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Kammouh, O.; Chahrour, N.

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Indicator-based framework to evaluate the resilience of transport infrastructure systems

O. Kammouh [a] and N. Chahrour [b]

[a]Faculty Technology, Policy, and Management, Delft University of Technology, Delft, Netherlands; [b]Gipsa-lab, Department of Automatic Control, University Grenoble Alpes, CNRS, Grenoble INP, GIPSA-lab, Grenoble, France

ABSTRACT

As modern societies increasingly rely on transport infrastructure, ensuring its resilience is essential, particularly under climate change. Traditional simulation-based methods are often complex and resource-intensive, limiting their widespread use. In contrast, indicator-based approaches offer a practical alternative; however, a comprehensive and multidimensional indicator set remains underdeveloped. This paper proposes an indicator-based framework for assessing the resilience of transport infrastructure systems across physical, operational, and social dimensions. The framework enables a structured evaluation of how systems withstand, adapt to, and recover from disruptions while maintaining essential functions. A thorough literature review was conducted to identify and categorize a robust set of indicators. These indicators are adaptable and may be integrated with advanced techniques such as Machine Learning, Bayesian Networks, and Fuzzy Logic to strengthen resilience analysis. A case study demonstrates the framework's applicability and highlights how combining indicators with analytical tools can enhance the assessment and management of infrastructure resilience.

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Resilience; infrastructure; transport; indicator; systematic review; recovery

1. Introduction

Infrastructure systems such as transport systems (e.g., road and rail, or telecommunication networks), are 'big', ranging from regional to global scale, 'slow', with development times of years to even centuries, 'expensive' with investments up to many billions of euros, and 'boring' as they go unnoticed when they work right. Furthermore, infrastructures are deeply networked systems, both 'horizontally', connecting users in complex topologies of mass, energy, and information flows, and 'vertically' as different infrastructures are interconnected and interdependent. Infrastructures are also strongly path-dependent and deeply interwoven with social systems, having co-evolved with the local, regional, and global society. As such, they shape and are shaped by formal and informal institutions such as policies and laws, values, norms, and beliefs. Unfortunately, infrastructure systems are subject to various hazards, uncertainties, and transitions that can disrupt their operations and lead to negative social, economic, and environmental consequences. To minimize the impact of these disruptions and ensure the continued provision of essential services, improving the resilience of infrastructure systems is crucial. Resilience is generally defined as the capacity of a system to withstand, adapt to, and recover from unfavorable events while maintaining its essential functions and services (Cimellaro et al., 2016). To provide a structured foundation for this study, we adopt Bruneau and Reinhorn's (2007) definition, which characterizes resilience through four key dimensions: robustness, redundancy, resourcefulness, and rapidity (4 Rs).

Infrastructure systems are characterized as complex adaptive systems (Oughton et al., 2018); hence, evaluating their performance requires carefully selecting appropriate methods. By 'Infrastructure system', we do not refer to the physical infrastructure network but rather to the combination of the infrastructure network, the organization responsible for managing it, and the environment in which everything is embedded. In this context, 'environment' includes the natural, social, and economic conditions in which the physical infrastructure is embedded. It includes factors like climate and geography that affect performance, community reliance and interaction with infrastructure, and financial elements such as funding, resource allocation, and operational support. The interactions between the three components of an infrastructure system shape how the system would

CONTACT O. Kammouh o.kammouh@tudelft.nl

respond to a hazardous event. These interactions are complex, and they change over time in response to new hazards, development, and technology. For example, the emergence of technology has changed the way the infrastructure is operated and how the users interact with it.

Simulation-based methods are commonly used to assess the resilience of infrastructure systems (Cassottana et al., 2022; Wang, Xue, & Zhou, 2020). Infrastructure simulation modeling is considered domain-specific, as the operational and functional characteristics vary significantly across different types of infrastructures (Kammouh, Gardoni, & Cimellaro, 2019, 2020; Marasco et al., 2021). Consequently, various modeling techniques are employed. Agent-Based Modeling (ABM) simulates the actions and interactions of individual components or 'agents' in a system to explore emergent system-level patterns (Helbing, 2012). In transportation systems, ABM can simulate the decisions and interactions of individual travelers, providing insights into congestion patterns and transport dynamics (Bernhardt, 2007). System Dynamics (SD) focuses on feedback and accumulations to study how systems evolve over time (Karnopp, Margolis, & Rosenberg, 2012). It is used in energy systems to analyze feedback and accumulations in the generation, transmission, and consumption of energy. Network Modeling, which employs graph theory, is used to visualize and analyze the relationships within a system (Guizani et al., 2010). These techniques are good at modeling various physical scales. For example, in the electric energy systems domain, scales can range from extensive multi-conductor transmission line networks spanning thousands of kilometers to compact voltage distributions on the scale of centimeters (Cremasco et al., 2021). To fully understand the interactions of such complex systems, multi-modeling can be used. Multi-modeling refers to the integration of two different models that interact with each other, such as an economic model and a social model. This approach requires a well-defined interface for data exchange and ensures input-output compatibility between the models (Cuppen et al., 2021). It can include technical, economic, and environmental considerations and is used in sectors like transportation infrastructure (e.g., route optimization, traffic management, etc) (Raimbault, 2018), and the energy sector (e.g., incorporation of renewable energy sources and the design of efficient power grids) (Bollinger et al., 2018).

However, the simulation-based approaches suffer from significant challenges and limitations. A notable drawback is the lack of cross-disciplinary interactions, often leading to an incomplete examination of the complex interactions between various systems, neglecting the broader socio-technical system context, which is crucial for a holistic understanding of infrastructure resilience (Min, 2014). Additionally, these methods are constrained by the extensive requirement for data collection and substantial computational resources. This demand poses a significant challenge in terms of the time and financial resources required, which might not be feasible in resource-limited settings. Furthermore, the effectiveness of these simulations is heavily dependent on the underlying assumptions, which may not always accurately reflect real-world scenarios (Saidi et al., 2018). For instance, linear cause-and-effect relationships are often presumed, whereas real-world systems exhibit complex feedback loops and emergent behaviors (Vanclay, 2014). Another common assumption is rational decision-making by all stakeholders, yet in practice, human behaviors, policy constraints, and unforeseen socio-political influences significantly impact infrastructure performance and resilience (Casas, 2023). This reliance on assumptions raises concerns about the reliability of these methods in practical decision-making processes. The complexity inherent in these models also presents interpretational challenges, particularly for stakeholders who may not have a technical background in simulation methodologies. This complexity can hinder the effective communication and application of the findings derived from these simulations, limiting their utility in real-world settings (Min, 2014).

Indicators are a promising alternative approach to evaluating the resilience of complex systems such as infrastructure (Cutter, Ash, & Emrich, 2014). Unlike simulation-based methods, indicators provide a practical and straightforward way of measuring the resilience of infrastructure systems (Kammouh & Cimellaro, 2018). They can be tailored to reflect diverse operational and functional characteristics across various infrastructure types. They are capable of capturing critical performance aspects, such as functionality under normal operations, adaptability to disruptions, and recovery capabilities following adverse events. Indicators are often perceived as a less complex alternative to measuring the resilience of infrastructure systems, making them a more accessible tool for decision-makers (Balbi et al., 2018; De Iuliis et al., 2021; Kammouh, Marasco, et al., 2018). In the context of infrastructure, indicators can offer a more inclusive view of the system, integrating technical, economic, and environmental considerations without the need for complex multi-modeling techniques.

The existing research on infrastructure resilience indicators reveals key shortcomings, especially in choosing and using resilience indicators. Although many indicators have been suggested, there is no clear agreement on the most effective or comprehensive ones for evaluating infrastructure resilience. This issue partly arises from some studies focusing only on certain system aspects, leading to an incomplete view of resilience. Moreover, many indicator sets lack standardization and validation, reducing their usefulness and dependability in various situations. Another oversight in current research is the focus mainly on physical components of infrastructure, neglecting the impact of human factors and environmental interactions. The resilience of any system relies on the interactions between human elements, environmental factors, and physical infrastructure. Integrating these factors is key to a more complete understanding of infrastructure resilience.

The development of a comprehensive set of infrastructure resilience indicators can empower other research to develop new and innovative methodologies for assessing infrastructure resilience. One such way is through the use of Bayesian Networks and Fuzzy Logic, which are hierarchical methods that use nodes and links, making them useful for structuring relationships between indicators. Bayesian Network uses probabilities to model dependencies and update outcomes based on new data, making them helpful for analyzing uncertainty (Leśniak & Janowiec, 2020). Fuzzy logic relies on expert-defined rules to handle imprecise or qualitative data by categorizing information into different levels (Yadav et al., 2018). These techniques can be used to analyze the relationships between the various indicators and their impact on the resilience of the infrastructure system.

This paper focuses on transport infrastructure due to its essential role in maintaining societal and economic stability. The goal is to develop a comprehensive set of indicators that covers all relevant aspects of transport infrastructure. These indicators are designed to facilitate communication among stakeholders, empower communities in decision-making and adaptive management, and support the development and implementation of resilience-strengthening strategies.

The rest of the paper is organized as follows. Section 2 presents a review of available indicator-based methods for infrastructure resilience with focus on transport infrastructure. Section 3 describes the methodology used for identifying and selecting the resilience indicators for the transport infrastructure system. Section 4 presents the identified indicators and their categorization into dimensions and components. Section 5 and Section 6 present an application of the proposed framework. Finally, Section 7 provides the conclusions and outlines future research directions.

2. Review of indicator-based methods for infrastructure resilience

Several studies have investigated the use of indicators for measuring the resilience of infrastructure systems (CORDIS, 2018; Cutter, 2016; Cutter, Burton, & Emrich, 2010; De Iuliis et al., 2021; Ghosn et al., 2016; A. Jovanović, Øien, & Choudhary, 2018; Kammouh & Cimellaro, 2018; Kammouh, Noori, et al., 2018; Kammouh et al., 2019; Peris-Mora et al., 2005; Sharifi & Yamagata, 2016; Yang et al., 2022). Cutter, Burton, and Emrich (2010) provided a methodology for measuring baseline characteristics of whole communities, highlighting spatial variations in disaster resilience. This approach facilitates monitoring changes in resilience over time and comparing resilience across different regions. Cutter (2016) explored a range of tools and approaches for disaster resilience assessment, presenting insights into common attributes and capacities essential for community disaster resilience. A. S. Jovanović et al. (2016) and Guo, Shan, and Owusu (2021) conducted state-of-the-art reviews of resilience assessment frameworks for infrastructure systems. Sharifi and Yamagata (2016) focused on urban resilience in the face of disasters, providing a set of principles and indicators crucial for aiding planners and decision-makers in developing strategies for more resilient cities.

Building on this foundation, Kammouh, Marasco, et al. (2018) proposed two indicator-based methods for evaluating community resilience based on the PEOPLES framework, including a deterministic and a fuzzy-based method. Similarly, A. Jovanović, Øien, and Choudhary (2018) presented an innovative approach for assessing the resilience of smart critical infrastructures using a holistic methodology structured in multiple levels, from individual resilience indicators to the broader city context. Tachaudomdach, Arunotayanun, and Upayokin (2018) conducted a systematic literature review specific to transport, identifying two dimensions and ten principles that can guide resilience assessments in this domain. Kammouh et al. (2019) later extended these ideas by introducing an indicator-based approach for urban community resilience, focusing on the interdependencies among infrastructure systems, local governance, and social factors. More recently, A. S. Jovanović et al.

(2020) investigated how resilience indicators and international standards could be applied to healthcare infrastructure under the stress of the COVID-19 pandemic, and Osei-Kyei et al. (2022) compiled 28 resilience criteria for critical infrastructure – ranging from organizational resilience to performance loss and economic concerns – through a rigorous three-stage systematic review.

While previous studies have established a foundation for indicator-based resilience assessment across various systems, their applicability to transportation infrastructure remains a subject of ongoing inquiry. Transport infrastructure exhibits fundamental differences from other critical systems due to its high degree of spatial connectivity, dynamic demand fluctuations, and increased vulnerability to external disruptions. These distinctive characteristics have necessitated the development of transport-specific indicators that capture several aspects of transport infrastructure resilience (Tachaudomdach, Arunotayanun, & Upayokin, 2018; Yang et al., 2022).

A number of studies have proposed key physical and functional indicators that determine transport infrastructure resilience. Jenelius (2009) and Ip and Wang (2011) highlight physical and functional indicators, such as road width, lane capacity, and road density, as pivotal in determining how a transport network adapts to partial failures or shutdowns. Tamvakis and Xenidis (2012) add that facility condition and maintenance frequency are strong predictors of performance under stress, particularly when hazards like flooding or earthquakes strike. Litman (2006) and Cox, Prager, and Rose (2011) show that resource scarcity – whether in the form of limited fuel, inadequate shelters, or insufficient communication devices – can quickly produce disruptions, hence the need for indicators capturing resource availability and backup infrastructure.

Beyond physical and resource-related factors, user-centric metrics also appear in the literature. Soltani-Sobh et al. (2016) point to travelers' perception and reaction speed as important indicators, illustrating how real-time decisions (e.g., sudden route changes) can intensify or mitigate network congestion. Tobin (1999) similarly notes that local expertise and driving experience can facilitate rapid adjustments during emergencies, reinforcing the argument that indicators must account for a community's behavioral and educational profile (Tachaudomdach, Arunotayanun, & Upayokin, 2018). On the organizational side, poor communication has been identified in multiple case studies – such as Hurricane Rita evacuations (Cox, Prager, & Rose, 2011) – as a critical bottleneck that diminishes overall resilience. Researchers recommend measuring communication effectiveness, policies, and previous emergency experience, since these administrative features fundamentally shape how quickly a transport infrastructure can respond to and recover from extreme events (Godschalk, 2003; Soltani-Sobh et al., 2016; Tierney & Bruneau, 2007).

Several authors also expand transport resilience to include environmental and climatic aspects. Forman and Alexander (1998) demonstrate how roadside vegetation and interactions with local ecosystems (e.g., wildlife corridors) can affect roadway stability over time, while Dorbritz (2011) observes that vegetation buffers may reduce runoff and lessen road surface damage. Similarly, Wilson et al. (2012) highlight the risks from volcanic ash or similar hazards that degrade visibility and clog essential infrastructure. Including indicators for natural hazard vulnerability, air quality, or noise pollution acknowledges the broader ecological context in which transport systems operate (Karakoc et al., 2020; Soltani-Sobh et al., 2016).

The literature indicates a shift from single-focus indicator sets, which primarily emphasize physical network attributes, toward multidimensional approaches that integrate organizational, behavioral, socioeconomic, and environmental factors (De Iuliis et al., 2021; Kammouh, Noori, et al., 2018). However, challenges remain in standardizing indicators and ensuring comprehensive coverage of transport infrastructure resilience (Cutter, 2016; Saidi et al., 2018). This emphasizes the need for a comprehensive, yet flexible indicator-based framework that can adapt to diverse transport contexts while still providing a structured methodology for measuring and comparing resilience. The following sections build on existing literature to develop and demonstrate such a framework, aiming for a balanced coverage of all aspects of transportation infrastructure resilience.

3. Identifying and categorizing resilience indicators

This section outlines the methodology for identifying and selecting resilience indicators for the transport infrastructure system. The process involves three key steps: collecting a range of indicators, assigning specific measures to these indicators, and categorizing them into relevant components and dimensions for organizational clarity. Figure 1 provides a visual representation of the methodology. The research question guiding this literature review is: 'What are the key indicators of resilience for transport infrastructure systems, and how can these indicators be systematically measured and categorized?'

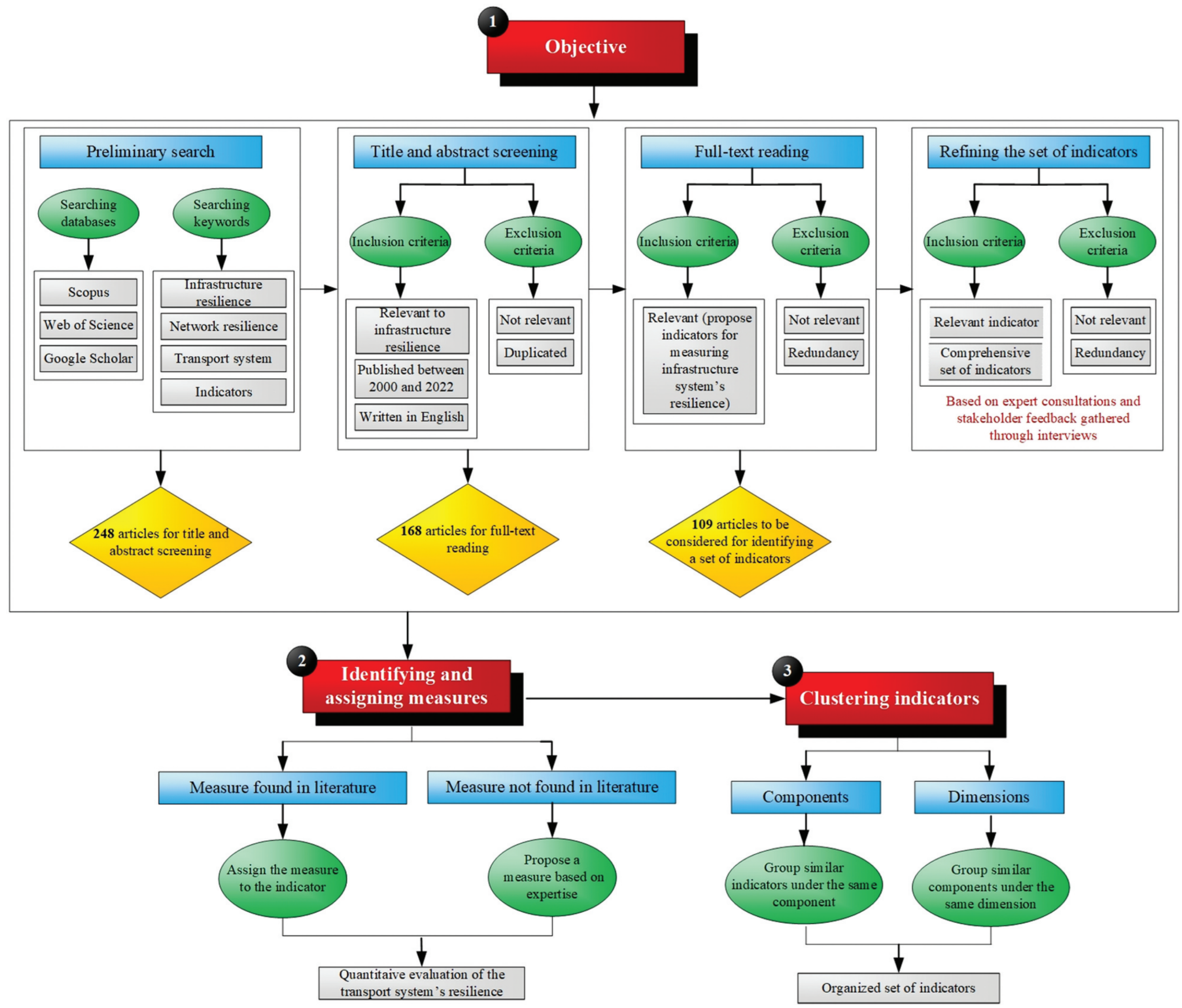

Figure 1. Methodology for identifying and categorizing resilience indicators.

The following subsections detail each aspect of the methodology.

3.1. *Collecting indicators*

A systematic literature review was conducted to identify existing indicators to develop a comprehensive set of W/R indicators for the transport infrastructure system (Nightingale, 2009; Pati & Lorusso, 2018; Xiao & Watson, 2019). To ensure a rigorous and comprehensive review, we applied the PRISMA framework (Page et al., 2021). The selection and refinement of indicators were based on a structured process combining literature analysis, expert consultation, and stakeholder feedback.

The search was conducted using several scientific databases, including Scopus, Web of Science, and Google Scholar, with search terms such as 'infrastructure resilience,' 'infrastructure wellbeing,' 'network resilience,' 'transport systems,' and 'indicators.' A total of 248 articles were initially identified and screened based on inclusion and exclusion criteria.

To ensure the relevance and quality of the data, we employed stringent inclusion and exclusion criteria. Articles were considered for inclusion if they focused on proposing indicators for measuring infrastructure resilience, were published in peer-reviewed journals, and were published in English between the years 2000 and 2024. Duplicate articles and those that were not directly related to our research focus were excluded.

The screening process was thorough. Each article's title and abstract were first reviewed to assess relevance, followed by a quick full-text review for those that passed the initial screening. This two-stage review process led to the exclusion of 80 articles after the abstract review, mainly due to irrelevance or duplication. The remaining 168 articles underwent a detailed full-text review. During the full-text review, criteria such as the specificity of the indicators to transport infrastructure resilience, the methodological soundness of the studies, and the clarity in indicator definition were emphasized. This further review resulted in the exclusion of an additional 59 articles, primarily due to a lack of focus on W/R indicators specific to transport infrastructure or insufficient methodological details.

The final set of 109 articles was then subjected to an in-depth analysis to extract and compile a list of W/R indicators. Each indicator was evaluated for its relevance and applicability in the context of transport infrastructure. To further refine our set of indicators, we interviewed 17 experts to gather their insights and feedback on each indicator. Experts were selected based on their expertise in transportation engineering, resilience, and infrastructure planning. To ensure diverse representation, we included academic researchers, industry professionals, and policymakers. Recruitment was conducted through professional networks and invitations to relevant organizations. Data collection was carried out via surveys and interviews, depending on the interviewee's preference. Experts participated individually to minimize potential biases. Responses were analyzed using qualitative coding to synthesize expert input. Conflicting responses were addressed through follow-up discussions with the experts where experts reviewed discrepancies and, in most cases, adjusted their responses to better align with the broader consensus. In a few cases where strong disagreements remained, we used an averaging approach while excluding clear outliers. The questionnaire used in the interviews is provided in Appendix A.

3.2. Identifying and assigning measures

The indicators are not meant to define calculation methods on their own but should be understood as titles representing broader aspects. To make indicators quantifiable, each indicator must be linked to a corresponding measure that specifies how it can be numerically calculated. Quantitative measures provide a precise and objective means of assessment compared to qualitative indicators. For instance, an indicator of the transport system's resilience could be the recovery speed after disruptions. To measure this indicator, the associated measure could be the time required to restore transport services after an event. This quantifiable measure allows for the comparison of different disruptions and objectively evaluates the transport system's resilience.

In this study, each indicator was assigned only one measure to ensure that it accurately reflects the specific aspect of resilience the indicator represents. For some indicators, measures were identified from existing literature. For example, the indicator 'road density' was measured by the number of alternative links between an origin and destination divided by a benchmark value (BV). The BV serves as a standard or reference point against which other values are compared. It allows for consistent and comparable evaluations across different contexts. The measures were carefully evaluated and selected to ensure they accurately reflect the indicators' intended meaning. In cases where measures could not be found in the literature, alternative measures were proposed based on the authors' expertise in infrastructure resilience.

To further validate the identification and assignment of the measures, they were reviewed and discussed with experts in the field of transport infrastructure systems. These experts provided valuable feedback on the appropriateness and relevance of the proposed measures. For example, an expert might suggest adjusting the measure for 'serviceability' from a simple availability metric to one that includes travel time reliability and accessibility of service points.

3.3. Clustering indicators

The collected resilience indicators were clustered under components and dimensions to enhance organization and comprehensibility. This process involved grouping similar indicators under the same component and aligning similar components under the same dimension, creating a meaningful and structured organization of the indicators. For example, indicators related to the physical structure of the infrastructure system, such as the age of the assets and the condition of the facilities, were grouped into a component called 'Physical Infrastructure.' Another example is the 'User Behavior' component, which includes indicators like trip-making behavior and driving experience. These components were then categorized under broader dimensions such as 'Physical Characteristics' and 'User Interactions,' respectively.

However, this clustering process encountered several challenges. One issue was the potential overlap between indicators, where certain indicators could reasonably belong to multiple components or dimensions. For instance, an indicator like 'accessibility of service points' could be classified under both 'Physical Infrastructure' and 'Serviceability,' leading to ambiguities in categorization. Additionally, ensuring the indicators' relevance and avoiding redundancy required careful analysis and expert consultation, as some indicators were too broad or too specific.

Another challenge was achieving a balance between comprehensiveness and practicality. While it was important to include a wide range of indicators to capture the sociotechnical nature of infrastructure resilience, having too many indicators could complicate the assessment process and overwhelm stakeholders. To address this, the selection process involved filtering out less critical indicators and focusing on those that provided the most significant insights into infrastructure resilience.

The identification of commonalities among the proposed indicators also required significant effort. For instance, determining whether indicators like 'road density' and 'link redundancy' should be grouped under a single component or treated separately involved consideration of their interrelationships and impacts on resilience.

The refinement of the categories followed an iterative process. In the first iteration, indicators were initially grouped based on conceptual similarities, either logical or based on evidence found in the literature. This step also involved tagging indicators with ambiguous overlap or cases where a clear category was not immediately obvious. In the second iteration, experts were asked to process the ambiguous cases, where they could vote on which category the indicators should belong to. In some cases, new categories were proposed to accommodate indicators that did not fit into any of the available groups. This refinement process was carried out during the interviews conducted with experts.

4. PURPOSE: Indicator-based resilience assessment framework for transport infrastructure

The following section presents the seven dimensions for assessing the resilience of the transport infrastructure system with their corresponding components and indicators. The seven dimensions are summarized under the acronym PURPOSE and include 1) Physical Infrastructure, 2) User Behavior, 3) Resources, 4) Preparedness and Planning, 5) Organization and Management, 6) Socioeconomic, and 7) Environment and Climate.

Figure 2 presents a snapshot of the framework, including dimensions, components, indicators, and measures, to provide a quick overview of the key elements identified in this study. This snapshot helps to illustrate the categorization and organization of the indicators into their respective groups. The full list of all dimensions, components, indicators, and measures is provided in Appendix B, including all references where the indicators were found.

4.1. Physical infrastructure

The physical characteristics of transport infrastructure play a crucial role in the proper functioning of the system, especially during unexpected events such as earthquakes, floods, hurricanes, landslides, and traffic accidents (Soltani-Sobh et al., 2016). The presence of adequate redundant capacity within these infrastructures can help minimize the impact of adverse events and keep the system relatively stable. For example, suppose a road is blocked due to a car accident. In that case, roads with many lanes or safety elements, such as an emergency lane or with a variable message sign (VMS), can provide drivers with alternative routes, allowing them to avoid the accident and keep the traffic flowing smoothly.

The Physical Infrastructure dimension is divided into five components: Links/Edges, Vehicles, Facilities/Structures, Accessories, and Serviceability. The Links/Edges component includes indicators such as accessibility, road density, and road width, while the Vehicles component includes mode of transport, vehicle fuel efficiency, and vehicle age. The Facilities/Structures component comprises facilities, critical components, and traffic load capacity, while the Accessories component includes availability of emergency equipment and alternative transport. Lastly, the Serviceability component includes travel time reliability and accessibility of service points.

4.2. User behaviour

The behavior of users is critical in determining the resilience of a transport infrastructure system, as it directly impacts traffic demand and supply. The way users respond to system disruptions is therefore an important factor in modeling traffic demand.

Stochastic and statistical analysis reveal that travelers usually choose their routes or modes of transport based on the minimum expected travel cost, which is typically measured by travel time (Soltani-Sobh et al., 2016). This perceived travel cost is influenced by their knowledge of road capacity and congestion and their past experiences. However, the lack of public knowledge, or what is known as perception error, can

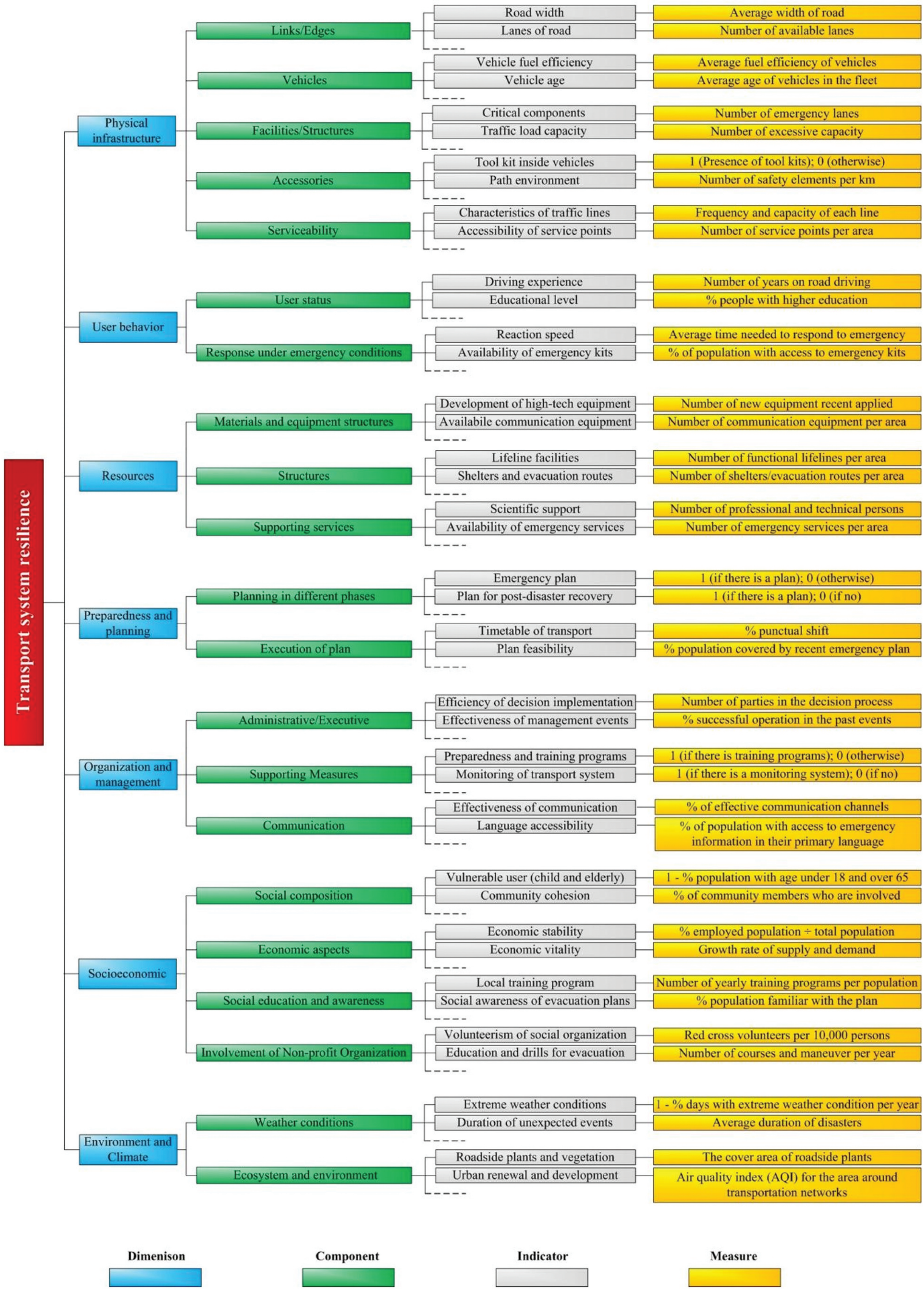

Figure 2. Snapshot of the framework, including dimensions, components, indicators, and measures.

significantly impact the resilience of the system. For instance, people often choose the shortest path, assuming it will result in the minimum travel cost. Nevertheless, when traffic flow reaches the route capacity, the reliable performance of the system reduces. Moreover, perception error can also affect the selection of transport mode, as seen after the London underground bombing and Madrid train bombing, where the number of passengers taking the attacked modes fell by 8.3% over four months (Prager et al., 2011) and 4–6% for two months (López -Rousseau, 2005), respectively. Consequently, more individuals switch from statistically safer travel modes to riskier road travel (Cox, Prager, & Rose, 2011). Individual reaction rates and experiences with emergency conditions can also affect the stability of the transport system. Experienced travelers are able to react quickly to unexpected situations and avoid accidents.

The User Behaviour dimension has two components: User Status and Response Under Emergency Conditions. For User Status, there are five indicators: user's trip making behaviour, driving experience, educational level, user's knowledge, and traveler's perception. For Response Under Emergency Condition, there are five indicators, including reaction speed, operation under emergency condition (sensitivity to recognize potential risks), availability of emergency kits, emergency plan awareness, and availability of emergency training.

4.3. Resources

Resources are crucial in maintaining normal functions and absorbing disturbances of adverse events. Having adequate resources is fundamental in restoring the damaged system, as a lack of resources can extend the recovery time and even cause further disorder. For example, during Hurricane Rita in 2005, a lack of fuel supply caused significant traffic congestion. Without access to water, food, medical treatment, and public services, panic and civil disorder developed. In addition to having adequate resources, professional technicians and specialists play a crucial role in managing these resources efficiently and effectively. They are responsible for allocating resources based on their experience, manipulating different devices, and checking and maintaining them within a fixed period.

The Resources dimension has three components: Materials and Equipment, Essential Facilities, and Supporting Services. The component Materials and Equipment includes the indicators: available fuel, development of high-tech equipment, inventories, availability of alternative energy sources, and availability of communication equipment. The component Essential Facilities includes lifeline facilities, temporary facilities, shelters and evacuation routes, and availability of backup infrastructure. The component Supporting Services includes scientific support, checking and renewal of resources, availability of emergency services, availability of public utilities, availability of emergency supplies, and coordination with private sector.

4.4. Preparedness and planning

Effective planning is essential for the resilience of transport systems, especially in the face of disasters or emergencies. Plans should be developed well in advance and cover all stages of an emergency, including preparedness, response, recovery, and restoration. Regular drills and training sessions are also necessary to test and refine these plans, ensuring their effectiveness when put into practice.

It is also crucial to consider the needs of vulnerable populations in emergency planning. People who are disabled, poor, or ill are often more affected by disasters and may require special assistance or accommodations. Failing to account for these populations in emergency planning can lead to ineffective responses and worsen the overall impact of the disaster, as was seen in response to Hurricane Katrina.

In addition to these considerations, emergency plans should also specify the responsibilities of different authorities involved in the response, including government agencies, emergency services, and other relevant organizations. By clearly defining the roles and responsibilities of each organization, the response can be more efficient and effective, leading to a better overall outcome.

The Preparedness and Planning dimension consists of two components: Planning in Different Phases and Execution of Plan. The Plan in Different Phases component has indicators such as pre-disaster preparedness and response skills of citizens, emergency plan, plan for post-disaster recovery and reconstruction, simulations and exercises, funding for emergency management, and public participation. On the other hand, Execution of Plan component includes effective response by responsible authorities, timetable of transport, special treatment for vulnerable groups, plan feasibility, renewal of plan, and integration of private sector.

4.5. Organization and management

The dimension Organization and Management concerns the way the transport system is managed and coordinated to effectively respond to a disruptive event. It involves the ability of the system to be flexible and adaptive to both internal and external stressors.

Information flow is particularly important as it plays a vital role in the entire system's functionality. A free flow of information can make the system respond to disruptive events more quickly. On the other hand, poor communication can lead to the system's failure, reducing people's confidence in the government. For example, during Hurricane Rita, many people were blocked on the road for more than 20 hours due to poor communication (Cox, Prager, & Rose, 2011). To enhance the effectiveness of the transport system during crises, organizations need to collaborate with other stakeholders, such as the private sector, communities, and local government. Effective communication is also crucial for coordinating efforts with relevant authorities and stakeholders. This ensures that critical decisions are made in time.

The dimension Organization and Management includes three components: Administrative/Executive, Supporting Measures, and Communication. Administrative/Executive includes indicators such as dissemination of information, effectiveness of decision implementation, effectiveness of management events, and effectiveness of information about road conditions. Supporting Measures includes policies, previous experience dealing with extreme conditions, preparedness and training programs, monitoring of the transport system, mutual trust between citizens and government, and distribution and logistics of resources. Communication includes effectiveness, accessibility, timeliness, language accessibility of communication, and communication redundancy.

4.6. Socioeconomic

The sixth dimension is Socioeconomic. The economy plays an indirect role in the stability and ability to return to the normalcy of the transport system. A diverse economy is generally more resistant to external changes, and infrastructures that are covered by insurance can receive sufficient funding for reconstruction and recovery, reducing the time required to return the damaged system to normalcy. Moreover, population size is an important factor that can significantly impact the performance of a transport system during unexpected events. A notable example is the heavy snow that hit China in the winter of 2008, which destroyed a key railway from Guangzhou to Beijing and resulted in chaos for nearly half a million passengers (Ip & Wang, 2011). A larger population can act as a catalyst, amplifying the effects of any disruption to the transport system. In addition, education and training programs are crucial to simulate real situations and help stakeholders and the public understand what to do in case of an event, enabling them to respond quickly and efficiently. However, it is important to note that transferring principles into actions can be challenging.

The Socioeconomic dimension includes four components: Social Composition, Economic Aspects, Social Education and Awareness, and Involvement of Non-profit Organization. Social Composition includes indicators such as population density, vulnerable user (child and elderly), vulnerable populations, and community cohesion. Economic Aspects includes economic stability, diversity, and vitality, special economic support, allocation of limited budget, car ownership, the price of public transport, investment for new routes, maintenance, and insurance. Social Education and Awareness includes educational programs for local communities, local training programs, emergency preparedness of local communities, and social awareness of evacuation plans. Involvement of Non-profit Organization includes volunteerism of social organizations, educational curriculum and drills for evacuation, funding for non-profit organizations, volunteer training and development, and coordination with the public sector.

4.7. Environment and climate

The seventh dimension is Environment and Climate. This dimension aims to measure the impact of environmental and climatic factors on the transport infrastructure system. The resilience of a transport infrastructure system is directly impacted by the environment. Different weather conditions can affect the infrastructure's physical performance and people's behavior. For example, heavy rainfall or storms can reduce the friction of road surfaces, including airport runways. As a result, vehicles are more susceptible to accidents due to longer braking distances and decreased visibility. Additionally, heavy rain can cause power outages and telecommunication network collapses. Volcanic eruptions can also cause ash falls that similarly affect transport systems (Wilson et al., 2012).

On the other hand, vegetation on roadsides and isolation strips can protect roads from animals and provide drivers with good driving conditions. Vegetation also helps to absorb pollutants and reduce noise pollution. Green infrastructure such as permeable pavements and rain gardens can reduce the amount of runoff from heavy rainfall, mitigating the risk of flooding and erosion. In this way, natural systems can enhance transport systems' resilience while providing other environmental benefits.

The dimension Environment and Climate includes two components: Weather Conditions and Ecosystem and Environment. Weather Conditions includes indicators such as extreme weather conditions, magnitude and duration of unexpected events, impact on infrastructure, preparedness for extreme weather, and disaster recovery time. Ecosystem and Environment includes living species, roadside plants and vegetation, urban renewal and development, air quality, noise pollution, and natural disaster vulnerability.

5. Application of the PURPOSE framework: resilience evaluation of a transportation system

This section presents an illustrative example to demonstrate the application of resilience indicators within a realistic transportation infrastructure system. An adapted version of an example originally presented in Kammouh et al. (2020) is used here for illustrative purposes to support the current discussion. The objective of this example is to employ the indicators together with a modeling technique, namely Dynamic Bayesian Network (DBN), to measure the system's resilience, illustrating the effectiveness of these indicators when combined with other techniques. It is important to note that the use of DBN is one of several possible applications for these indicators. The application of DBN in this study is not directly tied to the proposed framework; rather, it is employed as an inference system that replaces a basic aggregation of numbers. The PURPOSE framework itself is flexible and can be used with any method capable of handling nodes (i.e., indicators). Depending on the application, various techniques can be applied, including fuzzy logic, Bayesian networks, or artificial neural networks, when sufficient data is available.

First, background information on DBN will be provided to establish a foundational understanding. Then, the focus will shift to modeling the system' resilience using the developed PURPOSE framework. In this example, only the physical dimension of the transportation system is considered due to data limitation. The study relied solely on open data sources, where information on the physical infrastructure dimension was the most accessible. Therefore, this application is to be seen as proof of concept to demonstrate the applicability of the proposed framework.

5.1. Dynamic Bayesian networks

A Dynamic Bayesian Network (DBN) extends the classical Bayesian Network (BN), which is a graphical model used to represent stochastic relationships among a set of variables. BNs are static and represent a snapshot in time while DBNs incorporate temporal dynamics, making them suitable for modeling systems where performance changes over time, such as before and after a disaster (Murphy & Russell, 2002). The DBN includes a structure known as a temporal plate, which includes the variables that evolve over time. These variables are the part of the DBN that can be unrolled. However, nodes that have a constant value at every time step are considered a waste of memory and computational power if copied in each time step. Therefore, it is wise to introduce these nodes outside the temporal plates. The collection of these nodes is called the contemporal space, and the nodes are called contemporal nodes (Murphy & Russell, 2002). Additionally, there are two special types of nodes, anchor nodes and terminal nodes (Hulst, 2006). Anchor node (A) is a node that is outside the temporal plate but has at least one child node inside the temporal plate in the first time slice of the unrolled DBN. Terminal node (T) is a node that is outside the temporal plate and has at least one parent inside the temporal plate in the last time slice of the unrolled DBN.

Figure 3(a) presents a single time slice of a DBN (a snapshot of the system) where all variables appear static. Figure 3(b) shows a general DBN where the variables within the temporal plate (the dotted rectangle) are repeated when the DBN is unrolled, while the variables outside the temporal plate are static (contemporal, anchor, or terminal) nodes. Figure 3(c) shows the unrolled DBN, with the variables inside the temporal plate connected through temporal arcs and appearing at every time step, whereas the other variables appear only once since their values are constant. For more information on Bayesian networks, see (Koski & Noble, 2011).

5.2. Dynamic resilience model

The resilience model used in this example is based on the resilience definition by Bruneau and Reinhorn (2007) who describe the resilience of a system using four components, also known as the four R's of resilience (4 Rs):

- *Robustness* (R_1): refers to the ability of a system to stand a certain level of stress, preserving its functionality.

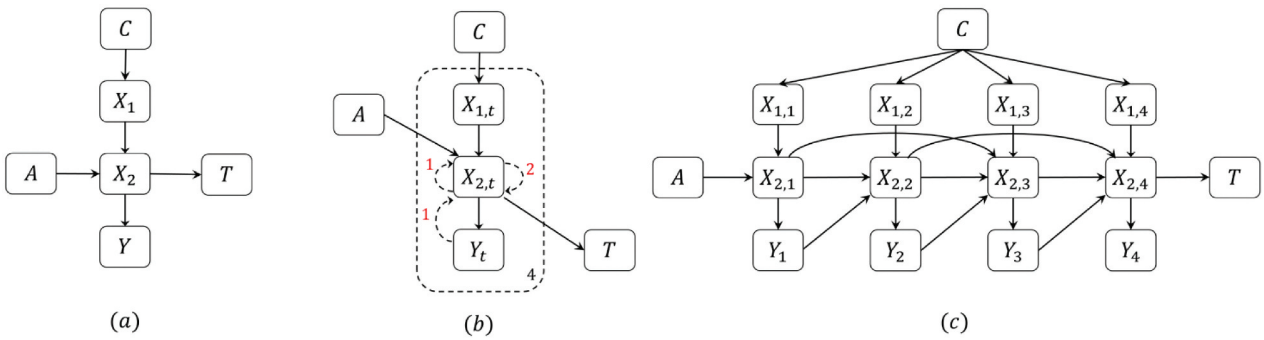

Figure 3. (a) The initial network of a DBN, (b) the 2 DBN or a second-order DBN, (c) the unrolled DBN model for T= 4 slices.

- *Redundancy* (R_2): indicates the alternative resources in the recovery stage when the primary ones are inadequate.
- *Rapidity* (R_3): the capacity to contain losses and avoid future disruption. It represents the slope of the functionality curve during the recovery phase.
- *Resourcefulness* (R_4): considers the human factor and the capacity to move needed resources.

As shown in Figure 4, the first two resilience components (R_1 and R_2) define the damage level the system may encounter if exposed to a certain hazard. Robust and redundant systems would most likely experience less damage and function almost normally after the disaster. On the other hand, once damage occurs, the system's recovery starts. The recovery process is defined by the recovery capacity and resources available, such as human resources. Thus, the other two components (R_3 and R_4) interfere during the recovery stage as they are the main drivers of the system's recovery.

5.3. Network structure and elements connectivity

A DBN is a series of Bayesian networks with changing conditions over time, where elements are connected across different time steps. For example, element A_t can be linked to B_{t+1} if B_{t+1} depends on At, using expert knowledge or past data. Figure 5 shows such connections, where each element at time-step t affects itself at time-step t + 1 (i.e., A_t affects A_{t+1} and B_t affects B_{t+1}).

The four resilience components (4 Rs) are integrated into the network at different stages. Initially ($t = 1$), the system's state is assessed without these components, representing its performance before any hazard occurs. At $t = 2$, the system's damage level from a hazard is evaluated using information about the hazard (H) and system characteristics (R_1 and R_2). These parameters help predict how the system will respond under specific conditions, thus R_1 and R_2 are included at this step.

After assessing the damage, the recovery phase is analyzed over multiple time steps, as recovery is a gradual process. This phase is divided into several time steps, during which the rapidity and resourcefulness (R_3 and R_4) of the system are considered to determine how the indicators evolve. From $t = 3$ to t=T, the same Bayesian network is used to model these changes.

Each Bayesian network yields a performance point, and together these points form a resilience function

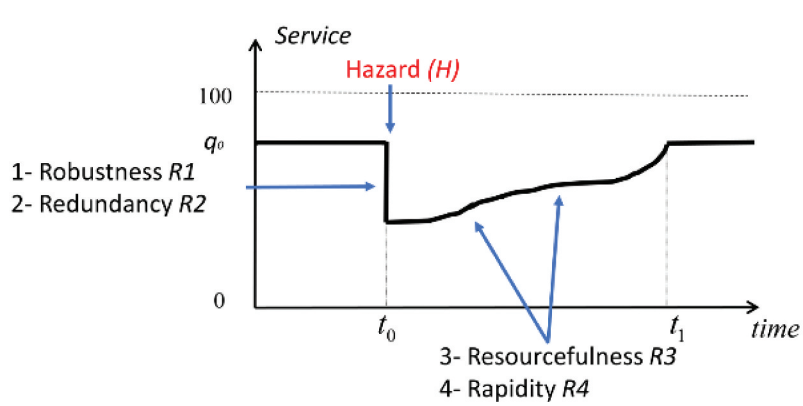

Figure 4. The four resilience components (4Rs) and their interaction with the resilience curve.

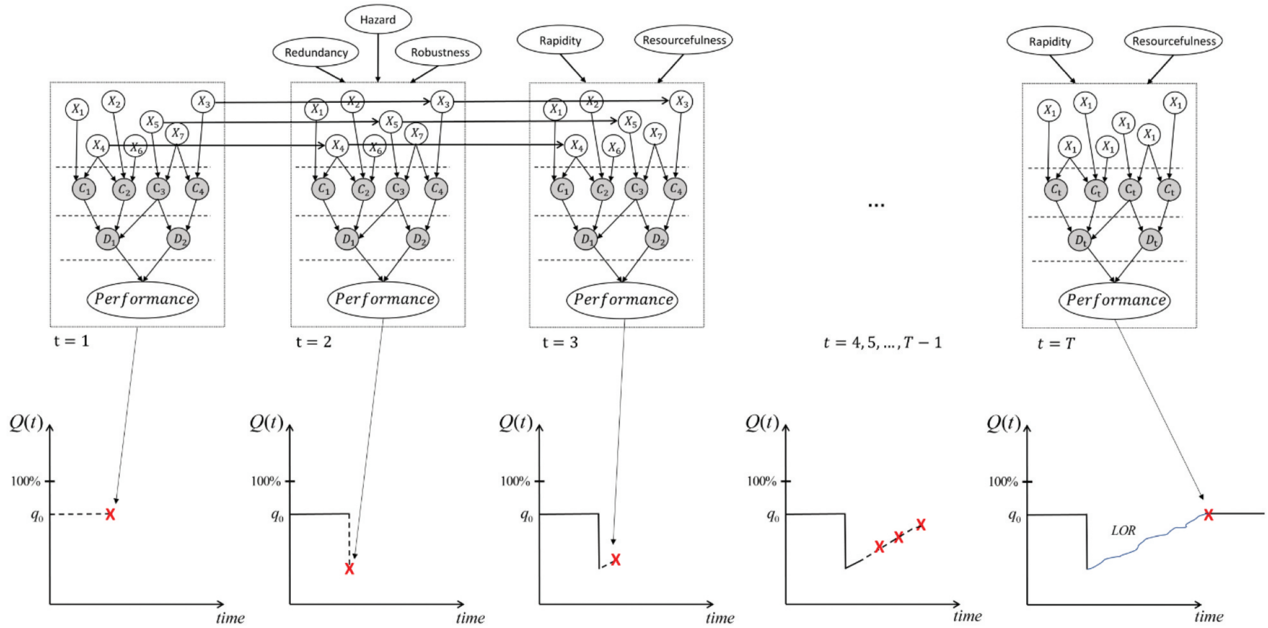

Figure 5. Dynamic Bayesian network of an engineering system considering external factors such as the resilience characteristics (4Rs) and the hazard.

that depicts the system's performance from an initial stable state to a fully recovered state. This resilience function can then be used to calculate a resilience index. One method involves measuring the area above the resilience curve to quantify 'loss of Resilience' (Bruneau & Reinhorn, 2007; Cimellaro, Reinhorn, & Bruneau, 2010), while other methods use different metrics to assess resilience (Sharma, Tabandeh, & Gardoni, 2018).

5.4. Joint probability distribution

In DBNs, Conditional Probability Tables (CPTs) are essential components that specify the probability of a variable given the states of its parent variables. CPTs capture the dependencies and conditional relationships between variables, allowing the DBN to model how the system's state evolves over time. For static variables, the probabilities remain constant, reflecting stable aspects of the system. For dynamic variables, CPTs are updated at each time step to incorporate the impact of changing conditions such as hazards and recovery efforts.

5.5. Modeling the resilience of a transportation system

To model the resilience of a transportation network, we apply the PURPOSE framework developed in Section 4. The resilience indicators serve as the nodes of the Dynamic Bayesian Network (DBN). For simplicity, only the first dimension (Physical Infrastructure) is considered in this study. This dimension is expanded with a list of components, indicators, and measures as shown in Appendix B. The indicators are divided into two categories: static and dynamic. Figure 6 shows a graphical representation of static and dynamic indicators. For static indicators, the functionality remains constant with time, given that they are not affected by hazards. Dynamic indicators, on the other hand, are affected by hazards, and consequently, their functionality changes with time. Dynamic indicators are defined using a set of variables (q_0, q_1, q_f, T_r) where q_0 is the normalized serviceability before the event, q_1 is the residual functionality after the disaster, q_f is the functionality after recovery, T_r is the restoration time or the time needed to finish the recovery process.

Each indicator is normalized against a fixed benchmark value (BV). The system's current functionality at any given time is compared to this benchmark to assess the extent of functionality loss.

5.6. Network structure and elements connectivity

Figure 7 presents the network structure and elements connectivity using the software GeNIe (BayesFusion 2016). The network has been built following Section 5.3. A color code is used to distinguish the variables in

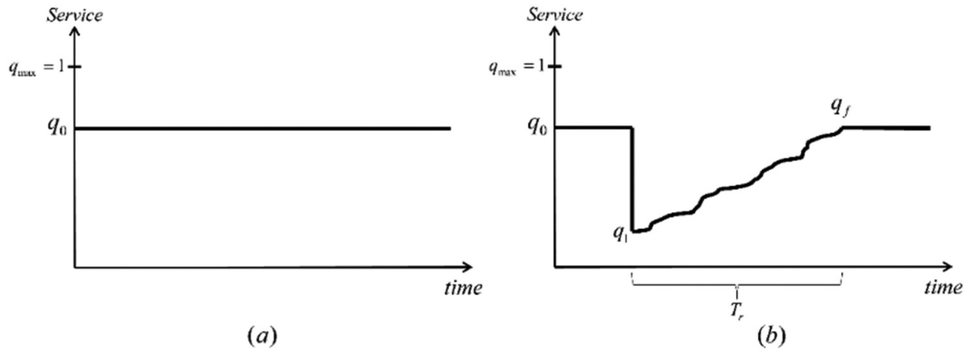

Figure 6. (a) Event-non-sensitive indicator (static) (b) event-sensitive indicator (dynamic).

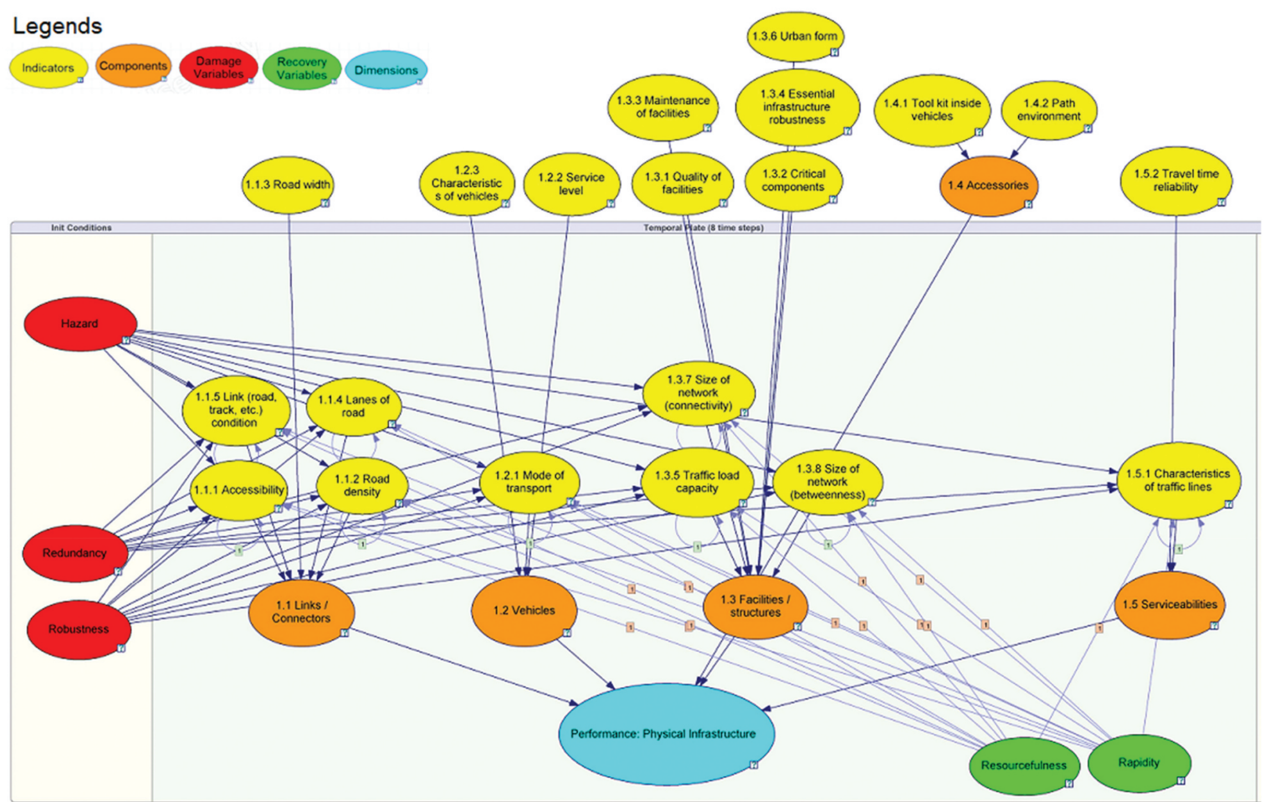

Figure 7. DBN connectivity of the transportation network model.

the network. Variables that are outside the box are static variables. They are assigned unconditional probability tables (UPTs) that do not change throughout the analysis. Variables inside the green box are dynamic variables. The dynamic indicators (i.e., variables inside the green box and colored in yellow) are assigned UPTs for the first time-step and CPTs for the remaining time steps. The CPTs are used to define the functionality of the indicator at time $(t + 1)$ given its functionality at time (t) and given external variables (i.e., damage and recovery variables). The damage variables H, R_1, and R_2 are used to determine the amount of damage the indicators are exposed to following the hazard. Therefore, the damage variables interfere only at the second time-step (see Figure 5) and their effect is reflected in the CPTs of the dynamic indicators at time slice 2. On the other hand, the recovery variables R_3 and R_4 feed the dynamic indicators from time slice 3 until the last time-slice (see Figure 5). The effect of these variables is reflected in the CPTs of the dynamic indicators for all time slices starting from time slice 3. For the first time-slice, the system is assessed for its initial condition. That is, the effect of the damage and recovery variables is not considered, and so the dynamic indicators have no father nodes for this time slice. The tool used for the analysis allows determining at what step each variable interferes.

Other variables inside the green box are the variables colored in Orange (components) and Blue (dimensions). Such variables are dynamic, and their value is defined using CPTs that consider the values of their father nodes. The father nodes of the components are the indicators, while the father nodes of the dimensions are the components. The damage and recovery variables do not affect the components or the dimensions directly. Their effect is transmitted through the indicators to the lower levels of the network. The connectivity between the indicators and the components or between the components and the dimensions can be defined using expert knowledge and experience.

CPTs are assigned to variables that have father nodes in the same or different time-slice. For example, 'components' are assigned CPTs that consider their father nodes (i.e., indicators), while each dynamic indicator (i.e., indicators with a temporal link) is assigned a CPT that considers the indicator itself at a previous time-slice as well as the damage and recovery variables, depending on the time step.

6. Results

Five scenarios have been implemented for comparative analysis to validate the input-output consistency of the method. The method was tested under different starting conditions to assess its sensitivity and ensure that the inference system responds appropriately to variations in input data. These scenarios represent distinct community profiles, with different levels of hazard intensities and resilience attributes – redundancy, robustness, resourcefulness, and rapidity (4 Rs). Table 1 summarizes the inputs of damage and recovery variables across these scenarios. For simplicity, each variable is categorized into one of three levels: High, Medium, and Low. Typically, when information about the variables is scarce, the states of static indicators are assigned a uniform probability distribution. However, with available data, different probability distributions among these states can be implemented. The outcome of the analysis is depicted as a curve illustrating the system's performance fluctuations over time. The analysis incorporates four time-steps (or time-slices) as the interval. Each scenario is examined individually, followed by a comparative analysis that highlights how different variables influence the system's performance level.

Scenario 1 (Figure 8) sets the damage variables to high negative impact (H = 'High', R1 and R2 = 'Low') and recovery variables to high positive impact (R3 and R4 = 'High'). Initially, the probability of achieving 'High' performance for the 'Performance' node (blue) is very low due to the severe initial damage. However, as time progresses, the high recovery capacity leads to a rapid increase in the probability of 'High' performance, eventually reaching a stable state. This scenario demonstrates the system's ability to recover effectively despite significant initial damage. The probability of 'Low' performance, which starts high, decreases at the same rate, reflecting the system's improvement over time. The probability does not reach 1 due to uncertainties in static indicators that propagate through the network.

Scenario 2 (Figure 9) retains the high damage variables (H = 'High', R1 and R2 = 'Low') but lowers the recovery variables (R3 and R4 = 'Low'). The initial probabilities mirror those of Scenario 1, with a low starting probability for 'High' performance. However, due to the limited recovery efforts, the probability of 'High' performance remains low throughout the time steps, indicating a sustained negative impact and insufficient recovery. The 'Low' performance probability stays high, highlighting the prolonged adverse effects due to inadequate recovery measures.

Scenario 3 (Figure 10) changes the damage variables to low (H = 'Low', R1 and R2 = 'High'), while keeping the recovery variables low (R3 and R4 = 'Low'). In this case, the 'Performance' node starts with a high probability of being 'High' and maintains this level consistently over time. The low initial damage means there is minimal disruption to the system, and the low recovery variables have little impact as there is no significant damage to address. This scenario illustrates the system's robustness in the face of minor disruptions.

Table 1. Values for the different input variables.

Input	Scenario 1 (Figure 8)	Scenario 2 (Figure 9)	Scenario 3 (Figure 10)	Scenario 4 (Figure 11)	Scenario 5 (Figure 12)
Hazard (H)	High	High	Low	Low	High
Redundancy (R_1)	Low	Low	High	High	Low
Robustness (R_2)	Low	Low	High	High	Low
Resourcefulness (R_3)	High	Low	Low	High	Medium
Rapidity (R_4)	High	Low	Low	High	Medium

The red color implies a negative impact on the functionality, the green color implies a positive impact, and the orange color implies a medium impact.

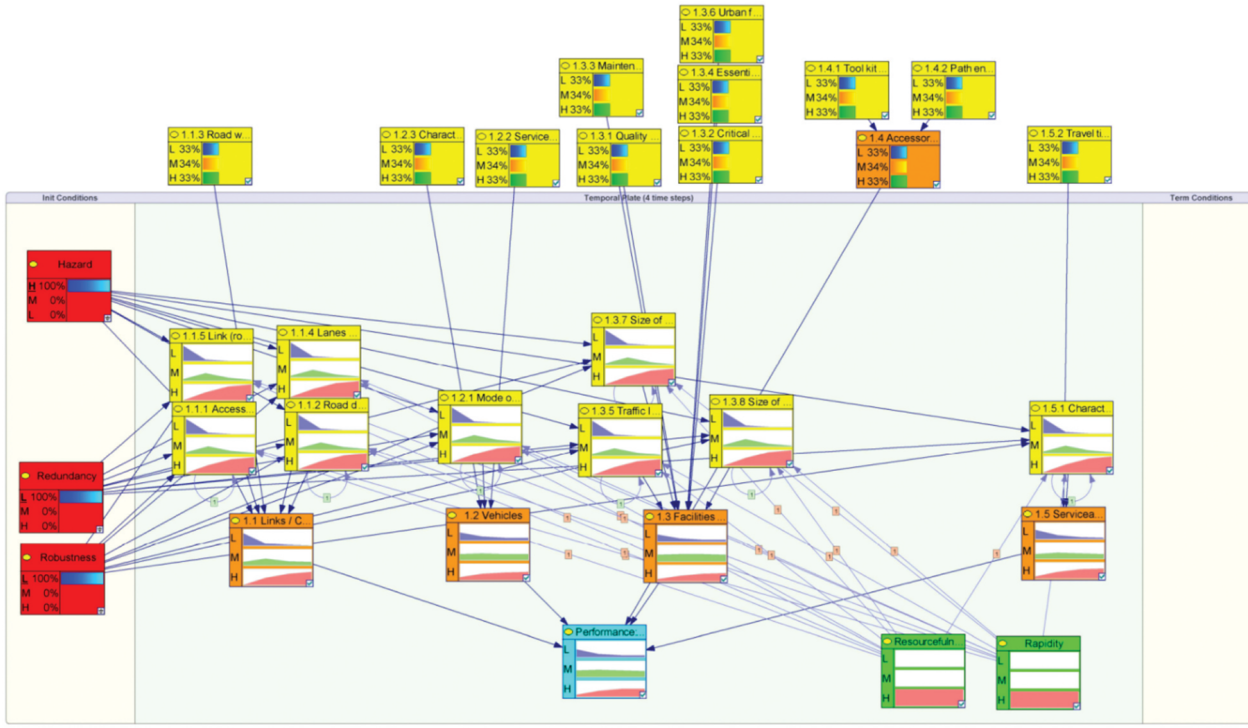

Figure 8. System's performance results for the first scenario of the simulation (high damage, high recoverability).

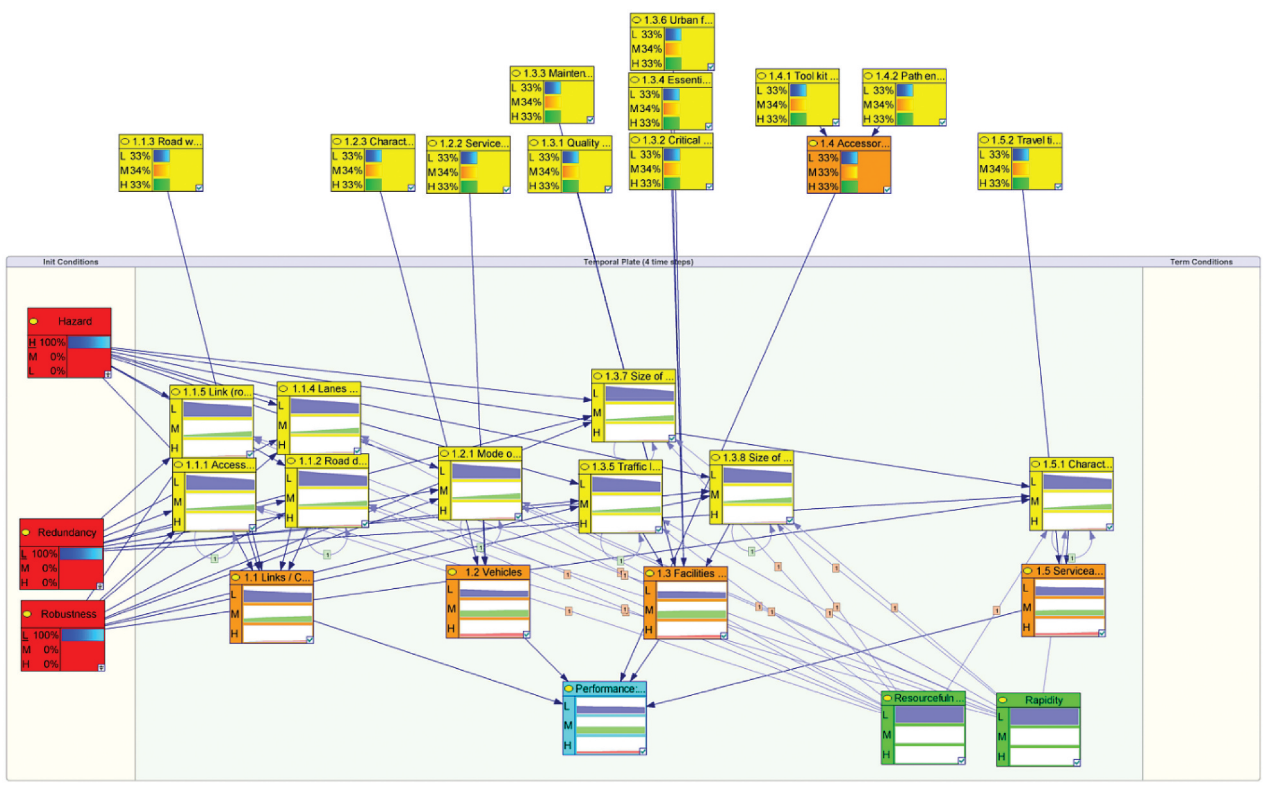

Figure 9. System's performance results for the second scenario of the simulation (high damage, low recoverability).

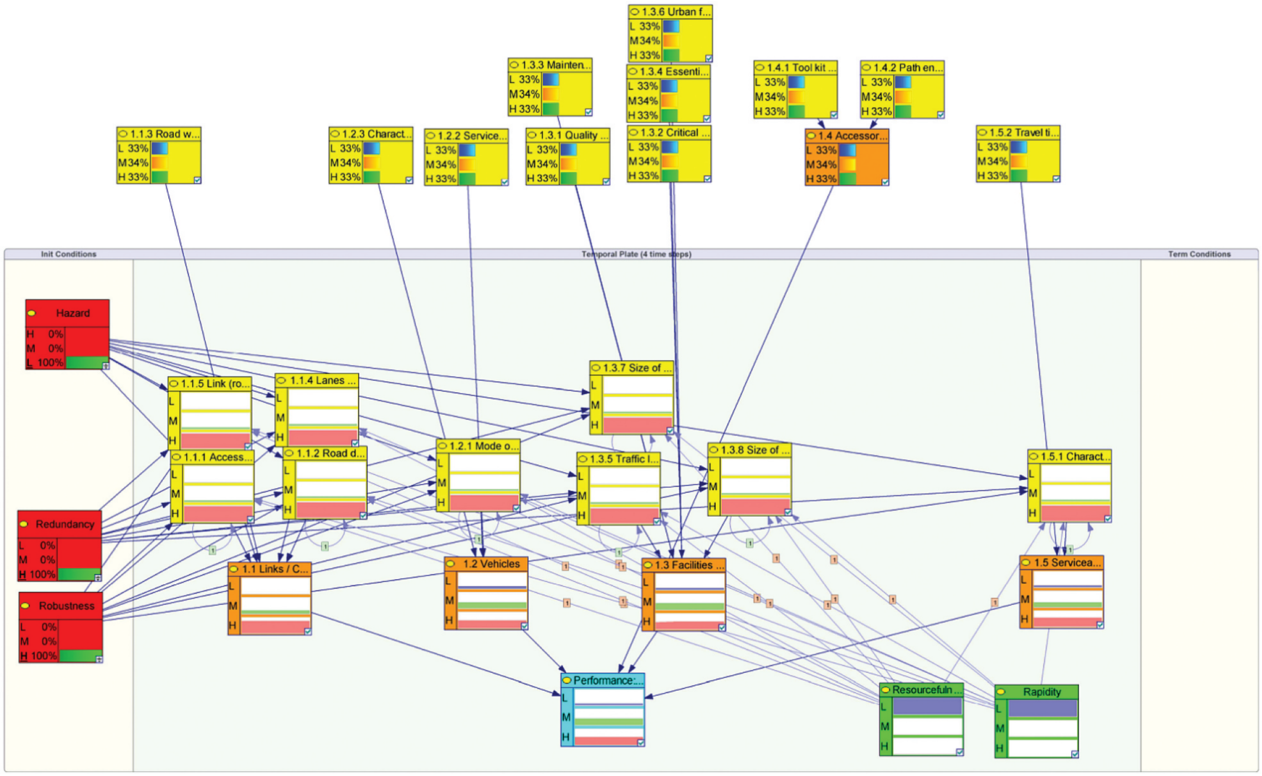

Figure 10. System's performance results for the third scenario of the simulation (low damage, low recoverability).

Scenario 4 (Figure 11) maintains low damage variables (H = 'Low', R1 and R2 = 'High') and switches the recovery variables to high (R3 and R4 = 'High'). The probability of 'High' performance starts relatively high and increases slightly before stabilizing. The increase is marginal because the high recovery capacity is not fully utilized due to the low initial damage. Nonetheless, this scenario highlights the system's readiness to recover rapidly if needed.

Scenario 5 (Figure 12) mirrors Scenario 1 regarding damage variables (H = 'High', R1 and R2 = 'Low'), but sets the recovery variables to medium (R3 and R4 = 'Medium'). Consequently, the probability of 'High' performance increases steadily, though less sharply than in Scenario 1, and eventually stabilizes. The 'Medium' recovery capacity provides a moderate improvement, showcasing the system's gradual recovery process under these conditions.

Across all scenarios, the state of 'Medium' performance maintains a certain probability due to the uncertainties introduced by the static indicators. These uncertainties are propagated through the network, impacting the dynamic variables inside the temporal box. The dynamic indicators are particularly affected by their previous states due to temporal links, which show how past performance influences future functionality.

7. Discussion and conclusions

Infrastructure resilience has gained significant attention in recent years due to the increasing frequency and magnitude of natural and man-made disasters. Assessing the resilience of infrastructure systems can be a complex task, requiring the consideration of various factors that impact the ability of infrastructure to withstand, adapt to, and recover from disruptive events. To address this challenge, a comprehensive set of infrastructure resilience indicators tailored for the transport infrastructure system was proposed in this paper. The indicators have been classified under a wide range of dimensions and components, forming an indicator-based framework with the acronym PURPOSE. Compared to simulation-based approaches, indicator-based approaches are considered more practical and straightforward. They also allow incorporating factors beyond recoverability, such as hardness and adaptive capacity, and can be adapted to communities of different types and sizes.

PURPOSE framework can be used along various techniques, which demonstrates its flexibility and effectiveness in assessing the resilience of transport systems. The case study, for instance, utilized Dynamic Bayesian Networks (DBNs) to model and evaluate different scenarios. Moreover, the framework has been developed with different user capabilities in

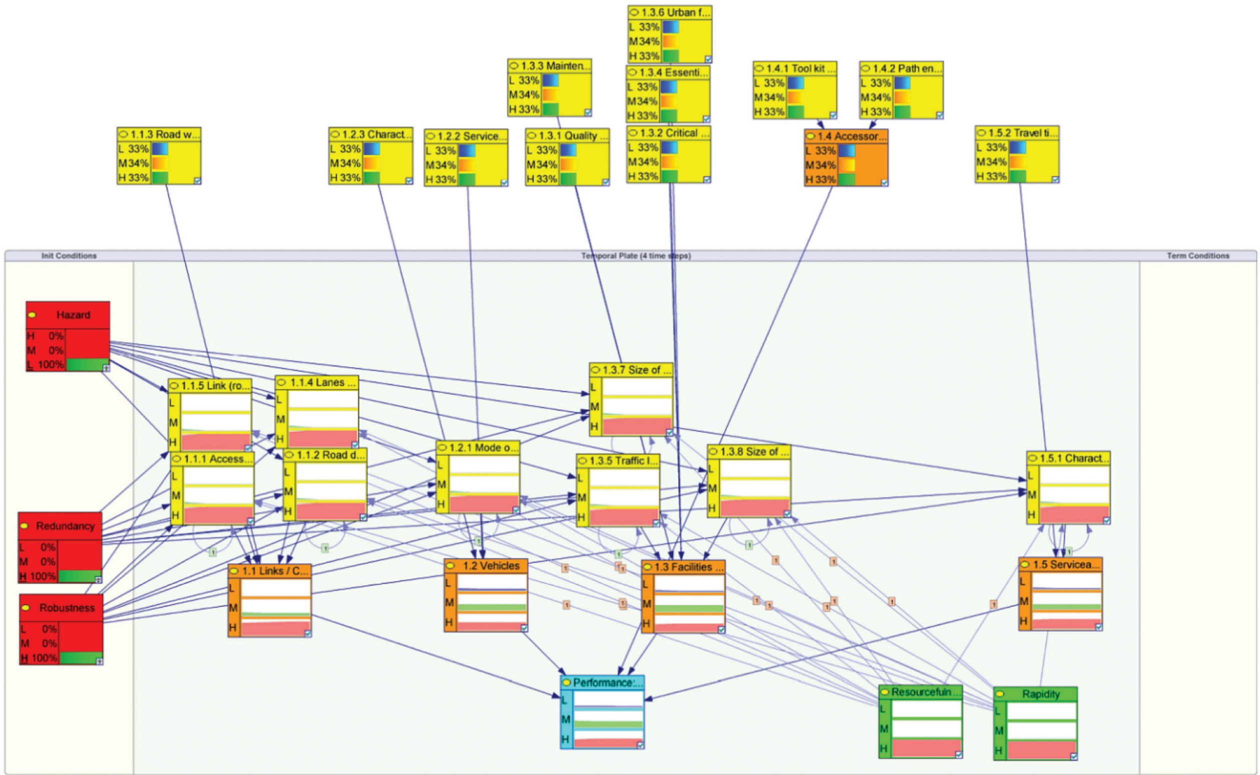

Figure 11. System's performance results for the fourth scenario of the simulation (low damage, high recoverability).

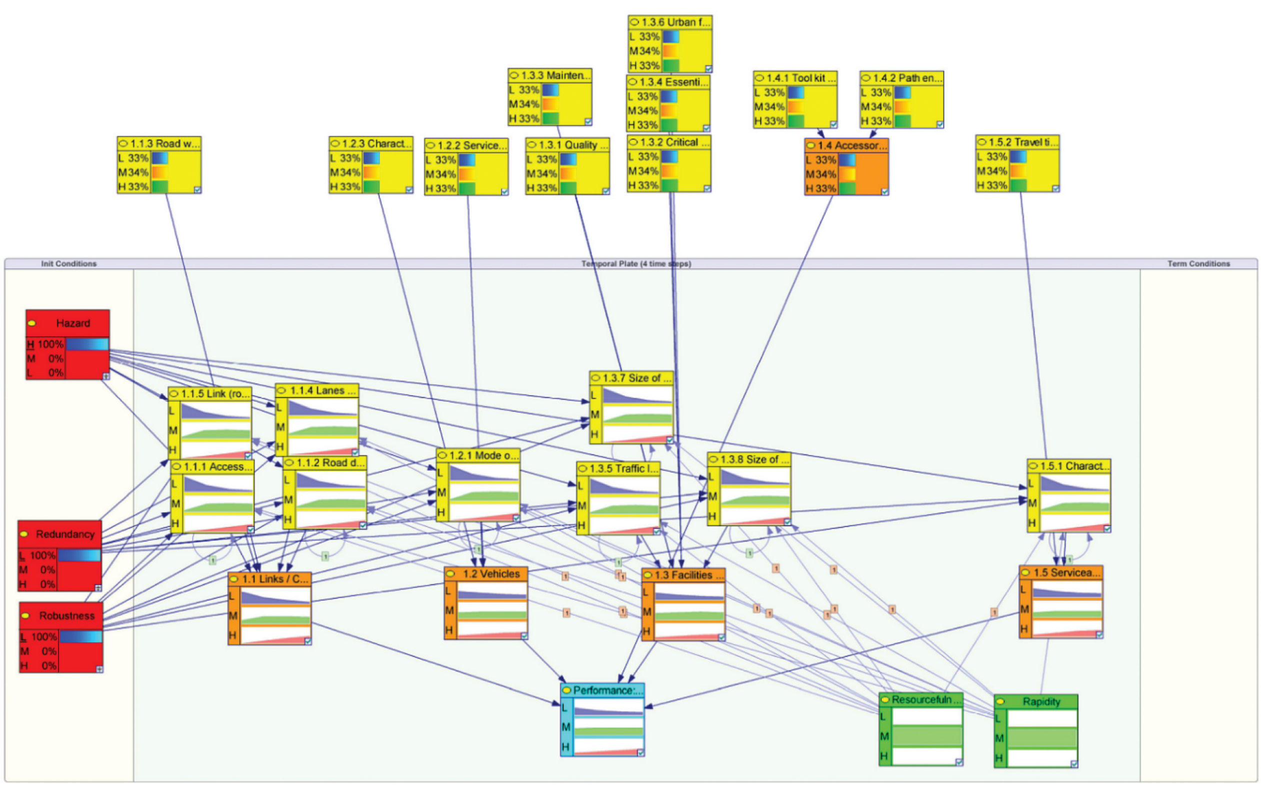

Figure 12. System's performance results for the fifth scenario of the simulation (high damage, medium recoverability).

mind. For example, if DBN is not accessible, users can apply a simple weighted aggregation. Data availability is an important factor in selecting the appropriate aggregation technique, as different methods require varying levels of data input. However, aggregation itself is not an inherent part of the framework. The strength of the framework lies in its flexibility, allowing it to be used with any suitable aggregation technique based on the user's needs and available data.

The proposed (W/R) indicators offer significant potential for advancing research on transport infrastructure systems. These indicators have been developed using a comprehensive approach and can be employed by various methodologies and techniques, including Machine Learning and Bayesian Networks, to provide a comprehensive understanding of the resilience of infrastructure systems.

The proposed W/R indicators provide several potential uses for stakeholders to assess and improve the performance of transport infrastructure systems. Firstly, they provide a common language and framework for communication between different stakeholders, helping to identify and prioritize critical factors that impact the infrastructure's functionality. Secondly, these indicators can enhance community involvement in assessing and improving transport infrastructure resilience as they recognize the critical role that communities play in building and maintaining resilient infrastructure. Thirdly, by using the proposed indicators to assess the resilience of transport infrastructure before and after an event, stakeholders can evaluate the effectiveness of existing and new resilience-strengthening strategies and identify areas for further improvement. Relevant stakeholders include governing bodies responsible for infrastructure resilience, including municipalities for city-level analysis, regional authorities for broader regional assessments, and national governments when evaluating resilience at the country level. Typically, strategic personnel from disaster management departments and other relevant agencies are responsible for managing the implementation and assessment of resilience measures.

Nevertheless, the extensive nature of the indicators may make it challenging to use them in practice. Therefore, stakeholders may need to prioritize the most relevant indicators to their specific context, goals, and resources. While the indicators cover a wide range of aspects, assessing the resilience of infrastructure systems remains multifaceted and context-specific. Hence, stakeholders may need to supplement indicators with additional data sources and qualitative information. Moreover, it is strongly recommended to use the full set of indicators within the PURPOSE framework for a comprehensive resilience assessment. However, in some cases, stakeholders may focus on specific aspects, particularly after implementing interventions to improve a particular dimension. In such cases, applying only part of the framework can still provide meaningful insights.

Furthermore, indicator weighting plays a crucial role in resilience assessment, as it helps prioritize indicators based on their relative importance and impact within a given framework. It ensures that certain factors that have a greater influence on resilience are appropriately emphasized in the evaluation process. In this study, indicator weighting is not explicitly addressed within the PURPOSE framework, as it is inherently part of the adopted aggregation system and has already been explored in previous research (Kammouh & Cimellaro, 2018; Kammouh, Noori, et al., 2018). In addition, research on the cost-effectiveness and feasibility of using the proposed indicators in practice is necessary to ensure that a wide range of stakeholders can use them. Finally, there is a need for research on evaluating the applicability and transferability of the indicators across different types of infrastructure and geographic contexts.

Author contributions

CRediT: **O. Kammouh:** Conceptualization, Data curation, Formal analysis, Methodology, Project administration, Validation, Visualization, Writing – original draft, Writing – review & editing; **N. Chahrour:** Conceptualization, Data curation, Formal analysis, Methodology, Project administration, Validation, Visualization, Writing – original draft, Writing – review & editing.

Disclosure statement

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

Notes on contributors

O. Kammouh is a faculty member at Delft University of Technology, focusing on infrastructure resilience, optimization, and system interdependencies. His work integrates computational modeling, network analysis, and complex systems theory to support the design and management of critical infrastructures under uncertainty. He has contributed to national and European projects addressing cross-sector infrastructure challenges, including recovery planning and stakeholder coordination. Kammouh holds degrees in Civil and Environmental Engineering from

Beirut Arab University, the University of Bologna, and a Ph. D. from Politecnico di Torino, where he developed frameworks for assessing infrastructure resilience. His research is published in peer-reviewed journals and contributes to interdisciplinary efforts in resilience engineering and infrastructure systems.

N. Chahrour is a postdoctoral researcher specializing in reliability analysis, deterioration modeling, and maintenance optimization of critical infrastructure systems. Her research integrates quantitative modelling, stochastic processes, and uncertainty analysis to support data-driven decision-making in construction management. She is a Civil Engineer with a Ph.D. degree in Automatic Control and Systems Engineering from Université Grenoble Alpes. Her work has been published in peer-reviewed journals and contributes to the interdisciplinary field of infrastructure resilience.

ORCID

O. Kammouh http://orcid.org/0000-0002-8859-061X

Data availability statement

The authors confirm that the data supporting the findings of this study are available within the article

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Appendix A. Expert feedback questionnaire on W/R indicators for transport infrastructure

Section 1: Expert Details

- Name:
- Affiliation:
- Area of Expertise:
- Years of Experience in Infrastructure/Resilience:
- Email (optional):

Section 2: Instructions for Experts

- Please review each indicator listed in the table below and provide your feedback.
- Rate the Relevance of each indicator on a scale of 1 (least relevant) to 5 (most relevant).
- Comment on any Clarity and Applicability issues for each indicator.
- Indicate if there is any Redundancy or Overlap with other indicators.
- Suggest alternative indicators where you see fit.
- Feel free to provide additional comments for each indicator.

Section 3: Indicator Evaluation Table

Indicator Number	Indicator Description	Relevance Rating (1–5)	Clarity and Applicability Issues	Redundancy/Overlap (Yes/No)	Alternative Indicator Suggestion	Additional Comments
1	[Description]					
2	[Description]					
3	[Description]					
…	…	…	…	…	…	…

Section 4: Suggestions for New Indicators

- If there are any additional aspects of W/R in transport infrastructure that you believe are not captured by our current set of indicators, please suggest new indicators here:
  - o New Indicator Suggestions:

Section 5: Final Remarks

- Please provide any other general feedback or comments that may assist in refining the indicators:
  - o General Feedback:

Appendix B. PURPOSE dimensions, components, indicators, and measures

Dimension/component/indicator	Measure (0 ≤value ≤1)	Reference
1- Physical Infrastructure		
1–1- Links/edges		
– Accessibility	Number of links/passageways per destination ÷ BV	Ip and Wang (2011)
– Road density	Number of alternative links between an origin and destination ÷ BV	Jenelius (2009)
– Road width	Average width of road ÷ BV	Jenelius (2009)
– Lanes of road	Number of lanes available ÷ BV	Litman (2006)
- Link (road, track, etc.) condition	% links with full functionality during the event	
– Load capacity of links	Maximum load capacity of links ÷ BV	
- Link (road, track, etc.) redundancy	Number of alternative links between an origin and destination ÷ BV	
- Link (road, track, etc.) flexibility	% links with the ability to change direction and/or reroute during the event	
– Intermodal connections	Number of intermodal connections per destination ÷ BV	
1–2- Vehicles		
– Mode of transport	Number of multi-mode choices per destination ÷ BV	Ip and Wang (2011)
– Service level	Average speed of vehicles in normal condition ÷ BV	

(*Continued*)

Dimension/component/indicator	Measure (0 ≤value ≤1)	Reference
– Characteristics of vehicles	Degree of preference of specific vehicles (performance, comfort level, etc.) ÷ BV	
– Vehicle fuel efficiency	Average fuel efficiency of vehicles in normal condition ÷ BV	
– Vehicle emission levels	Average emission level of vehicles in normal condition ÷ BV	
– Vehicle age	Average age of vehicles in the fleet ÷ BV	
1–3- Facilities/Structures		
– Quality of facilities	1- (% deficiency of facilities in past events ÷ BV)	Tamvakis and Xenidis (2012)
– Critical components	Number of roundabout/emergency lanes ÷ BV	
– Maintenance of facilities	Number of maintenance during an interval of period ÷ BV	Tamvakis and Xenidis (2012)
– Essential infrastructure robustness	% infrastructures that remained operational during emergencies in past events	UNISDR (2012)
– Traffic load capacity	Number of excessive capacity (emergency lanes, tracks, airlines, etc.) ÷ BV	Cox, Prager, and Rose (2011)
– Urban form	Number of city centers per 100,000 people ÷ BV	Mishra, Welch, and Jha (2012)
- Size of network (connectivity)	Number of connectivity of intersection ÷ BV	Zhang et al. (2011)
- Size of network (betweenness)	1-(Number of betweenness of intersections ÷ BV)	Zhang et al. (2011)
– Proximity to emergency facilities	Number of emergency facilities (hospitals, fire stations, police stations) per area ÷ BV	
– Number of evacuation routes	Number of evacuation routes per area ÷ BV	
1–4- Accessories		
– Tool kit inside vehicles	1 (Presence of tool kits, like extinguisher, escape hammer, etc.); 0 (otherwise)	
– Path environment	Number of safety elements (isolation strips, traffic lights, etc.) per km ÷ BV	Soltani-Sobh et al. (2016)
– Availability of emergency equipment	1 (Presence of emergency equipment, like first aid kits, defibrillators, etc.); 0 (otherwise)	
– Availability of alternative transportation	Number of alternative transportation options during an event ÷ BV	
1–5- Serviceability		
– Characteristics of traffic lines	Frequency and capacity of each line ÷ BV	Dorbritz (2011)
– Travel time reliability	Number of punctual service assisted by control system ÷ total number of service	Leu, Abbass, and Curtis (2010)
– Accessibility of service points	Number of service points per area ÷ BV	
– Availability of travel information	% of travelers who have access to real-time travel information during events	
2- User Behaviour		
2–1- User status		
– User's trip making behaviour	% people prefer to use more reliable mode of transport	Soltani-Sobh et al. (2016)
– Driving experience	Number of years on road driving ÷ BV	Tobin (1999)
– Educational level	% people with higher (college) education	
– User's knowledge	% people who take yearly education and training program	Soltani-Sobh et al. (2016)
– Traveler's perception	Number of road users familiar with congestion and capacity condition ÷ BV	Soltani-Sobh et al. (2016)
2–2- Response Under Emergency Condition		
– Reaction speed	Average time needed to respond to emergency ÷ BV	
- Operation under emergency condition (sensitivity to recognize potential risks)	% people take part in emergency training program	
– Availability of emergency kits	% of population with access to emergency kits in their vehicle or home	
– Emergency plan awareness	% of population who are aware of the emergency plan and how to follow it	
– Availability of emergency training	% of population who have received emergency training in the past year	
3- Resources		
3–1- Materials and Equipment		
– Available fuel	The liter of fuel ÷ BV	Litman (2006)
- Development of high-tech equipment	Number of new equipment recent applied ÷ BV	

(*Continued*)

Dimension/component/indicator	Measure (0 ≤value ≤1)	Reference
– Inventories	Available number of resources per 100,000 persons ÷ BV	Cox, Prager, and Rose (2011)
– Availability of alternative energy sources	Number of alternative energy sources available per area ÷ BV	
– Availability of communication equipment	Number of communication equipment (radios, satellite phones, etc.) per area ÷ BV	
3–2- Essential Facilities		
– Lifeline facilities	Number of functional lifelines per area ÷ BV	Cutter, Ash, and Emrich (2014)
– Temporary facilities	Number of generators, telecommunication equipment ÷ BV	
– Shelters and evacuation routes	Number of shelters and evacuation routes per area ÷ BV	Cutter, Ash, and Emrich (2014)
– Availability of backup infrastructure	% of critical infrastructure with backup systems in place	
3–3- Supporting Services		
– Scientific support	Number of professional, scientific and technical persons ÷ BV	Cumming et al. (2005)
– Checking and renewal of resources	Period of time to control (checking of numbers and quality) and renewal of resources ÷ BV	
– Availability of emergency services	Number of emergency services (police, fire, medical) per area ÷ BV	
– Availability of public utilities	% of households with access to basic services such as electricity, water, and sanitation	
– Availability of emergency supplies	% of households with basic emergency supplies such as food, water, and medicine	
– Coordination with private sector	% of private sector businesses involved in emergency planning and response	
4- Preparedness and planning		
4–1- Planning in different Phases		
- Pre-disaster preparedness and response skills of citizens	Non-profit organizations workshop participants per 10,000 persons ÷ BV	Cutter, Ash, and Emrich (2014)
– Emergency plan	1 (if there is a plan); 0 (otherwise)	
- Plan for post-disaster recovery and reconstruction	1 (if there is a plan); 0 (otherwise)	
– Simulations and exercises	Number of simulations and exercises conducted per year to test emergency plan effectiveness	
– Funding for emergency management	% of local government budget allocated to emergency management	
– Public participation	% of population involved in emergency planning and response activities	
4–2- Execution of Plan		
– Effective response by responsible authorities	Number of effective implementation of the plan in past events ÷ BV	
– Timetable of transport	% punctual shift	
– Special treatment for vulnerable group	1 (if there is plan directed to vulnerable people); 0 (otherwise)	
– Plan feasibility	% population covered by recent emergency plan	Litman (2006)
– Renewal of plan	Time period of renewal ÷ BV	
– Integration of private sector	% of private sector businesses who have participated in emergency planning and response	
5- Organization and management		
5–1- Administrative/Executive		
– Dissemination of information	1 - (Time interval when the traveler receive the message ÷ BV)	Litman (2006)
– Efficiency of decision implementation	Number of involving disasters ÷ total hazard events	
– Effectiveness of management events	% successful operation in the past events	Cox, Prager, and Rose (2011)
– Effectiveness of information about road conditions	% timely and effective message received by travelers in the past events	Soltani-Sobh et al. (2016)
5–2- Supporting Measures		
– Policy	Number of policies giving priority to execute emergency plan ÷ BV	
– Previous experience dealing with extreme conditions	Number of involving disasters ÷ total hazard events	Tierney and Bruneau (2007)
– Preparedness and training programs	1 (if there is continuous training programs); 0 (otherwise)	Godschalk (2003)
– Monitoring of transport system	1 (if there is a monitoring system); 0 (otherwise)	
– Mutual trust between citizens and government	Number of accurate and effective information given by authorities ÷ total number of information	

(*Continued*)

Dimension/component/indicator	Measure (0 ≤value ≤1)	Reference
– Distribution and logistics of resources	1 (Timely arrival of resources with adequate amount under emergency conditions); 0 (otherwise)	
5–3- Communication		
– Effectiveness of communication	% of communication channels that are effective during emergencies	
– Accessibility of communication	% of population who have access to communication channels during emergencies	
– Timeliness of communication	Average time it takes for emergency information to be disseminated to the public	
– Language accessibility	% of population that has access to emergency information in their primary language	
– Communication redundancy	% of communication channels that have backup systems in place in case of failure	
6- Socioeconomic		
6–1- Social Composition		
– Population density	1 - (average number of people per area ÷ BV)	Ip and Wang (2011)
– Population density	1 - % population with age under 18 and over 65	Litman (2006)
– Vulnerable populations	1 - % population that is considered vulnerable (e.g., low-income, homeless, disabled)	
– Community cohesion	% of community members who are involved	
6–2- Economic Aspects		
– Economic stability	% employed population ÷ total population	Burton (2015)
– Economic diversity	% population employed in second and third industries ÷ total employed population	Cutter, Ash, and Emrich (2014)
– Economic vitality	Growth rate of supply and demand ÷ BV	Cox, Prager, and Rose (2011)
– Special economic support	Amount of governmental refunds ÷ BV	
– Allocate limited budget	% budget for improvement of infrastructures and resources	Miller-Hooks, Zhang, and Faturechi (2012)
– Car ownership	1 - % owned cars	
– Price of public transport	1 - (average price per kilometer ÷ BV)	
- Investment (for new routes, maintenance, etc.)	Amount of money for new investment ÷ BV	Cox, Prager, and Rose (2011)
– Insurance	% infrastructure facilities covered by insurance programs	
6–3- Social Education and Awareness		
– Educational program for local communities	Number of education programs (by local government) per each local community per year ÷ BV	UNISDR (2012)
– Local training program	Number of yearly training programs per population ÷ BV	Burton (2015)
– Emergency preparedness of local communities	% community participation in disaster risk reduction preparedness	UNISDR (2012)
– Social awareness of evacuation plans	% population familiar with the plan ÷ BV	
6–4- Involvement of Non-profit Organization		
– Volunteerism of social organization	Red cross volunteers per 10,000 persons ÷ BV	Cutter, Ash, and Emrich (2014)
– Educational curriculum and drills for evacuation	Number of courses and maneuver per year ÷ BV	
- Funding for non-profit organizations	% of government funding allocated to non-profit organizations involved in emergency planning and response	
– Volunteer training and development	Number of training and development programs provided to non-profit organization volunteers per year	
– Coordination with public sector	% of non-profit organizations involved in emergency planning and response activities with the public sector	
7- Environment and Climate		
7–1- Weather Conditions		
– Extreme weather conditions	1 - % days with extreme weather condition in a year	
– Magnitude of unexpected events	Average magnitude of disasters ÷ BV	Soltani-Sobh et al. (2016)
– Duration of unexpected events	Average duration of disasters ÷ BV	Soltani-Sobh et al. (2016)
– Impact on infrastructure	Average damage to infrastructure caused by extreme weather events (e.g., flooding, wind damage)	

(*Continued*)

Dimension/component/indicator	Measure (0 ≤value ≤1)	Reference
– Preparedness for extreme weather	% of population that takes steps to prepare for extreme weather events (e.g., stocking up on supplies, reinforcing homes)	
– Disaster recovery time	Average time it takes for the community to recover from extreme weather events	
7–2- Ecosystem and Environment		
– Living species	1 - (Number of animals inhabit in the vicinity of transportation networks ÷ BV)	
– Roadside plants and vegetation	1 - (Number of animals inhabit in the vicinity of transportation networks ÷ BV)	Forman and Alexander (1998)
– Urban renewal and development	Land area interacting positively with transport system ÷ BV	
– Air quality	Air quality index (AQI) for the area around transportation networks	
– Noise pollution	Average decibel level of transportation noise in residential areas	
– Natural disaster vulnerability	% of population living in areas at risk of natural disasters (e.g., earthquakes, wildfires)	

BV: Benchmark Value