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Evaluating the value of new metro lines using route diversity measures: the case of Hong Kong's Mass Transit Railway system

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Abstract

The Mass Transit Railway (MTR) serves as the backbone of the Hong Kong public transportation network and continues to be expanded in phases. Nevertheless, occasional but severe disruptions have raised concerns about whether the proposed MTR expansions will benefit the system resilience. To assess the value of each stage of MTR network expansion, it is key to identify the distributive effects of new metro lines on both accessibility and resilience. This paper applies the route diversity index, a relatively new accessibility indicator, to assess the effects of new lines and evaluate their spatial distribution, variation, and changes at nodal, dyadic, and network levels. The results indicate that the effects on accessibility and resilience will differ between each stage of MTR expansion. On the accessibility front, the benefits of reduced travel times and increased route diversity will be successively extended to more districts with each MTR expansion, and the spatial equity will also be improved gradually by the expansion, especially in isolated regions such as the northern and western New Territories. In contrast, on the resilience front, although the overall network vulnerability will be reduced, the vulnerability of certain parts of the network will be increased, which might necessitate additional resources to protect these stations. However, some new lines will reduce this vulnerability and provide a complementary solution to enhance network resilience. Overall, the insights from this study could assist in cost-effective resource allocation and informed decision-making for the prioritization of future railway investments and cost-effective resource allocation.

Keywords: Resilience, Accessibility, Route diversity, Equity, Public transport, Network expansion, Hong Kong

1. Introduction

The Hong Kong Mass Transit Railway (MTR) serves as the backbone of the Hong Kong public transportation network, accounting for 43.4% of daily public transportation trips on average (Transport Department, 2019). The system is still under expansion to increase its coverage and service quality, and the passenger modal share is projected to rise to approximately 45%–50% in 2031 with the completion of several new lines (Transport and Housing Bureau, 2014). Nevertheless, occasional disruptions have caused the public to doubt the network's resilience. In particular, natural disasters (Bono and Gutiérrez, 2011; Lu et al., 2014) and manmade activities (Loo and Leung, 2017; Lordan et al., 2014; Parkes et al., 2016) may put stations or lines temporarily out of service, thus affecting the overall efficiency of the rail network. For example, on February 10, 2017, an arson attack in Tsim Sha Tsui Station resulted in a station closure for more than six hours. On August 5, 2017, an electrical power failure led to the closure of six stations for more than two hours. On September 16, 2018, a super typhoon led to bus service suspension due to extensive road closures, and the MTR faced overwhelming passenger flows for more than 10 hours. On March 18, 2019, a train collision on the Tsuen Wan Line occurred in Central Station, one of the largest transfer stations, and caused the partial closure of the Tsuen Wan line for two days. On September 17, 2019, a train derailed between the Mong Kok East and Hung Hom stations, leading to a service suspension on the East Rail Line for a day. Unlike road network accidents, rail accidents not only cause traffic delays on the lines involved but also have a broader effect on passengers at other stations along the lines, or even passengers at stations on other lines, and thus generally cause greater social disruption.

During the MTR's more than 100-year history, the prevention of network failures and system disruptions through investments in new infrastructure (e.g., construction of new lines, replacement of old signal systems) has been a major endeavor. On the research front, meanwhile, graph theory and complex network theory have emerged in the past 10 years in analyses of the effects of new transit lines on the resilience and vulnerability of existing urban rail networks. Jenelius and Cats (2015) evaluated the robustness of a new cross-radial line in Stockholm, Sweden in terms of travel times under disruptions caused by supply and demand uncertainties. Subsequently, Cats (2016) studied the network development plan in Stockholm and concluded that it would improve network robustness by reducing the average travel time losses during disruptions. It is widely understood that new lines do not necessarily bring equal benefits to all parts of such a network. However, studies that use a disaggregate assessment approach remain relatively limited.

This study aims to provide evidence for the necessity of studying the distributive effect of network expansions by a disaggregate assessment approach. In this context, by supplementing traditional measures of increased utility due to shorter travel times, we adopt a relatively new accessibility indicator—route diversity—to evaluate network performance in terms of the number of behaviorally effective paths during disruptions explicitly from the travelers' perspective (Xu et al., 2018a). Within this analytical framework of route diversity, we assess the effects of new lines and evaluate their spatial distribution, variation, and changes at the nodal, dyadic, and network levels in a case study of the Hong Kong MTR system.

Although the concepts of reliability and resilience are closely related to the general subject of vulnerability (Gu et al., 2020), these terms have different research scopes. Reliability focuses on the probability of providing a certain level of performance, whereas resilience concerns the susceptibility of a network to perturbations (i.e., changes in network performance) without accounting for the probability component. Although the MTR reports a high reliability of 99.9%

(MTR, 2019), there is a salient possibility of low resilience, which is therefore investigated in this paper.

2. Literature Review

2.1 Network resilience/ vulnerability analysis

There is no single definition of transportation resilience, but it is commonly understood to relate to system performance under perturbations (Gu et al., 2020). Bruneau et al. (2003) introduced four concepts of resilience applicable to transportation studies, namely robustness, redundancy, resourcefulness, and rapidity, and this interpretation has been widely adopted in the context of transportation. Robustness and redundancy represent the static aspect of resilience, namely, a system's capability to maintain its function, whereas resourcefulness and rapidity represent the dynamic aspect by emphasizing the rate at which a system returns to equilibrium after a disturbance (Jenelius and Mattsson, 2020). Within the broad concept of transportation resilience, a vulnerability analysis is often the first step to assess the ability of a network to resist the effects of perturbations. Indeed, vulnerability is a component enshrined in the concept of resilience.

Network topology influences network resilience in terms of resistance and recovery abilities (Zhang et al., 2015). Many studies have investigated the topological characteristics of metro networks by using graph theory and complex network indices to evaluate the network performance. In graph theory, a real transportation network is represented by an abstract graph composed of a set of nodes connected by links (Kansky, 1963). The network could be undirected or directed (i.e., edges without or with direction, respectively) and unweighted or weighted (edges without or with a numerical value attached, respectively), depending on the applications. Several measures and indices are used to assess the efficiency of transportation networks in terms of connectivity and accessibility (Zhang et al., 2015). The Alpha, Beta, and Gamma indices represent the connectivity and complexity of a network. The Alpha index considers the relationship between the number of cycles and the maximum number of cycles, the Beta index is expressed by the ratio between the number of links and the number of nodes, and the Gamma index quantifies the relationship between the number of observed links and the maximum possible number of links. The above indices are also used to quantify network growth in terms of connectivity improvement (Chen et al., 2014; Wang et al., 2014). As they are solely based on the numbers of nodes and links, those three indices have a limited capacity to reveal structural differences between networks of equal size (Rodrigue, 2020). The limitations of these measures have led to the development of new metrics by introducing transportation engineering characteristics into a network-based methodology. López et al. (2017) conducted an accessibility-based network vulnerability analysis by investigating the changes in node closeness and betweenness in different disrupted scenarios. Sarlas et al. (2020) proposed a new centrality measure called betweenness-accessibility to measure the accessibility of stations during disruptions. The estimation of the above static performance measures depends on two main parameters: the link/node weight and the shortest path length.

On the other hand, studies regarding dynamic resilience of transportation networks often requires more information, such as travel demand and supply data, to represent the service supply dynamics and passengers' responses to such events. Cats and Jenelius (2014) extended the measure of betweenness centrality with real-time traffic information to account for interactions between supply and demand and the accumulated effect of disruptions on the system performances of public transportation networks. Sun et al. (2018) extended the purely topological analysis by using passenger flows as link weights and used the weighted network as the basis for a dynamic model of cascading failures due to flow overloads following an initial disruption at a station. Cats and Jenelius (2018) and Malandri et al. (2018) demonstrated an advanced approach with an agent-based behavioral model, by which travelers' responses to disruptions and their further repercussions for other travelers could be simulated reasonably well. The richer set-up of these studies allows the definition of more intuitive effect measures and the capture of a wider spectrum of consequences of disruptive events. However, the availability of data and models determines what can be studied in a concrete situation. Moreover, it is difficult to study how the vulnerability of a network develops over time (Mattsson and Jenelius, 2015), especially with future expansion, as this would require predicting the future travel demand and changes in land use in an as-yet nonexistent situation, which may change in practice after the project's completion.

Using a plethora of approaches, researchers have attempted to overcome some of these limitations of topological studies. Recent studies extended various graph-based metrics by relaxing the assumption that all passengers have perfect knowledge of the system conditions and that they always choose the shortest path available. Derrible and Kennedy (2010) suggested that the number of cyclic paths available in a subway network is correlated with the vulnerability of the system and thus represents the number of alternatives from the aggregate perspective of the whole network. El-Rashidy and Grant-Muller (2016) evaluated road network redundancy by using the clustering coefficient, (i.e., transitivity), which represents an alternative possibility that measures the overall probability that the network would have interconnected adjacent nodes. Cats and Jenelius (2014) developed alternative formulations of the betweenness index based on the probabilistic route choice and the dynamic demand and supply environment. Lam (2016) defined the resilience of a node in the infrastructure network as the weighted sum of all reliable independent paths of all nodes in the network. Hawas et al. (2016) presented an approach to measure network effectiveness based on route diversity that represents the number of all possible routes to and from different regions via transit services. Wang et al. (2017) used several robustness metrics that emphasize alternative paths and their lengths.

Some studies started with a more realistic description of the travelers' responses to the provision of optional routes between the origins and destinations during disruptive events. Xu et al. (2018a) presented route diversity measures based on the concept of reasonable routes, taking the view that travelers would be unlikely to consider all possible routes as realistic alternatives. Thus, only routes that are reasonably quick relative to the shortest path are considered when assessing the network accessibility performance. This is especially useful for vulnerability analysis by accounting for the fact that commuters are more likely to consider shorter detoured routes, given an acceptable travel cost, as reasonable alternatives when the primary or secondary route is not available. Yang et al. (2017) demonstrated the feasibility of route diversity metrics for the Beijing metro network and identified the vulnerable stations. Jing et al. (2019) showed how such metrics could better uncover the existence of alternative paths compared with the standard measures of network connectivity for four different metro networks. Although the route diversity measure is based on the topology network, it considers the travelers' route choice behavior and enables us to explicitly describe the effective connections and rerouting opportunities provided to travelers.

In this paper, we adopt the route diversity measure, which fulfills various purposes: (1) reflecting the reality that passengers may not reroute immediately and optimally when networks change due to new lines or disruptions and (2) providing disaggregate information at the dyadic level to reveal the disparate topological effects of different new lines for each origin–destination (O-D) pair. Following the direction of Xu et al. (2018), we customize the route diversity measures to our longitudinal analysis of the evolutions of networks. The details of the algorithmic procedure can be found in Section 4.

2.2 Resilience effect of new lines

A recent trend in transportation planning is to argue that new lines add value in terms of robustness and redundancy and thus contribute to a more resilient transportation system. However, railway construction represents a significant change to the local area and affects a considerable population. The potentially huge effects of new metro lines have attracted interest from researchers in a variety of fields, who study issues such as travel behaviors (Loo, 2009; Weckström et al., 2019) and land use (Mejia-Dorantes et al., 2012; Tan et al., 2019). In the context of network performance, both traditional utility assessments during normal operations and vulnerability assessments during disruption scenarios have been studied.

Regarding utility assessments during normal operations, some studies have examined network robustness from the perspective that graph-based metrics can reveal the network efficiency and thus contribute to network robustness. Chen et al. (2014) investigated the metro network in Guangzhou, China and found that the gains from network development in terms of connectivity and accessibility were not spread evenly among the regions, which emphasized the importance of matching developments with different regional situations. Kim and Song (2015) examined the longitudinal changes in network accessibility and reliability in relation to different evolutionary stages of the subway system in Seoul, South Korea. Cats (2017) conducted a longitudinal analysis of the topological evolution of a multimodal rail network by investigating the dynamics of its topology and network indicators for the case of Stockholm during 1950–2025. Song et al. (2018) examined the distributive benefits in terms of the spatial coverage and service levels from a major expansion of the transit network in Gwangju, South Korea. Dai et al. (2018) investigated the evolving structure of the Southeast Asian air transportation network during 1979–2012 from a complex network perspective. Yang and Chen (2018) adopted machine learning theory to identify future trends in the metro network of Shanghai, China based on topological data and metrics in complex network theory. Weckström et al. (2019) investigated the metro extension in Helsinki, Finland and argued that the unequal distribution of benefits and burdens in terms of travel times and transfers had been overlooked due to the use of an aggregate approach.

Regarding vulnerability assessments during disruption scenarios, studies have examined how building new lines enables a public transportation network to better withstand disruptive events and their consequences. De-Los-Santos et al. (2012) studied the network efficiency under disruption scenarios in the commuter system of Madrid, Spain and proposed potential new links that could increase the passenger robustness of the network. Jenelius and Cats (2015) evaluated the robustness of a new cross-radial line in Stockholm in terms of the travel times under disruptions of supply and demand. Cats (2016) studied the network development plan in Stockholm and concluded that it would improve the network robustness by reducing the average travel time losses during disruptions. Hong et al. (2017) investigated the effects of different expansion plans on the vulnerability of the subway network in Wuhan, China and identified the optimal plan from the network redundancy perspective. Zhu et al. (2018) investigated the appraisal of alternative lines and their effects on network performance during adverse events, using the case of line extension of a network in Beijing, China. Nian et al. (2019) evaluated the benefits of different alignments of new lines with respect to reducing network vulnerability in Shanghai. Cats and Krishnakumari (2020) investigated network performances under disruption scenarios for the short and long development patterns of metro networks in London (U.K.), Shanghai, and the Randstad (Netherlands). That study provided more nuanced evidence on the relation of the network structure and development pattern with its robustness.

Although the above review of existing studies is by no means exhaustive, it does indicate that building new transit lines is a crucial consideration in the growing field of transportation resilience. Among those studies, some (Nian et al., 2019; Song et al., 2018; Weckström et al., 2019) provided evidence for the need to study the distribution of network extension effects in detail. This would require a disaggregate assessment approach. However, the findings of those studies may not be universally applicable because of the specific features of their cases and research contexts. This review highlights that more empirical evidence is needed to assess the distribution of the effects of new lines on resilience.

2.3 Distributive effect of new lines

The distributive dimension of a public transportation provision has long been recognized as a key aspect of transportation equity (Banister, 2018; Hay, 1993; Pereira et al., 2017; Verlinghieri and Schwanen, 2020). The past decade has witnessed growing concerns over the equity effects of public transportation investments (Bocarejo and Oviedo, 2012; Golub and Martens, 2014; Karou and Hull, 2014), particularly railway transit projects, which are increasingly being constructed worldwide (Bhandari et al., 2009; Bianco et al., 2015; Dorantes et al., 2011; Kim and Sultana, 2015; Weckström et al., 2019). In general, equity refers to the fairness and justice with which the benefits and costs of transportation projects are distributed. One useful approach for measuring transportation equity as a target is to distinguish horizontal from vertical equity (Litman, 2002). Horizontal equity, also known as spatial equity, focuses on the equal distribution of benefits from public service to all target groups or locations. Vertical equity, also known as social equity, considers the geographical unevenness of socioeconomic conditions and focuses on whether the relative service quality benefits transport-disadvantaged populations (Foth et al., 2013). In this paper, we focus solely on the spatial scale and evaluate the equity effects of the metro expansion plan at different stages by examining the uneven distribution of benefits in the metro network.

To evaluate transportation equity, it is important to measure the benefits from new additions to the public transit service. From the passengers' viewpoint, the degree of benefits from new lines is commonly represented by accessibility (i.e., access to the intended destination) and resilience (i.e., maintenance of travel quality under perturbations), as discussed in the previous section. However, the diversity of possible benefits from public transportation and the numerous definitions of equity, combined with the difficulty of matching executive plans to these definitions, have complicated both the theoretical and practical aspects of public transportation equity (Foth et al., 2013). This study investigates the inequity of route choice (route diversity) resulting from the specific circumstances of a metro network and how the topological effects of different new lines might improve this situation. In terms of the availability of travel alternatives, users can be divided into two groups: choice and captive transit users (Mortazavi and Akbarzadeh, 2017). Choice users are those who have access to at least two motorized travel modes, whereas captive users have access to only one motorized mode to accomplish their urban trips. Although this concept is most commonly applied to distinguish between users who can or cannot select between a transit and a paratransit mode, a similar distinction could be applied to users' route choices within a transit mode (i.e., whether users have reasonable alternatives, and if so, how many, when the primary route is not available), which is the focus of this paper.

Various approaches to the quantification of the equity concept are proposed in the literature. The Gini coefficient is a well-known inequity measure applied in various contexts (Delbosc and Currie, 2011; Guzman et al., 2017; Jang et al., 2017; Ricciardi et al., 2015). This measure of statistical dispersion is intended to represent inequities of services and benefits within any group in a population. Some studies have attempted to analyze spatially extended inequity effects.

Mortazavi and Akbarzadeh (2017) evaluated the imbalance between service provision and local travel needs for public transportation by assessing their conformity to one another using Spearman correlation ranks and the Gini index. They studied the public transportation network in Isfahan, Iran and found that the new bus rapid transit lines would not improve the Gini index but would improve the Spearman rank correlation, indicating that the Spearman correlation can capture another angle of transportation equity. Jenelius (2010) presented a rare example of a vulnerability study by comparing an efficiency-based measure with an equity-based measure of the uneven increases in travel times distributed among travelers. Notably, when identifying the most important links in a road network, the equity-based measure was able to distinguish certain local roads from the largest and busiest roads, the latter of which are usually identified as the more critical components in a network vulnerability analysis. Inspired by the above research, we assume that the distribution of station vulnerability with respect to local hazards reflects local needs, and that stations with greater needs receive a greater enhancement of resilience. To this end, we investigate the conformity between the need for and the benefit from new lines in terms of resilience.

The inclusion of the resilience and equity effects of a public transportation investment is increasingly in demand from policy makers (Jenelius and Cats, 2015; Manaugh and El-Geneidy, 2012), suggesting that this aspect of the Hong Kong MTR merits further evaluation. In this paper, the route diversity measure is explored to evaluate the extent to which metro expansion plans in the Railway Development Strategy (Transport and Housing Bureau, 2014) provide equitable value in two respects: (1) the distributive effect of each new line in terms of the potential time savings and route diversity improvement across O-D pairs, and (2) the distribution of need (station vulnerability) and benefit (resilience enhancement) from each new line throughout the metro network.

3 Case study

Hong Kong adopts a transit-oriented development approach with its self-financing public transportation. Approximately 90% of the 12.9 million daily motorized trips in Hong Kong are made by public transportation (Transport Department, 2019), one of the highest rates of any developed region worldwide. With the government's stated policy of "using railways as the backbone of Hong Kong's public transportation system," the Hong Kong MTR accounts for 43.4% of the average daily public transportation trips (Transport Department, 2019). Fig. 1 shows the general spatial structure of the city, which comprises Hong Kong Island, Kowloon, and the New Territories. The main urban areas of the city lie on either side of Victoria Harbour. As of 2019, the MTR has 10 operational lines and 93 stations with a total length of 187.4 km. The MTR is experiencing rapid expansion to meet the increased travel demand in recent years. Herein, the five major line expansions recommended by the Railway Development Strategy (Transport and Housing Bureau, 2014) are used as the case study (Fig. 1). Several new lines are planned to be in operation by 2031, bringing the total railway length to 235.3 km, as shown in Table 1. The rail share of overall daily motorized trips will increase to approximately 50% with the completion of these projects. However, metro networks are vulnerable to incidents that threaten the efficiency of the overall system. Recently, such failure events have occurred more frequently in Hong Kong (RTHK News, 2019a, 2019b), and the regularity of serious disruptions has prompted the public to wonder whether the new lines will add redundancy (i.e., alternative routes) to the existing MTR system.

Table 1
The spatial expansion of the MTR network in Hong Kong (Transport and Housing Bureau, 2014).

Year	Lines	Stations (1)	Links	Route length (km)	Average travel time T_N (mins)	Route diversity D_N	P [1]	New railway lines
2019	10	93	99	**187.4**	29.47	1.116	.587	-
2021	10	98	114	204.4	27.01 (-8.35%)	1.137 (+1.88%)	.567	Shatin to Central Link (2)
2023	11	101(3)	118	215.1	27.93 (+3.41%)	1.145 (+.70%)	.566	Northern Link (NOL)
2025	12	105	123	222.9	27.63 (-.01%)	1.147 (+.17%)	.547	East Kowloon Line (EKL)
2026	13	110	129	23.3	27.93 (+.01%)	1.151 (+.35%)	.533	South Island Line West (SILW)
2031	14	112	133	**235.3**	26.67 (-.05%)	1.165 (+1.22%)	.555	North Island Line (NOL)

Note: (1) Not including the Light Rail and the Airport Express; (2) comprising two parts of the extended segments of the existing East Rail Line and Ma On Shan Line; (3) including new stations at Hung Shui Kiu, Tuen Mun South (TMS), and Tung Chung West (TCW).

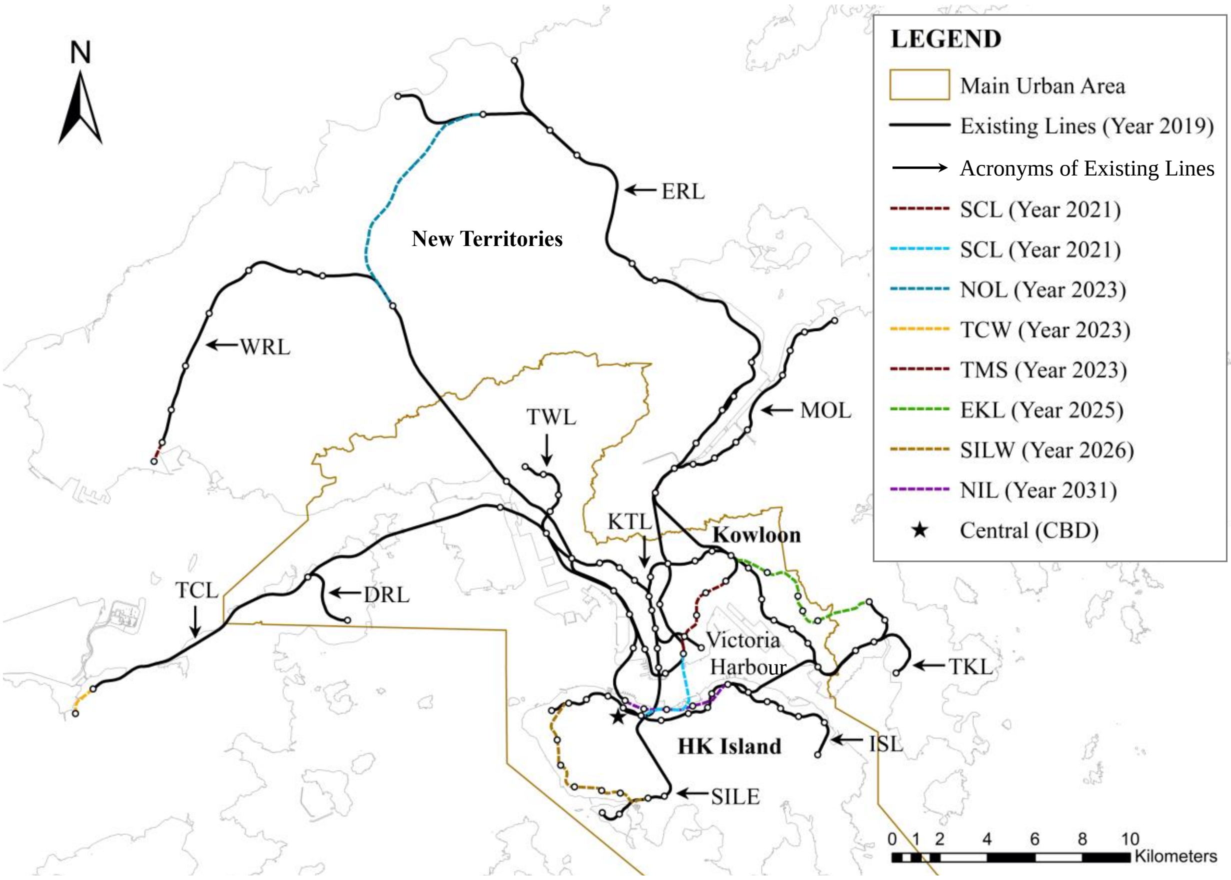

Fig. 1. Map of the Hong Kong MTR system in 2031

To better illustrate the ring-radial network structure, following the study of Roberts et al. (2016), we transform the MTR map into a concentric circle map as shown in Fig. 2. In a radial-centric network, each radial segment connects two outer-city areas as it passes through the city center. However, such a network can also contain circumferential segments, which intersect the radial lines to allow transfer between them, thus constituting a route-diverse network. This network structure generates bottlenecks along the circumferential line segments where branches merge and lines intersect. As we can see, most of the new lines will be in the circumferential form. The Northern Link (NOL), East Kowloon Line (EKL), South Island Line West (SILW), and North Island Line (NIL) can be considered as forming a partial ring that integrates the network by allowing shortcuts, thus enhancing robustness. The only exceptions are the new line segments named the Shatin to Central Link (SCL). These consist of two parts: a southern extension of the Ma On Shan Line (MOL) connecting with the West Rail Line (WRL) to form the new Tuen Ma

Line (TML), and a southern extension of the East Rail Line (ERL) to the Island Line (ISL) to form the new North-South Line (NSL). The SCL will improve the connections between the northern and western inner suburbs and provide a more direct cross-Harbour alternative for the northern area.

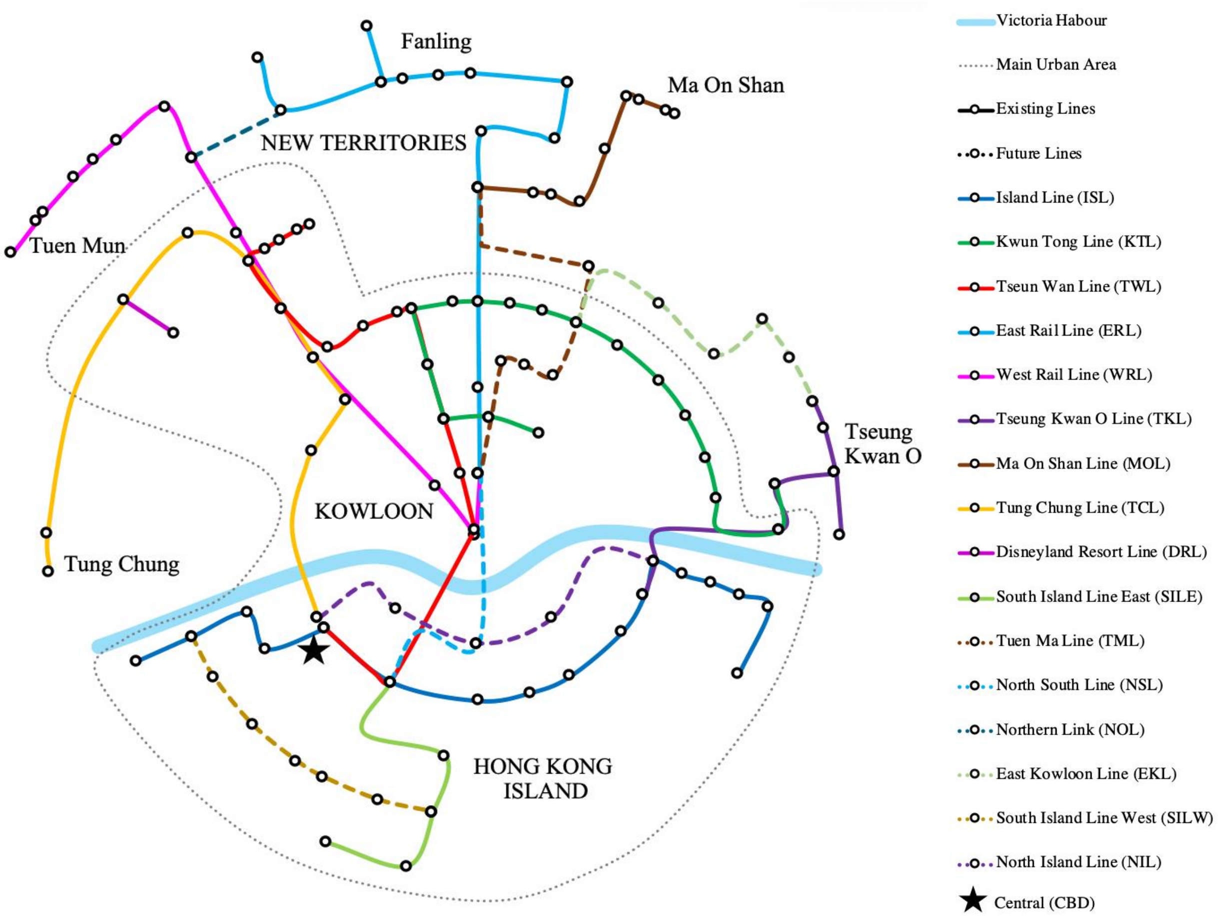

Fig. 2. Concentric circle representation of the Hong Kong MTR system in 2031.

4 Methodology

A method to analyze the value of new metro lines with respect to the topology of the network is proposed. This method entails performance evaluation of route diversity and travel time under normal operating conditions, and vulnerability analysis by a full consideration of possible station failure scenarios. The following sub-sections describe the network representation and the set of routes, followed by the measures of performance and station vulnerability deployed in this study.

4.1 Network representation and basic topological properties

The MTR network is represented by a weighted matrix $M(N, A)$, where N is a finite set of nodes (stations) and A is a finite set of links (connections between adjacent stations). Any node in N can be an origin or a destination of an O-D trip. Each link in A is weighted with the time cost attribute c_a. This representation is based on the L-space graph commonly used in studies of public transportation networks from the complex network perspective (Luo et al., 2019). Similar to the representation used by Sun et al. (2015) and Jing et al. (2019), each interchange station in the network matrix is divided into virtual nodes, each of which has a particular node degree. These virtual nodes are considered to be located on separate MTR lines, and the virtual links between those lines determine the required transfer times, including transfer walking and average waiting times (assumed to be half of the service headways). We assume the access and egress walking times to/from the origin and destination stations to be uniformly 1 minute. This assumption is consistent with the trip planner service on the official website (MTR, 2020). The graph representation has two key features: (1) it enables simulation by allowing one to add both in-vehicle and transfer time attributes when evaluating the set of reasonable routes, under the assumption that travelers choose their routes based on the time cost; and (2) it enables comparison by allowing simple modification of graphs when existing stations become new interchange stations through the addition of virtual stations and links as new connections.

4.2 Assessment of route diversity

We are interested in the route set of each O-D pair in both regular operation and disruptive events. Considering that travelers do not necessarily choose the shortest path, the route choice factors, which are related to the travelers' level of knowledge about the alternative routes, are implicitly considered. This accommodates the likelihood that some travelers will choose their routes with imprecise knowledge of the disrupted network during an actual event, and there may well be some heterogeneity in the routes chosen.

A reasonable route between an O-D pair (m, n) is defined as a route whose links are reasonably short relative to the shortest path (Leurent, 1997; Xu et al., 2018a). The link constraint can be described mathematically as:

$$(1+\tau_m^a)\big(c_m(a_h)-c_m(a_t)\big)\geq c_a,\quad \forall a\in A_k, m\in N \tag{1}$$

where a_h and a_t are the head and tail nodes, respectively, of link a; $c_m(a_h)$ and $c_m(a_t)$ are the minimum time costs from origin m to the head and tail of link a, respectively; τ_m^a is an acceptable elongation ratio for link a with respect to origin m, with τ usually set to 1.5 for urban areas (Tagliacozzo and Pirzio, 1973), consistent with similar studies of route diversity (Jing et al., 2019, 2020; Yang et al., 2017); and A_k is the set of links in route k.

The sets of reasonable routes for each O-D pair (m, n) $K_{mn} = \{R_1, R_2, \ldots, R_i\}$, are obtained using Eq. (1). With the travel time of each reasonable route t_i, the average travel time T_{mn} is calculated as:

$$T_{mn}=\frac{1}{R_{mn}}\sum t_i \tag{2}$$

When quantifying the size of route sets, we take route overlapping into consideration to enable comparison among travelers' route choices. We adopt the similarity coefficient SC_{kh} (Russo and Vitetta, 2003) to penalize the links shared by multiple routes in calculating the route diversity. Hence, with the number of reasonable routes R_{mn}, the route diversity D_{mn} for each O-D pair is calculated as:

$$D_{mn}=R_{mn}-\sum_{k\neq h\in K_{mn}} SC_{kh}, \forall m\neq n\in N \tag{3}$$

$$SC_{kh}=\frac{c_{kh}}{\sqrt{c_k c_h}}, \forall k\neq h\in K_{mn}, m\neq n\in N \tag{4}$$

where c_{kh} is the length of common links between routes k and h; c_k and c_h are the lengths of routes k and h, respectively; and K_{mn} is the set of reasonable routes for O-D pair (m, n).

We aggregate the route diversity into the network level to enable the comparison of disruption scenarios and extended networks. The aggregate route diversity is defined as the average of the route diversity for all O-D pairs:

$$D_N = \frac{1}{|N|(|N|-1)} \sum_{m \neq n \in N} D_{mn}, \forall m \neq n \in N \tag{5}$$

Similarly, the performance of the network in terms of average travel time is:

$$T_N = \frac{1}{|N|(|N|-1)} \sum_{m \neq n \in N} T_{mn}, \forall m \neq n \in N \tag{6}$$

The detailed process of the solution algorithm for the aforementioned calculations is summarized in Table 2.

Table 2

Pseudocode for algorithm for network performance calculation

Initialization: Input all nodes $\{\boldsymbol{m} \in \boldsymbol{N}\}$, all links $\{\boldsymbol{a} \in \boldsymbol{A}\}$, and the time cost matrix u
Procedure:
  Step 1.1: obtain a reasonable adjacency matrix $\boldsymbol{u_m}$ by deleting unreasonable links (i.e., links that do not fulfill the criteria in Eq. (1))
  for $\boldsymbol{1} \leq \boldsymbol{m} \leq |\boldsymbol{N}|$ do
    set $\boldsymbol{u_m} = \boldsymbol{u}$
    for $\boldsymbol{1} \leq \boldsymbol{a} \leq |\boldsymbol{A_m}|$ do
      Calculate the shortest route cost from origin r to head $\boldsymbol{a_h}$ and tail $\boldsymbol{a_t}$ with the Dijkstra algorithm
        if $(\boldsymbol{1} + \boldsymbol{\tau_m^a})(\boldsymbol{c_m}(\boldsymbol{a_h}) - \boldsymbol{c_m}(\boldsymbol{a_t})) \geq \boldsymbol{c_a}, \quad \forall \boldsymbol{a} \in \boldsymbol{A_k}$
          then $\boldsymbol{u_m}(\boldsymbol{a_t}, \boldsymbol{a_h}) = \boldsymbol{0}$
        else
          keep $\boldsymbol{u_m}(\boldsymbol{a_t}, \boldsymbol{a_h})$
        end if
    end for
    Step 1.2: construct the route set $\boldsymbol{K_{mn}}$ by obtaining all possible routes from origin $\boldsymbol{m}$ to all nodes with $\boldsymbol{u_m}$
    $\boldsymbol{DFS}(\boldsymbol{u_m}, \boldsymbol{m})$
      set $\boldsymbol{S}$ an empty stack
        for $\boldsymbol{1} \leq \boldsymbol{j} \leq |\boldsymbol{N}|$ do
          set visited [$\boldsymbol{j}$] = false
          push $\boldsymbol{S}, \boldsymbol{v}$
          while $\boldsymbol{S}$ is not empty do
            $\boldsymbol{u}$ = pop $\boldsymbol{S}$
            if not visited [$\boldsymbol{j}$]
            then visited [$\boldsymbol{j}$] = true
              for each unvisited neighbor $\boldsymbol{i}$ of $\boldsymbol{j}$
                push $\boldsymbol{S}, \boldsymbol{m}$
              end for
            end if
          end while
        end for
    end $\boldsymbol{DFS}()$
    Step 1.3a: calculate the number of reasonable routes $\boldsymbol{R_{mn}}$ for each O-D pair (m, n) using Eq. (1)
    Step 1.3b: calculate the average travel time from $\boldsymbol{m}$ to all nodes $\boldsymbol{n}$, $\boldsymbol{T_{mn}}$ using Eq. (2)
    Step 1.3c: calculate the similarity coefficient $\boldsymbol{SC_{kh}}$ and the route diversity $\boldsymbol{D_{mn}}$ from $\boldsymbol{m}$ to all nodes $\boldsymbol{n}$ using Eqs. (3-4)
  end for
  Step 2a: calculate the network-level route diversity $\boldsymbol{D_N}$ using Eq. (5)
  Step 2b: calculate the network-level travel time $\boldsymbol{T_N}$ using Eq. (6)
  outputs
    O-D-level performance index: route diversity $\boldsymbol{D_{mn}}$ and average travel time $\boldsymbol{T_{mn}}$
    Network-level performance index: route diversity $\boldsymbol{D_N}$ and average travel time $\boldsymbol{T_N}$

4.3 Resilience effects of new lines

The benefit of a network expansion under normal operating conditions is evaluated as the difference in network performance between the extended and reference networks. Two indicators are used: route diversity D_N and average travel time T_N. A new line can serve as a complement (adding redundancy through route diversity) or a substitute (raising efficiency through reduced travel time) to other lines. Thus, the value of a network expansion is first evaluated in terms of the overall effect on passengers.

In parallel with the network performance analysis, we perform the vulnerability analysis of each station to illuminate the variations between stations and identify the strategic importance of each station's served area. Conceptually, identifying vulnerable components and investigating their temporal evolution under different development projects can help cost-effective resource allocation to enhance the network's resiliency. Identifying critical elements is a standard assessment procedure in vulnerability analysis, which can effectively reveal the weaknesses of the network (Jiang et al., 2018; Mattsson and Jenelius, 2015; Xu et al., 2018b; Zhang et al., 2019).

When a station is closed, some passengers may be redirected to a smaller set of alternatives. For the vulnerability analysis, when a station is disrupted, it is assumed that the travel time remains constant for the non-disrupted components, as in the study by Rodríguez-Núñez and García-Palomares (2014). The nodal vulnerability V_r for station r is based on the overall effect of the disruption on the number of available routes, and is defined as:

$$V_r = \frac{D_N(O) - D_N(r)}{D_N(O)}, \qquad \forall r \in N \tag{7}$$

where $D_N\,(O)$ and $D_N\,(r)$ are the network route diversity during normal operations and with closure of station r, respectively.

Network expansion generally benefits passengers under both normal and disrupted conditions, in terms of shortening travel times and increasing route diversity. However, it does not necessarily benefit passengers to the same extent under both conditions, meaning that some areas may be more vulnerable to the effects of disruptions. The value of a network expansion for individual station r under disrupted conditions is evaluated as the difference between the station's vulnerability during disruption in the extended network $M+$ and the reference network M_0:

$$U_{\ r}(\Delta M) = V_r(M_+) - V_r(M_0) \tag{8}$$

4.4 Distributive effect of new lines

4.4.1 Network level: Gini coefficient

The overall distribution of the benefits of the new lines among passengers is analyzed by calculating the Gini coefficient (Allison, 1978). This measure of statistical dispersion indicates the distance of the current situation from the ideal situation, i.e., a situation of complete equity in which all process gains are equally distributed among travelers. The Gini coefficient has a value between 0 (perfect equity) and 1 (perfect inequity). A Gini value of less than 0.20 denotes low inequity, a value between 0.20 and 0.50 indicates medium inequity, and a value above 0.50 represents high inequity (Haidich and Ioannidis, 2004). In this way, the distribution of Lorenz curves at different stages of development, a visual representation of equity, can be compared mathematically. The Gini coefficient G is calculated as follows (Delbosc and Currie, 2011):

$$G = 1 - \sum_{k=1}^{n} (X_k - X_{k-1})(Y_k - Y_{k-1}) \tag{9}$$

where X_k and Y_k are the cumulative proportion of the population and public transport service variable respectively, for $k = 0, 1, 2, \ldots, n$, with X_0, $Y_0 = 0$ and X_n, $Y_n = 1$.

4.4.2 Dyadic level: Two-step clustering

As mentioned earlier, a new line could benefit different groups of passengers in different ways: as a complement providing a reasonable alternative route or as a substitute providing a superior alternative route. Other than the measures that are computed at the network level, indicators defined at the dyadic level (Eqs. (2)–(3)) allow investigation of the spatial disparity of topological characteristics among O-D pairs. Spatial clustering is commonly used to evaluate the differential effects of a transportation infrastructure investment (González-González and Nogués, 2019; Pereira et al., 2019), and passengers are often clustered into several groups based on their origins and destinations (Kroon et al., 2015; van der Hurk et al., 2018). In this paper, a two-step cluster analysis is applied to differentiate O-D pair clusters with two major continuous variables: changes in travel time and route diversity.

The cluster analysis involves two steps (pre-cluster and cluster steps) and is effective for very large datasets with both continuous and categorical variables (Tkaczynski, 2017). In the first step, observations are pre-clustered using log-likelihood distances to create a cluster-feature tree. In calculating the log-likelihood, the continuous variables are assumed to be normally distributed, and the categorical variables are assumed to follow multinomial distributions. The resulting sub-clusters are further grouped in the second step by comparing their distances to a specified threshold or pre-defined number of clusters. The distance D (j, s) between two clusters j and s is defined as the decrease in log-likelihood due to the merging of the two clusters:

$$D\ (j, s) = \zeta_j + \zeta_s - \zeta_{\langle j,s \rangle} \tag{10}$$

where

$$\zeta_j = -N_j \left[\sum_{k=1}^{K^A} \frac{1}{2} \log\left(\hat{\sigma}_k^2 + \hat{\sigma}_{jk}^2\right) + \sum_{k=1}^{K^B} \hat{E}_{jk} \right] \tag{11}$$

and

$$\hat{E}_{jk} = -\sum_{l=1}^{L_k} \frac{N_{jkl}}{N_j} \log \frac{N_{jkl}}{N_j} \tag{12}$$

where K^A is the total number of continuous variables used, K^B is the total number of categorical variables, L_K is the number of levels for the kth categorical variable, N_j is the number of observations in cluster j, $\hat{\sigma}_k^2$ is the variance of the kth continuous variable in the original data set, $\hat{\sigma}_{jk}^2$ is the variance of the kth continuous variable in cluster j, N_{jkl} is the number of observations in cluster j for which the kth categorical variable takes the lth level, and $\langle j, s \rangle$ represents the cluster formed by merging clusters j and s. Because all variables in this study are continuous, the above ζ_j can be reduced to $-N_j \left[\sum_{k=1}^{K^A} \frac{1}{2} \log\left(\hat{\sigma}_k^2 + \hat{\sigma}_{jk}^2\right) \right]$.

The two-step cluster component in IBM SPSS Statistics 26 is used to find the correct number of clusters by running a simulation, which determines the clusters automatically, accurately, and quickly. The two-step process clusters together groups of stations with similar characteristics to enable comparative analysis between different new lines.

4.4.3 Nodal level: Spearman's rank correlation coefficient

In addition to assessing the distributive effects of new lines in normal operation, we assess the conformity between the need and benefit in terms of resilience using the Spearman rank correlation coefficient. This coefficient has a value between -1 and 1 and indicates the strength and direction (negative or positive) of a relationship between two variables. We assume that the distribution of nodal vulnerability to hazards reflects the local needs, and thus stations with greater needs would require a greater resilience enhancement to reduce the effect of a disruption on overall network performance. Once the distribution of the need for vulnerability enhancement for each station and the benefits from each new line are evaluated in the vulnerability analysis in Section 4.3, we sort the list of stations according to need and benefit. We then assess the conformity among the ranked stations in terms of need and benefit by using Spearman's correlation rank-order coefficient ρ:

$$\rho = 1 - \frac{6 \times \sum_{r=1}^{m} d_r^2}{(m^3 - m)} \tag{13}$$

where d_r indicates the difference between a station's ranking positions in the two lists (nodal vulnerability V_r and received value from new lines U_r) and N indicates the number of stations. ρ follows a t-distribution with the degrees of freedom equal to $m - 2$ and, therefore, its statistical significance can be determined (Siegel, 1956).

5 Value of New Lines Assessed with Route Diversity Measures

5.1 Value of new lines for network route diversity

We use the route diversity measures to assess the performance of the Hong Kong MTR network. These measures quantify the feasible routes available for travelers. More available routes correspond to more alternative routes in the event of disruption. The network-level route diversity is first evaluated with the statistic of route availability distribution during normal operation. For the existing network, the proportion of all O-D pairs connected by only one reasonable route P[1] is calculated as 0.587, and the network-level route diversity index is 1.116. We find that the routes with the greatest route diversity (greater than 3) are from East Tsim Sha Tsui to Sham Shui Po and from Prince Edward to Austin. This is understandable given that these stations are located at the center and serve as a hub for local coverage. Many stations in the center form a grid pattern, which increases the number of alternatives. However, due to the high efficiency of the radial lines for trips between main urban and suburban areas, the alternative routes provided by the circumferential lines are comparatively much less feasible. Trips originating or terminating in the outer city generally have fewer alternatives (i.e., lower route diversity). For example, trips between the northern and western parts of the New Territories, which on average require more than 60 minutes, are considered long journeys. The radial segments of the ERL and WRL provide efficient routes for those O-D pairs. Although the circumferential segments provide alternative routes, they are not considered reasonable by Eq. (3). Therefore, while some O-D pairs enjoy higher route diversity (more choices), others offer a shorter travel time.

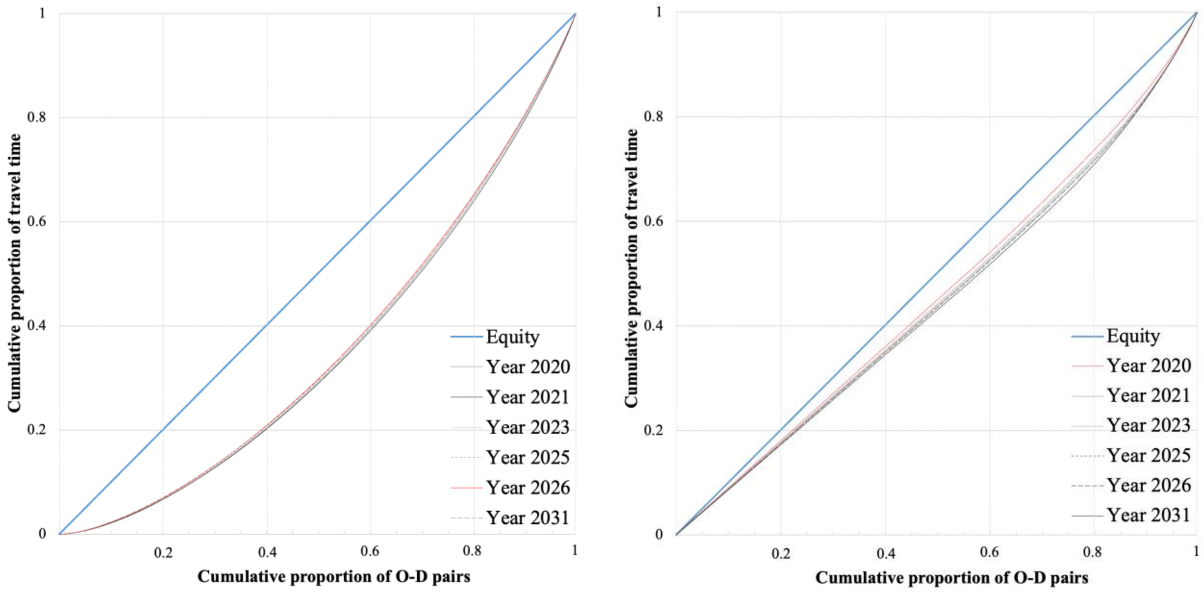

Fig. 3. Lorenz curves of O-D pairs and travel time (left) and route diversity (right) from 2020 to 2031

Table 3
Gini coefficient for different phases of the proposed expansions from 2020 to 2031.

Station	Year					
	2019	**2021**	**2023**	**2025**	**2026**	**2031**
Gini coefficient (Travel time)	.294	.299 (+.005)	.291 (-.008)	.288 (-.003)	.284 (-.004)	.287 (+.003)
Value rank	-	5	1	3	2	4
Gini coefficient (Route diversity)	.083	.097 (+.014)	.101 (+.004)	.105 (+.003)	.106 (+.001)	.113 (+.007)
Value rank		5	3	2	1	4
Value rank (Overall)		5	2	3	1	4

We further examine how the addition of new lines will enhance resilience by improving route diversity and reducing travel time, and thus benefit spatial equity, with the above measures. Table 2 summarizes the extent of the planned MTR expansion from 2019 to 2021, 2023, 2025, 2026, and 2031. The cumulative frequency distributions of route diversity and travel time are presented in Fig. 3 to further illustrate the association between these two measures at the O-D level. The results reveal a gradual improvement of the network in terms of increasing route diversity (where lower cumulative proportions are preferable) and reducing travel time (where higher cumulative proportions are preferable). This tendency is more distinguishable in 2021 and 2031, suggesting that critical transitions occur in those years. The main reason for the considerable enhancement of route diversity is the completion of the SCL and NIL, which benefit the network due to their location in the inner city and enable a large number of O-D pairs to make use of the new lines. They also shorten some existing trips, as indicated by the significant drop in average travel time. However, as shown in Table 3 and Fig. 3, the spatial equity of travel time is worsened by the expansion, as the improvement in accessibility is concentrated in the main urban area along the primary MTR corridor, near the already advantaged central area. Besides the SCL and NIL, the other new lines mostly offer local connectivity in disadvantageous suburban areas, and the spatial equity is therefore improved. In contrast, the spatial equity in route diversity would worsen gradually from 2020 to 2031. This indicates that the improvement in the provision of redundant alternatives for existing O-D trips is not evenly distributed. Notably, the value of P[1] slightly increases in 2031. This suggests that the NIL provides such an improvement that previous path alternatives for certain O-D pairs become comparatively inferior, which mathematically appears as a worsening of resilience and equity. However, it remains difficult to determine exactly how much relative significance one should attribute to the two aspects of the value of new lines when only information at the network level is available. Thus, disaggregate information is needed to delve deeper into the dyadic and nodal levels, as discussed in the following sections.

5.2 Value of new lines for dyadic level route diversity

Although the results show an improvement of overall value as the network complexity increases over time, this does not necessarily imply that all users at the dyadic level benefit from the new lines. Our assessment of the value of the new lines is therefore carried down to the dyadic level, by evaluating the improvements in route availability and time saving for the O-D pairs. This investigation focuses on clusters of O-D pairs of the network over different time scales. The information is then used to identify the prominent network topologies that contribute to the route diversity. Three clusters of O-D pairs are identified (Table 4). Group A represents O-D pairs that are provided with faster routes owing to the network expansion, identified by the reduced average travel time and route diversity. Travelers in this group enjoy much faster journeys than before. As the new routes have much shorter travel times, the previous route sets in the old network become unattractive and disfavored. Group B represents O-D pairs for which the number of alternative routes increases. This group benefits from the new lines specifically from the route diversity perspective. Travelers perceive a new alternative route as an increase in utility, even if it does not provide significant time saving. Group C represents O-D pairs that are unaffected in terms of route diversity and travel time. This group derives no benefit from the new lines as they provide neither significant time saving nor additional reasonable routes between the O-D pairs. Although theoretically they might benefit from congestion relief in cases where a new route offering a faster journey option removes some passenger flow from the associated routes, a full discussion of the passenger flows and congestion is beyond the scope of this paper. Therefore, the benefit of new lines at the dyadic level is determined as the total percentage of O-D pairs in Groups A and B.

The completion of the SCL in 2021 and NIL in 2031 has an obvious topological effect on the O-D pairs. The SCL provides a connection between two major areas in the New Territories that are served by large numbers of stations. The radial properties of this L-shaped line, which passes through the city center, contribute to travel time reduction between the inner and outer cities for 24.3% of O-D pairs. Due to the radial properties of the new line, its benefits spread indirectly to some other O-D pairs (a further 9.0%) by providing alternative routes. In comparison, the NIL makes a similar contribution, in terms of travel time reduction and alternative routes, to the O-D pairs. However, it acts more like a circumferential line in the main urban area to provide shorter connections between radial segments. The other lines, such as the NOL, EKL, and SILW, lie on the edge of the network topology. Their effects are more local than those of the SCL and NIL. Their topological effects on the network are limited, influencing less than 4% of O-D pairs. Overall, the route diversity measure captures the topological effects of the new lines differently from the conventional consideration of the path with the shortest travel time, quantitatively reflecting the advantages of the new lines in providing alternative routes.

Table 4
Groups of O-D pairs identified in the evolution of the network from 2021 to 2031.

Group	A	B	C
Characteristics	O-D pairs provided with faster routes	O-D pairs provided with more alternatives	Unaffected O-D pairs
Year 2021 (SCL)			
Description	Benefit: 33.3% of O-D pairs; Value rank: 1		
Size	2810 (24.3%)	1036 (9.0%)	7709 (66.7%)
Route diversity	-0.16 (-0.09%)	**+0.67 (+0.62%)**	0.00 (0.00%)
Travel time (mins)	**-5.37 (-0.16%)**	-0.86 (-0.03%)	-0.08 (-0.00%)
Year 2023 (NOL)			
Description	Benefit: 3.3% of O-D pairs; Value rank: 4		
Size	299 (2.2%)	148 (1.1%)	12893 (96.6%)
Route diversity	-0.06 (-0.07%)	**+0.89 (+0.45%)**	0.00 (0.00%)
Travel time (mins)	**-18.88 (-0.55%)**	-0.50 (-0.01%)	-0.02 (-0.00%)
Year 2025 (EKL)			
Description	Benefit: 3.6% of O-D pairs; Value rank: 3		
Size	250 (1.7%)	274 (1.9%)	14238 (96.5%)
Route diversity	-0.25 (-0.26%)	**+.56 (+0.30%)**	0.00 (0.00%)
Travel time (mins)	**-5.74 (-0.17%)**	-.20 (-0.01%)	0.00 (0.00%)
Year 2026 (SILW)			
Description	Benefit: 0.2% of O-D pairs; Value rank: 5		
Size	12 (0.1%)	16 (0.1%)	16228 (99.8%)
Route diversity	-0.09 (-0.09%)	**+0.34 (+0.16%)**	0.00 (0.00%)
Travel time (mins)	**-3.00 (-0.18%)**	0.00 (0.00%)	0.00 (0.00%)
Year 2031 (NIL)			
Description	Benefit: 20.0% of O-D pairs; Value rank: 2		
Size	2365 (13.1%)	1249 (6.9%)	14476 (80.0%)
Route diversity	-0.25 (-0.25%)	**+0.69 (+0.38%)**	0.00 (0.00%)
Travel time (mins)	**-6.02 (-.24%)**	-0.77 (-0.02%)	-0.11 (-0.00%)

The spatial variation of the largest topological effects from the construction of SCL and NIL, regarding the clusters of O-D pairs, is further illustrated in Fig. 4. Considering Group A, it is immediately clear that the existing ERL/MOL and WRL directly benefit from the SCL with respect to travel time. In the extended network, the MOL connects with the WRL in the city center while the ERL connects with the terminus of the extended MOL. However, unlike the ERL and MOL, the WRL not only benefits with respect to time saving but also increased route diversity for some O-D pairs. It is interesting that both ends of the new lines should gain the same topological benefit from the new expansion. Overall, the topological effect of the SCL is spread across the entire network. No part of the network receives a significantly larger or smaller share of the benefits, according to the evaluation of route diversity and travel-time saving. In contrast, upon the extension of the NIL, the eastern part of the network gains the most topological benefit in both travel-time saving and route diversity. Considering that the ERL and TCL connect directly to the NIL, it is surprising that neither benefits from the NIL in both respects at once. Rather, the ERL only benefits from travel-time saving while the TCL only benefits from the increased route diversity for a limited number of O-D pairs. Overall, the topological effect of the NIL is less evenly distributed among O-D pairs, although it does affect a significant percentage of O-D pairs according to the measures adopted here.

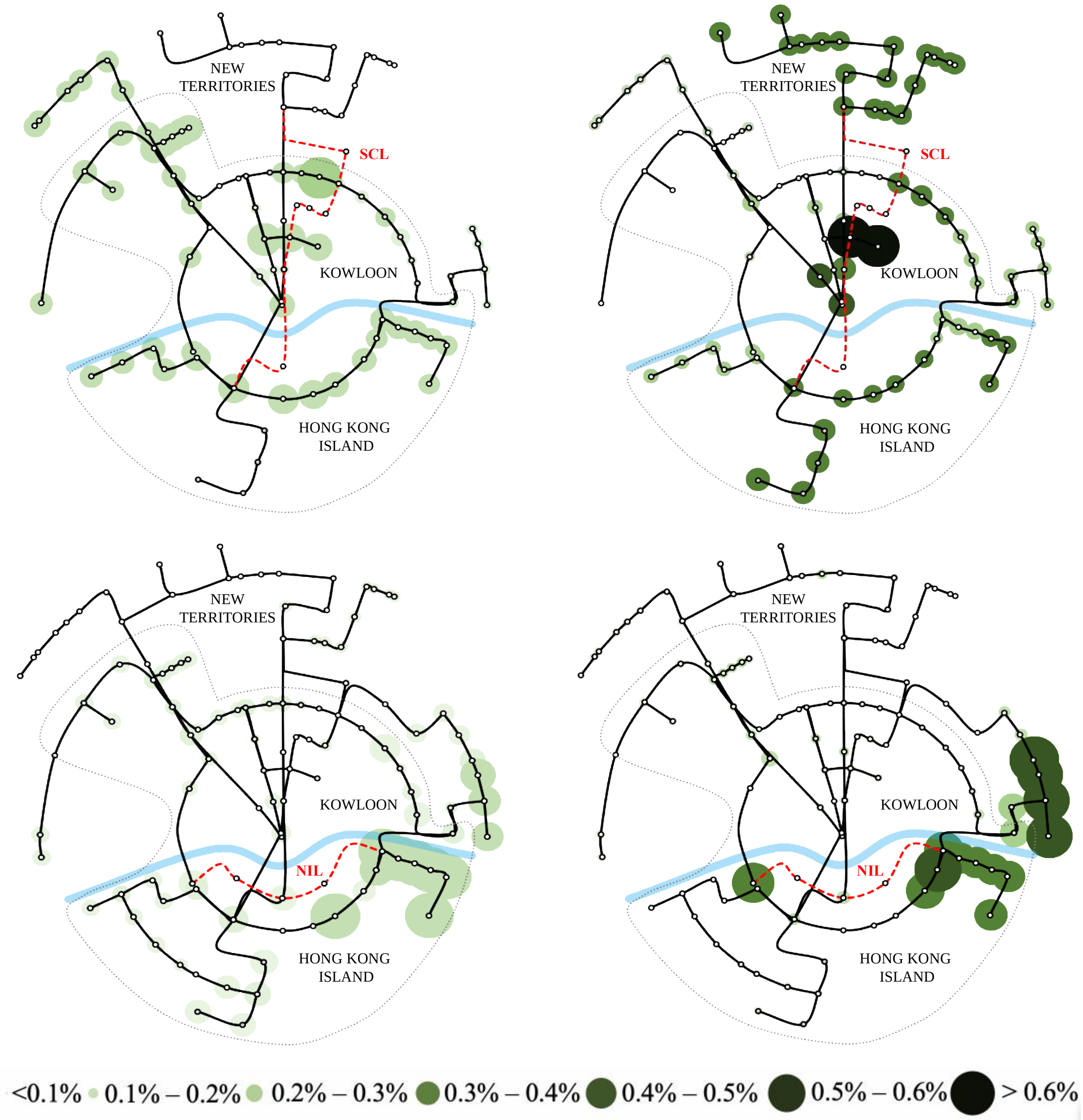

Fig. 4. Distribution of the effects of the construction of the SCL and NIL on different O-D pairs. Circles with deeper color and larger size indicate higher percentages of O-D pairs originating from or terminating at those stations.

5.3 Value of new lines for reducing nodal vulnerability

To further analyze the performance of the MTR network during adverse events, we use the route diversity measure as an indicator to evaluate the vulnerability and identify critical stations under disruptions. We use a full-scan approach in which each station is disrupted in turn and the vulnerability of every other station is calculated with Eq. (7). As shown in Fig. 5 and Table 5, the identity of the 10 most vulnerable stations is straightforwardly intuitive, as nearly 80% of the vulnerable stations in the selected years are transfer stations in the main urban area. Such stations have more lines passing through and are typically considered as the most important. Many of the vulnerable stations are located on radial segments in the inner city, reflecting their importance as transfer nodes to the circumferential lines. However, not all of the 10 most vulnerable stations are transfer stations. This indicates that a station's location, in addition to its connectivity, may play a role in its importance in a metro network. For example, Austin station, ranked 10th, is not a transfer station, but is a close neighbor of East Tsim Sha Tsui (ranked 2nd) and is located on a radial line connecting the center with the western part of the network. The overall results indicate that the radial segments crucially serve as the backbone of the network but are vulnerable to disruption due to poor route redundancy. For comparison, Wu et al. (2018) studied the MTR network using the metric of betweenness centrality. Although they included some of the same stations (e.g., Kowloon Tong and Prince Edward) in the top 10 list, some of the key stations in the network were absent. For instance, in our study, Tsim Sha Tsui is ranked 3rd, reflecting its role as a transfer station between the Tseun Wan Line (TWL) and WRL. Although the relatively long transfer time reduces its importance according to centrality measures, which focus on the shortest routes, its role as a transfer station increases the number of reasonable routes for which it offers an alternative transfer option. When its transfer role is taken into account, the topological advantages of this station emerge, as it can be considered an important transfer node between two efficient radial lines. This highlights that the calculation of the shortest path may not fully reflect the importance of transfer nodes in the network. As a result, the proposed measures in this study, which integrate the characteristics of the travelers' route choice preferences, are more useful. The route diversity measures in this study provide a more comprehensive topological analysis by identifying vulnerable stations from the perspective of travelers' route choices. When considering the locations that are most susceptible to disruption, these vulnerable stations emerge as an essential focus for future expansion and reconstruction projects.

The vulnerability of stations changes as the network is extended from 2019 through 2031. As shown in Table 5, some stations are identified as vulnerable in multiple selected years but ranked differently. For example, Admiralty becomes less vulnerable than East Tsim Sha Tsui in 2021, a reversal from 2019. The 10 most vulnerable stations, which are all located within Hong Kong's urban area, provide information on the weakness of the metro network. For instance, in 2021, two vulnerable components (radial segments in the inner city) gain topological benefits from the opening of the SCL, as indicated by the reduction in vulnerability shown in Fig. 5. The extension of the ERL to Hong Kong Island offers transfer alternatives between the radial lines, which reduces the vulnerability of Tsim Sha Tsui and East Tsim Sha Tsui. However, there are still four vulnerable stations located on the radial segments of the ISL, indicating its high vulnerability. Meanwhile, some stations remain on the list even after several expansions. Transfer stations like Nam Cheong and Tsim Sha Tsui, for example, stay near the top of the list. Admiralty, as a transfer hub, also remains high on the list, although its vulnerability is reduced through the introduction of new lines. We highlight that Austin, despite being a non-transfer station, remains vulnerable over time. These findings may imply blind spots in the planning process. The rise of new vulnerable stations (Hong Kong, Kowloon, and Olympic) connecting to the new line NIL should not be ignored in future planning.

Table 5. Trends in the ranking of station vulnerability in different phases of the proposed expansions. Top 10 stations are highlighted for each reference year. Stations are sorted in descending order based on the cumulative number of years being ranked in the top 10.

Station	Year					
	2019	2021	2023	2025	2026	2031
Transfer stations						
Admiralty TWL	**.058 (1)**	**.040 (6)**	**.040 (7)**	**.037 (8)**	**.038 (7)**	**.036 (9)**
East Tsim Sha Tsui	**.057 (2)**	**.048 (2)**	**.052 (2)**	**.049 (2)**	**.047 (2)**	**.051 (1)**
Nam Cheong WRL	**.046 (6)**	**.049 (1)**	**.054 (1)**	**.052 (1)**	**.048 (1)**	**.049 (2)**
Tsim Sha Tsui	**.052 (3)**	**.039 (8)**	**.040 (8)**	**.037 (7)**	**.037 (8)**	.034 (13)
Admiralty ISL	.037 (15)	**.045 (3)**	**.045 (5)**	**.041 (5)**	**.039 (5)**	**.036 (7)**
Mei Foo WRL	.148 (-)	.140 (-)	**.049 (3)**	**.045 (4)**	**.045 (3)**	**.047 (4)**
Tsuen Wan West	.127 (-)	.120 (-)	**.042 (6)**	**.039 (6)**	**.039 (6)**	**.046 (5)**
Yau Ma Tei TWL	**.046 (4)**	.025 (19)	.024 (23)	.024 (28)	.023 (29)	.026 (29)
Kowloon Tong KTL	**.046 (5)**	.020 (37)	.020 (42)	.024 (26)	.023 (28)	.027 (22)
Nam Cheong TCL	**.045 (7)**	.028 (15)	.029 (17)	.029 (15)	.028 (16)	.034 (14)
Prince Edward KTL	**.042 (9)**	.022 (32)	.022 (35)	.025 (20)	.024 (23)	.026 (25)
North Point ISL	.027 (26)	**.039 (10)**	.037 (14)	.034 (12)	.032 (12)	.025 (37)
Hung Hom WRL	.041 (11)	.037 (12)	**.039 (10)**	.027 (18)	.021 (37)	.035 (12)
Hong Kong	.020 (32)	.025 (19)	.026 (19)	.025 (24)	.025 (23)	**.040 (6)**
Non-transfer stations						
Austin	**.041 (10)**	**.044 (4)**	**.048 (4)**	**.046 (3)**	**.044 (4)**	**.049 (3)**
Wan Chai	.028 (23)	**.041 (5)**	**.040 (9)**	**.036 (9)**	**.034 (9)**	.024 (40)
Causeway Bay	.028 (24)	**.040 (7)**	.039 (11)	**.035 (10)**	**.033 (10)**	.023 (52)
Jordan	**.044 (8)**	.024 (21)	.023 (27)	.023 (31)	.022 (34)	.025 (31)
Tin Hau	.027 (25)	**.039 (9)**	.038 (12)	.034 (11)	.033 (11)	.022 (54)
Kowloon	.020 (33)	.023 (25)	.024 (24)	.023 (33)	.023 (31)	**.036 (8)**
Olympic	.021 (31)	.022 (30)	.023 (29)	.022 (37)	.022 (35)	**.036 (10)**
Average vulnerability of top 10 stations	.047	.038	.045	.038	.040	.039

Table 6
Conformity between ranking positions of need and benefit for different phases of the proposed expansions.

	Year				
	2021	2023	2025	2026	2031
Spearman's correlation coefficient	.29**	.15*	.50**	.49**	.19*
Value rank	3	5	1	2	4

** Correlation is significant at the 0.01 level.
* Correlation is significant at the 0.05 level.

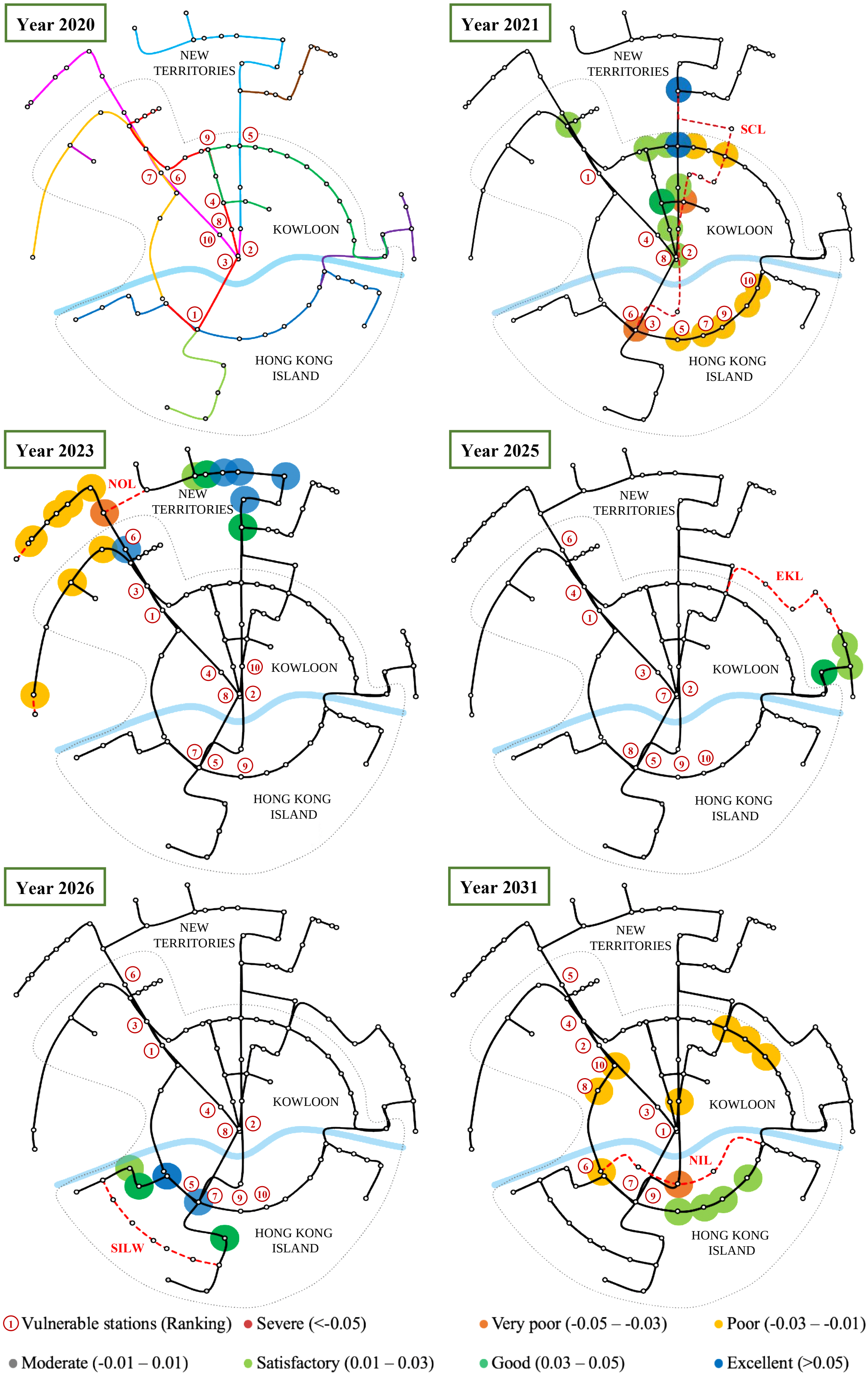

Fig. 5. Vulnerable stations and the value of new lines for reducing nodal vulnerability.

With a view to improving network resilience, we would like to remedy the existing weaknesses by building new lines as long-term adaptive measures. Nevertheless, new lines do not afford equal improvements in all disruption scenarios, even though they always increase route diversity. In fact, the effects of disruption are not consistently lower in the extended network than in the reference network in terms of the station vulnerability. Stations could be more vulnerable in the extended network for some cases because the new lines do not necessarily increase route diversity to the same extent during disruptions as under normal operating conditions. That is, the new lines cannot be fully utilized as an alternative travel route by passengers affected by disturbances. This implies that the value of resilience of some new lines is negative for some scenarios. Therefore, we investigate the conformity between the ranking positions of need (station vulnerability) and benefit (resilience enhancement) for different phases of the proposed expansions using Spearman's rank correlation coefficient. We assume that it is preferable for stations with greater vulnerability to receive a greater enhancement of resilience, whereas any negative changes in resilience are preferably distributed among stations with low vulnerability.

As shown in Table 6, the EKL in 2025 and SILW in 2026 have the highest conformity, in that the stations' rankings of need are statistically proportional to their rankings in terms of the received benefit. The EKL and SILW provide enhancement to the isolated regions of the network, namely the eastern New Territories and southern Hong Kong Island, respectively. This greatly reduces the vulnerability of stations at cut links (i.e., where disruptions cause some stations to be disconnected/isolated from the main part of the network), which require redundant enhancement. In addition, the introduction of the EKL and SILW does not cause any stations to become more vulnerable. In contrast, the introduction of other new lines does increase vulnerability: for example, the SCL adds to the network several new vulnerable stations on the circumferential line on Hong Kong Island. The ultimate cause of high vulnerability is always a lack of rerouting alternatives in the case of disruption. It is not surprising that there is a lack of redundancy on Hong Kong Island. The rise of the vulnerability ranking of these stations shows the necessity of providing them with redundant routes. Nevertheless, inspection of the map of planned lines from 2019 to 2031 suggests that the NIL in 2031 could be a complementary solution to this problem. As shown in Fig. 5, the NIL brings about a topological benefit to the aforementioned segments by reducing their vulnerability. The NIL offers a bypass alternative parallel to the ISL, and rerouting possibilities for disruption scenarios. This evidence suggests that the complementary relationship of the NIL and the SCL, which individually both have low values of Spearman's coefficient, reduces each other's vulnerability and provide a more robust metro network. Hence, to determine whether the overall contribution of a new line is positive, the consequences in the event of its disruption have to be taken into consideration. The changes in station vulnerability thus have implications for the prioritization of future robustness investments and resource allocation.

6 Conclusions

In this paper, the spatiotemporal effects of the planned development of a metro network were investigated using a new network performance measure, route diversity. In the case study of Hong Kong, the MTR network continues to expand rapidly, which has resulted in stepwise increases in route diversity and reductions in travel time. We assessed the effects of new lines and evaluated their spatial distribution, variation, and changes at the nodal, dyadic, and network levels. At the network level, the expanding MTR network gradually results in increased route diversity and reduced travel times, with slight variations in spatial equity. At the dyadic level, O-D pairs exhibit differentiated patterns of improvement, which can be divided into three clusters: O-D pairs provided with faster routes, those provided with more alternatives, and unaffected O-D pairs. The cluster analysis allows a fuller understanding of the situation after the new lines are built. At the nodal level, we studied the performance of the network in disruption scenarios to assess how each new metro line would benefit stations by reducing their vulnerability. By comparing the consequences of disruption in the expanded and current networks, our findings clearly show that the new lines would not lessen the consequences of disruptions in all scenarios but may sometimes exacerbate them. This result emphasizes the importance of matching the vulnerable parts of the existing network with the resilience benefits of new lines. Fig. 6 summarizes the value of new lines for different phases of the proposed expansions. A remaining issue involves the level of relative significance that should be attributed to the different aspects of importance when prioritizing projects. This is difficult to answer in exact terms and may be a matter for a political discussion.

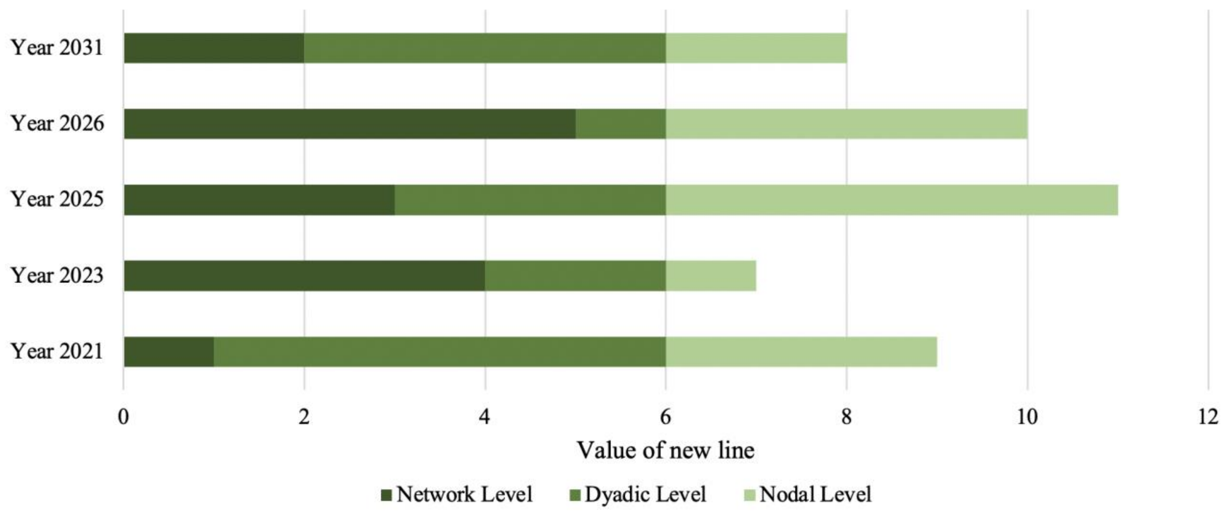

Fig. 6. Values of new lines in different phases of the proposed expansions. A five-point Likert scale is used to measure the benefit according to the value rank at three levels (5 points for rank 1 and 1 point for rank 5).

Our study evaluates the distributive improvements in both accessibility and resilience resulting from future expansions of the metro network at different stages, which limits our focus solely to the spatial scale. The effects of new lines are not only associated with spatial accessibility but also with social equity issues, such as differences in MTR demands according to different kinds of work and income status (He, 2020). Nonetheless, our focus only on the spatial scale does not undermine the contributions of this study, for two reasons. First, during the onset of any transportation infrastructure project, spatial scales have primacy because at this stage, cities are the focal point, as opposed to individual passengers (van Wee and Roeser, 2013). Second, addressing the social equity effects of future expansion could be problematic because this kind of analysis would require one to predict the social needs and mode choices of various groups, changes in the land use and flow pattern, and thus the congestion effects in a future situation (van Wee and Roeser, 2013), which may change in practice after construction. Although route diversity measures and vulnerability analyses provide vital information about the properties and development of urban rail transit networks, research should be extended to the planners' perspective, which focuses on the station and line capacities (Xu et al., 2018a). Travel demand is not considered in this paper, as we only consider the route diversity dimension to evaluate the value of new metro lines. The future variations in passenger demand merit analysis from other perspectives, which might lead to different conclusions from those of this paper. This research direction will be pursued when the operational and scheduling data become available.

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