The Journal of Transport and Land Use jtlu.org
Vol. 18 No. 1 [2025] pp. 447-466

A spatio-temporal node-place-ridership model for classifying metro station areas: The case of Shenzhen, China

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Abstract: The node-place model has been widely applied for uncovering the coordination between transit network and land use but overlooks the critical role of ridership and its temporal variations. Focusing on the dynamic nature of urban activities and ridership, this study develops a spatio-temporal node-place-ridership model for evaluating and classifying metro station areas. The extended model emphasizes ridership as a third dimension in addition to the node and place dimensions and focuses on intra-week (weekday versus weekend) and intra-day (day-time versus night-time) temporal variations. Using a case study in Shenzhen, China, results show that ridership is more associated with the place values (i.e., land-use pattern) than with the node values (i.e., network accessibility). The variation in ridership between weekday and weekend is related to non-work activities and land-use types. As for intra-day variation, station areas with a high proportion of commuting ridership face imbalance between node and place values and between job and housing functions. This study highlights the importance of the incorporation of ridership dynamics in understanding the transit and land-use integration and assists urban planners and policymakers in making more informed, flexible, and responsive urban development strategies. The extended model is transferable and valuable for other cities.

Keywords: Station area typology, node-place-ridership model, spatio-temporal, transport-land use integration, Shenzhen

Article history:
Received: August 7, 2024
Received in revised form:
January 2, 2025
Accepted: May 27, 2025
Available online: July 14, 2025

1 Introduction

Sustainable transportation has long been at the heart of discussions on sustainability (Banister, 2008). The growth of urban population and expansion of urban areas have posed significant challenge to urban mobility and traffic (Poku-Boansi & Cobbinah, 2018; Zhao & Hu, 2019). Transportation sector is one of the most important contributors to air pollutants (Churchill et al., 2021). Public transport priority is widely considered an effective way to the planning of sustainable cities and society (Banister, 2008). As the bone of the urban public transport system, metro network plays a vital role in providing urban transportation services and shaping urban development (Paulsson, 2020). The complex interactions between metro network and land-use pattern have been emphasized

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https://doi.org/10.5198/jtlu.2025.2573

The *Journal of Transport and Land Use* is the official journal of the World Society for Transport and Land Use (WSTLUR) and is published and sponsored by the University of Minnesota Center for Transportation Studies.

by many studies (Hu & Iseki, 2019; Newman & Kenworthy, 1996). On the one hand, land-use pattern presents the spatial distribution of various urban activities and shapes the spatial structure of residents' travels (Wang, Han et al., 2022). On the other hand, metro network has profound influences on urban land-use dynamics (Štefančić et al., 2014). During the urban expansion and evolution process, the interaction relationship between metro network and land use has become increasingly complicated (Aljoufie et al., 2013).

The integration between transport infrastructure and land use is of great significance for sustainable transport and urban planning (Banister, 2008). Transit-Oriented Development (TOD) is advocated as a sustainable strategy of promoting transport and land-use integration (Loo & du Verle, 2017), which suggests concentrating urban land-use development and human activities around transit (e.g., metro) stations to promote public transit usage and reduce private car travel (Calthorpe, 1993). Previous studies have proposed "3Ds" (Density, Diversity and Design) principles to improve the degree of TOD. Some studies further extended "3Ds" to "5Ds" by introducing "Destination accessibility" and "Distance to transit" (Cervero et al., 2009). The node-place model developed by Bertolini (1996, 1999) has become an operational method for assessing the coordination between transport and land use. This model conceives station areas simultaneously as "nodes" of the transport network and "places" of the city, and classifies stations based on the balance between node and place values. The node-place model has been widely applied in cities around the world (e.g., Caset et al., 2018; Chen & Lin, 2015; Chorus & Bertolini, 2011; Kim et al., 2018; Monajem & Ekram Nosratian, 2015; Vale et al., 2018; Zhang et al., 2019).

To improve the node-place model, some scholars attempted to incorporate a third dimension in addition to the node and place dimensions. Vale (2015) combined the node-place model with the pedestrian shed ratio indicator. Lyu et al. (2016) extended the node-place-oriented model by adding a new "Oriented" dimension, which is mainly focused on built environment characteristics that are favorable to transit usage. Based on the above two studies, Zhang et al. (2019) further named the extended node-place model with a third "design" dimension as the node-place-design model. Li et al. (2019) developed the node-tie-place model which incorporates both the morphological and functional ties between transport and land use. Su et al. (2021) constructed the node-functionality-place model where the new functionality dimension focuses on the urban design characteristics that can facilitate walking or riding to/from transit stations.

To incorporate ridership into the application of the node-place model, Cummings and Mahmassani (2022) examined the effects of land use and transport changes on ridership using the node-place-accessibility model. Rodríguez et al. (2020) compared the differences in ridership performance among station area types. Wu et al. (2023) represented the place and node attributes respectively by local accessibility within the station area and regional accessibility at the network scale. Furthermore, significant relationships between both local and regional accessibility with stational-level ridership were revealed.

In existing studies, however, few attentions have been paid to ridership and its coordination with node and place dimensions. An exception is the node-place-ridership model developed by Cao et al. (2020), which is the first attempt to introduce ridership as a third dimension. The extended model classifies station areas into 5 types according to three dimensions, i.e., node, place and ridership, using the K-Means clustering algorithm. Caset et al. (2019) introduced ridership and people's motivation of traveling to specific stations as additional dimensions to the node-place model. More efforts are needed to explore the complex interactions between node, place and ridership dimensions. Furthermore, in high-density and compact cities, the spatio-temporal dynamics of ridership are of great significance to land use and transport planning. Previous studies have demonstrated that the travel behaviours of metro riders vary significantly from weekdays to weekends and within one day (Tang et al., 2020; Wu et al., 2018). To our knowledge, however, the development of node-place model still lacks consideration of the temporal variations in node, place and ridership dimensions.

Aiming to fill the above research gaps, this study develops a spatio-temporal node-place-ridership model by incorporating the ridership dimension and the temporal variations in three dimensions. Firstly, we introduce ridership into the node-place model as the third dimension. The model classifies metro station areas based on three dimensions (i.e., node, place and ridership) using the K-Means algorithm. Secondly, we further investigate the intra-week (weekday versus weekend) and intra-day temporal variations (day-time versus night-time) in three dimensions and the classifications of metro station areas. The methods are operationalized and verified in a case study of Shenzhen, China. Shenzhen has established a large metro network with 11 lines which serves 5.45 million passengers each day on average in 2021 (Shenzhen Metro, 2022), making it a suitable study area for investigating metro transport-land use interactions.

2 Data and methods

2.1 Study area

As one of the most successful special economic areas in China, Shenzhen has become a megacity with 17.68 million residents by the end of 2021 (Shenzhen Yearbook Editorial Committee, 2022). Shenzhen consists of 11 districts (Figure 1). By the end of 2018, Shenzhen's metro network consists of 8 metro lines and 165 stations. There is a significant disparity in the ridership of these metro stations. Previous studies have revealed that the metro system mainly influences the surrounding areas of stations (Zhou et al., 2020). In this research, the metro station area is defined the circle area with 800m radius, which is approximate to 15-minute walking distance (Ministry of Natural Resources of the People's Republic of China, 2021). The metro network-land use interactions in Shenzhen have been examined by quite a few studies from various perspectives, for example, the nonlinear and moderating relationships between land-use factors and ridership (Shao et al., 2020; Yang et al., 2016) and new attributes to evaluate TOD degree and its performance (Zhou et al., 2020).

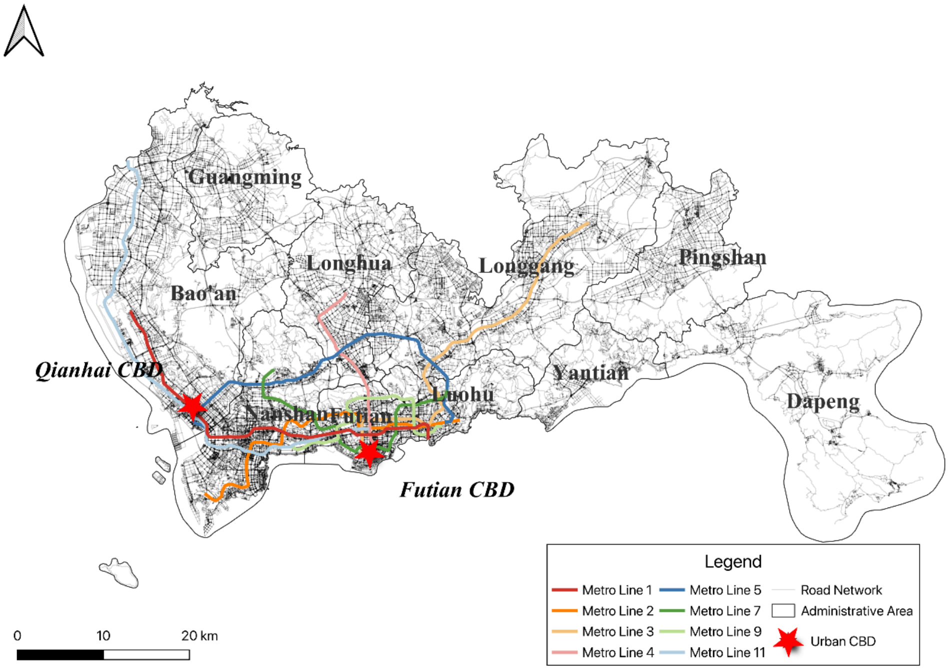


Figure 1. The metro network in Shenzhen

2.2 Analytical framework

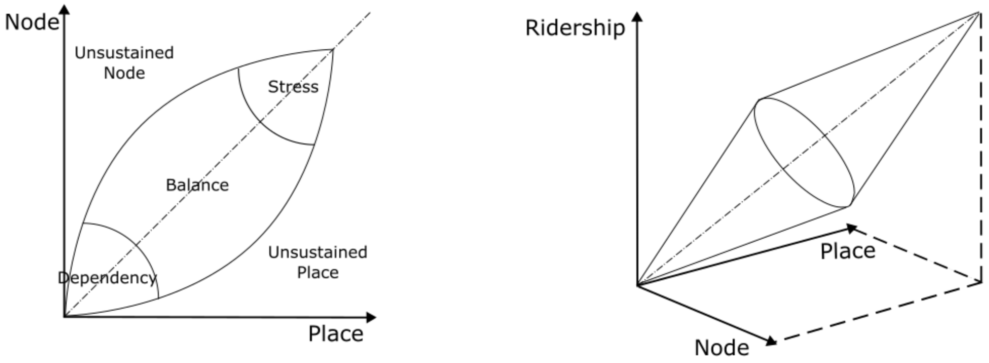
The theoretical foundation of the node-place model is embedded in the transport-land use interactions (Chorus & Bertolini, 2011). On the one hand, land-use functions formulate the places of human's activities, and land-use patterns shape travel behaviours (Meyer & Miller, 2001). On the other hand, transport infrastructure (including metro system) can improve the potential accessibility of certain locations and therefore influence people's travel behaviours (Paulsson, 2020; Sun et al., 2020). This relationship is usually described as the "land use-transport feedback cycle" (Giuliano, 2004; Meyer & Miller, 2001). The two-way influences have also been widely examined by empirical studies (Ewing & Cervero, 2010; Zhong et al., 2021). However, the traditional node-place model mainly considers the node and place values of station areas, but overlooks actual transit ridership at each station. According to the above studies, the node and place features of metro station areas and their associations have the potential to influence residents' actual travel behaviours. Therefore, it is a straightforward way to incorporate ridership into the node-place model.

Furthermore, there might be significant temporal variations in metro ridership, which could be observed at various time granularities, including intra-week and intra-day variations. The former focuses on the variation between weekdays and weekends, while the latter is mainly related to the difference between peak hours and nonpeak hours. The differences in residents' travel behaviours (e.g., travels by metro) between weekdays and weekends have been fully recognized and analysed by existing studies (Farber et al., 2016; Shao et al., 2020). As for the intra-day variations, the significant differences in metro ridership between peak and nonpeak hours and the importance of traffic and commuting travels have also been revealed (Caset et al., 2019; Zhao & Hu, 2019; Zhou et al., 2020). Scholars have also emphasized the role of job-housing balance in generating commuting travels (Bautista-Hernández, 2024; Ma & Banister, 2006; Sun et al., 2016; Zhao et al., 2011). Based on the above theoretical analyses, this study proposes to develop a spatio-temporal node-place-ridership model.

2.3 The spatio-temporal node-place-ridership model

As shown in Figure 2a, the node-place model classified station areas into five types: the unbalanced node, the unbalanced place, stress, balance, and dependence. The stress area features high values for both node and place, while the dependence goes vice versa. Correspondingly, if one aspect of the value surpasses the other one, like the node value is higher than the place value, then these areas would be classified as unbalanced node. Unbalanced places are mainly featured with higher place values or node values. As for the balance stations, the node and place values are relatively balanced.

To more comprehensively explore the role of ridership in metro station area functions, this study extends the node-place mode by incorporating an additional dimension of ridership. Three dimensions in the node-place-ridership model represent different functions of the station areas (see Figure 2b). The "node" dimension mainly characterizes stations' accessibility in the transport network, the "place" dimension represents the potential transit travel demand induced by the land uses within station areas, and the "ridership" dimension represents the actual metro ridership.



a) Node-place model (Bertolini, 1999) b) Node-place-ridership model

Figure 2. The node-place and the node-place-ridership model

The indicators of the spatio-temporal node-place-ridership model are detailed in Table 1. The indicators of the node dimension are determined with reference to existing studies (Zhou et al., 2020). The node dimension mainly consists of two types of indicators, i.e., centrality (1.1. Distance to CBD, 1.2. Travel time to CBD and 1.3. Closeness centrality) and connectivity (1.4. Bus transfer availability, 1.5. Metro departure interval, and 1.6. Number of exits). The variation in the number of exits and the effects on accessibility of metro stations to potential destinations have been demonstrated by existing studies (Yan et al., 2024). Quite a few previous studies have considered the number of exits as an indicator in the evaluation of metro station areas (Amini Pishro et al., 2022; Yao et al., 2024). The place dimension indicators are identified based on the "3D" framework (Cervero et al., 2009), i.e., Density (2.1.1. population vitality, 2.1.2. Weekday/weekend population vitality, 2.1.3. Job-housing ratio, and 2.2. Total floor area), Diversity (2.3. Functional mixing degree), and Design (2.4. Road network density, and 2.5. Road junction density). All the indicators are calculated within the station areas (i.e., within 800m of the station) by ArcGIS.

Table 1. The indicators of the node-place-ridership model

Dimension	Number	Indicators	Description
Node	1.1	Distance to CBD	Total distance to two CBDs by public transport
	1.2	Travel time to CBD	Total travel time to the two CBDs by public transport
	1.3	Closeness centrality	The sum of distances from the node to all other nodes in the network
	1.4	Bus transfer availability	The number of transfer buses within 800m of the station
	1.5	Metro departure interval	The least metro departure intervals at this station
	1.6	Number of exits	The number of exits of this station
Place	2.1.1	Population vitality	The average population density each day within 800m of the station
	2.1.2	Weekday/weekend population vitality	The density of the average daily population during weekdays/weekends within 800m of the station
	2.1.3	Job-housing ratio	The ratio of working population to residential population within 800m of the station
	2.2	Total floor area	The total floor area within 800m of the station
	2.3	Functional mixing degree	The average of mixing entropy of different categories of AOI (Area of Interest) and POI (Point of Interest) within 800m of the station
	2.4	Road network density	The road network density within 800m of the station
	2.5	Road junction density	The road junction density within 800m of the station
Ridership	3.1.1	Daily metro ridership	The average daily ridership of each station, including inbound and outbound ridership
	3.1.2	Weekday/weekend metro ridership	The average daily ridership of each station during weekdays/weekends, including inbound and outbound ridership
	3.1.3	Proportion of commuting ridership	The proportion of peak-hour (7-9 a.m., 18-20 p.m.) inbound and outbound ridership to the total ridership of each station on weekdays

Despite the static spatial distribution (i.e., spatial analysis) of metro station areas, this study further investigates the intra-week (i.e., weekday versus weekend) and intra-day (i.e., daytime versus nighttime) temporal variations in station areas' node, place and ridership values. These two types of analyses of temporal variations are termed as the intra-week and intra-day temporal analysis, respectively. To reflect spatio-temporal dynamics, the indicators of three dimensions are modified to account for temporal variations.

Spatial analysis mainly investigates the interaction between the urban metro network and land use, revealing the spatial structure of different station areas of the whole city. It employs two critical indicators in the node-place-ridership model, i.e., 2.1.1. Population vitality and 3.1.1. Daily metro ridership. Population vitality is represented as the average amount of population during a week. Daily metro ridership is calculated based on the average total inbound and outbound ridership of all days. Based on the selected indicators, the node, place, and ridership values are calculated and used for classification.

In the intra-week and intra-day temporal analyses, some indicators of the ridership, node and place dimensions might vary by time. In this study, the focus is on the temporal variations induced by land-use structure, which are mainly captured by indicators 2.1 population vitality and 3.1 ridership, with other indicators remaining the same. Temporal variations in the nodal indicators are neglected because they are less related with urban spatial structure and data are unavailable to quantify them.

Intra-week temporal analysis focuses on the temporal variations between weekdays and weekends. It introduces two indicators, i.e., 2.1.2. weekday/weekend population vitality and 3.1.2. weekday/weekend metro ridership. Classification of station areas is separately conducted for weekday and weekend and then compared to reveal the differences in classified types between weekday and weekend.

Intra-day temporal analysis focuses on the temporal variations within one day. In this case, the focal point is the job-housing separation and consequent commuting travels (Martin, 2004). The former is dependent on job and residence-related land-use types, whereas the latter is related to the commuting transit ridership. Therefore, the population vitality indicator is measured by the job-housing ratio, i.e., the ratio of working population to residential population within the station area. The ridership indicator is represented by the proportion of commuting ridership. Due to the lack of personal user level smart card data, it is impossible to infer commuting trips. Therefore, this indicator is approximatively measured by the proportion of peak-hour (7-9 a.m., 18-20 p.m.) inbound and outbound ridership to the total ridership of each station on weekdays. Intra-day temporal analysis can contribute to our understanding of the job-housing mismatch debates in cities (Martin, 2004).

2.4 Data collection and processing

The workflow of this study consists of three steps: data treatment, station area classification, and analysis of results (Figure 3). Firstly, multi-source data are collected and prepared. Secondly, these data are integrated into the node-place-ridership models, and entropy method is used to calculate the weights. K-Means clustering algorithm is employed to determine the optimal classification of station area. Thirdly, the results are visualized by ArcGIS and spatio-temporal analyses are performed.

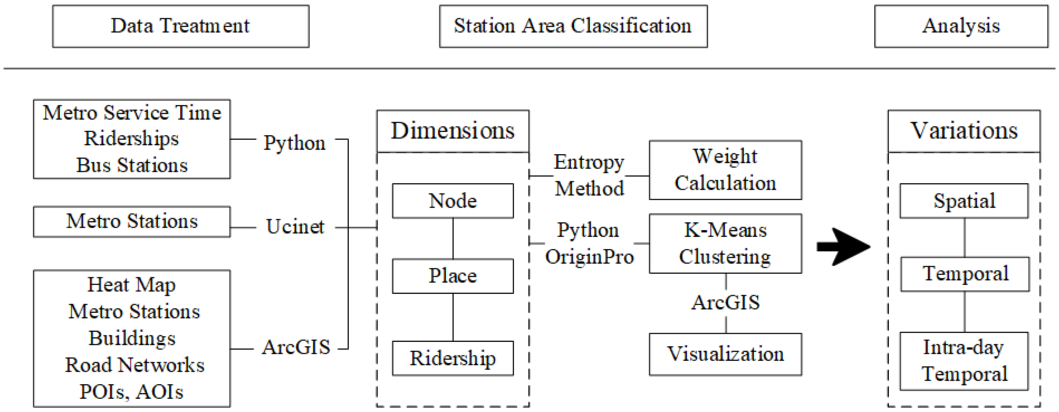


Figure 3. Workflow to apply the node-place-ridership model

The data sources are introduced as follows. Shenzhen government open data platform (https://opendata.sz.gov.cn/) is the official data platform of Shenzhen, which provides various data for us. The dataset of metro station coordination data provides the geographical locations of all 165 metro stations at the end of 2018, the distribution of bus stations, eight polyline data of metro lines. We also gather POIs and 31.15 thousand pieces of AOIs data, which provides detailed information about the land use. The metro ridership data includes hour-by-hour inbound and outbound ridership at each station from Aug. 1 to Aug. 7 and Sept. 1 to Sept. 7 in 2018, which was obtained from the Transport Bureau of Shenzhen. Previous studies have revealed that the in-bound and out-bound ridership of metro stations area can influence the land development around stations (Zeng et al., 2022; Zhao et al., 2022). By contrast, the passenger flows passing through stations without stop have few direct connections with the land-use components around stations. Therefore, it should be an appropriate setting to consider inbound and outbound ridership. Building distribution data, including 577,648 polygons with area, height, and geographic coordinates, was collected from Amap (https://ditu.amap.com/).

We used Python to obtain the data of metro service time and station exit data from the Shenzhen Metro official website (https://www.szmc.net/). This data was used for calculating the metro departure intervals and exit numbers. The neighboring relationship between stations was also collected to calculate the closeness centrality by the spatial neighboring matrix tool in Ucinet. Road network data was obtained from OpenStreetMap (OSM, https://www.openstreetmap.org). Geospatial coordinates of two city centers of Shenzhen, i.e., Futian CBD and Qianhai CBD, were drawn from Amap (https://ditu.amap.com/), one of the most popular map services in China. Distance and Time to CBDs (Futian and Qianhai) were calculated using Amap routing API (Application Programming Interface).

The grid-level population heatmap data were obtained from Baidu Huiyan (https://huiyan.baidu.com/), a spatio-temporal big data provider, which includes population in 3.52 million grids in Shenzhen between June 25 and July 9, 2020. The indicator 2.1.3 job-housing ratio was calculated by the population during a specific period within the station areas. Job-related population was defined as individuals active during 10-12 a.m. and 14-17 p.m. on weekdays, while residence-related population was defined as individuals active during 1-6 a.m. on weekdays. Subsequently, this indicator represents the ratio of the average job-related population and housing-related population over two weeks.

Table 2. Data source and description

Name	Field	Source
Metro station	Station name, type, line, longitude, latitude	Shenzhen government open data platform
Building distribution data	Number, height, area	
POI data	POI name, class, longitude, latitude	
AOI data	AOI name, class, polygon shapefile	
Bus station data	Station name, longitude, latitude	
Metro line data	Name, polyline shapefile	
Hour-by-hour metro ridership data	Station, hour, inbound ridership, outbound ridership	
Base map data	District name, polygon shapefile	Open Street Map
Road network data	Name, type, polyline shapefile	
City center of Shenzhen	Center name, longitude, latitude	Amap
Metro service time data	Station name, service time	Shenzhen metro, Shenzhen Bendibao
Metro station exit data	Station name, exit code, longitude, latitude	Shenzhen Metro, Amap
Population distribution data	Heat Map of population distribution	Baidu Huiyan

2.5 Station area classification method

The value of each indicator was first standardized into the range 0 to 1. Then the Entropy-Weight method was used to determine the weights of indicators in each dimension. Based on the standardized indicators and weights, the comprehensive values of three dimensions at each station areas were calculated. Finally, the K-Means clustering algorithm was used to identify the optimal number of clusters. As a kind of unsupervised clustering algorithm, the K-Means algorithm is easy to apply without training dataset. It effectively classifies objects based on their similarity. If there is n observations of data, which could be classified into k clusters, then the specific function could be described as follows (Ding et al., 2007):

$$J_{k-means}(X,v) = \sum_{j=1}^{n} \min_{1\le i\le k} \left(\left\|x_j - v_i\right\|\right)^2 \tag{1}$$

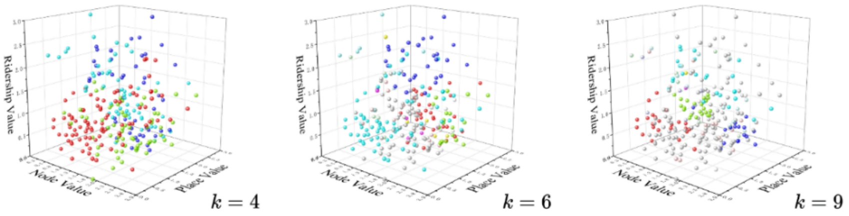
where the total number of observations is n, the number of clusters is k, $X = \{x_1, x_2, x_3, \cdots, x_n\}$ is a set of the attributes of observations, and $\{v_1, v_2, v_3, \cdots, v_k\}$ is a set of k clusters.

An important procedure in K-Means clustering is to identify the optimal k, i.e., the optimal number of clusters. Prevalent methods include the elbow method and the silhouette coefficient method. The elbow method relies on the sum of squares due to error (SSE). The turning point, visually resembling an elbow, signifies the optimal value of k. Usually, with the increase of the number of clusters, SSE would increase before turning point and then decrease after turning point. However, the variation could be insignificant under some circumstances. Therefore, it is better to combine the silhouette coefficient method, which calculates the coefficient for each observation as follows:

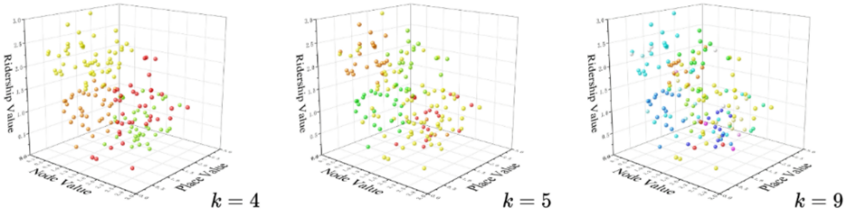
$$SC = \frac{b-a}{max\{a,b\}} \tag{2}$$

where a is the mean distance to other observations in the same cluster, and b is the mean distance to observations in other clusters. Usually, a higher value of silhouette coefficient represents a better performance of clustering.

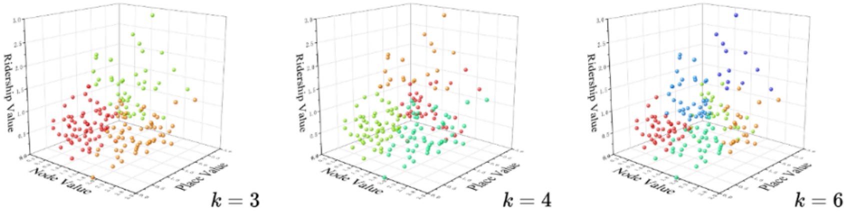
Combining both the elbow method and silhouette coefficient, we identified the optimal value of K. Based on the K-Means clustering algorithm, the elbow method and silhouette coefficient method were used by testing value of k from 2 to 9, which were later analysed using OriginPro 2023b. Based on the different clustering results of two methods, three best values of k are visualized as Figure 4. Taking Figure 4a as an example, when $k = 4$ or $k = 9$, the distinctions between balanced and imbalanced areas are not clear enough, so the optimal value of k was designated as 6 in this scenario. The same procedures were employed for other three scenarios, where the values of k were designated as 4, 4, and 4, respectively.



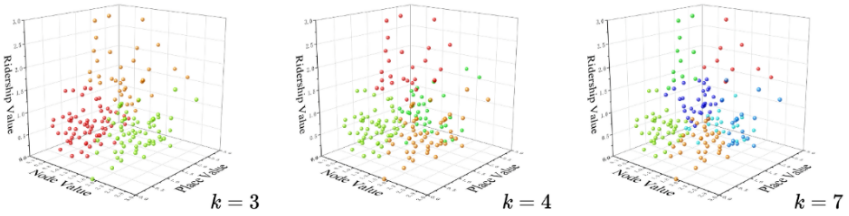
a) Spatial Distribution Results



b) Intra-day Temporal Distribution Results



c) Intra-week Temporal Distribution Results (Weekdays)



d) Intra-week Temporal Distribution Results (Weekends)

Figure 4. Distribution of observations with various *k* values

3 Results

3.1 Spatial distribution

In the spatial distribution analysis, metro station areas are classified into 6 clusters. Figure 5 shows the average values of three dimensions of each cluster and their spatial distribution. Cluster 1 and Cluster 2 (total = 43) have relatively high node and place values, but moderate ridership values. They are mainly located close to the CBDs.

Cluster 4 and Cluster 5 (total = 47) have relatively high place values, moderate node values, and relatively high ridership values. They are mainly situated along the fringe of the central city, with moderate distances to the CBDs. In addition, these two types of stations are usually located along the midsection of the metro lines, with moderate accessibility to other metro stations.

Cluster 3 (total = 42) and Cluster 6 (total = 33) are much more unbalanced, with a higher place value or node value, respectively. These unbalanced places (Cluster 3) and unbalanced nodes (Cluster 6) are both associated with relatively low ridership, indicating that the balance between node and place values is necessary to improve transit ridership.

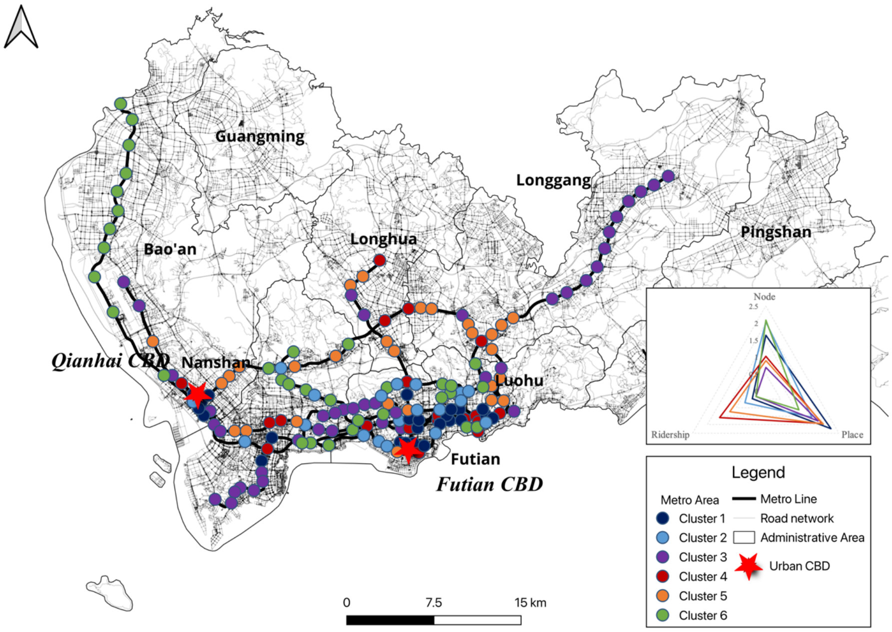


Figure 5. The spatial distribution clustering results

3.2 Intra-week temporal variation

This section further explores the intra-week temporal variation in the node, place and ridership dimensions and the classification results between weekdays and weekends. Station areas are classified into 4 clusters for weekdays and weekends, respectively. Comparison reveals that the types of some station areas (12 out of 165) changed from weekdays to weekends. These stations are presented in Figure 6 and Table 3.

From weekdays to weekends, some station areas experience increases in all dimensions, such as Children's Palace, Dafen, and Longsheng. They share the same characteristic that land uses are more mixed than others, which provide more leisure functions on weekends. For instance, there is an art museum adjacent to the Dafen station, and two amusement parks surrounding Longsheng station, which could attract a lot of ridership to come in weekends for relaxation purpose compared to weekday scenario.

The second group of station areas experience place value decreasing and ridership value rising in weekends compared to weekdays. Some examples include the Lingzhi and Baishizhou station, serving as transit hubs to leisure destinations, so the residents would only stop for a very short period at these stations. That's partly the reason why their ridership values increase, while their place values decrease.

The third group of station areas experience place value increasing and ridership value decreasing, including Shenzhen University station and Hi-tech Park station. They are busier on weekdays due to proximity to employment opportunities. There are comprehensive service facilities around there stations, which could meet the need of students from university and worker from the Hi-tech Park.

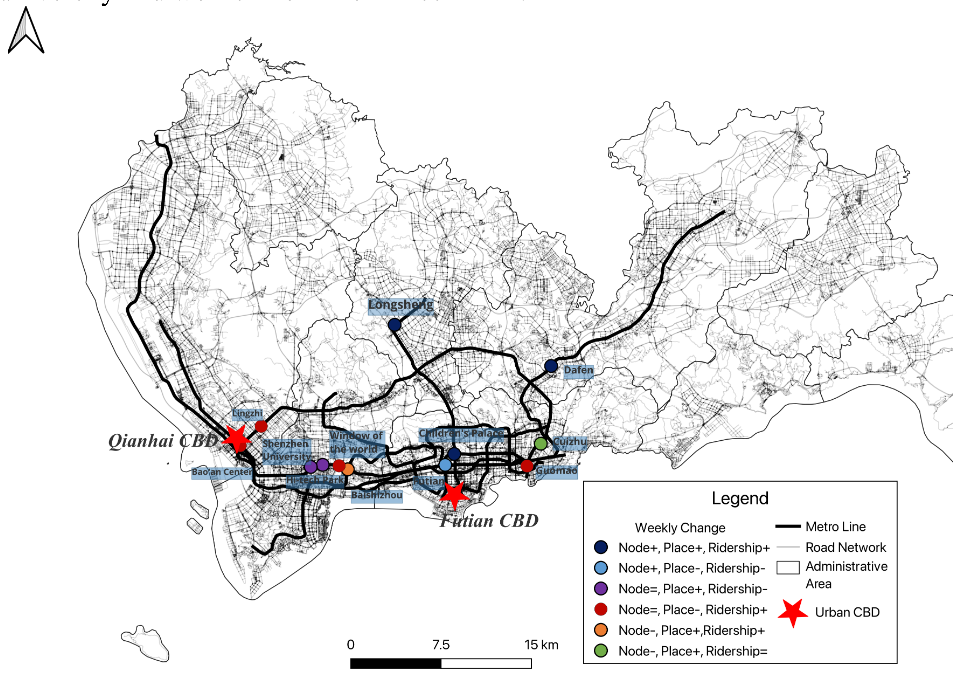


Figure 6. The intra-week temporal variations in node, place and ridership values between weekday and weekend

The comparison above reveals that the interactions between node, place and ridership are complex and dynamic. The availability of leisure places significantly improves the ridership values on weekends, while the concentration of employment opportunities would decrease the ridership values on weekends correspondingly. However, since the place values are tightly connected with land-use pattern and are hard to modify, it is a good way to adjust node values to reach the balance. For example, for some station areas with amusement park or shopping centers, it is suggested to shorten the interval of metro shifts during weekends.

Table 3. The changes in node, place and ridership values from weekdays to weekends

Station Name	Metro line	Changes in three dimensions
Children's Palace	3, 4	All increase
Dafen	3	
Longsheng	4	
Futian	2, 3, 11	Node increase, place and ridership decrease
Hi-tech Park	1	Node constant, place increase, ridership decrease
Shenzhen University	1	
Bao'an Center	1, 5	Node constant, place decrease, ridership increase
Guomao	1	
Baishizhou	1	
Lingzhi	5	
Window of the world	1, 2	Node decrease, place and ridership increase
Cuizhu	3	Node decrease, place increase, ridership constant

3.3 Intra-day temporal variation

This study also explores the intra-day temporal variation in node-place-ridership coordination, focusing on the commuting ridership and day-time/night-time dynamics in transport network and land use. The results are visualized in Figure 7. The station areas with a higher job-housing ratio are concentrated around the two central CBDs. On the opposite, the station areas with more night-time population are scattered in the fringe regions. Therefore, this figure illustrates a significant spatial separation between workplace and residence in Shenzhen.

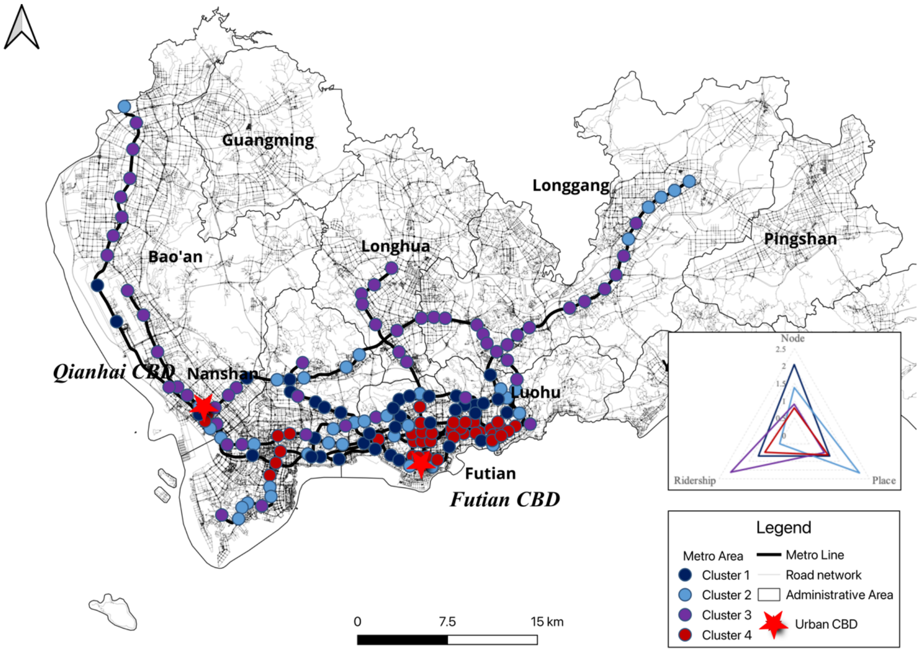


Figure 7. The intra-day temporal variation clustering results

In this scenario, the ridership dimension is measured by the proportion of commuting ridership to the total ridership. Notably, some station areas in the inner and outer suburbs exhibit the highest commuting ridership proportions, such as the Airport East Station on Line 1, Longhua Station on Line 4, Yangmei Station on Line 5, and Qiaotou Station on Line 11. Based on the housing data from Anjuke (https://shenzhen.anjuke.com), the average housing price of around Yangmei Station and Bantian Station is 55,000-64,000 RMB/m^2, while the price around Yonghua Station and Longsheng Station is 65,000-75,000 RMB/m^2, which is at the middle level in Shenzhen. With convenient metro transportation, residents tend to live in the inner and outer suburbs along the Line 4 and Line 5 and work in the central city. Therefore, some station areas have relatively low node and place values but attract high proportion of commuting ridership.

Based on the analyses above, high proportions of commuting ridership are associated with relatively low place values, especially low-mixed land-use patterns (represented by low entropy of POIs/AOIs). High proportions of commuting ridership indicate that transit passenger flows are concentrated during peak hours. These stations are mainly located in the inner and outer suburbs. By contrast, the station areas with high place value and moderate node value or high node value and moderate place value usually have relatively low high proportions of commuting ridership. Note that no clusters of station areas with high node, place and ridership values (i.e., stress station areas with high ridership) have been obtained. The reason is that the land uses within stress station areas are usually highly developed, and passenger flows from or to these station areas are caused by diverse purposes.

4 Discussion and conclusions

This study aims to contribute to the development of the node-place model from two aspects. Firstly, this study develops the node-place-ridership model and introduces the K-Means clustering algorithm to classify station areas. Previous studies on the node-place model have not fully consider the importance of the ridership. Some scholars took ridership into consideration but are defective in classifications method. By leveraging the K-Means clustering algorithm, metro station areas can be classified in a more comprehensive way integrating the node, place and ridership dimensions. An insightful finding given by the node-place-ridership model is that ridership tends to be less associated with the node values, namely, network accessibility and connectivity. This means that node-related countermeasures such as more frequent shifts or more exits of metro stations might not necessarily improve ridership. Instead, place-related countermeasures (e.g., high density, mixed land use and walking-friendly design) should be more effective in facilitating transit ridership. Notably, the above findings cannot be yielded by the traditional node-place model overlooking ridership dimension. In addition, it is different from the findings of Cao et al. (2020), where the node value has a larger impact on ridership than the place value. A possible reason might be the differences in land use and metro network characteristics across different urban contexts.

Secondly, this study emphasizes the intra-week and intra-day temporal variations in ridership, land-use functions and their connections. In the intra-week temporal variation analysis, we reveal changes in the station area types from weekdays to weekends, especially in station areas with non-work (e.g., leisure or commercial) land-use functions. It is suggested to increase the node values of such stations to meet the transit travel demand induced by non-work activities on weekends. In the intra-day temporal variation analysis, it demonstrates that high proportion of commuting ridership is associated with relatively low place values, especially low-mixed land-use patterns. These station areas usually have very high or low job-housing ratios, indicating obvious job-housing imbalance (Wang, Zhou et al., 2022). This would cause the coexistence of one-way congestion and relative low total ridership, which leads to low efficiency of the transit-land use system. In sum, this highlights the dynamic variations in the node, place and ridership values of transit stations as well as the coordination relationship between three dimensions.

Similar attempts have been made by several previous studies (e.g., Caset et al., 2020; Yang et al., 2024). Caset et al. (2020) considered the temporal variations in ridership, but did not explicitly introduce the corresponding temporal variations in land use and metro service components. Yang et al. (2024) found that inter-annual variations in node and place dimensions are related with the ecological sustainability of station areas. In their study, however, average daily ridership was only treated as an indicator in the node dimension, and finer variations in ridership and other components were not considered. Our findings suggest that the complex temporal variations in node and place dimensions and their associations with ridership are worthy of further studies. Therefore, this study contributes to the literature by conducting an exploratory study on the spatio-temporal node-place-ridership model.

Our results can also provide policy implications. Firstly, differentiated policies or strategies should be adopted for different types of station areas. Based on the spatial distribution analysis, it is suggested to strengthen network accessibility for those stations in the middle parts of the metro line, and to intensify land-use density and diversity around the stations at the ends of metro lines. Some middle stations are faced with relatively weak connections with surrounding places, where countermeasures such as providing transferring buses or shared bikes could strengthen the land use-metro connections and encourage metro ridership. Secondly, from the intra-week temporal variation analysis, the schedule of metro service needs to be dynamically adjusted to be more coordinated with land-use dynamics and residents' travel demand. For example, the Window of the World station could be more balanced by improving the frequency of metro service on weekends. Thirdly, metro lines have important roles in mitigating job-housing separation problem, but would lead to unbalanced ridership between peak and nonpeak hours. It is suggested to improve the mixed land use around metro stations and provide affordable housings around stations close to job centers, or strengthen the network accessibility of stations with large commuting population living around. Fourthly, land use-related countermeasures are more effective in encouraging metro usage than node-related ones. Therefore, policymakers should pay more attention to concentrate land developments around metro stations and strengthen the diversity of land-use functions.

Nevertheless, there are still some limitations to this study. Our research focuses on Shenzhen in 2018, while some indicators are calculated based on the data in 2020 due to limited data availability. In fact, there were no new lines constructed from 2018 to July 2020 in Shenzhen, and the daily average metro ridership changed slightly from 2018 to 2020 (5.14, 5.52 and 4.42 million in three years, respectively). The decline in 2020 was caused by the COVID-19. Therefore, the influences of inconsistent data collection time on the reliability of analysis results should be slight and acceptable. Besides, the ridership data consists of only the inbound and outbound ones, excluding those passenger flows passing the stations without stop. Lastly, while metro ridership provides significant insights, it's also essential to consider other modes of transportation and their interplay within the urban ecosystem.

Acknowledgments

The authors would like to thank the anonymous reviewers for their constructive comments. This work was funded by the National Natural Science Foundation of China [grant number 42471262 & 42101189].

Author contribution

The authors confirm their contribution to the paper as follows: conceptualization, methodology, original draft: Dejiang Wang, Zhuolin Tao; data curation, analysis: Dejiang Wang; writing – review, editing & polishing: Jiangyue Wu, Zhuolin Tao; supervision and project administration: Zhuolin Tao.

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