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Association between Built Environment and Bus Usage among Older Adults: Urban–Rural Differences in the Nonlinearities

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Abstract: Public transport improves mobility and well-being for the rapidly aging population. However, few planning interventions have addressed the urban–rural disparity in bus usage among older adults. Using data from Zhongshan, China, this study adopts the eXtreme Gradient Boosting (XGBoost) model to examine urban–rural differences in the nonlinear relationship between built environment and daily bus usage among elderly adults. The results indicate nonlinearities across all built environment variables and stronger effects of the built environment in rural areas. Distance to transit contributes the most in urban neighborhoods but least in rural ones. Furthermore, dwelling unit density and green space accessibility play the biggest roles in the rural context. Additionally, the most effective ranges of intersection density, land use mixture, and CBD accessibility are greater in rural areas. The findings facilitate fine-grained and diversified planning interventions to facilitate bus usage among older adults in both urban and rural areas.

Keywords: urban–rural differences; nonlinearities; built environment; XGBoost; bus use; older adults

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1. Introduction

Urban and rural areas are interdependent, and they integrate with and complement each other [1,2]. During rapid urbanization over the past decades, the inadequate rural development [3] has led to substantial urban–rural disparities [4], posing an inevitable threat to sustainable development [5]. Due to uneven social and land use development and infrastructure investment, a huge gap exists in urban–rural public transport system [6,7]. Public transport is a key to mobility and well-being, especially for seniors in developing countries [8]. It is imperative to improve rural public transit service and promote the integration of urban and rural public transport systems.

Due to rapid population aging around the world, the global aged population (65 years or over) in 2050 is expected to exceed 1.5 billion, doubling from about 730 million in 2020 [9]. The main purpose of sustainable development is to improve the health status and well-being of people of all ages [5]. Statistically, the greatest percentage increase in the aged population will occur in Eastern or South-Eastern Asia [9]. As the most populated country, the aged population in China is expected to boom in upcoming decades.

In urban and rural areas of China, bus usage deserves extra attention when studying the travel behavior of older adults for several reasons. First, the population of older adults in China has significantly increased in recent years [9]. By 2021, the Chinese aged population (aged 60 and above) exceeded 191 million, covering 13.5% of the general population. China will have a super-aged society in 2033 as the percentage of older adults surpasses 20% [10]. Second, for Chinese older adults, the bus is among the most convenient and accessible transport modes [11]. Additionally, bus use can promote transportation-related walking, increasing mobility levels and facilitating the physical activity of older adults [12,13]. Furthermore, many older adults in rural areas need extra social and transportation support because their children do not live with them [14–16]. Compared to elderly individuals in rural area, urban dwellers usually have more transportation options and supporting resources.

Although a strategy for public transit priority has been proposed for about 20 years in China, planning interventions to promote bus usage among elderly adults are still rare [8,17]. When studying the travel behavior of elderly adults, limited research has been conducted to systematically examine urban–rural differences in bus use. Meanwhile, most prior studies between bus usage and built environment employed linear models, and the findings may deviate from the reality. These linear models based on a pre-defined linear assumption, which can make potential nuanced relationships between variables unobservable [18].

To fill the above gaps, this study was conducted on urban–rural differences in daily bus trips of older adults in Zhongshan, China. An eXtreme Gradient Boosting (XGBoost) algorithm was utilized to explore different associations with the built environment, as well as socio-demographics and attitudinal attributes. In the following parts, Section 2 reviews the related research. Section 3 shows the variables and associated data sources. Section 4 introduces the XGBoost algorithm. The results and recommended effective ranges of each built environment variable are discussed in Section 5. Then we conclude with the main findings and propose policy implications in the last section.

2. Literature Review

2.1. Associations between Built Environment and Bus Usage by the Elderly

The characteristics of travel behaviors among elderly adults are unique due to the limitations of their body conditions [19]. Public transport service is a potentially attractive option for older adults, and older adults often consider the quality of public transport to be a significant part of their quality of life [7]. For example, more bus trips are partly linked to greater participation in physical activity and mediation of social isolation [20]. Table 1 summarizes recent studies on association between the built environment and bus usage among older adults.

Table 1. Studies on association between the built environment and bus usage among older adults.

Authors	Location	Bus Usage	Built Environment Variables with Significance
Yang et al. [21]	USA	Public transport trips	Street connectivity, Walk score, Distance to the nearest park
Hess [22]	Buffalo and Erie County, New York, USA	Transit ridership	Objective and perceived walking distances to access fixed-route transit
Barnes et al. [23]	British Columbia, Canada	Odds of using transit	Walk score, Transit score
Zhang et al. [8] Wang et al. [17]	Zhongshan, China	Public transport trips	Public transport service, Green space, density, Land use mixture, CBD accessibility
Aceves-Gonzalez et al. [11]	Guadalajara, Mexico	Tendency to choose bus	Pedestrian infrastructure

Several studies have proved that the built environment is significantly related with travel behavior, physical activity, and associated health outcomes [18,24,25]. People with poor daily walking conditions are more likely to be overweight or obese, while land use mixture is the most prevalent built environment factor to affect personal body mass index (BMI) [25,26]. It is well acknowledged that a walking- and bus-friendly environment is crucial for older adults to promote their bus usage and enhance their mobility and well-being [17,21,23,27]. However, limited studies have conducted quantitative research on the associations between the built environment and bus usage among elderly adults for effective planning interventions.

The existing literature found that built environment attributes displayed statistically significant differences between older bus users and older non-bus users [22]. Built environment factors involving the "5Ds" and aesthetics are related with bus usage among elderly adults [11,17,21–23,28]. In dense and mix-developed areas with well-connected street networks and walking routes, bus ridership rates and probability of choosing to travel by bus are significantly high [8,11,21,22]. Living closer to various destinations, e.g., CBD, clinics, and parks, is associated with more bus trips [8,17,21,28]. Satisfying bus service and dense bus stops are related to a high propensity to choose a bus [8,17,23,28]. Older adults residing in urban areas will make more bus trips than their counterparts in rural and suburban areas [21].

2.2. Urban–Rural Differences in Travel Behaviors

A gap exists in urban and rural transport development [29,30]. For example, rural residents in economically undeveloped areas take fewer trips with longer travel distances and average travel times compared with residents in economically developed areas [31]. Rural bus service coverage is weaker than in urban areas [32]. To realize integrated development in urban–rural transport, an urgent task is to facilitate understanding of urban–rural differences in travel behaviors [33]. Table 2 summarizes recent studies on urban–rural differences in travel behaviors. Generally, such research is insufficient [6,31].

In terms of active travel, significant urban–rural differences have been observed in walking and cycling behaviors [34,35]. Rural residents' walking participation is low-er than that of urban residents [34]. The travel behavior of rural and urban bicyclists is also significantly different [36]. The environmental attributes related to walking or cycling in urban regions may not as effective as in rural areas [34,35]. More investment in the built environment could increase participation in active travel in rural neighborhoods [37]. There is a great need to modify urban-focused studies to accommodate the rural context and facilitate walkability and bike-ability in rural areas [36].

Table 2. Studies on urban–rural differences in travel behaviors.

Authors	Location	Methodology	Travel Behavior
Yin et al. [38]	China	MNL Factor analysis	Mode choice
Zhao and Bai [39]	China	Logit regression	Household car ownership
Zhang et al. [40]	USA	Ordinary Least Squares (OLS) regression	AARP (American Association of Retired People) Livability Index
Whitfield et al. [35]	USA	Logistic regression, Stepwise model	Walking for leisure or transportation
Tribby and Tharp [36]	USA	RF, Logistic regression	Bicycling behaviors
Berry et al. [34]	South Australia	Negative binomial regression	Walking frequency

Regarding urban–rural differences in bus use, prior literature indicates that bus use among rural residents remains low, and further investment and improvement in a bus-friendly built environment deserve more attention [29]. To facilitate public transport in rural areas, four types of strategies have been proposed, including management, policy, public service, and marketing [30]. In both urban and rural areas, higher household income is significantly correlated with the growth of car ownership [39]. However, the aggravation of urban–rural household income inequality seems to be widening the gap of car ownership. In addition, built environment, personal voluntary choice, family life events, and institutional constraints are all important factors influencing inequalities in car ownership.

2.3. Nonlinear Associations between Travel Behavior and the Built Environment

In the past ten years, transport research has progressively matured and deepened. The nonlinear machine learning algorithms have been widely used to study route optimization, environmental protection, traffic prediction, intelligent transportation systems, decision service, etc. [18]. These studies indicate that many scholars question the rationality and accuracy of these pre-defined linear models. These models include the Poisson regression model [41], negative binomial regression model [42], logistic regression [43], ordered probit regression model [44], structural equation model [26], and multinomial logit model [29]. They argue that these pre-defined models could mask the nuanced connections between research variables. Compared with the results of these linear models, nonlinear methods can indicate whether independent variables have promoting or inhibiting effects and also reveal potential threshold effects when the independent variable changes [18].

In recent years, the most used nonlinear methods in related research include random forest (RF) models and gradient boosting decision trees (GBDTs) [45–47]. They tend to interpret complex relationships better than linear models and have higher prediction accuracy. XGBoost (eXtreme Gradient Boosting) was proposed in 2016 and has a very good reputation in data science competitions [48]. In various application domains, XGBoost performs well in solving machine learning challenges [49]. Previous studies suggested the XGBoost method may perform better than linear models, traditional gradient boosting decision tree models, and other machine learning algorithms [50,51]. Employing the XGBoost model, recent studies in China observed nonlinearities among all environmental variables associated with older adults' cycling and bus trips [17]. Built environment variables relating to density, diversity, distance to transit, and aesthetics show positive impacts on bus usage among elderly adults within certain effective ranges (thresholds) [17]. Taking Xiamen as an example, the results of the XGBoost model showed that the relationships between elderly active travel and all built environment variables are nonlinear, and the impacts of some variables are different within origin and destination areas [50]. Due to the outstanding performance of the XGBoost model, we choose to utilize this model in the present study.

2.4. Research Gap

As discussed, although there are some studies on the association between the built environment and bus usage among older adults [8,11,17,21–23], most of them ignored the difference between urban and rural areas. Meanwhile, many recent studies on urban–rural differences in travel behavior focused on mode choice [38], car ownership [39], walking [34,35], cycling [36], etc. However, urban–rural difference studies on the association between the built environment and bus usage is rather limited. Moreover, most studies employed a linear-based model, ignoring the potential nonlinearity between the built environment and travel behavior.

To fill the above research gaps, this study attempts to discover associations between built environment and bus usage among older adults from a novel perspective, by exploring urban–rural differences in nonlinearities.

3. Research Data

3.1. Study Area

This research was conducted in Zhongshan City, which is located in the Guangdong Province of southern China. As a medium-sized city, the total land area of Zhongshan is 1783.67 km^2, and the population is 4.42 million. The bus system in Zhongshan includes 111 bus lines. Considering the level of economic development and travel patterns of Zhongshan, the research findings of this study can be informative to similar Chinese cities [52]. Among the entire 274 neighborhoods in Zhongshan, 74 neighborhoods are located in urban areas and 200 in rural areas, based on the administrative division [52,53].

3.2. Data Sources

The data were provided by the Zhongshan Natural Resources Bureau. The bus usage and socio-demographics data of respondents were collected by the household travel survey. The Zhongshan household travel survey adopted a stratified random sampling method with a 2% sample rate, which included a self-reported travel diary, personal or household socio-demographics, and attitudes towards different travel modes. Overall, the mode share of bus is 4.69% in Zhongshan based on the survey results. The sample size of older respondents (aged 60 and above) was 4329, including 1992 older respondents in urban areas and 2337 older respondents in rural areas. Among these older respondents, 491 (11.3%) of them took at least one bus trip per day, including 252 (12.7%) from urban areas and 239 (10.2%) from rural areas. The neighborhood-level raw data regarding the built environment and social environment included number of dwelling units, intersections, bus stops, and area coverage of major land use types.

3.3. Variables

We chose the number of bus trips per day as the dependent variable to represent bus usage among elderly adults. Trip frequency is often used to reflect the level of physical activity, with a higher bus service level usually linked with a greater probability of reaching the required physical activity level [54].

There are five categories of independent variables in this study, including personal variables, attitudinal variables, household variables, social environment variables, and built environment variables. Personal variables refer to the socio-demographic attributes of respondents, including their gender and age. Attitudinal variables reflect respondents' preference for active travel, public transport, and motorized modes [21]. Household variables refer to the socio-demographics of the household, such as household size, level of annual household income, and household ownership of different transport vehicles.

Meanwhile, four social environment variables and six built environment variables are also included in this study [55]. Compared to other categories of variables which are measured at the personal or household level, all social environment variables and most built environment variables are measured at the neighborhood level, based on the home address of each survey respondent. The social environment factors are measured by the ratio of low-, medium-, or high-income households and the ratio of elderly adults in a community [8]. Five out of six built environment variables are generated based on the "5Ds" [56]. Dwelling unit density is involved as a density indicator for each neighborhood, based on the dwelling unit data provided by the local government. Intersection density stands for road network design, which is counted within each neighborhood using the OpenStreetMap street network. The land-use mixture measures diversity and is determined by an entropy index [52,57], and was calculated for each neighborhood by utilizing land-use data. According to the home address of each respondent, the distance to the CBD and distance to the nearest bus stop are determined using the OpenStreetMap street network to measure destination accessibility and distance to transit, respectively. Based on the land-use data, the last built environment variable represents aesthetics by measuring the ratio of green space to all land uses within each neighborhood. Prior studies suggest that well-designed greenery, e.g., parks, gardens, and roadside plants, encourages older adults to choose active travel and public transport more frequently [58–60]. All variables utilized in this study are listed in Table 3. For built environment variables, the average distance to the bus station for rural regions is longer than in urban regions, which further reflects the unequal bus supply between urban and rural regions. Though, the values of other five items are lower within rural areas than those of urban areas.

Table 3. Descriptive statistics of variables.

Variable	Variable Description	Urban		Rural	
		Mean	S. D.	Mean	S. D.
Bus trips	Number of daily bus trips (count)	0.26	0.76	0.21	0.65
(1) Personal variables					
Gender	1 = Male, 0 = Female (binary)	0.57	-	0.63	-
Age	Age of the respondent (years)	67.24	6.58	66.91	6.73
(2) Attitudinal variables					
Pre_Walk	Ratio of respondents who prefer walking most (scale)	0.32	-	0.23	-
Pre_Bike	Ratio of respondents who prefer bike most (scale)	0.14	-	0.19	-
Pre_E-bike	Ratio of respondents who prefer e-bike most (scale)	0.05	-	0.07	-
Pre_Bus	Ratio of respondents who prefer bus most (scale)	0.22	-	0.23	-
Pre_Motor	Ratio of respondents who prefer motorcycle most (scale)	0.11	-	0.13	-
Pre_Car	Ratio of respondents who prefer private car most (scale)	0.03	-	0.03	-
(3) Household variables					
HH_Size	Number of family members in the household (count)	2.65	1.36	2.59	1.29
Low_Inc	The household income is low [1] (1 = yes or 0)	0.28	-	0.45	-
Med_Inc	The household income is medium [1] (1 = yes or 0)	0.52	-	0.44	-
High_Inc	The household income is high [1] (1 = yes or 0)	0.20	-	0.11	-
Num_Bike	Number of bikes in the household (count)	0.57	0.70	0.67	0.71
Num_E-bike	Number of e-bikes in the household (count)	0.17	0.43	0.26	0.47
Num_Motor	Number of motorcycles in the household (count)	0.77	0.83	0.75	0.87
Num_Car	Number of private cars in the household (count)	0.16	0.43	0.17	0.45
(4) Social environment variables					
P_Low_Inc	Ratio of low income household [1] in the neighborhood (scale)	0.04	-	0.26	-
P_Med_Inc	Ratio of medium income household [1] in the neighborhood (scale)	0.57	-	0.65	-
P_High_Inc	Ratio of high income household [1] in the neighborhood (scale)	0.40	-	0.09	-
P_Older	Ratio of older adults (scale)	0.15	0.07	0.12	0.05
(5) Built environment variables					
Dw_Den	Dwelling unit density (1000 units/km^2)	5.87	4.96	0.90	0.93
Inter_Den	Intersection density (five intersections/km^2)	4.51	3.60	1.15	1.48
Land_Mix	Land use mixture entropy (scale)	0.71	0.19	0.69	0.17
Dis_CBD	Euclidean distance from home to CBD (km)	2.08	0.85	1.85	1.05
Dis_Bus	Distance from home to the nearest bus stop (km)	0.42	0.31	0.58	0.39
P_Green	Ratio of green space among all land uses (scale)	0.08	0.09	0.06	0.07

Note: [1] Household income has been categorized into low (<20,000 RMB/year), medium (20,000–60,000 RMB/year), and high (>60,000 RMB/year).

4. Methodology

XGBoost and GBDT both belong to the boosting machine learning method. The boosting method can improve the performance of any given algorithm. The main purpose of boosting is to continuously reduce the residual error of the previous tree by growing new trees. Overall, XGBoost can better handle nonlinearity, and it has some unique advantages over other models for this study [17,59]. First, the computational loss of XGBoost is smaller compared with traditional decision tree models because it uses the second derivative of the approximation term for Taylor expansion on the objective function. Second, XGBoost adds a regular term to control model complexity, which can effectively avoid overfitting. Meanwhile, XGBoost supports column sampling, which reduces both overfitting and calculation and improves operation efficiency. Finally, XGBoost can handle missing values by identifying the direction of split.

XGBoost model error mainly comes from training loss and model complexity. In XGBoost, the objective function or loss function can be defined as:

$$obj = \sum_{i} l(y_i, \hat{y}_i) + \sum_{k} \Omega(f_k) \tag{1}$$

where the first part represents the degree of fitting for training dataset, and the second part represents the complexity of the model. Meanwhile, $(y_i - \hat{y}_i)^2$ can be used to represent $l(y_i, \hat{y}_i)$, which is the square loss for the regression problem. In this study, y_i represents actual bus use among older adults, and $\hat{y}_i$ represents the predicted daily bus trips. Then, we can add a new tree and rewrite the objective function, where $\Omega(f_t)$ represents the complexity of tree f_i:

$$obj^{(t)} = \sum_{i=1}^{n} l\left(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)\right) + \Omega(f_t) + constant \tag{2}$$

Based on the second-order Taylor expansion, we can expand the objective function. Then we can remove the constant term in further calculations. The constant measures the difference between the predicted value in the previous iteration and the actual value [48]:

$$obj^{(t)} \backsimeq \sum_{i=1}^{n} \left[l\left(y_i, \hat{y}^{(t-1)}\right) + m f_t(x_i) + 1/2 p_i f_t^2(x_i) \right] + \Omega(f_t) \tag{3}$$

$$m_i = \partial_{\hat{y}^{(t-1)}} l\left(y_i, \hat{y}^{(t-1)}\right), \ \ p_i = \partial^2_{\hat{y}^{(t-1)}} l\left(y_i, \hat{y}^{(t-1)}\right) \tag{4}$$

where m_i and p_i represent the first-order and second-order partial derivative, respectively. The objective function only rests with m_i and p_i for each data point in the error function. The complexity is defined as follows [10]:

$$\Omega(f_t) = \gamma T + 1/2 \lambda \sum_{j=1}^{T} \omega_j^2 \tag{5}$$

where w_i shows the score on the ith leaf, T shows the number of leaf nodes, γ is a threshold parameter, controlling the number of leaf nodes, and λ is used for regularization, controlling the score of the control leaf node. Then, define $I_j = \{i | q(x_i) = j\}$ as the instance set of leaf j, $M_i = \sum_{i \in I_j} m_i$, $P_i = \sum_{i \in I_j} p_i$. The objective function can be rewritten again as follows:

$$\begin{gathered} obj^{(t)} \backsimeq \sum_{i=1}^{n} \left[m_i f_t(x_i) + 1/2 p_i f_t^2(x_i) \right] + \Omega(f_t) \\ = \sum_{i=1}^{n} \left[m_i \omega_{q(x_i)} + 1/2 p_i \omega^2_{q(x_i)} \right] + \gamma T + 1/2 \lambda \sum_{j=1}^{T} \omega_j^2 \\ \sum_{j=1}^{T} \left[\left(\sum_{i \in I_j} m_i \right) \omega_j + 1/2 \left(\sum_{i \in I_j} p_i + \lambda \right) \omega_j^2 \right] + \gamma T \\ \sum_{j=1}^{T} \left[M_j \omega_j + 1/2 (P_j + \lambda) \omega_j^2 \right] + \gamma T \end{gathered} \tag{6}$$

The optimal weight $w_j^* = -M_i / (P_i + \lambda)$. Then, the optimal objective function value can be expressed as follows:

$$obj^{(t)} = -1/2 \sum_{j=1}^{T} \frac{M_j^2}{P_j + \lambda} + \gamma T \tag{7}$$

Enumerating all possible tree structures is impossible. We choose the greedy algorithm to enumerate varying types of tree structures. A better tree structure is equal to a smaller score [49]. Then we can obtain the optimal model. After the split, we define the loss reduction as follows (the left and middle parts in the brackets represent the score of the left node and right nodes, while the right part in the brackets represents the score without tree splitting):

$$obj_{(split)} = 1/2\left[\frac{\left(\sum_{i\in I_L} m_i\right)^2}{\sum_{i\in I_L} p_i + \lambda} + \frac{\left(\sum_{i\in I_R} m_i\right)^2}{\sum_{i\in I_R} p_i + \lambda} - \frac{\left(\sum_{i\in I_I} m_i\right)^2}{\sum_{i\in I_I} p_i + \lambda}\right] - \gamma \tag{8}$$

This study will use relative importance and partial dependence plots to visually present the results, which are the most frequently used methods of explaining machine learning models [50].

5. Results

5.1. Model Performance

We adopted XGBoost to predict the daily bus trips of elderly adults in urban or rural regions and investigate the relative importance of independent variables. The XGBoost model was developed based on the "xgboost" package in Python, and a five-fold cross validation was conducted. Then, we illustrated nonlinear associations between bus use and built environment variables by depicting the corresponding Partial Dependence Plots (PDPs), and several important thresholds were concluded in these PDPs.

We compared the model performance of traditional multiple linear regression, GBDT, and XGBoost models by calculating mean square error (MSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). According to the results in Table 4, the XGBoost model performed best by all three indicators.

Table 4. Comparison among XGBoost, GBDT, and multilinear regression models.

Area	Model	MSE	MAE	MAPE
Urban	Multilinear regression	0.66	0.55	26.02
	GBDT	0.23	0.35	19.39
	XGBoost	0.21	0.29	16.46
Rural	Multilinear regression	0.41	0.45	25.04
	GBDT	0.21	0.31	18.76
	XGBoost	0.22	0.25	14.32

5.2. Feature Importance of Independent Variables

Relative feature importance is commonly employed to interpret machine learning models [38]. A variable with higher relative importance demonstrates a stronger effect on the prediction. The total contribution is equal to 100%, because the relative importance of each variable is scaled and measured in a relative way (Figure 1).

The collective relative importance of different categories of independent variables in predicting bus usage for urban and rural elderly adults in the form of percentages is presented in Figure 2. Built environment categories play the most important role in prediction in both urban and rural areas (Figure 2), which is consistent with prior literature utilizing nonlinear methods [17,46,49,50,61]. This finding illustrates the efficacy of built environment interventions in promoting bus usage for elderly adults. However, the relative importance of the built environment in rural regions (49.05%) is significantly higher than in urban areas (34.75%). On the contrary, household, personal, and attitudinal variables contribute more highly in urban regions than in rural regions. The relative importance of the social environment in both urban and rural areas is similar. The results reflect that well-being differences and unbalanced development do exist in urban and rural regions [4]. Despite achievements in the construction of rural roads, urban areas are still ahead of rural areas in public and infrastructure construction, cultural industries, entertainment activities, etc. [29]. This enables urban older adults to pay more attention to themselves, and self-preference and personal factors are more relevant to travel demand and choices for them, whereas in rural areas the built environment is still the critical facilitator of bus usage among rural elderly adults.

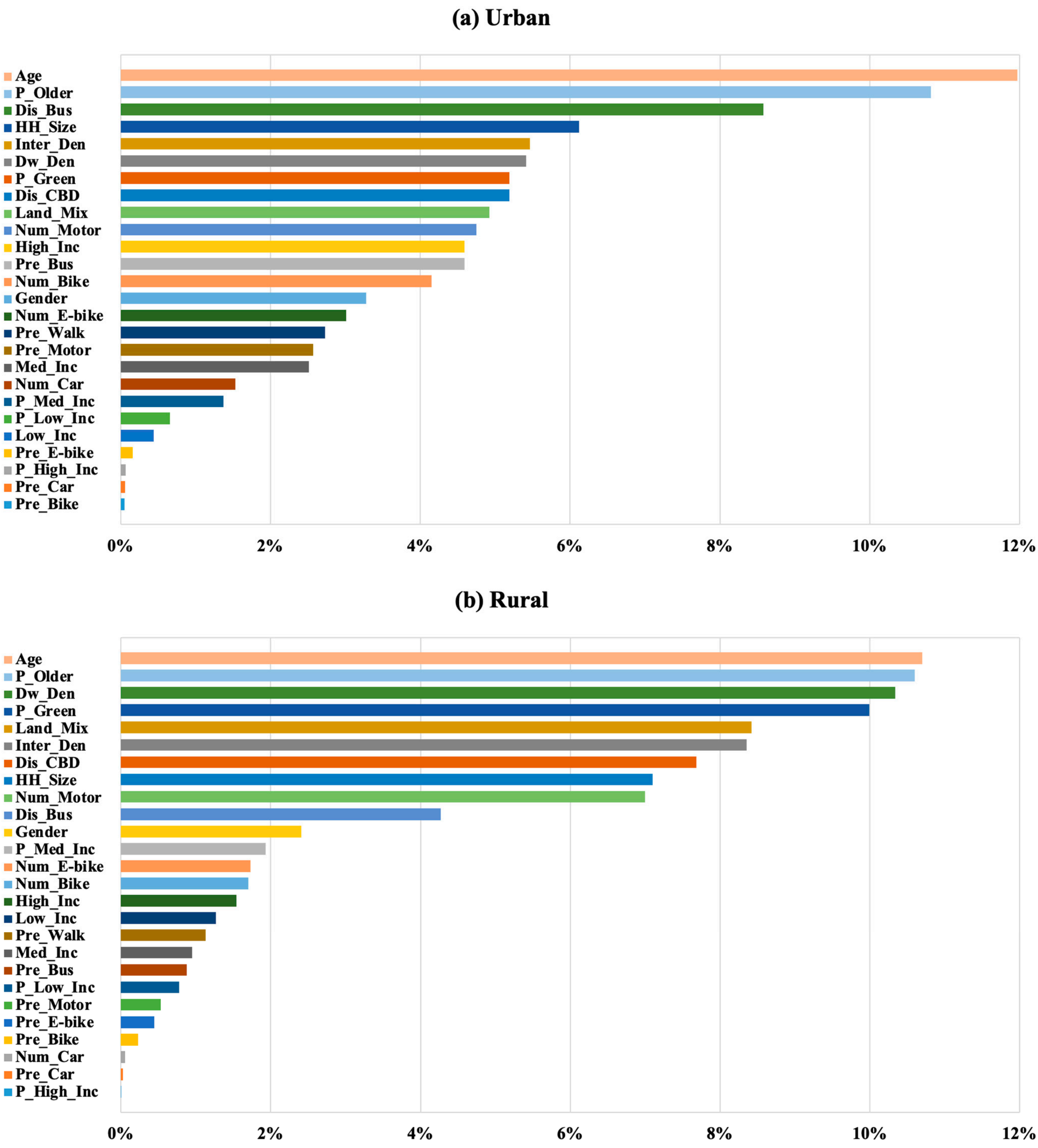


Figure 1. Relative importance of independent variables in urban and rural areas.

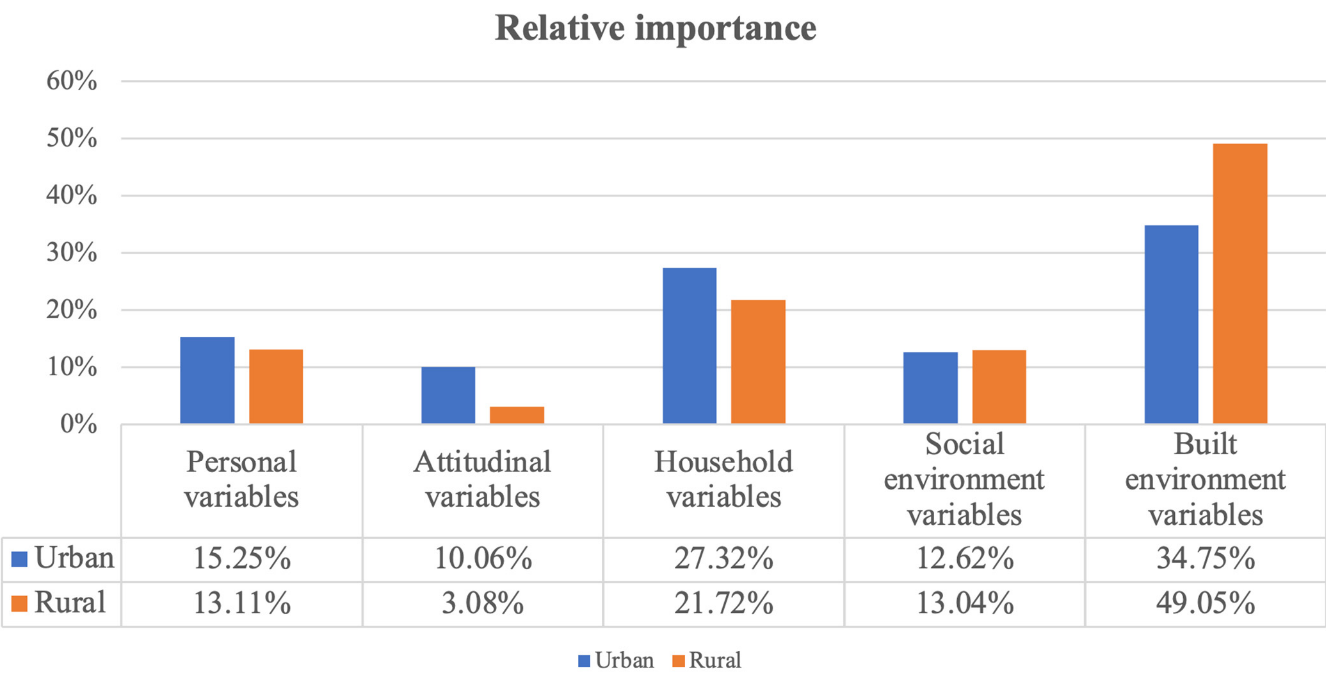


Figure 2. Differences in relative importance of the five categories.

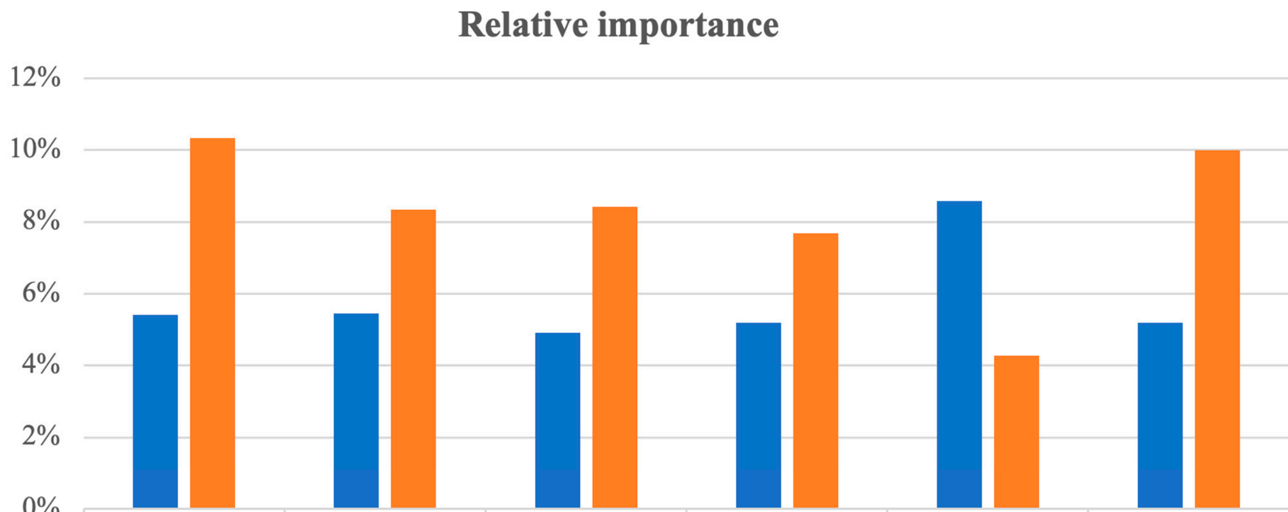
Based on the size of the relative importance, all six built environment variables are within the top ten most important variables (Table 5).

Table 5. Relative importance of the top ten most critical variables.

Rank	Urban		Rural	
	Predictors	Relative Importance	Predictors	Relative Importance
1	Age (PV)	11.97%	Age (PV)	10.70%
2	P_Older (SE)	10.82%	P_Older (SE)	10.60%
3	Dis_Bus (BE)	8.58%	Dw_Den (BE)	10.34%
4	HH_Size (HH)	6.12%	P_Green (BE)	9.99%
5	Inter_Den (BE)	5.46%	Land_Mix (BE)	8.42%
6	Dw_Den (BE)	5.41%	Inter_Den (BE)	8.35%
7	Dis_CBD (BE)	5.19%	Dis_CBD (BE)	7.68%
8	P_Green (BE)	5.19%	HH_Size (HV)	7.10%
9	Land_Mix (BE)	4.92%	Num_Motor (HV)	7.00%
10	Num_Motor (HV)	4.75%	Dis_Bus (BE)	4.27%
	Total	68.41%	Total	84.45%

Notes: PV: Personal variables; HV: household variables; SE: social environment variables; BE: built environment variables.

In the urban context, the distance from home to the nearest bus stop contributes the most among six built environment variables, with a relative importance of 8.58% (Figure 3). Interestingly, this variable plays the smallest role in the rural context, with a relative importance of only 4.27%. This finding indicates urban–rural differences between the effects of transit service on bus usage among elderly adults. The relative importance of the remaining five built environment variables in the urban contexts ranges from 4.92% to 5.46%. In the rural context, the relative importance of dwelling unit density and ratio of green space to all land-use types is close to 10%, ranking in the top two among six built environment variables. Besides the built environment, the remaining four variables in the top ten come from three categories: personal, household, and social environment. The age of the respondents plays the most crucial role in bus use for both urban and rural older adults, with relative importances of 11.97% and 10.70%, respectively. Similarly, the ratio of older adults in the neighborhood ranked second among all variables in both urban (10.82%) and rural (10.60%) regions. For household variables, household size and motorcycles ownership are both among the top ten variables.



	Dw_Den	Inter_Den	Land_Mix	Dis_CBD	Dis_Bus	P_Green
Urban	5.41%	5.46%	4.92%	5.19%	8.58%	5.19%
Rural	10.34%	8.35%	8.42%	7.68%	4.27%	9.99%

Urban Rural

Figure 3. Relative importance of built environment variables in urban and rural area.

5.3. Urban–Rural Differences in the Nonlinear Associations of the Built Environment

5.3.1. Dwelling Unit Density

In urban areas, the curve of dwelling unit density resembles an inverted u-shape (Figure 4a). Bus use rises rapidly when the dwelling unit density changes from 17 to 2400 units/km^2. Afterward, it remains almost steady when the dwelling unit density increases from 2400 to 9500 units/km^2. Beyond this range, bus use declines as the dwelling unit density is extremely high. In rural areas, within the range of 100 to 500 units/km^2, bus use among older rural adults increases sharply and then fluctuates from 500 to 1200 units/km^2 (Figure 4b). Beyond the threshold of 1200 units/km^2, it drops rapidly with some volatility.

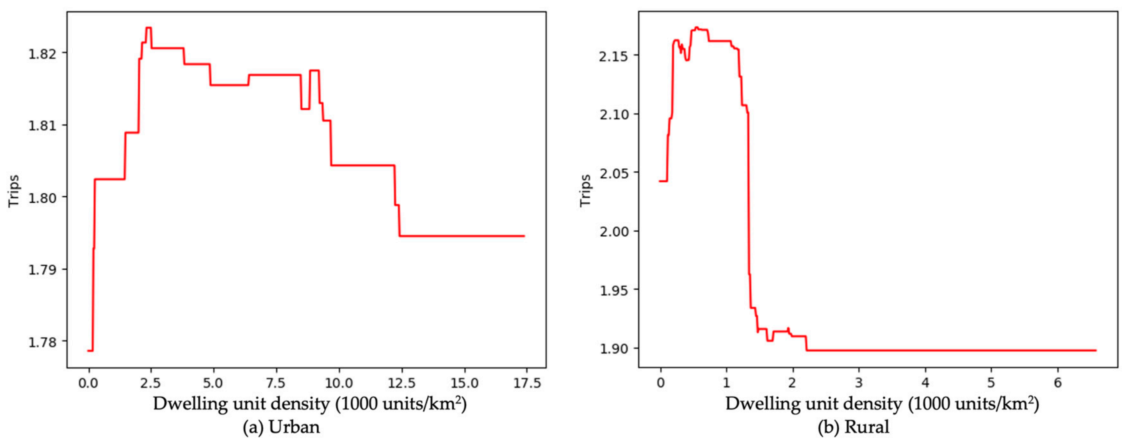


Figure 4. The effects of dwelling unit density in urban and rural areas.

Dwelling unit density is linked with a high propensity of bus use among older adults when it is between 300 and 1100 units/km^2 in rural areas or between 2400 and 5000 units/km^2 in urban areas. However, the most effective range of dwelling unit density is between 2400 and 5000 units/km^2 in urban areas. These effects gradually decline when the dwelling density is beyond these effective ranges. In a highly densified neighborhood, there are more destinations which can be accessed within a short walking distance. Therefore, older adults can meet most of their needs without taking a bus [45]. Another possible reason is that ultra-high-density development is related to more passengers and crowded carriages [17]. That will increase the risk of falls among elderly adults [7,45]. The fear of falling may lower the bus ridership of older adults [11]. The negative effects of high dwelling density on bus usage among older adults are not consistent with previous studies, which concluded that high residential density may decrease the likelihood of taking a bus among younger people but increase bus usage among older people [62].

5.3.2. Intersection Density

Figure 5a demonstrates that bus usage among older urban adults appears to steadily increase almost linearly within the range of 0 to 15.1 intersections/km^2. It reaches a peak when intersection density is in the effective range of 15.1 to 27.1 intersections/km^2. Afterward, it drops sharply. Figure 5b shows that the number of daily bus trips of elderly rural adults fluctuates at a high level within the range of 7.5 to 26.8 intersections/km^2. Finally, it undergoes a sharp decrease when the intersection density is over 28.1 intersections/km^2.

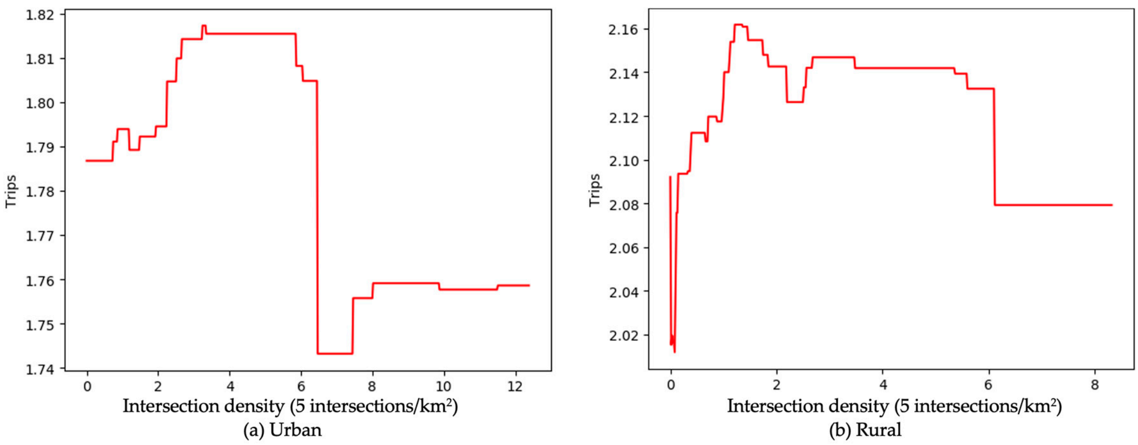


Figure 5. The effects of intersection density in urban and rural areas.

For older urban and rural adults, although the nonlinear trends of intersection density are different, their daily bus trips both drop sharply beyond the threshold of around 27 intersections/km^2 (Figure 5a,b). This is reasonable for several reasons. High intersection density is often related with high traffic accident risk and long waiting times for red lights, which may greatly affect the bus travel experience among older adults [63]. Meanwhile, denser intersections mean better street connectivity, which can provide more alternative routes and shorter distances to different destinations [45]. Older adults may opt for active travel in such neighborhoods. Other studies also found positive effects of intersection and road connectivity on metro usage and active travel for older adults, and the effective ranges are also different in urban and rural areas [64,65].

5.3.3. Land Use Mixture

In urban areas, when the entropy index increases from 0 to 0.42, bus usage among older adults rises to the highest point (Figure 6a). Bus usage remains stable when the EI ranges from 0.42 to 0.57, following by a subtle decrease. In rural contexts, mixed development is positively associated with bus use (Figure 6b). Bus use increases stably and reaches a high point when the entropy index ranges from 0.08 to 0.52. After some volatility between 0.52

and 0.75, bus use fluctuates at a higher point and arrives at its peak as the entropy index reaches a threshold of 0.85.

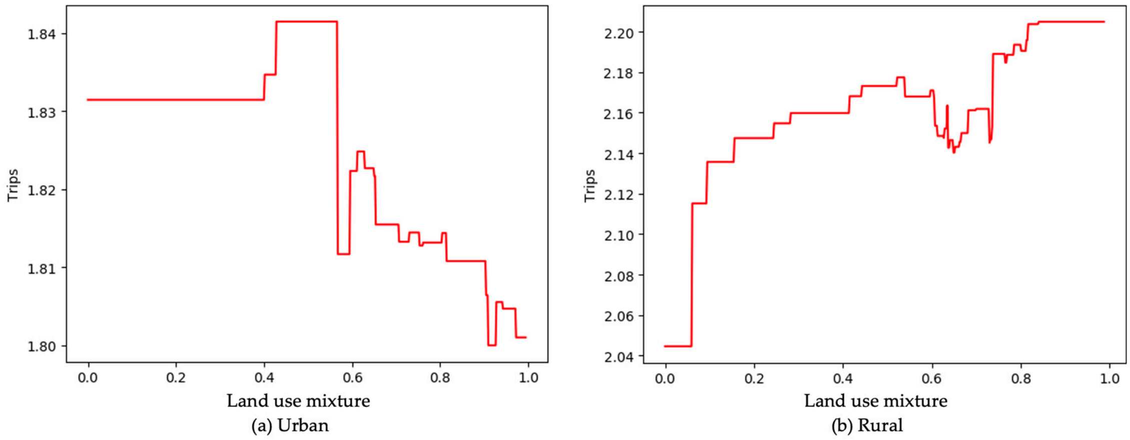


Figure 6. Impact of land use mixture on bus usage in urban and rural areas.

The travel purposes and daily activities of older adults are unique [66]. For Chinese older adults, popular outdoor activities include park walking, mahjong playing, and friend visiting [67]. The mode choices of older adults are associated with the accessibility of entertainment venues, fitness facilities, and services [68]. They also have a high demand for convenient medical services, especially within the neighborhood [11,69]. Thus, the degree of the land use mixture is closely correlated with the travel choices of older adults.

The effective and reliable range of the mixture for rural older adults is generally higher than that for urban ones (Figure 6a,b). Low land use mixture in rural contexts usually refers to high ratio of land with residential and agricultural functions, which does not attract older adults to travel more. Therefore, an increase in land use mixture will play a foreseeable role in improving bus usage among older adults [61]. However, in urban areas, once the EI exceeds a threshold value of 0.57, bus trips drop sharply (Figure 6a). Similar effects of land use mixture have also been found by prior studies on metro usage and e-bike ownership [65,70]. However, the nonlinear impacts of land use mixture on walking duration are quite different, with a u-shaped curve among older adults [24]. A possible reason is that the daily needs of older adults can be satisfied within the vicinity of their homes if the land use is more complex. In this context, older people are more inclined to choose walking or cycling over public transit.

5.3.4. Distance from Home to the CBD

For older urban adults, the distance from home to the CBD is negatively associated with bus use (Figure 7a). The number of daily bus trips first drops sharply with increasing distance ranging from 0 to 0.25 km. Afterward, it flattens with slight fluctuations when the distance grows from 0.25 to 2 km. Beyond this range, bus use further declines gradually. In rural areas, the number of daily bus trips drops slightly when the distance from home to the CBD rises from 0.04 to 1.25 km (Figure 7b). Then bus use among older rural adults experiences a subtle increase when the distance is beyond 1.25 km. Once the distance is beyond a threshold of 2.73 km, bus use decreases sharply.

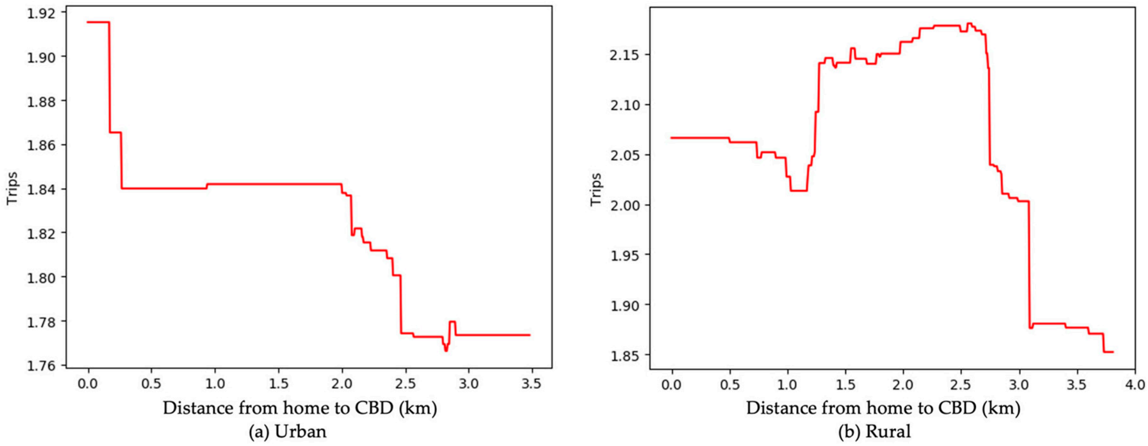


Figure 7. The effects of distance from home to the CBD in urban and rural areas.

Urban older adults who live near the CBD are more willing to travel by bus, since bus service is more accessible in such neighborhoods (Figure 7a). When the distance from home to the CBD becomes longer, especially beyond 2 km, they may change to other modes with satisfying service for medium-to-long trips, such as car, taxi, or car-sharing services. In rural area, older adults rely more on public transport to access the CBD because car ownership rates are relatively low, and long-distance transport modes are limited [6]. However, another study concluded that a long distance from home to the city center can increase the likelihood of choosing a bus over a private car, no matter for younger or older people [62].

5.3.5. Distance from Home to the Nearest Bus Stop

In urban areas, when the distance from home to the nearest bus stop is within the effective range of 0.18 to 1.0 km, bus use remains at a high level and peaks at approximately 0.32 to 0.6 km (Figure 8a). When the distance is shorter than 0.2 km or longer than 1.0 km, the effect on bus use is limited. Figure 8b illustrates that the distance from home to the nearest bus stop is negatively correlated with the number of daily bus trips of older rural adults. Bus use declines stably when the distance changes from 0.15 to 0.6 km. Following that, bus use remains flat.

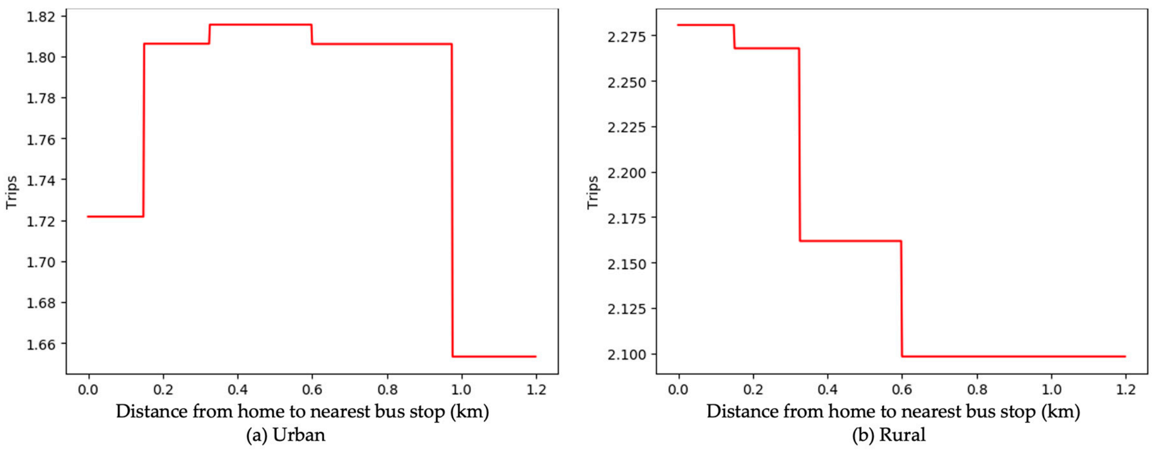


Figure 8. The effects of distance from home to the closest bus stop in urban and rural areas.

Generally, nonlinear associations with the distance to transit are consistent with our expectations. Within a shorter range, the distance between home and the closest bus stop improves bus usage for elderly adults in urban and rural regions. Other studies also found that a long distance from home to the nearest bus stop can be a barrier for older adults, due to physical strength requirements and safety concerns [11]. Some older adults need support from their family members to reach bus stops [71]. Meanwhile, it is noticed that the most effective range in rural areas is smaller than in urban areas (Figure 8a,b). A possible reason is that older rural adults have fewer options to access bus stops, and a long access distance can limit their willingness to choose the bus.

5.3.6. Ratio of Green Space

The PDP for the ratio of green space to all land use types in the urban areas is illustrated in Figure 9a. The number of bus trips of older urban adults rises and remains steady as the ratio increases from 1% to 19%. Beyond a threshold of 19%, bus use drops slowly with some fluctuations. Figure 9b shows the nonlinear association with the accessibility of green space. Within the range of 1.0% and 2.6%, the ratio of green space land use is significantly correlated. Bus use remains nearly constant if the ratio is between 2.6% and 6.5%. When the ratio is beyond 7.8%, the positive impact is trivial.

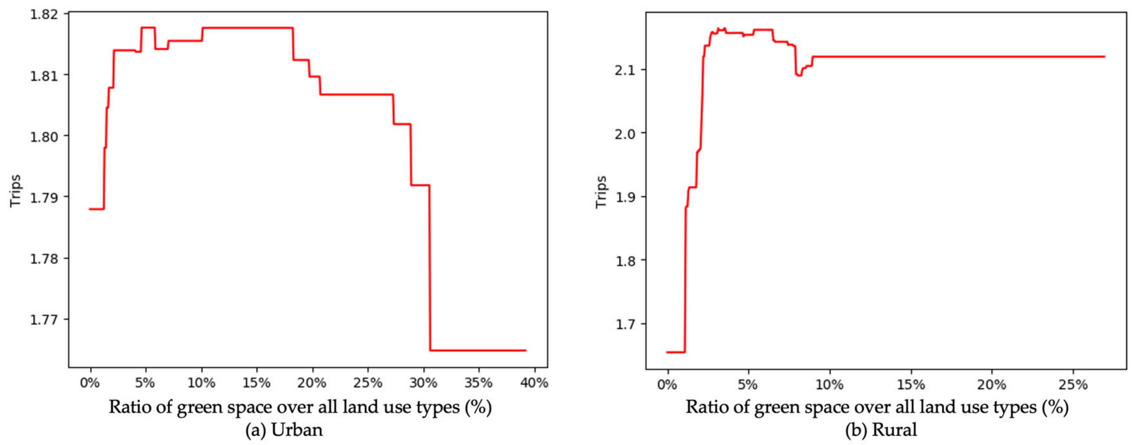


Figure 9. The effects of the ratio of green space to all land use types in urban and rural areas.

Figure 9 indicates that an appropriate amount of green space is effective to increase bus use, albeit among different ranges across urban and rural neighborhoods. For older urban adults, the most effective and reliable range is between 5% and 19%. In rural areas, the most influential range is 2.6% to 6.5%. Existing literature has found significant differences in the types and accessibility of green spaces, as well as opportunities to use them, between urban and rural regions [72,73]. There are more natural green spaces in rural areas, while greenways, ecological corridors, parks, and other leisure green spaces exist in urban areas [73]. Hence, the positive effect on older rural adults is limited with an increasing proportion of green space. In urban areas, excessive greenery may even hinder older adults' travel needs for the bus, as it is likely to block their sight and routes and reduce the convenience of walking or cycling to the bus stop [74].

5.4. Effective Ranges of Built Environment Variables in Urban and Rural Areas

To summarize the above-mentioned findings in urban areas, the number of daily bus trips of older urban adults may be higher when (Table 6):

(a) The dwelling unit density is high (2400–5000 units/km^2)
(b) The intersection density is high (15.1–27.1 intersections/km^2)
(c) The land use mixture is medium (0.43–0.57)
(d) The distance from home to the CBD is short (<0.25 km)
(e) The distance from home to the nearest bus stop is medium (0.32–0.6 km)
(f) The ratio of green space land use is medium to high (5–19%)

Table 6. Effective ranges of built environment variables on bus usage for urban and rural elderly adults.

Built Environment Variables	Urban	Rural
Dwelling unit density, units/km^2	2400–5000	300–1100
Intersection density, intersections/km^2	15.1–27.1	7.5–26.8
Land use mixture, *EI*	0.40–0.57	0.42–0.82
Euclidean distance between home and CBD, km	0–0.25	1.25–2.73
Distance between home and the closest bus stop, km	0.32–0.6	0–0.32
Ratio of green space to all land uses, %	5–19%	2.6–6.5%

According to the results in rural areas, older rural adults may choose the bus more often when (Table 6):

(a) The dwelling unit density is low to medium (300–1100 units/km^2)
(b) The intersection density is medium to high (7.5–26.8 intersections/km^2)
(c) The land use mixture entropy index (EI) is medium to high (0.42–0.82)
(d) The distance from home to the CBD is long (1.25–2.73 km)
(e) The distance from home to the nearest bus stop is short (<0.32 km)
(f) The ratio of green space land use is low (2.6–6.5%)

The threshold effects of the six built environment variables indicate different characteristics in urban and rural regions. The most effective ranges of intersection density and land use mixture in urban areas overlap those in rural areas. Older urban adults tend to generate more bus trips if they live in high-density neighborhoods adjacent to green space and the CBD. Meanwhile, the likelihood of rural elderly adults to take a bus becomes higher if the walking distance from home to the nearest bus stop is shorter.

6. Conclusions and Implications

This study attempts to explore urban–rural differences in bus usage among old-er adults, with data from Zhongshan, China and the eXtreme Gradient Boosting (XGBoost) model. The contributions of this study to the literature are threefold. First, it reveals the relative importance of built environment variables, together with socio-demographic, attitudinal, and social environment variables, in predicting older adults' bus trips in urban and rural neighborhoods. Second, it compares urban–rural differences in nonlinear associations between the built environment and daily bus usage among elderly adults. Third, it proposes effective ranges of built environment variables in urban and rural regions to guide planning interventions.

In this study, we chose five categories of independent variables from three aspects: socio-demographics, attitudes, and the neighborhood-level social and built environment. Relative importance indicates that built environment variables have the largest effect in both urban and rural areas but play a more important role in rural regions (49.05%) than in urban regions (34.75%). On the contrary, household, personal, and attitudinal variables contribute more highly in urban areas. The social environment has similar relative importance in both urban and rural areas.

Based on relative importance, all six built environment variables are within the top ten variables in both urban and rural areas. In urban areas, the distance from home to the nearest bus stop contributes the most, whereas this variable plays the smallest role in rural areas. This result suggests urban–rural differences between the effects of facilitating transit service on bus usage among elderly adults. In a rural context, the relative importance of dwelling unit density and green space ratio to all land use types rank top two among the six built environment variables. This indicates the potential of improving density and aesthetics on the bus ridership of elderly rural adults. Besides built environment variables, the age of the respondents and the ratio of older adults in the neighborhood rank top two among all variables in both urban and rural areas. Additionally, two household variables—-household size and motorcycle ownership—-are both among the top ten variables.

The twelve partial dependence plots reveal the most effective ranges of the six built environment variables in either urban or rural regions. Currently, in Zhongshan, like many other Chinese cities, urban areas are undergoing intensive urban renewal and construction of new cities. It is important to build a bus-friendly environment for older urban adults during that process. Policymakers and planners are suggested to develop high-density neighborhoods adjacent to the CBD and increase green space land use for a high propensity of bus usage among elderly urban adults. An increase in intersection density to 15.1–27.1 intersections/km^2 is recommended to increase older urban adults' bus ridership. A medium level (between 0.40 to 0.57) of land use mixture is also recommended, as ultra-mixed development may impact the bus ridership of older urban adults negatively.

The built environment of rural areas in Zhongshan is changing rapidly due to new village construction. Traditionally, allocation of rural land use is scattered, and bus service is poor. To promote bus usage among elderly rural adults, planners should be aware of urban–rural differences between the effects of the built environment and apply well-tailored planning strategies. Medium-dense and medium-to-high-mixed development are suggested in rural neighborhoods to facilitate bus usage among older adults. Another potential intervention is to increase intersection density. Currently, in rural areas, the intersection density is low, and traffic volumes are smaller. Although the effective range of intersection density is as high as 26.8 intersections/km^2, we suggest raising the intersection density to the medium level to examine the actual effects on bus use. Additionally, we recommend shortening the distance to bus stops by designing new bus stops adjacent to rural residential areas.

Our findings may help policymakers and planners to understand the complex relationship between the built environment and bus usage among elderly urban and rural adults. Hence, they can adopt fine-grained and diversified built environment interventions to facilitate bus-friendly neighborhoods in urban and rural areas. This study has a few limitations. First, this paper used cross-sectional data and discussed correlation. Further studies are encouraged to use time-series data or panel data to explore causality. Second, although the utilized methodology can be applied universally, the results may not be generalizable to other cities. Finally, this study did not include other variables that may associated with older adults' bus trips, such as the weather or the built environment attributes at destinations. Further studies should explicitly explore these research aspects to better inform land use and transportation planning strategies.

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