

Article

Exploring Nonlinear Effects of the Built Environment on Employment Behavior Among Older Adults: Evidence from Metro Station Catchment Areas

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Abstract: Social interaction, such as voluntary employment, can promote well-being and mental health for older people. Since walking and public transit are two major commuting modes for older adults, understanding the determinants of older employment behavior near metro stations is critical for the government and urban planners to encourage older employment. Using the mobile signaling data of 1,640,145 older employees and other multi-source spatiotemporal datasets in Shanghai, the Light Gradient Boosting Machine (LightGBM) is employed in this study to explore the nonlinear effects of the built environment on older employment near 333 metro stations. Results show that density, diversity, and design variables have a significant contribution on older employment, while distance to the city center, employment density among all age groups, and the number of older residents are the top three important variables. Partial dependence plots reveal that all independent variables have irregular nonlinear impacts on older employment. Each variable needs to reach an associated threshold to maximize older employment, and their nonlinear impacts are only effective when they are within certain ranges. Research findings can promote older employment and benefit mental health among older people by helping the government prioritize urban planning policies or interventions.

Keywords: older employment; social participation; built environment; nonlinearity; mental health; older adults



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1. Introduction

Accelerated population aging has caused a series of physical and mental challenges for older adults [1–3]. The mental health disorders can lead to several consequences, such as mild cognitive impairment [4] and disease burden [5], and it can even be harmful to physical health (e.g., increase the risk of disability [6] and suicide [7]) among older adults. Under this circumstance, employment and social participation have been proven to be significantly associated with mental health, well-being, and quality of life amongst the older population [8,9]. The promotive effects of elderly employment and retirement delay on the mental health of older people have been explored by many studies in different contexts [9,10]. Therefore, understanding employment behavior is essential for the government and policymakers to promote the physical and mental health for older adults by facilitating their social participation.

Given the safety concerns and inconvenience of driving or cycling for older adults, the integrated usage of walking and public transit (e.g., metro, bus) has become the major commuting choice for older employees [11]. The integrated usage of walking and public transit also echoes the promotion of reducing car dependency brought by the 15 min city urban planning concept. Transportation subsidies have been provided for older adults

to facilitate the use of public transit systems in many Chinese cities [12]. In this context, older employees tend to choose jobs close to their housing or a metro station, which can be easily accessed by the integrated use of walking and the metro system [13]. Consequently, it is crucial for urban planners to explore the determinants of older employment behavior around metro stations.

Among several categories of factors that may affect the behavior of older adults, the built environment has been progressively investigated by different scholars. In the past few decades, the built environment has been widely examined from different perspectives, gradually from “3Ds” (density, diversity, design) [14] to “5Ds” (distance to transit, destination accessibility) [15] and “7Ds” (demand management, demographics) [16]. Specifically, the built environment has been proven by many previous studies to affect several behaviors among older adults, such as active travel [17], physical activity [18], walking time [19,20], depression [21], bus use [12], cycling frequency [22], walking duration [13], propensity to walk [23], body mass index (BMI) [1], mental well-being [24], etc. Therefore, it is reasonable to assume that the built environment can be one of the critical determinants of employment behavior among older adults, while previous studies failed to address this issue.

Among previous studies on the built environment, many of them have investigated the effects of the built environment by employing linear-based models (e.g., multivariate linear regression, ordinary least squares regression), ignoring the potential nonlinearity between the built environment and elderly behavior [20,25,26]. Meanwhile, most of the previous studies based on survey or questionnaire results from older individuals ignored the areal characteristics and group behavior from a regional perspective [10,25]. With the development of computer science and big data, many scholars have attempted to examine the nonlinear relationship between the built environment and elderly behavior by utilizing different machine learning algorithms, such as Gradient Boosting Decision Trees (GBDTs), Random Forests (RFs) [19], eXtreme Gradient Boosting (XGBoost) [12,24], and Light Gradient Boosting Machines (LightGBMs) [27]. However, studies on the nonlinear relationship between the built environment and elderly employment with machine learning approach is rather limited.

To fill these gaps, we employ the LightGBM, a nonlinear machine learning approach to estimate the impacts of the built environment on older employment near metro stations in Shanghai, China by collecting multi-source datasets. This study tries to address the following questions: (1) What is the relative importance of each built environment factor for affecting elderly employment near metro stations? (2) What is the nonlinear relationship between these variables and employment among older adults? Research findings on these questions can inform government and policymakers identify critical factors on affecting older employment near metro stations and help develop associated strategies to promote the mental health of older adults by facilitating their employment and social participation.

The subsequent part of this manuscript is organized as follows: The next section introduces the materials and methods, including the study area, data sources, variables, measurement, and methodology. Section 3 presents the model results from different perspectives. Section 4 discusses the major research findings. Section 5 summarizes the paper and points out the limitations.

2. Materials and Methods

2.1. Study Area

We conducted a case study in Shanghai, a megacity that has the longest metro operation mileage in the world and where over 25% of the population is elderly [28]. Overall, the buffer area of 333 metro stations among 15 metro lines was selected to evaluate the elderly employment and built environment near metro stations (Figure 1). According to the average distance between metro stations and acceptable walking distance for aging people, the 500 m buffer was selected for each metro station to evaluate the station-level older employment and built environment. In this study, the 400 m buffer may not compre-

hensively present the station-level built environment in the suburban area, while the 800 m buffer can have a significant overlapping area and lead to ecological fallacy.

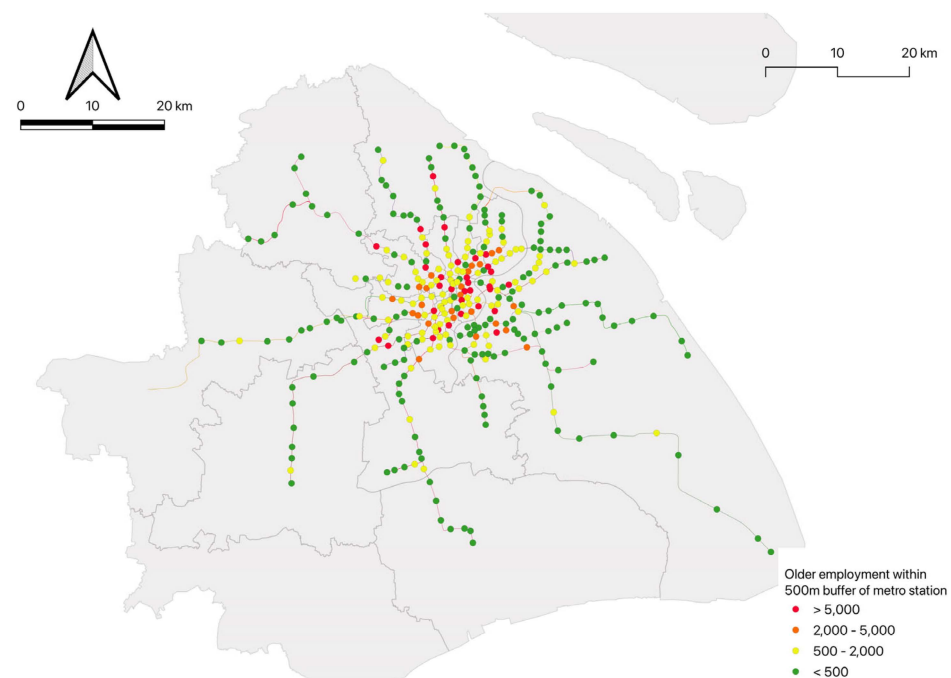


Figure 1. Older employment within 500 m buffer of metro stations in Shanghai.

2.2. Variables

The dependent variable is the number of older workers within a 500 m buffer of each metro station. The number of older employees was determined based on the employed population provided by mobile signaling data. Mobile signaling data are utilized to identify the employed population, if their stay locations are relatively fixed during the working hours of consecutive weekdays.

According to the mobile signaling data of April 2021, a total of 9,723,707 people were identified as the employed population in Shanghai by the mobile operator. Based on the registered personal information, 1,640,145 older adults (aged 60 or above) were identified as the employed population. Among these elderly employees, 488,626 of them were recorded within the 500 m buffer of selected 333 metro stations.

Twenty independent variables were involved in this study to estimate the impacts of the built environment on elderly employment near metro stations, including nineteen built environment variables and one metro ridership variable (Table 1).

Density:

Population density within a 500 m buffer of each metro station was calculated based on WorldPop population data with a 100 m resolution. Employment density among all age groups and the residential population of older adults within a 500 m buffer of each metro station are also determined by mobile signaling data.

Diversity:

Land use mixture was calculated for each station to evaluate the diversity by estimating the percentage of different land use types around metro stations. Meanwhile, the ratio of 4 types of points of interests (POIs), including catering, public service, shopping, and entertainment was calculated for each station, respectively.

Design:

Sidewalk density, the number of intersections with a zebra crossing, rooftop area, and pedestrian shed ratio were selected to evaluate the street design and walkability for older employees around metro stations.

Table 1. Statistics of all variables.

Category	Variable	Definition (Unit)	Mean	St.Dev	Data Sources
Dependent Variable					
	Older employment	Employed population of older adults within 500 m buffer (count)	1467.35	2892.96	Mobile signaling data
Independent Variables					
Density	Population density	Population density among all age groups (1000 people/km ²)	18.28	16.17	WorldPop population data
	Employment density	Employment density among all age groups (1000 employees/km ²)	14.97	37.98	Mobile signaling data
	Older residents	Residential population of older adults within 500 m buffer (count)	1236.97	2283.04	Mobile signaling data
Diversity	Land use mixture	An entropy index that measures different types of land use (scale)	0.72	0.14	Land use data
	Catering ratio	Ratio of catering points of interest (POIs)	0.26	0.13	Point-of-interest (POI) data
	Public service ratio	Ratio of public service points of interest (POIs)	0.09	0.06	Point-of-interest (POI) data
	Commercial ratio	Ratio of commercial points of interest (POIs)	0.21	0.11	Point-of-interest (POI) data
	Entertainment ratio	Ratio of entertainment points of interest (POIs)	0.12	0.08	Point-of-interest (POI) data
Design	Sidewalk length	Sidewalk length within 500 m buffer (km/km ²)	5.56	1.98	OpenStreetMap data
	Intersection	Number of 3-way or more intersections with zebra crossing (count)	9.49	6.22	OpenStreetMap data
	Rooftop area	Ratio of built-up area within 500 m buffer (scale)	0.18	0.08	Vectorized rooftop area data
	Pedestrian shed ratio	Ratio of pedestrian shed area within 500 m buffer (scale)	0.56	0.20	OpenStreetMap data
Destination Accessibility	City center	Straight distance to the People's Square station (km)	12.70	9.13	OpenStreetMap data
	City sub-center	Straight distance to the nearest sub-center (km)	6.76	5.40	OpenStreetMap data
Distance to Transit	Bus stop	Number of bus stops within the buffer (count)	6.49	3.71	Baidu Map API
	Bus line	Number of bus lines cross the buffer (count)	17.20	11.19	Baidu Map API
	Nearest bus stop	Distance from metro station to the nearest bus stop (km)	0.13	0.08	Baidu Map API
Demand Management	Public parking facilities	Number of public parking facilities (count)	2.95	3.44	Public parking facility data
Demographics	House price	Average resale housing price (10 ³ Yuan/m ²)	56.39	20.57	Secondhand housing price data
Station Attributes	Metro ridership	Average daily metro ridership of the station (count)	40,195.37	34,970.26	Metro smartcard data

Distance to transit:

To consider the influences of other public transit modes, the number of bus stops, bus lines, and distance from the metro station to the nearest bus stop were utilized to evaluate the bus service level near metro stations.

Destination accessibility:

Local and regional accessibility were estimated by two variables, including distance to the city center and distance to the city sub-center.

Demand management:

The convenience of parking for older adults and employees was analyzed by the number of public parking facilities around metro stations.

Demographics:

Since it is difficult to investigate the socio-demographic attributes of all people around metro stations, the average housing price was utilized to approximately present the income level.

Metro station attributes:

Since higher metro ridership may bring more employment opportunities for older adult, the daily metro ridership of each station was employed to evaluate the impacts on the number of older employees near metro stations.

All variables were measured for each metro station in a geographic information science (GIS) platform called QGIS version 3.34 (Figure 2). Table 1 shows the statistics of all variables.



Figure 2. Older employment within 500 m buffer of metro stations in Shanghai.

2.3. Methodology

This study employed the Light Gradient Boosting Machine (LightGBM) to analyze the impacts of the built environment on elderly employment near metro stations. The LightGBM is a Gradient Boosting Decision Tree (GBDT) implementation with high efficiency and accuracy [29].

LightGBM has several advantages for this study. Compared to traditional statistical regression models and based on the linear or generalized linear assumption, machine learning models like LightGBMs can discover the potential nonlinear associations between variables [30]. Meanwhile, it can inherently handle the multicollinearity issue by itself.

Traditional statistical regression models usually conduct the significance test or confidence interval to estimate the contribution of each variable, while the LightGBM can automatically generate the feature importance during tree splitting and make the contribution of each variable more comparable. Moreover, interpretable machine learning methods, including SHapley Additive exPlanations (SHAPs) [31] and Partial Dependence Plots (PDPs) [32] are utilized in this study for model interpretation.

Mathematically, the LightGBM and GBDT aim to minimize a loss function after several iterations. However, the LightGBM is better at high feature dimension and large data size than the GBDT because of two innovations, Gradient-based One-Side Sampling (GOSS) and Exclusive Feature Bundling (EFB) [29].

GBDT algorithms split the decision tree according to the information gain, which is usually determined by the splitting variance. With the GOSS technique, LightGBM keeps samples with high gradients in a subsample A and randomly chooses other samples into subsample B . The variance gain of GOSS can be estimated by the following:

$$\tilde{V}_j(m) = \frac{1}{n} \left(\frac{\left(\sum_{x_i \in A_l} g_i + \frac{1-a}{b} \sum_{x_i \in B_l} g_i \right)^2}{n_l^j(m)} + \frac{\left(\sum_{x_i \in A_r} g_i + \frac{1-a}{b} \sum_{x_i \in B_r} g_i \right)^2}{n_r^j(m)} \right) \quad (1)$$

where $\tilde{V}_j(m)$ is the estimated variance gain of splitting feature j at point m for the subset $A \cup B$. That is, compared to using real splitting variance by the GBDT, the GOSS of LightGBMs uses the estimated variance gain of a subsample to split the tree. EFB refers to an effective bundling technique for reducing the feature dimension. Due to GOSS and EFB in LightGBMs, the memory cost of computation is decreased, while the accuracy of the model is retained at a good level [29].

In a decision tree-based algorithm, the feature importance is determined as follows [33]:

$$FI_x = \sqrt{\frac{1}{T} \sum_{t=1}^T \sum_{m=1}^{M_t} d_m} \quad (2)$$

where m is the node of the decision tree, and d_m is the loss of optimization during the m^{th} tree split.

Shapley additive explanations (SHAPs) were also utilized in this study to interpret the results and visualize synergy effects [31]. The SHAP value [34] was calculated to estimate the influences of features as follows [31]:

$$\varphi_n = \sum_{z' \subseteq x'} \frac{|z'|!(N - |z'| - 1)!}{N!} [f_x(z') - f_x(z'/N)] \quad (3)$$

where N is the number of variables, φ_n is the SHAP value of feature n , $f(x)$ is the final model, and $|z'|$ refers to the number of elements in z' that are not zero.

In this study, the squared-error loss function was employed, and hyper-parameter tuning was conducted by grid searching. The optimal LightGBM model is obtained by 5-fold cross-validation and root-mean-square-error (RMSE) minimization. Tree depth and regularization were used to avoid overfitting. Finally, the number of estimators, learning rate, maximum leaves, and maximum depth were set as 2156, 0.001, 8, and 5, respectively. The pseudo- R^2 of the final LightGBM model is 0.82. The summary of the research design and methodology are shown in Figure 3.

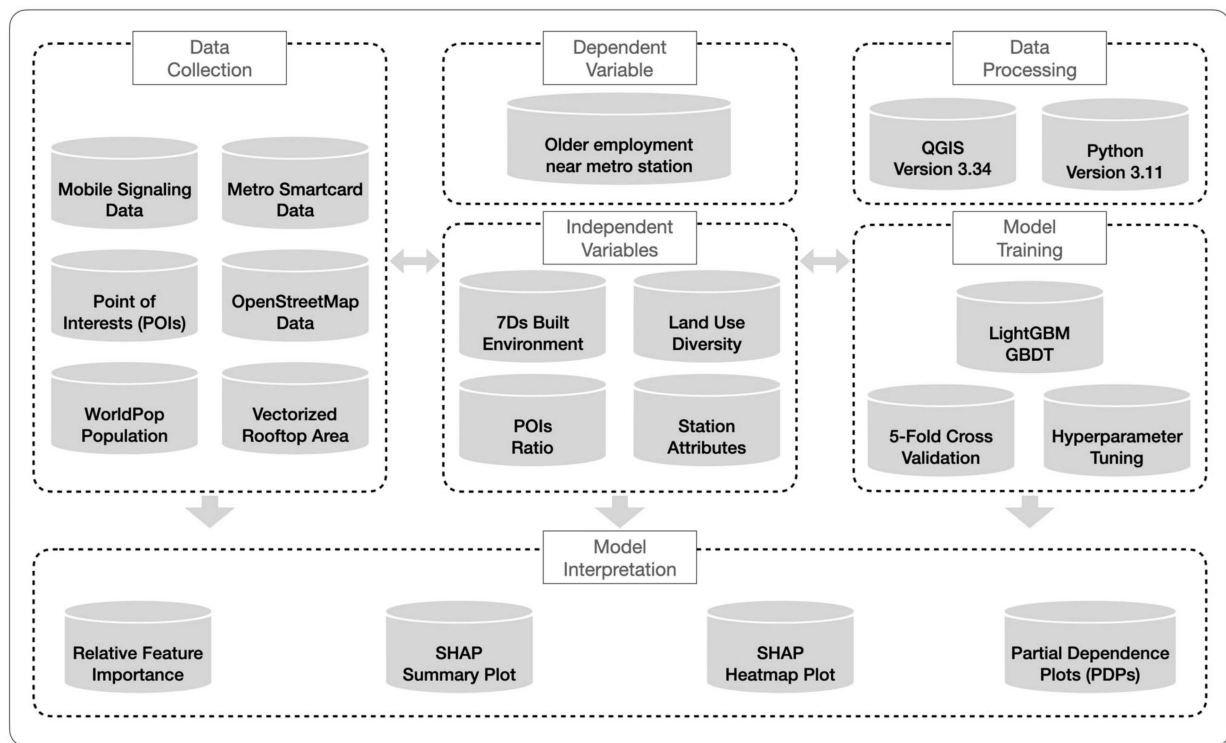


Figure 3. Summary of research design and methodology.

3. Results

3.1. Relative Feature Importance

The relative feature importance of each variable in determining elderly employment near metro stations is summarized in Table 2. The collective relative importance of all independent variables is 100%. Overall, the 3D (density, diversity, and design) built environment categories show a considerable similar contribution on elderly employment, with a collective importance of about 20% for each category, respectively. The contribution of other 5D categories (destination accessibility, distance to transit) is also noticeable but comparatively low, with about 13% importance for each category. However, the remaining 7D categories (demand management, demographics) and metro station attributes only have negligible effects on predicting elderly employment.

Specifically, the distance to the city center, the measurement of metro station locations and destination accessibility, contribute the most to elderly employment in the model (RI: 9.09%, Rank: 1st). The contribution of employment density and population density for all age groups are also notable, with the relative importance of 7.75% (Rank: 2nd) and 6.74% (Rank: 5th), respectively. As expected, the number of older residents near metro stations also has a considerable impact on older employment (RI: 7.03%, Rank: 3rd). The number of intersections with zebra crossings, the built environment variable that represents street design, unexpectedly has a considerable contribution on elderly employment (RI: 6.92%, Rank: 4th). Bus stops also show a significant importance on elderly employment near metro stations, with a relative contribution of 5.73%. As a measure of metro-bus intermodal connections, the distance from a metro station to the nearest bus stop is also important (RI: 4.92%). The integrated use of the metro and bus may be considered by some elderly employees to reduce the commuting walking distance.

Other built environment variables, including catering facilities (RI: 1.81%, Rank: 20th), entertainment facilities (RI: 2.10%, Rank: 19th), secondhand housing price (RI: 2.97%, Rank: 17th), and the bus line (RI: 2.68%, Rank: 18th), only have trivial effects on elderly employment.

Table 2. Relative feature importance of variables.

Category	Variables	Relative Importance	Rank
Density (21.53%)	Population density	6.74%	5
	Employment density	7.75%	2
	Older residents	7.03%	3
Diversity (19.15%)	Land use mixture	5.41%	9
	Catering ratio	1.81%	20
	Public service ratio	3.49%	16
	Commercial ratio	6.35%	6
	Entertainment ratio	2.10%	19
Design (20.48%)	Sidewalk length	4.48%	12
	Intersection	6.92%	4
	Rooftop area	4.95%	10
	Pedestrian shed ratio	4.13%	13
Destination accessibility (13.08%)	City center	9.09%	1
	City sub-center	4.00%	14
Distance to transit (13.33%)	Bus stop	5.73%	8
	Bus line	2.68%	18
	Nearest bus stop	4.92%	11
Demand management (5.83%)	Public parking facilities	5.83%	7
Demographics (2.97%)	House price	2.97%	17
Station attributes (3.63%)	Metro ridership	3.63%	15

3.2. SHAP Summary Plot

Although relative importance can give an overview of feature contributions on the model output, the positive or negative impacts of each variable on older employment are still vague. Compared to the statistical regression analysis model, the machine learning algorithm can use SHapley Additive exPlanations (SHAPs) to interpret the model.

The SHAP summary plot sorts features from top to bottom by their average SHAP value (Figure 4). In a SHAP summary plot, each dot presents a data sample. The color of the dots shows their associated feature value on each row, while the location of dots on the horizontal axis shows their impacts on elderly employment (SHAP value). To control the figure size, the top ten variables with the highest average SHAP value are displayed in Figure 4, and the collective impacts of the other ten features on the model output are summarized in the last row.

As shown in Figure 4, the distance to the city center, employment density, and population density are the top three important built environment variables by sorting the average SHAP value, which is slightly different with the feature importance results. The associations between the impact factors and the number of older employees have also been explored in the SHAP summary plot. The distance to the city center appears to be negatively related with elderly employment, since all samples in red color (long distance to the city center) have negative SHAP values. As expected, employment density is positive associated with employment among older adults, while all samples in red color (high employment density) increase the elderly employment, and most samples in blue color (low employment density) lower the number of older employees. Interestingly, high population density (in red color) can have either high positive impacts or negative impacts on older employment, while low population density (blue dots) can only show negative effects on elderly employment.

Although the SHAP summary plot can display how each factor affects elderly employment for each station, it is difficult to identify and analyze the effects (location) of a certain sample (metro stations) in each row. To address the above concerns, a SHAP heatmap plot is depicted in the following section.

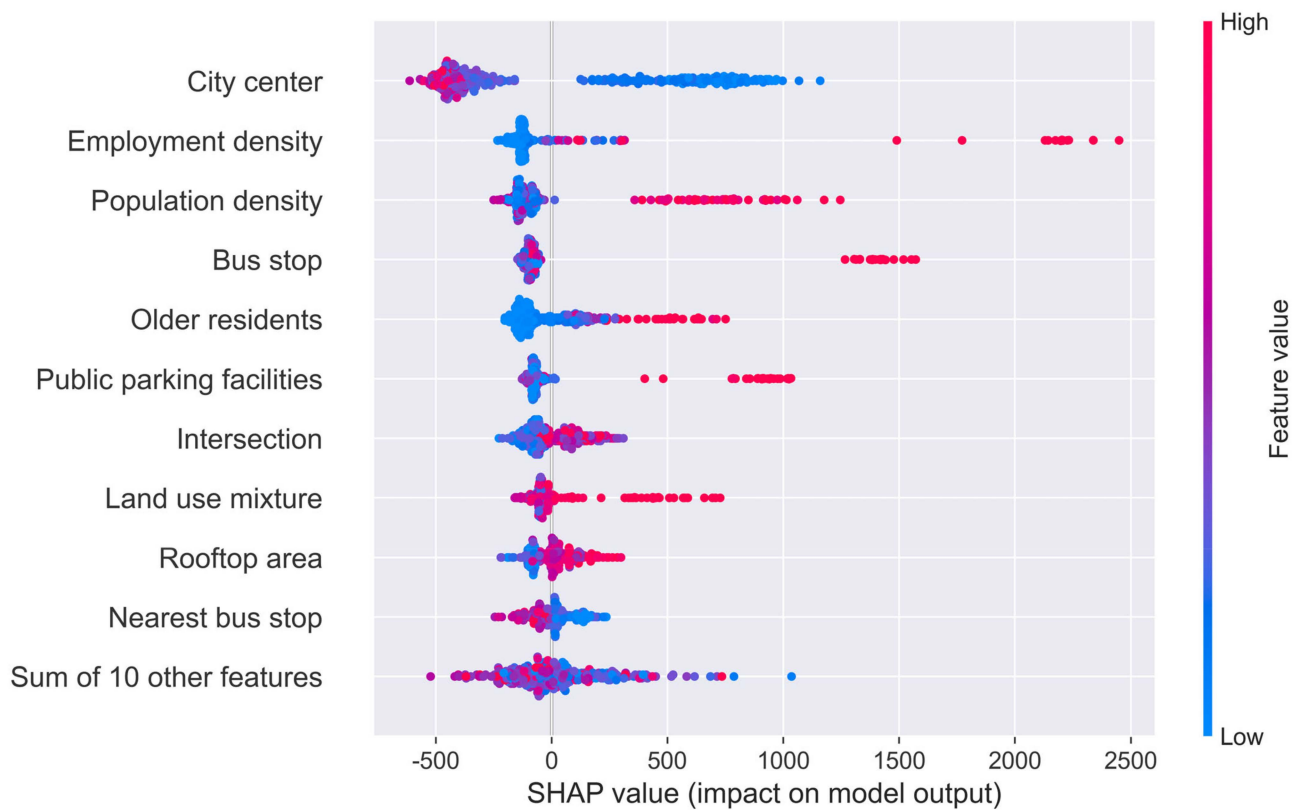


Figure 4. SHAP summary plot.

3.3. SHAP Heatmap Plot

By contrast, we generate the SHAP heatmap plot by sorting the feature from top to bottom based on their maximum SHAP value, which refers to the horizontal amplitude of each row in the SHAP summary plot and is shown as the black bar plot in the SHAP heatmap plot (Figure 5). In the SHAP heatmap plot, the data sample is shown on the x -axis, and independent variables on the y -axis. The color of each sample is the SHAP value, and the model output is displayed on top of the heatmap plot as $f(x)$. The $f(x)$ is centered at the dash line by the average model output, which is the average predicted elderly employment for each station.

As shown in Figure 5 employment density, bus stop and population density are the top three important built environment variables by sorting the maximum SHAP value. Public parking facilities, which only ranked 6th in summary plot, are the 4th important feature in heatmap plot. On the contrary, the distance to the city center, which has the largest average SHAP value, only ranked 5th by the maximum SHAP value.

For metro stations with more than average elderly employment ($f(x) > 0$), it is noticed that they either have high employment or population density (left part of the plot), more bus stops (right part of the plot), or more public parking facilities (middle left of the plot). It is also interesting to notice that the overall color pattern of the SHAP value of the distance to the city center is quite similar to the value of $f(x)$. That is, the SHAP value of the distance to the city center is positively associated with the predicted elderly employment. For stations with more than average older employment ($f(x) > 0$), the distance to the city center always has positive impacts on elderly employment (in red). For stations with less than average elderly employment ($f(x) < 0$), the distance to the city center shows negative effects (in blue color). The negative effects in blue color are much darker than any other variables, which means that the long distance from the metro station to the city center is the main driving factor to reduce the elderly employment near metro stations.

As shown at the bottom of the SHAP heatmap plot, the impacts of other built environment variables with a small SHAP value on elderly employment are less significant, because the color of each sample is relatively lighter.

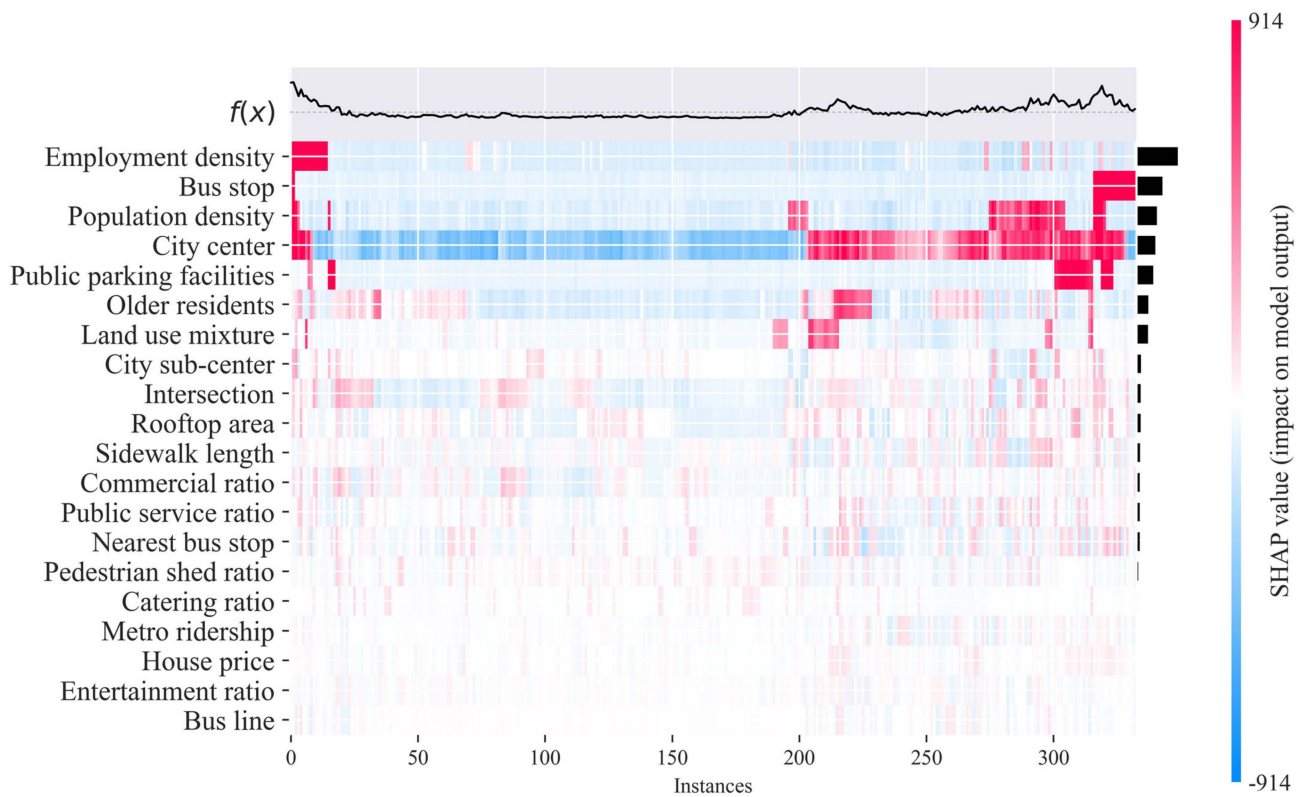


Figure 5. SHAP heatmap plot.

3.4. Partial Dependence Plots

Partial dependence plots are utilized to visualize the association between the built environment and elderly employment around metro stations (Figure 6). Overall, all built environment variables have irregular nonlinear impacts on predicted elderly employment. Meanwhile, each built environment feature needs to reach an associated threshold to maximize the elderly employment, and their nonlinear impacts are only effective when the built environment is within certain ranges.

As shown in Figure 6, employment density among all age groups is positively associated with elderly employment near metro stations. The number of older employees rises by about 500 when the employment density among all age groups grows from 0 to 100. However, when the employment density reaches 100, elderly employment suddenly rises by more than 2000. Population density also has positive nonlinear impacts on elderly employment. The older employment around metro stations keeps nearly stable when population density is lower than 35,000 people/km². However, when the population density grows from 35,000 to 40,000 people/km², the elderly employment substantially increases by about 800.

The distance to the city center shows negative effects on elderly employment near metro stations (Figure 6). When the distance from the city center is shorter than 5 km, the number of average older employees is about 2500. As the distance to the city center grows from 5 to 10 km, the elderly employment suddenly dropped by about 1500. The association between distance to city sub-center and elderly employment shows a reverse V-shape pattern. The largest older employment occurs when the distance from a metro station to the nearest city sub-center is around 5 km.

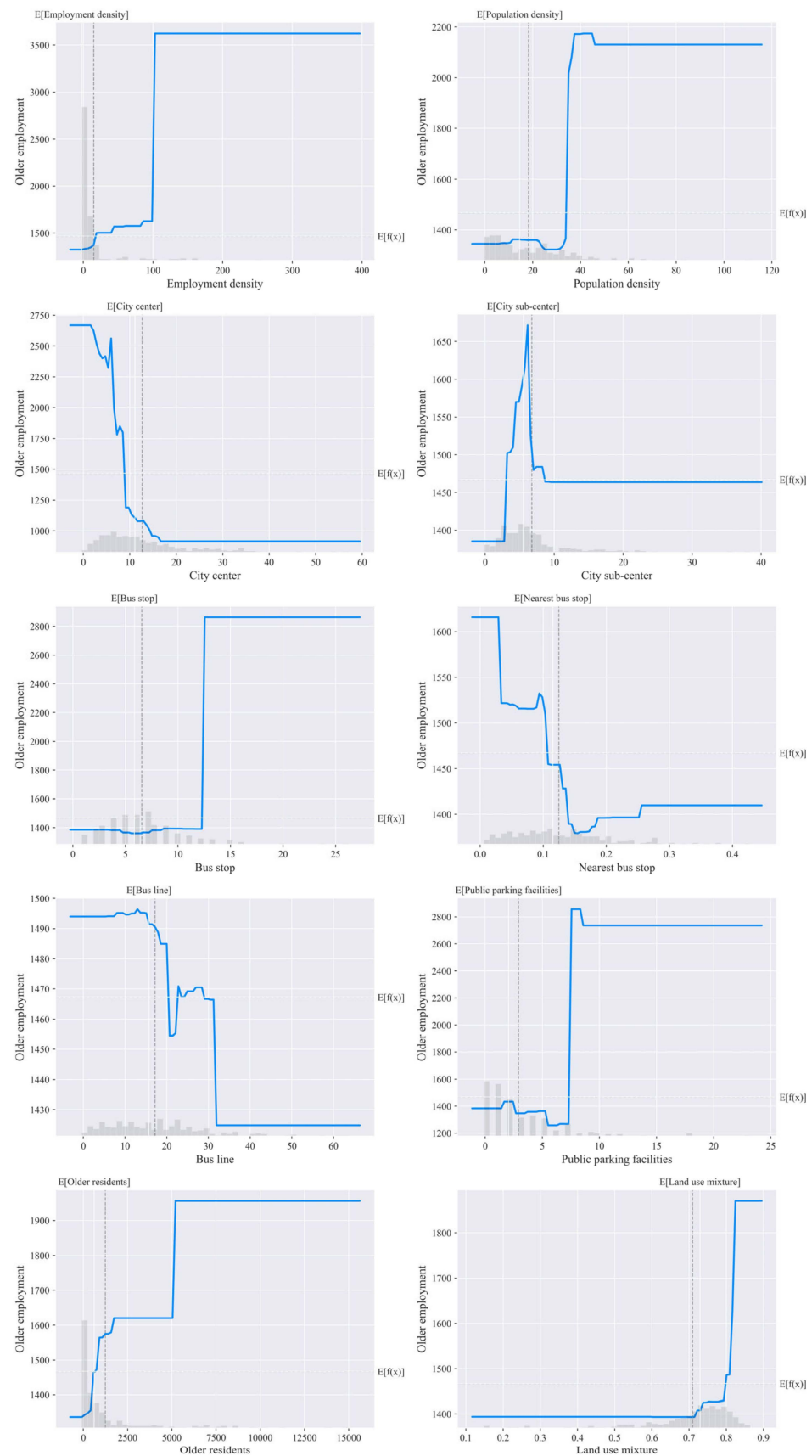


Figure 6. Partial dependence plots of independent variables.

The nonlinear associations between the bus service and elderly employment are complicated. Bus stop shows positive effects on elderly employment near metro stations with an obvious threshold (Figure 6). When the number of bus stops is less than ten, elderly employment keeps almost constant, while the number of older employees increases by about 1500 when the number of bus stops is more than 13. As expected, the distance to the nearest bus stop has negative associations with elderly employment. The number of older employees near metro stations becomes the lowest when the distance from a metro station to the nearest bus stop is more than 100 m. However, the bus line has unexpected negative impacts on elderly employment.

Parking facilities have positive nonlinear effects on elderly employment, with a threshold effect at eight. When the number of public facilities is more than eight, the older employees almost double from 1400 to 2800. The number of older residents also influence elderly employment near metro stations in a positive way. When the number of older residents rises from 0 to 2500, the number of older employees grows by about 200, and there is no further increase in elderly employment when the number of older residents grow from 2500 to 5000. However, once the number of older residents is beyond 5000, it can bring 400 more older employees within a 500 m buffer of metro stations.

Meanwhile, as the land use mix increases from 0.7 to 0.8, the number of older employees grows by about 500. However, the difference in land use mix beyond this interval does not show impacts on elderly employment.

4. Discussion

Understanding the effects of station-level built environments on elderly employment near metro stations is essential for the government to promote the social participation and mental health of older adults. Utilizing metro station-level data from various sources in Shanghai, China, this study combined a machine learning algorithm (LightGBM) and interpretable machine learning methods (relative importance, SHAPs and PDPs) to discover the contribution of the built environment and its impacts on elderly employment near metro stations.

According to the feature importance, the collective contribution of built environment categories in 3Ds (density, diversity, design) is higher than other categories in 7Ds. The distance from the metro station to the city center has the highest importance on elderly employment. The closeness to a central business district is also related to higher population density, residential density, or employment density. It is plausible that the population density and employment density near metro stations are highly related with regional vitality and elderly employment opportunities. The number of older residents near metro stations also has considerable impacts on elderly employment, which can be used to estimate the infrastructure and convenience of life for aged people. The significant contribution of the number of intersections is plausible; considering the slow walking speed and safety risks of elderly people, older adults may prefer overpasses or underpasses to cross the street than the zebra crossing. Transit accessibility for older adults, including the bus stop density and distance to a bus stop, also affects the number of older employees near metro stations in a positive way. It is reasonable that the higher density of bus stops can improve the accessibility of the entire metro catchment area and thus reduce the walking distance from the public transit station to the workplace for older adults. The integrated use of the metro and bus may be considered by some elderly employees to reduce the commuting walking distance.

It is noticeable from the partial dependence plots that all the built environment variables appear to have nonlinear effects on elderly employment. Population density and employment density among all age groups have positive effects on elderly employment, while the effects become trivial when they are beyond 40,000 people/km² or 100,000 employees/km², respectively. Similar positive and threshold effects of density have been found on active travel and walking behaviors (e.g., walking trip duration) among older adults [13,35]. It is plausible that densified areas usually have more walking-friendly

infrastructures or public facilities for older employees [36], while over-densified areas may increase the risk of falling or injury [19]. From the perspective of bus service, more bus stops and short walking distances to the nearest bus stop can enhance the elderly employment near metro stations, while more bus lines seem to be less effective. Since walking is an important access mode for public transit (e.g., metro, bus), it is reasonable that densified bus stops can reduce the commuting walking distance from public transit station to the origin or destination for older employees and thus make it convenient for older employees [37]. More intersections with zebra crossings and appropriate sidewalk density are usually associated with various route choices for pedestrians [38,39]. It can also encourage walking by providing pedestrian-friendly street design, especially for the older adults and older employees [40]. Compared to other types of POIs, the ratio of commercial and retail POIs has a significantly positive impact on elderly employment. With higher commercial accessibility, it is more convenient for older adults to access their daily needs by walking short distances [41,42], which can further facilitate their physical activities and social participation [13].

5. Conclusions

This study reveals the nonlinear effects of the built environment at the station level on elderly employment near metro stations. Multi-sources data and machine learning algorithms are utilized for modeling, while relative feature importance, SHAP values, and partial dependence plots are employed for result interpretation. Overall, the built environment variables show significant contributions on older employment near metro stations, especially the density, diversity, and design categories. All independent variables have multiplex nonlinear impacts on older employment. The built environment variables can promote older employment near metro stations if they are beyond certain thresholds or within effective intervals. In planning practice, these empirical findings can encourage voluntary employment among older adults and thus promote their mental health by providing guidance for the built environment interventions.

This study also has some limitations, which merit further investigation. First, this study uses areal independent variables to evaluate older employment within metro station areas, while qualitative data (e.g., interview, questionnaire, personal information) can be utilized to analyze employment behavior among older individuals. Second, since some significant determinants (e.g., climate change adaptation, safety, environmental quality, and proximity to health infrastructure) of older employment may be ignored in this study, further studies are encouraged to estimate the influences of other factors from more comprehensive perspectives. Third, although machine learning algorithms can be used to discover the nonlinear relationship, traditional model and statistical analyses are also meaningful to test the significance of different variables. The combination and comparison of traditional regression models and machine learning models are welcomed in further studies. Fourth, the effect mechanism of the built environment on older employment can be quite different between metro catchment areas and other city areas, megacities and small town, Western countries and countries in the Global South. Therefore, more empirical studies are welcomed to validate or invalidate the results in different contexts.

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