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Enhancing infrastructural dynamic responses to critical residents' needs for urban resilience through machine learning and hypernetwork analysis

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ABSTRACT

The increasing frequency of extreme weather events poses ever greater challenges to urban resilience and residents' quality of life. Despite a growing trend advocating for an anthropocentric approach to urban resilience, there remains an inadequate understanding of the evolving hierarchical needs of residents during post-disaster periods, especially considering the interplay with infrastructure service restoration. This study aims to address the gap by elucidating how emergency governance and urban infrastructure repairs can effectively address critical residents' needs, providing empirical insights for improved resource allocation in infrastructure rush-repair scenarios. First, we categorize residents' needs into three layers (safety and health, social livelihood and civic engagement) using Latent Dirichlet Allocation topic modeling. Subsequently, we present an urban resilience assessment framework that traces the recovery of residents' needs alongside dynamic infrastructural functionality restoration, benchmarking against pre-disaster levels. Additionally, hypernetwork analyses are adopted to identify critical and evolving patterns of residents' post-disaster needs over time. The robustness of our proposed framework is validated through its application to a dataset comprising 220,567 records from residents' appeals during three recurrent rainfall events in Beijing. Theoretically, this study models the dynamic interactions between residents' needs and infrastructure response during urban post-disaster recovery. Practically, the pinpointed critical needs guide efficient infrastructure rush-repairs and proactive disaster prevention in infrastructure maintenance.

1. Introduction

Urban areas worldwide are witnessing an alarming increase in precipitation trends, a phenomenon exacerbated by climate change and urbanization, culminating in frequent and intense rainstorms with severe socio-economic implications and environmental damage (Zheng et al., 2015; Salimi & Al-Ghamdi, 2020; Tabari, 2020). For instance, in 2021, Zhengzhou in China endured rainstorms, leading to over 380 fatalities and 40 billion RMB in damages. Similarly, a rainfall that persisted for over 20 days in Germany claimed the lives of 160 individuals. In 2023, California experienced heavy rainfall, resulting in nearly 1 million people evacuation. Recently, an unprecedented rainstorm struck Beijing on July 29th, 2023, affecting more than 1.31 million residents. The serious causalities and economic loss caused by increasingly frequent and intense rainstorm events highlight the urgency for urban resilience study (Meerow et al., 2016; Meerow & Newell, 2019; Wang et al., 2020).

Urban resilience is used to describe "the ability of a city to maintain the effects of disruptions when they occur, to carry out recovery activities, and to adapt to the desired functions" (Holling, 1973; Campanella, 2006; Elmqvist et al., 2019). A human-centric perspective is widely acknowledged in emergency governance and urban infrastructure repairs during post-disaster periods. This necessitates a comprehensive understanding of the hierarchy and dynamics of residents' needs to better synergize infrastructural repair recovery and address critical residents' needs (Shekhar et al., 2019; Podesta et al., 2021). However, the current understanding of which services are most pressing to residents' needs and how these needs evolve over time remain unclear. Although some conceptual frameworks have been proposed by previous scholars to model residents' needs during post-disaster recovery (Stokols

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et al., 2013; Zhao et al., 2022; Pan et al., 2022; Ye et al., 2023), these frameworks often rely on static indicators with fixed time spans, making them incapable of modelling the evolving nature of residents' needs and the influence of recurrent disaster events (Roy et al., 2019; Muñoz-Erickson et al., 2021; Yang et al., 2023).

This study introduces new methodologies and insights to capture the temporal fluctuations in residents' needs and how infrastructural repair responses impact overall urban resilience performance. These findings aim to contribute to an improved dynamic interaction between residents' satisfaction and infrastructural functionality, thus directly enhancing residents' quality of life during post-disaster periods (Dargin & Mostafavi, 2020; Kong et al., 2023). The novelties and contributions of the study are summarized as follows:

(1) This study constructs a multi-layered model of post-disaster residents' needs using empirical data-driven methods, which offers valuable guidance on adaptive resource reallocation during infrastructural rush-pair to effectively respond to residents' hierarchical needs.

(2) This study introduces a quantitative model to capture the dynamic interplay between residents' needs satisfaction and the recovery of infrastructural functionality. This model serves as a guiding framework for the restoration of essential infrastructural services, considering the dynamic resolution of post-disaster residents' needs over time.

(3) A normalized residents' needs satisfaction degree was proposed as a metric to assess urban resilience performance. This novel approach not only enhances the utility and generalizability of the evaluation framework but also provides a tangible and standardized measure. The robustness of our proposed framework is validated through its application to the extreme rainfall event in Beijing on July 29, 2023, providing empirical support for its effectiveness.

(4) Leveraging hyperedge network analysis, our study reveals critical and evolving patterns in residents' needs during post-disaster periods. This analytical approach provides proactive insights for repair management, aiding in the formulation of strategies for preventive or timely infrastructural interventions in response to residents' evolving needs.

2. Literature review

2.1. Hierarchical residents' needs during disaster recovery and access sources

Recent paradigm shifts towards a human-centric perspective in urban resilience assessment places an increased emphasis on prioritizing residents' needs and overall quality of life (Tanner et al., 2014; Pan et al., 2022). This orientation aligns closely with global framework like the Sustainable Development Goals and the New Urban Agenda (The United Nations, 2015; Li et al., 2023). Infrastructural routine maintenance and post-disaster rush-repair are all expected to prioritize the satisfaction of residents' needs, in both perceptual and tangible service supply (Diener et al., 2018; Chester et al., 2021).

The complexity arises from the intricate and subtle nature of residents' needs juxtaposed with the constraints of limited infrastructural repair resources (Zhao et al., 2022). Drawing inspiration from Maslow's human motivation theory (Maslow, 1943), Pan et al. (2022) proposed a hierarchical structure of residents' needs post-disaster, including survival needs, safety and health needs, and extending to social life and spiritual well-being. While this conceptual framework provides an initial understanding of residents' needs, the empirical manifestation of these needs from bottom-up communication channels remains unclear. Existing studies, such as Wang (2020) modelling spatial-temporal patterns of public responses to urban flooding based on social media data and Podesta et al. (2021) quantifying post-disaster public activity variations using digital trace data, offer valuable insights. However, they are limited by the skewed demographics of social media users and the inability to track if residents' needs are adequately responded to and addressed.

In addressing this gap, our study leverages residents' appeals records data to provide a full-circle solution. Unlike indirect data sources, residents' appeals records offer critical feedback on overarching urban issues, providing insights not only into identifying residents' needs but also understanding the resolution processes. This approach ensures alignment with the genuine needs and concerns of the community during disaster recovery. Building on successful applications of city informatics in previous studies, such as Wu (2020) analyzing 311 system users' behavior and Peng et al. (2020) categorizing urban issues for appropriate municipal department responses using urban hotline data, our study extends the utility of residents' appeals records during disaster recovery. We employ this data to capture emergence and resolution information directly from residents, enabling the clustering of their needs. This methodological advancement addresses the limitations of previous approaches and offers a more nuanced and direct understanding of the evolving hierarchy of residents' needs during the intricate phases of disaster recovery.

2.2. Measuring urban resilience through urban performance curves

Urban performance curve, often modelled as an assessment and diagnosis tool, relies on established standardized indicators for city services. This includes indicators for quality of life as per ISO 37120 (2018) and indicators for resilient cities outlined in ISO 37123 (2019), endorsed by the International Organization for Standardization (ISO). These metrics serve as fundamental gauges in evaluating city serviceability and reflecting residents' livelihoods, particularly in post-disaster scenarios (Marans, 2015; Wey & Huang, 2018; Mouratidis, 2021; McClymont et al., 2022; Giulia, 2023). Residents' satisfaction, viewed as the ultimate milestone, effectively mirrors changes in post-disaster urban life quality, closely connected to urban services and resource allocation (Gilbert et al., 2015; Hayashi & Suzuki, 2016; Pan et al., 2022; Zhao et al., 2022). Despite its prominence, the existing methodologies and frameworks in quantifying urban resilience through urban performance curves reveal notable gaps.

Performance based methods are introduced by Bruneau et al. (2003) to model urban resilience. Further refinement to standardize the time scale are made by Henry and Emmanuel (2012); Cimellaro et al. (2016) to enhance performance measurement. A critical parameter for resilience is identified as the area under the system's performance curve over time (Zhao et al., 2018; Pan et al., 2022). Despite the new perspective, the simplification of system performance curves into straight lines based on varying layers of need indicators poses challenges in compromising the dynamic nature of need evolution, impacting the precision of resilience assessment, particularly in the context of multi-wave disruptions.

Addressing this gap, a more nuanced understanding of the evolution of needs is crucial for depicting the urban performance curve and accurately assessing resilience during complex, multi-phase disruptions. Noteworthy innovations by Kontokosta and Malik (2018) and Podesta et al. (2021) introduce the normalization of the urban performance curve by setting pre-disaster human activities as the standard for the desired performance. By comparing the urban performance curve to pre-disaster levels, this approach allows for normalization, facilitating a more precise calculation of resilience (Hong et al., 2021; Liu et al., 2023). However, despite these advancements, challenges persist in reconciling evolving needs with performance-based assessments.

Our research aims to bridge these gaps by incorporating a more sophisticated understanding of the dynamic evolution of needs during multi-wave disruptions to provide a more accurate depiction of urban performance curves. This approach will contribute to a nuanced and context-specific assessment of urban resilience, addressing the limitations observed in existing methodologies and setting the stage for more robust urban planning and policy interventions.

2.3. Networking analysis to model system dynamics in urban resilience

In post-disaster scenarios, the intricate connections between the urban infrastructure network and its ability in meeting residents' needs significantly influence overall urban resilience (Yuan et al., 2021). Previous studies have ventured into understanding the interplay between residents' satisfaction degree and various infrastructural systems. Network methods have been employed to uncover dependencies, vulnerabilities and critical components within different sub-systems. For example, Jayaram and Srinivasan (2008) applied network topology to model water distribution networks and measure network reliability by network-based surrogate metrics. Hartmann (2014) identified key nodes and includes critical links to the urban resilience. Huang and Ling (2018) utilized analytical network process to measure resilience in confronting various disruptions. However, these network analysis methods, primarily designed for pairwise connections, reveal limitations when applied to the intricate relationships within the triad of residents' satisfaction, infrastructural system functionality, and urban resilience performance.

Furthermore, traditional network analysis, especially those applied to the social dimension, often confine themselves to homogeneous nodes or sub-urban systems, restricting their ability to comprehensively capture broader social and human aspects of urban resilience. Notable studies such as Campbell et al. (1976) and McCrea (2007) have explored the linkages between objective attributes of life domains and satisfaction, as well as integrated model of quality of life into urban physical and social environments, respectively. Despite these efforts, gaps persist in effectively representing the intricate relationships within the urban fabric.

Our proposed innovation lies in the development of a hypernetwork capable of effectively capturing these complex relationships. Utilizing hyperedges, this approach enables rapid cooperation and resource sharing among the different layers of the network (Feng et al., 2019; Gao et al., 2023). Hyperedges accommodate heterogenous relationships and other complex characteristics that go beyond the scope of pairwise connections. This departure from aggregation or equally weighted methods provides a promising perspective for resilience assessment. Hyperedge analysis can also offer a nuanced understanding of collective reflections on urban resilience by capturing and identifying critical linkages indispensable for urban overall resilience. Therefore, by addressing the limitations of traditional network analysis methods and introducing the concept of hypernetworks, our research aims to provide a more holistic and dynamic representation of the relationships between residents' needs and infrastructural functionality during post-disaster periods. This innovation is not only a methodological advancement but also a strategic move towards a more comprehensive understanding of urban resilience.

3. Methodology

Owing to the exploratory and analytical nature of this study, a combination of qualitative and quantitative methods was adopted to analyze residents' needs oriented urban resilience. The research approach involves the development of a residents' needs hierarchy framework. Subsequently, the study quantifies urban resilience across three rainstorms events, utilizing residents' satisfaction degree as a metric to measure urban performance. To further investigate the dynamics of changes in residents' needs and the influence of infrastructural elements underpinning urban resilience, a hypernetwork modeling and hyperedge analysis are conducted. The workflow of this study is illustrated in Fig. 3.1.

3.1. Data sources and case study

Residents' appeals records data, administered by the municipal government, serve as the primary platform for collecting residents' concerns and providing timely feedback in response. This study combined multiple comprehensive sets of residents' appeals records data, including "12345" citizen hotline, "12369" and "12320" service data, as well as Sina Weibo and WeChat reports, all focusing on hazard-related issues.

The data were obtained from the municipal government for this study from July 1 to August 1 in 2021. The hotline received 220,567 requests data related to urban infrastructure issues directly caused by rainstorms, as reported by residents. Each data record is structured to contain the dispatch time of the report, resolution time of the issue, detailed descriptions, associated locations, handling departments, and outcomes of the process. Specifically, the residents' private information was encrypted and anonymized.

The case involved collecting residents' appeals records and feedback data following rainstorms in Beijing, China, to test the research framework. Starting July 12, 2021, Beijing experienced successive rainstorm events for several weeks, greatly affecting the lives of its 21 million residents. In response to the disaster, the municipal government issued multiple red flag flood warnings, setting the warning level to its highest. In this flood season, with a total precipitation of 627.4 mm, the rainstorms set a new record for the city, surpassing records dating back to 1951. Compared to the average seasonal precipitation of 373 mm, there was a notable 70 % increase (The People's Government of Beijing City, 2021).

3.2. Clustering residents' needs using LDA during rainstorm recovery

Topic models are a type of statistical modeling method for

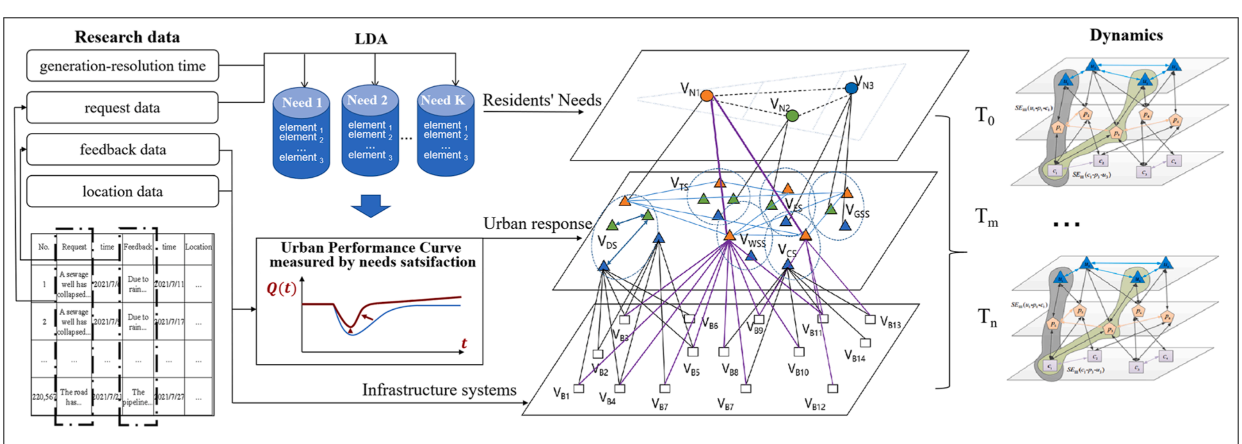

Fig. 3.1. Workflow of this study.

discovering the "topics" that are hidden in large amounts of data (Oliveira Capela et al., 2019). Latent Dirichlet Allocation (LDA) modeling, a widely adopted generative probabilistic model for topic extraction was used to analyze large corpus of documents (Blei et al., 2003). In recent years, the LDA model has gained attention in urban studies, particularly for classifying urban activities (Bi & Ye, 2021; Zhao et al., 2023), responding to emergencies (Yao & Wang, 2020), and analyzing infrastructure resilience (Urquiza et al., 2021). As an unsupervised machine learning technique, LDA is a powerful tool to generate the probability distributions of latent topics from the distribution of words in each document.

The LDA model is based on the Bag of Words (BoW) algorithm, for a document, BoW starts by identifying all the different tokens that exist in it and considers each document as a vector of word frequencies. Each document is represented as a probability distribution over various topics, where each topic is in turn a distribution over terms. During topic clustering, LDA extracting features from text and assigns topics to each document. The request data were extracted from citizen database directly impacted by the rainstorms. In more detail, Fig. 3.2 illustrates the analysis process of need patterns. The specific LDA topic generation process can be discussed as: a) For each resident's request document in the total term label, select a distribution term pattern $\theta_d \sim \text{Dirichlet}(\alpha)$. b) For each term in residents' request d, select a pattern $z \sim \text{Multinomial}(\theta_d)$, $z \in \{1,\ldots,K\}$, and for each topic $k \in \{1,\ldots,K\}$,select a need term distribution $\phi_k \sim \text{Dirichlet}(\beta)$. c)generate the new term label $w \sim \text{Multinomial}(\phi_z)$. In a document, the probability of the word will appear:

$$p(w|d) = \sum_{k=1}^{K} p(w|z=k, \phi_k) p(z=k|\theta_d)$$

Here, w indicates the frequency of word in each resident's request document d, while z denotes the topic k in document d. The parameter θ_d, ϕ_k indicate the distribution from the Dirichlet distribution with hyperparameters α, β, respectively.

The data analysis process is outlined in Fig. 3.3, including data gathering, data processing, model training, and topic visualization. For visualizing the topics patterns extracted from our dataset, we utilized PyLDAvis, where circles represent extracted residents' needs topics, and circle size indicates their significance. The panel provides information on relevant terms and frequencies, and the optimal topic count is determined by comparing inter-topic distance maps. Residents' needs are divided into different layers based on urgency and significance in the rainstorm recovery stage. This prioritization aids emergency management in identifying and addressing the most critical needs, enhancing disaster recovery efficiency.

3.3. *Residents' needs evolution and urban performance curve*

Based on the identified residents' needs during rainstorm recovery, the study further quantifies the needs' evolution features through infrastructure capabilities and demands of the population during the recovery phase. Understanding the interplay between infrastructure responses and residents' needs during recovery is crucial for urban post-disaster resource allocation. If the infrastructure fails to deliver required services after disasters, residents will experience unmet needs, leading to a decline in urban performance which are positively correlated with the rise of the unsatisfied needs. The calculation follows two assumptions: first, each request among filtered items independently contributes to the cumulative performance index, despite the potential influence of other needs; Second, satisfying one need does not affect other needs to be satisfied.

The evolution of residents' needs within this study is illustrated through the Urban Performance Curve, which delineates the varying service capacities of infrastructure systems and their relationship to meeting residents' needs. The Urban Performance Curve is determined through a two-step quantification process that assesses the degree to which key needs are met.

1) **Category residents' Needs**. This step involves categorized residents' needs and layers according to different infrastructure services through the request data. The post-disaster service and capability impact the satisfaction of needs.

2) **Quantify each type of residents' needs.** Calculate the daily unmet volume for each demand type using the feedback data described in Section 3.1. This feedback data encompasses needs emergence and resolution, thereby enabling the tracking of the extent to which these needs are satisfied.

3) **Derive the urban performance curve.** Each need category receives a dynamic weight daily, based on the urgency determined by that day's volume of unmet demand. The performance curve is derived by aggregating the weighted satisfaction scores of all need categories.

4) **Calculate the resilience**. To calculate urban resilience, the methodology quantifies urban performance by integrating the area between the post-disaster performance curve and the baseline. This baseline was quantified using data from residents' appeals of each type of need before the disaster. For each identified shock, the study adjusts the baseline through the decomposition of the performance curve preceding the event and compute resilience. The resilience is calculated using the formula:

$$R = \frac{\int_{t_0}^{t_1} (Baseline - P(t))dt}{t_1 - t_0} \times SR_1 / SD_1 \times RD_1$$

Here, "R" denotes the resilience value; "Baseline" and "P(t)" represent performance over time "t"; "SR" is the slope of recovery; "SD" the slope of

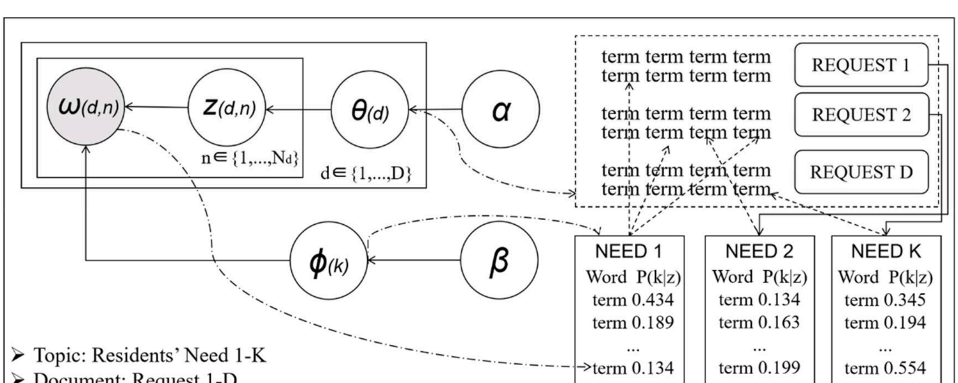

Fig. 3.2. The LDA topic generation process of residents' needs.

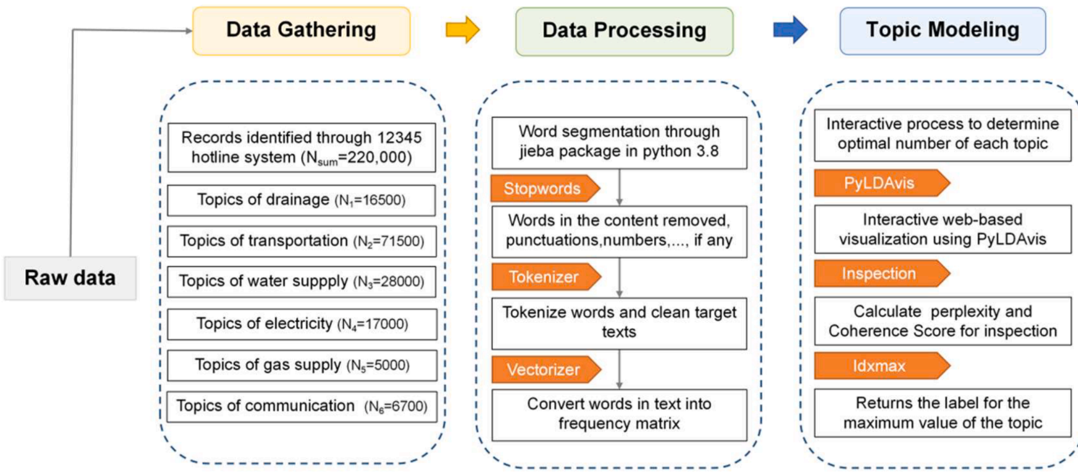

Fig. 3.3. Data processing of LDA Topic modeling.

decline; and "RD" the degree of recovery, respectively. This enables us to measure the cumulative impact and each system's ability to return to its pre-disaster performance level facing overlapping disaster events.

3.4. *Infrastructural dynamic responses to residents' needs in hyperedges*

The hypernetwork model integrates dynamic model and complex network model, adeptly processing cross-layer and interconnected data. First proposed by computer scientist Peter Denning in 2012, the hypernetwork shows its efficacy and excellent ability in various fields, including transportation, supply chain, and knowledge networks. This approach not only simulates urban recovery processes but also reveals interdependencies between residents' needs and infrastructure responses through modeling and simulation. Therefore, this study adopts the hypernetwork model to assess infrastructural dynamic responses to critical residents' needs for resilience.

Based on hypernetwork theory, this study constructed a model with three layers consisting of vertex sets and hyperedge sets. These layers represent residents' needs, urban performance, and the built environment. During the restoration process, the degree of residents' needs satisfaction is influenced by urban performance. Additionally, urban performance is affected by infrastructure systems in the built environment. The study developed a hypernetwork model encompassing the residents' needs sub-network, urban response sub-network, and built environment sub-network, as depicted in Table 3.1. In this model, the residents' needs sub-network is formed by clustering residents' appeal data using LDA modeling. following the assessment of needs evolution, the urban response sub-network's nodes are formed by the results of need satisfaction, as depicted by the urban performance curve. The built environment sub-network's nodes comprise infrastructural response feedback data and engineering entities corresponding to each resident's request.

To facilitate the hypernetwork, our study utilizes hyperedges to connect heterogeneous elements across sub-networks, allowing the grouping of multiple nodes. Unlike traditional network analyses that prioritize critical nodes, hyperedges drives the evolution of residents' needs and investigates the interplay between needs and infrastructural response during the restoration process. Data from each resident's request, related feedback, and infrastructure responses within one document, creating a hyperedge between heterogeneous subnetworks. Records or documents, as the primary source of data from residents collected by government proxies such as social media, hotlines, or websites, yield hundreds of thousands of records following rainstorm disasters.

The sequences of states and transitions are the system dynamics (Battiston et al., 2020). Using hyperedges, it becomes possible to model changing networks and their temporal dynamics. In a hypergraph, the state is represented by a hyperedge association matrix H, capturing the sub-network's structure at a given time. State transitions in the hypergraph occur with changes in the hyperedge, namely, when tokens are produced or consumed. This mirrors the evolution of needs influenced by the dynamic response of infrastructure during the recovery process. This study examines the dynamic temporal evolution of hypernetwork structures, focusing on growth and change patterns of hyperedges, by considering the static structures at various points and their dynamic evolution over time.

1) hyperedge degree, similarity, and distance were used to track the intensity, patterns, and variations in hyperedge interactions. The hyperedge degree represents the number of non-orthogonal columns that correspond to the given hyperedge. The formula is as follows,

$$\text{Hyperedge degree} = \sum_{j=1}^{|E|} \operatorname{sgn}\left(\sum_{k=1}^{|V|} h_{ij}h_{kj}\right) = \sum_{j=1}^{|E|} \operatorname{sgn}(H_i H_j)$$

The hyperedge similarity measures the degree of similarity between the entities that a given hyperedge and others. The similarity in two hyperedges can be expressed as the cosine between vectors. The similarity between SE_i and SE_j is as follows,

$$\text{Hyperedge similarity}_j = \frac{\sum_{k=1}^{|V|} h_{ki} \times h_{kj}}{\sqrt{\left(\sum_{k=1}^{|V|} {h_{ki}}^2\right) \times \left(\sum_{k=1}^{|V|} {h_{kj}}^2\right)}}$$

Hyperedge distance characterizes the control of network flow between node pairs along the shortest path. The distance between SE_i and SE_j is defined as the shortest path connecting the two hyperedges through their common nodes.

$$DIS_i = \frac{\sum_{j=1}^{|E|} DIS(SE_i, SE_j)}{|E|}$$

Table 3.1
Networks and vertices in the hypernetwork model.

Network	Vertex	Group
Residents' needs	Needs	Layers of residents' needs
Urban performance	Functionality	Serviceability of infrastructures
Built environment	Infrastructure systems	Engineering elements of infrastructure systems

Where, the association matrix H is represented as |V| nodes × |E | hyperedges. The row i corresponds to the i th node and the column j corresponds to the j th hyperedge.

2) clustering and evolution coefficients were utilized to reflect fluctuations in migration levels of hyperedges during post-disaster recovery. Our temporal evolution analysis provides insight into the relationship between linked hyperedges and inherent attributes of the built environment from a temporal perspective. Overtime, new hyper-triangles emerge while old ones disappear. These transformations are captured by the evolution coefficient, which signifies alterations in the focal state. Additionally, the fluctuations in information stemming from changes in hyperedges offer valuable insights into the dynamics of the urban recovery process. We employ the following equations to assess the robustness of connections within the hypernetwork (clustering coefficient C_t) and explore changes in structural attributes (evolution coefficient E_t) driven by alterations of hyperedges:

$$C_t = \frac{6 \times \text{number of triangles}}{\text{number of paths of length two}}$$

$$E_t = \frac{6 \times \left(\text{number of hyper\_triangles}\right)_{t-1}}{\left(\text{number of paths of length two}\right)_{t-1}} \times \frac{\text{hyper\_triangles}_t + \text{hyper\_triangles}_{t-1}}{\left(\text{number of hyper\_triangles}\right)_t}$$

Where, a hyper-triangle is defined as a sequence of three distinct vertices and hyperedges of the form. The clustering coefficient C_t assesses the robustness of connections within a hypernetwork, which can be determined by the fraction of nodes engaged in the creation of hyper-triangles. The computation is founded on the average transitivity coefficient calculation within the field of transfer science. Moreover, the evolution coefficient E_t explores changes in the structural attributes driven by the alterations of hyperedges, aiming at restoring the satisfaction of residents' needs.

4. Results

4.1. Hierarchical residents' needs reflected in LDA topics

To categorize residents' needs during disaster recovery, data from three successive 18-day rainstorm events were selected. All of the data were directly related to or impacted by the disaster, and a total of 220,567 data entries were chosen. The resident-generated data were processed as documents to create a document-word matrix, calculating the frequency of occurrence for various needs-related topics. Subsequently, LDA topic modeling was applied to each infrastructure type, illustrated in Section 3.2, enabling the identification of distinct topics across various infrastructure systems.

The study categorized eighteen needs indicators of various infrastructure systems: six were related to drainage and power supply systems, eight were associated with transportation and water supply systems, and four covered areas such as communication and gas, as detailed in Table 4.1. Perplexity metrics were used to calculate the optimal number of topics associated with these infrastructures. Building on this, the needs were categorized into three layers encompassing eighteen indicators, as illustrated in Fig. 4.1. Appendix A featured the visualization of LDA process outcomes, which showcase the residents' appeal terms across various topics, thereby highlighting residents' concerns within each topic.

In the safety and health needs layer, six key indicators have been identified: wiring hazards mitigation in the electricity system, water pipe bursts prevention and water quality and odor control in the water supply system, road safety in the transportation system, residential flooding prevention in the drainage system, and security hazards in others. These indicators represent the most urgent needs of residents following rainstorms. Failure to address these basic needs could pose a threat to residents' lives. For example, security hazards on roads and in transportation frequently arise after heavy rainstorms, highlighting the critical importance of urban responses to these unsafe conditions. Addressing these safety and health needs is critical, as it demonstrates a city's ability to maintain its basic quality of life following a rainstorm, taking precedence over all other needs.

Table 4.1
Needs indicators for infrastructure systems across three layers.

Systems	Basic needs layer	Social needs layer	Advanced needs layer
Electricity	Need 1: Wiring hazards mitigation	Need 2: Power outage avoidance	Need 3: Stable power voltage
Water supply	Need 4: Water pipe bursts prevention Need 5: Water quality and odor control	Need 6: Water outage avoidance	Need 7: Stable water pressure
Transportation	Need 8: Road safety	Need 9: Efficient resident travel	Need 10: Tidy road appearance Need 11: Reliable bus schedules
Drainage	Need 12: Residential flooding prevention	Need 13: Flooding on roads mitigation	Need 14: Clean and orderly living environments
Gas and others	Need 15: Safety of gas supply facilities	Need 16: Gas outage avoidance Need 17: Signal outage avoidance	Need 18: Convenient elderly care services

In the social needs layer, six key indicators includes: power outage avoidance in the electricity system, water outage avoidance in the water supply system, efficient resident travel in the transportation system, flooding mitigation in the drainage system, gas and signal outage avoidance in other systems. These indicators represent the social life needs of residents during recovery, highlighting how daily necessities are impacted by prolonged rainstorms. Failure to address these needs can significantly disrupt residents' social lives, as exemplified by power outages resulting from intense precipitation. It is imperative for residents affected by these outages to restore their social routines.

The civic engagement layer comprises six advanced needs indicators: stable power voltage in the electricity system, stable water pressure in the water supply system, tidy road appearance, reliable bus schedules in the transportation system, clean and orderly living environments in the drainage system, and convenient elderly care services in various systems. These indicators reflect the residents' pursuit of advanced civic engagement in urban governance. For instance, the emphasis on roadway appearance signifies the demand for an aesthetically tidy urban environment. Addressing these advanced needs of urban residents enables the restoration of high-quality life in the city. This approach aligns with the "Build Back Better" strategy in disaster recovery (Fernandez & Ahmed, 2019; Dube, 2020).

4.2. Urban performance curves during rainstorm recovery

This section presents the overall performance curve over three rainstorm events in Beijing City (see Fig. 4.2). The first 60 mm rainfall event lead to a rapid decrease in residents' satisfaction degree, reaching the lowest point on July 12, and gradually returning to baseline around July 16. The second 50 mm rainfall event on July 17 resulted in another decline, with a partial rebound before being interrupted by the third 35 mm rainstorm shock. Following calculation, the city displayed urban resilience values of 0.52, 0.55, and 0.60 across three rainstorm events, indicating an increasing trend. The curve shows a sharp decline in urban performance after each rainstorm, followed by several days of recovery, highlighting the challenges in maintaining residents' quality of life

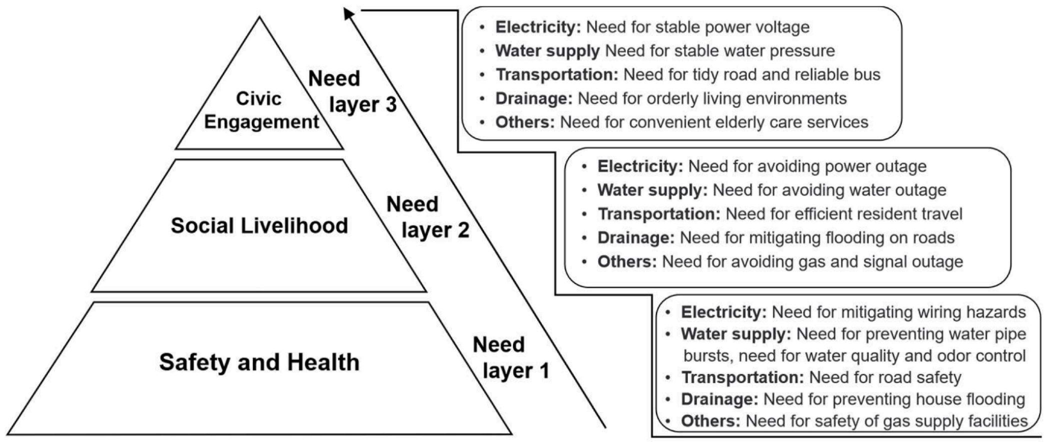

Fig. 4.1. Hierarchical residents' needs of each infrastructure system.

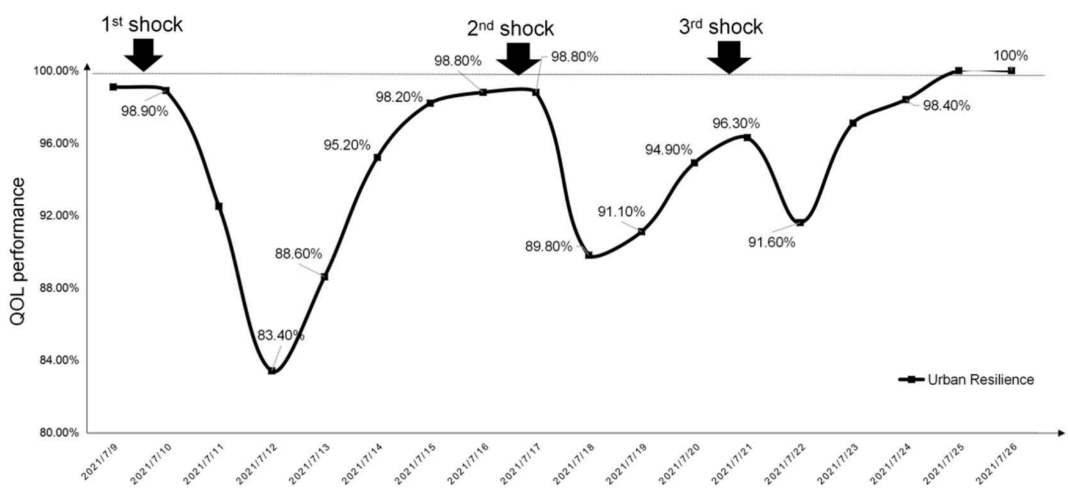

Fig. 4.2. Performance curves across three rainstorm events.

during crisis.

The infrastructure-level results showed that the drainage, transportation, and electricity systems displayed resilience patterns similar to the overall urban resilience, showing an upward trend over time (see Fig. 4.4). During the initial rainstorm event, the drainage system, transportation and electricity system demonstrated resilience values of 0.31, 0.47 and 0.71, respectively. The transportation showed a notable one-day lag compared to the drainage system. In addition, the gas and communication systems remained stable and did not exhibit fluctuations in performance curves.

However, a notable anomaly was observed in the resilience value of the water supply system. The resilience scores for the first two events were 0.67 and 0.56, indicating decreasing resilience with slower recovery and deeper impact during continuous rainstorms (see Fig. 4.3). The trend of the water supply system resilience is concerning and seemingly contradicts common sense. Upon analyzing the data, it was discovered that older residential areas in urban and suburban regions, along with some towns, relied on self-provided wells for water supply. This suggests that the municipal water supply pipe network refurbishment project has not been fully implemented in Beijing. As a result, these self-provided wells become vulnerable during the flood season, affecting water quality. The situation is exacerbated during rainstorm events.

To enhance understanding of resilience across various spatial characteristics, we assessed differences in system performance and recovery time in downtown and suburban areas. T-test results reveal significant spatial disparities in the recovery times of both drainage and water supply systems ($p < 0.001$), as shown in Fig. 4.5. This indicates that recovery times for these systems were longer in the downtown area than in the suburban area. The disparity observed may stem from the complex, interconnected system structures in urban areas, which requires more time and resources for restoration. Inadequate drainage infrastructure was identified as the primary cause of the waterlogging issue. For example, in one case we studied, overflow from a sewage well, led to blockage of the sewage pipes by mud and sand. This is also corroborated by real-world observations. Following the July 11, 2021, rainstorms, the government reported approximately 500 waterlogged areas, about 67 % of which were in downtown areas. It took approximately 7 days to remove accumulated water in downtown areas, compared to 5 days in suburban areas.

Nonetheless, the power supply systems were an exception. The recovery duration did not significantly differ between regions, suggesting that the power supply coverage in the case is relatively comprehensive. This observation lends further support to the conclusion presented in Fig. 4.4, where the power supply system was shown to have the highest resilience value of 0.71.

4.3. Dynamics of infrastructural responses to residents' needs represented in hyperedges

To discover infrastructural dynamic responses to critical residents' needs, we developed the hypernetwork model by implementing the process in the methodology. Table 4.2 provides a detailed listing of the

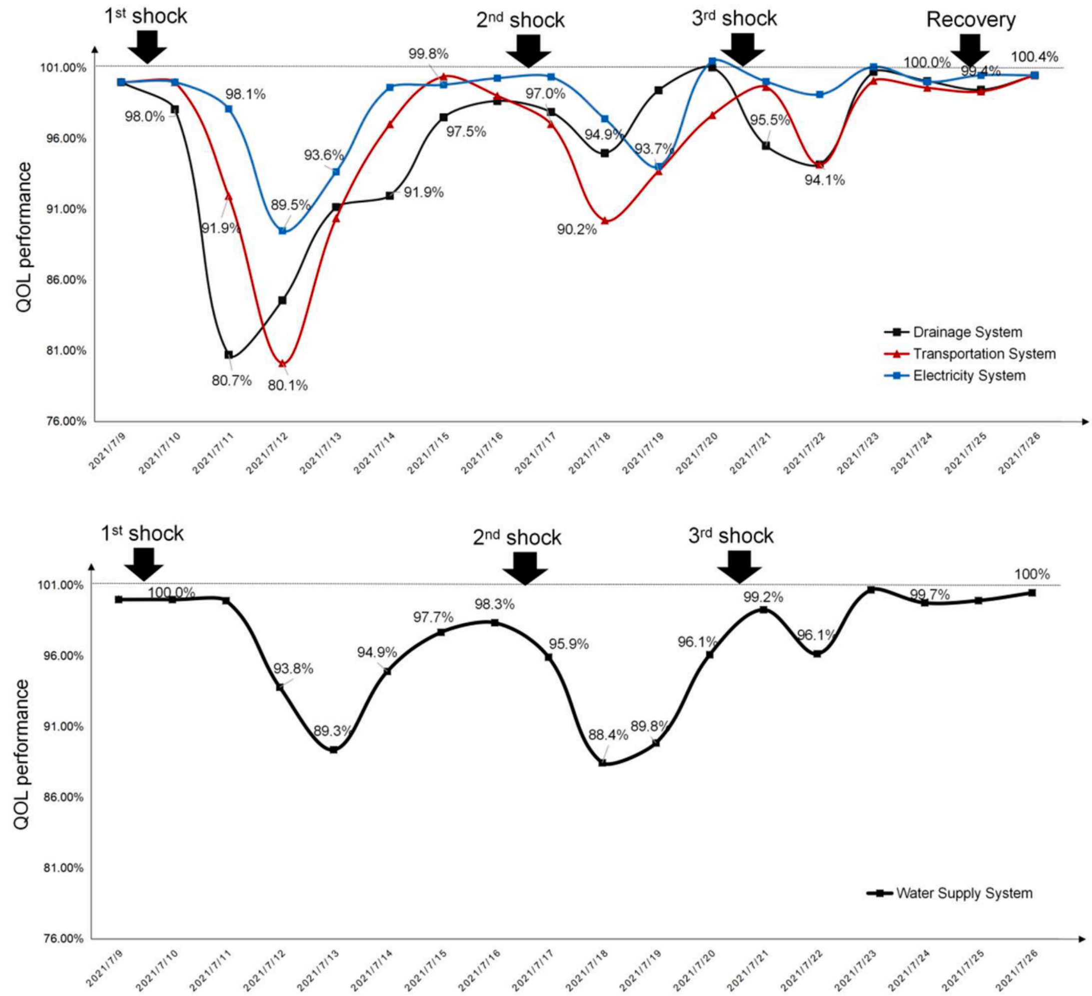

Fig. 4.3. Performance curves of infrastructure system across three rainstorm events.

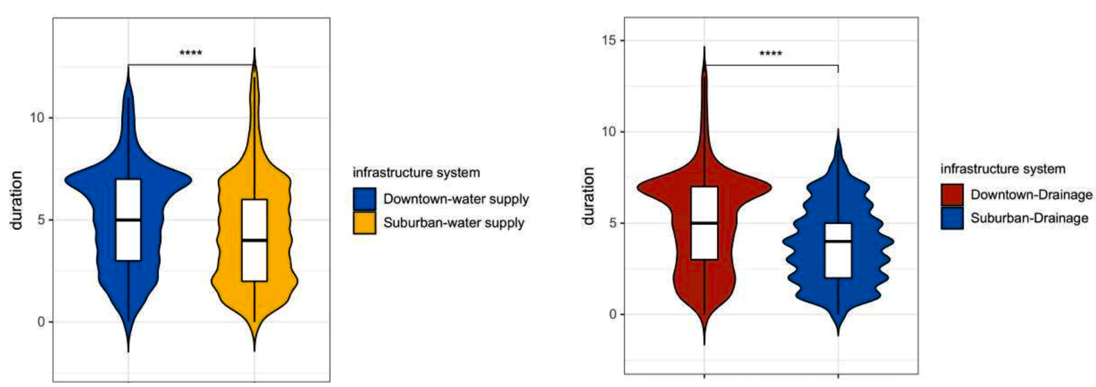

Fig. 4.4. Spatial Features of infrastructural recovery duration under rainstorms.

vertices and categories within the hypernetwork. The distribution of information across different layers follows a bottom-up logic, with each layer conveying diverse information and holding the potential to influence the layers above. Fig. 4.5 illustrates the states and transitions of hyperedges from Time 1 to Time 8 during rainstorm recovery.

We first employed structural attributes to assess the hypernetwork states. Hyperedges in the hypernetwork are shown in Table 4.3. The study utilized hyperedge degree, hyperedge similarity, and hyperedge distance for a scenario analysis during the rainstorm event T_{1-5}. Fig. 4.6 presents the computed results for each indicator. The analysis shows that, for hyperedges HE_{1-3} and $_{7-12}$, the hyperedge degree exceeds 10 and the hyperedge similarity surpasses 0.5. The higher value signifies a stronger correlation between safety and health needs with other hyperedges, facilitating the centralized allocation of resources to fulfill the basic residents' needs. In terms of hyperedge distance, a high value suggests a lengthy path between a specific hyperedge and others, complicating cross departmental resource coordination in rush-repair of different infrastructure systems. In the case, $HE_{12,14}$ and HE_{23-25} have the maximum values exceeding 2, emphasizing specific operational requirements for certain needs, such as street light maintenance, and

Table 4.2
Vertices and categories in the hypergraph.

Network	Vertex	Categories
Residents' needs	$VN_{1–3}$	Safety and health, social livelihood, and Civic engagement
Urban response	$DS_{1–4}$, $TS_{1–4}$, $ES_{1–4}$, $WSS_{1–5}$	Topics of urban response in each infrastructure system
Built environment	VB_1	Manhole cover, rainwater grate, drainage pipeline, et al.
	…	…
	VB_5	Collapsed road, pothole, damaged, muddy road, et al.
	…	…
	VB_8	Electric wires, transformer, electric box, circuit, high-voltage line
	…	…
	VB_{13}	Burst pipe, leaking pipeline, water meter, et al.
	VB_{14}	Private well, associated pipeline construction, et al.

water supply operation.

Subsequently, we utilize hyperclustering and evolution coefficients to pinpoint dynamic shifts with critical hyperedges, which are reflected in fluctuations in urban performance curves. The hyperclustering coefficient serves as an indicator of interconnections among hyperedges at various network layers. A higher value indicates a greater number of needs requiring resolution. Illustrated in Fig. 4.7, the hyperclustering coefficient progressively rose between July 10 and 12, peaking at 0.375. In contrast, from July 13 to 15, it declined to its lowest value of 0.3. This trend totally contrasts with the performance curve depicted in Fig. 4.3, indicating an inverse relationship between these trends.

Moreover, the evolution coefficient investigates hyperedge transformations in the recovery process and reflects the gradient of change of the urban performance curve. For instance, the coefficient reaches 0.198 by July 11, with the hyperedge $\{V_{N1},\ DS_2,\ V_{B1}\}$ acting as the driving force in this transformation. During the recovery process, the coefficient increases to 0.237 by T_4, with three driving hyperedges emerging: $\{V_{N1},\ TS_1, V_{B1}\}$, $\{V_{N1} - TS_2 - V_{B9}\}$, and $\{V_{N1} - WSS_1 - V_{B12}\}$. This indicates a newly collaborated correlation of water and electricity systems during this phase. Thus, a higher coefficient corresponds to a quicker transformation of hyperedges, leading to a faster recovery of urban performance.

Through capturing the hyperedges dynamic in Table 4.4, the study reveals what infrastructural resources should be allocate according to dynamic residents' need priority as the restoration stage changing. The first rainstorm, which lasted from T_1 to T_5, led to a decline in residents' satisfaction during $T_{1–3}$ and rebounded during $T_{3–5}$. The second and third rounds of the rainstorm subsequently occurred in $T_{5–6}$ and $T_{6–7}$, respectively.

During the first rainstorm $T_{1–5}$, the critical hyperedge is HE_7 at $T_{1–2}$, addressing residents' need for stable power is the most pressing, necessitating repair resources for electricity system. In the subsequent phase $T_{2–3}$, critical hyperedges shift to $HE_{2,8,9}$, with critical needs changing to housing leaks and power outages, the focus of resource allocation should be the drainage and power supply systems. During phase $T_{3–4}$, critical hyperedges transit to $HE_{5,8,12}$, corresponding with a shift in critical needs towards water logging, the allocation should be the transportation and water supply systems. In the phase $T_{4–5}$, critical hyperedges shift to HE_6, reflecting a shift in critical needs to residential traffic, resource allocation should prioritize transportation systems. During the second rainstorm $T_{5–6}$, the core hyperedges are $HE_{3,8}$, the critical demands are power outage and waterlogging, necessitating a focus on restoring drainage and power supply systems. During the third rain $T_{6–7}$, the critical hyperedge are $HE_{8,11}$, emphasizing the need to prioritize the restoration of the water supply system.

Accordingly, the engineering entities requiring repair in each infrastructure system at each stage are detailed in Table 4.5 and Fig. 4.8. During the first rainstorm, rush-repairs are needed for pipeline issues in the drainage system. Specifically, manhole cover issues constituted 26.9 % of the problems in $T_{2–3}$, and potholed roads represented 24.6 % in $T_{3–4}$. During the second rain, the most critical issues are pipeline problems in the drainage and water supply systems. Manhole cover issues accounted for 14.9 %, and private well problems for 19.3 %. During the third rain, supply pipe and private well issues in the water supply system were the most pressing, accounting for 21.8 % and 20.2 %, respectively.

5. Discussion

This study pioneers quantitative methods to model the dynamic interplay between residents' needs and infrastructure response in the post-disaster recovery. By incorporating appeals and feedback data, we quantified the residents' satisfaction degree within each infrastructure system, deriving an urban performance curve. The incorporation of hyperedge analysis facilitates a nuanced understanding of the intricate relationships, enabling adaptive resource allocation for infrastructure rush-repairs. The human-centric approach enhances urban resilience by addressing residents' needs more effectively.

5.1. Multi-layered structure of residents' needs

Exploring residents' needs during recovery reveals a multi-layered structure using empirical data-driven methods, resonating with theoretical frameworks by Gilbert et al. (2015), Zhao et al. (2022), and Cardoso et al. (2022). This study further observed that residents' appeals follow a pyramid pattern of hierarchy, ranging from basic needs to societal and civic concerns during post-disaster periods. Specifically, under normal daily conditions, residents' appeals are evenly distributed across the three layers, each accounting for one-third of the total. However, during heavy rainfall events, a notable shift occurs in this distribution: Safety and health needs surge to 50 %, while social needs maintain at one third, and advanced civic needs decrease to 20 %. This transformative pattern underscores a critical insight—during crises, basic needs assume paramount importance, forming the foundational tier of the pyramid. Social and advanced needs subsequently follow in significance.

The observed resilience in urban infrastructure substantiates and reinforces this hierarchical shift. Notably, the diminished resilience of drainage and transportation systems is primarily attributed to the heightened vulnerability of road safety and residential flood protection—both essential components of basic needs during rainstorms. This hierarchy plays a pivotal role in guiding urban recovery strategies, ensuring that resource allocation aligns seamlessly with the prioritization of residents' needs. Recognizing the prominence of basic needs during crises is imperative for crafting effective recovery plans and efficiently deploying resources to safeguard essential aspects of urban life.

5.2. Dynamic urban performance curve

The urban performance curve tracks the evolution of residents' needs during rainstorms from appeal report to resolution, offering a dynamic view of urban performance dynamics. Unlike static indicators adopted in prior studies (Podesta et al., 2021; Pan et al., 2022), this approach measures satisfaction levels for ongoing needs, emphasizing the importance of responding to evolving needs. Additionally, our results revealed infrastructure-level resilience trends, guiding adaptive recovery strategies to enhance overall urban functionality. During the three rainstorms, the drainage, transportation, and electricity systems exhibited an upward trend in resilience. Nevertheless, a counter-intuitive resilience pattern manifested in the water supply system, characterized by decreasing resilience, slower recovery, and deeper

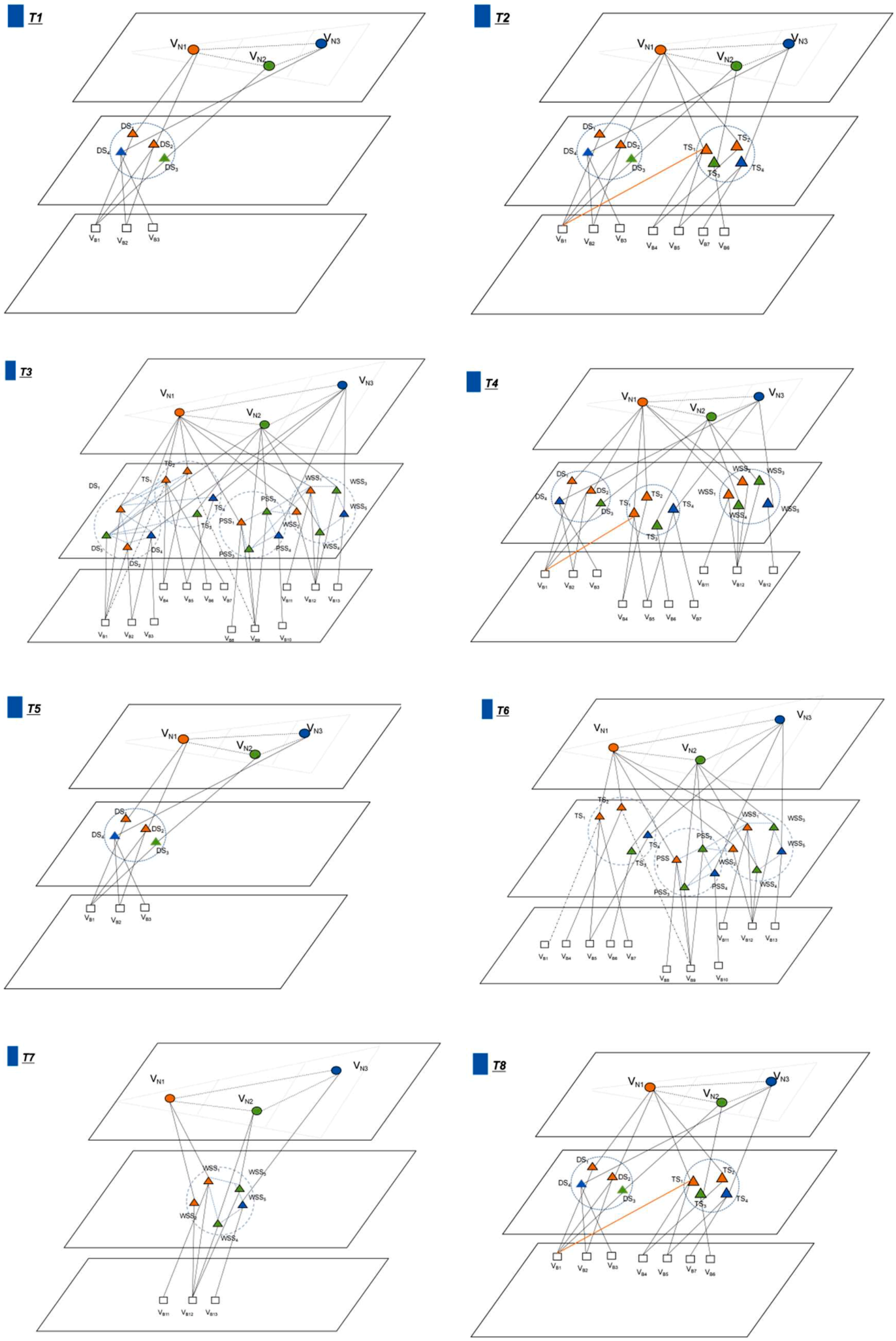

Fig. 4.5. Hyperedge shifts influenced by rainstorm events (T_1 to T_8). Note: T_1 represents the rainstorm occurrence time; and T_8 represents the recovery time of all rainstorm events.

Table 4.3
Hyperedges in the hypernetwork.

Hyperedge	Residents' needs Sub-Network	Urban Response Sub-Network	Built environment Sub-Network
HE_1	VN_1	DS_1	VB_1
HE_2	VN_1	DS_2	VB_1
…	…	…	…
HE_6	VN_3	DS_4	VB_3
…	…	…	…
HE_{24}	VN_2	WSS_4	VB_{13}
HE_{25}	VN_3	WSS_5	VB_{14}

impact in rainstorms. This unexpected phenomenon can be attributed to the incomplete renovation of city's water supply pipelines that year. The inadequacies in the infrastructural led to self-provided wells exceeding their capacity during continuous rainstorms, resulting in water quality issues and subsequent water outages.

5.3. Hyperedge analysis for adaptive allocation

Hyperedge analysis uncovers the dynamic interplay between evolving residents' needs and critical infrastructure systems, enabling tailored emergence repairs, that is, shifting focus based on evolving needs during recovery. Demonstrated in our findings, initially, the repair efforts should be centered on addressing pipeline and road issues. However, as the recovery process progressed, the focus should be shifted towards repairs in housing, transportation, and water supply. This shift emphasizes the crucial necessity for adaptable and responsive disaster management strategies capable of effectively address changing needs during crises.

Moreover, our observations highlight that residents often identify issues such as damaged rainwater grates or potholed roads before these

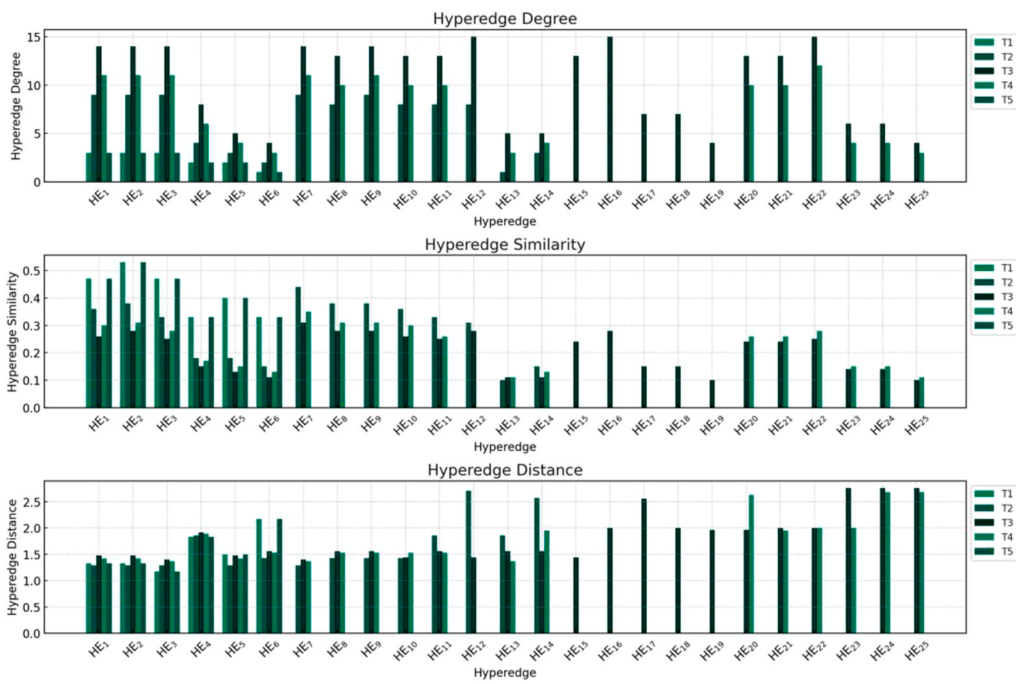

Fig. 4.6. Hyperedge degree, hyperedge similarity and distance during the recovery.

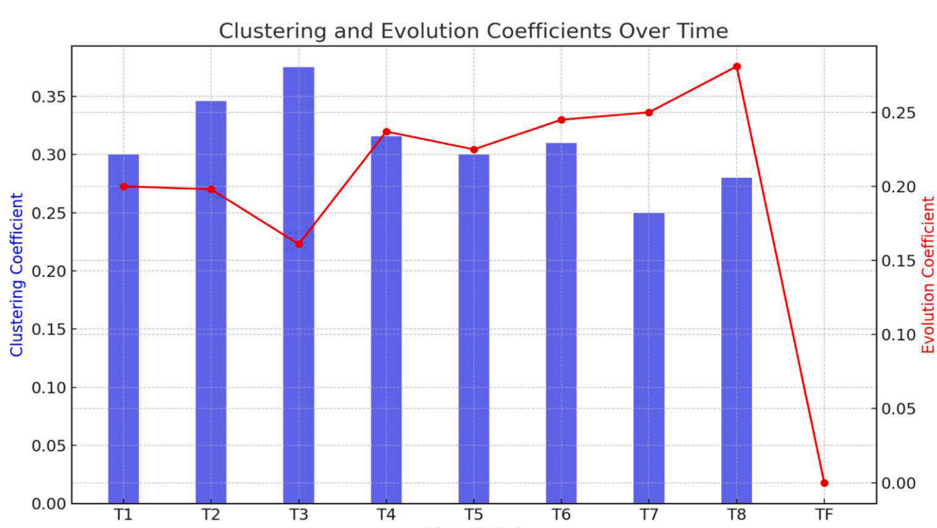

Fig. 4.7. Hyperclustering and hyperevolution coefficients during the recovery.

Table 4.4
Relationships between residents' needs, urban performance, and infrastructures based on critical hyperedges.

	T_{1-2}	T_{2-3}	T_{3-4}	T_{4-5}	T_{5-6}	T_{6-7}
Critical Hyperedge	HE_7	HE_2, HE_{8-9}	HE_5, HE_8, HE_{12}	HE_6	HE_3, HE_8	HE_8, HE_{11}
Residents' needs	Advanced needs	social needs Basic needs	social needs	Advanced needs	social needs	Basic needs
Urban performance	Unstable power voltage	power outage, grid security, waterlog, house leaks	waterlog, residential traffic, water outage	residential traffic	power outage, waterlog	water quality safety
Infrastructure system	Electricity	Drainage, Electricity	Transportation, Water supply	Transportation	Drainage, Electricity	Water supply

Table 4.5
The changing entities of each infrastructure system.

Infrastructures	Entities	T_{1-2}	T_{2-3}	T_{3-4}	T_{4-5}	T_{5-6}	T_{6-7}
Drainage system	manhole cover	11.2 %	26.9 %	20.5 %	17.1 %	14.9 %	9.3 %
	sewage well	7.6 %	37.3 %	18.4 %	10.8 %	17.8 %	8.1 %
Transportation system	Potholed road	15.7 %	14.9 %	24.6 %	20.3 %	9.6 %	14.9 %
	Collapsed Road	8.8 %	15.9 %	24.8 %	23.9 %	11.5 %	15.0 %
Electricity system	Circuit	16.8 %	35.2 %	12.8 %	13.1 %	10.1 %	12.1 %
	switch	19.5 %	31.4 %	16.8 %	11.9 %	14.1 %	6.5 %
Water supply system	Supply pipe	10.6 %	12.0 %	21.3 %	18.5 %	15.7 %	21.8 %
	Private well	15.4 %	15.4 %	20.5 %	9.1 %	19.3 %	20.2 %

problems exacerbate during rainstorms. The resident-driven awareness functions an early warning system, enabling quicker responses from urban management teams—a concept we team "humans as sensors". The dynamic infrastructural responses strategies not only ensure the maintenance of urban functionality during crises but also contribute to the early detection of potential problems that could adversely affect urban life.

Our hypernetwork analysis also corresponds with Max-Neef's Needs Theory, enhancing various need satisfiers to meet residents' needs (Max-Neef, 1991). This theory emphasizes the dimensions of being, interacting, doing, and having, to align urban resilience strategies with human needs. Resonating with this theory, intervention strategies should adjust residents' expectations and reshape the needs pyramid (being), enhance urban performance through executing efficient deployment and allocation during disasters (interacting and doing), and strengthen the physical assets in the urban environment (having).

5.4. Limitations and future research directions

This study acknowledges several limitations. Firstly, the practical application of hyperedges for dynamic resource reallocation is constrained by governmental coordination expenses and the costs incurred in implementing these adaptive infrastructural rush-pair strategies. While our findings offer valuable insights, the feasibility and scalability of such dynamic approaches should be evaluated in light of budgetary constraints and resource availability.

Secondly, the absence of social demographics in our analysis represents a limitation in understanding the nuanced impact of urban natural disasters. Future studies are encouraged to incorporate individual perspectives and consider the influence of social demographics on residents' needs and recovery experiences. Comprehensive field studies would be instrumental in validating and expanding upon our current findings.

Thirdly, regional characteristics play a crucial role in shaping urban resilience, and our framework's direct transferability to other areas warrant considerations. However, data from both downtown and suburban areas are leveraged in this study to assess performance and recovery disparities to increase the generalization of our findings. In the future, a more detailed spatial analysis is encouraged for a comprehensive understanding of regional variations. Benefiting from that, the applications of our framework could account for unique regional factors, thereby ensuring its effectiveness in diverse geographical contexts.

6. Conclusion

In this study, a research framework was constructed to quantitatively associate emergency governance and dynamic infrastructure repair with the residents' needs evolution in post-disaster recovery, providing empirical insights for resource allocation in infrastructure rush-repair situations. Utilizing LDA topic modeling, this study categorized residents' needs into three layers: safety and health, social livelihood, and civic engagement, forming a basis for the urban resilience assessment. Then, we captured the dynamic evolution of these needs, reflecting changes in priorities and satisfaction levels, thereby effectively depicting urban performance curves and evaluating urban resilience. Finally, through hyperedge network analysis, our approach uncovered the infrastructural response mechanisms driving these evolving needs. This approach offers vital insights into how urban infrastructure and residents' well-being interact in the aftermath of disasters. By performing empirical study on real-life datasets comprising 220,567 records from residents' appeals in rainstorms of Beijing city, we validated our proposed framework.

The findings of this study offer several recommendations for government urban planning agencies to optimize dynamic resource allocation during the varying post-disaster stages. Firstly, agencies should formulate adaptive policies for critical infrastructural services during peak demand times, ensuring that resource allocation aligns seamlessly with the prioritization of residents' needs. Secondly, special attention should be given to address some counter-intuitive resilience patterns, such as those observed in the water supply system, by developing tailored recovery strategies. Finally, the innovation of our model, supported by hyperedge network analysis, lies in its potential for dynamic behavior analysis and for fostering a long-term understanding of the interplay between residents' needs and infrastructural responses. This approach, rooted in a bottom-up analysis of human needs and public perceptions, aligns closely with the principles of sustainability and urban transformation. We offer a valuable framework for assessing and

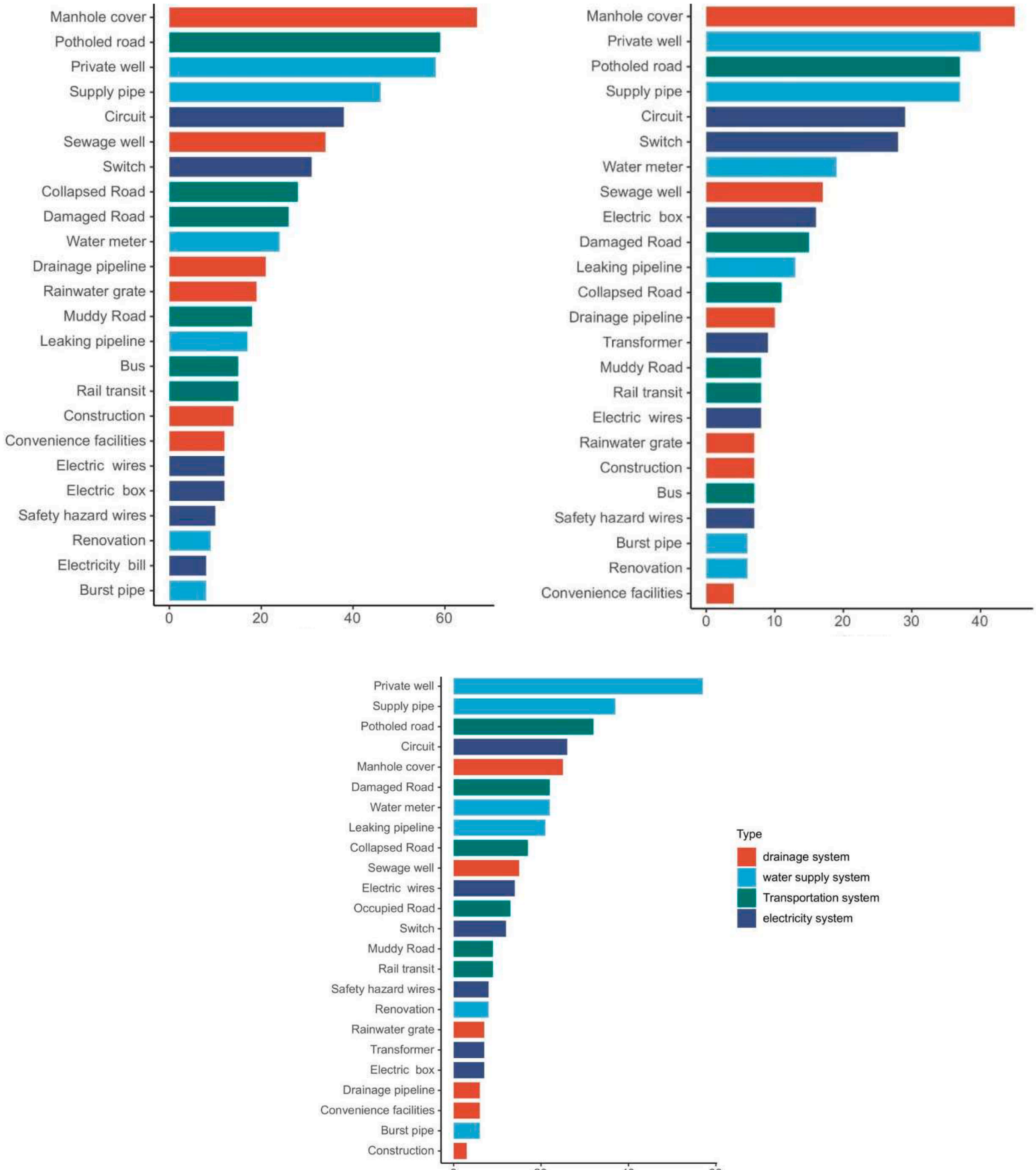

Fig. 4.8. Engineering entities impact residents' needs in infrastructure systems (1st, 2nd, and 3rd rainstorms, respectively).

enhancing urban resilience from a human-centric perspective, formulating responsive infrastructural interventions, thus paving the way for a more resilient urban future.

CRediT authorship contribution statement

Zeyu Zhao: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Xiaoshan Zhou:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Yuhan Zheng:** Writing – original draft, Methodology, Investigation, Formal analysis. **Tianguang Meng:** Writing – review & editing, Resources, Funding acquisition, Data curation. **Dongping Fang:** Writing – review & editing, Writing – original draft, Supervision, Funding acquisition, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that there are no conflicts of interest.

Data availability

Data will be made available on request.

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