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Route choice and parallel routes in subway Networks: A comparative analysis of Beijing and Shanghai

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ABSTRACT

In megacities worldwide, subway systems have become a prevailing transport mode for residents' daily travel. The expansion of subway networks has given people more route choices and increased the appeal of online maps for route selection. Since few studies have investigated route choices across the entire transport network based on online maps, we introduce the concept of parallel routes with a network analysis approach. Based on that, we offer a comparative analysis between the Beijing and Shanghai subway networks with a network analysis approach combining an online map application programming interface (API). Moreover, we investigate to what extent route choices by subway can be explained by built environment factors within the metro station buffer. The results indicate that online maps do not always offer reasonable route choices due to the complex topology of subway networks. Empirical analysis shows that route choices of the Beijing and Shanghai subway networks follow a distance decay law: the closer to the city center the metro station, the more parallel the routes. Compared with Beijing, the subway network in Shanghai provides more route choices within more parallel routes within the same distance. Furthermore, there is a positive correlation between route choices and land-use mixture around metro stations. In general, our findings are useful for promoting transit-oriented development in megacities.

1. Introduction

Transit is an important travel mode in many megacities where subway systems play an essential role. Since the first subway system in London in 1863, the popularity of subway systems has significantly increased due to their reliability and rapidity. With the urban sprawl of megacities, subway networks have been greatly extended. Also, their metro line density and station density have been increased. As a result, passengers have multiple route choices between their destinations and origins, regarded as a type of parallel route (Jánošíková et al., 2014; Sheffi, 1984). By offering various travel choices for people, parallel routes effectively reduce congestion and guarantee the stability of transport networks (Jansson and Ridderstolpe, 1992; Arnott et al., 1993). Meanwhile, mobile map applications are major tools to guide route selection with the increasing popularity of smart mobile phones, while few studies have examined the accuracy and completeness of these applications. Thus, one arising question is whether mobile map applications offer the shortest travel route and all potential alternative routes.

With the research question above, this paper performs a comparative subway network analysis in Beijing and Shanghai, two typical megacities in China with comparably sized subway networks (Sun et al., 2016). Subway networks in these two cities are substantially complex, with line density at 0.03 and 0.11 km per square kilometer, and station density at 0.02 and 0.05 per square kilometer, respectively. While Beijing subway is the busiest subway system over the world with two loop lines, there are more transfer stations in Shanghai subway, which may offer more route choices. A standardized analytical framework on these two subway networks can enhance the understandings of their topologies, shedding light on analyzing subway networks from the aspect of route choices.

To some extent, subway systems reshape urban structures and change urban lifestyles. For example, the number of daily passengers in the Beijing Subway system increased from 6.5 million in 2011 to 10.9 million in 2019 (the latest data before the COVID-19 pandemic). Consequently, urban structure has co-evolved with subway network expansion (Huang et al., 2019). Some studies have investigated the

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relationship between transit route choices identified and land use variations, offering new insight for urban planning and transport network design (Cao et al., 2016). Apart from the built environment on the ground, the difference in transfer duration caused by the complexity of urban underground space has significantly affected route selection (Guo and Wilson, 2011; Huang and Levinson, 2015; Cui and Nelson, 2019; Peng et al., 2019; Fu et al., 2018; Fu et al., 2020). Since Beijing and Shanghai are both pioneers in promoting Transit-Oriented Development (TOD) strategies but different in urban forms, exploring the relationship between subway network structures and built environment in these two cities is helpful for uncovering the relationship between transport and land use (Huang et al., 2021).

Since there has been little research about parallel routes in the subway network of two comparative megacities applying multiple methods, this paper contributes to the current literature by offering an analytical approach from the perspective of route choice. Another contribution from this paper is to investigate the spatial disparity of route choice from the perspective of the built environment. The following section provides a literature review in three subsections, then Section 3 gives the analytical framework. Section 4 introduces study areas followed by results in Section 5. Section 6 concludes our findings.

2. Literature review

2.1. Parallel routes in subway systems

The identification and analysis of parallel routes is a classic topic in transport research due to growing transport demand. In transport modeling, most studies apply traffic equilibrium models to discuss the route choice and travel cost, especially in the case of traffic congestion (Arnott et al., 1992; Chen et al., 2011; Long and Szeto, 2019). In transport geography, research has been conducted on developing GIS-T (Geographic Information System - Transportation) for optimal route selection based on the theory of parallel routes (Papinski and Scott, 2011). Also, several researchers have employed travel cost functions to study the impact on average travel cost after GIS-T was introduced (Wu and Huang, 2003), or put their focus on travel cost changes when there are parallel routes in a congested transport system (Lam et al., 1999).

The concept of parallel routes is derived from routes with an approximate topological distance according to nodes and links visited (Prato et al., 2012). In fact, monetary cost or travel time may be different even if topological distances of routes are equal. Hence, monetary cost or travel time is further considered and regarded as the core in the identification of parallel routes in transport modelling. In such cases, parallel routes are identified according to the equivalent travel cost (Abdel-Aty et al., 1995; Hainen et al., 2011. In addition, travel mode is another element that has been considered with the estimates of generalized travel cost (Scheiner and Holz-Rau, 2007). Studies on parallel routes in subway systems focus on the identification of parallel routes with equivalent and reasonable travel cost in the subway system (Fig. 1). In practice, these parallel routes are alternatives in the route selection of passengers.

In the route choice of subway passengers, travel cost consists of monetary cost, time cost (or distance cost), transfer and others (Sun et al., 2014; Fu et al., 2022) (Fig. 2). In general, factors like congestion, service level are of little influence in travel behavior and route choices since they are basically same for most of passengers. Despite the positive correlation between travel time and travel fare, monetary cost has little influence on route selection for subway passengers in most cities in China (Yang et al., 2010). Indeed, the travel fare presents a small discrepancy in the Beijing and Shanghai subway systems. Hence, time cost rather than monetary cost is more commonly used from the actual travel perspective (Burns and Inglis, 2007; Mavoa et al., 2012; Hou and Jiang, 2014; Huang et al., 2014). According to Zhang and Yao (2015), total travel time consists of waiting time, in-vehicle time, and transfer time.

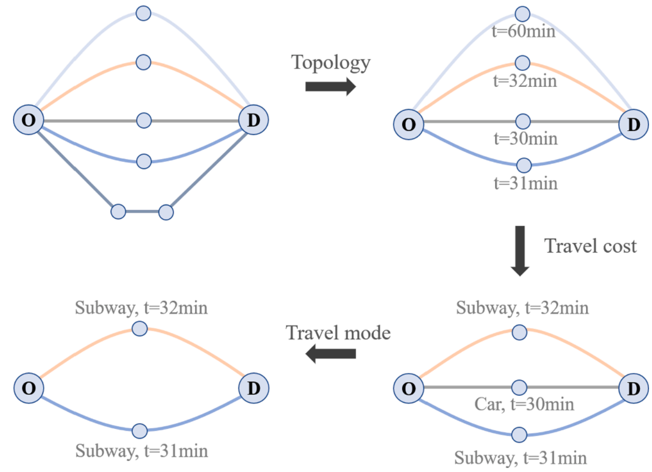


Fig. 1. Illustration of parallel routes in subway systems.

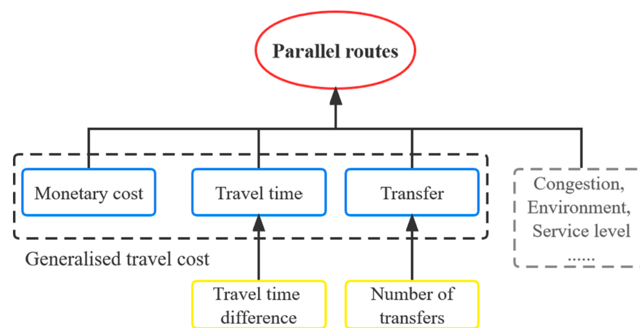


Fig. 2. Key components of parallel routes.

Currently, there has been a growing research interest from the perspective of individuals. Following this stream, scholars have simulated and analyzed actual travel choices and travel behavior with individual utility models on the basis of travel cost, travel habits, and other personal factors (Levinson, 2003; Raveau et al., 2011; Xu et al., 2013). Moreover, there are some studies on route choice in subway systems employing new data sources such as smart card data, cell phone data, and so forth on account of the emergence of big data (Jin et al., 2017; Jin and Kim, 2018). Following studies reviewed, this paper conducts network analysis on subway systems and further develop the concept of parallel routes from the perspective of travel time cost. With the network analysis, we can enhance the accuracy of transit route choice at the local level.

2.2. Network analysis approaches for subway networks

Network analysis approach has become prevalent in transport studies since graph theory was introduced in the 1950s (Derrible and Kennedy, 2011). The literature can be divided into two main streams. Some scholars have investigated basic structures of transport networks like street networks (Porta et al., 2006; Turner, 2007) and railway networks (Sen et al., 2003; Cao et al., 2019). Another focus is route choice with the application of optimal route planning algorithms (Prato, 2009; Manley et al., 2015; Zhu and Levinson, 2015; Idri et al., 2017).

With the rapid development of transit systems, there has been a growing interest in network analysis of subway systems. Methods and indicators of network science came to be core concepts in subway network analysis (Lin and Ban, 2013). Generally, the majority pay attention to topology characteristics of subway networks, employing indictors like connectivity, centrality, and clustering. For example, some studies find that the subway networks of several megacities show characteristics of small-world networks (Latora and Marchiori, 2002; Zhu and Luo, 2016). Scholars also investigate the relationship between metro station connectivity and passenger flows (Lee et al., 2008; Derrible and Kennedy, 2009; Feng et al., 2017), or robustness and reliability of subway networks (Zhang et al., 2011; Cats and Krishnakumari, 2020).

Methods such as the shortest path algorithm and the K-shortest path algorithm have been applied to investigate route choices in subway networks (Liu et al., 2017; Xu et al., 2018). Some studies also utilize online map APIs to investigate route choices and travel behavior in various situations like a disruption of transit service or pandemic (Lin et al., 2018; Gao et al., 2019; Shamshiripour et al., 2020). As a cost-effective approach to obtain route information in dynamic traffic conditions, map APIs based on real-time mapping database perform smoothly in real-world route analysis (Socharoentum and Karimi, 2015). Yet, through reducing the cost of data collection and calculation, most of map APIs are open-source and immediate services, sometimes suffering shortcomings like inaccuracy and instability (Zhang et al., 2018). Only a small body of literature have conducted research on reliability of route choice provided by map APIs. Moreover, a combination of online map API and network analysis approaches employed in evaluating route selection remains limited.

2.3. Transit-oriented development and network expansion

The interaction of transport systems and land use has received wide attention in the fields of transport studies and urban planning. Among a great body of literature, the relationship between transit systems and station-area land use have emerged as a major growth area with transit-oriented development (TOD) in megacities (Padeiro et al., 2019; Xu and Chen, 2021). Previous studies found that subway systems contribute to higher commute efficiency and more land use variation (Knowles, 1996; Golias, 2002). Indeed, co-evolution of subway systems and land use has been confirmed in many studies (Hess and Almeida, 2017; Chen et al., 2019).

To gain better knowledge of urban design, some scholars have investigated how the built environment affects travel behavior (Cheng et al., 2020; Xu and Yan, 2021; Cheng et al., 2022). In this context, studies have examined the relationship between subway ridership and land use patterns mainly characterized by land-use mixture and density (Lin and Gau, 2006; Lee et al., 2013; Jun et al., 2015). Most studies reviewed above examine which built environment determinants contribute to higher subway ridership and identify the optimal radius of the TOD area. Some of them confirm that walkability serves as the crucial part of the station-area built environment, referring to the definition of station catchment area (Wang and Cao, 2017; An et al., 2019). Apart from the built environment around the stations, the attributes of stations have been discussed in some literature, indicating that transfer stations and terminal stations usually perform differently in increasing station ridership (Sohn and Shim, 2010; Zhao et al., 2013).

However, an existing research gap is that few studies have investigated the correlation between the built environment and route choices at the station level. This correlation is significant to investigate for increasing transit ridership and improving the density or diversity in station-area land (Sahu, 2018). Moreover, this correlation should be examined with the network expansion so that urban planners can assess the performance of transport and land use systems and facilitate new station construction. In addition, it is worth noting that Beijing and Shanghai Subways have been experiencing network expansion, which is necessary to investigate.

Motivated by the literature above, the first objective of this paper is to examine the reasonable and alternative route options provided by an online map API (application programming interface) within the analytical framework on parallel routes. With the empirical analysis in Beijing and Shanghai subway networks, the second objective is to investigate the relationship between route choices and built environment. With these objectives, we could better understand the linkage between route choice diversity and the land use at the station level and then offer policy implications for Transit-Oriented Development.

3. Research design

3.1. Parallel route selection

In this study, we employ time cost in the route selection referring to previous studies mentioned in 2.2. To be more specific, we identify parallel routes according to their travel time difference compared to the shortest travel time between origin and destination stations. We assume that a route with a smaller travel time difference is more likely to be a parallel route for the shortest travel time route. In the assessment of travel time difference, we include the influence of the shortest travel time and relative time difference, as the shortest travel time determines the acceptable duration threshold. For example, when the shortest travel time is about 100 min, routes with 10 more minutes may be acceptable, whereas it is not acceptable if the shortest time is only 20 min. Thus, the study defines travel time difference as a ratio compared to the shortest travel time (details can be seen in Section 3.1.1).

In addition to travel time, transfer is another important factor in the route selection in subway systems. More specifically, the complex subway network structure contributes to various transfer choices, and likewise, the variety of transfer combinations provides a considerable number of parallel routes (Xiao et al., 2019). Here, we measure transfer duration with the total number of transfers, and estimate the walking time according to the underground complexity of each transfer station. Note that we exclude transfers that are not reasonable from the perspective of travel behavior. In the route selection, we chose parallel routes with transfer minimization and reasonable transfers. To sum up, we utilize travel time difference and transfer as the two main indicators for parallel route selection.

3.1.1. Time difference

To assess time differences for each OD, we first identify the shortest travel time route, and then calculate travel cost for every possible route. For each possible route, the travel time difference ΔT is calculated as:

$$\Delta T = (T_i - T_{min})/T_{min} \tag{1}$$

where T_i is travel time of route i for the OD pair, and T_{min} is the shortest travel time between the OD pair.

3.1.2. Transfer

Since different designs lead to underground space diversity in metro stations, transfer is a key component of individual travel preference (Qian et al., 2016; Seaborn et al., 2009). The complexity of underground space affects the transfer time due to the different walking times inside each transfer station. We set one restriction on the number of transfers. The upper limit of transfers is restricted to four in route selection. It is worth noting that some suburban transit lines, such as Yanfang Line in Beijing, connect to the subway system via Yancundong Station on the Fangshan line. For OD pairs that need to transfer at that station, the upper limit is set as five. The same situation can be found in Line 5 of the Shanghai subway system.

3.2. Parallel route identification

3.2.1. Route options from an online map API

With the increasing utility of smartphones and development of route planning, online maps are widely used in route selection. This study collects preliminary route selections from an online map API, as these services usually offer several possible routes with estimated travel time. Here, we chose the Baidu Maps API (https://map.baidu.com/). According to its route planning service, the calculation of travel time includes distance between two adjacent stations, service frequency, and the underground space of transfer stations (Yan and Yang, 2010).

In this paper, our OD pairs are generated between every two stations in the two subway systems. In the preliminary selection, we seek routes for each OD via the online map API. As the maximum number of possible routes provided by the API is five, we obtain at most five parallel routes for each OD. This implies that the online map API may underestimate the number of parallel routes for OD pairs with more than five parallel routes. An example is shown for travelling from National Library Station to Fuxingmen Station in Beijing. Since the topology of the subway network between the OD above is complicated, there are multiple options to choose. The Baidu Maps API shows that four routes are covered and the travel times of these routes are close to the shortest travel time (Fig. 3). In brief, for each OD, we obtain at most five routes containing information on their travel distance, travel time, and stations along the routes.

3.2.2. K-shortest-route Method

As mentioned, route selection offered by the Baidu Maps API may not cover all parallel routes. To verify the results from the Baidu Maps API, we employ the K-shortest paths algorithm (KSP) (Floyd, 1962). Compared with algorithms that can only calculate the shortest routes between two points in the network, KSP is capable of searching any k-shortest routes for a given OD (k could be any natural number). A recent improvement on KSP allows it to find all parallel routes in a huge network, like road and subway networks. Furthermore, researchers have also put more efforts into KSP applications for transit route planning, such as adding transfer restrictions to the algorithm (Xu et al., 2012).

In our study, the KSP algorithm is employed by a shortest simple routes function (Yen, 1971) in the NetworkX 2.4 library of Python. The input parameters are an adjacency matrix of graph, origin, destination, and k. Here, k determines the maximum number of routes in the algorithm and returns to each OD. With the results in the preliminary selection via the Baidu Maps API, we utilize KSP to evaluate those ODs with five routes, since there are likely to be more than five parallel routes for these ODs. The value of k is set as 400 to cover as many results as possible. The adjacency matrix is built as:

$$A_{ij} = \begin{cases} t & \text{when station } i \text{ is next to station } j \\ inf & \text{when station } i \text{ is not next to station } j \end{cases} \tag{2}$$

where A_{ij} represents the element in station i and station j of the adjacency matrix, t represents the shortest travel time when station i is next to station j, and inf indicates travel time set to infinity when station i is not next to station j.

Based on the adjacency matrix above, we identify all routes of ODs with five routes in the preliminary selection. The basic function is as follows:

$$path = k\_shortest\_paths(G, O, D, k) \tag{3}$$

In the function above, G represents the directed weighted graph to be analyzed. The weight of every edge in G is the shortest travel time between two nodes on this edge.O and D refer to the node label of the origin and destination, respectively, k is the number of parallel routes, and the route is presented by sequence of node labels in the graph.

For each route calculated by KSP, the total travel time is calculated with in-vehicle time, waiting time, and total transfer time. According to the adjacency matrix, we obtain the in-vehicle time of each route. As the average train frequency in the Beijing and Shanghai subway systems is almost every 2 min or even 1.5 min for several lines (Yang, 2016), the waiting time is regarded as 2.5 min. Transfer time estimates included the number of transfers and the walking time inside the transfer station. We assume that walking speed is 4 km/h and collect transfer distance from the Baidu Maps API, then estimate the time of each transfer (Yamagata et al., 2020). Thus, the function of total travel time is:

$$T = INT + TTT + TWT \tag{4}$$

where T represents the total travel time, and INT, TTT, and TWT are in-vehicle time, total transfer time, and total wait time, respectively.

To sum up, we combine the Baidu Maps API and KSP in the study of parallel routes for subway systems. We use the online map in the preliminary route selection, and employ KSP to complement analysis for ODs whose parallel routes may be more than five. With the methods above, we obtain a dataset including ODs between every station and all routes accordingly.

4. Study areas

The study is based on the subway networks of Beijing and Shanghai in January 2020 (Fig. 4). As the first city with a subway in Mainland China in 1971, Beijing is served by a subway system of 24 lines and 331 stations. The Beijing subway is the busiest in the world, with 6,475 vehicles in use and a passenger volume of 10.86 million per day in 2019. Lines 2, 4, 5, 10, and 13 are all congested lines during the peaked period (Wang, 2010). As for the Shanghai subway, with the longest operating mileage in the world, it has 20 lines and 345 stations in operation[1]. There were over 5,000 vehicles in use and 1.06 million passengers per day in 2019. The most congested lines are Lines 2, 8, 10, 11, and 17.

In January 2020, there were 60 transfer stations in Beijing and 63 in Shanghai (Fig. 4), accounting for 18.13% and 18.26% of all metro stations, respectively. There are three level-3 transfer stations in Beijing and no level-4 transfer stations, while Shanghai has 14 level-3 transfer stations and three level-4 transfer stations (Table 1). Most transfer stations are located inside the loop line of the subway networks. Though the total mileage of metro lines is less, the annul passenger volume of Beijing subway is 1.17 times as large as that of Shanghai subway in 2019, indicating that Beijing subway may hold higher service capacity.

5. Results

5.1. Examination of route selection from an online map API

For each OD, we calculate the time difference of every route offered by the Baidu Maps API. Then we observe the relationship between the shortest travel time along OD pairs and the time difference of possible routes, as shown in Fig. 5. Compared to the shortest travel time, the maximum time difference is 25% while the minimum is about 9%. As the shortest travel time increases, the time difference declines. Case studies of Beijing and Shanghai present similar trends. With this finding, we set the upper limits of time difference in the parallel route identification as below (Table 2). In detail, the upper limit of each travel time sequence is determined by the 75th percentile of the time difference distributions shown in Fig. 5.

With the upper limits of time difference above, we seek parallel routes in the route sets from the KSP algorithm. We select ODs with five parallel routes by Baidu Maps API, then employ KSP algorithm to search the potential parallel routes of them. The results can be seen in Fig. 6(a). Overall, there are 10,916 parallel routes for 1,081 OD pairs in Beijing, and 40,277 parallel routes for 3,548 OD pairs in Shanghai. In total, 95.01% of aforementioned ODs hold more than five parallel routes which are ignored by the online map API, accounting for 1.93% of all ODs. Among them, 31.89% ODs obtain 5–10 parallel routes in Beijing, and 24.28% ODs in Shanghai.

Then we combine results from the Baidu Maps API and KSP. Results show that there are 283,177 parallel routes for 109,230 ODs in Beijing and 379,079 parallel routes for 118,680 ODs in Shanghai, and the average number of parallel routes for each OD is 2.59 and 3.19, respectively. This collaborates that the density of Shanghai metro

[1] Line 3 and line 4 of the Shanghai subway shared the same subway segment from Yishan Road Station to Baoshan Road Station.

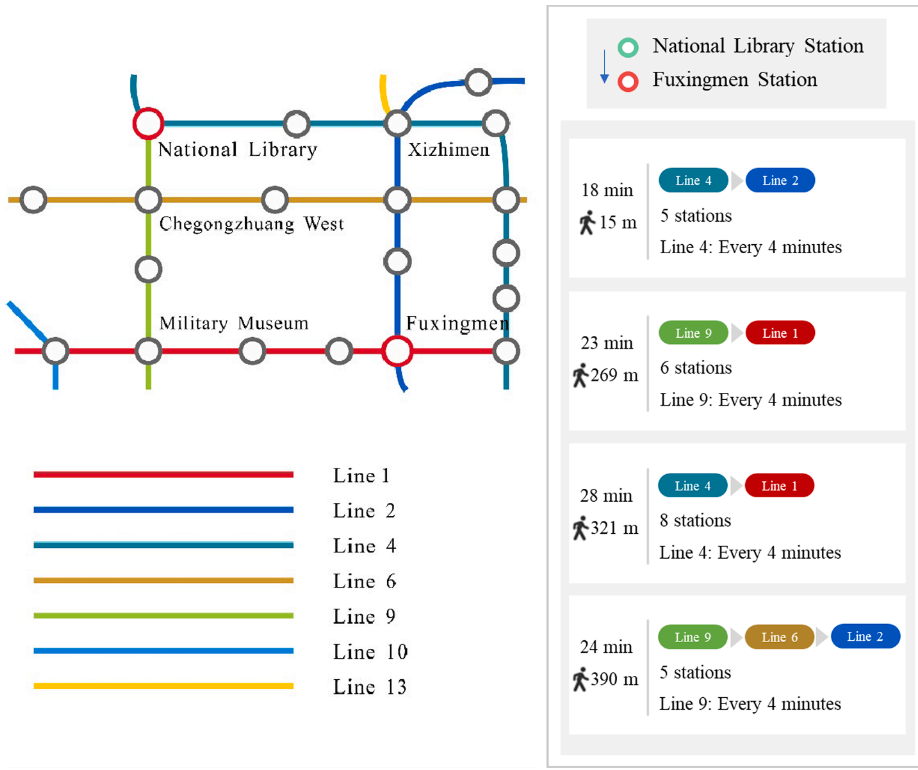


Fig. 3. The subway network between National Library Station and Fuxingmen Station in Beijing and the corresponding route planning results from Baidu Maps.

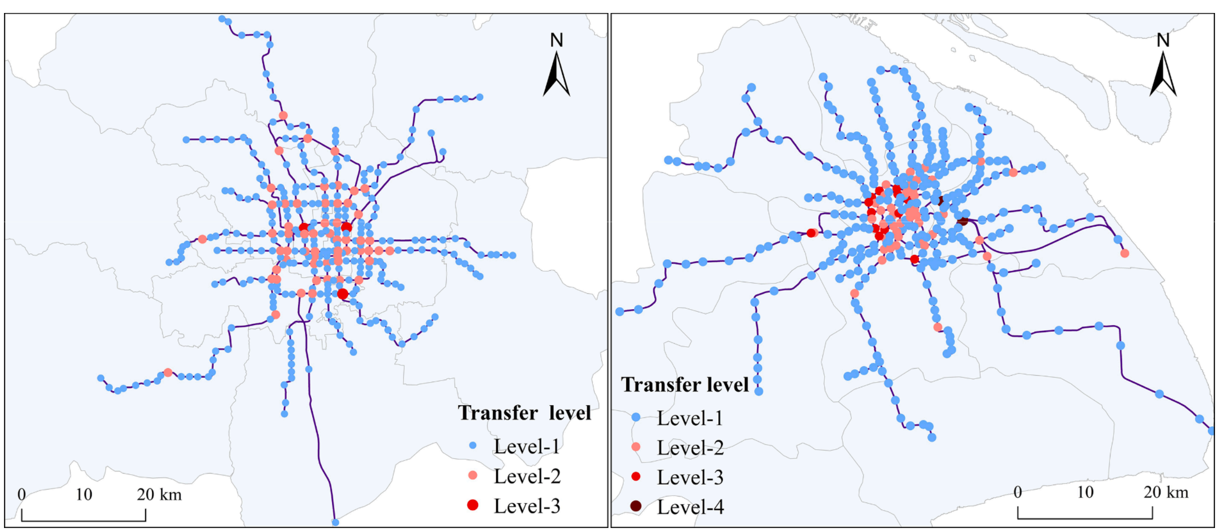


Fig. 4. Metro stations in Beijing and Shanghai (in January 2020). The station level denotes how many lines go through the station.

Table 1
Basic statistics in Beijing and Shanghai subway networks (till 2020.1.31).

	Beijing	Shanghai
Stations	331	345
Lines	24	20
Level-2 stations[2]	57	47
Level-3 stations	3	14
Level-4 stations	0	2
Total mileage	678	705
Annul passenger volume (billion)	4.53	3.88

[2] Here the number of levels refers to how many subway lines cross the station.

stations is higher than that of Beijing. In detail, over 70% of ODs contain multiple parallel routes in both Beijing and Shanghai, among which, ODs with four parallel routes account for the largest proportion, 32.12% and 31.24% respectively (Fig. 6(b)). In both subway networks, ODs with more than five parallel routes hold the lowest proportion, only accounting for 0.99% and 2.99%. The results show that subway networks in Beijing and Shanghai enable passengers to choose multiple routes between most stations. Due to longer total mileage, more transfer stations connecting multiple lines (Fig. 6(b)) and more complex network topology, route choices for passengers in Shanghai are slightly more than Beijing.

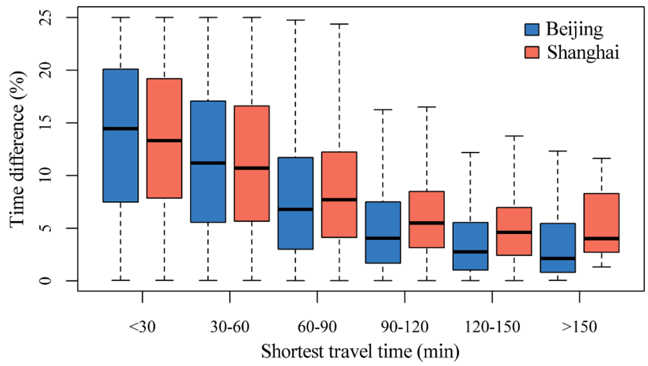


Fig. 5. Time difference of parallel routes based on the online map API and restrictions on metro transfer.

Table 2
Upper limit of relative time difference on different shortest travel times.

Shortest travel time (minute)	0–30	30–60	60–90	90–120	120–150	>150
Upper limit of time difference (%)	20%	18%	13%	8%	7%	7%

5.2. Average travel time and parallel routes

For each station, we calculate the average travel time of all OD pairs originating there. In the estimation of average travel time (Fig. 7(a)-(b)), we consider the influence of all parallel routes identified in Section 5.1. In such cases, we measure the location of stations from the perspective of travel time. Also, we calculate the average parallel routes of all OD pairs originating from a certain station. For each station, the average number of parallel routes is obtained (Fig. 7(c)-(d)). In terms of average travel time, both subway systems present an increasing trend from the center to the periphery, that is, the closer to the network center, the shorter the average travel time to other stations and the greater the accessibility, and vice versa. The average travel time in Beijing is 70 min, slightly higher than the 65 min in Shanghai.

As for the average parallel routes, the results show that stations close to the center district of the subway network tend to have fewer route choices in the subway than those in the edge of a subway network (Fig. 7(c)-7(d)). However, the decreasing tendency of parallel routes is not similar to that of average travel time. We find some exceptions where stations in the central district have a considerable number of parallel routes. Compared with Beijing, there are more stations with more than three parallel routes on average in Shanghai. The proportion is 54.49% in Shanghai while only 8.46% in Beijing, in line with results at the OD scale (Section 5.1). Furthermore, the city center of Beijing is Tiananmen Square and that of Shanghai is People's Square, both of which are near metro centers. In the context, we can draw that positive correlation exists between distance to city center and number of parallel routes.

We analyze the relationship between average travel time and the number of parallel routes for each OD to further explore route choice differences in the two subway systems. A Random Sample Consensus (RANSAC) algorithm is applied for better fitting results when identifying and excluding abnormal values (Fischler and Bolles, 1981). In general, the longer the travel time, the more parallel route options. The R-squared of Beijing is 0.64, while that of Shanghai is 0.41, showing that the law performs better in the Beijing subway system (Fig. 8).

The main difference between the two subway systems lies in the second quadrant and the fourth quadrant. As shown in Fig. 8, the points in the second quadrant of Shanghai are more disperse, indicating that some stations in Shanghai subway have both short travel time and multiple route choices. This is mainly due to more high-level transfer stations and thus more transfer choices in the Shanghai subway system, enabling more stations in the central district with both high efficiency and multiple choices. A similar pattern can be observed in the fourth quadrant, which implies that several stations in Shanghai subway have both long travel times and few route choices. In summary, compared with Beijing, the Shanghai subway performs better from the aspect of route choice.

5.3. Relationship between parallel routes and the built environment

As illustrated in 5.2, for a metro station, the number of parallel routes is positively correlated with average travel time. In other words, route choice also presents the location and accessibility of each station. Recalling the literature review (Section 2.3), we further investigate the correlation between built environment and route choices at the station level.

First, to remove the effects of average travel time or location, we employ a simple ratio R of parallel route numbers and average travel time for each station. Second, to measure the influence of the built environment, we collect POI data from Baidu Maps. Then we calculate two indicators, namely, the number of POI and land-use mixture to represent the station-area built environment. The latter is calculated by the Shannon entropy method (Yue et al., 2017). We choose these two factors as they are commonly regraded as the most important built environment variables in the TOD design (Ogra and Ndebele, 2014).

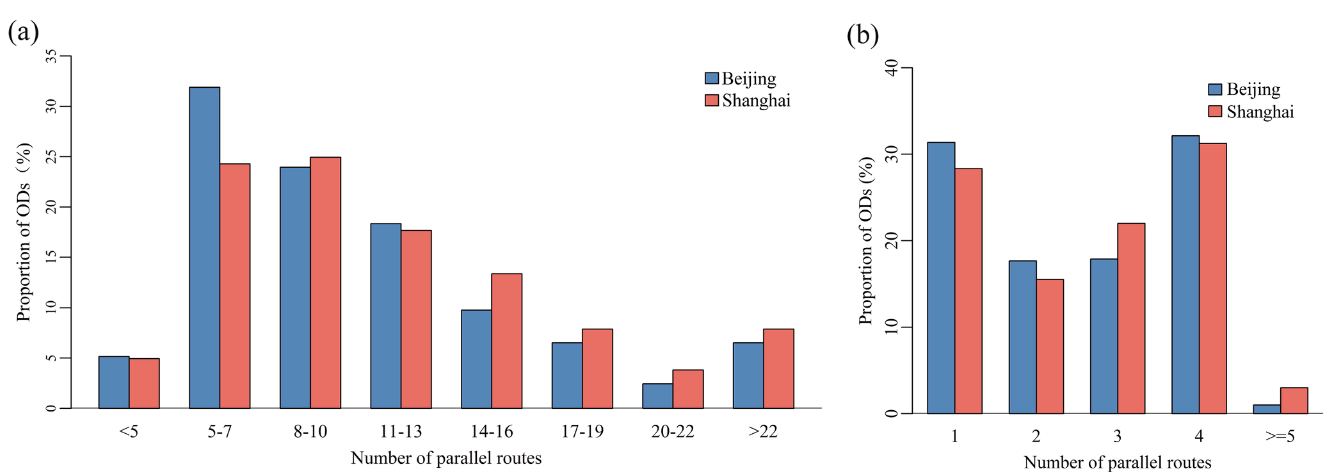


Fig. 6. Distributions of parallel routes. (a) results by k-shortest path algorithm (Note: ODs here are those with five parallel routes by Baidu Maps API). (b) results with the combination of the Baidu Maps API and k-shortest path algorithm.

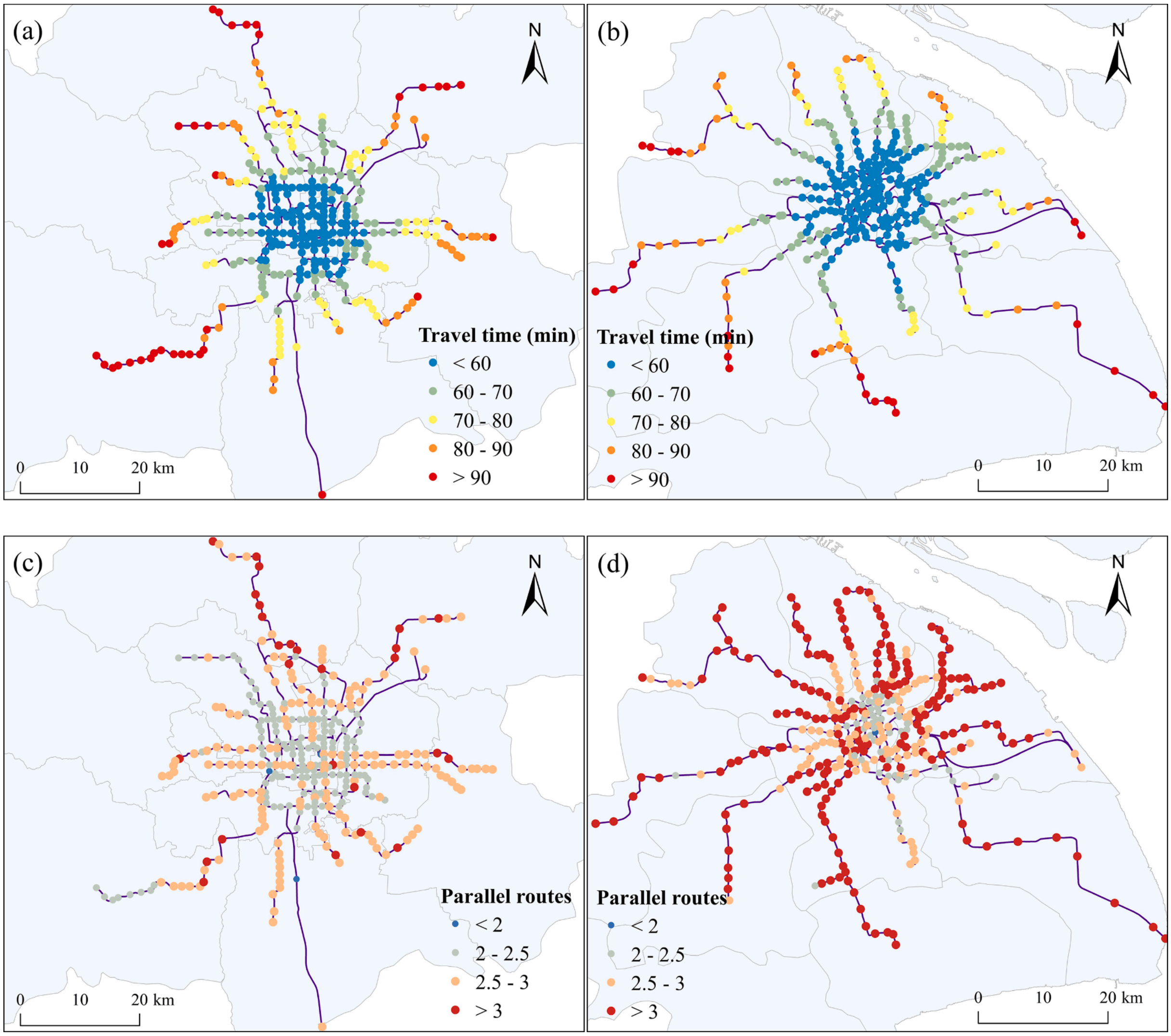
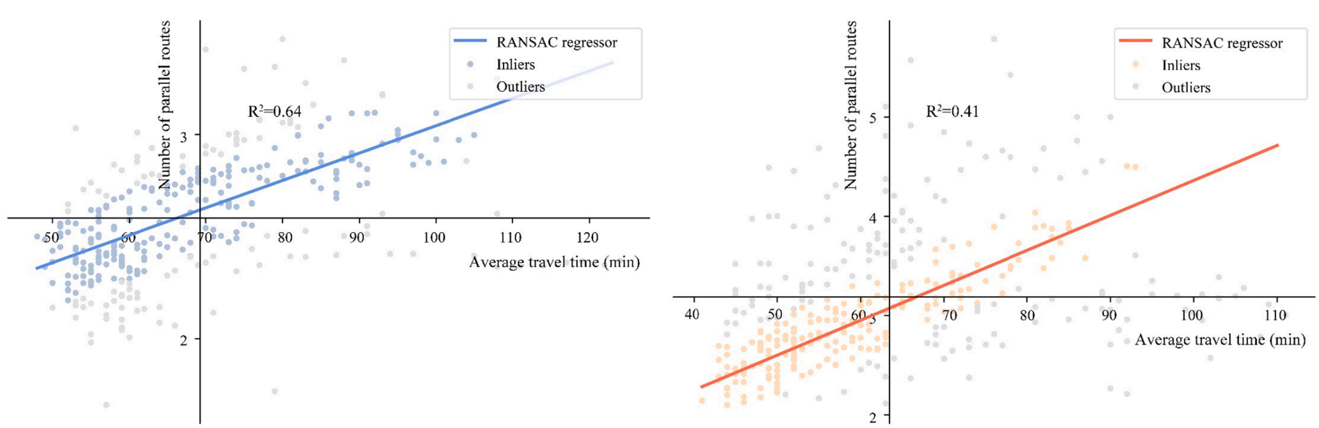


Fig. 7. Average travel time and the number of parallel routes by stations. (a) average travel time in Beijing. (b) average travel time in Shanghai. (c) parallel routes in Beijing. (d) parallel routes in Shanghai.



(a) (b)

Fig. 8. Relationship between average travel time and the average number of parallel routes. (a) Beijing, (b) Shanghai. (Note that each point represents a station, and the origins of coordinates are determined by average value of travel time and average value of parallel routes in the two subway networks).

With consideration of the catchment area referring to TOD definition and previous work on Beijing and Shanghai, we chose three types of radiuses in the buffer analysis to measure these two indicators, namely 500 m, 1,000 m, and 1,500 m (Pan et al., 2011; Yang et al., 2016; Pan et al., 2017; Su et al., 2021; Tan et al., 2022). In detail, buffers of 500-meter radius represent the core area of TOD, and those with 1500-meter radius indicate the potential area of TOD.

In Table 3, we investigate the correlation between the ratio R representing route choices and the number of POI and land-use mixture in three buffers. We find that all correlation coefficient values are positive and statistically significant. In others words, stations in buffers of more POI and higher land-use mixture are likely to have more route choices. This finding matches well with the development strategy of TOD (Nasri and Zhang, 2014). In comparison of Beijing and Shanghai, the correlation differs with different buffer sizes. Overall, the value by number of POI increases with the radius, and reaches the highest when the radius of the buffer is 1,500 m. As for the land-use mixture, the result table shows that the correlation with land-use mixture appears to be the highest in a 1,000-meter radius buffer in Beijing, while the value reaches the highest at a 1,500-meter radius in Shanghai. The difference may have been caused by higher land-use mixture and higher density of metro stations in Shanghai, which is in line with previous studies (Huang et al., 2021).

Furthermore, we also investigate the differences between transfer stations and other stations. According to Fig. 4, we divide all stations in the two subway systems into transfer stations and others, then perform the same calculation as mentioned. It is obvious that the difference between transfer stations and other stations in Beijing is not significant (Table 4). However, compared with other stations, transfer stations in Shanghai show lower correlation with lower statistical significance (Table 4). The disparity also lies in buffer sizes. As for land-use mixture, in Beijing, the value of transfer stations reaches its highest in the 500-meter buffer, while the value of other transfer stations is highest in the 1,000-meter buffer. The results of Shanghai show the opposite pattern, that is, the buffer radius with the highest correlation is 1,000 m for transfer stations and 500 m for other stations. In summary, our findings show that the relationship between route choices and station-area land-use mixture tends to be closer for transfer stations in Beijing. On the contrary, among transfer stations in Shanghai, the relationship is lower and less significant compared with other stations. These phenomena may indicate that there are other factors relevant to route choices in the subway system of Shanghai, such as the service level, frequency of the transit system, and transfer station allocation strategies (Yao et al., 2012).

6. Conclusions

In this paper, we conduct an analysis to identify parallel routes and examine route choices provided by the Baidu Maps API, then analyze the choice diversity of subway systems in Shanghai and Beijing. By parallel route identification and comparison, we find that the results from the map API have covered the majority of routes but omitted some choices. It is confirmed that the network analysis method is conducive in parallel route identification. Most ODs contain four parallel routes but only a few of them contain five or more routes, indicating that the design of the subway network has given consideration to both reliability and efficiency. Compared with the subway network in Beijing, Shanghai offers more route choices due to its complex topology.

We also investigate the relationship between the average number of parallel routes and average travel time for each station. The common feature of the two subway systems is the negative correlation between distance to average travel time as well as city center and number of parallel routes. The discrepancy in travel within Shanghai is greater than that of Beijing, which is mainly caused by more high-level transfer stations and high density of the central region in Shanghai. Furthermore, we probe into the relationship between route choices and the built environment. The results show that a positive correlation exists and

Table 3
Correlation coefficient value of *R* and two built environment indicators. (Note: *R* is the ratio of the parallel route number and average travel time for each station).

Radius	Beijing		Shanghai	
	Land-use mixture	Number of POI	Land-use mixture	Number of POI
500 m	0.262***	0.382***	**0.280*****	0.353***
1,000 m	**0.318*****	0.470***	0.240***	0.371***
1,500 m	0.298***	**0.524*****	0.241***	**0.390*****

Table 4
Correlation coefficient value of *R* and two built environment indicators in Beijing and Shanghai (Note: *R* is the ratio of parallel route number and average travel time for each station).

Beijing	Transfer stations		Other stations	
Radius	Land-use mixture	Number of POI	Land-use mixture	Number of POI
500 m	**0.293*****	0.356***	0.225***	0.327***
1,000 m	0.224***	0.402***	**0.300*****	0.411***
1,500 m	0.208***	**0.473*****	0.260***	**0.463*****
Shanghai	**Transfer station**		**Other station**	
Radius	**Land-use mixture**	**Number of POI**	**Land-use mixture**	**Number of POI**
500 m	0.066	0.121**	**0.306*****	0.296***
1,000 m	**0.092****	0.120**	0.244***	0.319***
1,500 m	0.075*	**0.135****	0.249***	**0.343*****

differs among cities, buffer sizes, and types of station.

From the discussion above, analysis on parallel routes from a route selection perspective is a significant approach to understand the network structure of subways. The policy implications can offer new insights in urban transport planning and management for decision makers. The value of transfer stations should be considered from the perspective of route choices so that subway networks can provide better service for route selection. Also, increasing connections among subway lines in suburban districts is useful for improving the connectivity of stations far away from the city center, which contributes to enhanced travel equity. As for TOD in megacities, it is necessary to investigate the relationship between built environment and route choice by transit in station catchment areas, which contributes to evaluate on how the TOD strategies perform (Lyu et al., 2016). Moreover, it provides insights in delineating the reasonable precincts of TODs in different cities. Nevertheless, one limitation is that our calculation and analysis may overlook the impact brought by travel supply and demand, such as service capacity changes like frequency of metro during peak hours and non-peak hours, or weekdays and weekends.

CRediT authorship contribution statement

Jie Huang: Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing. **Meicheng Xiong:** Methodology, Formal analysis, Visualization, Writing – original draft. **Jiaoe Wang:** Conceptualization, Methodology, Writing – review & editing.

Declaration of Competing Interest

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

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