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Correlation between the built environment and dockless bike-sharing trips connecting to urban metro stations

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Abstract: The influence of the built environment on dockless bike-sharing (DBS) trips connecting to urban metro stations has always been a significant problem for planners. However, the evidence for correlations between microscale built-environment factors and DBS-metro transfer trips remains inconclusive. To address this, a framework, augmented by big data, is formulated to analyze the correlation of built environment with DBS–metro transfer trips from the macroscopic and microscopic views, considering Beijing as a case study. The trip density and cycling speed are calculated based on 11,120,676 pieces of DBS data and then used to represent the characteristic of DBS-metro transfer trips in a multiple linear regression model. Furthermore, a novel method is proposed to determine the built-environment sampling area around a station by its corresponding DBS travel distances. Accordingly, 6 microscale built-environment factors are extracted from street-view images using deep learning and integrated into the analysis model, together with 14 macroscale built-environment factors and 8 potential influencing factors of socioeconomic attributes and metro station attributes. The results reveal the significant positive influence of greenery and presence of barriers on trip density and cycling speed. Additionally, presence of streetlights is found to be negatively correlated with both trip density and cycling speed. Presence of signals is also found to have an influence on DBS-metro transfer trips, but it only negatively impacts trip density.

Keywords: Bike sharing, built environment, metro station, street-view image,cycling speed

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1 Introduction

In the context of city carbon peaking and neutrality, bike sharing has been widely recognized as a green, convenient, and economical travel mode (Ma et al., 2020). It offers several advantages such as alleviating traffic congestion (Fan & Zheng, 2020), reducing carbon emissions from transportation (Chen, Zhou, et al., 2020; Chen, Zhang, et al., 2022), promoting personal health (Bullock et al., 2017; Clockston & Rojas-Rueda, 2021), and improving travel experience (Chen, van Lierop, et al., 2020). Additionally, with dockless bike-sharing (DBS) systems, it can effectively extend the service range of urban metro by solving the first- and last-mile travel problems (Li et al., 2019; Li et al., 2020). A solid interdependence has been established between metro stations and DBS systems (Zhao & Li, 2017). Furthermore, a substantial number of studies have described the impact of built environments on DBS usage. Recently, built-environment features influencing the integrated usage of bike-sharing and urban metro systems have also been studied (Guo et al., 2021; Guo & He, 2021; Li et al., 2021).

A preliminary issue that needs to be addressed to analyze the impact of built environments around metro stations on DBS trips is the influence range of metro stations. Previous studies have referenced the definition of urban Metro-Transit Oriented Development (TOD) and adopted a fixed value for all metro stations (typically 300 m to 4500 m circular buffers) to extract built environments (Hu et al., 2022; Wang, Lu, et al., 2020; Weliwitiya et al., 2019). These studies, however, neglected the fact that the TOD area for a metro station is not equal to its influence range for DBS trips, because the actual cycling distance of certain DBS trips may exceed the TOD area. Recent advances in relevant research have overcome this limitation by using the 85% cumulative distribution of bike-sharing travel distances as the threshold to delineate the influence scope of metro stations (Li et al., 2021; Zuo et al., 2018). However, this threshold is calculated using the travel distance of all DBS trips, which overlooks the heterogeneity among different stations. Ideally, the delineating threshold of the influence scope for a station should be a unique value calculated based on its corresponding DBS trips. This could, in turn, enhance the comprehensiveness and representativeness of built-environment factors.

An issue lies with the commonly used "5D" framework for evaluating the built environments around metro stations. This framework, which describes the built-environment features for a common urban area through density, diversity, design, destination accessibility, and distance to transit, is a well-established approach; however, it is limited in specificity and comprehensiveness when analyzing the integrated usage of urban metro and DBS. Specifically, the "5D" framework mostly considers surface features of stations, such as whether the station is an interchange or terminal station and the number of metro lines passing through the station (Guo & He, 2020; Hu et al., 2022; Ni & Chen, 2020). The topological characteristics of a station in the metro network, such as the degree centrality, betweenness centrality, and eigenvector centrality, are not sufficiently considered. Additionally, although the "5D" framework includes the dimensions of "diversity" and "design", existing research is mainly limited to analyses based on macroscale built-environment factors (Guo et al., 2021; Li et al., 2021). Little discussion has been devoted to the quantified effects of microscale built-environment factors such as greenery, openness, and colorfulness on DBS trips. Thus, a correlation analysis that comprehensively considers built-environment factors at both macroscale and microscale may provide convincing evidence for exploring the relationship between built environment and DBS-metro transfer trips.

So far, research has only recognized the total number or density of bike-sharing trips as a factor representing users' DBS usage (Guo et al., 2021; Wu, Lu, et al., 2021). Although the total number and density of trips are the most basic characteristics of regional DBS usage, the characteristics of trips can also be reflected by other variables such as the regional average cycling speed (Mateo-Babiano et al., 2016). For instance, Vansteenkiste et al. (2017) indicated that teenagers cycle slower than adults on low-quality cycling tracks. In addition, Boufous et al. (2018) found that the cycling speed might be higher on shared paths that support separation from pedestrians, such as visual segregation. Although extensive research has been conducted to prove the relationship between cycling speed and cyclists' comfort, feeling, and safety (Boufous et al., 2018; Gao et al., 2018; Hatfield & Prabhakharan, 2016), very few studies have quantitatively investigated whether the cycling speed is influenced by the built environment around metro stations.

Therefore, considering Beijing as a case study, the correlations of built-environment factors at both the macroscale and microscale levels with DBS–metro transfer trips were comprehensively and quantitatively analyzed in this study. To delineate appropriate sampling ranges for every metro station, a novel concept called the urban metro station influence scope was also defined. This refers to the actual influence range of the built environment around a station on DBS trips from/to that station and is determined by the 85% cumulative distribution of its corresponding DBS travel distances, thus considering the entirety of the samples and the heterogeneity among sampling areas. A built-environment evaluation framework for the urban metro station influence scope was constructed by reviewing relevant studies and planning documents.And the independent variables were extracted using multi-source data from the urban metro station influence scopes. Subsequently, linear regression models were constructed to investigate: (1) What are built-environment factors and how do these factors affect DBS–metro transfer trips, especially those that have not been revealed in previous studies? (2) Is the average DBS cycling speed correlated with the built-environment factors in the urban metro station influence scope, apart from the DBS–metro transfer trip density?

The main contribution of this study is twofold. First, microscale built-environment factors such as greenery, openness, building enclosure, colorfulness, and the presence of typical road infrastructure were integrated into the regression model using street-view images and deep learning. This enabled quantitative correlations between these factors and DBS–metro transfer trips to be elucidated. Second, the correlation between built environment and DBS cycling speed in the urban metro station influence scope was verified, and the significant influencing factors were identified. These research results are expected to provide new insights into understanding the relationship between urban built environments and DBS–metro transfer trips, in addition to facilitating guidelines that could support relevant planning practices.

The remainder of this paper is organized as follows. Section 2 summarizes the existing literature relating to the influence of built environments on DBS–metro transfer trips. Section 3 describes the study area and the method adopted for extracting the necessary data from multiple sources. Section 4 explains the definition and delineating approach for the urban metro station influence scope employed in this research and focuses on the dependent and independent variables used for analyses. Section 5 presents the regression analysis results and discusses the notable phenomena based on groups. Finally, Section 6 presents the study's major findings, policy implications, limitations, and conclusions.

2 Literature review

In recent years, the essential link between built environments and urban transportation systems has gained increasing attention. With rapid urban development, built environments have become more intricate; however, most studies are restricted to the traditional "5D" framework to extract built-environment factors (Liu & Lin, 2019; Wu, Kim, et al., 2021; Yang et al., 2020). Although this approach can effectively evaluate the built-environment elements for most urban spaces, researchers have progressively realized that it is not entirely applicable to the description of urban metro station area, especially for exploring bike–metro transfer issues (Guo et al., 2021; Hu et al., 2022; Li et al., 2020). Thus, certain factors were modified and new ones were added to reflect the characteristics of urban metro station area more accurately and comprehensively. To summarize the potential factors influencing DBS-metro transfer trips, they can be divided into three categories: socioeconomic factors, metro station factors, and built-environment factors.

2.1 Delineation of influence scope around metro stations

In studies relevant to bike–metro transfer trips, a basic step involves associating the bike-sharing trips with the corresponding metro stations. Therefore, the catchment area approach is commonly used to judge the attribution of bike-sharing trips, with the range of the catchment areas varying between cities. For example, a questionnaire survey conducted in Shanghai revealed that most of the bike-sharing usage commences or ends at a location within 500 m of a metro station, followed by a bike–metro transfer trip from/to this station (Li et al., 2021). In Shenzhen, a study found that, in bike–metro transfer trips, cyclists tend to park the bikes within 100 m of the entrance or exit of a metro station (Guo et al., 2021; Wu et al., 2019). However, this bike–metro catchment approach could only associate bike-sharing trips with the metro stations; it failed to reflect the cycling distance to/from the metro stations. Therefore, other methods were used to determine the actual service coverage area of stations for DBS cyclists, defined as the urban metro station influence scope in this study.

Initially, the most commonly used method for delineating the urban metro station influence scope entailed creating a circular buffer with a fixed radius. For example, Gan et al. (2021) considered all built-environment elements within a radius of 1500 m around each metro station, to investigate the associations between built environments, perceived bikeability, and metro transfer patterns. The advantage of this approach is that it is straightforward; however, it fails to account for the actual cycling distance, leading to inconsistencies between the sampling range of the built environment and the actual cycling range of bike-sharing trips. Therefore, certain researchers have used the actual riding distance to delineate the urban metro station influence scope; however, they still extracted built-environment elements according to a fixed radius for all metro stations (Guo & He, 2020; Li et al., 2021). To reflect the actual cycling distance, a common method is to select the 85% cumulative distribution of bike–metro transfer trip distances as the threshold for defining the urban metro station influence scope for metro stations (Zuo et al., 2018). This approach considers the effect of the actual cycling distance, but it assumes that the distance distributions of different stations are identical, neglecting the heterogeneity among metro stations and their corresponding urban metro station influence scope. In a recent study, Wu, Lu, et al. (2021) proposed a novel method that considered demarcating the actual cycling space by aggregating all endpoints of bike-sharing trips; in this manner, the urban metro station influence scope could be generated with a more reasonable definition. However, this method is intricate and difficult to implement in cities with complex metro networks and a large number of DBS–metro transfer trips.

2.2 Socioeconomic factors

In previous studies, there has been disagreement regarding the role of density indicators in exploring their association with bike-sharing trips. Some suggested that only basic socioeconomic factors, such as residential and working population densities, should be considered, while others argued that more specific factors, such as the age composition and income distribution, may also be correlated with DBS–metro transfer trips. Guo et al. (2021) found that the population density was positively correlated with the number of bike–metro transfer trips under morning-access, morning-egress, and evening-egress. Chen, Cheng, et al. (2022) explained that the population around metro stations has a positive impact on both the average daily ridership of station-based bike-sharing and the free-floating bike-sharing for rail transit access. Conversely, Gan et al. (2021) clarified that their results did not support the argument that a higher population density corresponded with more bike–metro transfer trips for the urban metro station influence scope. Regarding specific socioeconomic factors, Caspi and Noland (2019) suggested that areas with a lower average income generated fewer bike-sharing trips. Ji et al. (2017) investigated whether the population's gender, age, income, trip purpose, and bicycle theft experience affected the usage of public bikes for metro access; they revealed that female, older, and low-income rail commuters were less likely to use public bikes to access rail transit. Lin et al. (2018) considered the individual metrics of age, gender, income, car ownership, and bike ownership in a discussion on built environments and public bike usage for metro access. They reported a positive correlation between age, income, and driving license ownership and public bike usage in Beijing, which contradicts the reports applicable to Taipei and Tokyo. This discrepancy warrants further exploration.

It is noteworthy that the socioeconomic variables in most previous studies were derived from census data at the community level or traffic analysis zone (TAZ) level, which is somewhat inconsistent with the analyses for the urban metro station influence scope (Guo et al., 2021; Guo & He, 2020; Wang & Chen, 2020). For instance, Guo et al. (2021) calculated the population and employment density in the 800–1500 m buffer zone for a metro station based on the TAZ to measure the potential demand of bike–metro transfer trips. Wang and Chen (2020) identified the population and job density at a 1000 m2 raster level using census data; however, they extracted spatial characteristics such as the bike route length and the number of bus stops using a 500 m buffer. This disparity in scales between the analysis and data extraction units weakens the persuasiveness of previous findings, since the variables failed to accurately reflect the socioeconomic conditions in the analyzed areas. Nonetheless, the emergence of new data, in addition to the rapid development of data mining technology, has enabled the extraction of accurate socioeconomic data for more specific units from novel platforms such as the Baidu Huiyan (Gibbs et al., 2020; Jin et al., 2021; Sanche et al., 2020). The most recent studies, therefore, gradually started to acknowledge the reliability of these platforms as data sources, and adopted the corresponding refined socioeconomic data for analyses. For instance, Zhang et al. (2020) used the Baidu Heat Map, a product of the Baidu Huiyan platform, to compare human activity density and greenspace supply. Jin et al. (2021) extracted travel data from the Baidu Huiyan platform to identify the borders of activity spaces and quantify the border effects on intra-urban travel. However, few studies have used these refined socioeconomic data to conduct a correlation analysis between built environments and bike–metro transfer trips in the urban metro station influence scope.

2.3 Metro station attribute

With regard to studies on DBS–metro transfer trips, increasing emphasis has been placed on determining how the inherent properties of a metro station affect the surrounding DBS usage. Such research has focused on the metro attributes of distance to the job center, location, passenger flow, and transfer, among others. Several studies have revealed that passenger flow and the location of metro stations can affect DBS–metro transfer trips (Guo et al., 2021; Guo & He, 2020; Wu, Lu, et al., 2021). Moreover, the characteristics of a metro station as part of the entire transportation network have been reported by scholars; this has provided new insights into the integrated usage of the metro and DBS. For instance, according to Wu, Lu, et al. (2021), metro station accessibility, measured by the average travel time in the metro network, positively affects the number of DBS–metro transfer trips from/to the station. In addition, Chen and Ye (2021) calculated metro station accessibility considering the distance from road network nodes to metro stations based on the distance-decay effect and explored its influence on free-floating bike sharing usage.

Previous studies have mainly focused on the influence of certain simple variables representing station attributes. Integrating new variables indicating the topological characteristics of a station in the metro network (such as that between centrality, degree centrality, and eigenvector centrality) in the analyses may lead to unexpected discoveries. This idea has also been applied in previous studies analyzing the interactions between DBS and other travel modes (Wu, Chung, et al., 2021; Zhang, Zhuge, et al., 2021). To our knowledge, however, very few studies have explored the existence of a correlation between the topological characteristics of metro stations and DBS usage.

2.4 Built-environment factors

2.4.1 Macroscale factors

A large and growing body of literature has investigated the influence of transportation factors on bike-sharing usage. Much of this literature has been devoted to transport infrastructure, such as road levels, road length, and intersection density. Lin et al. (2018) revealed that arterial intersection density is positively correlated with public bike usage in Beijing, although it shows a negative correlation in Tokyo. Similarly, Gan et al. (2021) found that the number of intersections is correlated with the number of DBS trips in Nanjing. Ni and Chen (2020) found that areas with a higher density of branches and fewer signalized intersections may result in increased DBS usage. Further, mutual promotion and competition between DBS and other travel modes are also major concerns for scholars. Zhang et al. (2017) studied the interaction between the public bus system and public bikes in the same region, considering the effect of the number of bus stops, distance to the closest public bus stop, and whether the stop was a terminal, a transfer hub, or an intermediate stop. Gan et al. (2021) also found that the number of bus lines is correlated with bike-sharing usage, indicating that accessibility to buses influences DBS–metro transfer trips from the perspective of traffic mode choice.

Land use related indicators have attracted considerable attention in discussing factors influencing bike-sharing trips. Several studies have directly extracted indicators from government documents (Guo & He, 2020; Zhang et al., 2017), whereas in other studies, researchers have calculated indicators based on points-of-interest (POI) data (Liu et al., 2020; Wu et al., 2019). Many previous studies have focused on identifying and evaluating the impact of different land-use types on bike-sharing usage. Commercial, residential, and industrial land uses have been considered; these works have proved that an appropriate layout of urban land use can expand the service scope of metro stations and increase residents' willingness to ride for transfer trips (Gan et al., 2021). A typical example is the study conducted by Zhang et al., in which a residential area was subdivided, suggesting that DBS trips were more likely to end in areas with a higher proportion of public residences, rather than areas with private residences (Zhang, Shen, et al., 2021). In addition to analyzing the impact of single land-use types, researchers have also applied land-use mixtures to characterize regional land use and further explore its correlation with DBS usage. Guo et al. (2021) revealed that land-use heterogeneity was positively correlated with the number of local bike-metro transfer trips. Guo and He (2020) calculated the land-use mixture of four land-use types to discuss the interactions between built environments and DBS-metro transfer trips. Their results showed that the land-use mixture contributed towards generating DBS-metro transfer trips during peak times, and the urban metro station influence scopes with higher industrial land-use shares typically attracted more DBS-metro transfer trips.

The emergence of POI data has afforded the possibility of characterizing regional land-use in greater detail; therefore, these data have been introduced into research pertaining to built environments and DBS usage. Wu et al. (2019) used the POI of commercial, park, leisure, and public transportation within metro station buffers as land-use indicators to measure the destination accessibility of bike–metro transfer trips. Wu, Lu, et al. (2021) analyzed commercial, park, and education accessibility based on the average road network distance between each type of POI and the metro station; they found that commercial accessibility was negatively correlated with bike-sharing usage for the urban metro station influence scope in Shenzhen. Zhao et al. (2021) investigated the correlations between 15 types of POI and public bicycle trip characteristics; they found that the influences of residence, employment, entertainment, and metro station were statistically significant. Regardless of whether these previous studies employed indicators extracted from government documents or those calculated based on POI data, their starting points and general analytical frameworks were the same.

2.4.2 Microscale factors

The microscale built-environment can be defined as street scene elements that affect residents' behaviors through visual perception. Greenery is a popular topic in the relevant research fields. Lu (2019) revealed that the quality and quantity of street greenery can promote enthusiasm for recreational green physical activities. Liu et al. (2019) discussed the link between greenness exposure and depression in China, confirming that residential greenness is negatively correlated with depression. Wang, Lu, et al. (2020) explored the relationship between eye-level greenness and cycling frequency around metro stations, while Lu et al. (2019) revealed that street greenery has a more significant positive correlation with the probability of cycling than the normalized difference vegetation index suggests. Furthermore, Chen, Tu, et al. (2020) confirmed the positive impact of eye-level greening on dockless shared bicycles. Additionally, the influence of other microscale built-environment factors, such as openness, blueness, and enclosure, on residents' cycling behavior has been discussed qualitatively (Dai et al., 2021; Ma et al., 2021), though a comprehensive quantitative analysis has yet to be reported.

To conduct quantitative studies relevant to microscale built environments, a prerequisite is the large-scale extraction of urban visual space elements. Over recent years, the integration of street-view images (SVI) and deep learning technologies have become an effective route for automatically extracting microscale built-environment variables, reducing the reliance on field investigations (Biljecki & Ito, 2021). Hence, SVI–deep learning techniques have been used in several microscale built-environment studies, including related research on cycling (Campbell et al., 2019; Hankey et al., 2021). Helbich et al. (2019) used deep learning to extract green and blue spaces based on SVI to investigate their relationship with geriatric depression. Wang, Lu, et al. (2020) used a semantic image segmentation technique called fully convolutional neural network (FCN-8s) to assess eye-level greenness exposure. Tran et al. (2020) also used a semantic segmentation technique to extract cyclists' perception index of greenery, crowdedness, and outdoor enclosure from SVI to evaluate bikeability from an essential aspect: cyclists' exposure to traffic-related air pollution. However, few quantitative studies have been conducted to comprehensively explore the correlations of microscale built-environment factors with DBS–metro transfer trips. The current study aims to fill this gap in existing literature.

2.5 Summary of previous studies

Previous studies have established a solid foundation for the current study in terms of urban metro station influence scope delineation, variable selection, and data extraction methods. However, several limitations can still be identified. Most previous studies simply delineated the urban metro station influence scope with a fixed threshold, neglecting the heterogeneity among metro stations. In addition, few studies have comprehensively considered built-environment factors on both the macroscale and microscale to investigate their influences on DBS–metro transfer trips in the urban metro station influence scope. This potential absence of essential factors could lead to non-negligible model endogeneity, which, in turn, would severely affect the reliability of regression analysis results. Moreover, in relevant studies, the dependent variable was unitary; this implies that the amount of DBS usage is the sole dependent variable in the analysis. However, the characteristics of DBS–metro transfer trips can also be reflected by other variables such as the average cycling speed. Therefore, this study aims to provide new insights into the correlations between built environments and DBS–metro transfer trips in the urban metro station influence scope by addressing these limitations of previous studies. The additional variables considered in this study are introduced in detail in the subsequent sections.

3 Data

3.1 Study area

As the capital of China, Beijing has a population of approximately 22 million and a total area of 16,411 km2. To promote carbon peaking and carbon neutrality, the Beijing government has constructed a "green" transportation system, such as the urban metro and DBS. As of March 2019, there were 22 metro lines and 329 stations in operation, with a total length of 637 km, as shown in Figure 1. The total daily metro ridership was 10.856 million in 2019 (Beijing Metro, 2019). Meanwhile, the DBS trips amounted to 490 million, with a daily average cycling distance of 1.5 km and cycling time of 10.3 min for the residents in 2019, increasing the percentage of green trips in the central city to 74.1% (Beijing Transportation Institute, 2020). According to the "Beijing Railway Network Planning (2020–2035)," a major basic long-term development strategy is to cultivate the "subway + slow" travel mode, while focusing on creating a cycling system within 3 km of the metro stations (Beijing Municipal Commission of Planning and Natural Resources, 2021).

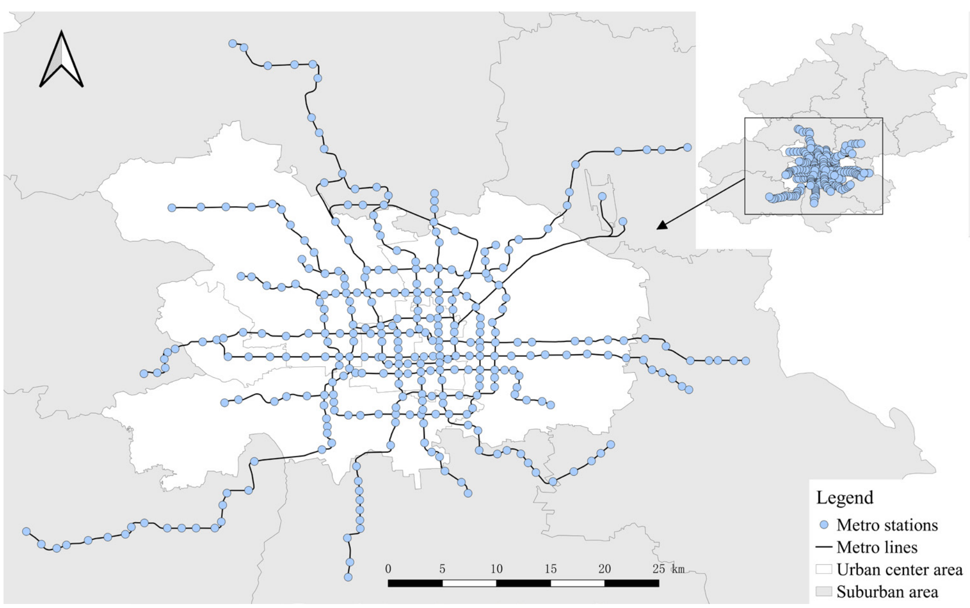

Figure 1. Distribution of metro lines and metro stations in Beijing

3.2 Data preparation

This study collected data from various sources, which were divided into five categories: DBS data, socioeconomic data, transportation data, land-use data, and SVI. Notably, the socioeconomic data and SVI were collected in 2021, while EULUC-China data was collected in 2018, and all other data were extracted in 2019.

Dockless bike-sharing data. These data were collected by the official traffic data management department of Beijing from March 4 to March 10, 2019, during a period of sunny weather. The data included trip ID, start time, start location, end time, and end location for each trip, but lacked trajectories. After removing invalid data, including incomplete travel information, unmoved bikes, irrational travel times, irrational travel distances, and irrational speeds, a total of 11,120,676 DBS trips were screened out to be further connected to metro stations.

Socioeconomic data. Recent studies have recognized the Baidu Huiyan platform as a reliable source for extracting socioeconomic data to investigate urban transportation issues (Gibbs et al., 2020; Sanche et al., 2020; Yang et al., 2021). Therefore, the Baidu Huiyan platform was selected as the data source for the present study to identify the socioeconomic attributes of the urban metro station influence scope, including population activity, residential population, working population, income hierarchy, and car ownership ratio.

Transportation data. Data relevant to the metro/bus system were obtained from related management companies, including metro networks, bus networks, and metro ridership. Geographical data for roads, intersections, and bike lanes were obtained from OpenStreetMap (OSM). The road congestion index was evaluated based on the road traffic conditions extracted from the open Baidu platform (lbsyun.baidu.com). The level of road traffic conditions was collected from November 24 to November 30, 2021, at half-hour intervals from 6:00 to 23:30 hours. Based on the metro network, the degree centrality, between centrality, and eigenvector centrality of the stations were further calculated. Metro ridership was in the form of hourly passenger flow access and egress to and from metro stations. The extraction dates were March 6 and March 10, 2019, a weekday and a weekend day, respectively, within the time when the DBS data were collected.

Land-use data. The land use of the study area was determined according to the EULUC-China data, covering five categories: residential, recreational, transportation, industrial, and office (Ke et al., 2021; Song et al., 2021; Xu et al., 2021). The POI data for 2019 was captured from a web mapping service application "Amap" (lbs.amap.com), including coordinates for all POI. POIs were generally divided into 14 categories: restaurants, tourist attractions, public facilities, enterprises, shopping, transportation services, science/culture and education services, finance and insurance services, life services, commercial housing, sports and recreation, medical services, and accommodation services.

Street-view images. SVI have been recognized as a reliable data source for large-scale urban analyses (Biljecki & Ito, 2021; Meng et al., 2022; Wang et al., 2021). Sampling points along the streets in the urban metro station influence scope at 100 m intervals were selected and their coordinates were recorded. The SVI of the four directions at the sampling points were then extracted using the Baidu map application programming interface (lbsyun.baidu.com). As a result, 306480 SVI were collected from 76620 sampling points. Subsequently, a fully convolutional neural network named FCN-8s trained with the ADE-20 K dataset was used to extract the microscale built-environment variables according to the pixel area ratio of different objects from the SVI (Dai et al., 2021; Wang et al., 2019). Figure 2 shows the method of extracting microscale built-environment elements about semantic image segmentation technique.

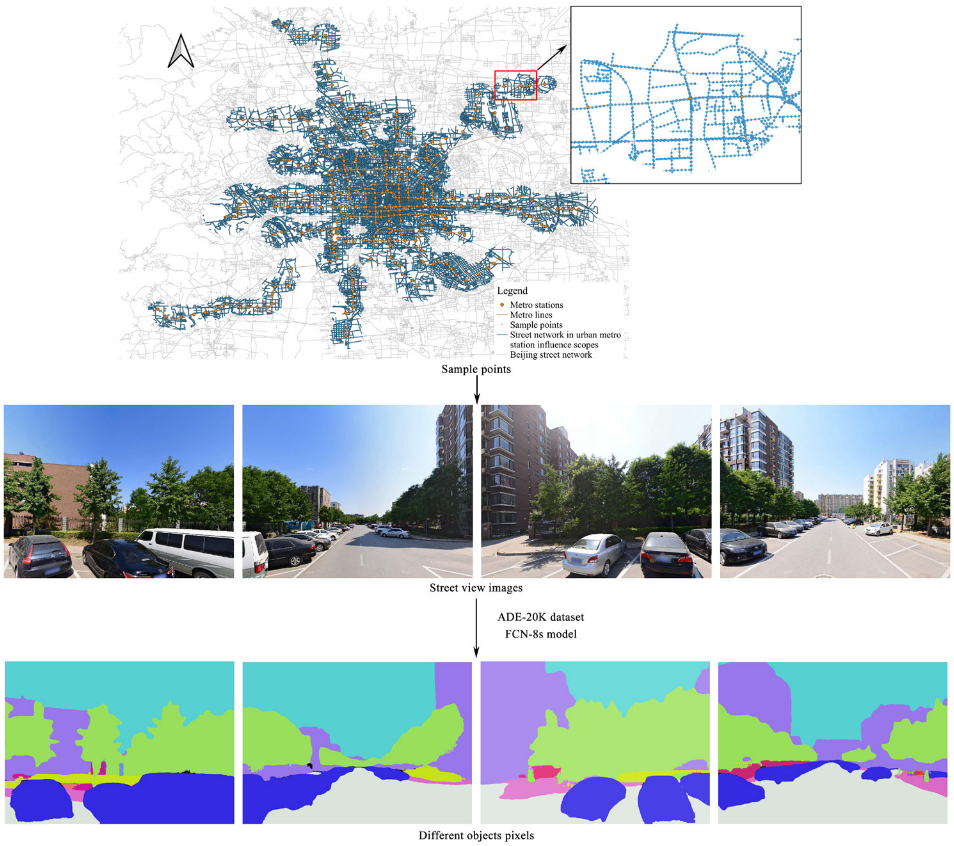

Figure 2. Illustration of the semantic image segmentation technique

4 Methodology

4.1 Analytical framework

The methodology of this study was summarized in Figure 3. The DBS data were processed, including distinguishing the DBS–metro transfer trips and connecting these trips with the corresponding metro stations. The urban metro station influence scope was delineated for the stations according to the actual cycling distances of their DBS–metro transfer trips. Then, 5 socioeconomic indicators, 5 metro station indicators, 16 macroscale indicators and 8 microscale indicators of the built environment in the urban metro station influence scope, classified into 5 categories, were calculated as independent variables using the socioeconomic data, transportation data, land-use data, and SVI. Subsequently, the influence of the built environment in the urban metro station influence scope on the trip density and cycling speed of the DBS–metro transfer trips were successively analyzed using multiple linear regression. Finally, a discussion on the major findings and policy implications based on the regression analysis results was conducted. These major findings were expected to support reliable planning and provide new insights for planners.

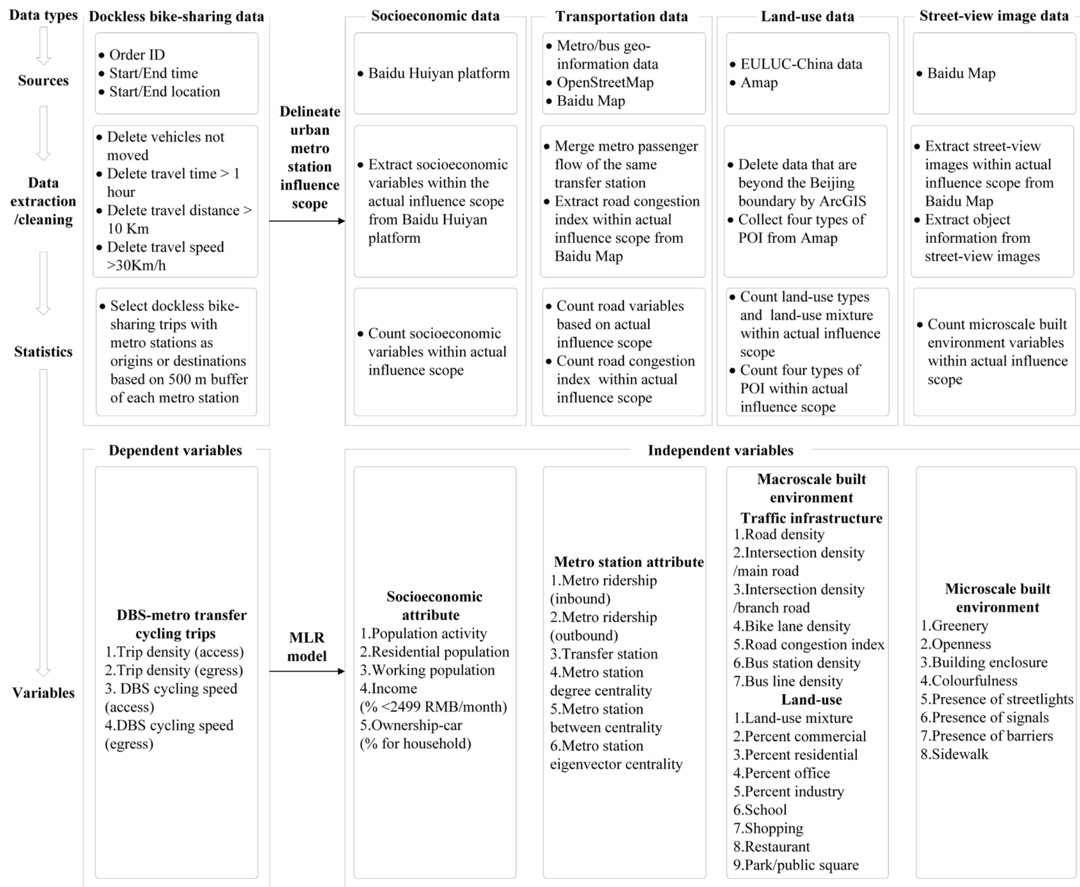

Figure 3. Analytical framework of current study

4.2 Delineating urban metro station influence scope

To investigate correlations between the built environment around metro stations and DBS–metro transfer trips, two issues must be addressed: connecting DBS trips with origin/destination metro stations and determining the actual influence range of the built environment. This study solves these problems by defining two different ranges around metro stations: the metro station catchment area and the urban metro station influence scope.

In this first step, the metro station catchment area, which is the area where bike pick-up/drop-off occurs around metro stations, was defined to connect DBS trips with the metro stations. Previous studies used a radius of 100 m for the metro station catchment area (Guo et al., 2021; Guo & He, 2020; Wu, Lu, et al., 2021). It is reasonable to consider this as an acceptable walking distance from the DBS parking space to the metro station entrance. However, in this case, the coordinates of the metro entrances were not available. If a parking ring with a size of 100 m is used to delineate the catchment area of a metro station, it may not cover all the entrances for certain metro stations. Therefore, the method proposed in other similar studies (Hu et al. 2022; Li et al., 2021; Wang, Cheng, et al., 2020) was adopted, where a geometric centroid point was used to represent each metro station and the DBS usage was connected with metro stations using a 500 m buffer, as shown in Figure 4. Moreover, it was verified that, for each metro station in Beijing, a 500 m buffer from the station centroid point could cover the DBS parking hot spots around all exits. The study conducted by Li et al. (2021) revealed that more than 75 % of DBS trips within the 500 m buffer of metro stations are related to metro usage; Accordingly, in this study, the DBS trips that commenced or ended within the metro station catchment area of a station were recognized as the DBS–metro transfer trips from/to this station. The overlaps of the metro station catchment areas were further separated using the Thiessen polygon, and it was also assumed that a DBS cycling trip belongs to the closest metro station if its origin and destination lie in different metro station catchment areas. Consequently, a total of 567,364 access DBS-metro transfer trips and 581,798 egress trips were identified and used for model construction.

The second step was to determine the influence range of the built environment on the DBS trips. Unlike previous studies that used a fixed range to sample the built-environment factors around metro stations, this study defines a new concept, the urban metro station influence scope, to indicate the comprehensive influence area of built environments on DBS–metro transfer trips. The influence scope of a station is determined by the 85% cumulative distribution of the DBS cycling distances from/to this station, indicated by the blue area in Figure 4. Compared with the traditional methods that used a single fixed value calculated based on DBS cycling distances of all metro stations, the adaptive catchment area delineation proposed in this study ensures that each station has its own unique range of cycling influence, which balances both the entirety of sampling and the station heterogeneity.

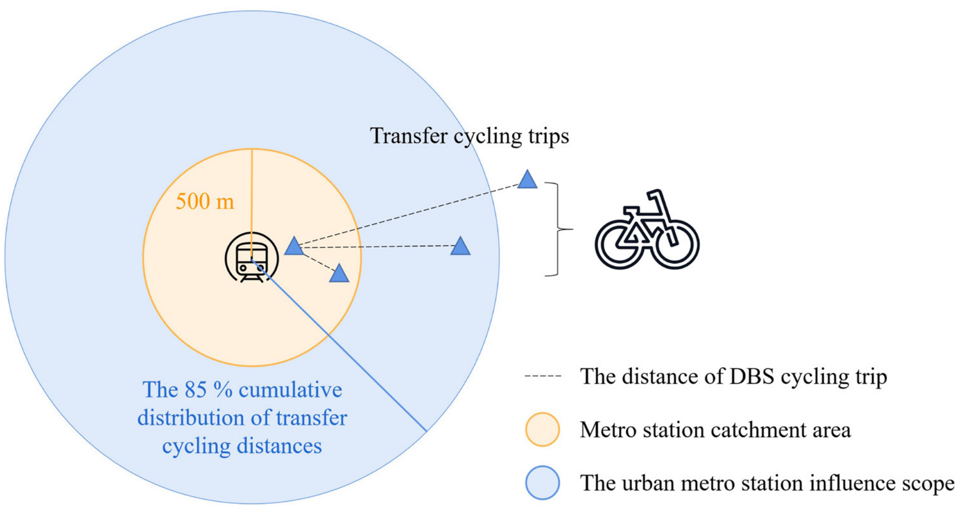

Figure 4. Schematic of delineating the urban metro station influence scope

4.3 Model construction

By conducting a review of the studies on the correlation between built environment and DBS trips, an exhaustive list of alternative built-environment indicators was summarized and merged with similar ones. Considering that certain indicators such as the attributes of stations and microscale indicators have not been quantitatively analyzed, these indicators were also added to the list. After revisions, 34 indicators were selected as alternative independent variables, as shown in Table 1. These indicators were classified into 5 categories, reflecting the potential influencing factors from multiple dimensions, including socioeconomic attribute, metro station attribute, transport infrastructure, land use, and microscale built environment. For further regression analyses, it was necessary to ensure that no significant multicollinearity existed between the independent variables. Thus, all the independent variables were checked using the variance inflation factor (VIF) test. According to the rule of thumb (Kutner et al., 2004), factors with a VIF value exceeding 10 were excluded. Thus, a total of 28 indicators were adopted as the independent variables for the regression analyses.

In addition to trip density, which has been the focus of many previous studies, the average cycling speed was also included in the analyses of DBS trips as an indicator closely relating to comfort and safety. Owing to the lack of actual trajectories, the cycling speed was extracted under the assumption that all the cycling trajectories follow the shortest paths between the origins and destinations, calculated based on Euclidean distance. Metro station access and egress trips were analyzed separately to investigate whether a significant distinction existed. In summary, four dependent variables were analyzed: access trip density, egress trip density, access cycling speed, and egress cycling speed.

Table 1. Description of variables

Category		Description	Unit	VIF			
				density-access	density-egress	speed-access	speed-egress
Dependent variables							
DBS–metro transfer trips	Trip density (access)	Daily DBS–metro transfer trip density (access)	numbers/ km^2	-	-	-	-
	Trip density (egress)	Daily DBS–metro transfer trips density (egress)	numbers/ km^2	-	-	-	-
	DBS cycling speed (access)	Average cycling speed of DBS–metro transfer trips (access)	km/h	-	-	-	-
	DBS cycling speed (egress)	Average cycling speed of DBS–metro transfer trips (egress)	km/h	-	-	-	-
Independent variables							
Socioeconomic attribute	Population activity	Number of population activities / urban metro station influence scope	thousand /km^2	48.29*	48.31*	48.29*	48.31*
	Residential population	Number of the residential population / urban metro station influence scope	thousand /km^2	17.41*	17.32*	17.41*	17.32*
	Working population	Number of the working population / urban metro station influence scope	thousand /km^2	24.64*	24.71*	24.64*	24.71*
	Income (% <2499 RMB/month)	Percentage of residents with monthly incomes below 2499 RMB	%	3.30	3.30	3.30	3.30
	Ownership-car (% for household)	Percentage of household with cars	%	1.78	1.78	1.78	1.78

Table 1. Description of variables

Category		Description	Unit	VIF			
				density-access	density-egress	speed-access	speed-egress
Metro station attribute	Metro ridership (inbound)	Daily metro ridership / urban metro station influence scope (inbound)	thousand /km^2	1.79	-	1.79	-
	Metro ridership (outbound)	Daily metro ridership / urban metro station influence scope (outbound)	thousand /km^2	-	1.76	-	1.76
	Transfer station	Transfer station = 1; other = 0	-	4.64	4.64	4.64	4.64
	Metro station degree centrality	Describes the number of nodes that connect with a node	-	5.32	5.32	5.32	5.32
	Metro station between centrality	Number of shortest paths through a node to describe the node’ s importance	-	2.65	2.65	2.65	2.65
	Metro station eigenvector centrality	Considers the number of adjacent nodes and the impact of these adjacent nodes	-	5.77	5.77	5.77	5.77
Macroscale built-environment factors: transport infrastructure	Road density	Lengths of road / urban metro station influence scope	km/km^2	39.55*	39.55*	39.55*	39.55*
	Intersection density/main road	Number of intersections (main road) / urban metro station influence scope	numbers/km^2	3.58	3.59	3.58	3.59
	Intersection density/branch road	Number of intersections (branch road) / urban metro station influence scope	numbers/km^2	43.61*	43.60*	43.61*	43.6*
	Bike lane density	Lengths of bike lanes / urban metro station influence scope	km/km^2	2.69	2.69	2.69	2.69

Table 1. Description of variables

Category		Description	Unit	VIF			
				density-access	density-egress	speed-access	speed-egress
Macroscale built-environment factors: transport infrastructure	Road congestion index	Traffic congestion status (1 to 4 represent clear, slow, congestion, severe congestion)	-	2.70	2.70	2.70	2.70
	Bus stop density	Number of bus stops / urban metro station influence scope	numbers/km^2	8.89	8.89	8.89	8.89
	Bus line density	Lengths of bus lines / urban metro station influence scope	km/km^2	8.00	8.00	8.00	8.00
Macroscale built-environment factors: land-use	Land-use mixture	Land-use mixture with 12 patterns	-	2.66	2.65	2.66	2.65
	Percent commercial	Percentage of commercial land	%	1.36	1.36	1.36	1.36
	Percent residential	Percentage of residential land	%	4.38	4.38	4.38	4.38
	Percent office	Percentage of office land	%	5.85	5.85	5.85	5.85
	Percent industry	Percentage of industrial land	%	2.16	2.15	2.16	2.15
	School	Number of school POI / urban metro station influence scope	numbers/km^2	3.41	3.41	3.41	3.41
	Shopping	Number of shopping POI / urban metro station influence scope	numbers/km^2	8.54	8.56	8.54	8.56
	Restaurant	Number of restaurant POI / urban metro station influence scope	numbers/km^2	12.00*	12.00*	12.00*	12.00*
	Park/public square	Number of park/public square POI / urban metro station influence scope	numbers/km^2	2.10	2.10	2.10	2.10

Table 1. Description of variables

Category		Description	Unit	VIF			
				density-access	density-egress	speed-access	speed-egress
Microscale built-environment factors	Greenery	Proportion of average tree, plants, and glass pixels at the sampling points	%	6.56	6.55	6.56	6.55
	Openness	Proportion of average sky pixels at the sampling points	%	38.02*	37.99*	38.02*	37.99*
	Building enclosure	Proportion of average building and tree at the sampling points	%	47.64*	47.64*	47.64*	47.64*
	Colorfulness	Mixing entropy of street dominant colors (Simpson index)	-	2.23	2.23	2.23	2.23
	Presence of streetlights	Proportion of sampling points with streetlights	%	5.43	5.43	5.43	5.43
	Presence of signals	Proportion of sampling points with traffic signal, sign, and screen	%	2.61	2.61	2.61	2.61
	Presence of barriers	Proportion of sampling points with fence and barrels	%	2.60	2.60	2.60	2.60
	Sidewalk	Pixels proportion of sidewalk to road	%	11.53*	11.53*	11.53*	11.53*

Note: * indicates variables with VIF values exceeding 10

5 Results and discussion

5.1 Basic features of urban metro station influence scopes

The first set of analyses examined the basic features of urban metro station influence scopes and DBS–metro transfer trips. The distribution of urban metro station influence scopes is presented in Figure 5. The radii of these urban metro station influence scopes are 0.8–3.65 km, and approximately 75 % of them are smaller than 2 km. Unlike previous studies, which reported that the bike–metro catchments in peripheral areas are commonly larger than those in urban centers (Wu, Lu, et al., 2021), the urban metro station influence scopes in this case did not show a significant distinction in terms of size between the urban central and peripheral areas. However, the metro stations near tourist attractions (such as Beihai North Station, Nanluoguxiang Station, and Tiananmen Xi Station) featured larger urban metro station influence scopes, as compared with those of other stations. This indicated that the DBS–metro transfer trips for tourist travel may be accompanied by longer distances than those during commuting and other daily travel.

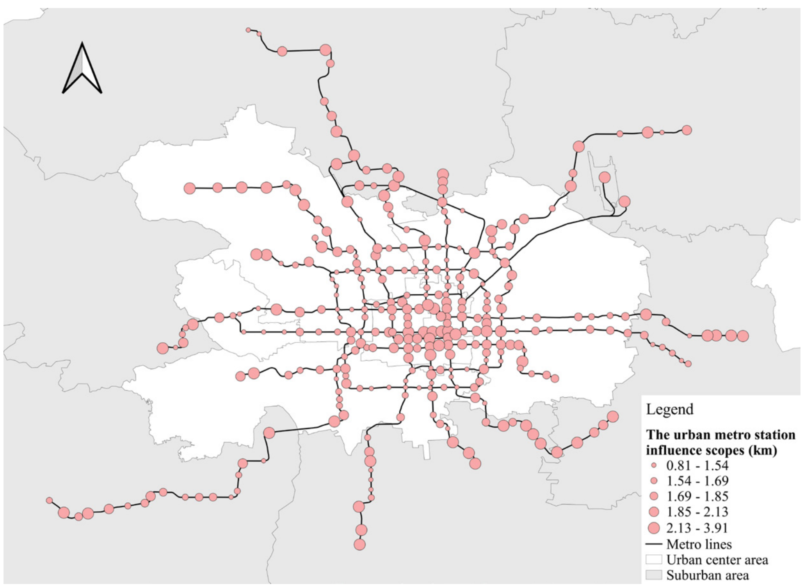

Figure 5. The urban metro station influence scopes in Beijing

Figure 6 reveals that the trip density and cycling speed do not differ significantly for the access and egress trips. The DBS–metro transfer trips were concentrated in the urban central area, leading to a decrease in the trip density of the urban metro station influence scopes from downtown to suburban areas. However, the cycling speed of the urban metro station influence scopes at the urban periphery was higher than that of the urban metro station influence scopes at the urban center, ranging from 6.5 to 9.5 km/h. An interesting phenomenon was noted in that the urban metro station influence scopes near tourist attractions also differed in terms of the cycling speed being lower than those of the other urban metro station influence scopes. A possible explanation for the longer cycling distance and lower cycling speed in these urban metro station influence scopes may be the lack of travel time constraints and the unique built environments around tourist attractions. Closer inspections revealed that certain urban metro station influence scopes were associated with extremely few trips. Therefore, to enhance the reliability of the regression analyses, 22 urban metro station influence scopes with fewer than 10 daily DBS trips were excluded from the sample set.

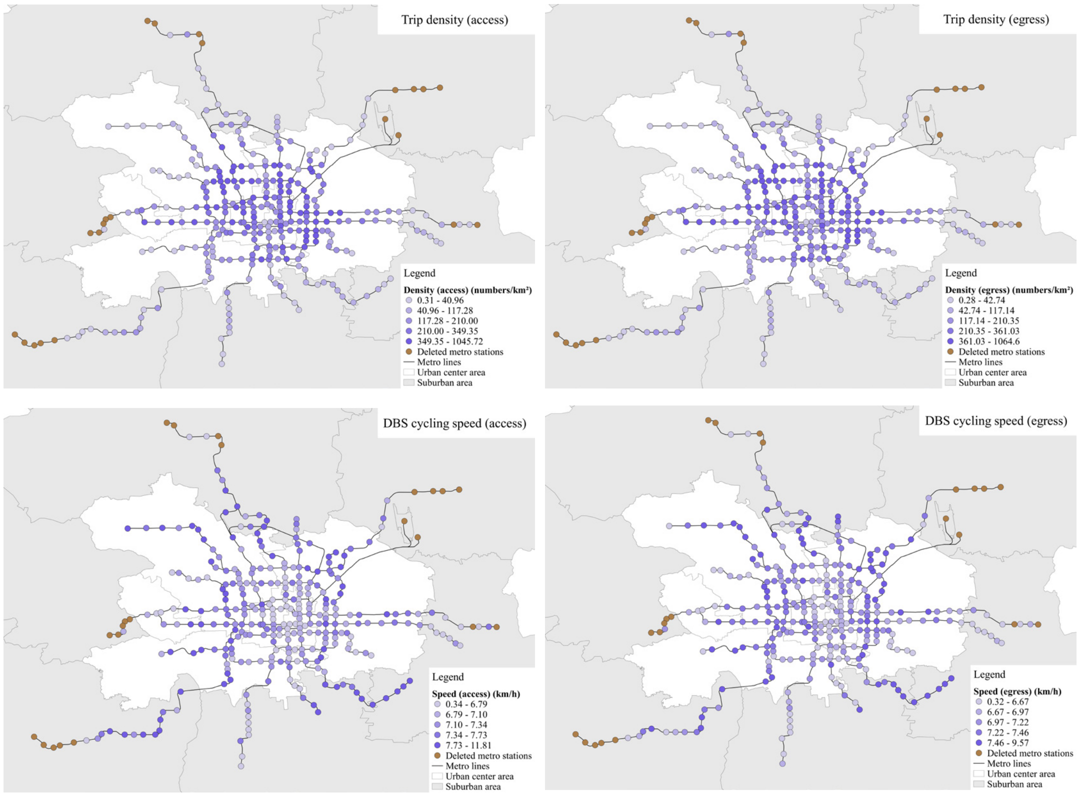

Figure 6. Trip density and cycling speed of DBS–metro transfer trips in urban metro station influence scopes

5.2 Regression analysis results

The regression analysis results for the four models are presented in Table 2. The goodness-of-fit of the models were assessed using the adjusted coefficient of determination (adjusted R^2). On comparing the models for access with the models for egress, only small differences were noted for both the trip density models (adjusted R^2 = 0.811 for access and adjusted R^2 = 0.798 for egress) and cycling speed models (adjusted R^2 = 0.364 for access and adjusted R^2 = 0.372 for egress). In addition, the significant influencing factors on access and egress trips were identical. Therefore, no differentiation was made between the access and egress trips for most built-environment factors in this discussion. The adjusted R^2 of the trip density models was approximately 0.8, indicating a satisfactory goodness-of-fit and a strong correlation between the selected built-environment variables and the DBS–metro transfer trip density in the urban metro station influence scopes. There were 11 significant influencing factors for built environments, including 7 macroscale variables and 4 microscale variables, with a confidence interval of 90 %. The adjusted R^2 of the cycling speed models was lower. This could be attributed to the fact that the factors influencing the DBS cycling speed were more complex, as compared with those influencing the trip density. Additionally, the DBS cycling speed was calculated by taking the quotient of the travel distance divided by travel time; however, the calculation of travel distance in this study was based on the assumption that DBS cyclists ride along the shortest path for their trip, owing to the lack of actual trajectories; this might have also influenced the goodness-of-fit of the model for cycling speed. Despite the lower adjusted R^2 of the cycling speed models, several independent variables, specifically 2 socio-economic variables, 1 metro station variable, 8 macroscale built-environment factors and 3 microscale built-environment factors, were still identified as being significantly correlated with the DBS cycling speed in urban metro station influence scopes with a confidence interval of 90 %.

Table 2. Result of regression models (N = 307)

Variables	DBS–metro transfer trip density				DBS cycling speed			
	Density (access)		Density (egress)		Speed (access)		Speed (egress)	
	Coef.	p	Coef.	p	Coef.	p	Coef.	p
Socioeconomic attribute								
Residential population	11.269***	< .001	12.045***	< .001	0.036**	0.017	0.042***	0.003
Income (% <2499 RMB/month)	83.645	0.868	62.783	0.908	-4.750	0.218	-6.103*	0.095
Ownership-car (% for household)	-28.531	0.920	-18.862	0.951	-3.354	0.127	-1.458	0.482
Metro station attribute								
Metro ridership (inbound)	46.374***	< .001	-	-	-0.097**	0.024	-	-
Metro ridership (outbound)	-	-	45.559***	< .001	-	-	-0.117***	0.003
Transfer station	11.237	0.724	20.445	0.550	0.083	0.733	0.033	0.887
Metro station degree centrality	-10.580	0.221	-12.147	0.191	-0.013	0.839	-0.009	0.891
Metro station between centrality	-2.28e–4	0.965	3.24E-05	0.995	3.68E-05	0.352	5.46E-05	0.145
Metro station eigenvector centrality	163.955**	0.039	160.870*	0.06	0.555	0.361	0.384	0.504

Table 2. Result of regression models (N = 307)

	Variables	DBS–metro transfer trip density				DBS cycling speed			
		Density (access)		Density (egress)		Speed (access)		Speed (egress)	
		Coef.	p	Coef.	p	Coef.	p	Coef.	p
Macroscale built-environment factors									
transport infrastructure	Intersection density/main road	-2.416***	< .001	-2.792***	< .001	0.001	0.728	0.002	0.671
	Bike lane density	1.704	0.902	2.03	0.891	-0.192*	0.071	-0.099	0.323
	Road congestion index	138.639**	0.011	140.363**	0.017	0.141	0.736	0.343	0.384
	Bus stop density	1.401*	0.065	1.491*	0.068	-0.025***	< .001	-0.025***	< .001
	Bus line density	0.103	0.937	-0.088	0.95	0.025**	0.013	0.019**	0.044
Land-use	Land-use mixture	-66.494	0.398	-49.529	0.557	-1.377**	0.023	-1.381**	0.016
	Percent commercial	291.803	0.339	253.296	0.44	6.496***	0.006	4.667**	0.036
	Percent residential	-191.097***	0.002	-188.024***	0.005	-1.1928**	0.012	-1.389***	0.002
	Percent office	408.586	0.194	413.19	0.222	4.841**	0.045	5.699**	0.013
	Percent industry	65.431	0.667	43.142	0.792	-0.137	0.906	0.076	0.945
	School	2.543***	0.002	2.525***	0.004	-0.011*	0.078	-0.013**	0.025
	Shopping	-22.008***	0.001	-21.523***	0.003	-0.065	0.209	-0.056	0.253
	Restaurant	0.801*	0.084	0.880*	0.078	0.003	0.335	0.005	0.135
	Park/public square	16.81	0.188	20.015	0.145	0.015	0.878	0.011	0.903

Table 2. Result of regression models (N = 307)

Variables	DBS–metro transfer trip density				DBS cycling speed			
	Density (access)		Density (egress)		Speed (access)		Speed (egress)	
	Coef.	p	Coef.	p	Coef.	p	Coef.	p
Microscale built-environment factors								
Greenery	361.427*	0.098	451.706*	0.055	2.341	0.163	2.948*	0.063
Colorfulness	-110.21	0.762	-152.12	0.698	-4.468	0.111	-3.798	0.152
Presence of streetlights	-535.06	0.119	-626.178*	0.09	-8.375***	0.002	-6.603***	0.008
Presence of signals	-474.672*	0.075	-479.964*	0.094	0.949	0.641	0.397	0.836
Presence of barriers	1204.051*	0.099	1344.598*	0.087	3.185	0.569	9.401*	0.076
Sidewalk	-57.149	0.862	-32.865	0.926	-2.752	0.276	-1.106	0.643
Model fit information								
Adjusted R^2	0.811		0.798		0.364		0.372	

Note: ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

5.2.1 Effects of socioeconomic attribute and metro station attribute

Previous studies have reported inconclusive influence of population density on the DBS–metro transfer trips (Guo et al., 2021; Lin et al., 2018; Wang, Lu, et al., 2020); however, this work revealed positive correlations between residential population density and both the DBS–metro transfer trip density and cycling speed. This might be due to the separation of jobs and residences in Beijing, which creates strong demands for commuting among the residential population, thereby generating additional DBS–metro transfer trips. This could also explain why residents tend to ride faster when commuting. Similarly to Lu et al. (2019), no statistically significant correlations of the individual income (% <2499 RMB/month) and car ownership (% for household) with the DBS–metro transfer trip density were identified in this study. However, an unexpected finding was a negative association between income (<2499 RMB/month) and the DBS egress cycling speed. This could be because residents with lower incomes may not be subjected to time constraints and prefer leisurely cycling.

Regarding the metro station attributes, it was found that metro ridership, both inbound and outbound, is positively correlated with the DBS–metro transfer trip density, which is consistent with previous reports (Fan & Zheng, 2020; Guo et al., 2021). By contrast, it was found that a higher station ridership is likely to be accompanied by a lower DBS cycling speed in the urban metro station influence scope, likely due to the road crowding resulting from on-road DBS transfer cycling trips. As a novelty of the current study, three network topological properties of metro stations—degree centrality, betweenness centrality, and eigenvector centrality—were examined for their correlations with the DBS–metro transfer trips. The results revealed that, although none of them influenced the cycling speed, eigenvector centrality had a significant positive correlation with the trip density. Eigenvector centrality considers the number of adjacent stations connected to a station and also the importance of these adjacent stations for metro networks. A high value indicates that a station has a strong influence on the accessibility of the metro network. It is noteworthy that most metro stations with higher eigenvector centrality, such as Jianguomen, Dongdan, and Chongwenmen, are transfer stations or are located near transportation hubs. Although the VIF test indicated that no significant multicollinearity existed between eigenvector centrality and metro ridership, a large passenger flow, along with the strong transfer demand in urban metro station influence scopes, may explain the significant correlation between station eigenvector centrality and DBS trip density.

5.2.2 Effects of macroscale built environment

In terms of transport infrastructure in the urban metro station influence scope, the intersection density of the main road is negatively correlated with the DBS–metro transfer trip density; this was also reported by Guo and He (2020). An explanation for this might be that intersections on the main road typically involve traffic delays and safety concerns for cyclists, which affects their traffic mode choice behavior. The results of the current study confirmed a positive correlation between the road congestion index and DBS trip density, whereas the cycling speed seemed unrelated. This result may be explained by the fact that the travel modes of DBS and urban metro in congested road sections are more convenient than motorized travel modes. Furthermore, the bus stop density was positively correlated with the trip density and negatively correlated with the cycling speed. These results indicate that bus–metro transit increases with the number of bus stops, which leads to additional DBS usage. Nevertheless, bus stops typically have a complex influence on local traffic, which may compel cyclists to frequently observe their surroundings and decelerate. Moreover, the bus line density was positively correlated with the DBS cycling speed. This inconsistency may have occurred because urban metro station influence scopes with higher bus line densities are likely to comprise better road conditions, leading to more suitable environments for higher cycling speeds.

Regarding land use, the land-use mixture was found to be negatively correlated with the DBS cycling speed. This result may be attributed to the fact that a high land-use mixture typically indicates a complicated local cycling environment, which causes cyclists to decelerate. For commercial land use, considering that such areas are located in prosperous areas with satisfactory road infrastructure, its positive correlation with cycling speed can be easily understood. In terms of residential land use, the results demonstrate that the DBS–metro transfer cycling trips decrease under a higher percentage of residential land use, contrary to the results of a previous study (Zhang, Shen, et al., 2021). Although difficult to explain, this inconsistency might indicate that the road conditions are poor in certain residential areas, as compared with those in other land-use types; consequently, these areas do not attract more DBS–metro transfer trips. The lower DBS cycling speed around residential areas in urban metro station influence scopes is likely related to the frequent occurrence of spatial disorders such as illegal parking, cluttered buildings, and damaged infrastructure in the residential areas of Beijing (Tang & Long, 2019; Hsu et al., 2022). Interestingly, the percentage of office land use was positively correlated with the DBS cycling speed, which may partly be explained by the travel purpose of cyclists. Considering that cyclists in office land-use type areas are likely commuting, they may adopt higher cycling speeds. In relation to POI, school density was positively correlated with the DBS–metro transfer trip density but negatively correlated with the DBS cycling speed. These results may be attributed to the fact that students tend to prefer DBS–metro transfer trips due to their better physical condition and limited economic condition. In addition, the observed decrease in the DBS cycling speed around schools can be attributed to the common perception that people are encouraged to cycle slower around schools, considering student safety. These results indicate that the density of shopping facilities in urban metro station influence scopes is negatively correlated with the DBS–metro transfer trip density, which is consistent with previous studies (Wu, Lu, et al., 2021; Zhao & Li, 2017). The explanation provided by Wu, Lu, et al. (2021) seems reasonable, which emphasized that the integration of commercial facilities and metro stations reduces the DBS usage demand since passengers can directly enter the metro stations from these commercial facilities. With regard to restaurant density, the results support previous research indicating that the presence of restaurants can increase the local DBS usage (Chen, Cheng, et al., 2022; Maas et al., 2020). It is reasonable for travelers to choose DBS after meals as a form of exercise. Academic arguments regarding the association between the density of park/public squares and DBS usage are common (Guo & He, 2020; Wang & Chen, 2020; Zhao & Li, 2017). However, in this study, no significant correlation between the park/public square density and DBS–metro transfer trips for urban metro station influence scopes was noted.

5.2.3 Effects of microscale built environment

Colorfulness, which describes the effect of spatial colors on human vision, is an essential concern in urban street landscape design. In this work, no significant correlation was noted between colorfulness and the DBS–metro transfer trips; this may help slightly alleviate certain restrictions for urban designers. Although street comprehensive colorfulness was not correlated with the DBS–metro transfer trips, a key component of colorfulness—greenery—has been proven to be a non-negligible influencing factor for DBS cycling. The significant positive correlation between greenery and the DBS–metro transfer trip density noted in this study provides concrete evidence for a previous notable result that the eye-level greenness exposure positively promotes cycling frequency around metro stations (Wang, Lu, et al., 2020). Several factors may explain this positive correlation. First, exposure to greenery can enhance positive emotions and reduce stress among travelers; thus, higher amounts of greenery typically indicate that the local environment is pleasant and attractive for DBS cyclists. Secondly, the main contributor to street greenery, i.e., trees, can provide shade and help lower the body temperature of cyclists. Moreover, cyclists with relaxed emotions in comfortable environments tend to subconsciously ride faster; this results in a positive correlation between greenery and the egress cycling speed.

In regards to the presence of transport infrastructures, one unexpected finding was that the presence of streetlights was negatively correlated with both the DBS cycling speed and egress trip density in the urban metro station influence scopes. This is likely due to the fact that the data in the regression analysis was not divided into daytime and nighttime. Streetlights may provide convenience for cycling at night, but their unsatisfactory design and space occupation may render them as obstacles that negatively affect the cycling environment during the day. And the number of cycling trips during the day is significantly greater than that during the night, which may partially explain the decrease in DBS–metro transfer trips with an increase in the presence of streetlights. Similar to the intersection density of main roads, as explained previously, the presence of traffic signals negatively affects the DBS trip density in urban metro station influence scopes due to the traffic delay they cause among cyclists. Conversely, the presence of barriers within the urban metro station influence scopes positively affected the transfer cycling density and speed. This may be explained by the fact that these barriers separate the cars and bikes on the road, thus making cycling safer and faster. It remains unknown why the barriers only influence the cycling speed of egress trips but have no correlation with that of access trips.

5.3 Policy implication

The construction of a bike-friendly environment has been widely regarded as an effective means for encouraging DBS-metro transfer trips in urban areas and an essential route towards a sustainable urban transportation system. Although the factors that are correlated with residents' DBS using behavior are diverse and involve complex processes, the findings from this study may provide relevant planning and management departments with decision references to improve the bike-riding environment.

Among the 14 built-environment factors that proved to be correlated with the DBS–metro transfer trip density, road congestion condition, bus stop density, greenery, barriers, and streetlight are relatively dynamic. Even in urban built-up areas, these factors can be adjusted through adopting proper measures. Therefore, their correlations with the DBS-metro trips identified in current study can provide potential solutions for urban planners to increase the ratio of DBS-metro trips in stock planning. On the other hand, the factors including residential population, metro ridership, metro station eigenvector centrality, school density, restaurant density, intersection density of main road, ratio of residential land use and shopping place density usually remain permanently stable in urban built-up areas. It may be infeasible to make major adjustments on these factors unless a large-scale urban renewal could be conducted. Nevertheless, the correlations between the above-mentioned factors and the DBS–metro transfer trip density could also be referenced by planners while making incremental planning. Planners can estimate the potential impact of alternative plans on residents' DBS-metro usage, in a way that the construction of sustainable transportation systems can be integrated into regulatory plans comprehensively for urban developing areas.

With regard to cycling speed, it is closely related to traffic safety and riding experience. Whether a higher or a lower cycling speed is preferable depends on the specific scenario and the requirements of traffic management. 14 factors were found to be correlated with cycling speed of DBS–metro transfer trips, which may support planners as evidence to formulate proper measures that can slightly adjust residents' riding speed according to the characteristics of the planning area. For instance, in residential areas with many commuters, increasing the proportion of green vegetation or optimizing the bus stop location may contribute to reducing travel time of DBS–metro transfer trips; in tourist areas, planners may expect tourists to ride slower to enjoy the scenery, which might be achieved by improving the local land-use mixture or designing bike lanes. The results of this study could also help traffic administration organs identify regions with higher average cycling speed of DBS–metro transfer trips. On this basis, preventive measures can be formulated and conducted to mitigate possible traffic safety concerns.

6 Conclusion

The use of dockless bike-sharing (DBS) services in tandem with urban metro systems has been widely recognized as a promising path toward more sustainable urban transportation. However, limited information regarding the impact of microscale factors on the trips generated by the integration of these two services remains available. Therefore, this study, taking Beijing as a case study, innovatively delineated the urban metro station influence scope for each metro station using the actual cycling distance of DBS trips connected to the station. Subsequently, the built-environment variables at macroscale and microscale were comprehensively extracted from multi-source data for the urban metro station influence scopes, in order to analyze their correlations with the trip density and cycling speed of DBS–metro transfer trips. The major findings of this study can be summarized as follows:

The urban metro station influence scope radii were 0.8–3.65 km and approximately 75 % of the urban metro station influence scopes were smaller than 2 km. No distribution pattern was noted for the urban metro station influence scopes. The access and egress DBS trips of the stations exhibited remarkably similar spatial distributions for both the trip density and cycling speed in the urban metro station influence scopes. The trip densities of the urban metro station influence scopes gradually decreased from the urban central area to the urban periphery, while the average cycling speeds were higher in the urban metro station influence scopes of downtown areas and lower in those of suburban areas. An unanticipated finding was that the urban metro station influence scopes near tourist attractions have wider ranges and lower cycling speeds.

Regarding socioeconomic attribute, metro station attribute, and macroscale built-environment factors, 10 independent variables were statistically correlated with the DBS–metro transfer trip density for urban metro station influence scopes; further, 11 independent variables were correlated with the cycling speed. The multiple linear regression models revealed that the trip density in an urban metro station influence scope is affected by the surrounding environment and is associated with the inherent attributes of the station, such as metro ridership and eigenvector centrality, which has rarely been reported in previous works. On comparing the regression analysis results for trip density and cycling speed, it was found that bus line density, land-use mixture, percent commercial, and percent office are important characteristics because their influences on DBS–metro transfer trips manifested only in terms of the cycling speed but not the trip density, which has not been reported previously.

Furthermore, for the microscale built-environment factors, the correlations of four independent variables with the DBS trip density and those of three variables with the cycling speed for the urban metro station influence scopes were identified. Interestingly, although the overall colorfulness has no significant influence on the DBS–metro transfer trips in urban metro station influence scopes, greenery plays an essential role in promoting cycling environments that attract more DBS trips and enhance the cycling experience. In addition, barriers make cycling safer by separating cars and bikes on the road, thus encouraging DBS–metro transfer trips and providing opportunities for faster cycling. Unexpectedly, the presence of streetlights leads to a decrease in the trip density and cycling speed in urban metro station influence scopes. This result is difficult to explain; however, it may be related to the tremendous difference in travel demands during the day and night, considering that streetlights can be perceived as visual distractions and obstacles that affect cycling comfort and safety during the day.

These findings have the potential to support the policy-making processes for relevant planning departments and operating companies, based on the following aspects. First, the adjusted R^2 of the regression models for trip density achieved a satisfactory level of approximately 0.8; they comprehensively integrated a majority of the built-environment factors. Therefore, the models constructed in this study could help governments and operators optimize bike distribution and management by precisely estimating the DBS usage demands around urban metro stations. Second, although the regression models for cycling speed may not be suitable for estimations and predictions, they provided statistical evidence indicating that built-environment factors affecting the DBS cycling speed exist at both the macroscale and microscale. This evidence, in turn, highlights the necessity for relevant departments to recognize built-environment factors such as bus stop density, land-use mixture, and the presence of streetlights; this is because their influence on the DBS cycling speed may lead to potential traffic safety hazards, which should be avoided in planning practice. Finally, the findings of the current study have significant implications for understanding how microscale built-environment factors such as greenery, the presence of streetlights, the presence of barriers, and the presence of signals affect DBS–metro transfer trips in urban metro station influence scopes. Compared with macroscale built-environment factors, the adjustments of these factors are more flexible during design practice. Therefore, the correlations between microscale built-environment factors and DBS trips should be included in the guidelines for urban renewal and TOD designs; this is expected to be helpful for achieving more bike-friendly designs.

Notably, there are certain limitations to the current study; nevertheless, these shortcomings indicate potential opportunities for further research. First, the microscale built-environment factors were extracted from SVI, suggesting that the extracted variables represent the situation during data collection. However, certain variables such as colorfulness and greenery vary with respect to the season, especially in North China, which might weaken the acceptance of the regression analysis results. Second, in future studies, additional microscale built-environment factors such as the spatial disorder degree, road flatness, and width of bike lanes need to be extracted from SVI via novel algorithms and integrated into the analyses. Third, owing to data limitations, the assumptions in the current study pertaining to the cycling trajectories, DBS trip belongings, and DBS travel purpose are significant and may not be completely consistent with actual situations. Furthermore, the temporal mismatch among SVI, EULUC-China, bike-sharing, and the other data may also affect the analysis results. In addition, the cross-sectional nature of the data precludes examination of causality. More insightful conclusions could be expected through conducting longitudinal surveys to gather multi-wave first-hand data, which will be addressed in future research. Fourth, some of the results seem difficult to explain, such as the negative correlation between cycling speed and the presence of streetlight. The possible reason causing these puzzling results may be that the bike-sharing data was not divided into smaller time granularity, such as daytime and nighttime. Therefore, analysis based on different temporal scales should be conducted to generate more persuasive and explainable results in future research. Finally, the scope of this study was limited in terms of the linear correlation analysis, which could be improved with nonlinear methods. For instance, methods such as gradient boosting decision trees and random forest could provide deeper insights into the correlation and threshold effect between built environments and DBS–metro transfer trips.

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