Effects of built environment on bus trip rates under rail transit competition

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Abstract

It’s important to explore ways to integrate bus and rail transit by combining both the effects of the built environment and their competition. Using Wuhan city in China as a case study, this study develops gradient boosting decision trees (GBDTs) to examine the threshold range of built environment impacts on bus transit trip rates and to further explore the competitive impacts of rail transit on bus transit within these threshold ranges. The results show that when the number of service point-of-interests (POIs) within a 500 m radius of bus stop reaches 350 and the distance to the destination is 5 km, the model split of bus transit is the highest. The competition impact shows that rail transit promotes bus transit trip rates in urban fringe areas, but restricts in high-density central areas and the regions dominated by short distance trips. These findings provide technical support for optimizing spatial layouts through transit-oriented development.

Key word: Bus transit travel, Multimodal transportation, Built environment, Gradient boosting decision trees, Nonlinear effects
1. Introduction

Owing to the advantages of low cost, flexible lines and high accessibility, bus transit has been a primary choice for urban travel. In the past decade, the rapid construction of rail transit in developing countries has led to a sharp decline in bus passenger volume, which has had a great impact on bus transit development. To avoid passenger losses, bus transit has to reduce prices and add lines. The continuing high investment and low income results in bus transit operating losses, which has become a common phenomenon in many cities in China. The ineffective competition between bus and rail transit not only leads to the waste of public transportation resources but also increases urban carbon emissions and noise pollution. Therefore, analyzing the causes and influence mechanism of this phenomenon will be of great significance to improve the efficiency of bus and rail transit cooperation. The built environmental characteristics are important factors for both bus- and rail-based transit planning (Kockelman, 1997; Vuchic 2005; Cervero, 2002; Stevens, 2017). This paper combines the impacts of both the built environment and rail transit competition to reveal the root causes of ineffective competition to provide a basis for developing sustainable multimode public transportation and transit-oriented urban spatial layout optimization.

A large number of previous studies have proven that the built environment has a significant impact on bus transit (Cervero, 2002; Stevens, 2017). Five-D variables—density, diversity, design, destination accessibility, and distance to transit—have important influences on vehicle miles traveled (VMT), vehicle hours traveled (VHT), and trip length (Kockelman, 1997; Frank et al., 1995; Stevens, 2017; Zhao et al., 2020). However, these empirical studies ignore the competition between bus and rail transit. Based on cases in developed countries, many researchers have investigated whether there is a competitive or cooperative relationship between bus and rail transit in different geographical locations of cities, resulting in positive or negative effects on the bus transit trip rate (Enrique Ramos-Santiago, 2021; Tamakloe et al., 2021). For developing countries, rail transit has only been constructed and perfected for nearly a decade, and the discussion about the cooperation and competition relationship between bus and rail transit focuses on traffic operation or revenue, such as cooperative profit allocation (Zhou et al., 2021) and multimode public transport route optimization (Ting and Schonfeld, 2005; Ciaffi et al., 2012). There is a research gap in exploring the influence mechanism of rail transit on bus transit from the perspective of the source of travel demand, spatial land use and built environment, which makes it difficult to develop concrete and operational strategies for guiding metro-bus integration planning (Guo and He, 2021).

Based on the previously mentioned limitations, taking Wuhan, China, as a study case, a
gradient boosting decision tree model is employed in this study to explore the impact threshold effect of the built environment on the bus transit trip rate and to further investigate the competition effects of rail transit on bus transit within the threshold range.

2. Literature Review

2.1 Built environment and travel behavior

A large number of existing studies have proven that the urban built environment is the main factor influencing travel behavior. Frank and Pivo (1995) found that the density and diversity of land use have a significant impact on travel mode choice. Cervero and Kockelman (1997) proposed the concept of three Ds of the built environment, pointing out that density, diversity and design play a positive role in reducing motor vehicle travel. Subsequently, Cervero (2002) added distance to stations and distance to destination to the definition of built environment after finding that they also influence travel mode choice. The proposal of the 5D concept of the built environment has attracted the support of other scholars in the field of planning and transportation. By traffic surveys and analysis, Pan et al. (2009) pointed out that pedestrian- or bicycle-oriented urban street design can alleviate the growth of motor vehicles. Moilanen (2009) confirmed that high-density construction can reduce the demand for long-distance commuting, which was also applicable in urban suburbs. Zhang et al. (2012) found that compact, mixed use, small street area and infill development can reduce vehicle mileage (VMT). Using Beijing as a case study, Zhao (2013) noted that high destination accessibility, separate bicycle lanes and mixed land use can improve the use of bicycles.

However, transit is the most widely distributed and numerous public transport facility in the city. Many scholars have investigated its relationship with the built environment through linear assumptions and put forward valuable suggestions for the optimization of bus lines, stops and urban land use (Sun and Dan, 2015; Zhao et al., 2020). Based on the linear hypothesis, some studies have confirmed the role of the built environment and rail transit in promoting bus travel and reducing motor vehicle commuting (Hong et al., 2014; Stevens, 2017). For instance, high-density and high-mixed land use can make the residents able to live closer to the place of employment and shorten commuting distance to improve public transportation and nonmotorized commuting and to reduce the use of cars (Cervero, 2002; Chatman, 2003; Sun and Dan, 2015). However, does this suggest that infinitely increasing land density and land use mix in planning practice will achieve transit-oriented mode choice? The answer is no. Excessive high-density development can also cause more centralized travel demand and serious traffic
congestion (Melia et al., 2011). How to further determine the impact threshold range of land-use density, diversity and accessibility is of great significance to propose spatial planning strategies to promote transit-oriented development.

Second, in recent years, relevant studies have found that the built environment and travel behavior involve nonlinear relationships within a threshold range. This implies that land-use strategies targeted to influence travel behavior by changing the built environment may be more effective at a certain range of built environment variables than at other ranges of the variables (Ding et al., 2018). Ding et al. (2018) applied a gradient boosting logit model to confirm the nonlinear relationship between built environment characteristics and commuting patterns at both residential areas and workplaces in Washington. By using travel surveys and POI data, Zhang et al. (2020) explored the nonlinear effect of accessibility on car trips and found that a density threshold range of 65–145 retail and service facilities per km\(^2\) within the 15-min neighborhood life circle can effectively reduce car travel. Chen et al. (2021) proposed a decision framework based on TAZ level data and revealed that the impact of accessibility on intermodal transit trips was greatest when the distance to rail stations exceeded the threshold of 2.5 km, and the possibility of transferring buses to rail increased sharply.

### 2.2 The impact of rail transit competition on bus transit

Owing to rapid urbanization, the high-intensity construction of rail transit in China has a great impact on bus transit (Ma et al., 2007). Taking Wuhan, China, as an example, according to the 2021 Wuhan Transportation Development Annual Report issued by the Wuhan Transportation Development Strategy Institute, in 2020, the total public transportation trip in Wuhan was 1.41 billion, of which rail transit and bus transit trips accounted for 44.2% and 40.4%, respectively. Rail transit has become the main mode of transportation. However, the proportion of bus transit decreased by 35.7%, as it constituted 76.1% of public transportation trips in 2010.\(^1\)

Empirical research studies have demonstrated that the impact of rail transit on bus transit is widespread but significantly different in different geographical locations in cities. Zhao et al. (2020) discovered that under the influence of rail transit construction, the bus transit trip rate decreases significantly in the urban central area but increases in the urban fringe residential area. By analyzing the multimode transit of the three cities, Aston et al. (2021) indicated that

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areas with high commercial agglomeration have low bus transit trip rates due to the construction of rail transit. In contrast, in areas with high sidewalk connectivity and high-density residential districts, the bus transit trip rate is less affected by rail transit competition. Based on a case study of Seoul, South Korea, Tamakloe et al. (2021) revealed that CBD has a greater performance of rail transit-oriented development compared with urban fringe areas, which results in a rise in rail transit trip rate but a decline in bus transit trip rate.

In view of the above questions, some researchers believe that the built environment in different geographical positions is a major factor determining the competition or cooperation between bus and rail transit (Verma and Dhingra, 2006; Wu et al., 2019). In some areas, the government constructs rail transit to guide traffic travel, while bus transit, as an auxiliary mode, tends to have a low trip rate. In contrast, travelers in urban fringes usually have to choose the bus-to-metro intermodal mode because of limited transit rail lines, which further promotes bus transit trips (Chen et al., 2021). In addition, when the destination is close, the low cost of bus transit makes it the dominant mode of travel and less influenced by rail transit. For major transit corridors where ridership is high, rail transit becomes the dominant travel mode due to its higher operating efficiency and lower operating costs per passenger mile than buses (Zhang, 2009; Zhao and Shen, 2019; Tamakloe et al., 2021).

In summary, current research has confirmed the nonlinear threshold relationship between the built environment and bus transit trip rate and found that the spatial heterogeneity of the built environment is attributable to the competition or cooperation between bus and rail transit (Calvo et al., 2019; Chen et al., 2021). However, the internal influence mechanism of built environmental factors on bus and rail transit competition still lacks in-depth research, which leads to unclear guidance for planning practice (Ding et al., 2018a). Incorporating the competition of rail transit, the analysis of the nonlinear threshold effect of the built environment on bus transit can better help to mitigate the ineffective competition phenomenon.

3. Method

3.1 Data and variables

Wuhan, located in central China, is the most important city of the middle YangTze River, with an area of 678 km\(^2\) in the central urban area and a population of 6.24 million (see Fig. 1). Since 2018, the Wuhan central area has operated 332 bus lines, 1615 bus stops, 7 rail transit lines and 144 rail transit stations (see Fig. 2). Approximately 90% of bus riders use IC cards.
owing to the approximately 80% discount off the single-ticket fare, which also brings effectiveness to the sample of this study (Zhao et al., 2020).

The dataset in this study includes four types: spatial locations of bus and rail transit stops, card-swiping records, parcel-based land use and points of interest data (POIs). The ArcGIS shape files of spatial locations and the card-swiping records of users were supplied by the Wuhan Transportation Research Center. Approximately 3,000,000 daily records in December 2018 were selected as samples after eliminating invalid data. Parcel-based land use in 2018 was collected by the Wuhan Natural Resources and Planning Bureau, including the land category, size, and floor area ratio (FAR) attributes. POI data were obtained from the Baidu Developer Platform. A total of 210,000 POI data points were collected, including shopping malls, merchants, enterprises, scenic spots, schools, hospitals and service centers. The POI data were further classified into three types: business, recreation and service. Business POI included banks, insurance companies, private corporations, etc. Recreation POIs consisted of malls, supermarkets, convenience stores, bars, KTVs, resorts, amusement parks, scenic spots, etc. Services involved government departments, schools, hospitals, neighborhood centers, sports centers, etc.

Figure 1 Study area and land use of Wuhan.

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Figure 2 The distribution of bus and rail stations in Wuhan.

Figure 3 Results of trip rates index of each bus stop in the study area.
To process, read, and analyze the original GIS data, the spatial analysis tools in ArcGIS 10.7 and the statistical tool box in MATLAB 2019a were used. First, the daily bus trips (including both boarding and alighting) for each bus stop was extracted based on IC card swiping records and spatially matched with the 1615 bus stops. Second, trip destination was determined to generate the variable *distance to destination*. The details of this data processing can be found in a previous study (Zhao et al., 2020).

This study used the bus trip rate index as the dependent variable to represent the transit use of each bus stop. It could be calculated as Eq. (1):

$$ Y_i = \frac{N_i}{(r_i / p_i)} $$  \hspace{1cm} (1)

where $Y_i$ is the bus trip rate index, $N_i$ is daily bus trips for each bus stop, and $r_i$ represents the total residential building area within a radius of 500 m from each bus stop. $p_i$ is per capita residential land area. Fig. 3 illustrates the results of the bus transit trip rate index.

Three types of built environments were taken as independent variables, including land use, point of interest (POI) and transportation accessibility (see Table 1). The land use factors are composed of density, diversity and residential density. Here, the density is denoted by the floor area ratio (FAR) within the 500 m buffer area from each bus stop. Diversity was generated from the entropy function of the land-use mix for the same spatial extent as the FAR (Kockelman, 1997). Residential density was calculated by calculating the total residential floor area divided by a 500 m buffer area from each station. POI variables include the POI number of business, recreation and service facilities within a 500 m radius from each bus stop. Furthermore, transport accessibility includes “distance to bus stop” and “distance to destination”, and both were calculated with the *Euclidean distance function* in ArcGIS 10.7 and extracted from the Euclidean distance tiff file based on its spatial location.

The rail transit accessibility variable is introduced to detect the competitive relationship between bus and rail transit. It is calculated by the number of rail stations within a 500 m radius area of bus transit stops by the spatial connection tool in ArcGIS. A total of 1615 bus stop samples were obtained by mapping the built environment and rail transit accessibility to the bus transit trip rate index. Table 1 illustrates the calculation methods and numerical characteristics of each variable.

### Table 1 Description of variables

<table>
<thead>
<tr>
<th>Variables</th>
<th>Variable Description</th>
<th>Mean</th>
<th>St. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Bus trip rates index</strong></td>
<td>bus trips/potentially covered population in 500 m buffer</td>
<td>0.04</td>
<td>0.07</td>
<td>0</td>
<td>0.60</td>
</tr>
<tr>
<td><strong>Built environment</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Land use</td>
<td>Density</td>
<td>Total building area/500 m buffer area</td>
<td>2.94</td>
<td>0.65</td>
<td>1.2</td>
</tr>
<tr>
<td>-------------------</td>
<td>-----------------------------------------</td>
<td>--------------------------------------</td>
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<td>-----</td>
</tr>
<tr>
<td></td>
<td>Diversity</td>
<td>Entropy function of the land-use mix</td>
<td>0.34</td>
<td>0.26</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Residential density</td>
<td>Total residential floor area/500 m buffer area</td>
<td>35.09</td>
<td>12.65</td>
<td>0</td>
</tr>
<tr>
<td>POIs</td>
<td>Number of business POIs</td>
<td>Number of business POIs in 500 m buffer</td>
<td>87.16</td>
<td>80.65</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Number of recreation POIs</td>
<td>Number of recreation POIs in 500 m buffer</td>
<td>108.03</td>
<td>96.69</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Number of service POIs</td>
<td>Number of service POIs in 500 m buffer</td>
<td>148.13</td>
<td>116.64</td>
<td>0</td>
</tr>
<tr>
<td>Transport accessibility</td>
<td>Distance to bus stops</td>
<td>Euclidean distance of bus stops (m)</td>
<td>516.47</td>
<td>286.16</td>
<td>100</td>
</tr>
<tr>
<td></td>
<td>Distance to destination</td>
<td>Euclidean distance of city center (km)</td>
<td>2.77</td>
<td>2.17</td>
<td>0</td>
</tr>
<tr>
<td>Rail transit accessibility</td>
<td>Number of rail stops in 500 m buffer</td>
<td></td>
<td>0.69</td>
<td>0.65</td>
<td>0</td>
</tr>
</tbody>
</table>

### 3.2 Modeling approach

This study developed a GBDT model to illustrate the impacts of built environmental variables on bus and rail transit competition. The GBDT model is a decision tree model developed by Friedman, originally developed in computer science (Friedman, 2001). Because it can effectively quantify the nonlinear effect between independent variables and dependent variables under different spatial units, it has been increasingly applied to examine the relationship between land use and transportation (Ding et al., 2018a; Gan et al., 2020).

Compared to traditional statistical models, GBDT has the following advantages. First, it can help address the multicollinearity among independent variables and accommodate missing values and outliers. Second, the GBDT approach is more likely to illustrate the true relationship among variables. Generally, if the relationship is nonlinear, traditional regression may produce a large P value, which leads to erroneous conclusions. In contrast, the GBDT does not prespecify the relationship among variables but reduces the error of mathematical statistics through the method of relative importance. Finally, this approach can generate partial dependence plots (PDPs) to evaluate the thresholds and interaction effects between two or more variables, making the results more functional in planning practice.

Based on insights from statistical and machine learning methods, the GBDT approach integrates a decision tree model and gradient boosting. Its core idea aims to fit the current decision tree by learning the residuals of the previous decision tree (Zhang & Haghani, 2015; Ding et al., 2018a; Yin et al., 2021). Mathematically, assuming that $x$ is a set of independent variables, $y$ is the dependent variable, and $F(x)$ is an approximation function of $y$ based on $x$. It aims to find the optimal function $F_M(x)$ with $M$ decision trees through the training dataset.
with \( N \) samples, which can minimize the loss function \( L[y,F(x)] \), as shown in Eq. (2):

\[
F_M(x) = \sum_{m=1}^{M} \theta_m \sum_{i=1}^{N} t(x;\mu_m)
\]  

(2)

where \( M \) is the number of decision trees, \( \mu_m \) presents the mean of split positions and terminal nodes in an individual tree \( t(x;\mu_m) \), and \( \theta_m \) is estimated by minimizing the loss function. To estimate the parameters of the GBDT model, the optimization process includes four iterative steps:

First, a total of 1615 samples \( T \) are input as training data, where \( (x_1,x_2,...x_N) \) is set of eight built environment variables for each bus stop and \( (y_1,y_2...y_N) \) is the trip rate index of each bus stop.

Second, an initialization function is given by:

\[
F_0(x) = \arg \min \sum_{i=1}^{N} L(y_i,F(x_i))
\]  

(3)

Then, as the number of iteration rounds from \( m = 1 \) to \( M \), run the following five programs:

① GBDT calculates the negative gradient \( r_{im} \) for each data sample \((i=1,2,...N)\) as residual errors:

\[
r_{im} = -\left[ \frac{\partial L(y_i,F(x_i))}{\partial F(x_i)} \right] F(x_i) = F_{m-1}(x)
\]  

(4)

② The optimal gradient can thus be estimated by setting the regression tree \( t(x;\mu_m) \) based on \( r_{im} \):

③ A gradient descent step size is computed as Eq. (5):

\[
\theta_m = \arg \min \sum_{i=1}^{N} L(y_i,F_{m-1}(x_i)) + \sum_{m=1}^{M} \theta t(x;\mu_m)
\]  

(5)

④ By combining Eqs. (4) and (5), and adding a learning rate \( \xi (0 < \xi \leq 1) \) to the approximation function can reduce overfitting (Friedman, 2001; Ding et al., 2016), the method can be shown as Eq. (6):

\[
F_{\infty}(x) = F_{m-1}(x) + \xi \theta m t(x;\mu_m), \ 0 < \xi \leq 1
\]  

(6)

⑤ Check whether the model result meets the preset accuracy requirements. If the accuracy requirement is reached, the calculation will be stopped; otherwise, return to ①.

Finally, the estimates of the final model \( F_M(x) \) are output.

The GBDT model can calculate the relative importance of each variable according to the best prediction results. The squared importance of independent variable \( I^2_{xi} \) can be calculated by averaging the square importance of all added trees \( T_m \) (Ding et al., 2016; Shao et al., 2020), which can be described by Eq. (7):

\[
I^2_{xi} = \frac{1}{M} \sum_{m=1}^{M} I^2_{xi}(T_m)
\]  

(7)
In addition, as a data-driven machine learning model, the GBDT approach does not assume a predetermined linear relationship between the independent and dependent variables, which makes it capable of capturing the interactions among rail transit accessibility, built environment and bus trip rate by partial dependence plots (PDPs). The PDP can be generated by Eq. (8) (Greenwell, 2017; Shao et al., 2020):

\[
\begin{align*}
F_s(x_s) &= \frac{1}{N} \sum_{i=1}^{N} \left[ f(x_s, x_C) \right] \\
F_s(x_C) &= E_{x_C} \left[ f(x_s, x_C) \right]
\end{align*}
\]

(8)

where \( x_C \) and \( x_s \) denote selected and remaining built environmental variables, respectively.

PDPs can not only intuitively reflect the threshold relationship between a single variable and dependent variable through a diagram but also illustrate the impact of the joint effects of multiple variables on the dependent variable. Therefore, the PDPs were employed to visually reflect the nonlinear relationship between the eight built environment variables and the bus transit trip rate. Then, three highly significant attributes (density, number of service POIs, distance to destination) were selected to explore the competition and cooperation between rail and bus transit within the threshold range.

4. Results and discussion

4.1 Model implementation

According to the model algorithm, a total of 1615 samples of data were input to the GBDT model, which was constructed by the \textit{gbm} R package, developed by Ridgeway (2005). To obtain more robust estimation results, a fivefold cross-validation procedure was chosen to regularize three important parameters: number of trees, shrinkage parameter and tree complexity. During cross-validation, this study divided the sample into five subsamples of similar size. The models were first estimated based on the four subsamples and validated by the fifth subsample. To achieve the best fitting effect without overfitting in decision boosting, the shrinkage parameter should be set between 0.001 and 0.1 (Ding et al., 2018a), and the tree complexity should be set between 4 and 8 (Hastie et al., 2009). In this study, the final model here set the shrinkage parameter at 0.001, with trees at 1500 and tree complexity at 6, and the pseudo R-square of the model is 0.25.

4.2 Relative importance of built environments

Table 2 presents the results of the relative importance of all built environment attributes.
in the bus trip rate index. Among the three types of built environmental variables, the number of POIs has the greatest influence on the bus trip rate index, with a contribution of 41.67%. This indicates that public facilities around bus stops play a dominant role in affecting bus transit mode choice. In addition, the contributions of land use and accessibility are 28.76% and 29.46%, respectively, showing that the two aspects of the built environment also have a prominent impact on the bus trip rate.

In terms of individual variables, the number of service POIs is the most important predictor of the bus trip rate and contributes 19.71%. This indicates that the layout of public service facilities around bus stops is more likely to attract bus transit than commercial and residential facilities. The second ranking indicator is the distance to destination, with a contribution of 15.59%, quantitatively confirming its importance to the transit travel rate. In addition, density, distance to bus stops, and the number of recreation POIs also show significant impacts. These results are consistent with previous studies showing that the density and accessibility of built environment attributes have a significant impact on the bus trip rate (Cervero, 2002; Pan et al., 2009).

In contrast, the number of business POIs, diversity, and residential density play minor roles in the bus trip rate, with contributions of 8.66%, 8.48%, and 5.96%, respectively. Two assumptions are proposed to explain these results. First, these three variables may have a nonlinear relationship with the bus trip rate index and only have an influence effect on a certain threshold. Second, rail transit may bring competition on bus transit, especially in commercial centers and residential areas. The following section will further demonstrate the two assumptions.

Table 2 Relative importance in transit trip rates

<table>
<thead>
<tr>
<th>Categories</th>
<th>Variables</th>
<th>Ranking</th>
<th>Relative importance (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Land use</td>
<td>Density</td>
<td>3</td>
<td>14.43</td>
</tr>
<tr>
<td></td>
<td>Diversity</td>
<td>7</td>
<td>8.48</td>
</tr>
<tr>
<td></td>
<td>Residential density</td>
<td>8</td>
<td>5.96</td>
</tr>
<tr>
<td>POIs</td>
<td>Number of business POIs</td>
<td>6</td>
<td>8.66</td>
</tr>
<tr>
<td></td>
<td>Number of recreation POIs</td>
<td>5</td>
<td>13.30</td>
</tr>
<tr>
<td></td>
<td>Number of service POIs</td>
<td>1</td>
<td>19.71</td>
</tr>
<tr>
<td>Transport</td>
<td>Distance to bus stops</td>
<td>4</td>
<td>13.87</td>
</tr>
<tr>
<td>accessibility</td>
<td>Distance to destination</td>
<td>2</td>
<td>15.59</td>
</tr>
</tbody>
</table>

Electronic copy available at: https://ssrn.com/abstract=3988132
4.3 Nonlinear effects of built environment on bus trip rates

Exploring the nonlinear relationship can find the marginal effect between the built environment and the bus trip rate, which provides a spatial threshold basis for further exploring the competition between rail transit and bus transit. The PDP package was applied to detect the threshold effect between the built environment and bus transit trip rate. To reveal the differences in the impacts of various relative impact variables, three highly significant factors (number of service POIs, distance to destination and density) and three minor impacting factors (number of business POIs, diversity and residential density) were chosen for discussion. As shown in Fig. 4, the results show that the threshold effects are demonstrated between all attributes and the bus transit trip rate index.

![Figure 4 The relationship between the built environment and bus trip rates:](https://ssrn.com/abstract=3988132)

In terms of the first three highly significant attributes, the impact thresholds for the number of service POIs, distance to destination and density range from 0.05 to 0.10. The positive coefficient of the number of service POIs indicates that when the clustering of service facilities within 500 m surrounding the bus stop increases from 0 to 300, the bus trip rates will increase sharply.

However, if the number of service POIs is more than 300, the bus transit trip rate index tends to be saturated at about 0.85, although there are some hot pixels. The above results are
consistent with the findings of previous studies that the more public service facilities there are, the more residents tend to travel by bus transit (Zhao et al., 2019; Zhang et al., 2020). Second, the distance to the destination presents an inverted U-shaped relationship, where residents prefer to choose the bus mode when the destination is 3-5 km away. However, the bus trip rate index decreases significantly when the distance to the destination is less than 3 km or more than 5 km. Actually, walking, bicycle and bus trips are dominant modes in short-distance trips, while rail transit or car trips are preferred in long-distance trips. Finally, consistent with existing studies, density shows a positive correlation (Pan et al., 2009; Hong et al., 2014). Specifically, when the density is within the interval of 3.0-4.6, it has a positive and approximately linear association with the bus trip rate. Beyond 4.6, the bus trip rate tends to saturate at 0.093.

In comparison, the number of business POIs, diversity and residential density have minor impacts on the bus transit trip rate, ranging from 0.06 to 0.08. From the perspective of the number of business POIs, in the interval of 0-300 per bus stop, it is positive and linearly associated with the bus trip rate. Then, the bus trip rate is saturated beyond the threshold of 300 per bus stop. The plot of diversity indicates that bus trips increase sharply when the land-use entropy grows from 0 to 0.26 but remain unchanged once it is higher than 0.26. Residential density has a relatively weak association with bus trips. The highest bus transit trip rate was achieved when the density of residential land within a 500 m radius of bus stations was 30%-50%.

The above results have great implications for the optimization of the urban spatial layout. First, a diversified and hierarchical spatial layout of commercial and public service facilities can promote transit-oriented development, where public transit stop coverage should be strengthened within 5 km surrounding the core area. Second, controlling the FAR limit at 4.6 can maximize the proportion of bus transit mode choice, which quantitatively provides an efficient regulation for restricting overexploitation. In addition, the threshold value of the other three minor impact variables also provides quantitative and specific guidance for transit-oriented built environment development.

4.4 The impact of rail transit competition on the bus transit trip rate in different built environments

To further analyze the competition between bus and rail transit, this section imports the rail transit accessibility indicator to explore the variation in the bus trip rate in different threshold values of the built environment. Fig. 5 shows the interrelationship plots among rail
transit accessibility, bus transit trip rate, and three significant built environment variables. The chromatogram in the upper part of Fig. 5 shows the bus trip rate when the built environment increases from 0 to the threshold range, and the number of rail stops increases from 0 to 2. Yellow indicates a high bus trip rate, and blue represents a low bus trip rate. The line chart in the lower half of Fig. 5 shows the change in bus trip rate under different built environment values when the number of rail stations increases from 0 to 1.

Figure 5 Interactive effects between the number of rail stations and built environment on bus trip rates

As shown in Figure 5, the cooperation or competition relationship between rail transit and bus transit depends on the built environment. Specifically, as shown in Fig. 5a), rail transit promotes the bus trip rate index in locations where the number of service POIs is less than 300. In particular, when the number of service POIs is less than 50, which means that in the urban fringe or underdeveloped areas, if one rail station is added, the bus transit trip rate index increases by 25% (from 0.04 to 0.05). In comparison, when the number of service POIs is greater than 300, most likely in urban concentrated commercial and service areas, rail stations will reduce the bus trip rate index and result in ineffective competition.

In Figure 5b), the construction of rail transit can promote bus transit trips in areas with a high proportion of medium-distance trips between 3 and 5 km, where the construction of rail transit increases the bus trip rate by 10% (from 0.08 to 0.088). However, in the regions dominated by short-distance (less than 3 km) or long-distance (greater than 5 km) trips, the construction of the rail station does not show impacts on the bus trip rate. In other words,
ineffective competition between rail and bus transit frequently occurs in areas with the majority of short-distance or long-distance trips.

The density is similar to the distance to destination. When the density increases from 0 to 4.6, the construction of rail promotes bus trips. Once it is above 4.6, this means that in the ultrahigh intensity development areas, ineffective competition between rail and bus transit always occurs. As shown in Fig. 5c), when the density grows to 4.0, if a rail station is set around the bus stop, then the bus trip rate increases by 11.1% (from 0.072 to 0.08). This implies that the travelers in these areas prefer to choose bus-rail intermodal transportation. Moreover, if the density is above 4.6, the involvement of rail transit will decrease the bus trip rate by 1.2% (from 0.085 to 0.084). This indicates that in dense urban centers, the rail transit mode will be chosen preferentially.

The above results provide ideas for policy formulation and planning design, therefore improving the interconnected development of bus and rail transit. First, in urban edge areas with limited service facilities and medium intensity regions (density less than 4.6), the bus trip rate can be promoted by setting rail-bus transfer hubs and increasing public transit facilities. Second, for high-intensity urban centers with densities higher than 5.0, the reduction in bus stations and the increase in rail stations with multiple lines should be considered. Third, in areas dominated by a 3-5 km travel distance, it is necessary to improve the transfer efficiency between rail and bus transit, such as by allocating dense bus facilities around rail stations. Finally, for short-distance (shorter than 3 km)-dominated areas, the configuration of service facilities for walking and bicycles should be optimized.

5. Conclusion

Based on bus trip data in Wuhan, China, this study applies the GBDT method to examine the threshold range of the built environment impacts on the bus transit trip rate and to explore the competitive impacts of rail transit on bus transit within these threshold ranges. The GBDT approach is able to identify the threshold of each built environment attribute that maximizes the bus trip rate. The number of service POIs, distance to destination and density have a great impact on the bus trip rate, and the bus trip rate is stabilized at the optimal value by controlling these variables within corresponding thresholds. In contrast, the number of business POIs, diversity and residential density have weak associations with the bus trip rate.

In addition, this study identifies areas where bus and rail transit cooperate or compete. Cooperation mainly occurs on the urban edge areas and medium-distance travel areas. These areas should further increase the investment in public transportation and develop bus-rail
interchange hubs. On the other hand, competition usually appears in high-density central areas and areas dominated by short-distance or long-distance travel. Strategies are also proposed to improve bus-rail transit cooperation and to avoid ineffective competition, such as developing a diversified and hierarchical urban center system, controlling the development intensity around the bus stop, and integrating public transit resources. This provides practical guidance for the optimization of land use and the collaborative development of bus and rail transit in developing countries.

Limited built environment variables are selected due to availability. The self-selection mechanism of residents, such as income, age, education and other characteristics of travelers, should be further explored in future improvements. In addition, the bus trip rate also depends on the bus capacity, such as vehicle size, service frequency, and road conditions (Zhang, 2009). Although there are some limitations, the study provides theoretical and practical guidance for the critical issues of the competition between bus and rail transit, which enriches the theory of transit-oriented and low-carbon oriented urban built environmental planning and design.

Data Availability Statement

All data, models, or code generated or used during the study are available from the corresponding author by request.

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