance, particularly how it models the progression of damage and recovery processes. "Intrinsic" indicates that the method inherently possesses dynamic simulation capabilities, whereas "Combination" indicates that the method requires integration with other methods to achieve dynamic capabilities. Time spans are categorised as "Long-term" or "Short-term".

LRFA, FTA, and BN do not inherently incorporate time-evolving processes, they typically require coupling with additional models, such as a simplified recovery function or a predefined repair sequence, to capture restoration process. The simplified recovery function, while more straightforward, provides limited guidance for decision-makers during the recovery phase. The predefined repair sequence, though adopting more realistic repair pathways, often appears overly subjective. The time span for these three approaches is usually long term from the start of earthquake to fully recovery.

In contrast, simulation-based organisational models naturally incorporate a temporal dimension. DES is predominantly used to simulate short term performance of hospital (days after an earthquake). Few studies employ DES across the entire hospital recovery timeline, possibly because most investigations focus on the acute phase of emergency care for earthquake casualties. By contrast, SD places emphasis on longer-term strategic horizons that unfold over weeks or months from the initial seismic event through full hospital recovery. The hybrid model offers greater flexibility. In practice, combining DES with reliability analysis is commonly used to predict short-term post-earthquake hospital performance, whereas integrating fault trees with Markov chains is applied to simulate long-term recovery processes.

Table 3 Comparison results for different methods

Methods	Data requirements			Dynamic capability		Interpretability	
	Quantity	**Accessibility**	**Granularity**	**Mechanism**	**Time span**	**Clarity**	**Traceability**
LRFA	Small	Easy	High	Combination	Long	Low	Low
FTA	Small	Easy	High	Combination	Long	Low	High
BN	Large	Hard	High	Combination	Long	Low	High
DES	Large	Hard	High	Intrinsic	Short	High	High
SD	Large	Hard	Low	Intrinsic	Long	High	High
Hybrid	Large	Hard	High	I./C.	S./L.	High	High

4.3 Interpretability

Interpretability is evaluated based on three indicators: clarity and traceability. Clarity refers to how straightforward and self-explanatory the outputs are, categorised as "High" or "Low". Traceability measures the ease with which users can track results back to the model's logic or data inputs, also rated as "High" or "Low". These factors can help stakeholders to define the short back of system.

LRFA, FTA, and BN all exhibit relatively low clarity. LRFA's functionality is transferred from financial metrics without revealing the organisational aspect of hospital. Although FTA successfully models complex interdependencies, it produces binary outcomes that fail to capture partial hospital functionality. BN improves the binary results of FTA by assigning multi-state nodes, yet the statements for each functional state are vague and plain and can not necessarily guide direct improvements in medical service quality. In contrast, simulation-based methods such as DES or SD yield more tangible outputs—like patient waiting times—offering clearer insights for operational decision-making. LRFA's monetary-centric perspective lacks traceability to the factors which caused the system malfunction. By comparison, FTA, BN, DES, SD, and Hybrid approaches have clear interdependency mechanism which provide higher traceability.

4.4 Future research direction

The literature review and comparative analysis highlight a fragmented landscape of methodologies for hospital seismic resilience assessment, each with unique strengths but insufficient to address the complexity of healthcare environments. While LRFA and FTA offer simplicity and low data demands, their reliance on static recovery functions and binary outputs fails to capture dynamic interdependencies or partial functionality states critical for operational decision-making. BN improves probabilistic granularity but struggles with validation in large-scale systems due to subjective conditional probability tables. DES and SD excel in short- and long-term dynamic modelling, respectively, but their high data specificity and computational costs limit scalability across diverse hospital settings. Even Hybrid Models, which combine reliability and operational insights, face practical barriers due to their complexity and institutional resource demands.

A critical finding is the absence of adaptable, scalable, and practical tools for consistent seismic resilience assessment in complex healthcare environments. Current approaches remain isolated, focusing either on detailed component-level analysis (e.g., FTA) or on broader macro-level analysis (e.g., SD), and they lack the necessary integration to effectively address multi-scale challenges. For example, DES may excel in modelling patient surge after earthquake but cannot link these results to long-term recovery strategies modelled in SD. Similarly, FTA identifies critical failure paths but ignores adaptive recovery behaviours like resource reallocation. This fragmentation results in inconsistent assessments, where hospitals must cobble together incompatible tools or oversimplify realities to fit methodological constraints.

The urgency for unified tools is amplified by healthcare systems' inherent complexity: urban hospitals with complex interdependent departments, small clinics with limited resources. Current approaches lack modularity to adapt to these contexts or scalability to balance precision with feasibility. Future frameworks must bridge this gap by integrating probabilistic dependencies (BN and FTA), and dynamic workflows (DES/SD) into a cohesive platform, enabling stakeholders to simulate scenarios without sacrificing rigor or practicality. Only then can hospitals achieve consistent, actionable resilience strategies that safeguard both infrastructure and human lives.

5 CONCLUSION

This paper reviews methods for assessing post-earthquake hospital functionality, detailing the principles of each approach and their applications in the context of hospitals affected by earthquakes. A comparative analysis is conducted based on data requirements, dynamic capability, and interpretability. Additionally, the input data and output results for each method are comprehensively summarised. The findings reveal that while each method has its strengths, there remains a lack of an adaptable, scalable, and practical solution to address the complexities of real-world healthcare environments.

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Table 4 Summary of the model inputs and outputs

Methods	Inputs		Outputs	
	Function	**Recovery**	**Function**	**Recovery**
LRFA	•Cost for repairing different components •Number of injuries and deaths	For LRFA, FTA and BN: •Community preparedness level •Repair time for components •Predefined repair sequence	•Earthquake-induced monetary loss	For LRFA, FTA and BN: •Resilience curve •Seismic resilience index
FTA	•System failure mechanism •Probabilities of certain damage states of component		•Hospital/Department/Service failure probabilities •Critical failure path	
BN	•System interdependency •Conditional probability table •Probabilities of various damage states of component		• Probability of different performance states of hospital/department/service	
DES	•Number of medical service units •Data related to different types of injuries: arrival rate, treatment process and duration distribution, movement probabilities	•Patients arrival rate	•Patient waiting time •Length of stay •Number of patients	
SD	•Causal relationship or feedback loops for hospital function and recovery process •Data presented as percentage: building, utility, resources damage •Data presented as rate: patient arrival, treatment, repair for building and replenishment of resources •Data presented as numbers: patients		•Number of patients •Resilience curve	•Seismic resilience index
Hybrid	•Medical service unit reduction mechanism •Probabilities or damage ratios of components in certain damage state •Data required for DES model	•Historical recovery time	•Similar to DES	•Similar to DES