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Measuring bicycle accessibility within the metro catchment area: An empirical study in Shanghai

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Abstract: Accessibility describes the potential to reach opportunities and is widely used to assess the ease of reaching destinations through urban transport systems. Although much attention has been given to investigate bicycle-accessibility and metro-accessibility methods, extending these methods to model bicycle-metro integration travel at the city scale remains challenging. Based on Hansen's accessibility model, this study proposes three different models to measure bicycle accessibility within metro catchment areas. In particularly, key factors such as trip purposes, bicycle suitability, total travel time, and traffic demand are incorporated into the accessibility models. These proposed models have been tested and compared using empirical data from Shanghai. Overall, metro stations with multiple interchange lines, cycling-friendly facilities and diverse surrounding activities tend to exhibit higher bicycle accessibility, particularly those located in the city center. For areas with low bicycle accessibility in the city, such as Baoshan Road Station and Anshan Xincun Station, targeted improvement measures can be implemented to enhance bicycle-metro integration and bicycle accessibility.

Keywords: accessibility, bicycle-metro integration, multiple data sources, metro catchment area, bicycle suitability

1 Introduction

Motor vehicle traffic has caused serious urban diseases such as air pollution, traffic congestion, and resource shortages. Cycling is a low-carbon, flexible, and space-saving mode of transport that has great potential to reduce motor vehicle use and alleviate these diseases (Nordback, 2014). However, motor vehicles remain the dominant mode of urban travel, partly because cycling is constrained by its limited catchment radius (Kager & Harms, 2017). The development of bicycle-sharing systems provides a promising solution to this limitation by offering greater flexibility and accessibility for urban trips (Rahman, 2020). Rather than functioning merely as an independent mode, shared bicycles play a vital role in addressing the last mile problem faced by transit passengers traveling from metro stations to their final destinations.

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Bicycle-metro integration refers to the use of bicycles as a flexible feeder mode to connect metro stations (Bi et al., 2024). Compared with walking, the speed advantage of bicycling provides a better solution to the last mile problem (Zuo et al., 2020). To improve bicycle accessibility, it is necessary to foster a conducive built environment to leverage the potential of bicycles to bridge the last mile gap. Key determinants include station location within the metro network, proximity to the city center, feeder station type, street greenness, and road intersection density (Zhang et al., 2024). Transforming station-based bicycle sharing systems into hybrid systems could be a viable option to expand bicycle accessibility. Hybrid systems allow riders to pick up and drop off bicycles at docking stations or public bicycle racks (Jin & Sui, 2024). Moreover, more supportive cycling facilities and free-ride promotions positively impact the usage of shared bicycles (Shen et al., 2018). For example, an increase in bicycle paths can further enhance the integration between bicycles and metro systems (Florindo et al., 2018). Although much attention has been given to the integration of bicycles and metro systems, modeling bicycle-metro integrated travel at the city scale remains challenging. Several important factors. such as trip purpose, bicycle suitability, passenger flow, total travel time, and traffic demand have not yet been considered simultaneously. This could result in an evaluation that does not reflect the real conditions of bicycle accessibility within the metro catchment area.

To address this issue, this study developed three accessibility models to measure bicycle accessibility within the metro catchment area by incorporating trip purposes, bicycle suitability, total travel time, and traffic demand. Based on multiple sources of empirical data, such as bicycle trajectory data, smart card data, bicycle level of service (BLOS) data, and point of interest (POI) data, these proposed models have been further tested and compared.

The rest of the paper is organized as follows. Section 2 provides a literature review on bicycle and metro accessibility. Section 3 describes research area and data source. Section 4 proposed three models to measure bicycle accessibility within the metro catchment area. Section 5 analyzes and compares the accessibility results from different models, and Section 6 provides discussion and conclusions.

2 Literature review

2.1 Bicycle accessibility

The accessibility model, first applied in the field of transportation by Hansen (1959), represents the ease of travel from one location to another within a given transportation system. This theoretical model laid the foundation for transportation accessibility research and has been widely applied and expanded over the past 65 years. Accessibility theory has been applied across various transport modes, including public transit, private cars, walking, and cycling. In studies examining factors that influence the level of bicycle accessibility, empirical evidence shows that the density of bicycle lanes, the accessibility of public transport, and the level of public safety are all important determinants of bicycle use (Sun et al., 2017). Bicycle accessibility is closely related to the number of bicycle trips, which are influenced by land-use diversity and travel impedance between origins and destinations (Saghapour et al., 2017). Furthermore, significant differences in accessibility exist among different groups of cyclists (Rosas-Satizábal et al., 2020). Different groups of cyclists have distinct route preferences and travel times, which may lead to variations in destination accessibility (Gehrke et al., 2020). Schneider et al. (2023) found that most cycling trips were between two and three kilometers, and that these distances were influenced by factors such as destination type, traveler gender and age, and bicycle type. In recent years, as urban transportation problems have become increasingly complex and diverse, scholars have further explored the application of accessibility analysis in bicycle transportation. Liu et al. (2021) employed social network analysis (SNA) to evaluate bicycle network accessibility and applied a spatial interaction model for correlation analysis, which not only accounted for interaction barriers within the bicycle network but also examined the influence of network structure. This method is straightforward to implement and requires relatively little data, providing an effective tool for bicycle traffic research. Van der Meer et al. (2024) established a standardized framework to measure the level of bicycle accessibility to transportation hubs. They used charts and maps to illustrate changes in accessibility under different criteria, providing an intuitive reference for urban planning.

2.2 Metro accessibility

Metro systems are efficient, fast, safe, and environmentally friendly modes of transportation that play a crucial role in modern urban development. Previous studies showed that the construction of metro systems plays a positive role in promoting daily accessibility, economic potential, and industrial development. Shao et al. (2022) conducted research on the impact of metro accessibility on the temporal and spatial flexibility of non-daily shopping trips, recognizing that high temporal and spatial flexibility contributes to environmental and social sustainability. Empirical evidence has shown that individuals living near metro stations exhibit higher levels of temporal and spatial flexibility in their shopping trips compared to those living in other areas. In addition, metro accessibility has also been found to influence increases in residential property values (Li, 2018). Using bicycles as an alternative transportation mode and integrating them with metro systems can improve overall metro accessibility, leading to greater population coverage and a higher degree of accessibility (Lin et al., 2023). Research has shown that accessibility indicators contribute more than 60% to the metro’s capacity to improve passenger flow prediction (Du et al., 2022). J. Liu et al. (2022) used the ratio of extra “buffer” time required for reliable arrival to average travel time to measure time reliability. They then integrated time reliability with accessibility indicators to comprehensively evaluate the accessibility of the urban rail transit network. This approach enhances the validity of accessibility evaluations, and the results can provide useful guidance for assessing metro network accessibility.

2.3 Multi-modal transportation accessibility

The integration of bicycles and metro systems is an effective solution to enhance metro accessibility and promote sustainable transportation. Previous studies mainly relied on survey data to evaluate cycling behavior (Chen et al., 2013; Zhao & Li, 2017). In recent years, dockless bicycle-sharing programs equipped with Global Positioning System (GPS) devices have provided a rich source of big data for analyzing cycling behavior. Wu et al. (2019) examined the competition between cycling and walking within 500 m of each metro station, using over three million bicycle-metro transfer trip records in Shenzhen to measure bicycle destination accessibility in metro station areas. Lin et al. (2023) employed actual dockless bicycle trajectory data to assess bicycle destination accessibility around metro stations and integrated metro crowdedness into the accessibility measurement. Fu et al. (2023) analyzed 15 days of dockless bicycle-sharing data from part of Beijing to investigate bicycle-metro integration at the origin-destination (OD) level, proposing a spatial embedding model (MGCN-XGB) to predict and interpret integrated flows. X. Liu et al. (2022) explored the differences in the integration of dockless bicycle-sharing and ridesourcing trips with metro systems in Shanghai using observed data from Didi Chuxing and Mobike. The results indicated that bicycle-metro integration was mainly concentrated in central urban areas, whereas ridesourcing-metro integration was more prevalent in suburban regions. Previous studies also paid attention to several factors influencing bicycle-metro integration. In particular, population density, enterprises, the number of universities, and shopping centers are positively correlated with bicycle-metro integration, whereas metro station density and educational services are negatively correlated (Hu et al., 2022; Ma et al., 2024). Providing sufficient and visible greenery along streets and cycling lanes around metro stations can also promote the integration between bicycles and metro systems (Wang et al., 2020).

Although previous studies examined various factors influencing bicycle-metro integration, the methods used to measure bicycle accessibility have not comprehensively incorporated multiple factors and have often considered limited aspects, such as distance impedance or metro crowdedness. To address this issue, this study developed three accessibility models to measure bicycle accessibility within the metro catchment area by incorporating trip purposes, bicycle suitability, total travel time, and traffic demand. These models were subsequently tested and compared using multiple sources of empirical data, including bicycle trajectory data, smart card data, bicycle level of service (BLOS) data, and point of interest (POI) data.

3 Research area and data

3.1 Research area

As a global commercial and financial center, Shanghai has over 24 million residents. In this study, the inner central area of Shanghai (Puxi area), with a scale around 80 km^2, was selected as the research area. The research area is the red section shown in Figure 1.

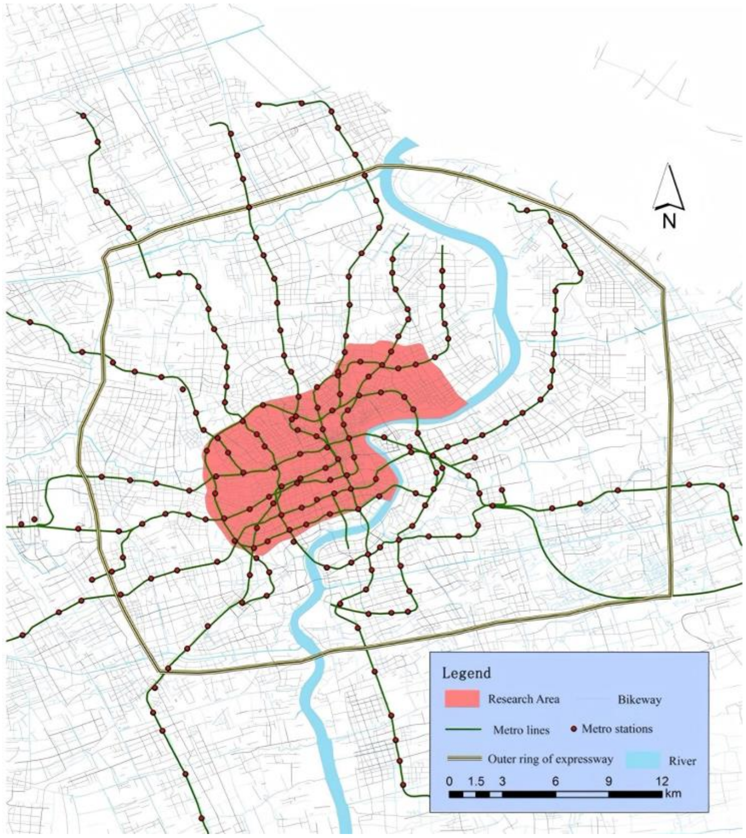

Figure 1. Research area

3.2 Data

In this study, four types of traffic data are used to empirically evaluate the bicycle accessibility within the metro catchment area, including bicycle trajectory data, smart card data, bicycle level of service(BLOS) data, and point of interest (POI) data.

3.2.1 Bicycle trajectory data

Bicycle trajectory can help identify the destination activities and routes that cyclists use to access metro stations, which is crucial for investigating the bicycle accessibility within the metro catchment area. In this study, the bicycle trajectory was recorded by the dockless bicycle-sharing from Mobike Technology Company, one of the largest bicycle-sharing companies in China. The entire dataset contains more than 1,000,000 bicycle-sharing orders within the research area from Aug. 1 to 31, 2016. Each record contains order_ID, bicycle_ID, user_ID, date, start_time, start_location, end_time, end_location, and location of trajectory point.

3.2.2 Smart card data

Smart card data provides detailed information on public transportation usage, including origin and destination. The passenger flow for the metro systems in Shanghai was recorded by the smart cards from Shanghai Public Transport Card Company. For each day, the smart cards can record more than 9,000,000 metro trips and more than 5,000,000 bus trips in Shanghai. The smart card dataset contains card ID, date, metro station name, travel time, and fare from Aug. 1-31, 2016.

3.2.3 Bicycle level of service (BLOS)

There are numerous ways of evaluating the bicycle suitability, including the Bicycle Level of Service (BLOS) (Kazemzadeh, 2020; Transportation Research Board, 2000), the Bicycle Compatibility Index (BCI) (Harkey, 1998; Jones, 2003), and the Bicycle Suitability Score (BSS) (Turner, 1997). Among these metrics, BLOS is the most commonly used indicator for measuring bicycle suitability and is adopted in this study. Level of Service (LOS) is a quantitative grading system for assessing transportation performance or service quality. Using a grading scale from A (best) to F (worst), the LOS framework simplifies the interpretation of evaluation results (Transportation Research Board, 2000).

Previous studies have examined the factors affecting bicycle suitability. Landis et al. (1997) demonstrated that lane markings and pavement quality significantly enhance the cycling experience. Li et al. (2012) found that physically separated bicycle lanes generally provide higher comfort than those delineated by pavement markings. Yao et al. (2011) identified key factors influencing riders' comfort on physically separated bicycle lanes, including lane width and the number of uncontrolled access points. In the context of China, specific indicators are essential, such as interference from roadside parking, bicycle lane encroachment, and number of traffic lights, because these factors reduce cycling speed and consequently affect the BLOS. Considering data availability constraints, this study modified the evaluation indicators to develop a BLOS framework suitable for bicycle usage within Shanghai metro catchment areas. Specifically, nine indicators were selected: separation type, number of bicycle lanes, pavement quality, number of traffic lights, roadside parking, landscaping, number of motor vehicle lanes besides bicycle lanes, bicycle lane encroachment, and traffic markings. Each indicator is assigned a score ranging from 0 to 3 (see Table 1). The scores were aggregated by summing the nine indicator values, resulting in a total score ranging from 0 to 27. Finally, based on the score distribution and rounding, the grading thresholds were defined as follows: 0–3 (Level F), 4–8 (Level E), 9–13 (Level D), 14–18 (Level C), 19–23 (Level B), and 24–27 (Level A), as shown in Figure 2.

Table 1. Scale of road evaluation indicators

Evaluation indicators	3	2	1	0
Separation type	Landscaped median	Guardrails, Concrete	Pavement marking	Unsegregated
Number of bicycle lanes	> 3 bicycles	3 bicycles	2 bicycles	1 bicycle
Pavement quality	Very high	High	Low	Very low
Number of traffic lights	0	0-1 per kilometer	1-2 per kilometer	> 2 per kilometer
Roadside parking	None	Low	High	Very high
Landscape	Very high	High	Low	None
Number of motor vehicle lanes besides bicycle lanes	None	One lane	Two lanes	Three lanes or more
Bicycle lane encroachment	None	Low	High	Very high
Traffic markings	Present			Absent

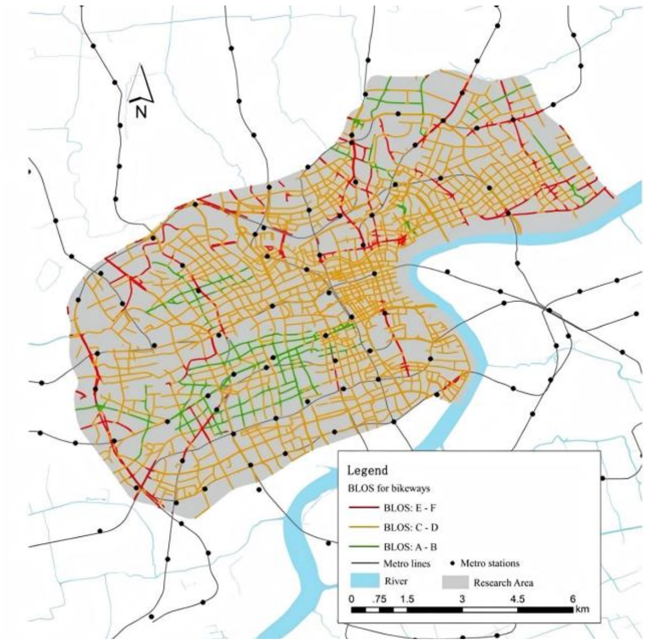

Figure 2. BLOS for selected bikeways

3.2.4 POI

Point of interest (POI) data can be used to identify the destination activities of bicycle trips (Li et al., 2020). In this study, we obtained POI dataset from Gaode, which is one of the largest navigational company in China. The entire POI dataset contains 513,549 records with different locations and 42 categories.

4 Models for bicycle accessibility within the metro catchment area

4.1 Hansen's early model

Four types of place-based accessibility measures are mainly used for bicycle traffic, including activity-based measures, topology-based measures, distance-based measures, and utility-based measures (Vale et al., 2016). This paper adopts the activity-based measures, which is the most widely used. One important activity-based measure is Hansen-type model (Hansen, 1959), which has the following form:

$$A_i = \sum_{j \neq i} E_j f(r_{ij}) \tag{1}$$

where A_i is the accessibility of place i; E_j is the intensity of relevant activities/opportunities at destination j; $f(r_{ij})$ is an impedance function that measures impedance between location i and j; r_{ij} is the cost of traveling between i and j.

When applied to bicycle travel, the cost of traveling can be measured using travel time, travel distance, or energy expenditure. For each cyclist, there is a trade-off between travel cost and available activities/opportunities. According to Hansen's definition (Hansen, 1959), a place with high bicycle accessibility means that cyclists can reach their destination easily and have plenty of choice for different purposes. Based on Hansen's early model, the following sections propose new models to empirically measure the bicycle accessibility for metro stations.

4.2 Measuring bicycle accessibility for different purposes (Model 1)

Trip purpose is one of the most important factors when modeling the bicycle accessibility (Iacono et al, 2010; Li et al., 2020). People can accept different riding distance for various trip purposes. For example, a survey in south Minneapolis shows that cyclists are more willing to ride a longer distance for recreation than work (Iacono et al., 2010).

For a certain type of destination activity k, the bicycle accessibility from metro station i to different grids j within the catchment area can be calculated as:

$$A_{i,k} = \frac{\sum_{j \neq i} E_j^k f_k(r_{ij})}{N_i} \tag{2}$$

where $A_{i,k}$ is the bicycle accessibility value of destination activity k for metro station i; E_j^k is the number of activity k within grid j; $f_k(r_{ij})$ is the impedance function for activity k; N_i is the number of grids within the catchment area for metro station i.

The bicycle accessibility value for metro station i can be further calculated based on the weighted sum of each type of activity:

$$A_i^1 = \sum_k \frac{E_k A_{i,k}}{E} = \frac{\sum_k (E_k \sum_{j \neq i} E_j^k f_k(r_{ij}))}{N_i E} \tag{3}$$

where A_i^1 is the bicycle accessibility value calculated by model 1; the weight of each activity is represented by the number of each activity E_k; E represents the total number of activities within the research area. Following Iacono et al. (2010) and Li et al. (2020), the impedance function $f_k(r_{ij})$ for bicycle travel is using the negative exponential form:

$$f_k(r_{ij}) = \begin{cases} 1 & (r_{ij} \leq a) \\ e^{-b*(r_{ij}-a)} & (r_{ij} > a) \end{cases} \tag{4}$$

where the impedance $f_k(r_{ij})$ denotes the cumulative percentage of bicycle trips with a travel cost r_{ij}; b is the decay parameter; a is the threshold for travel cost, which is set as 0.3 km for distance impedance and 3 minutes for time impedance.

Based on the Dirichlet multinomial regression topic model (DMR model) proposed by Li et al. (2020), ten main destination activities of bicycle trips can be identified, including home-related activity, work-related activity, school, clothing shop, electronics shop, home building shop, daytime dining, nighttime dining, beauty & recreation, and medical activity. The travel impedance for different travel purposes can be further calculated by combining the destination activities and cycling trajectories. The parameters of the impedance function for different bicycle travel purposes can be estimated using the non-linear ordinary least squares regression. Consistent with Li et al. (2020), the decay parameter b ranges from 0.470 to 0.510 for distance impedance. For time impedance, the decay parameter b ranges from 0.076 to 0.084.

4.3 Measuring bicycle accessibility for different bicycle level of service (Model 2)

Bicycle suitability is an assessment of perceived comfort and safety of a linear section of bikeway (Lowry, 2012), which is another important factor to evaluate the bicycle accessibility. A street suitable cycling has good bicycle suitability and can improve the bicycle accessibility. To measure the bicycle level of service for segments in shanghai, several indicators are selected (see Table 1). The layout of Shanghai bikeways with different BLOS can be seen in Figure 2.

The impedance function for different trip purposes can be combined with BLOS using the perceived impedance: $\beta_{BLOS}r_{ij}$, where the effect of BLOS on perceived travel impedance is measured by the modification factor β_{BLOS}, which varies with different values of BLOS (Li, 2018). The bicycle accessibility model (Model 2) can then be expressed as follows:

$$A_i^2 = \frac{\sum_k (E_k \sum_{j \neq i} E_j^k f_k(\beta_{BLOS} r_{ij}))}{N_i E} \tag{5}$$

where: A_i^2 is the bicycle accessibility value calculated by model 2; β_{BLOS} is the modification factor of travel impedance for various values of BLOS.

4.4 Measuring bicycle accessibility for different metro stations (Model 3)

The location of metro station within the metro network and the traffic demand of each station can also affect the bicycle-metro integration. The passenger flow of metro systems can reflect the traffic demand from each metro station, which is also regarded as an important factor when evaluating the bicycle accessibility. Besides, previous research indicated that the average energy consumption for the physical activity of daily travel follows a constant pattern (Kölbl & Helbing, 2003). The energy consumption and acceptable travel time for a certain traveler are limited. For metro stations with advantageous locations, travelers have a shorter average travel time within the metro network and are willing to accept a longer bicycle travel time. However, if the duration spent in the metro carriage during peak hours is excessively long, travelers may expend too much energy on the metro and are less likely to accept a longer bicycle travel time.

In Model 3, the traffic demand and the integrating travel impedance (time) spent on the metro and bicycle are jointly considered. Model 3 integrates multiple data sources, including bicycle trajectory data, smart card data, BLOS data, and POI data, to provide a more comprehensive measurement of bicycle accessibility within the metro catchment area. Model 3 is formulated as follows:

$$A_i^3 = \frac{P_i \sum_k (E_k \sum_{j \neq i} E_j^k f_k(\beta_{BLOS} t_{ij} + \overline{T}_i))}{P N_i E} \tag{6}$$

where j is a grid within the catchment area of metro station i, grids that contain the metro station itself are excluded from the set of destination grids; A_i^3 is the bicycle accessibility value calculated by model 3; P_i is the daily transfer volume for metro station i; P is the daily transfer volume for the total metro system; t_{ij} is the bicycle travel time between i and j; $\overline{T}_i$ is the average travel time from other metro stations to metro station i.

5 Results

5.1 Bicycle accessibility results for different purposes (Model 1)

Figure 3 illustrates the spatial distribution of bicycle accessibility to metro stations in the research area based on Model 1. In the figure, red points represent stations with the highest accessibility values, while green points indicate stations with lower accessibility. As shown in Figure 3, bicycle accessibility within the metro catchment area exhibits clear spatial heterogeneity. Overall, accessibility tends to be higher in the city center while decreasing toward the periphery. Stations with higher accessibility values are mainly concentrated within the inner urban core, whereas accessibility gradually decreases from the inner ring toward the outskirts, as indicated by the color transition from red and orange to yellow and green. Regarding regional characteristics, the eastern and parts of the southern areas perform relatively well, while the northern and western areas still show considerable potential for improvement.

Table 2 presents the metro stations with the highest and lowest accessibility rankings, together with their corresponding accessibility values. As shown in Table 2, Tiantong Road metro station records the highest bicycle accessibility value (2.29), whereas Yangshupu Road metro station exhibits the lowest (0.18). This contrast can be partly attributed to differences in the built environment. Tiantong Road metro station is surrounded by commercial complexes that attract cycling trips, while Yangshupu Road metro station is located near the river and lacks significant commercial activities. These findings suggest that the built environment plays a crucial role in shaping bicycle-metro transfer behavior. Metro stations with higher bicycle accessibility are typically situated in areas with a high density of enterprises and well-developed shopping facilities, whereas those with lower accessibility tend to be located in peripheral or less commercially developed zones. Nevertheless, some stations, such as Nanjing Road (E), are also surrounded by commercial complexes but do not have the highest bicycle accessibility, indicating that trip purpose alone may not adequately explain accessibility variations.

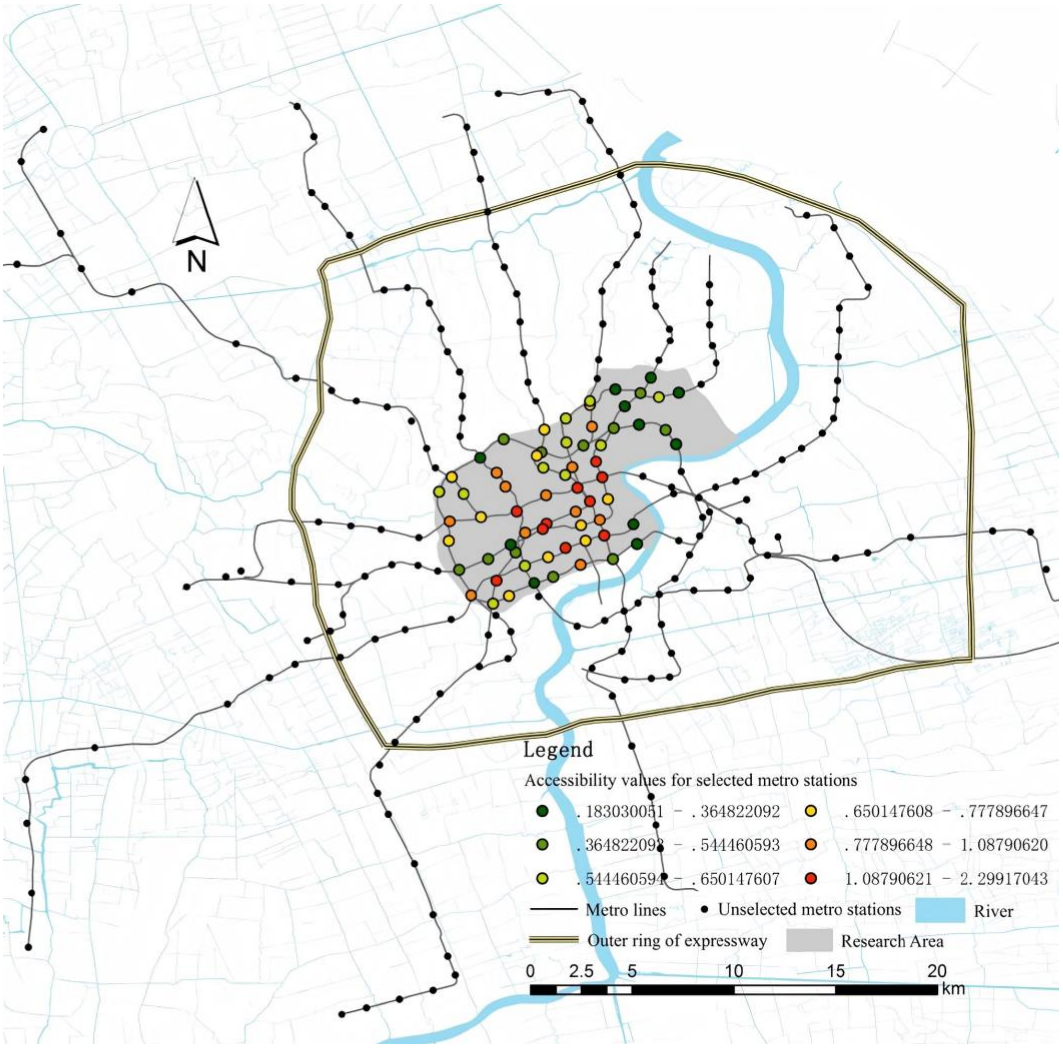

Figure 3. Accessibility values for selected metro stations in Model 1

Table 2. The bicycle accessibility for metro stations in Model 1

Rank	Metro station	Value of accessibility	Rank	Metro station	Value of accessibility
1	Tiantong Road	2.29	65	Yangshupu Road	0.18
2	People’s Square	2.06	64	Tongji University	0.21
3	Dashijie	1.55	63	Nanpu Bridge	0.28
4	Jing’an Tenple	1.49	62	Zhenping Road	0.28
5	Xujiahui	1.39	61	Quyang Road	0.30
6	Shaanxi Road(S)	1.30	60	Jiangpu Road	0.32
7	Dapuqiao	1.16	59	Xiaonanmen	0.33
8	Nanjing Road(E)	1.14	58	Linping Road	0.34
9	Lujiabang Road	1.10	57	Dong’an Road	0.35
10	Nanjing Road(W)	1.08	56	Youdian Xincun	0.35

5.2 Bicycle accessibility results for different bicycle level of service (Model 2)

The effect of the level of bicycle service on bicycle accessibility is incorporated into Model 2, as shown in Figure 4, with the corresponding accessibility values for each metro station reported in Table 3. Considering the spatial layout of Shanghai's bikeways with different BLOS (see Figure 2), stations with bicycle infrastructure of higher quality and more favorable road conditions exhibit modest improvements, whereas those with lower service levels experience slight declines. For example, the bicycle accessibility of Shaanxi Road (S) metro station increased from 1.30 to 1.31, and that of Dapuqiao metro station rose from 1.16 to 1.17. In contrast, the accessibility of Yangshupu Road metro station decreased from 0.18 to 0.17, and the ranking of Youdian Xincun metro station dropped from 56 to 58. Compared with Model 1, the results of Model 2 are very similar. This outcome is attributed to the spatial characteristics of the study area. Specifically, the dense metro network and relatively short distances between stations and destinations result in limited transfer options for commuters. For those who choose to cycle, the quality of bicycle infrastructure may not be a major influencing factor, rendering accessibility levels in areas with high BLOS values not substantially different from those in areas with low BLOS values. Overall, Model 2 integrates the BLOS and considers a broader range of dimensions than Model 1, thereby providing a more comprehensive characterization of cycling accessibility. The inclusion of this dimension enhances the model's practical utility, enabling researchers to select the most appropriate model based on available data and specific local conditions. In areas with dense metro networks and short transfer distances, when data are limited and BLOS information cannot be obtained, using the data and methods from Model 1 can still provide reliable measurements of bicycle accessibility.

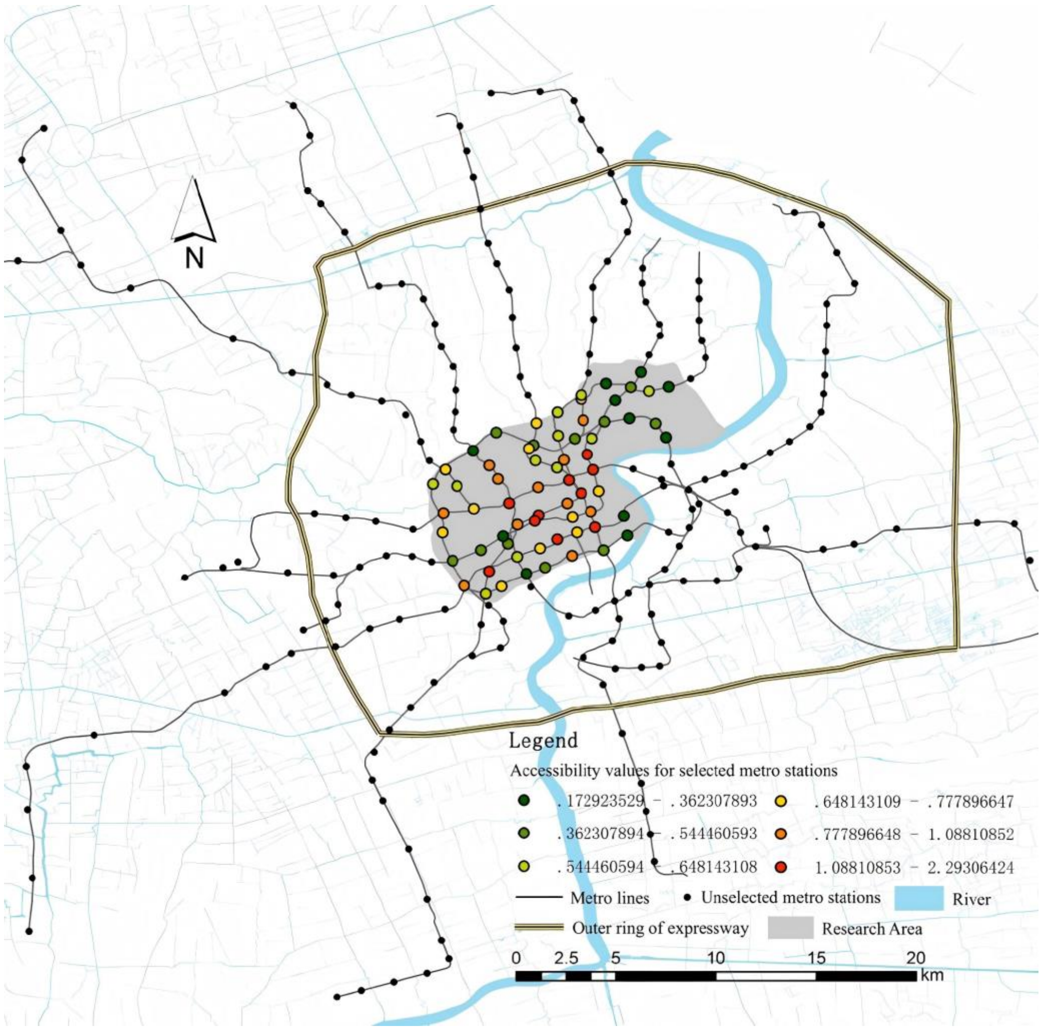

Figure 4. Accessibility values for selected metro stations in Model 2

Table 3. The bicycle accessibility for metro stations in Model 2

Rank	Metro station	Value of accessibility	Rank	Metro station	Value of accessibility
1	Tiantong Road	2.29	65	Yangshupu Road	0.17
2	People's Square	2.06	64	Tongji University	0.22
3	Dashijie	1.55	63	Nanpu Bridge	0.28
4	Jing'an Tenple	1.49	62	Zhenping Road	0.28
5	Xujiahui	1.39	61	Quyang Road	0.30
6	Shaanxi Road(S)	1.31	60	Jiangpu Road	0.32
7	Dapuqiao	1.17	59	Xiaonanmen	0.33
8	Nanjing Road(E)	1.14	58	Youdian Xincun	0.34
9	Lujiabang Road	1.10	57	Linping Road	0.34
10	Nanjing Road(W)	1.08	56	Dong'an Road	0.34

5.3 Measuring bicycle accessibility for different metro stations (Model 3)

The average access time is reported in Table 4, while Figure 5 presents the accessibility values of metro stations in Model 3. We further compare the results of Model 2 and Model 3, which show substantial differences (see Table 5). In the central urban area, metro transfer stations with multiple intersecting lines exhibit higher bicycle accessibility. For example, People's Square metro station is an interchange hub for three metro lines, with a relatively short average travel time. Its accessibility ranking rises from second place in Model 2 to first place in Model 3. In addition, its proximity to government institutions, large parks, and a diverse mix of commercial and office functions generates substantial travel demand. Tiantong Road metro station, which ranked first in Model 2, falls to fifth place in Model 3. Although it is surrounded by commercial complexes that attract cycling trips, its less advantageous position within the metro network and relatively long travel time reduce its overall accessibility. Notably, although Tongji University metro station is located farther from the city center and thus associated with longer travel time, its ranking shows a slight improvement. This reflects the strong and stable demand generated by the large number of students and staff, which offsets some of the disadvantages associated with its peripheral location.

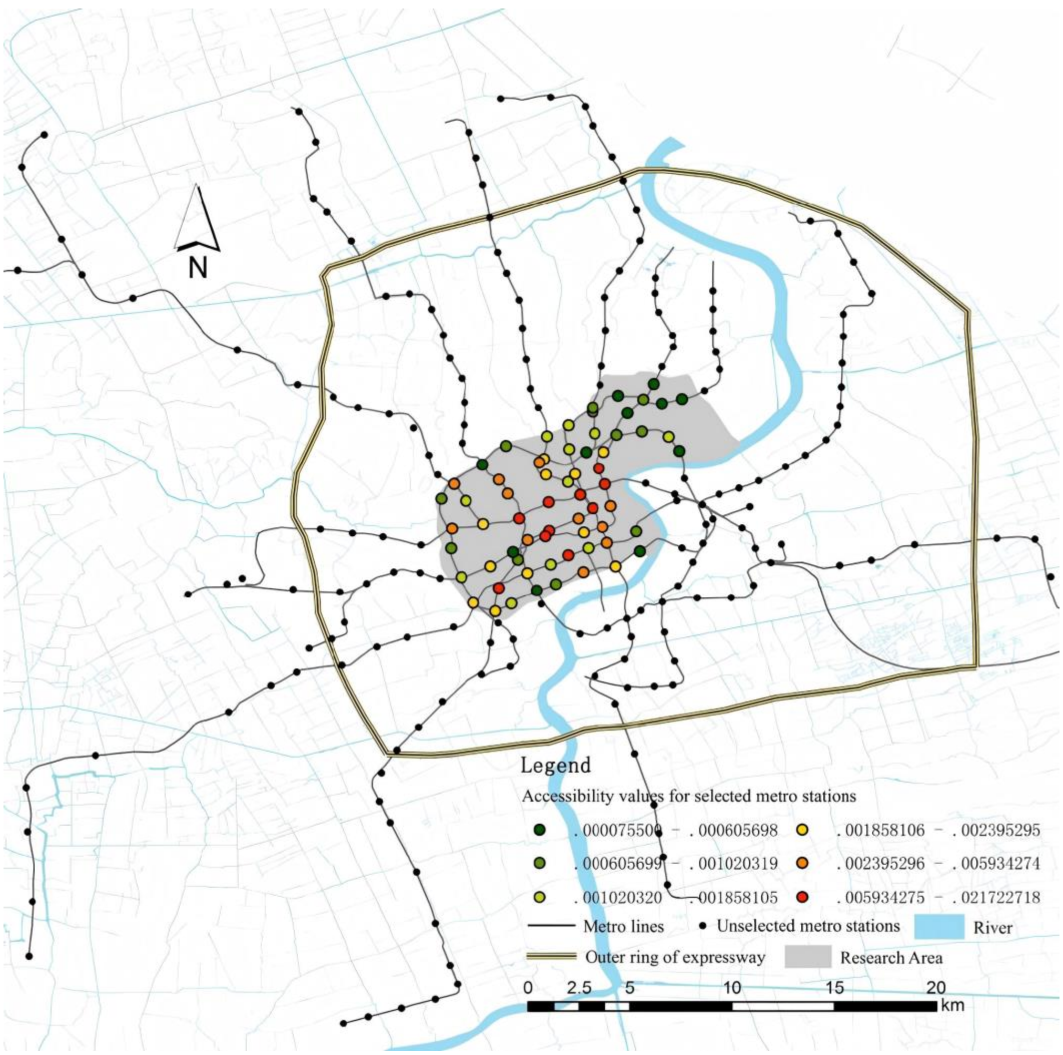

Figure 5. Accessibility values for selected metro stations in Model 3

Table 4. The average access time for metro stations in Model 3

Rank	Metro station	Average access time (min)	Rank	Metro station	Average access time (min)
1	People's Square	32.36	65	Yan'an Road(W)	63.74
2	Nanjing Road(E)	32.68	64	Jinshajiang Road	57.77
3	Nanjing Road(W)	33.02	63	Zhongtan Road	48.20
4	Laoximen	33.30	62	Jiangpu Road	45.53
5	Dashijie	33.33	61	Shanghai Railway Station	43.98
6	Lujiabang	33.52	60	Anshan Xincun	43.25
7	Xintiandi	33.67	59	Tongji University	43.23
8	Yuyuan Garden	33.73	58	Hongkou Football Stadium	43.19
9	Jing'an Tenple	33.75	57	Quyang Road	42.54
10	Xinzha Road	33.89	56	Caoyang Road	42.06

Table 5. The bicycle accessibility for metro stations in Model 3

Rank	Metro station	Value of accessibility	Rank	Metro station	Value of accessibility
1	People's Square	0.02172	65	Baoshan Road	0.00007
2	Xujiahui	0.01989	64	Anshan Xincun	0.00018
3	Nanjing Road(W)	0.01120	63	Zhenping Road	0.00044
4	Shaanxi Road(S)	0.01082	62	Dong'an Road	0.00044
5	Tiantong Road	0.00970	61	Yangshupu Road	0.00044
6	Dashijie	0.00764	60	Nanpu Bridge	0.00048
7	Jing'an Tenple	0.00761	59	Tongji University	0.00048
8	Nanjing Road(E)	0.00694	58	Shanghai Library	0.00054
9	Dapuqiao	0.00656	57	Youdian Xincun	0.00055
10	Huangpi Road(S)	0.00593	56	Jiangpu Road	0.00057

6 Discussion and conclusions

Measuring bicycle accessibility within the metro catchment area helps to analyze the differences in bicycle accessibility across metro stations. It can provide valuable guidance for promoting the integration between cycling and metro systems. Although previous studies examined various factors influencing bicycle-metro integration, most methods for measuring bicycle accessibility have considered limited aspects, such as distance impedance or metro crowdedness, while paying little attention to the combined effects of multiple factors. A more comprehensive analysis that expands data dimensions and integrates multiple influencing factors is essential for achieving precise and effective transport management.

This study proposes three accessibility models that incorporate trip purpose, bicycle suitability, total travel time, and traffic demand to measure bicycle accessibility within metro catchment areas. The models are validated and compared using empirical data from Shanghai. Overall, Model 1 incorporates trip purposes and shows that stations surrounded by commercial complexes exhibit the highest accessibility. This finding is consistent with the study by Hu et al. (2022). However, considering trip purposes alone does not necessarily imply higher accessibility. For instance, although Nanjing Road (E) metro station is also surrounded by numerous commercial facilities, its bicycle accessibility is not the highest, indicating the need to account for additional factors. Model 2 extends Model 1 by incorporating the Bicycle Level of Service (BLOS), slightly adjusting the rankings and producing more infrastructure-sensitive results. In Model 3, total travel time and traffic demand are jointly considered, leading to more pronounced changes in rankings and a closer reflection of real-world conditions. For instance, People's Square metro station, located in the city center, has the shortest travel time and high travel demand, making it the station with the greatest level of bicycle accessibility. This finding aligns well with empirical expectations.

Based on the results of this study, efforts to enhance bicycle-metro integration could focus on the following aspects. First, according to the results of Model 1, low accessibility in some areas may be attributed to a lack of public facilities, leading to insufficient travel attractiveness. In this regard, it is recommended to increase land-use diversity (e.g., shopping malls, parks, and public service facilities) to enhance the attractiveness of these areas. Second, the results of Model 2 indicate that poor accessibility may result from a lack of dedicated or connected bicycle lanes in some regions. To address this issue, it is recommended to expand the coverage of bicycle lanes, particularly through the construction of more dedicated cycling paths, thereby improving the safety and convenience of cycling and attracting more cyclists. Finally, considering transfer volume and total travel time, strategies for the areas identified in Model 3 should focus on expanding shared bicycle capacity and widening cycling routes. These measures would not only help alleviate traffic pressure during peak hours but also improve the comfort and safety of cycling, thereby encouraging more people to choose cycling as a primary mode of travel.

Although this study offers new perspectives and opportunities for future research on urban mobility, several limitations should be acknowledged. First, the analysis focuses on destination patterns, without considering differences among population groups. The varying needs of different demographic groups should be incorporated into future models. Second, this study does not take dynamic accessibility into consideration. Opportunities and traffic demand vary over time, and incorporating temporal variations can enable a more fine-grained assessment of bicycle accessibility. Finally, future studies should employ regression analysis to better explain the underlying causes of high accessibility levels and to quantify the extent to which various factors influence accessibility.

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Author contribution

The authors confirm their contribution to the paper as follows: conceptualization: Y. Huang, S. Zhang; data curation: Y. Huang; formal analysis: Y. Huang; funding acquisition: Y. Huang, S. Zhang; methodology: Y. Huang; writing-original draft: Y. Huang, C. Shi, C. Liu, S. Zhang; writing-review & editing: Y. Huang, C. Shi.

Data availability

If necessary, the authors can provide the original data through correspondence.

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