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Urban Transportation Networks Resilience: Indicators, Disturbances, and Assessment Methods

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ABSTRACT

Due to a surge in the frequency and intensity of disruptive events, such as natural disasters, the Covid-19 pandemic, and intentional attacks, the concept of resilience has attracted increased attention in recent years. Many scholars have focused on transportation network resilience because of its importance in society's well-being and recovery efforts after disturbances. Existing studies have suggested various definitions, indicators, and methods for assessing the resilience of transportation networks. This variation is due to differences in the nature, scale, and impact of disturbances. This systematic literature review presents resilience assessment methods for transportation networks, indicators, and disturbance categories. A new representation is suggested for the relationships between performance, time, and resilience, emphasizing other network characteristics and their association with resilience. Resilience indicators are categorized, and disturbance categories are analyzed. Approaches are grouped based on their methodologies and presenting their strengths and limitations. This paper directs future studies toward investigating emerging threats, including climate change, pandemics, cybersecurity, failure propagation, and the impacts of new technologies and paradigms on urban transportation resilience. Additionally, it highlights the benefits of identifying a reference metric. Finally, this paper promotes resilience-based thinking to address challenges facing cities worldwide as a cornerstone for creating lasting sustainable development.

1. Introduction

The intensity and frequency of disasters and their associated impacts are increasing. This situation questions the effectiveness of current design methodologies for built environments and other human-made systems (Addanki and Venkataraman, 2017, Liu and Song, 2020, The Resilience Shift 2019). Existing design approaches rely on the probability of limit exceedance based on the statistics of previous records. One limitation of these records is that they cannot predict significant variations due to climate change and fail to consider changes caused by development and urbanization. These uncertainties and accelerated disaster occurrence rates have focused attention on the concept of resilience in engineering designs (Liu and Song, 2020, The Resilience Shift 2019, Raouf and Al-Ghamdi, 2019, Wan et al., 2018).

The concept of resilience was first introduced in modern science by Holling (1973) to describe an ecological system's ability to endure damage under stress and regain a stable state (Holling, 1973). This concept was later introduced into other fields, such as management and engineering, with resilience definitions and assessment methodologies differing between fields (Soltani-Sobh et al., 2016). Most of these definitions combine several aspects represented by the concepts of "risk management, vulnerability, reliability, robustness, flexibility, and survivability" (Faturechi and Miller-Hooks, 2015), as illustrated in Fig. 1. For example, in infrastructure engineering, a resilient element such as a road could absorb (or sustain) a sudden disturbance and recover its normal traffic flow capacity within an acceptable timeframe (Calvert and Snelder, 2018).

These components affect the relationship, in the broader scope, between the Risk-Resilience-Sustainability Nexus. Sustainable development aims to create the optimal balance between its three pillars, economy, society, and environment, while considering the future needs (United Nations 1987, The Core Writing Team IPCC 2015). Additionally, such development increasingly aims to address the impacts of climate change through mitigation, adaptation, and risk management approaches which help build resilience, thus reducing vulnerability and exposure and improving robustness and reliability (The Core Writing Team IPCC 2015, Derrible et al., 2020, Butry et al., 2021). On the other hand, human development activities, even some sustainable

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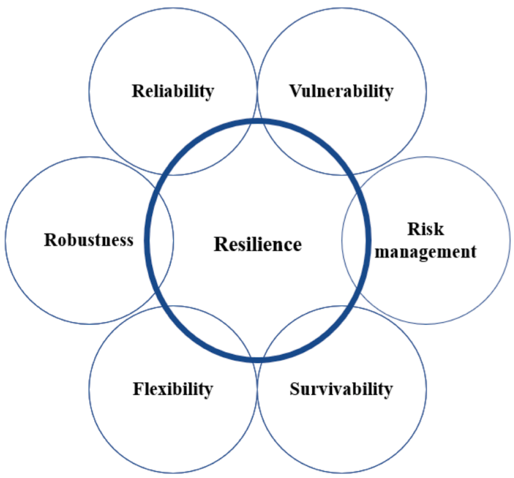

Fig. 1. Resilience components

development projects, include anthropogenic alteration of the environment, like releasing greenhouse gas, which adds to the Earth's natural variations and results in increased hazardous events intensity and reoccurrence rate (The Core Writing Team IPCC 2015). Subsequently, the increase in the impact and rate of these disasters motivates the need for sustainable and resilient developments. Fig. 2 illustrates the Risk-Resilience-Sustainability Nexus and the previous discussion regarding resilience components' contribution. This framework is developed based on the risk framework reported in the Intergovernmental Panel on Climate Change (IPCC) AR5 climate change report (The Core Writing Team IPCC 2015).

1.1. Importance of transportation networks in urban resilience

Accelerated urbanization and increased complexity and interdependency of urban infrastructures generated new threats and amplified their impacts. In recent decades, a trend of accelerated urbanization has spread worldwide. Approximately half of the world's population lives in cities and urban areas. These city dwellers are projected to increase to two-thirds of the world's population by 2050 (Addanki and Venkataraman, 2017, United Nations 2019). This trend has transformed urban centers into substantial economic, social, and demographic hubs. Thus, any damage to or loss of critical services (such as electricity, water, transportation, health, and communication networks) in these centers would result in grave consequences in terms of social, environmental, and economic costs. Such consequences would continue to increase until these services are restored (Liu and Song, 2020, Duy et al., 2019, Huck and Monstadt, 2019, Ilbeigi, 2019).

Transportation networks play a critical role in achieving Sustainable Development Goals (SDGs), and their resilience can help achieve such goals even in the social domain. Urban transportation networks affect all sustainable development pillars, including the economy, environment, and society; this is reflected mainly in SDGs 3,9, and 11 (SuM4All 2017, UNITED NATIONS 2021). The development of urban transportation is strongly associated with economic growth as a well-designed network with a suitable combination between different modes can reduce the time wasted on the roads and the cost of commuting for all city dwellers (Wang et al., 2020, Du et al., 2018, Pradhan and Bagchi, 2013, Pucher et al., 2007). Additionally, Transportation in general and urban transportation, in particular, produce huge amounts of Green House Gas (GHG) emissions; for example, in the United States, most of the greenhouse gas emissions come from the transportation sector (EPA 2020). However, the increase of urban transportation modes integration and the adoption rate of electric vehicles can substantially reduce GHG emissions (Zahabi et al., 2013, Bertaud et al., 2011). Lastly, the development of sustainable and resilient urban transportation networks plays an essential role in developing communities and reducing inequality (Najman et al., 2010, Arbués and Barberán, 2012, UN 2016).

The resilience of the transportation system affects the resilience of other critical systems and results in changes in a city's overall resilience and prosperity. A resilient transportation system allows people, goods, repair, relief, and disaster response teams to act effectively. Such a transportation system enables the necessary level of accessibility as other crucial services are restored after a disaster (Almoghathawi et al., 2019, Leobons et al., 2019, Li et al., 2019, Markolf et al., 2019, Twumasi-Boakye and Sobanjo, 2018). Under normal conditions, a resilient transportation network reinforces both the city residents' well-being and investors' trust (Didier et al., 2018). The ill-planned expansion of a city and its transportation system could make it vulnerable to permanent damage with unpredictable loss of lives and costs. Practices such as expansion on land with a low elevation and a lack of resilience considerations in planning could lead to rapid degradation. This rapid degradation could cause a disaster that would paralyze a city (Duy et al., 2019, Ilbeigi, 2019). However, despite these benefits and potential concerns, the resilience of transportation systems has rarely been adequately considered within general directions and initiatives concerning resilience (The Resilience Shift 2019, Huck and Monstadt, 2019).

The urban transportation concept includes various forms of mobility (modes) used by the urban population within the city limits, such as walking, biking, cars, buses, and the subway. However, in the literature, urban transportation networks generally describe roads and public

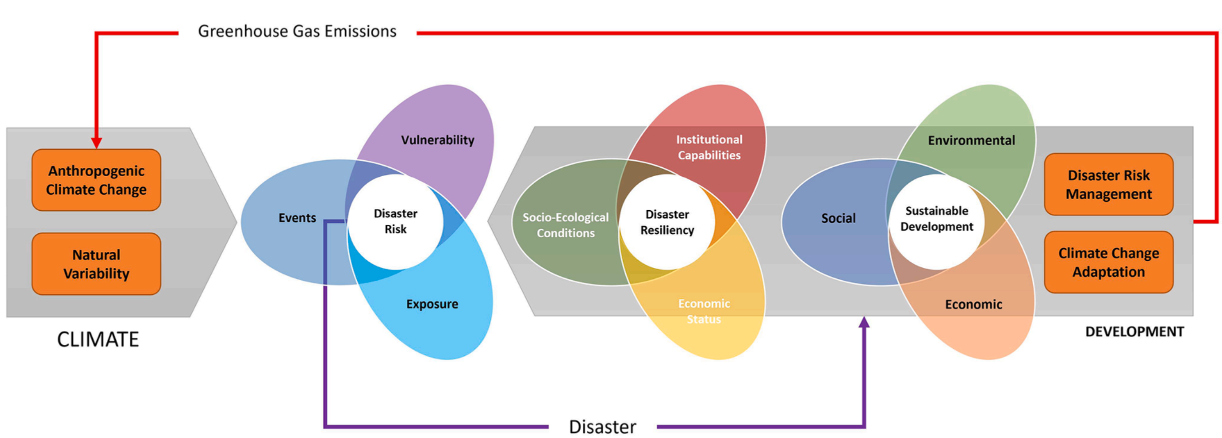

Fig. 2. Risk-Resilience-Sustainability Nexus. Risk, Resilience, and Sustainability are strongly interrelated, and understanding their balances helps develop and implement successful sustainable development strategies to combat climate change and other challenges. Resilience components are the connecting agents between this nexus's elements.

transition networks (Farahani et al., 2013). This practice is widespread, especially in the literature regarding urban transportation resilience. In resilience literature, most studies focus on the connectivity between different parts of the city or the performance of roads and public transportation networks (Gonçalves and Ribeiro, 2020). Other modes of transportation such as waterways and airways are typically considered on higher scales, e.g., Regional. However, they are used in some cities for internal transportation, but the studies regarding their resilience are limited (Ahmed and Dey, 2020).

1.2. Aspects affecting transportation network resilience

Different regions face distinct threats to their transportation networks. Even communities in the same region may have different resilience levels depending on the quality and level of initial design considerations and the quality of accumulated add-on systems, improvements, and enhancements (Ainuddin and Routray, 2012, Cutter et al., 2014, Yang et al., 2020). Transportation systems are vulnerable to terrorist attacks because of their scale; their availability to the public; their significant economic, social, and political roles; and the large number of potential victims resulting from an attack (Adjetey-Bahun et al., 2016, Ganin et al., 2019, Murray-tuite, 2006, Tonn et al., 2021). Several factors must also be considered when selecting the suitable indicator, significantly affecting the assessment method and its efficiency in identifying and evaluating a system's resilience (Liu and Song, 2020, Hosseini et al., 2016, Serdar and SG, 2021). Community behavior and adjustability to rely on or use different transportation modes or change behavior under specific stresses are factors that can be considered to have a stochastic nature (Nogal and Honfi, 2019, Reed et al., 2011, Nelson and Sterling, 2012). Tools or frameworks developed to assess resilience need to be adapted for specific regions. For example, in Hong Kong, tropical cyclones are the primary source of stress. At the same time, in Qatar and the Arabian peninsula, sea-rise, increasing rain intensity, and earthquakes are the primary sources of disturbance (Yang et al., 2019).

1.3. Aims and scope

The resilience of infrastructures is relatively a new concept; subsequently, the literature addressing the resilience of transportation networks is comparatively limited. However, the contributions of these sparse studies should be evaluated and built upon to identify the gaps and direct future research, especially as this topic has been quite vibrant in recent years (Butry et al., 2021, Hosseini et al., 2016). For example, Huck and Monstadt (2019) and Ayyub (2014) have reviewed the concept of systems resilience, including urban infrastructures and their governance (Huck and Monstadt, 2019, Ayyub, 2014), but not particularly transportation. Liu and Song (2020) and Rus et al. (2018) have focused on the resilience of urban infrastructures, assessment methods, and their interdependency (Liu and Song, 2020, Rus et al., 2018); however, transportation was only limited to a small part of these reviews. Wan et al. (2018) and Faturechi and Miller-Hooks (2015) have reviewed the resilience of transportation systems and compared it to other concepts describing system performance (Wan et al., 2018, Faturechi and Miller-Hooks, 2015). These reviews focused on the differences between concepts such as resilience and robustness in transportation systems. Similarly, Gu et al. (2020) have compared vulnerability, reliability, and resilience in terms of metrics and assessment methods, highlighting the differences between them at each stage of disaster and performance pattern (Gu et al., 2020). Ahmed and Dey (2020) and Sun et al. (2018) have conducted extensive literature reviews on transportation networks' resilience assessment. Ahmed and Dey (2020) have expanded on modeling techniques and indices and compared the resilience of different modes of transportation (Ahmed and Dey, 2020, Sun et al., 2018). However, these authors failed to recognize the differences between hazard categories that determine the effectiveness of metrics and assessment approaches, and subsequently, the reliability of resilience assessment results, as highlighted in our paper.

Developing a suitable framework or tool to assess a transportation network resilience requires considering anticipated threats and parts exposed to each type of hazard, along with suitable indicators. Thus, this paper analyzes the applied methods and associated indicators in the literature and evaluates their feasibility for assessing resilience concerning various disturbances. Gaps and challenges in the methods reviewed are discussed, and future research directions are suggested. This research aims to open the way for developing more inclusive and efficient assessment tools by addressing critical issues for developing such tools. These issues include resilience definition, suitability of the indicators, nature of the disturbances, and employed methodologies. Thus, contributing to the efforts of the Infrastructure Resilience Division (IRD), formed by the America Society for Civil Engineering (ASCE), and the applicability of the recently released Manual Of Practice No.144 (Hazard-Resilient Infrastructures analysis and design) (Butry et al., 2021).

The other contribution of this paper is the suggestion of a performance representation that connects different resilience components with their respective performance stage. Such an approach allows integrating results from components such as vulnerability into resilience assessment and enhancement methods. This systematic review primarily focuses on the ideas and concepts in the papers under review. The strengths and shortcomings of selected papers are only briefly discussed.

This review is organized into seven sections. The introduction (Section 1) provides a general idea of the importance of resilience in urban systems, the aspects affecting transportation system resilience, how it can be simplified into components and their association with the Risk-Resilience-Sustainability Nexus, and the paper's aim and scope. The methods and steps used to collect the relevant literature and the inclusion and exclusion criteria are explained in Section 2. The resilience indicators and definitions are discussed in Section 3, and a modified representation of resilience and its components is provided. Disturbance categories and their geographic distributions are grouped into tables and discussed in Section 4. In Section 5, resilience assessment methodologies and approaches are grouped into classifications, highlighting their strengths and limitations, with some examples from the literature briefly explained. Directions for future research are presented in Section 6, and Section 7 is the conclusion for this research.

2. Research Methods

The resilience concept is widely used in several fields. It was introduced into the engineering field only two decades ago and has gained momentum in recent years. The interest in resilience is fueled by the increasing proliferation of unpredictable stresses induced by climate change. Subsequently, most of the literature on this topic is relatively new (Hosseini et al., 2016).

The following steps were used to identify the literature of interest. In phase 1, a search was conducted using Google Scholar, Microsoft Academic, and Scopus (search engines with access to several databases). The following combinations of keywords were used in the search: resilience AND transport AND assessment OR metric OR measurement OR framework. The selected sources were limited to peer-reviewed literature such as journal papers, conference proceedings, and review papers (some other sources outside this search, such as websites, books, or reports, were included in exceptional cases). A second filtering action was implemented in phase 2, checking the titles, keywords, and abstracts. This process excluded any papers that did not explicitly address the resilience of urban transportation systems, infrastructures, or networks, as their primary focus. At the end of this step, approximately 170 papers remained (consistent with research results obtained by (Huck and Monstadt, 2019) considering the rate of increase in recent years). These papers were later examined in greater detail (phase 3), considering their full content and identifying their suitability for inclusion in the review. These steps are illustrated in Fig. 3.

The spectrum of the reviewed papers could be widened if we plugged in other resilience components instead of only using "resilience." Other components included "vulnerability, reliability, robustness, flexibility, or survivability." However, further processing is needed to ensure compliance with the scope of the intended review. A few such sources were used to expand examples about some methodologies.

The results were derived from various publishers and databases, including ScienceDirect, Taylor and Francis, American Society of Civil Engineers (ASCE), Springer, Institute of Electrical and Electronics Engineers (IEEE), and SAGE. (A few papers also appeared in Emerald and Jstor but were later eliminated during the second phase.) Most of the results appeared in the *Reliability Engineering and Systems Safety* journal, and most were published in recent years, as noted and illustrated in Fig. 4. This review is not exhaustive, and human judgment was used in the final step of filtering and analyzing the information.

3. Resilience Indicators And Definitions

Transportation networks have many properties and are subject to dynamic change. These characteristics mean a transportation network's situation can be reflected by several indicators, depending on the analysis or assessment method and the available data or sources, such as probe vehicles (Ilbeigi, 2019, Ahmed et al., 2019, Donovan and Work, 2017).

3.1. Resilience definitions and representations

The lack of a universally accepted definition of resilience raises significant uncertainty about what is being measured, limiting the ability to compare different approaches. When addressing resilience, researchers employ a range of concepts and definitions, which play crucial roles in shaping the assessment tools and determining their effectiveness and applicability (Wan et al., 2018, Faturechi and Miller-Hooks, 2015, Hosseini et al., 2016). However, most researchers focus on two aspects in resilience studies: impact reduction and swift recovery (Liu and Song, 2020, Sun et al., 2018, Balal et al., 2019). Further discussion of resilience definitions and their variation can be found in Faturechi et al. (2015) and Hosseini et al. (2016) reviews (Faturechi and Miller-Hooks, 2015, Hosseini et al., 2016).

Bruneau et al. (2003) have suggested the resilience triangle, one of the most commonly adopted network resilience expressions, representing resilience and other properties and quantifying resilience through mathematical integration (Bruneau et al., 2003). Several modified versions of the resilience triangle or other graphical representations of resilience methods have been used in several studies by various researchers (Hosseini et al., 2016). A modified version of the resilience triangle, based on a review of numerous papers and representations of resilience (shown in Fig. 5), is suggested in this research. This modified triangle helps quantify resilience and defines its components and their effects on the network.

The suggested representation lays the foundation for new methods to quantify resilience through a mixture of simplified, measurable, and well-investigated components. The representation helps divide resilience into simpler characteristics and associate them with expected performance to assess the resilience better and better manage the resulting risks; these characteristics are tightly related and contribute to the overall resilience of the system (Faturechi and Miller-Hooks, 2015). This representation highlights the main contribution of each characteristic to the system performance and resilience as follow: 1) Reliability can be expressed by excess capacity; 2) Vulnerability can be expressed by the network's resistance to the development of failure; 3) Survivability can be expressed by residual capacity; 4) Robustness can be expressed by the network recovery rate; 5) Flexibility can be expressed by improvability. This approach, to decompose the resilience to its components, can help to manage the infrastructure response to disturbances and better allocate the resources in different stages, pre-and post-disaster, tailoring the performance towards a specific set of goals and prerequisites related to each characteristic, rather than a brute reduction in the resilience triangle area. Furthermore, these characteristics' contributions to system resilience are projected on the performance-time chart to help quantify and relate these contributions and calculate the resilience triangle area, as in Fig. 5. The calculation of the resiliency triangle area can be conducted using the equation suggested by Bruneau et al. (2003) (Bruneau et al., 2003) with minor modifications, as follow:

$$R = \int_{t_0}^{t_2} [100 - Q(t)]dt$$

Where:

R: is the resilience index

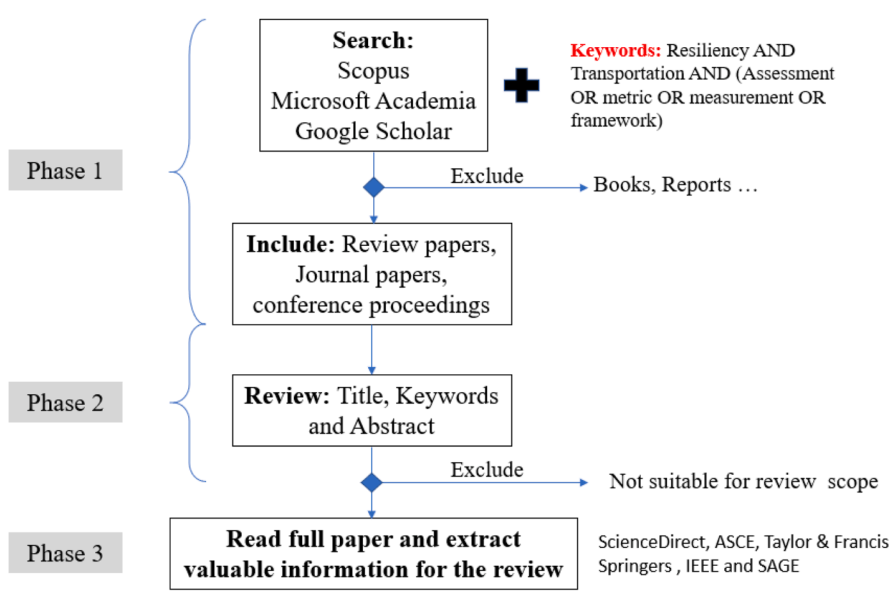

Fig. 3. Research methodology

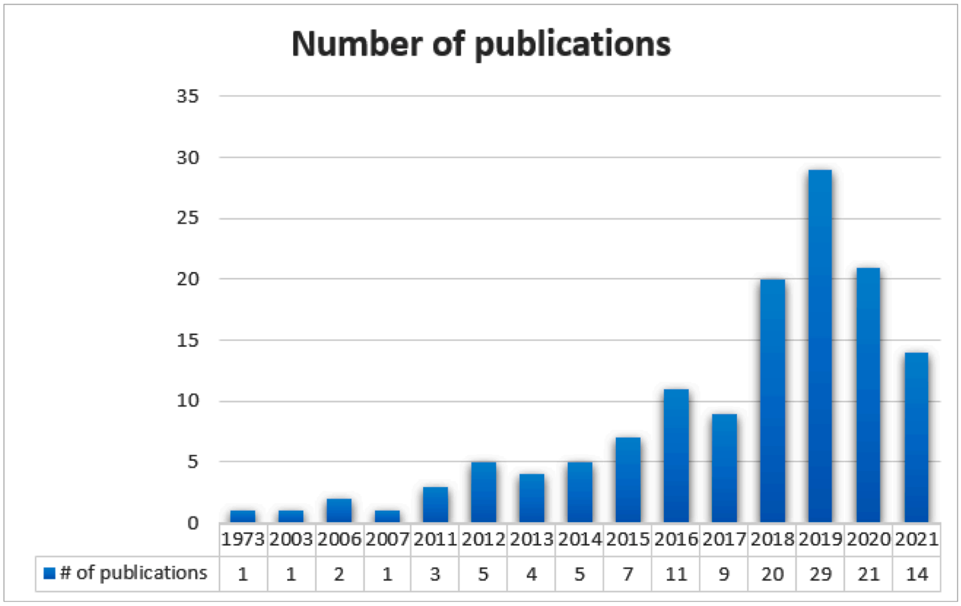

Fig. 4. Number of publications per year included in this review

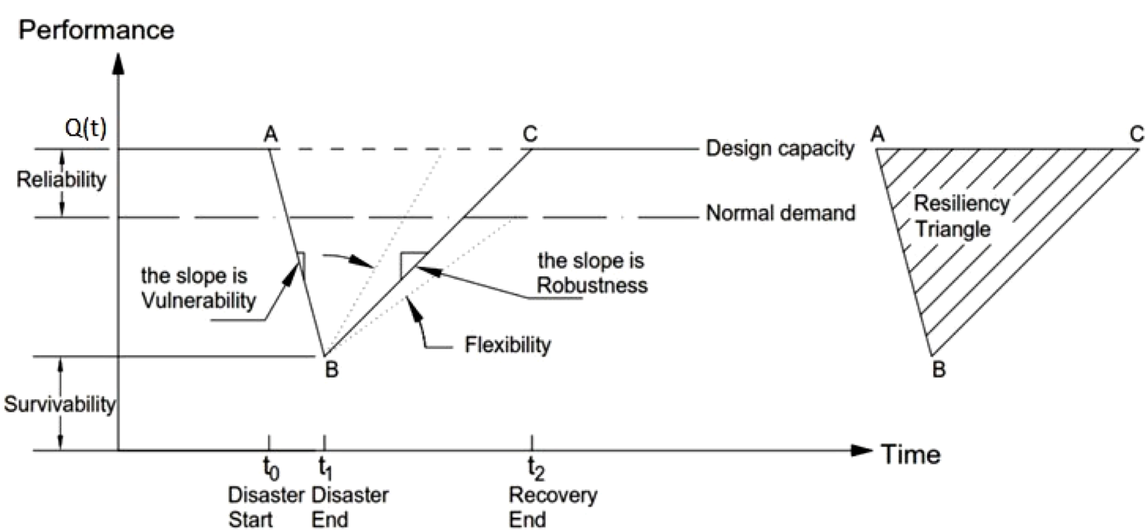

Fig. 5. The suggested resilience representation. The authors created this figure drawing on a review of various representations and resilience definitions. The most notable sources were (Faturechi and Miller-Hooks, 2015, Calvert and Snelder, 2018, Liao et al., 2018, Nogal et al., 2016, WANG et al., 2019, Koren et al., 2017, Cimellaro et al., 2018, Watson et al., 2018, Almoghathawi et al., 2019, Didier et al., 2018, Adjetey-Bahun et al., 2016, Sun et al., 2018, Bruneau et al., 2003, Janić, 2019, Janić, 2018, Aydin et al., 2018).

t_0 : is the time at which the disaster started
t_2 : is the time at which the disaster ended
$Q(t)$: is system performance at the moment (t)

3.2. Resilience indicators

Defining the indicators is an essential step in developing measurement tools. Many indicators have been introduced in the literature based on available data and assessment methodology.

Measuring a network's resistance and its response to disturbance is an effective way to reflect several characteristics that could indicate and define resilience, either on the network or in a particular element. Several studies have assessed resilience as the network's ability to absorb a disturbance (reduction in service due to an event, similar to vulnerability) and the time to recover from its effects (Adjetey-Bahun et al., 2016, Goldbeck et al., 2019, Mattsson and Jenelius, 2015). Others represented resilience in terms of damage cost and recovery budget allocations (Zhang et al., 2018, Asadabadi and Miller-Hooks, 2018, Asadabadi and Miller-Hooks, 2017, Asadabadi and Miller-Hooks, 2017, Chen and Resilience, 2012). Tamvakis and Xenidis (2012) have described resilience as the ability to preserve an operational level in both normal and abnormal situations (Tamvakis and Xenidis, 2012). Ye and Ukkusuri (2015) have considered the network performance recovery ratio when faced with reconstruction (Ye and Ukkusuri, 2015). Didier et al. (2018) have addressed resilience from the supply and demand viewpoint. In these authors' account, during a disturbance, the network adjusts to absorb an increase in demand and recovers by either returning to its pre-disturbance situation or reaching a new adjusted state, based on the post-disturbance conditions (Didier et al., 2018). Even focusing on the element level could provide a good representation of the situation faced by a network, especially if the elements are high-value links, such as bridges and tunnels. Some studies have considered disturbances at the element level and assessed how simple elements, such as roads (Calvert and Snelder, 2018), or important elements, such as bridges (Twumasi-Boakye and Sobanjo, 2018, Twumasi-Boakye and Sobanjo, 2019)), can sustain and recover the normal traffic flow promptly.

Network connectivity metrics are among the most adopted indicators in the literature. Based on complex networks (graph theory), connectivity can provide a simple yet efficient transportation network resilience indicator. Akbarzadeh et al. (2019) and Testa, Furtado, and Alipour (2015) have used node centralities to assess the resilience of road networks (Akbarzadeh et al., 2019, Testa et al., 2015). Zhang et al. (2018) have used graph theory to model a massive metro system (Zhang et al., 2018). Janić (2018) has focused on "high-speed rails" (Janić, 2018). However, in connectivity-based approaches, variation over time is disregarded, meaning that the assessment focuses on remaining connectivity after the distribution or change in a discrete pattern.

Preparedness, passive measures, and pre-disaster conditions could help estimate the network response to disturbances and hence its resilience. In this context, Liao, Hu, and Ko (2018) have considered the effects of preparation and recovery measures on their optimization model (Liao et al., 2018), while Akbarzadeh et al. (2019) have used the excess capacity of the network as a measure of resilience with no mention of recovery (Akbarzadeh et al., 2019). Duy, Chapman, and Tight (2019) have considered the redirection of traffic and evacuation with different options, depending on the flood level and available alternatives as indicators (Duy et al., 2019). Similarly, Nogal et al. (2016) have divided resilience into the ability to absorb a disturbance (perturbation resilience) and recover (recovery resilience) and identified the cost in terms of time as a result of people's choice of alternatives (Nogal et al., 2016). Wu and Chen (2019) have considered the mobility of medical emergency teams and the effect of additional health centers (Wu and Chen, 2019). To address resilience toward fuel shortage, Kelly et al. (2015) have used the percentage of electrified vehicles, while Martins, Silva, and Pinto (2019) recommended decreasing dependency on motorized engines and increasing walkability (Kelly et al., 2015, Martins et al., 2019). Serulle et al. (2011) have suggested nine indicators with different weightings, where the sum of the weighted scores yields a resilience index (Serulle et al., 2011). Another study has used a list of recommendations and assessed resilience in terms of their use (Nguyen et al., 2019).

Statistical analyses of data records and streams could provide insight into a transportation network's situation and detect abnormalities using the standard deviation or its derivatives. These indicators can be effective for comparative, post-event, and real-time assessments (Donovan and Work, 2017). For example, several studies used the mobility of taxi services as an indicator to represent the general traffic performance and variation during disasters. Those studies measured deviations in the pace of taxi travel during disasters and the time needed to recover the normal value (Ilbeigi, 2019, Donovan and Work, 2017). Further discussion of this indicator is presented in section 5.1 (Big data method).

The choice of a suitable indicator is a critical part of any resilience assessment, and it is usually related to many factors. Factors such as the available data, processing resources, stage of concern, and the assessment scale must be considered. To expand on selection processes and indicators further, the reader can refer to Leonbons et al. (2019) (Leobons et al., 2019). However, while the effectiveness and representativeness of the indicators vary, especially in qualitative approaches, it can be observed that:

1 Performance-based indicators (e.g., service level, capacity, and travel time) are the most common set of indicators. They typically reflect changes in performance over time (including impact, recovery stages, or both) to facilitate resilience assessment.
2 On an extensive network scale, it is common to use centrality (or connectivity) metrics (e.g., betweenness, node degree, clustering coefficient, and closeness) because of their simplicity, which occurs at the expense of accuracy and ignores traffic redistribution.
3 Using cost to represent the impact (e.g., direct disaster impact or indirectly caused by service disturbance) eases the degree of interpretation required by decision-makers and allows for the comparability of recovery budgets.
4 Statistical indicators can be employed when there is a continuous flow of data, as in smart cities and big data, to filter and detect any diversion from business as usual (e.g., changes in pace).
5 Qualitative indicators can evaluate a specific sector or aspect based on predetermined objectives or characteristics built on experience.

Several indicators exist with various levels of depth, complexity, and efficiency. Although many of these indicators seem different, they all include some reflection of the resilience components represented in Fig. 1 and Fig. 4. Using this way of thinking, the spectrum of suitable indicators can be expanded to employ investigated or easily accessible metrics used for these components, such as vulnerability and reliability (Faturechi and Miller-Hooks, 2015, Gu et al., 2020, Ahmed et al., 2019). Any metric reliability can be emphasized by introducing the associated uncertainty, which can help evaluate the overall assessment accuracy and allow comparison between different methods. Table 1 summarizes the main indicators.

4. Resilience Disturbance Categories And Geography

Each country, town, or region is prone to specific threats and risks and exposed to various stressors and vulnerabilities. This local distinctiveness directs the interest towards developing risk mitigation strategies considering local characteristics and available transportation networks and modes. The local context strongly influences resilience assessment approaches and indicators.

4.1. Resilience disturbance categories

Disturbances vary in nature, scale, impact, duration, and source. However, disturbances can be assigned to four main categories: natural hazards, intentional attacks, accidents, and failure propagation between

Table 1
Main resilience indicators.

Indicators	Remarks	Examples
Performance-based (service level, capacity, travel time)	Reflect performance over time in different stages	(Calvert and Snelder, 2018, Twumasi-Boakye and Sobanjo, 2018, Adjetey-Bahun et al., 2016, Goldbeck et al., 2019, Mattsson and Jenelius, 2015, Tamvakis and Xenidis, 2012, Ye and Ukkusuri, 2015, Twumasi-Boakye and Sobanjo, 2019)
Centrality (connectivity) metrics	Simple, suitable for large scale networks	(Janić, 2018, Zhang et al., 2018, Akbarzadeh et al., 2019, Testa et al., 2015)
Cost	Relatable by decision-makers and can expand to consider direct or indirect damage and recovery plans	(Zhang et al., 2018, Asadabadi and Miller-Hooks, 2018, Asadabadi and Miller-Hooks, 2017, Asadabadi and Miller-Hooks, 2017, Chen and Resilience, 2012)
Statistical indicators	Detect abnormality, suitable for real-time monitoring and assessment in smart cities	(Ilbeigi, 2019, Donovan and Work, 2017)
Qualitative indicators	Less reliable, based on experience or expert opinion	(Kelly et al., 2015, Martins et al., 2019)

interdependent infrastructures. Generally, most literature recognizes the first three as the hazard categories while considering the impact of failure propagation as an indirect threat that requires multistage assessment and excludes it from the list of hazard categories (Butry et al., 2021). However, due to the increased integration and interdependencies between various infrastructures and the predictability of susceptible assets, we decided to highlight the importance of failure propagation as a critical, realistic, and complex yet under-addressed hazard category. These categories are further discussed in the following sections.

4.1.1. Natural hazards

Natural hazards are associated with a city's local geographical characteristics and can range from historically recurring phenomena to an emerging threat due to climate change. Volcanic eruptions and earthquakes are recurring natural disasters causing devastating damage and substantial economic loss to the affected urban areas (Hayes et al., 2021, García Hombrados, 2020, Vega and Hidalgo, 2016). The extent of recurring disasters is substantial, and they can occur suddenly. Historical experience with such events has led to the development of protective practices and regulations to limit their impacts. Building codes and standards, for example, have developed in response to such disasters (Hayes et al., 2021, Sarcheshmehpour and Estekanchi, 2021, Cook et al., 2021, Nienhuys, 2016, Jones and Vasvani, 2017). Climate change has many impacts, including changes in precipitation patterns and ice glacier melting. These impacts have exposed many existing vulnerabilities or introduced new unprecedented ones to specific urban areas, such as the sea-level rise and flooding (The Core Writing Team IPCC 2015, Salimi and SG, 2020, Mori et al., 2021, Aalbers et al., 2018, Arnell and Gosling, 2016). Climate change-induced threats necessitate the development of predictory scenarios that can simulate such events' extent and their expected impact with an acceptable level of reliability (Salimi and SG, 2020, Andrić et al., 2019). Natural hazards have an extensive scale and can affect large areas with randomness in terms of not distinguishing between the impacted infrastructures' value or importance. However, by analyzing the area's characteristics and nature of the threat, such as flooding, the affected parts of a network and their damage level can be predicted with a certain level of accuracy.

The Covid-19 pandemic affected all aspects of life globally, including transportation networks at all levels and modes. The covid-19 pandemic is classified as a natural disaster with social, economic, and political impacts (IFRC 2021, Seddighi, 2020). Responses to this pandemic have included radical changes in work routines, social distancing, restrictions on movement, and lockdowns (Murano et al., 2021, Du and Rakha 2020). These measures were imposed to limit the spread of the virus. Initial studies have shown that the performance of transportation networks was improved through reduced congestion and traffic delays; additional benefits have included enhancements in emissions and energy efficiency (Du and Rakha 2020, Arellana et al., 2020). However, introducing these restrictions meant reducing service capacity and severely lowering the demand, especially the demand on public transport, which was among the most impacted sectors (Arellana et al., 2020, Gkiotsalitis and Cats, 2020). Despite the overall reduction in mobility, urban transportation modes were affected unevenly. For example, public and shared transportation means demand plummeted while cycling and personal cars use increased significantly (Bucsky, 2020, Aloi et al., 2020, de Haas et al., 2020). The operational measures taken regarding public transportation during this pandemic vary considerably from one country to another, aiming to lower the virus's spread and operational cost (Gkiotsalitis and Cats, 2020). However, these measures are constantly changing based on the stage of the pandemic and the decisions of policymakers. Table 2 shows the different levels of operational measures taken.

Table 2
Examples of operational measures taken for public transportation during Covid-19.

Measures	Examples
Total Lockdowns	China (Wuhan) (Jiang et al., 2020), India (Nationwide) (Gettleman and Schultz, 2020)
Operations reduction (time and/or stations)	UK (London), USA (Washington) (Gkiotsalitis and Cats, 2020)
No change in operations	China (Hong Kong) (Gkiotsalitis and Cats, 2020)

4.1.2. Intentional Attacks

Intentional attacks take many forms, including physical attacks or cyberattacks. Nevertheless, they are typically directed at high-value targets or aim to maximize damage to the affected network. These attacks can be motivated by political tensions or economic gain (i.e., ransom) (Levitin, 2007, Zhang and Ramirez-Marquez, 2013, Jang-Jaccard and Nepal, 2014, Bruyelle et al., 2014). The infrastructure undergoing an intentional attack needs to have the capacity and resources to limit the resulting damage. The attacker focuses on undermining such resistance, which creates an attacker defender scenario (Bricha and Nourelfath, 2013, Kosanoglu and Bier, 2020, Bruyelle et al., 2014). Subsequently, during intentional attacks, both attackers and defenders try to allocate their resources efficiently, turning the scenario into an optimization process mainly addressed through game theory approaches (Han et al., 2021, Zhang et al., 2018, Perea and Puerto, 2013, Argenti et al., 2018). Intentional physical attacks are generally associated with conflict zones and focus on strategic, economic, or symbolic targets belonging to the opposing party, such as Houthis attacks on Saudi Aramco (Chen et al., 2021). Meanwhile, cyberattacks could be used by states or individuals (such as hackers), leveraging on the technological advancements and rapid adaptations of smart city technologies (Pizzi, 2020, Zhu et al., 2019). The extent of the resulted damage depends on the available resources for each side, aim, and the original state of the network, however in some cases, even the consideration of relatively large centralized damage did not yield substantial direct damage to the transportation network (Kermanshah et al., 2014). However, the economic, social, and political impact of such attacks could be high and have a lasting effect long after the event on the usage of the transportation network due to the element of fear (Goodrich and Edwards, 2020, Cox et al., 2011).

4.1.3. Accidents

Accidents have a random nature and can happen in any infrastructure or network, and the state of the transportation network plays a significant role in reducing the associated impacts; this is evident by the unequal concentration of car's accidents fatalities of 93% in mid-and low-income countries, while only 60% of the total cars in the world exist in these countries (World Health Organization 2018). It is estimated that road accidents cost most countries approximately 3% of their gross domestic product (WHO 2021). Several random accidents, happening simultaneously, or a single one, affecting a critical link such as a bridge or a tunnel, should not threaten a resilient network. The assessment should evaluate the current network and plans based on available accident data in the local traffic department (Calvert and Snelder, 2018, Lu, 2018). Additionally, urban planners should avoid creating bottlenecks and provide alternatives (Twumasi-Boakye and Sobanjo, 2018, Twumasi-Boakye and Sobanjo, 2019). The impact of accidents varies depending on the affected links ranging from low in low importance roads to medium impacts when affecting critical links or in the case of several simultaneous accidents (Calvert and Snelder, 2018, Twumasi-Boakye and Sobanjo, 2018, Twumasi-Boakye and Sobanjo, 2019, Kermanshah et al., 2014).

4.1.4. Failure propagation between interdependent infrastructures

Urban areas and cities support densely populated developments while providing high living standards and efficient services. To meet these expectations, urban areas rely on a complex network of interdependent infrastructures (Avdeeva et al., 2018, Marzouk and Othman, 2020, Ercan and Kutay, 2021, Mohebbi et al., 2020). These infrastructures stretch throughout the city and support each other. However, this integration and interconnection can be a source of vulnerability and disturbances, especially in the case of smart cities (Kylili and Fokaides, 2015, Zhou et al., 2021, Ercan and Kutay, 2021). A disturbance damaging one infrastructure can spread into others, such as a cyberattack causing traffic jams (Wang et al., 2018, Wang et al., 2020), or electrical network damage limiting the availability of metro service in the city (Adjetey-Bahun et al., 2016). The impact of failure propagation varies depending on the level of integration and the original state of the interdependent network and its backup plans; however, the recovery in the dependent could not be achieved before the revival of the supporting network (Adjetey-Bahun et al., 2016, Wang et al., 2018, Wang et al., 2020).

Comprehensive approaches or those suitable for all threats are often difficult to apply, limited in scale, or demand a significant amount of resources. Single threat- or specific threat-oriented approaches are contained; however, they are usually tailored to suit a specific network or region. Various researchers have proposed a range of methodologies or metrics to address intended threats depending on data availability and possible anticipated threats. Some researchers have developed methods and frameworks applicable to disasters in general (natural or man-made) (Didier, Broccardo, Esposito, & Stojadinovic, 2018; Goldbeck, Angeloudis, & Ochieng, 2019; Leobons, Gouvêa Campos, & de, 2019; Liao, Hu, & Ko, 2018; Nguyen, Esteban, & Onuki, 2019; Serdar, Koc, & SG, 2021; Twumasi-Boakye & Sobanjo, 2019; Ye & Ukkusuri, 2015). Others have only addressed natural hazards such as flooding (Duy et al., 2019, Yang et al., 2019) and hurricanes (for the whole network (Ilbeigi, 2019, Donovan and Work, 2017, Serulle et al., 2011); or single crucial elements, such as bridges, as a reflection of the entire network (Twumasi-Boakye and Sobanjo, 2018)); or focused on human-made disasters (terrorist attacks) (Adjetey-Bahun et al., 2016, Zhang et al., 2018). Limited damage approaches that only address specific elements or significant decreases in service capacity are better suited for daily or occasional recurring events. Some studies have focused on measuring minor disturbances (such as weather or human-made events, which reduced the capacity but did not eliminate it completely) (Nogal and Honfi, 2019, Nogal et al., 2016, Akbarzadeh et al., 2019); normal traffic congestion (Calvert and Snelder, 2018); or events that limit the ability to use motorized vehicles (such as fuel shortage, or a sudden increase in prices) (Kelly et al., 2015; Martins, da, Rodrigues da Silva, & Pinto, 2019).

Identifying the addressed threat category during the development of a resilience assessment tool can favor approaches that better suit such a threat, especially in intentional attacks. It is also worth mentioning that failure caused by propagation from other infrastructure disturbances is the least addressed threat category. However, a resilient transportation network should be resilient to all possible threats. Table 3 summarizes the main disturbance categories and their properties.

4.2. Resilience and geography of studies

Each transportation network is exposed to different disturbances, unique to the geographical region, and varies within a country. For example, in the United States, the east coast is more likely to face storms, while the west coast is more exposed to earthquakes. The northern part is expected to suffer from blizzards, while the south could face droughts, fires, and tropical cyclones. These differences raise additional challenges when trying to unify resilience assessment methods and strategies. Similar trends can be noted in other countries, such as China.

Table 3
Main disturbance categories.

Disturbance category	Scale	Affected parts	Impact
Natural hazards	Large	Random, sometimes predictable	Vary
Intentional attacks	Small-medium	Predictable	Medium-High
Accidents	Small	Random	Low-medium
Failure propagation	Vary	Predictable	Vary

The original state of a transportation network can significantly affect its resilience, primarily as the standard design process cannot address the unexpected threats posed by climate change. Thus, parts performing poorly during normal situations and day-to-day functions would probably fail during a disaster and even deteriorate instead of recovering. This problem could be examined in less affluent countries where there is a lack of study on resilience, and the few available studies have shown low recovery rates, as in Haiti (Sheller, 2013). The standard design approach that relies on available historical records and is based on a statistical calculation of the maximum exceedance possibility is no longer valid. An example is a shift in the precipitation ratio and intensity seen in recent years in countries of the Gulf Cooperation Council (GCC), which has led to several costly floods because the sewer systems in the cities of this region are not prepared to handle such unprecedented events (Salimi and SG, 2020). Table 4 presents the disturbances addressed by some of the studies and their respective countries of origin.

5. Resilience Assessment Approaches

Assessment methodologies differ because of the available data, researchers' backgrounds, and the level of network complexity they should address.

5.1. Big data

Big data applications in transportation networks could provide an efficient method for assessing resilience. In recent years, advancements in sensors (such as probe cars) and the storage and processing of data have made a substantial flow of raw data possible. Large-scale databases of records have been developed in many fields. Although such data could provide a very useful source of information and possess high value, everything depends on how the data are handled, filtered, and processed to extract the much-needed parameters representing the topic of interest. Big data methods aim to introduce efficient approaches for handling the overwhelming flow of data with the lowest resource consumption to represent the situation of a transportation network and its dynamic changes (Ilbeigi, 2019, Donovan and Work, 2017, Biuk-Aghai et al., 2016).

Tracking data could represent the status of a transportation network, along with its response to disasters and overall resilience. Donovan and Work (2017) have proposed using the GPS data records of taxi services to assess the resilience of a transportation network. The authors applied several filters to remove errors and then normalized the trips by calculating the pace based on the travel distance and time. They also considered changes throughout the week. The Mahalanobis distance (statistical quantifying) was used to detect events (Donovan and Work, 2017). When this value goes above a threshold (this threshold is adjustable depending on the needed sensitivity), the time needed to return below the threshold represents the recovery time. This method has been proven to be efficient in detecting events such as Hurricanes Irene and Sandy (Donovan and Work, 2017). Building on their work, Ilbeigi (2019) has proposed a modified method (Ilbeigi, 2019). The same data were used, and the pace was again calculated, but for shorter periods. In addition, the deviation in the pace was detected through a "cumulative sum control chart," which used fewer data and required fewer resources (Ilbeigi, 2019). Chandramouleeswaran and Tran (2018) have similarly used the Mahalanobis distance to assess the resilience of an air transportation network (Chandramouleeswaran and Tran, 2018). These studies have faced challenges in predicting future behavior,

Table 4
Assessment methods by country of origin and threat category.

	General & others	Natural			Intentional
		Flooding	Earthquakes	Storms	
North America	(Balal et al., 2019, Twumasi-Boakye and Sobanjo, 2019, Ganin et al., 2017, Fotouhi et al., 2017, Roy et al., 2019, Cerqueti et al., 2019)		(Aydin et al., 2018)	(Ilbeigi, 2019, Twumasi-Boakye and Sobanjo, 2018, Donovan and Work, 2017, Janić, 2019, Testa et al., 2015, Hosseini and Barker, 2016, Chan and Schofer, 2016)	(Ganin et al., 2019, Murray-tuite, 2006)
China	(Liao et al., 2018, WANG et al., 2019)	(Yang et al., 2019, Zhenwu et al., 2019)			(Zhang et al., 2018)
Europe	(Didier et al., 2018, Nogal and Honfi, 2019, Goldbeck et al., 2019)				(Calvert and Snelder, 2018)
Japan	(Nguyen et al., 2019)		(Janić, 2018)		
Others	(Leobons et al., 2019, Ahmed et al., 2019, Akbarzadeh et al., 2019, Martins et al., 2019)	(Duy et al., 2019)	(Wu and Chen, 2019)	(Diab and Shalaby, 2019)	(Adjetey-Bahun et al., 2016, Kelly et al., 2015)

despite assertions that they could provide real-time information on resilience. They seem better suited for post-disaster assessment than for planning. Another limitation was their failure to account for the demand, which could affect the results and prevent detecting the actual damage to the network.

Analyzing different types of data from a transportation network can help express the economic and social aspects and results of a disaster, which can assess resilience. Diab and Shalaby (2019) have used the statistical analysis and filtering of metro line service records to assess resilience in terms of the "Lost Days of Service" caused by storms (Diab and Shalaby, 2019). Chan and Schofer (2016) have converted lost revenue records into the "Lost Days of Service" to compare the resilience values of two cases (Chan and Schofer, 2016). Social media could represent a significant source of data, which could provide several indicators if processed correctly. Roy, Cebrian, and Hasan (2019) have suggested a metric that uses data from the social media platform Twitter as tags associated with geolocation data to assess resilience based on human mobility after a disaster and found that an earthquake causes an increase in human mobility while a storm decreases it (Roy et al., 2019).

Some problems with this method are the data source, availability, and filtering process, which could impose changes in the results, resource demands, and limitations in predicting future performance. This method is sometimes challenged by misrepresenting network properties, such as topography, capacity, and actual physical damage. Table 5 summarizes several studies based on Big data classifications, data sources, and applications.

5.2. *Simulation*

Simulation is an important method for assessing transportation network resilience. It allows performance evaluation under actual, unprecedented, and hypothetical scenarios. These capabilities make it desired, especially for detecting vulnerabilities, weak performance, and critical elements. The major limitation of simulation-based approaches is the substantial processing capacity needed, limiting the size of what can be assessed or making it difficult to scale up to city scale, with few exceptions in some particular cases (Balal et al., 2019).

Simulation can be used for different modes of transportation networks to reflect their unique characteristics and even their interdependency. Adjetey-Bahun et al. (2016) have simulated mass railway networks under a terrorist attack. Although they considered a decrease in functionality during disturbances, these simulations had limitations because authorities were likely to close parts of the network in a terrorist attack, which was the main threat addressed by the study (Adjetey-Bahun et al., 2016). Nogal and Honfi (2019) have used a dynamic model of the behaviors of stochastic drivers in the case of decreases in the serviceability values of some links, but it was limited to minor decreases in the capacities of the links and could not be used in a disaster that

Table 5
Summary of several studies based on Big Data classifications.

Study	Big data classifications		
	Type	Source	Field of application
(Ilbeigi, 2019, Donovan and Work, 2017)	Structured	Taxi GPS Records	City's road network
(Chandramouleeswaran and Tran, 2018)	Structured	Airport traffic records	Air transportation network
(Diab and Shalaby, 2019)	Structured	Metro operational records	Metro network
(Chan and Schofer, 2016)	Semi-Structured	Metro revenue logs	Metro network
(Roy et al., 2019)	Unstructured	Geolocation tags on Twitter	Disaster detection and human mobility patterns

completely shut down some links (Nogal and Honfi, 2019). Goldbeck, Angeloudis, and Ochieng (2019) have also proposed a dynamic model but addressed the interdependency between different networks (transportation {metro} and electrical), identified assets and repair resources, and accounted for failure propagation. However, their solution relied on the minimum cost flow, which could not represent an electrical network's physical properties. People's behavior also required calibration concerning repairing resources to reflect the actual situation (Goldbeck et al., 2019).

The geographic information system (GIS) is an effective tool to help detect the vulnerable elements or parts of a transportation network and conduct a more realistic simulation. Duy, Chapman, and Tight (2019) have incorporated GIS data into hydrological system modeling to assess flood resilience in a transportation system near a city's coast. However, their approach primarily addressed the problem in terms of preparedness, rather than the intensity or recovery, by considering alternative options associated with flood level as an indicator (Duy et al., 2019). The effect of losing essential links such as bridges could also be modeled using GIS data. Although this method could classify the essential links in terms of the effects of their loss on the network, it could not account for the situation facing the rest of the network (Twumasi-Boakye and Sobanjo, 2018) or heavily depended on the correct assessment of the damage and time needed for recovery (Twumasi-Boakye and Sobanjo, 2019). Yang et al. (2019) have used GIS data to assess transportation network resilience to flooding, considering the interdependency between sewer systems and transportation (Yang et al., 2019).

A smart transportation system simulation can be a highly effective approach, especially when considering abnormal threats, such as a cyberattack. Ganin et al. (2019) have used OpenStreetMap and Google Earth to obtain data about the transportation network delay and density of several cities in the United States, which were used to formulate an equation that took into account the effect of traffic signals. A simulation was then conducted on a cyberattack targeting intelligent traffic signals, and the resilience of the system under different cases was assessed. It was found that locking the signals could cause longer delays than turning them off (Ganin et al., 2019).

This method can predict future scenarios and detect weak points. However, its main limitations are that it is very demanding in terms of resources, difficult to scale up to suit a city-scale network, and requires accurate calibration and high expertise in transportation network performance.

5.3. Model optimization

Optimization models are helpful for design and operation phases to ensure that the best results are achieved in terms of resilience under budgets and other constraints. Liao, Hu, and Ko (2018) have suggested that mathematical modeling and optimization methods are efficient and promising tools (Liao et al., 2018). However, the suggested methods have limitations because the recovery measures' effectiveness is based on human judgment, and the threats need to be identified using a yet-to-be-developed disaster database (Liao et al., 2018). Sommer, Tomforde, and Hähner (2016) have suggested integrating an optimization-based adaptive traffic signal system, which could reduce stops and congestion, optimize the flow to provide a more resilient traffic network, and even reduce pollution and fuel consumption (Sommer et al., 2016).

Optimization approaches could assist in the planning of post-disaster recovery strategies. Ye and Ukkusuri (2015) have suggested an optimization model for network recovery by identifying the optimal sequence for recovering links (such as bridges) to optimize resilience by selecting the highest capacity recovery rate. However, this approach depends on budget allocation and priorities in post-disaster management (Ye and Ukkusuri, 2015). Nogal et al. (2016) have applied dynamic equilibrium to a restricted assignment model of travel cost in terms of time. However, one limitation of this method was its dependence on the network impedance value (which affects the stress and resilience of the network), which was selected and calibrated based on a user survey. This approach made it difficult to expand it to a large scale and relied on the survey process's accuracy (Nogal et al., 2016).

These methods would be very efficient in a post-disaster situation, especially considering budget limitations, and could enhance recovery efforts. However, they also require significant computational resources, accurate mathematical formulation, and strategic policy-supported goals.

5.4. Graph theory and complex networks

Graph- or network-based representation is one of the most popular and effective methods for resilience management because of its simplicity compared with other approaches. This method can represent and simplify any system through nodes (representing origins/destinations or intersections) and links (representing the direct routes between neighboring nodes). It is best suited for air and water transportation and logistics networks and is widely used in urban transportation. For example, the nodes would represent airports, and the air routes between them can be links. Janić (2019) has addressed the logistics of air transportation and built on his previous resilience assessment method based on the centrality and "figure-of-merit" concepts (Janić, 2019, Janić, 2018).

The graph can present the relations between different network elements and facilitate extracting many characteristics that describe resilience and its components, including connectivity and centrality metrics. Centrality identifies critical and important nodes based on their impact on the network, with a node's degree used to quantify it. Akbarzadeh et al. (2019) have used node centralities to assess resilience and connectivity on the street and network levels. However, their approach did not address an important part of resilience characteristics, namely the recovery process length (Akbarzadeh et al., 2019). Zhang et al. (2018) have used graph theory to model an extensive metro system, but there were many limitations related to the recovery time, cost, and associated information, which limited the effectiveness of their method (Zhang et al., 2018). Janić (2018) has focused on "high-speed rails" and the effect of losing connectivity on the socio-economy, introducing the "figure-of-merit" to express resilience under a major disruptive event such as an earthquake (Janić, 2018).

Connectivity refers to the remaining number of connections in a system after it experiences losses from a discontinuity between two points. Connectivity metrics could allow resilience to be expressed in terms of reduction in the remaining critical connections and recovery as the regaining of these connections. Testa, Furtado, and Alipour (2015) have used connectivity to assess the resilience of a transportation network after the random removal of links and nodes, and then used an integrated program (called SLOSH) to simulate a storm surge to identify the damaged links and nodes in the network and measure the resulting resilience (Testa et al., 2015). Zhenwu et al. (2019) have addressed resilience in terms of connectivity to the largest cluster and applied the "percolation theory" to a network of Chinese cities acquired through GIS data to identify weak connections (Zhenwu et al., 2019). Cerqueti, Ferraro, and Iovanella (2019) have used weighted links to consider failure propagation (Cerqueti et al., 2019).

A network-based representation can provide the basis for testing and examining solutions combined with other methods such as optimization, simulation, and agent-based modeling. For example, Ganin et al. (2017) have used OpenStreetMap to acquire the transportation networks of several cities in the US and used a simulation to calculate the average delays under random disturbances and assess the resilience in each case concerning the alternatives (Ganin et al., 2017). Fotouhi, Moryadee, and Miller-Hooks (2017) have used a multilevel assessment to address the interdependency between transportation and the electrical grid in a small graph network experiencing different loss-of-service scenarios by comparing the pre-and post-event travel times (Fotouhi et al., 2017).

Agent-based modeling is adequate for representing the interaction between infrastructure and traffic; however, this type of modeling has not been adequately employed for resilience studies. Wang et al. (2019) have used agent-based modeling combined with the network method to assess the resilience of an airport network (WANG et al., 2019).

Although this method is easy to apply and develop, it has certain drawbacks. It cannot account for accidents, which could lower the links' capacity, resulting in greater vulnerability (this is a conservative assumption but is justified in terms of risk management (Watling and Balijepalli, 2012)). The graph method does not consider the different types of traffic using the links and the alternatives available for each one. For example, trucks cannot move on any road and may cause damage to the infrastructure if assigned randomly (Ferrari, 2011).

5.5. Probabilistic methods

Probability-based methods focus on measuring the possibility of failure and its impacts on network performance, reflecting its reliability as a metric for resilience. Reliability is an essential component of resilience and can play a crucial role in pre-disaster preparedness. Soltani-Sobh et al. (2016) have suggested a reliability-based (probability of surviving) model of a "Sioux network" with node clustering based on bridge locations and assessed resilience in terms of the reliability of the paths toward recovery centers (Soltani-Sobh et al., 2016).

A "Bayesian" probabilistic network combines graphical representation and probability to predict different network states based on the relations between individual elements and probabilities. Sharma and George (2018) have suggested a Bayesian-based model to assess a truckload transportation network's resilience based on the effectiveness probabilities of several measures (Sharma and George, 2018). The effectiveness was determined by interviewing the managers of large companies in the sector and included both the resisting and recovery phases (Sharma and George, 2018). Another application mentioned in the literature was using a Bayesian probability model for absorptive, adaptive, and restorative measures for inland ports to achieve resilience under different scenarios (Hosseini and Barker, 2016).

Probability-based methods help evaluate resiliency in terms of system reliability and probability of failure, which can be important when evaluating various arrangements for the network, development plans, or comparing different disturbances, each with a different probability. However, the effectiveness and accuracy of these methods rely on the correct estimation of such probabilities and statistical processing used to develop them.

5.6. Other methods

Some approaches either could not be included in the main categories or used indirectly to assess resilience. For example, one approach addressed single-link resilience (such as a section of the road) through mathematical calculations without accounting for traffic accidents (Calvert and Snelder, 2018). Others used the number of electrified cars as a measure because these could ensure a city's mobility during a fuel shortage (Kelly et al., 2015), but this approach is simplistic and does not reflect the resilience recovery characteristics. The walkability values in different city districts were used to address resilience to a fuel shortage (Martins et al., 2019), but this approach did not reflect recovery. Another general approach is a fuzzy system approach consisting of many indicators (Serulle et al., 2011). However, this is difficult to apply, especially because many of these indicators are subject to the weighting process, which means they need to be adjusted based on the evaluated network. Some studies have suggested indirect approaches to assess resilience. A method was proposed to introduce the relative resilience between districts of a city, with the values later combined to quantify the city's resilience (Leobons et al., 2019). Nguyen, Esteban, and Onuki (2019) conducted surveys and open-end interviews to measure how the network operators adhered to regulations that thought to increase resilience. However, this approach is limited in effectiveness than other methods and relied on the researchers' judgment, regulation effectiveness, and honesty of the operators (Nguyen et al., 2019).

Frameworks provide approaches that utilize holistic thinking for all the assessment steps and provide the basis for developing new methods or combine several well-established methods. For example, some researchers focused on developing a framework to analyze the physical interdependency between different infrastructures (transportation and stormwater sewer systems) (Yang et al., 2019). However, they did not account for flood contamination and the quality of external responses. Didier et al. (2018) have developed a mathematical framework that could detect many properties (e.g., fragility and inadequacy) of a network even before a disaster. Despite being accurate, this approach faces challenges in scalability and predicting changes in behavior patterns, which can undermine its results (Didier et al., 2018). Wu and Chen (2019) have suggested a framework that assesses the transportation infrastructure situation regarding post-disaster medical responses employing graph theory and optimization to assess the benefits of establishing additional health centers (Wu and Chen, 2019). Aydin et al. (2018) have proposed a framework that combines graph theory and Monte Carlo analysis to assess the effectiveness of different recovery strategies concerning the resilience to threats caused by earthquakes (Aydin et al., 2018). The main highlights of the concepts discussed in this review, including indicators, disturbance categories, and assessment methods, are summarized in Table 6–8.

Table 6
A summary of the resilience indicators highlighted in this review.

Indicators	Remarks	Related sources
Performance-based (service level, capacity, travel time)	Reflect performance over time in different stages	(Calvert and Snelder, 2018, Twumasi-Boakye and Sobanjo, 2018, Adjetey-Bahun et al., 2016, Goldbeck et al., 2019, Mattsson and Jenelius, 2015, Tamvakis and Xenidis, 2012, Ye and Ukkusuri, 2015, Twumasi-Boakye and Sobanjo, 2019)
Centrality (connectivity) metrics	Simple, suitable for large-scale networks	(Janić, 2018, Zhang et al., 2018, Akbarzadeh et al., 2019, Testa et al., 2015)
Cost	Relatable by decision-makers and can expand to consider direct or indirect damage and recovery plans	(Zhang et al., 2018, Asadabadi and Miller-Hooks, 2018, Asadabadi and Miller-Hooks, 2017, Asadabadi and Miller-Hooks, 2017, Chen and Resilience, 2012)
Statistical indicators	Detect abnormality, suitable for real-time monitoring and assessment in smart cities	(Ilbeigi, 2019, Donovan and Work, 2017)
Qualitative indicators	Less reliable, based on experience or expert opinion	(Kelly et al., 2015, Martins et al., 2019)

Table 7
A summary of the disturbance categories highlighted in this review.

Disturbance category	Scale	Affected parts	Impact	Related sources
Natural hazards (including pandemics)	Large	Random, sometimes predictable	Vary	(Hayes et al., 2021, García Hombrados, 2020, Vega and Hidalgo, 2016, Sarcheshmehpour and Estekanchi, 2021, Cook et al., 2021, Nienhuys, 2016, Jones and Vasvani, 2017, The Core Writing Team IPCC 2015, Salimi and SG, 2020, Mori et al., 2021, Aalbers et al., 2018, Arnell and Gosling, 2016, Andrić et al., 2019, IFRC 2021, Seddighi, 2020, Murano et al., 2021, 101, Arellana et al., 2020, Gkiotsalitis and Cats, 2020, Bucsky, 2020, Aloi et al., 2020, de Haas et al., 2020, Jiang et al., 2020, Gettleman and Schultz, 2020)
Intentional attacks	Small-medium	Predictable	High	(Levitin, 2007, Zhang and Ramirez-Marquez, 2013, Jang-Jaccard and Nepal, 2014, Bruyelle et al., 2014, Bricha and Nourelfath, 2013, Kosanoglu and Bier, 2020, Bruyelle et al., 2014, Han et al., 2021, Zhang et al., 2018, Perea and Puerto, 2013, Argenti et al., 2018, Chen et al., 2021, Pizzi, 2020, Zhu et al., 2019)
Accidents	Small	Random	Low-medium	(Calvert and Snelder, 2018, World Health Organization 2018, WHO 2021, Lu, 2018)
Failure propagation	Vary	Predictable	Vary	(Adjetey-Bahun et al., 2016, Avdeeva et al., 2018, Marzouk and Othman, 2020, Ercan and Kutay, 2021, Mohebbi et al., 2020, Kylili and Fokaides, 2015, Zhou et al., 2021, Ercan and Kutay, 2021, Wang et al., 2018, Wang et al., 2020)

Table 8
A summary of the assessment methods highlighted in this review.

Assessment method		Remarks	Related sources
Big data	Suitability/ Strength	• Suitable for smart city applications and resilience assessment through real-time system performance assessment, detecting the abnormalities, and reflecting on previous events. • Using correct indicators and the type of data (e.g., structured, semi-structured, or unstructured) play a central role in its effectiveness and resource consumption.	(Ilbeigi, 2019, Donovan and Work, 2017, Roy et al., 2019, Chan and Schofer, 2016, Diab and Shalaby, 2019, Biuk-Aghai et al., 2016, Chandramouleeswaran and Tran, 2018)
	Limitations	• Not suitable for predicting future performance toward unprecedented events.	
Simulation	Suitability/ Strength	• Suitable to assess fresh developments and unprecedented events, can consider different traffic compositions, network components, and their interactions • Resource-demanding, which makes it hard to scale up	(Duy et al., 2019, Twumasi-Boakye and Sobanjo, 2018, Adjetey-Bahun et al., 2016, Ganin et al., 2019, Nogal and Honfi, 2019, Balal et al., 2019, Goldbeck et al., 2019, Twumasi-Boakye and Sobanjo, 2019, Yang et al., 2019)
	Limitations	• Require calibration and deep understanding to apply it correctly	
Model optimization	Suitability/ Strength	• Suitable for post-disaster planning, preparedness, and recovery budget allocation	(Liao et al., 2018, Nogal et al., 2016, Ye and Ukkusuri, 2015, Sommer et al., 2016)
	Limitations	• Require good understanding of the system and threats to develop an efficient mathematical representation of the system	
Graph theory (complex networks, network topology)	Suitability/ Strength	• Suitable for large networks since it is simple and resource-efficient • Can be used in conjunction with other methods	(WANG et al., 2019, Janić, 2019, Janić, 2018, Zhang et al., 2018, Akbarzadeh et al., 2019, Testa et al., 2015, Ganin et al., 2017, Fotouhi et al., 2017, Cerqueti et al., 2019, Zhenwu et al., 2019, Watling and Balijepalli, 2012, Ferrari, 2011)
	Limitations	• Does not account for traffic composition, redistribution, and capacity reduction due to accidents (instead of the link elimination).	
Probability-based methods	Suitability/ Strength	• Suitable for assessing system resilience in terms of its reliability • Help to evaluate different arrangements and prioritizing severe disturbances mitigation plans	(Soltani-Sobh et al., 2016, Hosseini and Barker, 2016, Sharma and George, 2018)
	Limitations	• Complicated and rely on the accuracy and representativeness of the statistical data used in the development of probability estimations	
Miscellaneous methods		• Include approaches that do not fall into one of the previous classifications of methods. • Include frameworks, which combine multiple methods through organized steps to leverage their strengths	(Calvert and Snelder, 2018, Leobons et al., 2019, Didier et al., 2018, Yang et al., 2019, Aydin et al., 2018, Wu and Chen, 2019, Kelly et al., 2015, Martins et al., 2019, Serulle et al., 2011, Nguyen et al., 2019)

6. Future directions

Through revising and exploring the current literature on urban transportation resilience discussed and analyzed in this paper, we came across several challenges or research directions that need to be addressed in future studies, which are discussed below.

6.1. *Investigating transportation resilience during pandemics*

The emergence of Covid-19 has shaken the world in all aspects, including transportation networks and logistics. Covid-19 implications have exposed many vulnerabilities for transportation networks and their operators regarding protecting commuters' health and surviving during low service conditions, as in Colombia (Arellana et al., 2020). While this pandemic continues to be an evolving situation, it necessitates the development of new resilience assessment approaches, which consider limiting the spread of the virus as an indicator (this can be through Agent-based-Modeling). Another important topic is to explore the implications of combining different modes of transportations to reduce the operational costs during pandemics while ensuring the safety of individuals. This strategy may provide the necessary mobility, especially during prolonged lockdowns, and mitigate permanent damage to the operators of this critical sector.

6.2. Identifying a reference metric

The approaches in resilience assessment vary in terms of indicators and methodology. This variation and the need for comparability make it necessary to conduct extensive comparative assessments. These assessments can be undertaken by applying various methods and testing their effectiveness against a reference metric based on previous events records (Serdar et al., 2021). This process would allow identifying conversion coefficients and facilitate comparing and conducting assessments where there is a lack of information or resources and thus extract meaningful conclusions about the expected performance of various assessment approaches.

6.3. Investigating the micro-mobility paradigm in transportation systems

The rise of the micro-mobility paradigm and its application can significantly affect transportation network performance and resilience. Whether in the investigation or adaptation of micro-mobility applications, such as electric scooters, biking, and even improved walkability. This increased interest aims to bridge the "last mile," thus improving the mobility and performance of transportation systems. However, there is a lack of studies addressing the micro-mobility effect on transportation system resilience and how they can support or paralyze the system during disturbances; such studies would facilitate better planning and management of this new paradigm and ensure its success.

6.4. Investigating the impacts of technological development on transportation network resilience

The application of new and emerging technologies, such as Electric Vehicles (EVs), Autonomous Vehicles (AVs), and adaptive signals, can change the nature of transportation networks and their interdependency with other infrastructures thus affecting their resilience. EVs are expected to reduce the transportation sector's environmental impact and radically change the energy supply chain to a more discrete and even interchangeable manner; however, it will increase the dependency of transportation networks on the electrical network and threaten both of them (Kelly et al., 2015, Esteban and Portugal-Pereira, 2014). Adaptive signals and autonomous vehicles are expected to be applied on a wide scale in the coming years, affecting the resilience of transportation networks at different levels. For instance, connected cars are likely to ensure better flow and redirection to avoid congestion or closure of roads caused by accidents or disasters, further enhancing the capacity and, eventually, the resilience of transportation networks. However, new threats need to be addressed, such as cybersecurity and increased maintenance cost and recovery time (Ahmed et al., 2019). Cybersecurity is an emerging threat for the transportation network. The wide application of smart city infrastructure, which affects transportation networks (e.g., smart signals and assisted parking systems), would mean that the transportation network needs to cope with threats and show resilience in physical and cyber domains (Ganin et al., 2019). Despite the increasing application of such concepts, sufficient research has not been conducted to assess how resilience is affected, the benefits, threats, and challenges with such substantial developments in transportation networks.

7. Conclusion And Outlook

Transportation networks are the cornerstones of city functionality everywhere in the world. These networks play vital roles in ensuring residents' prosperity and quality of life, especially under rising stresses, such as rapid urbanization and climate change. Urbanization and climate change have been connected with an unprecedented number and severity of disasters. It is necessary to build resilience to face this changing situation. To build something, however, it is necessary to be able to measure it. Existing studies have suggested various definitions, indicators, and methods for assessing transportation networks' resilience. This variation is due to differences in the nature, scale, and impact of the disturbances.

This paper presents a systematic review and analysis of the literature on resilience assessment methods for transportation networks in terms of indicators, representations, disturbance categories, and geographical distribution. Fig. 2 summarizes the Risk-Resilience-Sustainability Nexus and presents a framework that connects them with resilience components. A new representation (Fig. 5) of the relationships between performance, time, and resilience, emphasizing other network characteristics and their association with resilience, is suggested. We presented and categorized various indicators mentioned in the literature and provided remarks to help choose suitable indicators (Section 3). We highlighted the variation between disturbance categories, which necessitate different considerations during assessments regarding their impact, extent, or affected parts of the network (Section 4). Finally, assessment methods were summarized. The strengths and weaknesses of the methods were presented to enable other researchers to understand their effectiveness and suitability (Section 5).

Future directions presented in Section 6 and the discussion throughout the paper highlights the importance of Investigating: emerging threats, including climate change, pandemics, and cybersecurity; identifying a reference metric that would help unify resilience definitions and enable better comparability between different methodologies providing meaningful results and conclusions about the expected performance of various assessment approaches; inspecting the impacts of adopting new technologies, such as (EVs) and (AVs), and paradigms, such as micro-mobility, on transportation network resilience and interdependency with other infrastructures. The investigation of these topics is crucial for resilience-based planning and development, which are necessary for preserving and creating lasting sustainable developments and achieve sustainable development goals (SDGs), especially in the changing and challenging world we live in today.

Declaration of Competing Interest

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

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