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Built environment impacts on bus-metro intermodal trips considering passenger trip generator features: A new method to delineate bus catchment areas for metro stations

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Abstract

Understanding intermodal trip generation is crucial for enhancing integrated public transit systems in megacities. This study investigates how the built environment affects bus-metro intermodal trips at the metro-station level. Existing research often overlooks defining bus catchment areas (BCAs) for metro stations, account for uneven demand distribution or address catchment overlaps. Using large-scale smart-card data, this study proposes a BCA delineation method that reflects passengers' actual travel choices. Built-environment factors across multiple spatial ranges—including pedestrian catchment areas and BCAs—are then extracted to analyze their linear and nonlinear effects on intermodal ridership using generalized additive models. Two indicators, inner and outer radius, are further introduced to explore bus-metro intermodal patterns.

A case study using two cross-sectional datasets from Beijing, China reveals consistent findings: (1) the proposed BCA delineation method outperformed benchmark methods in modeling intermodal ridership; (2) urban BCAs were unexpectedly larger than suburban ones, a finding not reported in previous studies; (3) metro stations served medium- and long-travel bus riders alongside short-travel riders; (4) population and land-use density in BCAs contributed most to the model, followed by metro accessibility, while transfer convenience contributed least. The proposed analytical framework provides a systematic tool for analyzing multimodal connectivity and informing bus–metro integration policies.

Key words: intermodal trips, bus and metro, catchment area delineation, built environment, catchment area overlap; generalized additive models

1 Introduction

Urban expansion can result in significant land use segregation (Ewing 1997; Frenkel and Ashkenazi 2008), which separates residential areas from commercial and shopping districts. It increases the demand for long-distance travel and private car use (Gakenheimer 1999; Zhao 2010; Zhang and Zhang 2018), posing challenges for sustainable transportation. Intermodal transit, which involve the use of multiple transportation modes within a single trip, such as integrating bus and metro services, provides cost-effective and eco-friendly choices for long-distance travel (Fu et al. 2025; Heinen and Mattioli 2019). To enhance the competitiveness of multimodal transit, a thorough understanding of intermodal trips is essential.

Research on the impacts of the built environment on transit trips is extensive (An et al. 2019; Li et al. 2024; Zhang et al. 2023; Zhu et al. 2024), but remains limited when considering intermodal trips (Chen et al. 2021; Wu et al. 2022a). The effects of the built environment may vary substantially across transit trip types. For instance, bus-metro intermodal trips often present different spatial and behavioral patterns compared to unimodal metro trips. As an example, Chen et al (2022) found that 80% of bus transfer trips occurred at only 20% of the metro stations in Nanjing, China. This raises key questions: How does the built environment influence intermodal trip generation? And how do its impacts differ between intermodal and unimodal transit trips? Addressing these questions can provide essential insights into multimodal integration and sustainable urban transport planning.

To explore these issues, this study examines how built-environment factors shape bus–metro intermodal ridership at the metro-station level. The primary step is to delineate station catchment areas, which serve as spatial units for characterizing potential trip generation. As a mass transit mode, metros attract passengers from vast areas around their stations through various feeder modes, giving rise to different catchment delineations, such as pedestrian catchment areas (PCAs), cycle catchment areas (CCAs), and bus catchment areas (BCAs). Among these, buses remain the dominant feeder mode to metro stations (Wang et al. 2016; Chen et al. 2022b). However, previous studies have often overlooked generating BCAs for metro stations, likely due to data limitation. Previous studies (Liu et al. 2022; Wu et al. 2022a; b) often uses 1000m circular buffer areas around metro stations, typically viewed as accessible walking zones (Liu et al. 2022), to explore influential factors for intermodal ridership between bus and metro. Not accounting for BCAs potentially leads to bias in understanding intermodal trips and it raises important research questions, of how can realistic BCAs be delineated for metro stations, what are the features of these BCAs, and how do population and land use within BCAs impact intermodal ridership?

Moreover, existing studies often ignore uneven potential demand and catchment overlaps, leading to less accurate estimates of how demographic and land-use factors affect ridership (Cui et al. 2022; Gutiérrez et al. 2011; Kimpel et al. 2007). Feeder modes such as buses, bicycles and ridesourcing substantially enlarge station catchments and offer passengers greater flexibility in station and route selection, resulting in extensive spatial overlaps and uneven demand distributions (see Appendix A for the degree of BCA overlaps). These challenges highlight a pressing need for more precise and realistic delineation methods to better capture intermodal accessibility and trip patterns, thereby supporting accurate modeling of intermodal demand forecasting.

To address these gaps, this study proposes a framework for analyzing intermodal trips, with two major contributions:

(1) Development of a behavior-based BCA delineation method. Leveraging large-scale smart-card data, this study defines realistic metro catchment areas for bus transfer passengers. The delineation expands to cover passengers' actual trip origins and incorporates a weighting function to account for spatially uneven demand and address catchment overlaps. Two indicators—the inner radius (R1) and outer radius (R2)—are introduced to quantify intermodal travel patterns at the station level, providing new behavioral insights into bus-to-metro transfers.

(2) Integration of multi-range built-environment analyses. This study demonstrates the roles of built environment factors across both BCAs and PCAs in determining bus-metro intermodal ridership. Results underscore the dominant influence of population and land-use attributes within BCAs, which have been largely neglected in previous intermodal ridership studies (Liu et al. 2022; Wu et al. 2022b; a).

This paper is organized as follows. Section 2 reviews prior studies on station catchment area, the built environment and issues of overlapping and uneven demand in station catchment areas. Section 3 presents the methodology for the study including, a specification for the datasets modelling process, and providing justification for considering multi-range built-environment factors. Section 4 reports the results in three parts: catchment area analysis, regression results and sensitivity analysis. Section 5 discusses the key findings and Section 6 outlines policy implications. Finally, Section 7 concludes the paper and summarizes the main insights.

2 Literature review

2.1 Station catchment areas

Station catchment areas refer to the geographic areas around a transit station, from which a significant portion of travelers originate to use its service (Dolega et al. 2016). Studying these areas is crucial yet complex. It helps reveal station choices (Lieshout 2012), provide scope for TOD development (Shao et al. 2020; Zhu et al. 2021), evaluate transport service quality (El-Geneidy et al. 2014), and predict travel demand (Andersson et al. 2021; Su et al. 2022). Factors such as population, land use, and connectivity to other modes of transport within catchment areas significantly influence station use (Andersson et al. 2021; Liu et al. 2021; Su et al. 2022). However, few studies have focused on generating catchment areas, possibly due to the lack of detailed trip data (Lieshout 2012), such as passengers' origin before accessing the metro station and their travel modes.

Several methods have been developed to delineate catchment areas: buffer methods (Gan et al. 2020; Andersson et al. 2021), statistical modelling (Jiang et al. 2012; Wu et al. 2021; Lin et al. 2019), and mathematical modelling (Lin et al. 2016; Lieshout 2012; Lin et al. 2014; Teixeira and Derudder 2021). Buffer methods are the simplest and require little data. They create a buffer ring around the station with a fixed threshold based on straight-line or road network distances. For instance, an 800m radius is commonly used to define PCAs for metro stations (Gan et al. 2020). Mathematical modelling is the most complex and requires extensive and detailed OD trip records, usually from surveys. Multinomial Logit or Huff models are often used to access a station's appeal to different regions. Statistical modelling is practical and accurate. It creates convex hull based on actual travel distances or times and incorporate geocoding tools to generate geographical boundaries for station catchment areas.

Walking, cycling, and bus are the main ways to connect to the metro. Research on PCAs and CCAs of metro stations has been more prevalent (Gutiérrez et al. 2011; Lin et al. 2019; Wu et al. 2021), while studies on BCAs are less common. Wang et al (2016) matched bus trip endpoints to their nearest metro stations based on survey data. They defined bus trip length as the radius and buffered it along the road network. Chen et al. (2022) defined mean bus distance from smartcard data as the BCA radius. Eom et al. (2019) drew the spatial outline of a BCA according to the percentage of passengers alighting at each bus stop. These studies provide some insights into BCA configurations and characteristics, but further research is needed to explore how best to determine BCAs.

2.2 The built environment and intermodal trips

The correlation between the built environment and travel behavior has long been a popular research topic. Many studies have shown that built environment factors significantly and nonlinearly affect transit ridership (Ding et al. 2019; Peng et al. 2023; Gan et al. 2020). However, research on bus-metro intermodal trips has mainly focused on the topic of network integration (Xu et al. 2024; Guo et al. 2023; Song et al. 2012) and collaborative operation (Zheng et al. 2022; Tan et al. 2020). Early studies used survey data to explore bus-metro transfer behaviors, investigating factors influencing passengers' intention and satisfaction with the transfer service (Navarrete and Ortúzar 2013; Cheng and Tseng 2016; Yang et al. 2015). While field studies or interviews can provide detailed information, they are costly and often face sample size limitations. To address this, some researchers have developed methods to evaluate transfer efficiency or quality using smart card data (Lee et al. 2019; Wang et al. 2018). Chen et al. (2022)

revealed metro transfer station choices in bus–metro intermodal trips. These studies mainly examined trip attributes such as travel time and number of transfers. Although they did not directly study how built environment affect intermodal ridership, they provided valuable insights into factors influencing bus-metro transfers. For instance, some studies highlighted that excessive walking time significantly diminished passengers' transfer intentions.

Studies on built environment factors influencing intermodal ridership between bus and metro are scarce. Chen et al. (2021) explored nonlinear and spatial effects of the built environment on intermodal trips at the Traffic Analysis Zone (TAZ) level. At the station-level, Wu et al. (2022) analyzed weather conditions (e.g. temperature, wind, and rainfall), while Liu et al. (2022) focused on bus and metro network attributes. Further investigation in this area could enhance understanding of bus-metro dynamics, leading to the design of more efficient and user-friendly public transit networks, potentially increasing mobility and reducing private car use.

Importantly, these station-level studies utilized one-kilometer circular buffers, typically considered as accessible walking areas (Liu et al. 2022). However, this range is insufficient to encompass the actual areas where intermodal trips originate and fails to represent the variations in size and irregular shape of BCAs across metro stations. Delineating metro catchment areas for bus transfer riders, a critical aspect as demonstrated in section 2.1, has been overlooked in this field.

2.3 Issues of overlap and uneven demand in station catchment areas

Station catchment overlaps and uneven potential demand within catchments are common in urban transit systems yet remain inadequately addressed in existing studies. Neglecting these issues can lead to over- or underestimating the influence of demographic and land use characteristics around stations on travel demand (Deepa et al. 2022).

Catchment overlaps improve accessibility by shortening walking distances and expanding station choices but may also intensify competition among stations, potentially diverting transit demand. Most studies either overlook this factor or address it with simplified methods. A typical approach uses the Thiessen polygon algorithm to delineate exclusive catchments (Gutiérrez et al. 2011; Li et al. 2024; Liu et al. 2019), assuming passengers always choose the nearest station. However, passengers also consider comfort, waiting time, and overall travel cost (Shao et al. 2015), making this assumption unrealistic. Another approach introduces competition-related variables, such as the number of nearby stations within a catchment (Chakour and Eluru 2016) or indicators of catchment overlap (Adler et al. 2022). But these indicators fail to represent the varying degrees of competition from other stations to the target station.

Potential demand distribution within a station catchment area is usually uneven (Eom et al. 2019; Lieshout 2012), a feature often ignored in prior studies. Gutiérrez et al. (2011) demonstrated that incorporating a distance-decay function to reflect passengers' declining willingness to walk to a station improves demand forecasting. Young and Blainey (2018) found that choice-based catchments improve model predictive performance compared to catchments assuming passengers choose the nearest station. These studies advocate defining dynamic, behavior-based station catchments instead of static buffers based on uniform demand or proximity.

Feeder modes such as bicycles, buses, and ridesourcing expand catchment areas, introducing cross-station competition and highly heterogeneous demand patterns. As a result, conventional delineation methods are inadequate for capturing intermodal travel dynamics. This highlights a methodological gap and calls for more adaptive delineation approaches that explicitly account for demand heterogeneity and spatial overlap among stations.

2.4 Summary of research gaps

The review of previous research has identified two important gaps when analyzing bus-metro intermodal trips and catchment areas, that are addressed in this manuscript:

(1) Few studies have focused on BCAs and most existing catchment research assumes uniform demand density or that passengers choose the nearest station, suggesting the need for more realistic delineation methods.

(2) There is limited research on how the built environment factors affect bus-metro intermodal trips, with little integration of BCA explorations, pointing to the need for more comprehensive research.

3 Material and methods

3.1 Problem formulation

This study aims to examine the effects of the built environment on intermodal trip generation and therefore focuses on bus-to-metro trips. The travel process is illustrated in Fig. 1. Intermodal passengers go through three stages: the bus ride, the transfer, and the metro ride. They walk from their origins to a bus stop to board, alight at a bus stop within the PCA of metro station, and take the metro to their destinations. Metro-to-bus trips are excluded; however, the proposed method can be applied to analyze them. Intermodal trips involving other modes, such as bicycle–bus–metro trips, are beyond the scope of this study.

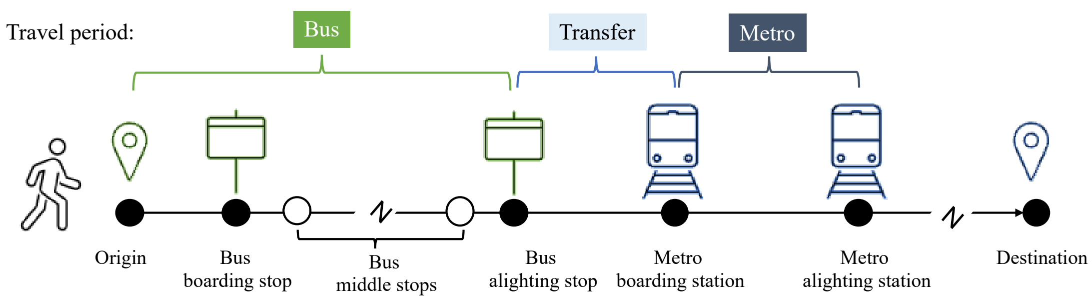


Fig. 1 The travel process of intermodal passengers from bus to metro

Existing studies (Liu et al. 2022; Wu et al. 2022b) usually examine the determinants of bus-metro intermodal trips by mapping factors within 1000 m circular buffers to ridership, as shown in Eq. (1).

$$y_i = f\left(\left[\boldsymbol{X}_{P,1k}, \boldsymbol{X}_{L,1k}, \boldsymbol{X}_{T,1k}, \boldsymbol{X}_o\right], \beta\right) \tag{1}$$

where y_i represents the intermodal ridership at metro station i; $\boldsymbol{X}_{P,1k}$, $\boldsymbol{X}_{L,1k}$ and $\boldsymbol{X}_{T,1k}$ denote population, land use and transfer convenience features in the 1000m-buffer range; $\boldsymbol{X}_o$ is other features unrelated to station catchment areas; and β is the set of parameters to be estimated.

However, Eq. (1) fails to address two key aspects of intermodal trips. First, it overlooks characteristics of trip-generation areas, including population and land use features around bus boarding stops. It also assumes uniform and isotropic catchment areas, ignoring variations in how metro stations attract bus riders and failing to account for directional differences. Second, it neglects the presence of overlapping catchments and the unequal distribution of potential demand within each catchment area. In a bus–metro intermodal network, extensive feeder bus services considerably enlarge the catchment coverage of metro stations, enabling passengers to choose among multiple station–route combinations. This expansion increases catchment overlaps and complicates demand distribution patterns. Addressing these spatial interactions is crucial for accurately estimating intermodal ridership.

To address these gaps, this study proposes an R-weighting method to generate more realistic BCAs. This method expands BCAs to contain areas where bus riders originate and generates real-time, anisotropic and station-specific catchments by setting different thresholds (R1 and R2) for each metro station. It further accounts for uneven demand and addresses catchment overlaps by constructing a weight function to each bus stop buffer area as shown in Fig. 2 (d) (see detailed method in Section 3.3) . The model is presented in Eq. (2).

$$y_i = f\left(\left[\boldsymbol{X_{P,R,w}}, \boldsymbol{X_{L,R,w}}, \boldsymbol{X_{S,R}}, \boldsymbol{X_{T,1k}}, \boldsymbol{X_A}, \boldsymbol{X_C}\right], \beta\right) \tag{2}$$

where $\boldsymbol{X_{P,R,w}}$ and $\boldsymbol{X_{L,R,w}}$ represent weighted population and land use attributes in BCAs; $\boldsymbol{X_{S,R}}$ represents socioeconomic factors in BCAs; $\boldsymbol{X_{T,1k}}$ represents transfer convenience attributes in PCAs, $\boldsymbol{X_A}$ represents metro station accessibility and $\boldsymbol{X_C}$ represents metro station characteristics.

Three benchmark ranges as shown in Fig. 2 (a-c) are set to compare the performance of the proposed R-weighting method. The range (a) is the 1000m-buffer range as used in previous studies (Eq. (3)). The range (b) is mean bus distance (MBD) buffer range (Eq. (4)), which uses 1000m and mean bus access distance as thresholds to form hollow circle buffers around metro stations. The range (c) (Eq. (5)) is the unweighted version of range (d).

$$y_i = f\left(\left[\boldsymbol{X_{P,1k}}, \boldsymbol{X_{L,1k}}, \boldsymbol{X_{S,1k}}, \boldsymbol{X_{T,1k}}, \boldsymbol{X_A}, \boldsymbol{X_C}\right], \beta\right) \tag{3}$$

$$y_i = f\left(\left[\boldsymbol{X_{P,MBD}}, \boldsymbol{X_{L,MBD}}, \boldsymbol{X_{S,MBD}}, \boldsymbol{X_{T,1k}}, \boldsymbol{X_A}, \boldsymbol{X_C}\right], \beta\right) \tag{4}$$

$$y_i = f\left(\left[\boldsymbol{X_{P,R}}, \boldsymbol{X_{L,R}}, \boldsymbol{X_{S,R}}, \boldsymbol{X_{T,1k}}, \boldsymbol{X_A}, \boldsymbol{X_C}\right], \beta\right) \tag{5}$$

where $\boldsymbol{X_{P,MBD}}$, $\boldsymbol{X_{L,MBD}}$ and $\boldsymbol{X_{S,MBD}}$ are population, land use and socioeconomic features in the MBD-buffer; $\boldsymbol{X_{P,R}}$ and $\boldsymbol{X_{L,R}}$ are population and land use features in the R-buffer.

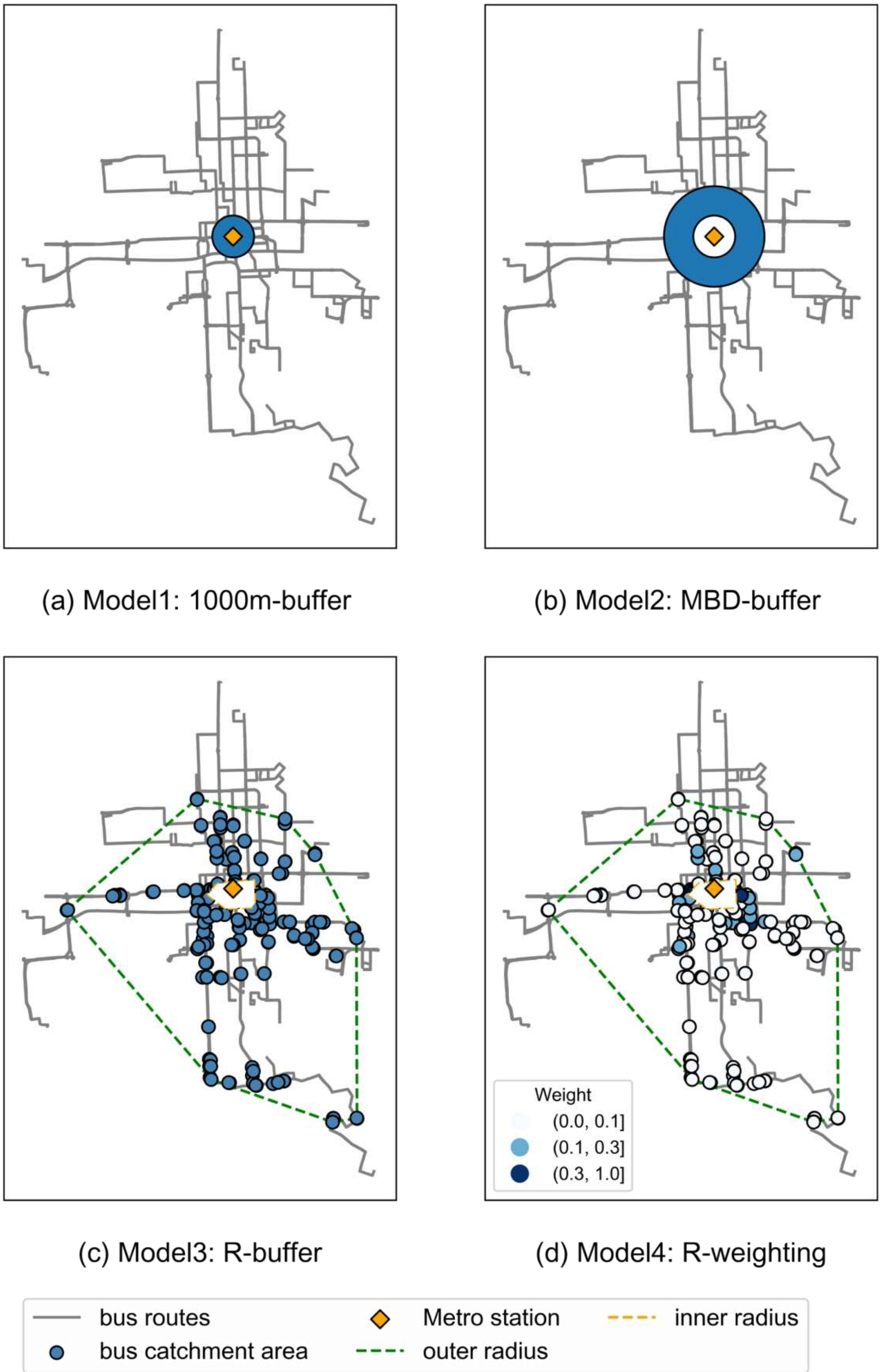


Fig. 2 Diagram of the four catchment areas in Model 1-4 (A real sample of Chong Wenmen

metro station in Beijing)

3.2 Study area and data

Beijing is one of the largest cities in China, with over 20 million permanent residents by 2022, served by a dense transit network (see Fig. 3). The network included 27 metro lines with 384 metro stations, and 1,225 bus routes with over 72,000 bus stops. All metro stations and bus stops were included in this study. Although Beijing spans 16,411 square kilometers, its metro stations are densely clustered within the 5th Ring Road, accounting for only 4% of the city's total area. Residents beyond the 5th Ring Road primarily rely on buses for public transit.

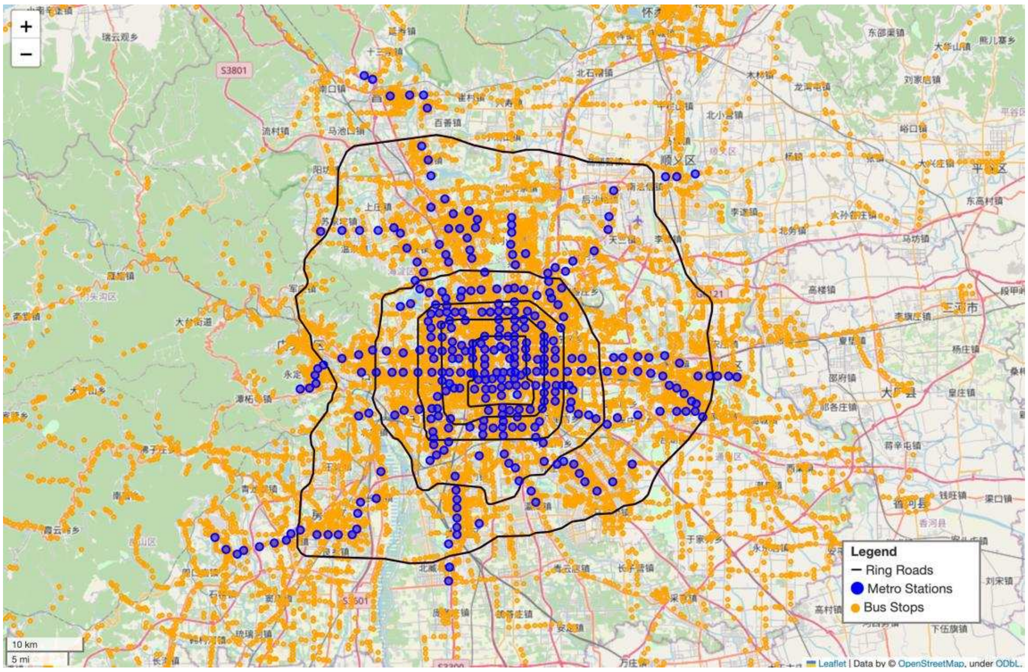


Fig. 3 Study area of Beijing (The innermost circle is the 2nd Ring Road, and the outermost circle is the 6th Ring Road)

The multi-source data sets used in this study are shown in Table 1. The primary dataset is the bus-metro smart card data, covering December 2021 and September 2022, with 6.40 million and 5.22 million trips respectively. Bus-to-metro intermodal trips are identified by matching passenger IDs within 30 minutes between bus alighting stops and metro boarding stations. Transfers between different bus routes are allowed. Trips from December 31 and September 9-12 are excluded to avoid the effects of new metro station openings and holidays, and metro stations with fewer than 30 average weekday intermodal boardings are removed.

It should be noted that the data were collected during the later stage of the pandemic. Both data collection phases occurred in the stable phase of the pandemic, when Beijing's control measures primarily targeted international and intercity travel, with no major restrictions on movement within the city. As our study focuses on residents' weekday intra-city travel, it was likely unaffected by these measures. September data are used for the main analysis, and December data are used for consistency and robustness checks.

Table 1 Overview of input datasets

Index	Data set	Information contained	Data source	Period	Used for
(1)	Bus-metro smart card data	Metro boarding time and station, bus boarding stop and alighting stop, on-bus time, intermodal ridership	Automatic Fare Collection System	09/2022，12/2021	BCA delineation in Section 3.3
(2)	Bus GIS data	Bus stop and route geometry	Beijing Rail Transit Network Management Co., Ltd.	2022	
(3)	Metro GIS data	Metro station geometry		2022	
(4)	Population data	Population counts (spatial unit: 100m*100m), type (resident or employment population)		2021， 2022	Influential factors calculation in Section 3.4.
(5)	Points of interest (POI) data	POI code, name, type, geometry	Amap (Gaode Map) [1]	2021， 2022	
(6)	Bus information data	Bus route code, direction, length, type, operating hours, bus stop names and order	8684 Bus Inquiry Website[2]	2021， 2022	
(7)	Metro smart card data	Metro boarding time, metro boarding and alighting station, travel time	Automatic Fare Collection System	09/2022，12/2021	
(8)	Housing price data	Housing prices and property fees	Anjuke Real Estate Platform (Beijing)[3]	2021， 2022	
(9)	Resident income data	Average annual resident disposable income	Beijing Municipal Bureau of Statistics[4]	2021，2022	

[1] https://lbs.amap.com/api/webservice/guide/api-advanced/search

[2] https://beijing.8684.cn/

[3] https://m.anjuke.com/bj/

[4] https://nj.tjj.beijing.gov.cn/nj/qxnj/2024/zk/indexch.htm

3.3 Bus catchment area generation and weighting variable calculation

3.3.1 Bus catchment area generation

The aim of generating BCAs is to identify the spatial boundaries around a metro station, where the majority of passengers originate to use the metro station's transit service via bus. Four elements of BCAs are determined as follows:

(1) **Base network**. A realistic base network is essential for precise delineation of BCAs. BCAs are broader and determined by fixed stops and routes. Omitting the base network could lead to errors by incorporating extensive areas inaccessible to bus stops. Thus, a real bus network is used as base network to generate BCAs in this study.

(2) **Thresholds**. Previous studies on catchment delineation commonly excluded 85%–90% of trips to remove outliers (El-Geneidy et al. 2014; Zuo et al. 2018; Wu et al. 2021).However, these approaches primarily eliminated extremely long trips while overlooking excessively short ones. In practice, travelers often choose to walk or cycle to metro stations for short distances. Therefore, this study defines both an outer radius (R2) to exclude abnormally long trips and an inner radius (R1) to exclude short-distance zones. The 5th and 95th percentiles of cumulative bus access travel time are adopted as R1 and R2, respectively. A sensitivity analysis comparing 5th/95th, 10th/90th, and 15th/85th thresholds indicates that the 5th/95th percentiles produce the best model performance (see Appendix B Table 9). Using travel times rather than distances also accounts for bus route speed variations and operational conditions.

(3) **Minimum units**. Bus-to-metro passengers typically originate from walking areas of bus boarding stops. Therefore, PCAs of the bus boarding stops are defined as the minimal units

of BCAs in this study. A 500m circular buffer is established around each bus boarding stop to represent the typical walking accessibility distance (Montero-Lamas et al. 2024).

(4) **Weights**. Weights are set for each bus buffer to measure the probability of each bus stop choosing the target metro station. These weights are determined by passenger's actual choice frequencies and calculated as follows:

$$w_{ij} = \frac{B_{ij}}{\sum_{i=1}^{N} B_{ij}} \tag{6}$$

where B_{ij} is the average weekday intermodal boardings from bus stop j to metro station i; N is the number of metro stations which have a connection relationship with bus stop j.

The BCA delineation method is shown in Fig. 4. First, the integrated network is established using Dataset (1) – (3). Dataset (1) provides the connectivity relationships between metro stations and bus boarding stops, and Dataset (2) and (3) offer geographical locations of bus stops and metro stations. Second, R1 and R2 derived from Dataset (1) are used as thresholds to create hollow isochrones outward from each metro station on the integrated network. The area between the R1 and R2 isochrones forms the catchment spatial boundary. Finally, 500m walking buffers are created around each bus stop within the catchment spatial boundary. The weight of each bus station is calculated and assigned to each bus stop buffer.

3.3.2 Weighting variable calculation

Variables of population and land use density in BCAs are weighted as follows:

$$X_i^{k,w} = \sum_{j \in BCA_i} w_{ij} \cdot x_j \tag{7}$$

where $X_i^{K,w}$ is the kth weighted variable of metro station i; x_j is the variables of population and land use density within the PCA of bus stop j; BCA_i is the set of bus stops which belong to the BCA of metro station i.

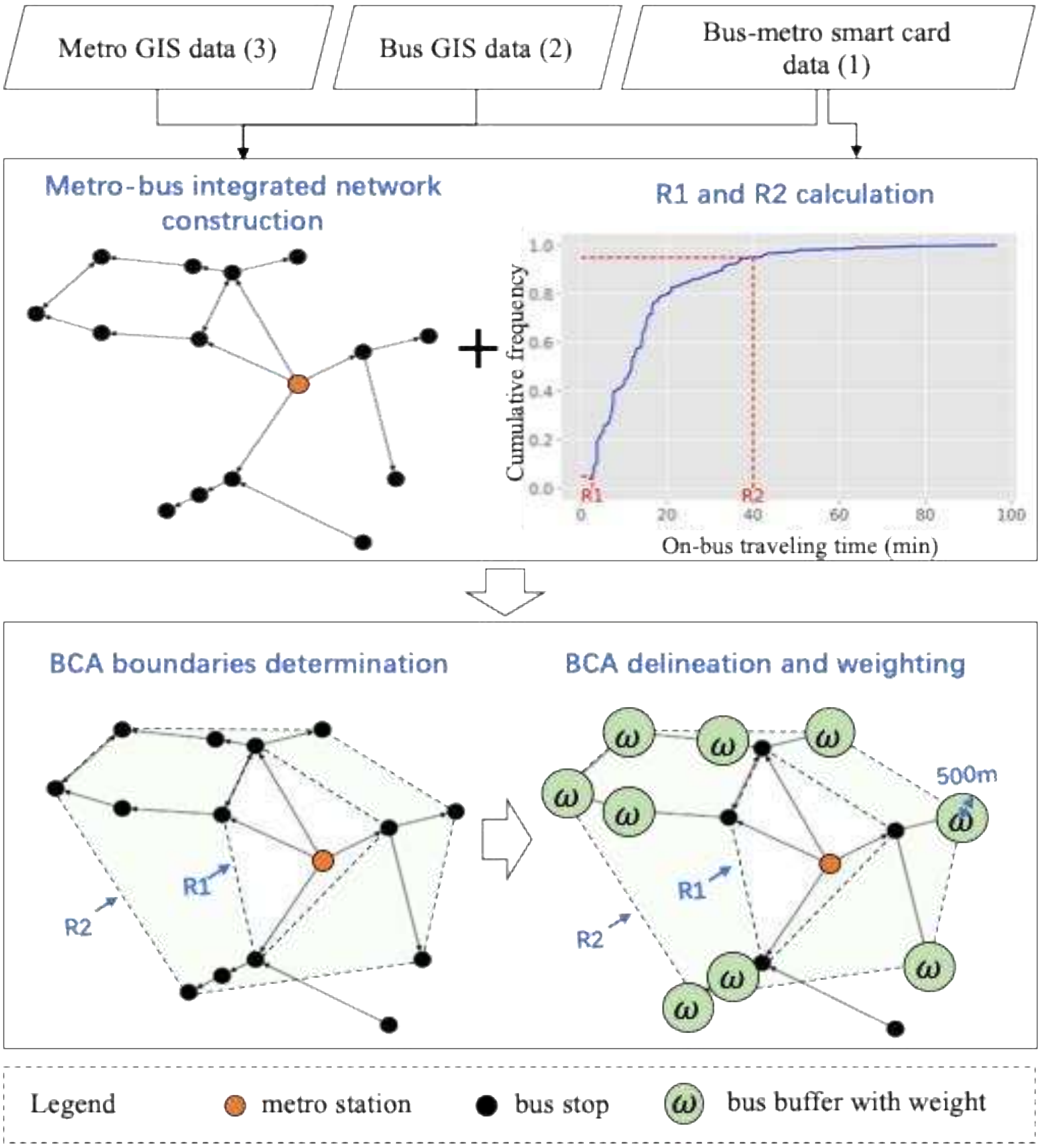


Fig. 4 Bus catchment area delineation method

3.4 Factors influencing intermodal trips

This study examines factors influencing intermodal trips, using average weekday metro boardings by bus as the dependent variable. Four categories of explanatory variables are incorporated: BCA variables, PCA variables, metro station accessibility, and metro station characteristic attributes. Socioeconomic characteristics —income, housing price, and property fee—serve as control variables. All variables are detailed in Table 2.

Table 2 Descriptions of variables in the model

Variable	Range	Type	Description
Dependent variable			
Intermodal boardings	—	Continuous	Average weekday metro boardings by bus.
Explanatory variables			
(1) Population and land use in BCAs			
Resident population	BCA	Continuous	Number of residential population in each BCA.
Employment population	BCA	Continuous	Number of employment population in each BCA.
Entertainment density	BCA	Continuous	Number of shopping malls, leisure facilities, restaurants, etc. per km^2 in each BCA.
Government density	BCA	Continuous	Number of government office building, administrative office location etc. per km^2 in each BCA.
Attraction density	BCA	Continuous	Number of tourist attractions per km^2 in each BCA
Education density	BCA	Continuous	Number of universities, colleges, schools and tutoring centers per km^2 in each BCA.
Hospital density	BCA	Continuous	Number of hospitals, clinics and rehabilitation centers, etc. per km^2 in each BCA.
Sports density	BCA	Continuous	Number of Stadiums, fitness centers, swimming pools, etc. per km^2 in each BCA.
(2) Transfer convenience (PCAs)			
Bus stop	PCA	Discrete	
Local bus route	PCA	Discrete	Number of local bus routes in each PCA (see classification criteria in section 3.4.2).
Regular bus route	PCA	Discrete	Number of regular bus routes in each PCA.
Long bus route	PCA	Discrete	Number of long bus routes in each PCA.
Commuting bus route	PCA	Discrete	Number of commuting bus routes in each PCA.
(3) Metro station accessibility			
Distance to	—	Continuous	Distance from each metro station to the city center

downtown			(unit: meter).
Accessible area	—	Continuous	Areas reachable by the metro network within 30/45/60 minutes (unit: km^2); see section 3.4.3 for the calculation methods.
(4) Metro station characteristics			
Interval	—	Continuous	The average length of metro lines between the object station and its adjacent consecutive stations along a route (unit: m).
Betweenness	—	Continuous	The betweenness centrality of metro station node u $D(u) = \sum_{s \neq v \neq t} \frac{\delta_{st}(u)}{\delta_{st}}$, where $\delta_{st}(u)$ is the number of shortest paths between station node s and t that pass through node u, δ_{st} is the number of shortest paths between station node s and t.
Terminal station	—	Dummy	Metro stations located at the end of the line.
Transfer station	—	Dummy	Metro stations that connect two or more lines.
BTI station	—	Dummy	Intermodal stations connecting bus terminals.
RAI station	—	Dummy	Intermodal stations connecting railways or airports.
(5) Socioeconomic attributes			
Income	District	Continuous	Average disposable annual income of residents in the metro station's administrative district (unit: CNY).
House price	BCA	Continuous	Average housing price per residential community (unit: CNY / m^2).
Property fee	BCA	Continuous	Property management fee for each residential community (unit: CNY / (month•m2)).

3.4.1 Population and land use variables in BCAs

Population and land use are found to have significant impacts on trip generation and travel patterns in previous studies (Kuby et al. 2004; Gutiérrez et al. 2011; Jun et al. 2015). In this study, resident and employment populations and land use variables are counted in each BCA unit using Dataset (4) and (5). The land use variables comprise six categories: entertainment, government, attraction, education, hospital, and sports densities.

3.4.2 Transfer convenience variables in PCAs

Bus facilities and services around metro stations directly affect passengers' transfer convenience. Generally, a greater number of routes and stops provides passengers with more transfer options, thereby improving transfer convenience. This study further categorizes bus routes serving daily activities and commutes in Beijing into four types: local, long, commuting, and regular. These bus route types serve distinct transit functions, potentially impacting intermodal trips differently. Their functions and classification criteria are shown in Table 3.

Table 3 Bus route types and their classification criteria

Bus route type	Serving for	Classification criteria
Local bus route	Short trips within communities and connecting to metro stations	Aligned with the "microcirculation" type as per 8684 bus inquiry website
Long bus route	Long trips connecting urban areas with the suburbs or neighboring towns.	One terminal in urban areas (within the 4th Ring Road) and the other in suburbs or neighboring towns
Commuting bus route	Commuters during specific time periods	Operated only during morning and evening peak hours on weekdays
Regular bus route	Medium trips in urban or suburban areas	Other bus routes falling under this category

3.4.3 Metro station accessibility variables

A metro station's attractiveness to intermodal passengers might increase with its accessibility. Distance to downtown is often used to measure a metro station's regional accessibility (Peng et al. 2023). If a metro station could reach more destinations within a certain time in the metro network, it is likely to attract more intermodal boardings. Thus, this study introduces a variable — accessible area — to measure a metro station's accessibility in the metro network. FigureFig. 5 shows the calculation method. First, stations reachable within 45 minutes[5] by the network from the target station are identified. Next, 1000m buffers are created around these stations. Finally, the total area of these buffers, after removing duplicate areas, is calculated.

[5] The travel times of 30, 45, and 60 minutes are tested, and the threshold of 45 minutes is selected as the optimal variable for the model.

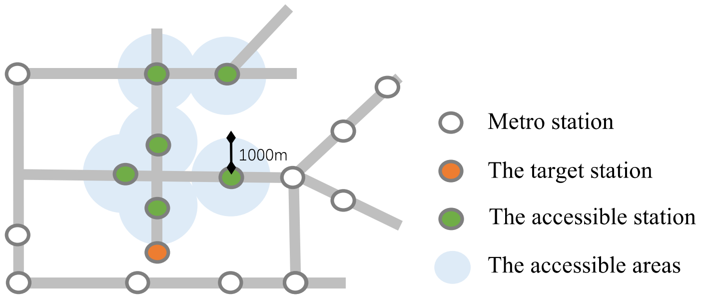


Fig. 5 Illustration of accessible area calculation

3.4.4 Metro station characteristic variables

Metro station characteristic variables include station interval, betweenness and station types. Station interval indicates metro service level; longer intervals usually suggest fewer options and longer wait times. Betweenness measures a metro station's connectivity in the metro network, with higher values indicating better connectivity and therefore a more active intermediate station. The calculation method is shown in Table 2.

Terminal, transfer, and intermodal stations are expected to have higher metro boardings than other stations (Ma et al. 2018; Wang et al. 2023). This study further distinguishes intermodal stations into two types: intermodal stations connecting railways or airports (RAI station), and intermodal stations connecting bus terminals (BTI station). RAI stations serve as gateways for transporting passengers into the city, while BTI stations facilitate significant transfers between bus and metro systems. These types of stations potentially influence bus-to-metro intermodal trips differently.

3.5 Generalized additive models

The generalized additive model (GAM) extends the generalized linear model (GLM) by allowing the dependent variable to linearly depend on an unknown smoothing function of certain explanatory variables, making GAM an effective tool for exploring and interpreting complex data patterns (Wood 2017).

In this study, some factors exhibit linear relationships with the dependent variable, while others are nonlinear. The GAM effectively addresses this issue by incorporating linear and smoothing functions for explanatory variables in a framework, allowing for a comprehensive analysis of both types of relationships. The formulation is:

$$g(\mu) = \beta_0 + \sum_{l=1}^{L} \beta_l X_l + \sum_{m=1}^{M} s_m(X_m) + \theta \tag{8}$$

where $g(.)$ is the link function that relates the explanatory variables to the expected value of the dependent variable μ. We use the log link, $g(\mu) = \log(\mu)$, and assume the dependent variable follows a Gaussian distribution; β_0 is the intercept; β_l is the coefficient of the linear variable X_l; L is the number of linear variables; $s_m(.)$ is the isotropic smooth function, here we use thin plate regression splines; X_m is the mth nonlinear variable and M is the number of nonlinear variables; θ is the error term.

The R "mgcv" package is used to estimate GAMs. The log transformation is applied to continuous and discrete explanatory variables, adjusting zero values to 0.0001, which is a standard practice in statistical modeling (Crown 1998). In this study, we found that log transformation helps capture the nonlinear relationship between explanatory and dependent variables, while without it, the GAMs tend to overfit. Explanatory variables with a variance inflation factor (VIF) above 10.0 are excluded from the model to eliminate multicollinearity (Kutner et al. 2004).

Explanatory variable selection follows a backward approach. Scatter plots are created for all explanatory variables and the dependent variable at first. Explainable variables showing linear relationships are set as linear, while the others are set as nonlinear. Then, we test if removing an included variable leads to a significant loss to the model in each step. Finally, variables significant in Model 3 (Fig. 2) but not in other models are retained to ensure comparability.

4 Results

4.1 Catchment area analysis

4.1.1 Catchment area characteristics

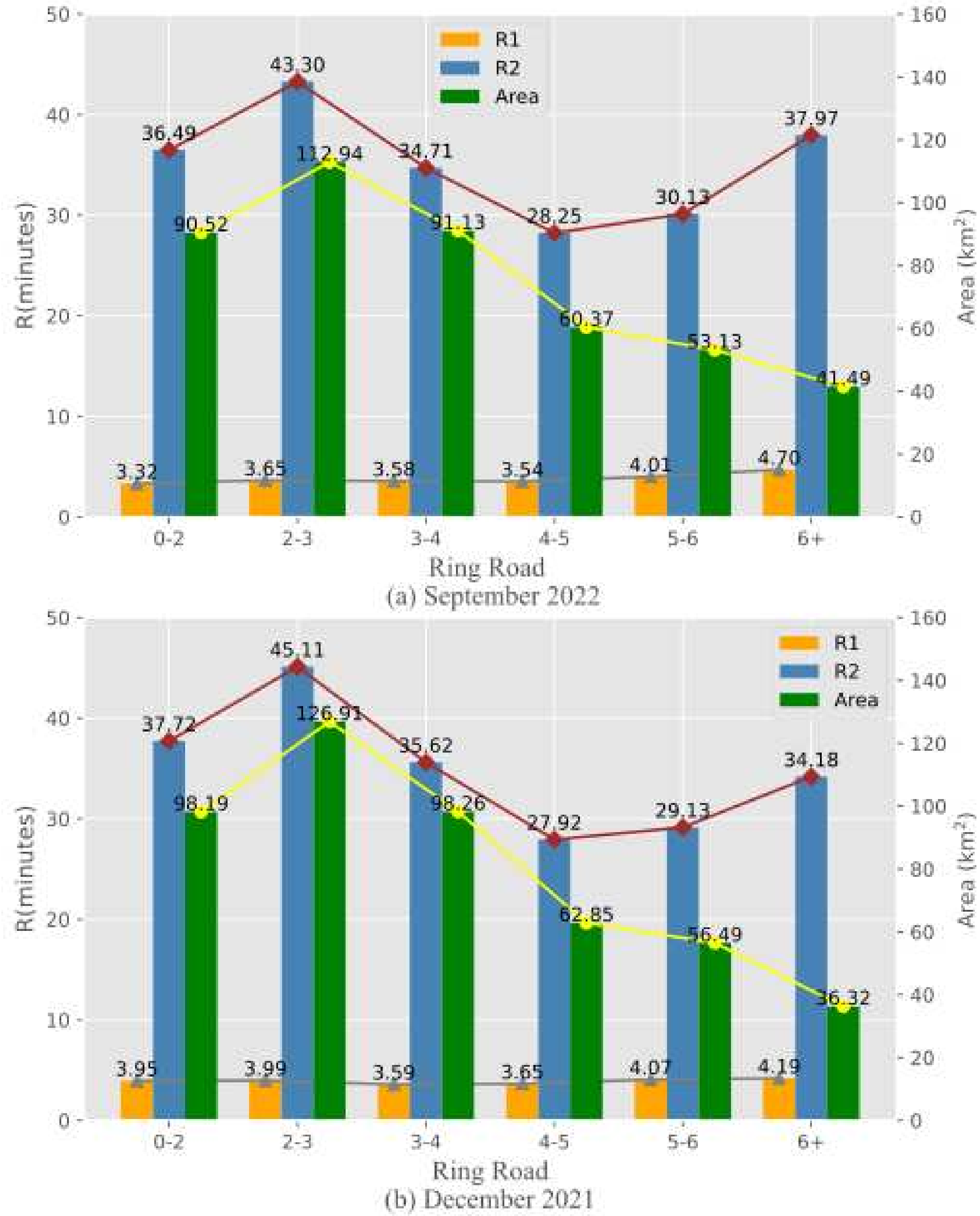
Table 4 presents the bus catchment characteristics—inner radius (R1), outer radius (R2), and area—for all Beijing metro stations. In total, 369 stations are analyzed for September 2022 and 333 stations for December 2021. The distributions of both R1 and R2 are generally similar and remained stable across the two periods. The mean R2 is approximately 34 minutes, with an interquartile range of about 22–40 minutes, suggesting that buses support a wide variety of intermodal trips rather than merely providing supplementary access to the metro. Some stations exhibit extreme values, with the largest R2 reaching approximately 125 minutes and the largest R1 exceeding 18 minutes, reflecting the complexity and diversity of bus–metro travel patterns in Beijing.

Table 4 Statistics of R1, R2 and area of bus catchment areas

	September 2022 (N=369)			December 2021 (N=333)		
	R1 (min)	R2 (min)	Area (km^2)	R1 (min)	R2 (min)	Area (km^2)
Mean	3.78	33.82	72.81	3.90	33.73	77.89
Std	1.94	18.16	51.80	1.93	17.75	53.90
Min	1.19	4.00	2.36	1.15	5.29	0.79
5%	1.77	14.66	9.74	1.92	13.00	12.57
25%	2.54	22.00	33.77	2.71	22.75	39.27
50%	3.26	29.50	64.40	3.47	30.00	71.47
75%	4.53	40.33	96.60	4.48	40.34	104.46
95%	7.33	66.00	161.63	7.22	64.59	170.75
Max	20.70	125.09	330.65	18.78	124.75	351.07

Figure Fig. 6 presents the mean catchment characteristics by Ring Road in Beijing. The spatial patterns are consistent across the two periods. R1 generally increases from the city center

(0–2nd Ring Road) towards the outer suburbs (outside the 6th Ring Road), indicating longer access times associated with lower metro network density. The catchment area peaks between the 2nd and 3rd Ring Roads, then declines with distance from the city center. R2 exhibits a similar but more complex pattern—rising initially, peaking between the 2nd and 3rd Ring Roads, decreasing toward the 4th–5th Ring Roads, and then increasing slightly beyond the 6th Ring Road. Metro stations in urban areas (0–4th Ring Road) serve bus riders from larger and denser catchment areas than those in suburban areas (outside the 4th Ring Road). Overall, these results suggest a stable spatial structure and persistent BCA features in Beijing, despite seasonal and annual variations.



(a) September 2022

(b) December 2021

Fig. 6 Average R1, R2 and catchment area grouped by Ring Roads

4.1.2 Metro station clustering

To reveal functional differences in serving bus transfer passengers, metro stations are clustered by R1 and R2 using the K-means method. Table 5 presents the three identified station categories across two periods—short, medium, and long bus catchment types. The mean R1 and R2 increase progressively from short to long categories, highlighting distinct scales of bus–metro connectivity.

In both periods, short-catchment stations dominate the network, accounting for 65.3% and 60.7% of all stations, respectively. These stations mainly serve bus transfer passengers with access times ranging from 3 to 24 minutes. Medium-catchment stations represent about 30–34% of the total and typically serve passengers within a range of 5 to less than 45 minutes. Long-catchment stations comprise less than 6% and serve broader catchments with access times extending from 6 to over 85 minutes. Spatially, short-catchment stations are distributed broadly across all ring roads. Medium-catchment stations mainly appear outside the 4th Ring Road and are often located at the terminal sections of metro lines extending into the suburbs. Long-catchment stations often locate between the 2nd and 4th Ring Roads. This pattern suggests a prevalent suburban-to-urban commuting behavior, where passengers travel long distances by bus before transferring to the metro closer to the city center. The consistent spatial structure across both periods points to stable functional hierarchies within Beijing's multimodal transport network. FigureFig. 7 illustrates the spatial pattern for September 2022, with a similar distribution observed in December 2021 (see Appendix C, Fig. 11).

Table 5 Station category and their distribution within each ring road across two periods

Period	Station category	R1 (min)	R2 (min)	Station percentage	Number of stations					
					0-2	2-3	3-4	4-5	5-6	6+
September 2022 (N=369)	Short	3.14	24.36	65.3%	27	29	42	49	79	15
	Medium	4.79	45.47	30.4%	15	15	19	10	41	12
	Long	6.32	94.88	4.3%	2	7	4	1	0	2
December 2021 (N=333)	Short	3.22	23.93	60.7%	22	21	37	42	64	16
	Medium	4.65	42.76	33.9%	15	17	20	13	37	11
	Long	6.76	86.96	5.4%	4	6	4	1	1	2

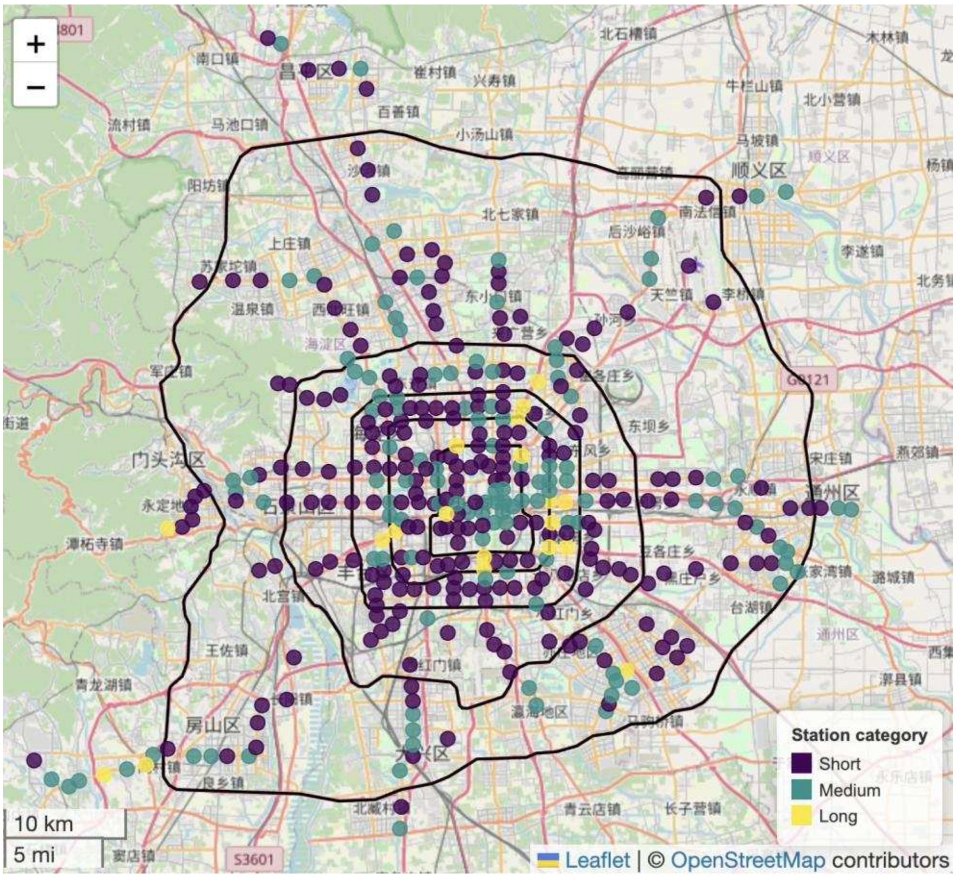


Fig. 7 Spatial distribution of station categories in September 2022 (the innermost circle is the 2nd Ring Road, and the outermost circle is the 6th Ring Road)

4.2 Regression results

4.2.1 Model comparisons

To develop the best model, we employ generalized linear models (GLMs) as benchmark models. Non-significant variables are removed from the models, including attraction density, housing price, regular bus route, distance to downtown, transfer station, and terminal station. The employed population variable is removed due to high collinearity.

Table 6 compares the model performance across four definitions of BCAs. Across both periods, model fit improves consistently from the 1000 m-buffer to the R-weighting approach.

The R-weighting model (Model 4) achieves the best overall performance, with the highest adjusted R^2 (0.740 and 0.819) and deviance explained (75.8% and 82.9%) values, alongside the lowest AIC and GCV scores. The R-buffer model (Model 3) also performs well, while the MBD-buffer (Model 2) and 1000 m-buffer (Model 1) approaches show markedly lower adjusted R^2 and higher AIC values.

While the GAM slightly outperforms the GLM overall, the same performance gradient among the four catchment definitions is observed under both modeling frameworks. Notably, GLM-Models 3 and 4 even exceed GAM-Models 1 and 2, emphasizing the effectiveness of the R-based methods even within simpler linear structures. The stability of these comparative results across models and timeframes suggests that the R-weighting method is relatively robust and transferable, with demonstrated capacity to adapt to seasonal variations and to represent complex bus–metro connectivity patterns.

Table 6 Comparison of the goodness of fit between different models

Period	Model	GAM				GLM		
		Adj. R^2	AIC	DE (%)	GCV	Adj. R^2	AIC	DE (%)
Sep-22	4 (R-weighting)	**0.740**	**1035.661**	**75.8**	**519.158**	**0.663**	**1110.253**	**67.7**
	3 (R-buffer)	0.725	1053.115	74.2	524.718	0.656	1189.298	67.0
	2 (MBD-buffer)	0.482	1285.330	51.5	664.592	0.426	1306.439	45.0
	1 (1000m-buffer)	0.477	1288.331	50.9	660.914	0.419	1311.204	44.3
Dec-21	4 (R-weighting)	**0.819**	**667.676**	**82.9**	**327.873**	**0.784**	**260.504**	**79.2**
	3 (R-buffer)	0.694	845.902	71.3	418.906	0.635	819.258	64.9
	2 (MBD-buffer)	0.636	903.174	65.9	448.315	0.519	982.842	53.8
	1 (1000m-buffer)	0.417	1054.296	44.5	522.175	0.371	1072.039	39.6

(Note: DE refers to Deviance Explained; GCV refers to Generalized Cross Validation score)

The regression results of GAM-Models 1 to 4 for September 2022 are presented in Table

7. Overall, the estimated coefficients and smooth terms show clear variations among the models, reflecting the sensitivity of results to how the BCA is delineated.

Across the models, the R-weighting approach (Model 4) provides the most stable and interpretable parameter estimates, with most indicators showing significant estimates and lower standard errors. The resident population exhibits strong positive associations with intermodal boardings in both the R-weighting and R-buffer models (coefficients = 1.180 and 1.519, $p < 0.001$), whereas the relationship became insignificant under the MBD-buffer and 1000 m-buffer definitions. Similarly, education, entertainment, and government density are highly significant in the R-based models, but less significant in the other models. These findings suggest that only when population and land use factors are measured within realistic catchments can their impacts on travel demand be effectively captured.

Previous research often assumes that built environment factors exert uniform linear or nonlinear effects on transit demand, but this assumption may not hold true (Van Wee and Handy 2016). Results from Models 3 and 4 reveal both linear and nonlinear effects. The resident population show a clear log-linear effect, while education, entertainment, and government density exhibit strong nonlinear effects, as evidenced by estimated degrees of freedom (e. d. f) much greater than 1.0. Metro station characteristic variables are all linear: interval and BTI station have strong positive effects, whereas betweenness and RAI station exert suppressive effects.

Of the fifteen variables significant in Model 4 for September 2022, twelve remain significant in the December 2021 dataset (see Appendix D, Table 10). The directions of coefficients for shared linear variables are also highly consistent: resident population, local bus route, BTA station, and income are positive, whereas betweenness and RAI station are negative. This cross-period stability of the model structure further suggests the robustness and generalizability of the R-weighting model, indicating that the identified relationships are not sample-specific but reflect persistent determinants of intermodal ridership.

Table 7 GAM regression results of estimating bus-to-metro intermodal boardings across four different buffer areas for September 2022

Category	Indicators	Model4 (R-weighting)			Model3 (R-buffer)			Model2 (MBD-buffer)			Model1 (1000m-buffer)		
		Estimate	S. E		Estimate	S. E		Estimate	S. E		Estimate	S. E	
	(Intercept)	-23.490	3.843	***	-36.182	4.098	***	-11.893	5.838	*	-16.164	5.328	**
BCA	**log(Resident population)⋆**	1.180	0.108	***	1.519	0.081	***	0.034	0.027		0.045	0.036	
Transfer convenience	**log(Local bus route)⋆**	0.152	0.038	***	0.115	0.039	**	0.244	0.054	***	0.207	0.052	***
Metro station characteristic	**log(Interval)⋆**	0.711	0.127	***	0.635	0.132	***	1.069	0.182	***	1.222	0.180	***
	log(Betweenness)⋆	-0.103	0.037	**	-0.091	0.037	*	-0.065	0.051		-0.096	0.051	.
	BTI station⋆	0.459	0.302	*	0.286	0.306	*	0.865	0.418	*	0.974	0.418	*
	RAI station⋆	-0.466	0.283	.	-0.602	0.289	*	-0.683	0.402	.	-0.828	0.406	*
Socioeconomic	**log (Income)⋆**	0.899	0.320	**	1.163	0.343	***	0.740	0.510		1.029	0.458	*
	Smooth terms:	e. d. f	F		e. d. f	F		e. d. f	F		e. d. f	F	
BCA	s(log(Education density))	6.374	2.029	***	3.233	0.550	**	1.938	0.707	***	1.809	0.295	*
	s(log(Entertainment density))	2.331	1.407	***	2.021	0.665	***	1.603	0.284	**	1.137	0.142	*
	s(log(Government density))⋆	1.344	0.881	***	2.403	1.015	***	1.129	0.163	*	2.080	0.353	**
Metro station accessibility	**s(log(Accessible area))⋆**	2.450	0.819	***	2.280	1.029	***	1.851	1.146	***	2.321	0.892	***
Transfer convenience	**s(log(Bus stop))⋆**	1.598	0.121	*	1.644	0.236	*	3.244	1.551	***	3.284	1.293	***
	s(log(Long bus route))⋆	1.719	0.110	.	1.789	0.212	*	2.446	2.821	***	2.508	3.447	***
	s(log(Commute bus route))⋆	1.298	0.534	*	1.401	0.062	*	1.320	0.384	.	1.008	0.289	
Socioeconomic	s(Property fee)	2.473	0.601	**	3.170	0.793	**	3.924	0.808	**	3.609	0.947	***

.$p<0.1$, *$p<0.05$, **$p<0.01$, ***$p<0.001$; ⋆ represents significant variable in December 2021 results; Number of samples: 369

4.2.2 Nonlinear effects

Figure Fig. 8 illustrates the nonlinear effects of main explanatory variables estimated using smooth splines in GAM-Model 4 (R-weighting) for September 2022, with rug plots marking data points.

The weighted education density levels briefly and then declines after reaching around 10 POIs per km^2 (log(Education_density_w) ≈ 1), indicating its limited influence at low densities but a gradual suppressing effect on bus-to-metro transfers once this threshold is exceeded. A likely explanation is that universities are typically located adjacent to metro stations, while primary and secondary schools depend more on dedicated shuttle services or private pickup, thereby reducing bus-to-metro transfer propensity. Both weighted entertainment density and weighted government density show nearly monotonic negative effects, indicating that BCAs dominated by government offices or leisure facilities are less conducive to intermodal transfers.

The accessible area displays a strongly positive yet saturating effect, with marginal gains diminishing beyond approximately 31,600 km^2 (log(Accessible_area) ≈ 4.5), suggesting that greater metro network accessibility enhances transfers up to a critical threshold. Regarding bus route types, the commute bus route exhibits a consistent positive trend, whereas the long bus route shows the opposite pattern[6].

Importantly, the nonlinear patterns of accessible area, commute bus route, and long bus route remain consistent between the two study periods (see Appendix E, Fig. 12). This indicates their impacts on intermodal ridership are long-term and structural.

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[6]Bus route variables were positive integers (0, 1, 2...). Zero values were adjusted to 0.0001to apply log transformation in modeling (section 3.5). Thus, the range below 0.0 had limited meaning when observing impacts on intermodal trips.

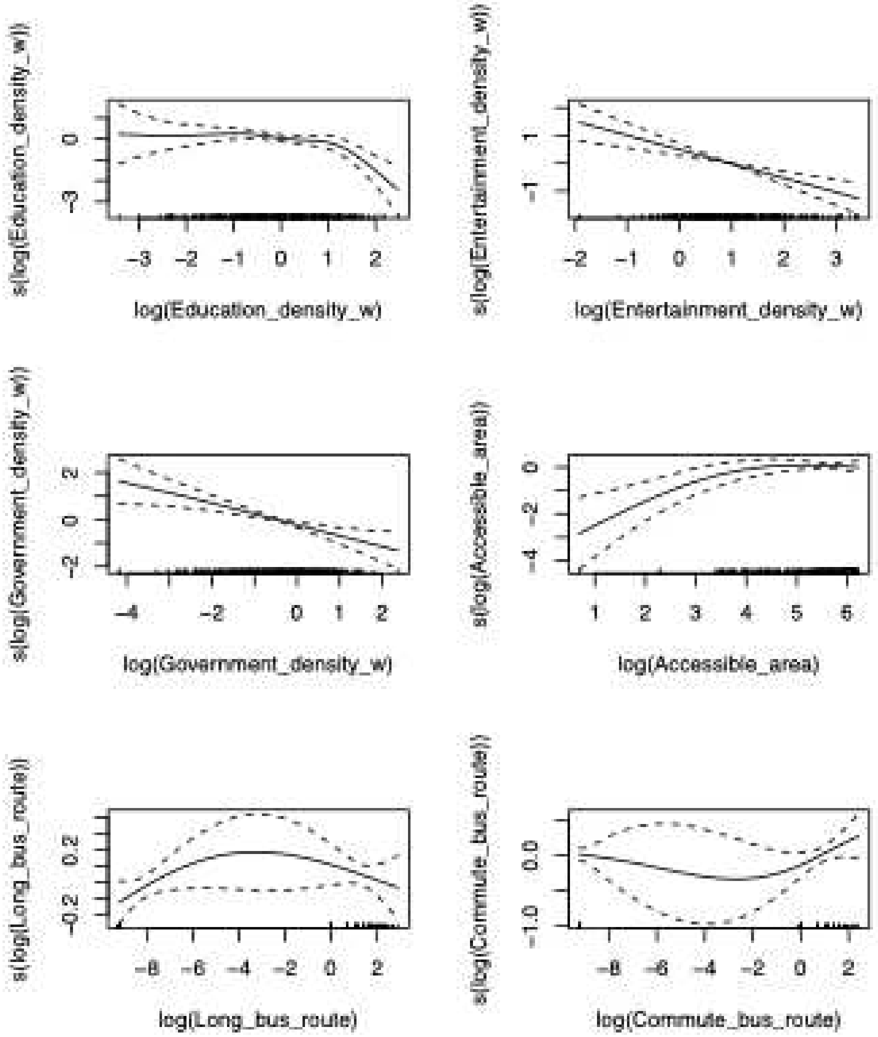

Fig. 8 Nonlinear effects of main explanatory variables estimated with smooth splines in GAM-Model 4 (September 2022)

4.2.3 Relative feature importance

This study adopts the decrease accuracy (DA) method to assess the relative importance (RI) of explanatory variables, where higher DA values indicate greater explanatory power (Chen et al. 2022a). The RI of each variable is defined as its DA value divided by the total DA values of all variables. This approach enables a comparison of both individual and grouped variable contributions to the intermodal ridership modeling.

Table 8 shows the RI values of explanatory variables in GAM-Model 4 for both periods.

Although the DA values differ across periods, the ranking of categories and most individual variables remain broadly consistent, indicating the stability of the model's structure. Among all categories, BCA variables rank first in both total and mean RI with an overwhelming influence on intermodal trip generation. Metro station accessibility follows as the second most important category in terms of mean RI. In contrast, transfer convenience variables contribute relatively little, suggesting that for bus–metro transfers, the built environment within BCAs and the accessibility of metro stations exert stronger impacts than transfer-related factors.

At the individual variable level, resident population within BCAs consistently ranks highest, with RI values of 0.410 and 0.607. Land-use variables in BCAs also contributed noticeably, although to a lesser extent. Government density ranks sixth and seventh in the two periods, respectively, indicating a moderate but stable effect. Entertainment and education density rank high in September 2022, but lose significance in December 2021, implying that non-commuting activities contribute more strongly to intermodal trips during warmer and back-to-school months when leisure and education travel increase. Accessible area and station interval show moderate relative importance across periods. Indices related to station type (BTI and RAI stations) and long bus routes have relatively minor contributions.

Comparing across the two periods reveals noticeable seasonal and behavioral differences. Population and accessibility factors remain consistently dominant, signifying their fundamental roles in sustaining intermodal demand. However, the changing significance of land use variables (e.g. entertainment and education density) and transfer convenience variables (e.g., local and commute bus routes) suggests that trip purposes and service patterns evolve over time, shaping intermodal behavior dynamics.

Table 8 Relative importance of explanatory variables in GAM-Model 4

Category	Indicator	September 2022				December 2021			
		RI	Rank	Total RI	Mean RI	RI	Rank	Total RI	Mean RI
BCA	Resident population	0.410	1	0.649	0.162	0.607	1	0.638	0.319
	Entertainment density	0.117	2			—	—		
	Education density	0.073	4			—	—		
	Government density	0.049	7			0.031	6		
Metro station accessibility	Accessible area	0.052	6	0.052	0.052	0.059	2	0.059	0.059
Metro station characteristic	Interval	0.113	3	0.145	0.036	0.048	5	0.137	0.027
	Betweenness	0.018	10			0.027	9		
	BTI station	0.008	13			0.017	12		
	RAI station	0.006	15			0.017	11		
Socioeconomic	Income	0.033	8	0.064	0.032	0.053	3	0.053	0.053
	Property fee	0.030	9			—	—		
Transfer convenience	Local bus route	0.054	5	0.091	0.023	0.008	13	0.113	0.028
	Commute bus route	0.016	11			0.052	4		
	Bus stop	0.014	12			0.030	7		
	Long bus route	0.007	14			0.024	10		

4.3 Sensitivity analysis for weight thresholds

The weights for bus stop buffers range from 0 to 1, but their distribution is highly left-skewed, with a median of only 0.02. To assess the influence of low-weight bus stop buffers on model performance, a sensitivity analysis is conducted for GAM-Model 4 in September 2022 by varying the weight threshold applied to BCAs. Built environment factors for bus buffers below each threshold are sequentially excluded from the model.

Figure Fig. 9 shows the impact of weight thresholds on model accuracy, expressed as the adjusted R^2. When the threshold is 0.0, the accuracy is 0.740 (Table 6). Increasing the threshold to 10^{-5} leads to a sharp decline to 0.666, after which the accuracy stabilizes across several intermediate thresholds (10^{-5} to 10^{-3}). A more substantial drop occurs when the threshold exceeds 10^{-2}. This pattern suggests that, although low-weight buffers represent marginal and infrequent bus–metro connections, they enrich the model's representation of intermodal travel behavior by capturing the long-tail effects of real-world travel demand. The result underscores the importance of incorporating low-weight buffers in the intermodal ridership prediction, which can enhance both model accuracy and practical applicability for future intermodal planning and engineering applications.

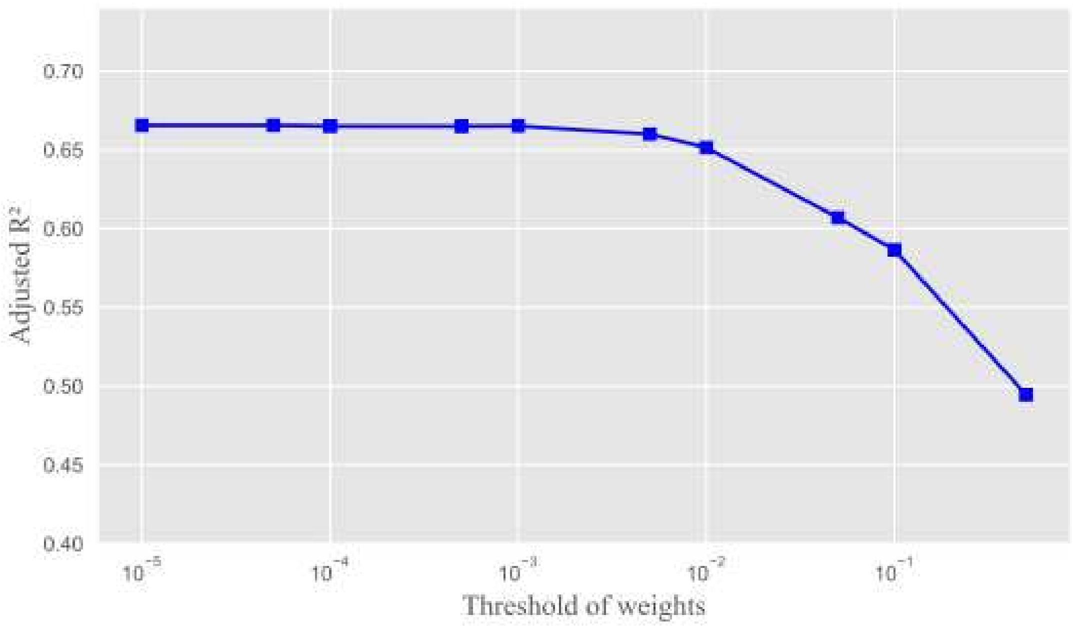

Fig. 9 The impact of weight thresholds on model accuracy

5 Discussion

5.1 BCA features

The results in Fig. 6 and Fig. 7 show that urban metro stations serve bus transfer riders from broader areas than suburban stations. This finding contrasts with Wang et al. (2016), who also used Beijing as their study area. They assigned trip endpoints to the nearest metro station to address incomplete survey data, which may oversimplify intermodal travel behaviors. Previous studies found that PCAs and CCAs in suburban areas are usually larger than those in urban areas (El-Geneidy et al. 2014; Zuo et al. 2018; Lin et al. 2019; Wu et al. 2021). As metro density usually decreases from the city center to the suburbs, suburban transit users often walk or cycle longer distances to reach metro stations. However, this pattern may not apply to bus-metro passengers. The average R2 of urban metro stations is over 35 minutes (Fig. 6), within which multiple metro stations are accessible. This suggests that bus transfer riders often bypass the nearest station, implying proximity is not their main consideration. This aligns with Chen et al. (2022), who found over 60% of bus transfer riders chose stations other than the nearest ones. It also agrees with Shao et al. (2015), who found transit users were willing to take a bus beyond the nearest train stations to reduce waiting times and travel costs. This finding emphasizes the distinctive nature of bus transfer behavior as opposed to walking and cycling around metro stations.

Chen et al. (2022) reported that suburban BCAs were larger than urban BCAs in Nanjing, China. This contradicts this finding, possibly due to differences in urban form. Beijing has a larger area and highly centralized functions, creating strong demand for suburban residents to reach the city center. Urban surface traffic in Beijing is usually congested during peak hours.

In this context, combining long-distance buses with downtown metro transfers could offer better service with fewer transfers, shorter trips, and more reliable travel times. In contrast, Nanjing has a more polycentric structure. Multiple centers could reduce the need for long-distance suburb-to-downtown travel. This suggests that while different urban layouts may lead to varying bus-metro travel patterns, the underlying logic of passenger choice remains largely consistent—they prefer high-quality services with lower total travel costs.

5.2 Multi-range built environment factor impacts

A large body of studies have suggested the importance of population and land use within catchment areas for estimating ridership (Kuby et al. 2004; Gutiérrez et al. 2011; Jun et al. 2015). Consistent with this evidence, this study finds that population and land use within BCAs are the predominant factors influencing intermodal transit trip generation, mirroring the findings of Chen et al. (2021) at the TAZ (traffic analysis zone) level. In contrast, Liu et al (2022) identified transfer facilities as the most influential factor for intermodal boardings, with population and land use having comparatively minor impacts. This discrepancy may step from their utilization of population and land use data within 1000m-buffer zones, which might not fully capture intermodal travel behaviors over broader areas. These findings underscore the importance of accurately defining catchment areas for understanding intermodal trip generation.

Previous studies usually report negative effects of bus routes around metro stations on intermodal boardings (Wu et al. 2022a). This contrasts with the expectation that feeder buses should attract intermodal passengers. The results in Table 7 show that different bus route types play various roles in intermodal trip generation. The local bus route has a positive effect, aligning with their intended objectives. The commute bus route also increases intermodal boardings, reflecting cooperation with the metro during commutes. In contrast, the long-distance bus route has a suppressive effect, indicating a competitive trend.

Interestingly, metro stations serving as transfer stations or located adjacent to railway stations and airports—which previous studies have generally associated with higher metro boardings (Ding et al. 2019; Ma et al. 2018; Wang et al. 2023)—exhibit limited or even negative effects on bus–metro intermodal boardings. A possible reason is that these stations are often overcrowded, which could discourage bus-to-metro transfers.

5.3 Catchment method performance

As BCAs expand from 1000m-buffer, MBD-buffer and R-buffer areas, the models show consistent performance improvements (Table 6). This suggests that examining built environments over broader areas of passenger trip origins can better explain and predict station feeder demand. This implication is consistent with Wu et al. (2021), who studied bicycle–metro intermodal trips, and Ma et al. (2025) who examined metro–ridesourcing integration.

Building on the R-buffer approach, the R-weighting method further enhances model performance. This indicates that incorporating the weight function effectively captures the uneven demand in the catchment area and addresses catchment overlaps as well, thus providing a more realistic representation of bus–metro connectivity. This finding aligns with previous studies (Gutiérrez et al. 2011; Kimpel et al. 2007; Young and Blainey 2018), which found that integrated catchments that reflect actual travel choices achieved superior predictive accuracy compared to those using traditional deterministic buffer methods.

6 Policy implications

6.1 Lessons learned from bus-metro travel patterns

Metro stations in Beijing display distinct functional roles in serving bus riders, with clear spatial patterns. These findings offer insights for optimizing the bus–metro integrated network and service design. Ongoing monitoring of transfer patterns can further inform strategies to maintain network efficiency and improve the overall passenger experience.

An important observation is that a small share of stations, mostly within the 4th Ring Road, connect to very long bus commutes up to 95 minutes, revealing potential inequities in accessibility. These users face high travel costs and need targeted support. Planners should build rapid bus corridors linking these stations to densely populated suburban areas and enhance long express bus services with more reliable operations (e.g. redundant routing and investment in real-time information systems), subsidized or capped fares, and comfort upgrades such as air conditioning and more seating. As long bus routes around metro stations tend to suppress the intermodal boardings, their intermediate stops should avoid PCAs of metro stations during off-peak hours to reduce competition and resource waste; however, the opposite approach can ease metro congestion during peaks. In long-term planning, a polycentric urban structure should remain a key goal to curb excessive long-distance commuting caused by urban sprawl.

Second, a moderate number of metro stations serve mid-distance bus riders (5–45 minutes), mainly in areas with sparse metro coverage. This indicates strong demand for long-distance public transport in these areas. Beyond strengthening bus connections, integrating other modes—such as park-and-ride, ride-hailing, and scooter facilities—can expand passengers' travel options.

Third, most metro stations primarily serve short-travel bus riders (3–25 minutes), highlighting the need to improve short-distance accessibility around these stations. Priorities include upgrading transfer infrastructure, synchronizing bus and metro timetables, and expanding feeder-bus coverage.

6.2 Lessons learned from multi-range build environment analysis framework

The resident population in BCAs is shown to be the most decisive factor in promoting bus-to-metro transfers. Higher residential density indicates stable travel demand. Thus, increasing population density within BCAs should be a long-term strategy. TOD (transit-oriented development) planning normally uses PCAs as spatial units, where dense, compact and mixed land uses (residential, business and leisure) are designed to increase transit ridership, but the limited size of PCAs restricts population capacity. This study recommends using BCAs—effective bus feeder areas—as spatial units for medium- to high-density, livable development that integrates housing, services, and amenities to support sustained population growth. On the other side, planners should monitor transport supply and population changes in BCAs and adjust bus frequency and capacity gradually to match demand.

This study identifies a threshold effect in the influence of metro station accessibility on bus-to-metro transfers. For stations with an accessible area below 31,600 km², increasing network accessibility—such as enhancing service frequency or extending new metro lines—will stimulate such transfers. For stations with high accessibility, additional investments in network expansion are likely to have limited effects on ridership growth.

The inhibitory effects of airports and railway hubs, and the positive effects of bus terminals around metro stations suggest that integrating bus terminals with regular metro stations—rather than concentrating intermodal facilities at large transport hubs—may more effectively promote bus–to-metro transfers.

The results show that expanding catchment areas to include passengers' origins and applying a weight function for actual travel choices systematically and substantially improve model accuracy and interpretability. Researchers and planners should avoid fixed-distance buffers, uniform-demand assumptions, and nearest-station assumptions, prioritizing behavior-based catchment areas as the spatial foundation for future studies on the built environment, demand modeling, land-use planning, and transport evaluation.

7 Conclusions

Using large multi-source datasets across two periods in Beijing, we propose an R-weighting method to generate real-time, anisotropic and station-specific BCAs that cover passengers' origins, reflect uneven demand and solve catchment overlaps. We integrate multi-scale built-environment variables into GAMs to examine linear and nonlinear effects on intermodal boardings. Key and consistent findings are:

(1) The R-weighting method consistently outperforms R-buffer, MBD-buffer, and the traditional 1000 m buffer in accuracy, simplicity, and interpretability for modeling intermodal ridership.

(2) Urban metro stations have broader and denser BCAs than suburban stations.

(3) The metro network shows a strategic balance: over 60% of stations primarily serve short-travel bus riders within 25 minutes, around 30% serve mid-distance transfers within 45

minutes, and 4-5% concentrate very long commutes over 60 minutes.

(4) Population and land use in BCAs emerge as the predominant factors in estimating intermodal transit ridership, with a mean RI of over 16%. Metro station accessibility followed at 5-6%, while transfer convenience around metro stations is the least at 2-3%.

Overall, incorporating the R-weighting BCA delineation approach with multi-range built-environment analysis provides a transferable framework for understanding bus–metro trips. This framework not only offers practical insights for optimizing bus–metro integration policy and planning but also holds strong potential for broader applications in intermodal trip analysis and demand forecasting, such as for bike–metro and taxi–metro connections.

Despite the contributions, this study has several limitations. First, due to data constraints, the transit card data were collected in the late and stable stage of the pandemic and may reflect pandemic effects. Using post-pandemic data could yield more comprehensive results. Second, individual-level attributes such as age, gender, and profession are not included due to data limitation. Third, the conclusions are from the Beijing case and may not generalize directly to other cities. Contextual calibration is required when applying the proposed method and framework to other cities.

Appendix A. Overlap degree of BCAs

Fig. 10 illustrates the distribution of the number of metro stations connected to each bus boarding stop. The majority of bus stops were connected to more than one metro station, with some connected to over 30 metro stations. This indicates a high degree of BCA overlaps between metro stations.

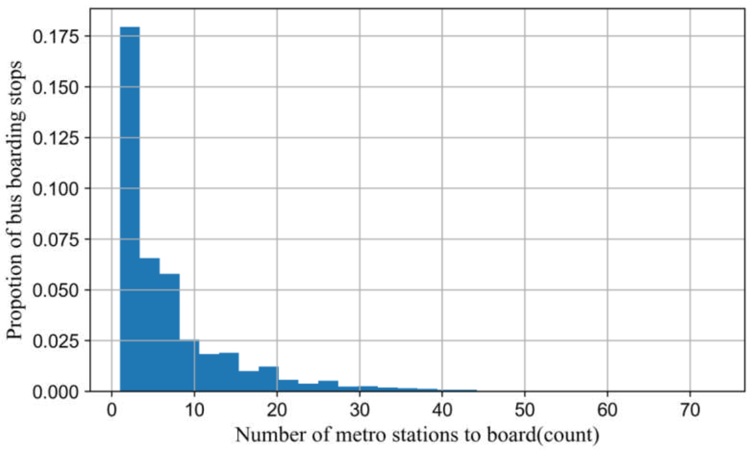

Fig. 10 Number of metro stations that a bus boarding stop had a connection with

Appendix B. BCA cutoffs sensitivity analysis

The 5th/95th percentiles gave the best model performance. This suggests that a broader BCA with more observable bus stops can improve intermodal trip fit and underscores the importance of the built environment around passenger origins for intermodal ridership.

Table 9 The performance of BCA cutoffs in the GAM-model 4

Cutoffs	Adj. R^2	AIC	DE	GCV
5th-95th	0.740	1035.661	75.8%	519.158
10th-90th	0.712	1081.346	73.2%	541.211
15th-85th	0.706	1104.174	72.6%	551.346

Appendix C. Spatial distribution of station categories for December 2021

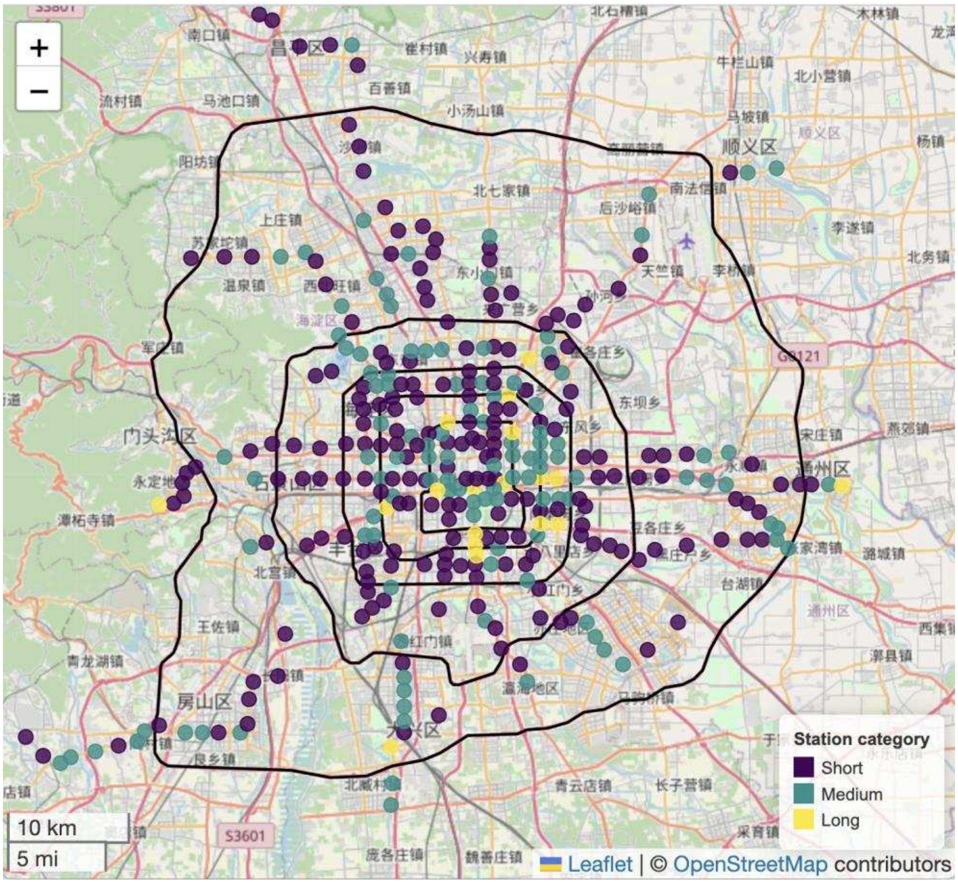

Fig. 11 Spatial distribution of station categories for December 2021

Appendix D. GAM regression results for December 2021

Table 10 GAM regression results of estimating bus-to-metro intermodal boardings across three different buffer areas for December 2021

Indicator category	Indicators	Model4(R-weighting)			Model3 (R-buffer)			Model2 (MBD-buffer)			Model1(1000m-buffer)		
		Estimate	S. E.		Estimate	S. E.		Estimate	S. E.		Estimate	S. E.	
	(Intercept)	-25.404	2.767	***	-30.135	3.715	***	-28.170	4.138	***	-20.217	5.051	***
BCA	log (Resident population)	1.579	0.064	***	1.364	0.080	***	1.234	0.084	***	0.194	0.076	*
Transfer convenience	log(Local bus route)	1.145	0.239	***	0.746	0.316	*	0.843	0.345	*	1.083	0.429	*
Metro station characteristic	log (Interval)	0.056	0.027	*	0.151	0.035	***	0.176	0.038	***	0.242	0.047	***
	log (Betweenness)	0.536	0.113	***	1.134	0.152	***	1.066	0.171	***	1.516	0.203	***
	BTI station	-0.082	0.025	**	-0.133	0.033	***	-0.125	0.036	***	-0.155	0.045	***
	RAI station	0.446	0.155	**	0.451	0.202	*	0.472	0.222	*	0.862	0.275	**
	Terminal station	-0.574	0.204	**	-0.843	0.265	**	-0.717	0.288	*	-0.737	0.366	*
Socioeconomic	log (Income)	0.458	0.126	***	0.521	0.163	**	0.349	0.176	*	0.310	0.224	
	Smooth terms:	e. d. f	F		e. d. f	F		e. d. f	F		e. d. f	F	
BCA	s (log (Government density))	2.205	0.536	***	2.882	3.233	***	3.885	9.938	***	0.346	0.043	
Metro station accessibility	s (log (Accessible area))	3.180	1.546	***	4.492	2.375	***	4.593	1.875	***	3.583	1.713	***
Transfer convenience	s (log (Bus stops))	1.959	1.151	***	2.533	0.491	**	1.771	0.381	*	1.632	0.700	***
	s (log (Long bus route))	1.288	1.050	**	1.230	0.428	**	0.805	0.242	.	0.942	1.973	***
	s (log (Commute bus route))	1.620	0.846	***	1.233	0.439	*	1.170	0.731	**	1.735	0.948	*

.p<0.1; *p<0.05; **p<0.01; ***p<0.001; Number of samples: 333

Appendix E. Nonlinear effects of explanatory variables for December 2021

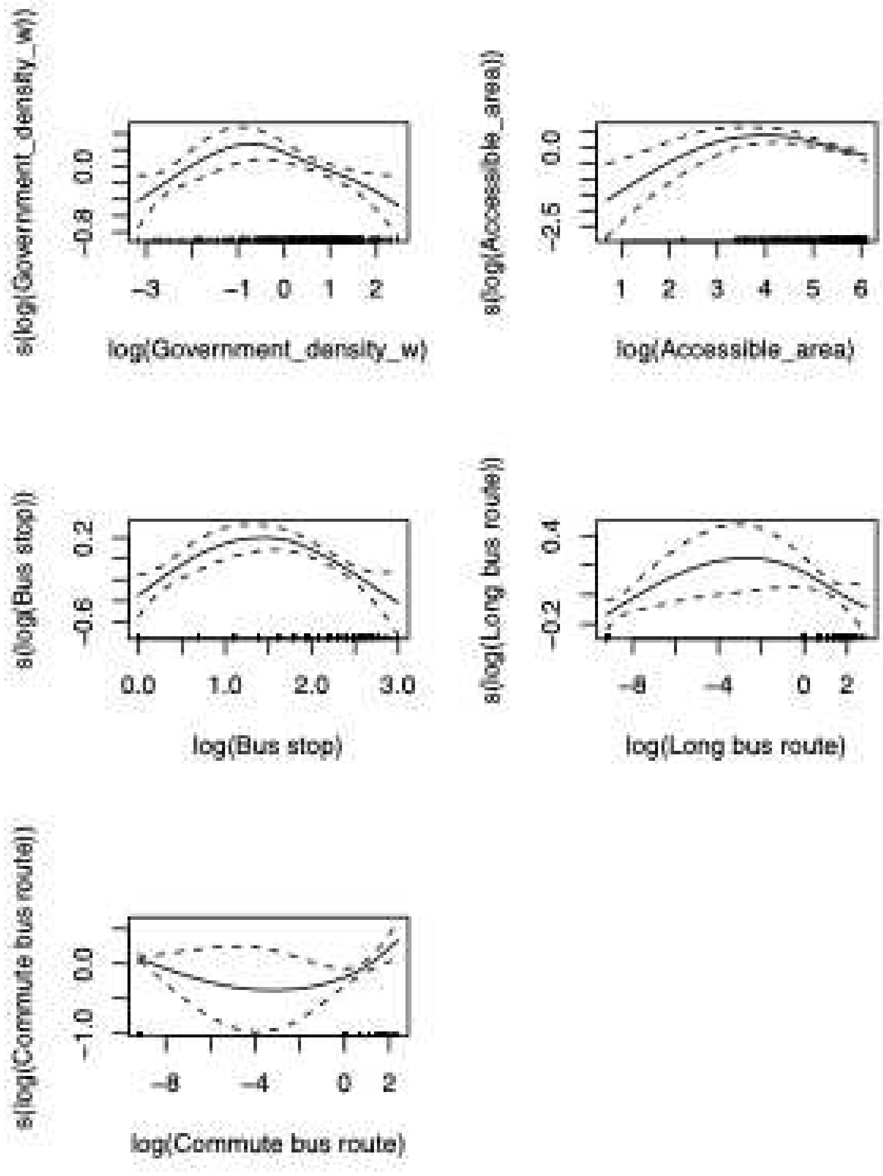

Fig. 12 Nonlinear effects of explanatory variables estimated with smooth splines in GAM-Model 4 (December 2021)

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