Resilience in socio-technical transportation systems: A random walk approach to demand-driven community detection in human mobility structures

Abstract

Existing scholarship on transportation resilience analysis has primarily focused on engineering resilience, often overlooking the intricate socio-technical dimensions. This oversight underscores the necessity for a more comprehensive understanding of the dynamic interplay between social, including travel behaviors, and technical infrastructure components within transportation systems. This article delves into the impact of "social shocks" on transportation systems, which are defined as disturbances affecting the social subsystem without yet affecting the technical subsystem. Drawing inspiration from C. S. Holling's ecological resilience, which signifies a system's ability to cope with change by adapting its structure and functionality, we propose a multi-level resilience assessment framework. It encompasses four mobility-related indicators: entropy (measuring network-level complexity), stationarity (assessing community compositional changes at the cluster level), and two node-level metrics — within-module degree and weighted participation coefficient — capturing location connectivity. These indicators proxy for evaluating the mobility structure and node functionality within the social subsystem. In a case study, we analyze historical smart card data to examine the mobility pattern's structural changes within Hong Kong, a rail-oriented metropolis, during a prolonged and city-wide protest. The framework and associated indicators provide an alternative perspective for transit planners and operators, allowing them to assess both the overall system and individual stations, moving beyond traditional assessments of service supply and patronage changes.

Keywords: Transportation resilience, Socio-technical; Urban structure; Community detection; Hong Kong

1. Introduction

In recent decades, resilience thinking has become a significant component of urban and transportation design (Mai and Chan, 2020; Wang, 2015). The term "resilience" originally found its roots in ecology, where it was used to measure the capacity of ecological systems to resist and absorb disturbances (Holling, 1973; Pimm, 1984). Over time, the concept of resilience has found applications in various fields, including economics, engineering, and transportation. A well-known resilience framework, as defined by Bruneau et al. (2003), characterizes resilience through the four "Rs": robustness, redundancy, resourcefulness, and rapidity. Robustness represents the strength of systems in withstanding degradation, while redundancy denotes the substitutability of network components. Resourcefulness highlights a network's ability to prevent, recognize, and cope with disturbances, and rapidity indicates the speed at which the network recovers following perturbations. In recent years, resilience has garnered significant attention for its application in the assessment of transportation networks (Ahmed and Dey, 2020; Gu et al., 2020; Janić, 2018; Mattsson and Jenelius, 2015; Mera and Balijepalli, 2020; Sun et al., 2020; Wan et al., 2018).

Urban transportation can be seen as socio-technical systems due to the intricate interaction between human and technological infrastructure elements (Amoaning-Yankson and Amekudzi-Kennedy, 2017; Chan et al., 2023a; Hickman, 2013; Roy et al., 2021; Schwanen, 2013). The socio-technical processes that compose the fabric of industrialized society are complicated by this fusion of social and technical subsystems. Consequently, decision-makers and practitioners face the challenge of adopting innovative approaches to facilitate accurate and swift decision-making for effectively managing these systems (Tsoi and Loo, 2021). Recent research has established a connection between social subsystem and resilience, enabling the examination of the far-reaching cascading effects (Jenelius, 2020; Tardivo et al., 2021; Teixeira and Lopes, 2020; Tirachini and Cats, 2020). These findings have paved the way for related studies that assess the unprecedented ripple effects of the coronavirus pandemic on both the economy and transportation infrastructures. To gain a comprehensive understanding of transportation resilience, Jenelius (2020) stressed the importance of considering both relatively understudied positive and negative demand shocks, in addition to supply shocks (Mattsson and Jenelius, 2015; Reggiani et al., 2015). While much attention has traditionally been directed towards the supply side, encompassing short-term responses (e.g., operational service adjustments (Jin et al., 2016; Tan et al., 2020)) and longer-term adaptations (e.g., the construction of new transportation infrastructure (Chan et al., 2021a; Jenelius and Cats, 2015)), a focus on demand disruptions resulting from sudden events like societal upheaval and crises can serve as valuable testbeds for the study of transportation resilience. However, the development of a practical method for resilience analysis that allows individuals to model and evaluate assessment approaches remains challenging, primarily due to the inherent complexity of socio-technical systems.

We begin with Holling's (1996, 1973) concept of ecological resilience, which represents a system's capacity to absorb disturbances without immediately altering its structure. It also encompasses the ability to transform, reorganize, or adapt to a new state or configuration following a disturbance. This concept highlights the notion that ecological systems maintain a stable operational range in which they can adapt to change while retaining their essential functions. Furthermore, it may involve a potential transition in the ecosystem's structure, functions, or dynamics to reach a new equilibrium. Holling also introduced the idea that multiple equilibrium points can coexist and nest within a hierarchical system, challenging the prevailing notion of a single global equilibrium. This contrasts with conventional performance indicators found in transportation literature, such as service levels. Holling's perspective paved the way for a deeper comprehension of the intricate relationship between social elements (e.g., demand and travel patterns) and technical components (e.g., network and services) within resilience theory. This viewpoint necessitates the use of multiple performance indicators, as adopted in this article. In light of this, we turn our attention to the structure of transportation networks, specifically how travelers interact with the transportation system. Recent network research (Dong et al., 2018; Wandelt et al., 2021) has unveiled significant connections between resilience and community structure. Surprisingly, these connections have not been empirically explored within transportation systems to the best of our knowledge. While recent transportation literature (Yap et al., 2019; Yildirimoglu and Kim, 2018) has shed light on how community mobility maps offer a comprehensive overview of public transit movement patterns, providing valuable insights for decision-makers in transit management, the temporal aspect of communities (such as how communities evolve over time) remains largely unexplored. A notable exception is the work of Zhang et al. (2021a), which investigates the annual changes in London's urban structure.

The socio-technical conceptualization of transportation resilience gains particular relevance when we consider social shocks to transportation systems that disrupt markets without causing physical infrastructure damage. Such disruptions typically stem from changes in societal behavior, preferences, or external factors that have a significant impact on the transportation industry (Chan et al., 2022a; Schwanen, 2021). For instance, global health crises like the coronavirus pandemic can lead to a noticeable decrease in travel demand as individuals opt to avoid unnecessary trips (Shortall et al., 2022). Measures such as social distancing and heightened public health concerns can disrupt the use of public transportation, air travel, and other modes, subsequently causing disturbances in the market (Chan et al., 2021b; Gutiérrez et al., 2021; Tsoi and Loo, 2023). These challenges prompt the need for adaptation by embracing technology, both in the social sphere (e.g., teleworking) and the technical sub-system (e.g., on-demand transport services) (Hörcher et al., 2022). Similarly, human-made events like mega sports events (Parkes et al., 2016) and political demonstrations (Chan et al., 2022a, 2023b) can induce short-term alterations in travel behavior, as individuals respond to changes in the timing of transport services and unfavorable travel conditions. The sustainability of these changes in the social subsystem is contingent upon external factors, such as permanent alterations to transit services and infrastructure (Loo and Leung, 2017). Economic recessions or financial crises can also have substantial consequences, resulting in reduced disposable income and decreased consumer spending. This, in turn, can lead to diminished demand for transportation services, particularly in sectors like tourism and business travel (Papagiannakis et al., 2018; Senbeto and Hon, 2020). Shifts in consumer preferences, such as the growing preference for telecommuting or remote work, can reduce the necessity for daily commuting and business-related travel (Beck and Hensher, 2021; Motte-Baumvol and Schwanen, 2024). These are aspects of the broader technical system that significantly impact market dynamics within the transportation sector. The above examples underscore the intricate relationship between the social and technical subsystems, indicating that effective management of a socio-technical transportation system requires the alignment of both social and technical components, ensuring that technology supports travel needs and accounting for the impact of individual actions through continuous improvement efforts.

A question naturally arises: How can we effectively assess the structural and functional changes within the social subsystems? Increasingly available sources of large-scale mobility data might assist with modeling human behavioral reactions to disturbances (Cheng et al., 2020; Ren et al., 2020; Zhou and Zhou, 2023; Zou et al., 2018). Detecting urban mobility structure from data (i.e., segmenting urban areas into partitioned clusters with similar mobility patterns) may be the first step toward improving our understanding of urban organization and how different parts of a city interact. This can improve decision-making and contribute to the achievement of urban sustainability, with efficient transportation systems and resilient societies. The availability of digital data in the transportation sector has allowed considerable research to improve our understanding of travel communities by identifying groups of individual users or stations that exhibit strong interconnectedness, which can be used to support evidence-based policymaking. Using a passenger transfer flow matrix constructed from smartcard data, Yap et al. (2019) delineated the spatial boundaries of transfer locations for the public transit network of the Hague, the Netherlands. They used a clustering technique to help public transit operators with schedule design and real-time controls to determine which lines to prioritize to facilitate transfers and improve synchronization. Yildirimoglu and Kim (2018) characterized the community structure of a city network using multi-layer graphs to represent the movement of disparate entities (i.e., private cars, buses, and passengers) in the Brisbane transportation network in Australia. They suggested that understanding spatial structure could assist with the detection of weak links in the network and improve the system's connectivity. Zhang et al. (2021) devised a machine learning approach using smart card data to reveal urban mobility structures in Shenzhen, China. The method synthesizes both mobility and static information in a data-driven manner, preserving the original urban topological structure and resident movement dynamics. The examples above demonstrate that emerging data still holds untapped potential for the development of new methods. With an emphasis on the need for a transferrable methodology, we use smart card data and employ multiple mobility indicators for assessing transportation resilience.

In this article, we delve into the resilience of the social subsystem within a transportation system. Our inquiry revolves around two key aspects: the preservation of social subsystems' mobility structure and the persistence of stations in their original roles after a social shock. We leverage smart card data and employ diverse mobility indicators to stand in for social structure and station functionality. This research contributes to the literature by providing an assessment of transportation system resilience that is informed by a socio-technical perspective.

2. Methodology

2.1 Community detection

Network structure shapes the flow in a system, leading to system-wide interdependencies. Therefore, a community detection method is used for spatial aggregation and pattern extraction to partition the network into smaller relatively independent areas. Specifically, an Infomap algorithm is used, as it is an efficient flow-based partitioning method for directed graphs and urban networks (Akbarzadeh et al., 2019; Bagrow and Lin, 2012; Lin et al., 2020; Zhong et al., 2014) using big data (Agreste et al., 2016) for detecting community structures. Community structure refers to the division of nodes or vertices (metro stations in our case) in a network into groups or communities, where nodes within the same community are more densely connected to each other than to nodes in other communities. At the core of Infomap is the idea of simulating random walks on the network. It assumes that a particle (or "random walker") starts at a node and moves to a neighboring node along an edge at each step (**Figure 1a**). The walker continues to move through the network, and this process is repeated many times to explore different paths. The goal of Infomap is to find the most efficient way to encode the sequences of nodes visited by these random walkers. It does this by trying to minimize the description length of the walker's trajectory. In information theory, shorter descriptions are preferable. As the algorithm progresses, it seeks to find natural boundaries within the network by optimizing the description length. It iteratively attempts to partition the network into different communities, where each community is a group of nodes that results in a more efficient description of the random walks. This process reveals the inherent duality between uncovering the cluster structure of a network and solving a coding problem: effectively labeling nodes requires partitioning $\boldsymbol{n}$ nodes into $\boldsymbol{m}$ clusters to minimize the expected description length of a random walk (**Figure 1b**).

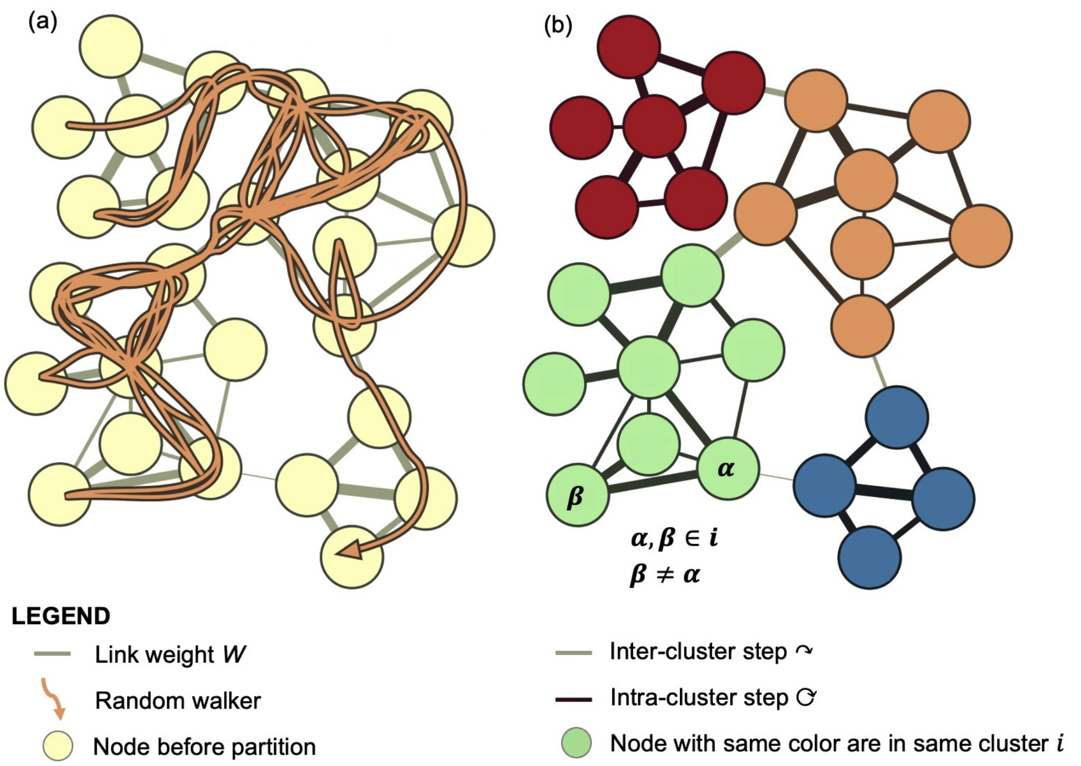


Figure 1. (a) Sample trajectory of a random walker on a network; (b) sample random permutation attempt of hierarchical partition (modified from Emmons and Mucha [2019])

The Infomap equation[1] describes the average description length for one step in the cluster configuration. $L(M)$ is the sum of the weighted average lengths of a walk inside each cluster and the steps to move from one cluster to another. It is mathematically expressed as follows:

$$L(M) = q_{\curvearrowright} H(Q) + \sum_{i=1}^{m} P_{\circlearrowright}^{i} H(P_i) \tag{1}$$

where q denotes the probability of switching clusters in each step and is defined as the sum of per-step probabilities that the random walker exits cluster i:

$$q_{\curvearrowright} = \sum_{i=1}^{m} q_{i\curvearrowright} \tag{2}$$

$H(Q)$ denotes the entropy of movements between clusters as follows:

$$H(Q) = \sum_{i=1}^{m} \frac{q_{i\curvearrowright}}{\sum_{j=1}^{m} q_{j\curvearrowright}} \log\left(\frac{q_{i\curvearrowright}}{\sum_{j=1}^{m} q_{j\curvearrowright}}\right) \tag{3}$$

$P_{\circlearrowright}^{i}$ is the sum of the fractions of the internal movements of walkers in clusters and the probability of exiting cluster ***i*** (the portion of time that a random walker spends in a cluster plus the probability of the walker exiting the cluster). It is mathematically described as follows:

$$P_{\circlearrowright}^{i} = q_{i\curvearrowright} + \sum_{\alpha \in i} p_{\alpha} \tag{4}$$

$\boldsymbol{p_{\alpha}}$ is the probability of visiting node α and equals the sum of the visiting rates over all source nodes $\boldsymbol{\beta}$ ($\boldsymbol{q_{\beta\to\alpha}}$) as follows:

$$p_{\alpha} = \sum_{\beta \neq \alpha, \beta \in i} q_{\beta\to\alpha} \tag{5}$$

$\boldsymbol{q_{\beta\to\alpha}}$ denotes the conditional probability that a random walker steps from node $\boldsymbol{\beta}$ to node $\boldsymbol{\alpha}$:

$$q_{\beta\to\alpha} = \frac{W_{\beta\to\alpha}}{\sum_{\alpha} W_{\beta\to\alpha}} \tag{6}$$

where $\boldsymbol{W}$ is the link weight, in this case the flow of the link. Cluster $\boldsymbol{i = 1, 2, \ldots, m}$ is the set of nodes, with nodes $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ belonging to it.

The final variable $H(P_i)$ is the entropy of internal movements in clusters:

[1] In the following equations, the subscript $\circlearrowright$ denotes intracluster steps (i.e., steps in which the source and target nodes belong to the same cluster) and the subscript $\curvearrowright$ denotes intercluster steps (i.e., steps in which the source and target nodes belong to different clusters).

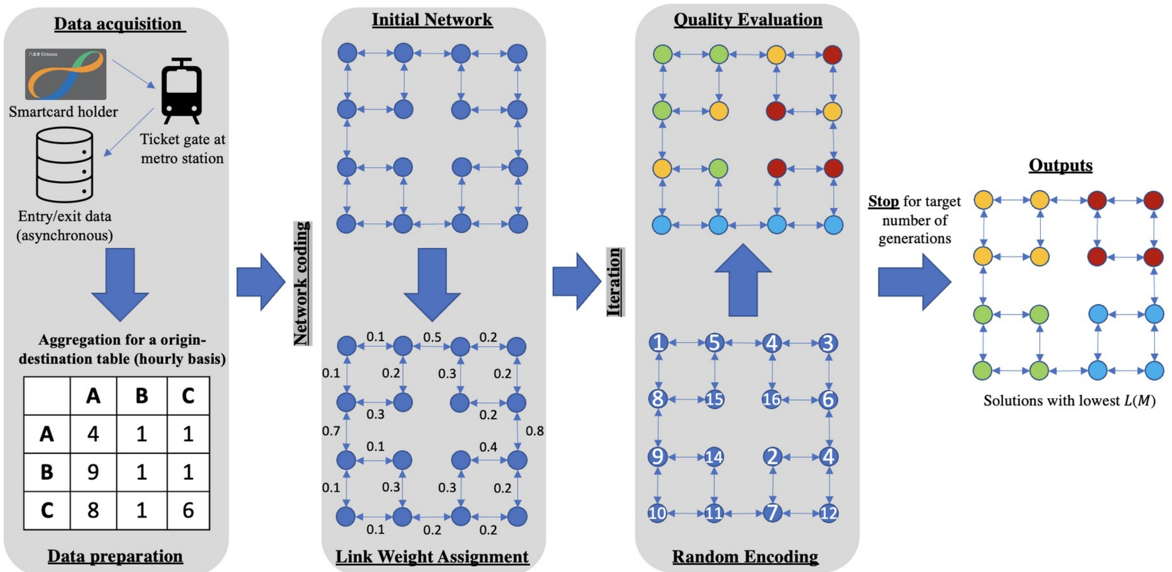
$$H(P_i)=\frac{q_{i\curvearrowright}}{q_{i\curvearrowright}+\sum_{\beta\in i}P_\beta}\log\left(\frac{q_{i\curvearrowright}}{q_{i\curvearrowright}+\sum_{\beta\in i}P_\beta}\right)+\sum_{\alpha\in i}\frac{q_\alpha}{q_{i\curvearrowright}+\sum_{\beta\in i}P_\beta}\log\left(\frac{q_\alpha}{q_{i\curvearrowright}+\sum_{\beta\in i}P_\beta}\right) \tag{7}$$

Incorporating the outputs of the above equations into the map equation yields the average description length for one step under a specific cluster configuration. Various clustering configurations are tested to find the configuration with the shortest average description length. In this study, solutions are based on the best hierarchical partition (i.e., the shortest description length) of 999 random permutation attempts. The number of clusters is determined within the algorithm (i.e., within the target number of random generations/attempts). The pseudocode of the Infomap algorithm is presented in **Table 1**.

Table 1. Infomap algorithm

Input: Graph ***G*** with each station describing a network node $\boldsymbol{N_\alpha}$ linked to every other station in the network by a set of directed edges $\boldsymbol{E_\alpha}$ weighted by a flow $\boldsymbol{w_\alpha}$ equal to the number of trips observed.
Output: Partition the network nodes $\boldsymbol{N_{1,2,\ldots,n}}$ into $\boldsymbol{M_{1,2,\ldots,n}}$ modules by minimizing the empirical flow $\boldsymbol{L(M)}$ through the network.

Procedure Infomap (G)
  $M(N_\alpha) \leftarrow M_{\alpha\beta}$
  while *min* $L(M)$ **do**
    Order $N_{1,2,\ldots,n}$ randomly
    for Each N_α **do**
      if $\exists M(N_\alpha) \leftarrow M_\beta$: $L(M)\downarrow$
      then
        $M(N_\alpha) \leftarrow M_\beta$
      else
        $M(N_\alpha) \leftarrow M(N_\alpha)$
return $M(N_\alpha)$

Illustration: Steps of adopted algorithm 

2.2 Community analysis

After identifying station communities in urban mobility networks, we analyze the station composition of communities, which requires a tool to advance our understanding of the station's importance as a travel node to a given community. We adopt the within-module degree ***Z*** (**Eq. 8**) and the participation coefficient ***P*** (**Eq. 9**) to estimate the importance of each node within and between communities (Guimerà and Amaral, 2005; Vargas and Wahl, 2014; Zhang et al., 2021b).

The within-module degree ***Z*** denotes the degree of connectivity of node ***i*** to other nodes within the module and is mathematically described as follows:

$$Z_i = \frac{k_{i,s_i} - \bar{k}_{s_i}}{\sigma_{ks_i}} \tag{8}$$

where s_i is the community to which node i belongs, k_is_i is the number of connections between node i and its community s_i, $\bar{k}s_i$ is the average of k_is_i over all nodes in s_i, and σks_i is the standard deviation of all nodes' degrees of connectivity within module s_i.

To represent stations' patterns of intracommunity connection, the weighted participation coefficient ***P*** is defined as follows:

$$P_i = 1 - \sum_{s=1}^{N} \left(\frac{k_{is}}{k_i} \right)^2 \tag{9}$$

where k_{is} is the number of links from node i to nodes in community s, and k_i is the degree of connectivity of node i.

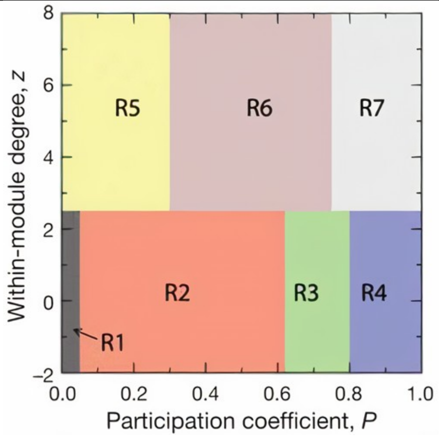
If a station is evenly connected with those of different communities, its participation ***P*** is close to 1. Conversely, if a station solely interacts with stations within its community, its participation coefficient is 0.

Following previous studies (Guimerà and Nunes Amaral, 2005; Y. Zhang et al., 2021b), we then classify stations into seven universal roles/functions according to the various combinations of ***Z*** and ***P*** values. This heuristic classification uses within-community degree ***Z*** as an identifier to decide whether a station is a hub and uses between-community degree ***P*** as an indicator to identify whether the station has the potential to be a transfer station. Thus, the role of a station can be determined by its ***Z-P*** scores. As shown in **Table 2**, the seven roles are as follows:

- Ultra-peripheral nodes (***R*** = 1) and peripheral nodes (***R*** = 2) indicate stations that have few connections to either their local areas or other travel communities.
- Non-hub connector nodes (***R*** = 3) and non-hub kinless nodes (***R*** = 4) are well-embedded stations in the network. Both groups play relatively essential roles at the metropolitan community level. ***R*** = 4 stations with high ***Z***-values are likely to be metropolitan community hubs with the potential to be future strategic transportation hubs.
- Provincial hubs (***R*** = 5) represent a group of stations that have strong and diverse connections with various external travel communities and limited interactions within its internal community.

- Connector hubs (***R*** = 6) have a medium degree of internal connections and a relatively high degree of external connections.
- Kinless hubs (***R*** = 7) play critical roles within and beyond metropolitan communities and are normally positioned as strategic transportation hubs.

Table 2. Parameters[2] of node connectivity in a network (adopted from Guimerà and Nunes Amaral, 2005; Zhang et al., 2021b)



Z-P scores diagram	Node role (*R*)	*Z*	*P*
	<u>*Non-hub*</u>		
	R = 1: Ultra-peripheral nodes	$Z < 2.5$	$P < 0.05$
	R = 2: Peripheral nodes	$Z < 2.5$	$0.05 < P < 0.62$
	R = 3: Non-hub connector nodes	$Z < 2.5$	$0.62 < P < 0.80$
	R = 4: Non-hub kinless nodes	$Z < 2.5$	$P > 0.80$
	<u>*Hub*</u>		
	R = 5: Provincial hubs	$Z > 2.5$	$P < 0.30$
	R = 6: Connector hubs	$Z > 2.5$	$0.30 < P < 0.75$
	R = 7: Kinless hubs	$Z > 2.5$	$P > 0.75$

2.3 Resilience analysis

Resilience is widely recognized as the ability to resist and recover from the effects of perturbations (Chan et al., 2021a; Gu et al., 2020; Mattsson and Jenelius, 2015). In this study, we investigate whether social subsystems maintain their mobility structure, which involves stations staying within the same community cluster, and whether stations continue to function while retaining their original roles, specifically in terms of changes in ***Z-P*** values, following a social shock.

Table 3 shows the analysis framework that incorporates the previously discussed indicators of interest:

- At the network level, ***L*(*M*)** is an indicator for movement entropy between/within clusters, while ***Q(N)*** is the total flow/patronage moving between stations in the network. The comparison between flow and entropy provides a general picture of how travel patterns during disruptions differ from those of normal days/hours.

- At the community level, q_{mt} is a modular-level indicator for flow to/from module ***m*** at time ***t***, and n_{Mt} is the dynamic number of stations ***n*** in community ***m*** at time ***t***. We are also interested in when a station moves from one community to another during the defined timeframe. This phenomenon of stations changing communities can be classified into two cases:

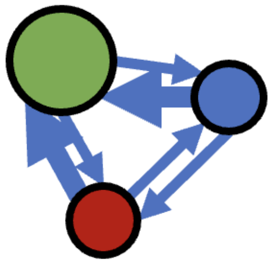
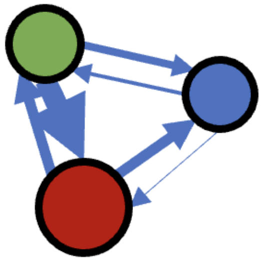
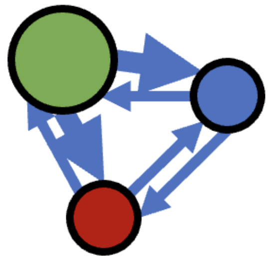
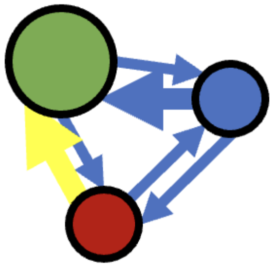
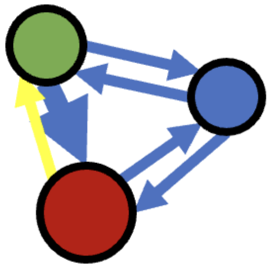
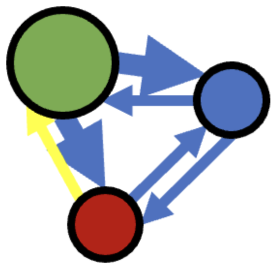
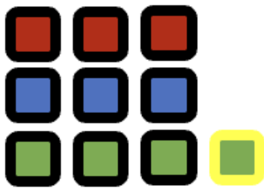
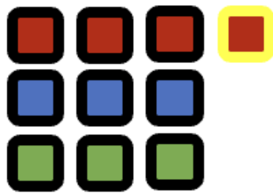
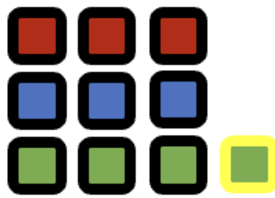
[2] We recognize that there is not a universally established method for determining the specific values of ***Z*** and ***P*** values for transport network (see a review by Zhang et al. (2021)). The current parameters are derived from a study on complex networks conducted by Guimerà and Nunes Amaral (2005), which provided examples of applications in social networks, food webs, and biochemical networks. Nonetheless, in alignment with the methodology employed in previous research by Zhang et al. (2021) specifically focusing on transport networks, we have maintained consistency to enable potential comparisons with our findings.

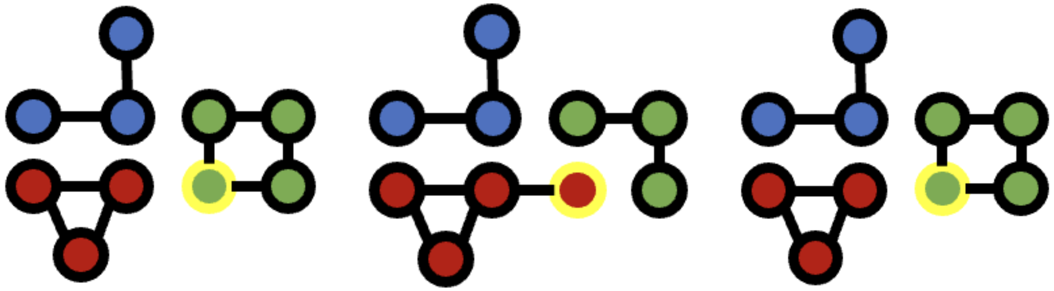
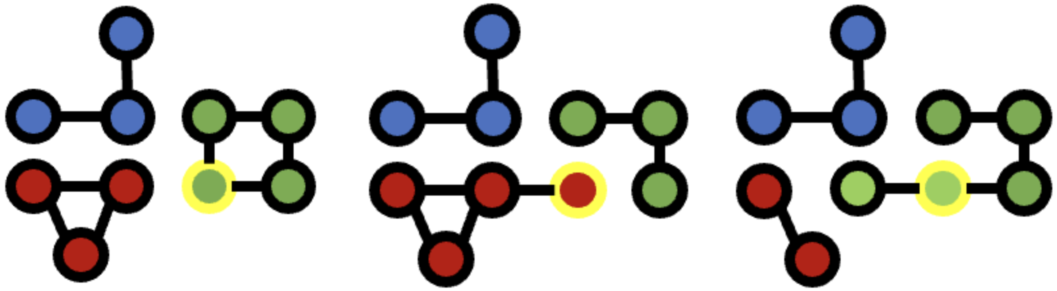
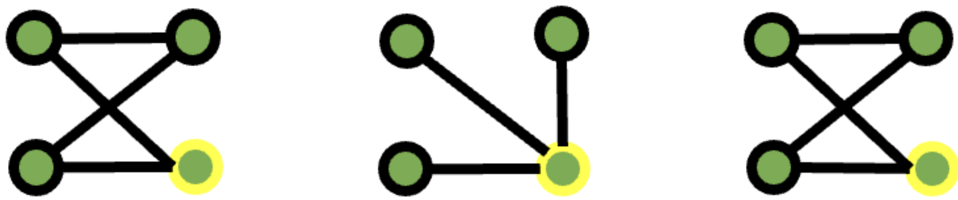
(a) Communities exchange a member (station); for example, member ***x*** in community ***s*** becomes a new member of community ***k*** and vice versa. This can occur when a group of stations is more coherent with one another than with the other stations of their previous communities.

(b) A station changes community independently (i.e., a node moves from community ***s*** to community ***k***, and no other nodes move from community ***s*** to community ***k***). This can occur when a station is disjointed from its original community before social disruption.

- At the station level, ***Z-P*** is a node-level indicator for the functionality of stations. We are particularly interested in how change in ***Z*** and ***P*** subsequently change ***R*** throughout a typical day and under a social shock to better understand the dynamics/resilience of stations in terms of their roles/functions. This study is an important example of using the ***Z-P*** scores approach to infer the stations' resilience based on the pattern of inter- and intracommunity connections.

Table 3 Analytical framework of multi-level resilience assessment of socio-technical transportation system

Property	**Description**	**Illustration**		
		Time = t_1	**Time = t_2**	**Time = t_3**
Network level				
Flow	How often agents move in the network?			
Entropy	How random/complex is the distribution of agent movement in the network?			
Community level				
Flow	How often agents move within and between communities?			
Stationarity	How often a community's composition changes?			

Disjointedness	How often a node independently changes communities?	
Coherence	How often a node changes community together with a node from its original community?	
Node level		
Functionality	How often a node changes its role in the network/community?	

2.4 The site and data

Hong Kong is a rail-oriented city where approximately 90% of daily motorized trips are made using public transportation, and the rail system (the MTR) accounts for over 40% of the average daily public transportation trips (Transportation Department, 2019). **Figure 2** shows the general spatial structure of the city, which includes Hong Kong Island, Kowloon, and the New Territories (West, North, Northeast, and East) and (Lantau) Islands. The main urban areas of the city lie on either side of Victoria Harbour. As of 2019, the MTR has 10 operational lines and 90 stations (excluding Airport Express).

We use the 2019 Anti-Extradition Law Amendment Bill (Anti-ELAB) Movement as a case study. In the realm of social movements, one important aspect of public transportation is its ability to enable the organized movement of people and resources for participation in political events. This particular movement commenced in May 2019, gradually evolving into a series of regular weekend demonstrations and assemblies (Choi, 2020). Notably, not only did the protesters make use of available transportation options for their activities, but non-protesters also had to exert extra effort in finding alternative transportation methods to maintain their routine travels (Chan and Zhou, 2021; He et al., 2024; Zhou et al., 2022). This situation led to the suspension or rerouting of dozens of bus routes due to unexpected temporary road closures, placing the burden on the transportation system to adapt to these changes. To gain insights into group travel behaviors during the protest period, we managed to obtain access to, and analyzed a few selected days' smart card data from the local metro company, which signed an agreement between one of the authors' employers. This data encompassed each metro journey made by smartcard holders, including swiping-in and swiping-out records in sequence, with measures taken to ensure anonymity and protect privacy. The recorded variables included hashed smartcard IDs, dates, entry and exit times, and station IDs for each transaction. **Table 4** shows an example of one pair of smartcard transaction records. Journeys with identical entry and exit stations were excluded from the analysis, as they were considered duplicates. Metro records are established on a daily basis. To establish a baseline for subsequent resilience analysis, we examined a typical non-protest day, selecting Sunday, June 2, 2019. This date was chosen because it was on the same day of the week and one week before June 9, which marked the onset of large-scale social protests. By comparing data from these two comparable days, we aimed to estimate the differences in travel patterns between days with and without protests, presuming that such disparities were primarily attributed to the influence of the large protests. To observe the spatial-temporal difference in ridership, the transactions/movements extracted from the Octopus card data were aggregated as movement counts between metro stations on hourly basis. These hourly origin-destination (O-D) matrices serve as input for the Infomap algorithm (Edler et al., 2024).

Table 4 Example pair of Octopus smartcard records for metro transactions

Octopus card ID	Transaction date	Transaction time	Use type	Card type	Metro station ID
0000001FF97B6016C35A	1/1/2020	15:05:53	ENT	ADL	74
0000001FF97B6016C35A	1/1/2020	15:30:45	USE	ADL	73

Note: *Octopus card ID*: unique passenger identification number (hashed to ensure privacy of smartcard holders); *Use type*: Usage/fare deduction or CSC entry; *Card type*: adult, child, disabled, senior citizen, or student; *Metro Station ID*: station entered/exited

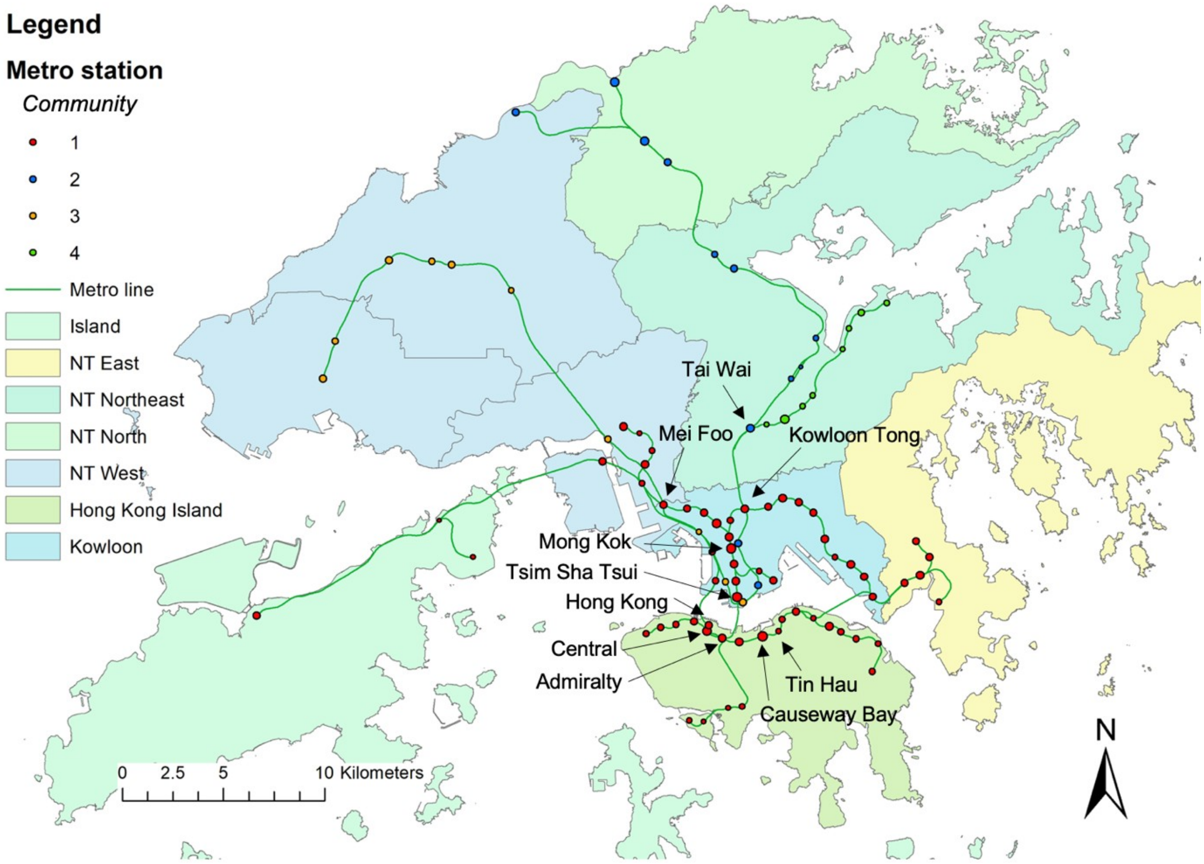


Figure 2. Spatial structure of Hong Kong and station communities on the MTR O-D network based on Infomap. The size of the station indicates its travel volume.

3. Results

3.1 Baseline analysis: Normal non-protest day

3.1.1 Network flow and entropy

We first consider the trends of and a comparison between the entropy estimated by **Eq. 1** and the patronage of the MTR network. As shown in **Figure 3**, the two indicators change differently over time. Patronage has a moderate peak from approximately 11:00 to 19:00, whereas entropy has two peaks, one in the morning (7:00 – 9:00) and one in the evening (17:00 – 19:00). Trips during the peaks are probably regular trips (i.e., common destinations with a lower complexity of travel patterns), whereas the trips during non-peak times are more random (i.e., to destinations with more complex travel patterns). This reveals the need to investigate trip patterns in a more disaggregated way to understand the underlying community structure and the potentially shifting functions/roles of stations. Protest day travel patterns and the resulting communities are discussed in later sections.

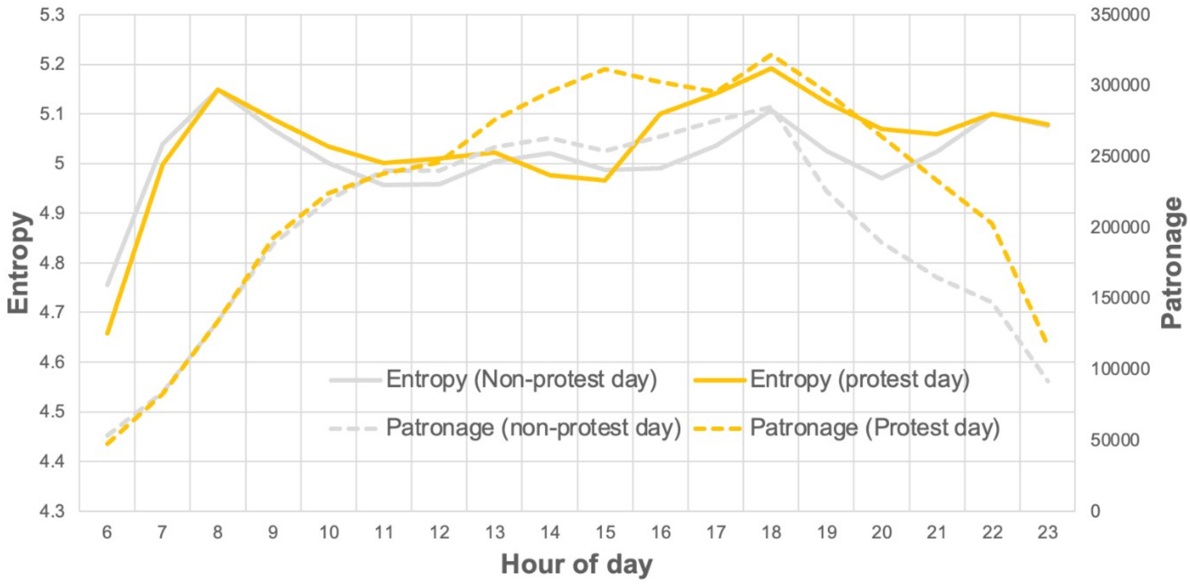


Figure 3. Entropy and patronage of the MTR network on (non-) protest days

As shown in **Figure 2**, the Hong Kong rail passenger O-D network typically has a modular community structure with four communities.[3] According to previous findings (Brockmann et al., 2006), network centrality is the most prominent factor that influences the intensity and connectivity of movement because most travel movement is geographically localized. We find that stations within the same community are typically on nearby interlinked lines. There are, however, some exceptions in which proximate stations have few interactions. For example, Hung Hom Station (belonging to Community 2 and colored in blue in **Figure 3**) shows a stronger interaction with stations in New Territories North (NTN) despite being located in Kowloon and most of its surrounding stations belonging to Community 1.

3.1.2 Flow between communities and their stationarity

We observe that identified communities are typically stable throughout the day (**Figure 4**). Community 3 is completely stable, whereas there are some interchanging stations between the other communities. For instance, Communities 2 and 4 merge at the start and end of the day, probably because their proximity facilitates trips between stations. These stations are regarded as coherent given that they change community mutually with stations of their previous community. Some stations (e.g., Kowloon Tong) are sometimes disjointed from their previous community (e.g., from 7 am to 8 am and from 10 am to 12 am), probably because they serve as important transfer stations between Communities 1 and 2.

[3] Identified communities are generally stable throughout a day. A typical result with the highest frequency (e.g., 9 am) in Figure 4 is selected and visualized in Figure 2.

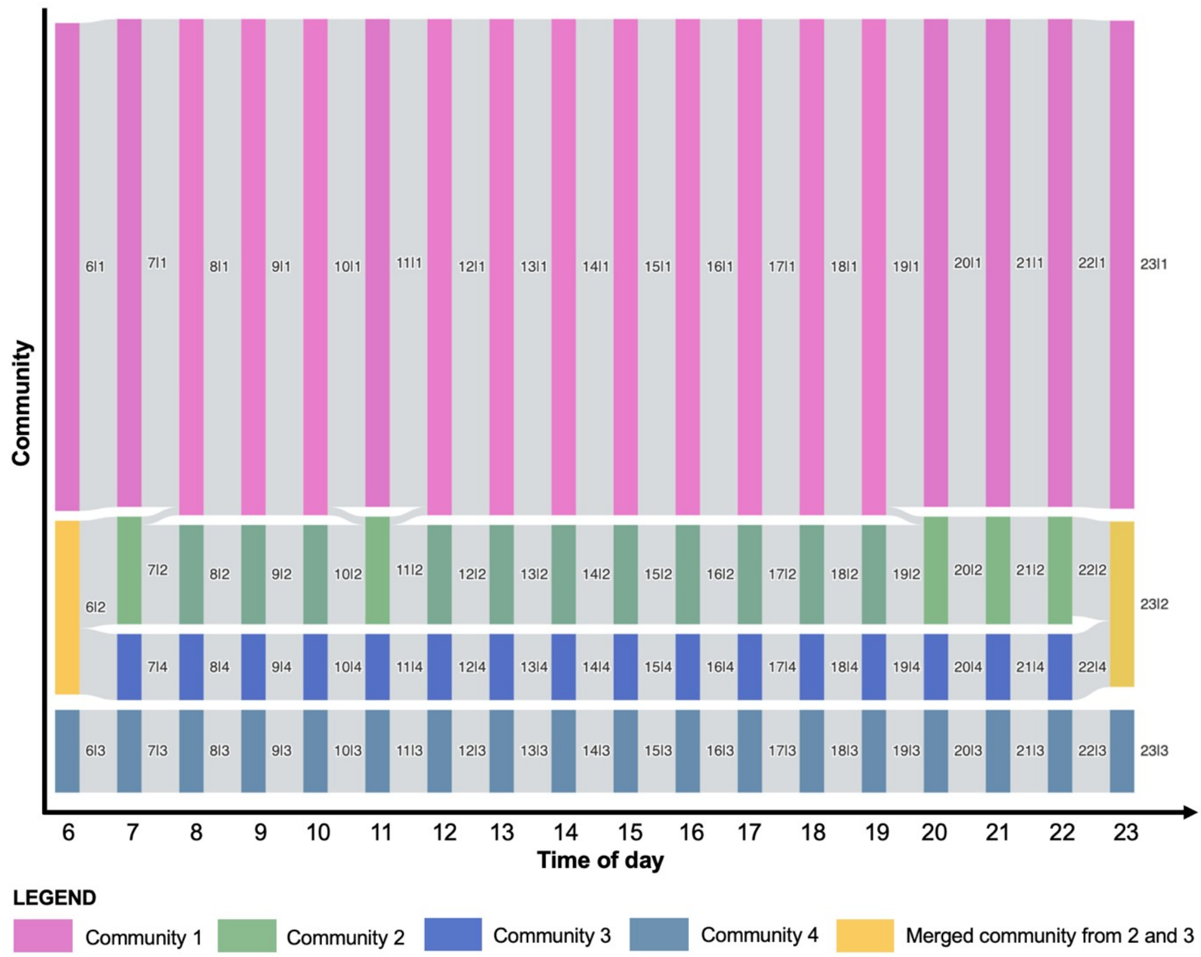


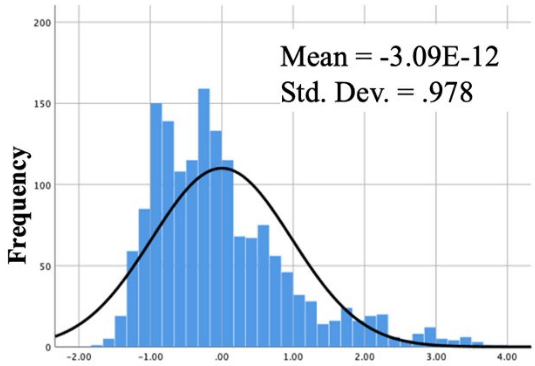
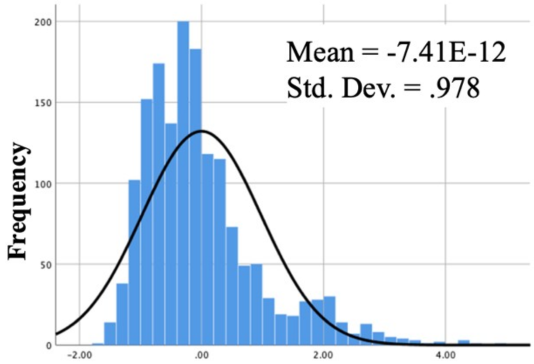
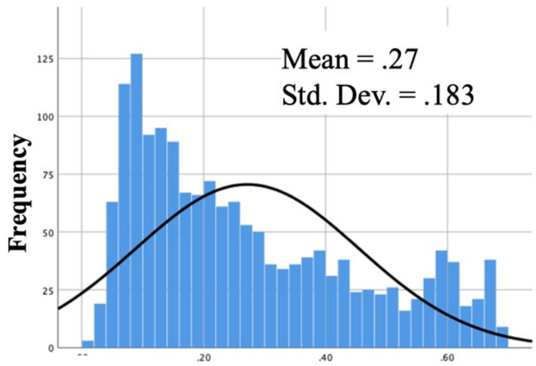
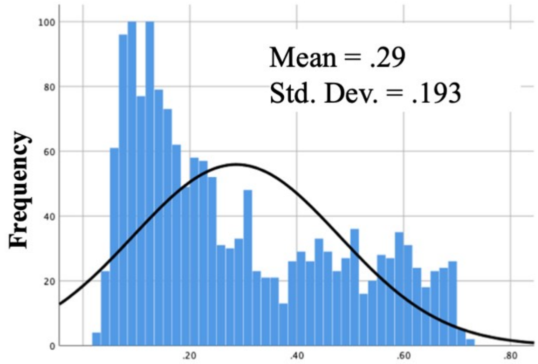
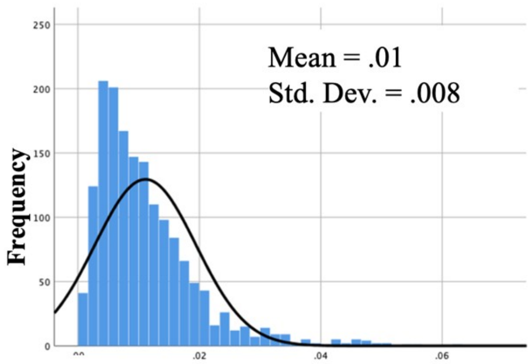
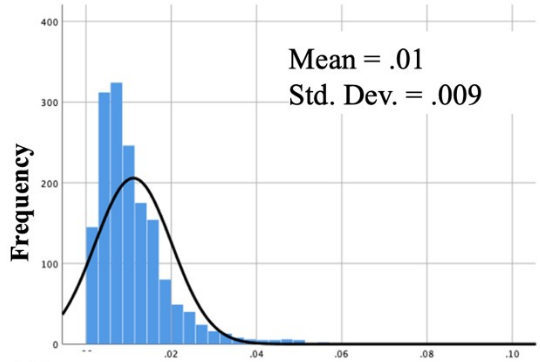
Figure 4. Community assignment for each station and hour-of-day on a non-protest day (June 2, 2019)

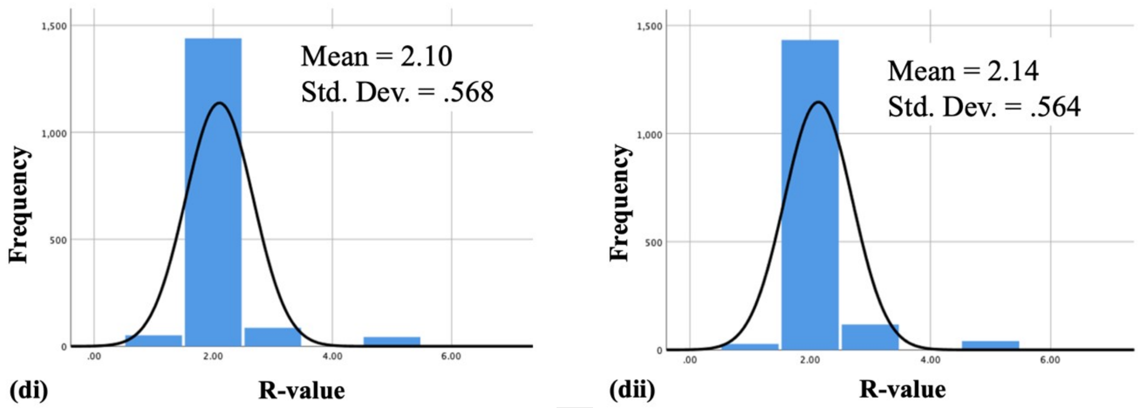
3.1.3 Station functionality

Table 5 shows a more disaggregated analysis tracking the four proposed indicators: the within-module degree *Z*, the participation coefficient *P*, the flow proportion *q*, and the station role *R*.

For the *Z-P* value, if we adopt a cut-off at $Z = 2.5$ in **Table 2**, 2.7% of records are $Z > 2.5$, indicating that they are hubs for their respective communities. Similarly, if we adopt a cut-off at $P = 0.6$, 7.2% of records are $P > 0.6$, indicating that they have potential as transfer stations between communities. Regarding the *R*-value, which depends on the *Z-P* value, 88.8% of records are $R = 2$, indicating that most of the stations serve local areas with no outstanding connections to destinations outside their respective communities. The remaining stations are 5.3% for $R = 3$ (e.g., Tai Wai as a local hub), 2.7% for $R = 5$ (e.g., centrally located in a central business area), and 3.1% for $R = 1$ (e.g., Tin Hau located in a residential area). Only Lo Wu station at 23:00 was $R = 6$, indicating its special role as a transfer node for cross-boundary trips (between mainland China and Hong Kong). When we examine the flow contribution of stations, a positively skewed distribution emerges. The majority of the stations contribute, at most, 1% of the total flow, while the remainder contribute more than 4%.

Table 5 Distribution of (a) Z-, (b) P-, (c) q-, and (d) R-values of individual records on a (non-)protest day (90 stations x 18 hrs)

Non-protest day	Protest day
	
(ai) Z-value	(aii) Z-value
	
(bi) P-value	(bii) P-value
	
(ci) Q-value	(cii) Q-value



In **Figure 5**, we visualize station functional profiles across hours of a day according to the four indicators. Selecting several stations of interest shows that the four indicators reveal different characteristics of stations. For instance, at Central Station, there are two *Z*-value peaks on a typical non-protest day. The morning (first) peak is congruent with the morning *q*-value peak, suggesting that the high *Z*-value is partially explained by high flow contribution. However, the evening (second) peak is not reflected in the trend of the *q*-value. It must therefore be explained by the differences between the amount and spatial distribution of flow. The majority of flows to/from Central Station in the evening are intracommunity flows, resulting in high *Z*-values. A similar interpretation can be applied to stations such as Tsim Sha Tsui, Mong Kok, and Causeway Bay. Another example is Tai Wai Station, which has a high *P*-value throughout the day, but relatively low *Z*- and *q*-values because of its importance as a transfer hub between Communities 2 and 4. A similar interpretation can also be applied to stations such as Kowloon Tong and Mei Foo. We observe that most of the changing roles of stations occur concurrently with changes between R = 1-2, 2-3, and 2-5. Tsim Sha Tsui, Mong Kok, and Central are the stations that fluctuate between intercommunity transfer hubs and local connectors.

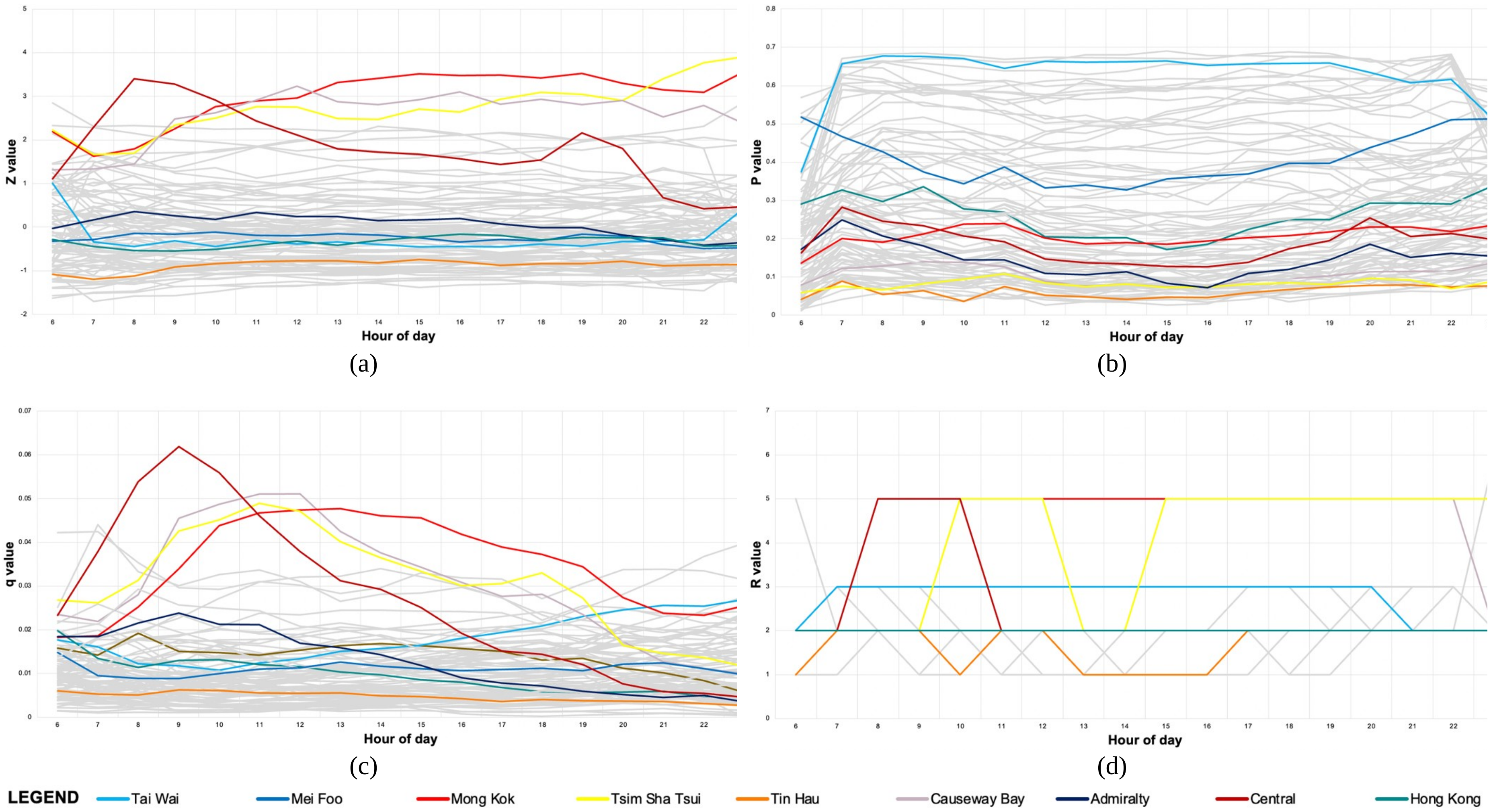


Figure 5. Station functional profiles across hours of a day in terms of (a) *Z*-, (b) *P*-, (c) *q*-, and (d) *R*-values

3.2 Resilience analysis: A case study of a social shock

We use the 2019 Anti-ELAB Movement as a case study. From June 2019 onward, Hong Kong was embroiled in the largest protest movement in its history (Lee et al., 2020), and protests continued into 2020, until being subdued by the coronavirus outbreak. We focus on the period during which the movement gained crucial momentum with an estimated 1 million people protesting on June 9, 2019, in a city of 7.5 million people. Importantly to this study, the volume of protesters traveling to and from a common protest site had the potential to strain and disrupt (mass) transit systems (Choi, 2020; Ng, 2020). Thus, it provides precious testbeds for us to study resilience of the local metro network. The main marches began from Victoria Park (between Causeway Bay and Tin Hau stations) and ended at the Legislative Council Complex near Admiralty Station, as shown in **Figure 6**. Seven stations, namely Fortress Hill, Tin Hau, Causeway Bay, Wan Chai, Admiralty, Central, and Hong Kong, were potentially affected by the ridership increase caused by the protests being within 800 meters[4] of these stations.

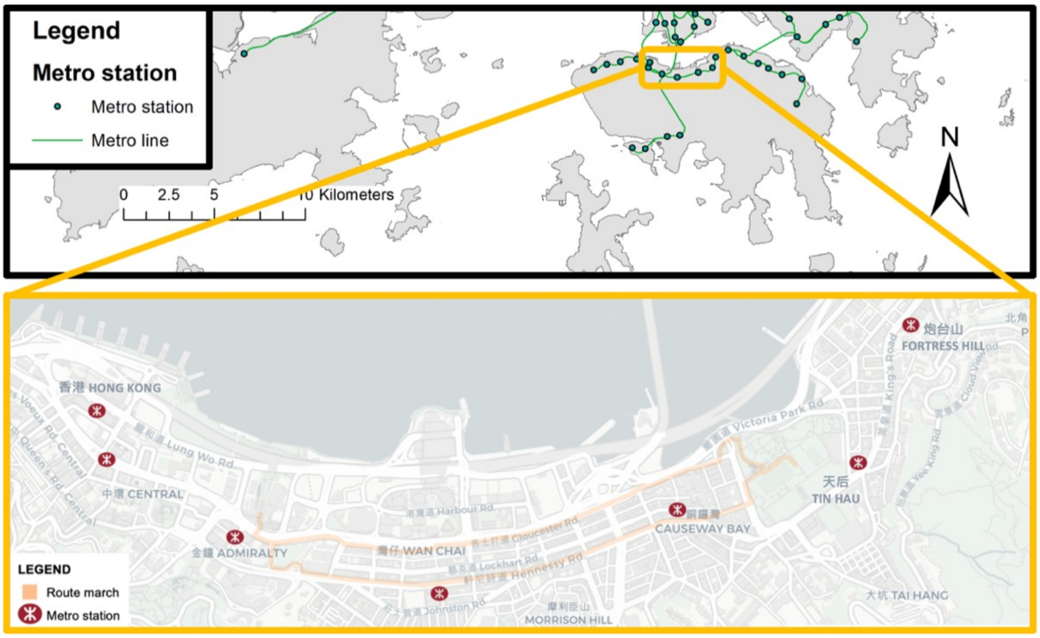


Figure 6. Stations potentially affected by the mass demonstration on June 9, 2019

3.2.1 Network flow and entropy

We first consider the trends of and a comparison between the entropy and MTR network patronage (**Figure 3**). Compared with a normal non-protest day, the trends of the two indicators are generally coherent. A few additional points of interest are noted as follows:

- Patronage on the protest day was generally higher, particularly after 12:00, probably because of high demand from protestors traveling to and from the protest or march route.
- Entropy has a higher value in the morning (8:00 – 12:00) and evening (17:00 – 23:00) but a lower value in the afternoon (13:00 – 15:00). The decrease in the afternoon is probably because of the mono-pattern of travel caused by a high proportion of trips to/ from the protest site. We hypothesize that the increase in the evening resulted from

[4] Building on earlier research in protests by Chan et al. (2022) and the regional travel survey conducted by the Transport Department (2014) in Hong Kong, we selected a threshold of 800 meters. This distance was chosen because it corresponds to an acceptable walking distance, roughly equivalent to a 10-minute walk.

protesters leaving protest sites and the unstable travel environment because of congestion. Some protesters were required to make a multi-modal trip to enter the rail system. For example, some reportedly took the ferry from the pier near Central Station to Tsim Sha Tsui Station, to leave the protest site. The occurrence of such improvised trips increased the movement entropy of the system. Station profiles are discussed in later sections.

Overall, these results again confirm the need to investigate trip patterns in a more disaggregated way to understand the underlying community structure and the potentially changing functions/roles of stations because of external interventions and/or the proactive or passive adaptions of riders.

3.2.2 Flows between communities and their stationarity

We again consider the resilience of travel communities by looking at the composition change when stations move from one community to another during the day. The identified communities are generally stable over time, as shown in **Figure 7**. Compared with a typical non-protest day, we note the following observations:

- Stations on the Tung Chong Line (from Tung Chong Station on Lantau Island to Hong Kong Station on Hong Kong Island) separated from Community 1 at 15:00 and returned at 16:00, probably because Hong Kong Station, the main transfer between the separated communities, is located at the epicenter of the protest site. The number of transfer trips decreased because of the unstable travel environment, and the connections between the separated communities were weakened.
- Tai Wai Station is the only station that moved from Community 2 to 4, at 22:00. This disjointed movement shows its increased importance as a transfer hub for Community 4.
- Kowloon Tong Station broke away from Communities 1 and 2, whereas Communities 2 and 4 largely resembled a normal day.

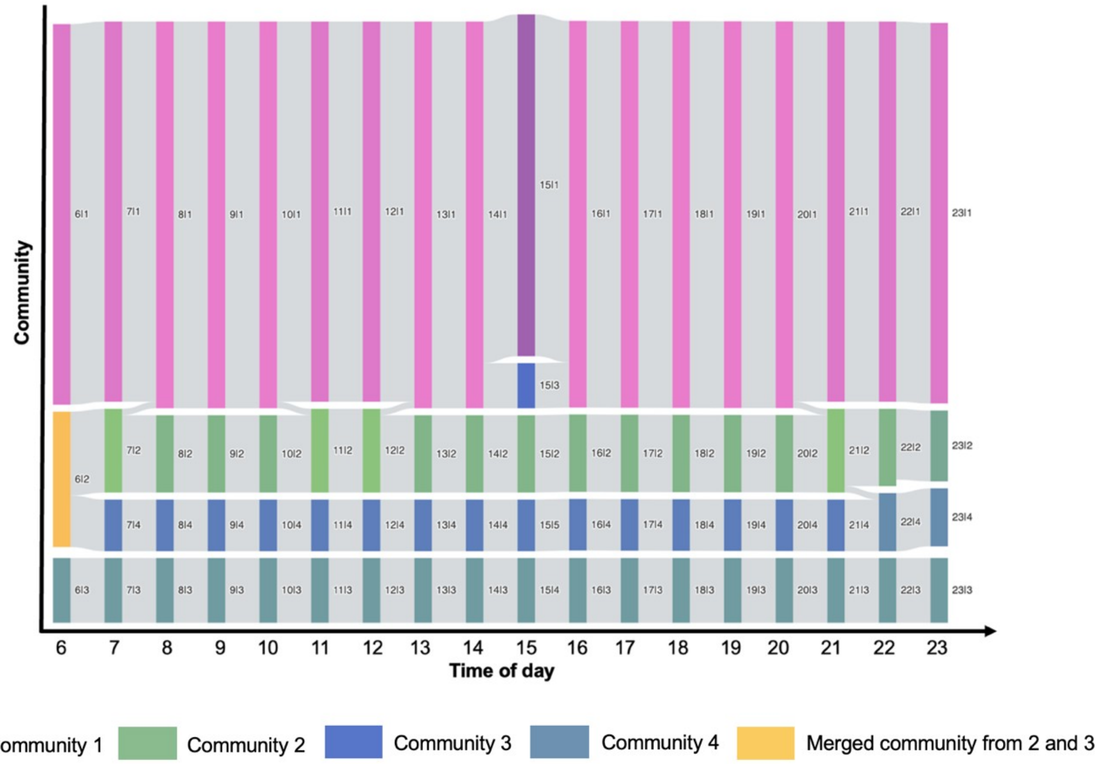


Figure 7. Community assignment for each station and hour-of-day on protest day (June 9, 2019)

3.2.3 Station functionality

We are also interested in station functionality as measured by the four proposed indicators, as shown in **Table 3**, and we adopt the same cut-off values as in **Section 3.1.3**. For the *Z-P* value, 2.7% of records are $Z > 2.5$, which is the same as that of a normal day, indicating that the functionality of stations as hubs for their communities was probably unaffected. The finding that 9.8% of records are $P > 0.6$, slightly higher than that of a normal day, demonstrates the increased demand for transfers between communities. Regarding the *R*-value, which depends on the *Z-P* value, 90.1% of records are $R = 2$, indicating that most stations serve local areas with no outstanding connections to particular destinations. The remaining stations are 7.2% for $R = 3$ (e.g., Tai Wai as a local hub), 2.5% for $R = 5$ (e.g., Central and Causeway Bay in the epicenter of the protest site), and 1.7% for $R = 1$ (e.g., Heng Fa Chuen located in a residential area). Only Lo Wu station at 6:00 and Admiralty at 23:00 were $R = 6$, which indicates their importance for both internal and external connections to/from Community 1 at the location of the protest site. When we examine the flow contributions of stations, a positively skewed distribution is again observed. The majority of the stations (77.3%) contribute at most 1% of the total flow, while a small cluster of stations contributes more than 4%.

We use **Figures 8** to present the functional and temporal resilience profiles of various stations using four key indicators. For a more focused analysis of value changes, we can direct our attention to **Figure 9**. As expected, there is a notable impact on the q-value (**Figures 8c** and **9c**) due to a sharp increase in demand caused by protest-related trips originating from stations near the protest epicenter (as shown in **Figure 6**). This leads to changes in the roles or functions (*R* values) of several stations compared to a typical day (**Figures 8d** and **9d**). A higher *R* value indicates that a station serves as a significant transport hub with flows coming from stations all around. The most pronounced changes are observed in the Kowloon area, particularly at Tsim Sha Tsui and Mong Kok Stations. At Tsim Sha Tsui Station, we notice a time shift in the role change from $R = 2$ to $R = 5$, occurring one hour earlier than on a normal day. One plausible explanation could be a shift in the departure times of some trips to avoid the protests. Although Mong Kok Station is not directly on the protest route, its *R* value significantly drops during the protest. This change cannot be fully captured by the variation in station in/out flow, as indicated by the *q* value. This highlights how the R value offers an alternative perspective on station functionality during adverse events. Additionally, the *Z-P* values provide unique insights from a community structural perspective. For example, concerning *Z*-values, we observe both positive and negative changes among stations. At 14:00, *Z*-value peaks are seen at Tin Hau (TIH) and Causeway Bay (CAB), which are situated near the starting point of the protest route (**Figure 8a**). However, the ΔZ for TIH is significantly higher than that of CAB (**Figure 9a**). CAB, being a popular shopping district on weekends, exhibits greater resilience to high demand due to its existing technical infrastructure support. These peaks to some extent correlate with the q-value trends. Later in the day, increased *Z*-values are noted at Wan Chai, Admiralty, and Central stations, which are situated in the middle or at the end of the protest route. Interestingly, these *Z*-value peaks are not reflected in the q-values, suggesting that the increased Z-values result from changes in travel patterns driven by a higher proportion of intracommunity flows. As for the *P*-values, there is a sharp peak at 15:00 for Hong Kong Station (**Figure 8b**) due to the previously mentioned split of Community 1 (**Figure 7**). A moderate peak is also observed at Tin Hau Station, indicating increased flows from other communities. In conclusion, while the *R*, *Z*, and *P* values do exhibit some degree of alignment in identifying critical stations, they evaluate stations from different perspectives. This underscores the importance of prioritizing resources to protect these stations when transit operators employ diverse operational management strategies.

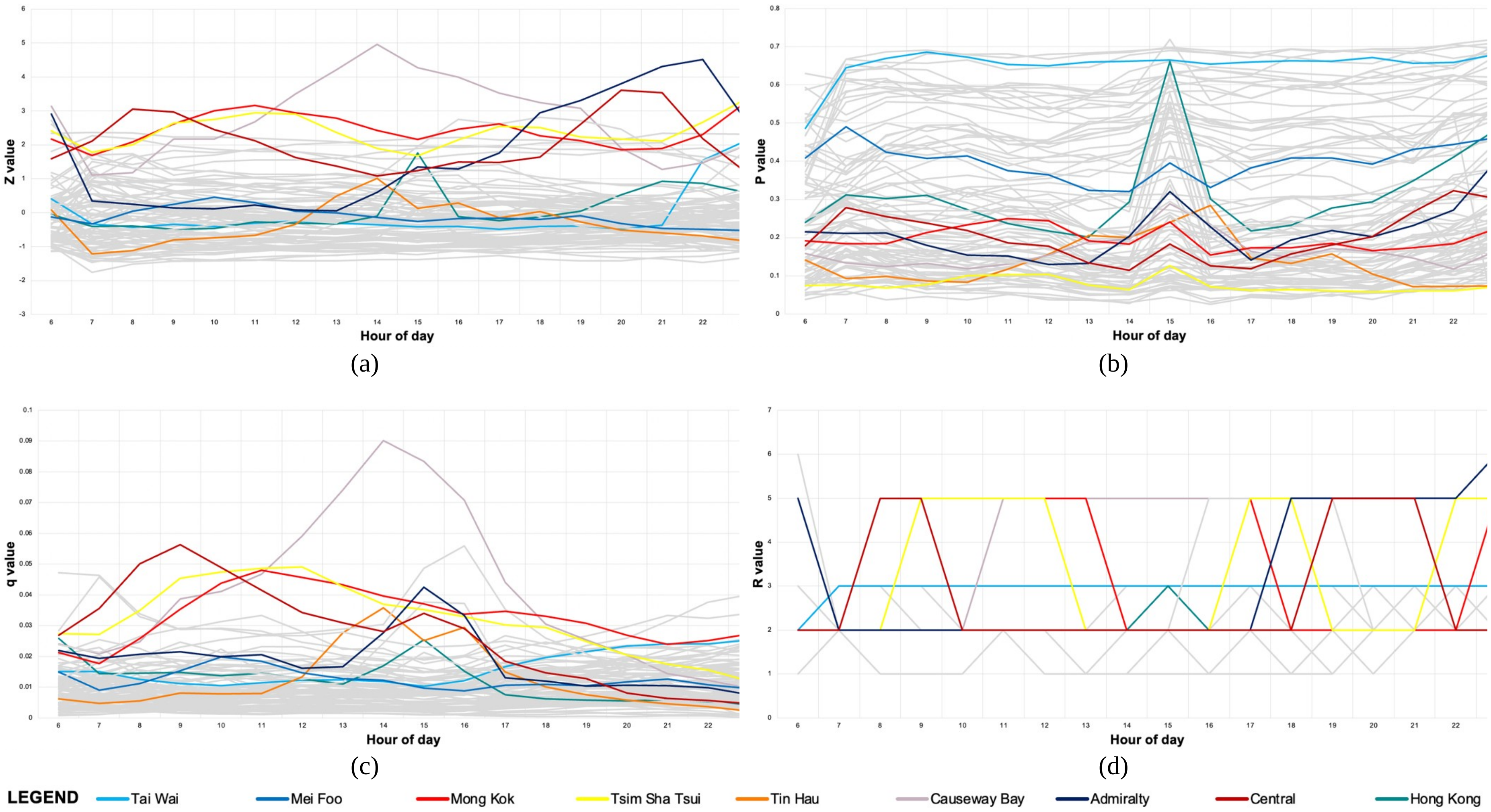


Figure 8. Station functional profiles in terms of (a) *Z*-, (b) *P*-, (c) *q*-, and (d) *R*-values.

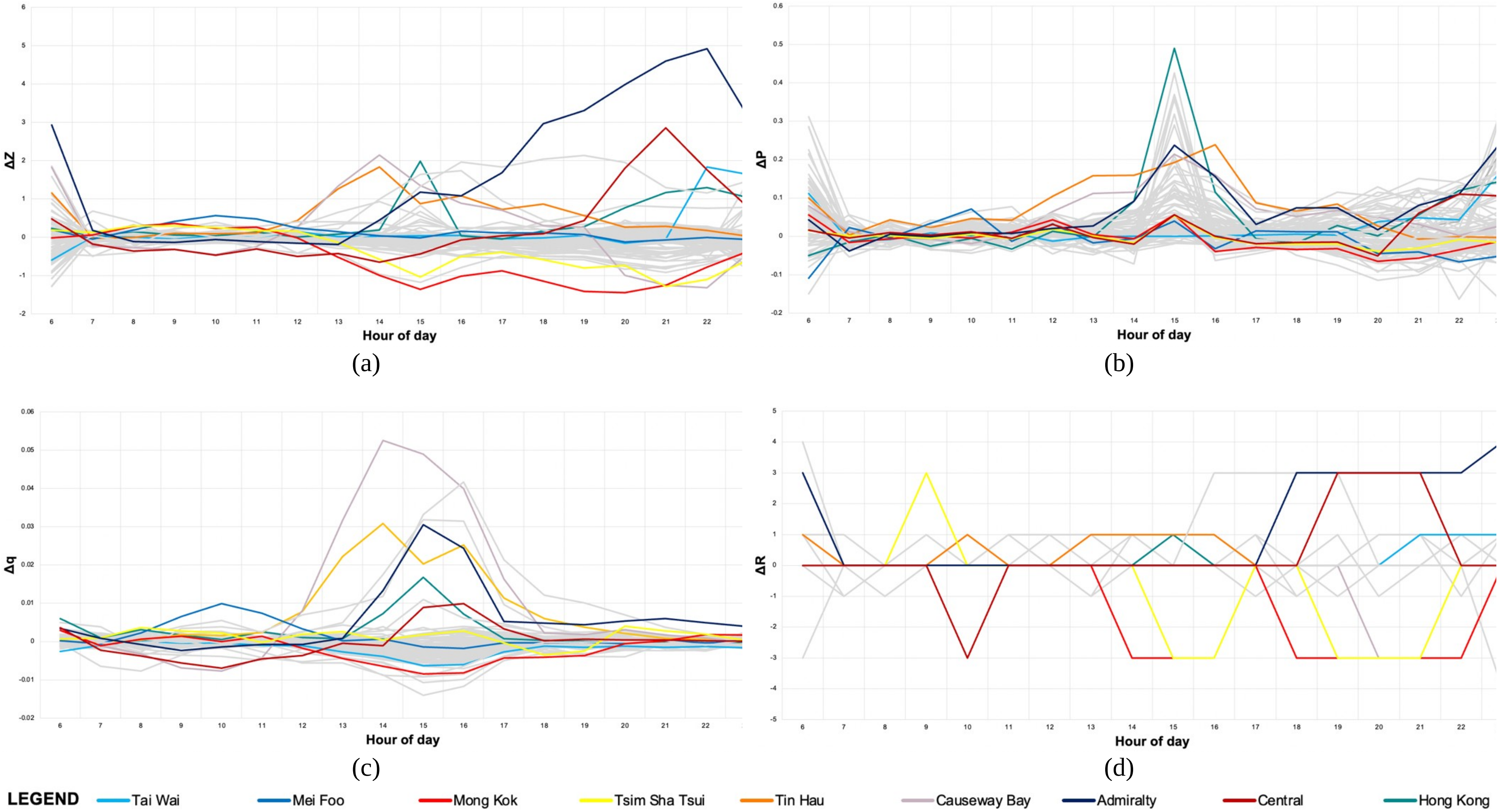


Figure 9. Station resilience profiles in terms of (a) *Z*-, (b) *P*-, (c) *q*-, and (d) *R*-values.

4. Implications

The spatial structure and underlying mechanisms of social sub-system of socio-technical transportation system revealed by the four indicators are potentially useful for enabling both short-term operational and longer-term planning responses of the technical sub-system.

For short-term operational responses, the concept of network-level entropy serves as a valuable tool for identifying deviations in the complexity of travel flows, be they unusually intricate or simplistic. As exemplified in **Section 3.2.1**, the comparison between network entropy and flow highlights their capacity to unveil unique facets of social shocks affecting the transportation system. Disruptions may manifest not only through atypical entry and exit flows but also through unexpected fluctuations in O-D flows. These observations carry implications not only for resource allocation, such as the management of train fleets but also for strategies to proactively prevent and alleviate congestion at specific stations. Take, for instance, the case of Hong Kong Station (depicted in **Figure 8b**), a critical link between Lantau Island and Hong Kong Island, which experienced disruptions on a particular day. The ripple effects on the entire transportation network might have been mitigated had tools of this nature been readily available. Another example to consider is the distinction between how we assess changes in station functionality (R-, Z-, and P-values) and the conventional approach of evaluating patronage changes (q-value). This distinction becomes evident when examining stations in both Hong Kong and Kowloon, as elaborated in **Section 3.2.3**, showing stations with insignificant patronage changes but substantial alterations in functionality. Such analytical tools empower transit operators to discern irregular travel patterns within a network, signifying areas where operational adjustments and network enhancements may be warranted. Furthermore, the implementation of automated dashboards, continually fed by the requisite data, could facilitate real-time detection and response to these anomalies. From a socio-technical perspective, the goal is not always to simply return to a “normal” state. Instead, both the social and technical aspects co-evolve toward a new equilibrium, sometimes leading to multiple equilibriums with distinct performance indicators. This can be illustrated by the contrast we have shown between patronage and functionality.

When considering longer-term planning responses, our findings underscore the dynamic nature of stations’ roles and functions for the social subsystem on both typical operational days and during disruptions. The four key indicators offer valuable assistance to transit planners in identifying pivotal stations for both intra- and intercommunity flows. For example, urban areas like Mong Kok, Tsim Sha Tsui, and Central stations serve as prominent local connectors and vital intercommunity hubs. These stations merit top priority for resource allocation due to their significance during routine operations (as depicted in **Figure 4**) and their pivotal roles in managing disruptions (as depicted in **Figure 8**). By developing and implementing policies aimed at enhancing and expanding the accessibility of such key stations, Hong Kong and other local cities can fortify the resilience of their transit networks against various social and external shocks. Furthermore, transportation planning studies have consistently indicated that the introduction of new metro lines brings value by offering redundant services, ultimately contributing to a more robust and resilient transportation system. The construction of railways not only significantly transforms the centrality and connectivity of an area but also has a substantial impact on the local population and businesses. This aspect has garnered the attention of researchers from various fields, exploring topics like travel behaviors (Loo, 2009; Weckström et al., 2019) and land use (Mejia-Dorantes et al., 2012; Tan et al., 2019). To encompass the broader socio-technical dimensions of transportation resilience, it is imperative to routinely assess the evolving dynamics of social structures concerning urban and transportation infrastructure development plans. Such assessments directly influence the travel frequencies and distribution patterns of citizens and are integral to the sustainable planning and development of transportation systems.

A socio-technical perspective emphasizes the dynamic interaction and interdependence between the social and technical elements of a transportation system. It extends beyond the mere user demand within the technical components, encompassing the broader nexus between individuals, technology, and the surrounding environment within a specific system. In this paper, we delve into the exploration of two distinct waves of socio-technical interactions. The first wave centers on the typical travel patterns during regular, non-disruptive days. These patterns emerge as a result of the structural constraints and facilitators inherent to the technical sub-system, including elements like the metro network and transit services, in conjunction with user demands and preferences. The second wave is initiated by a social shock, leading to shifts in travel perceptions, such as the perception of the railway company and metro travel safety (Chan and Zhou, 2021) and a broader impact on the adoption of digital technologies, exemplified by the use of mobile applications and instant messaging groups for disseminating transportation disruption information (Au, 2022; Chan and Zhou, 2021; Stokols, 2023). While our current research delves into the social aspects by investigating how travel patterns respond to change within the existing technical framework, the next logical step is to consider the adaptive responses of the technical system: how users can influence the system. At present, the technical subsystem is primarily governed by a set of technical specifications, often centered on daily operations, or preventing critical technical failures. An encouraging avenue for both planners and academia is to explore how socio-technical systems can adapt and evolve over time, effectively responding to the ever-changing needs of users, technological advancements, and shifts in society. This approach will not only promote the resilience of socio-technical systems but also ensure they remain agile and responsive in a rapidly evolving environment.

In this regard, the proposed indicators can help identify critical components in transportation networks and effectively reveal any weaknesses (Mattsson and Jenelius, 2015), with a focus on the interaction of socio-technical (i.e., demand-supply) interactions (Chan et al., 2022a; Jenelius, 2020). In addition, to cope with the negative impacts of potential perturbations on the operations of modern society, great efforts have been made to analyze and optimize network performance based on various measures, such as reliability (Bell, 2000; Chen et al., 2002; Soza-Parra et al., 2021), vulnerability (Berdica, 2002; Chen et al., 2007; Gu et al., 2024; Zhang et al., 2021), flexibility (Chan et al., 2022b, 2023c; Chen and Kasikitwiwat, 2011; Morlok and Chang, 2004; Thorhauge et al., 2020), redundancy (Chan et al., 2021a; Xu et al., 2018, 2022), and resiliency (Faturechi and Miller-Hooks, 2014; Wan et al., 2018; Xu et al., 2022b). Resilience is more comprehensive than other measures as it covers different network states throughout the lifecycle of perturbations (i.e., the performance degradation under perturbations, the travel choice adjustments, and network mitigation and restoration after perturbations). The proposed indicators derived from passive data (i.e., smart card data) can track the dynamic state of systems and facilitate the incident review process, which can create more resilient transportation networks that are less disruptive to society and people's daily lives, particularly in dense megacities such as Hong Kong.

5. Conclusions

Technical structure drives human flow, leading to system-wide interdependencies in the socio-technical transportation system. In this article, we focus on the social-subsystem – the flow and pattern of travelers and the responses to a social shock. Analysis is done at the station level, and we treat communities as groups of stations that are highly connected internally but with few connections externally. To better understand the community structure in metro-based mobility networks, we draw on community detection methods to analyze smart card data and depict a detailed profile of railway stations and travel communities in Hong Kong. A case study of the communities in a social shock is also presented to investigate resilience of socio-technical transportation system. Several key findings and implications are summarized.

Our study employs different temporal lenses to gain a comprehensive understanding of station functionalities in various temporal contexts, including periods of social shocks. This functionality is not solely based on stations' network properties but a product of social-technical configurations. This holistic perspective allows us to assess resilience of socio-technical transportation system more effectively. In addition, we utilize a diverse set of mobility-related metrics, operating at different spatial scales, to serve as proxies for both structure of social-subsystem and station functionalities. These metrics shed light on the intricate dynamics of the social subsystem during disruptive events, providing insights beyond the mere reduction of flows to a numerical demand. Our empirical findings, based on the case of Hong Kong, underscore the imperative need to investigate the change and resilience of the social subsystem within transportation systems. The traditional approach to participation metrics considers the diversity of a station's external connections and the significance of intercommunity links. By presenting a real-world case of Hong Kong, we illustrate how the socio-technical approach opens up new avenues for practical transportation analysis and planning, adaptable to various types of shocks, including events like the coronavirus pandemic.

We acknowledge both the strengths and limitations of our study. The strengths of this research lie in its socio-technical approach to assessing transportation system resilience. The use of smartcard data, coupled with a well-established multi-level assessment encompassing four mobility-related indicators, enhances the transferability of our work, as demonstrated by our illustrative case study in Hong Kong. However, our study does come with certain limitations. The comparison of data from two subsequent Sundays in our case study is inherently limited in scope, primarily focusing on weekend travel patterns. It does not provide a comprehensive assessment of the broader dynamics of the transportation system, particularly those related to weekday commuting trips. To draw more generalized conclusions with broader applicability, it is recommended to undertake a more extensive analysis. This should involve the inclusion of data from various days, encompassing both working days and different seasons. Such a comprehensive approach would provide a more holistic perspective on the system's resilience, strengthen the scientific robustness of the findings, and render them more valuable for transport planners seeking insights into system behavior under diverse conditions.

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