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The Non-Linear Effects of Urban Green Space on Promoting Physical Activity of Old Adults at Different Obesity Status in Semi-Arid Area: A Case Study of Lanzhou, China

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Key Points:

- Green spaces significantly impact elderly physical activity, with stronger effects on obese individuals than those of standard weight
- Obese elderly benefit more from green space quality and accessibility, while standard weight seniors respond to overall greenery amount
- Visibility of street greening is effective in promoting outdoor activities for obese older people

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Abstract A substantial body of research has linked the built environment to obesity risk in older adults, with physical activity reducing obesity risk. Most studies have focused on temperate and subtropical regions; however, results can vary due to different climate characteristics. This study examines Lanzhou, a representative of arid Northwestern China, to explore the nonlinear relationship between the built environment and physical activity among older adults, focusing on the role of green spaces. By using the XGBoost method, we analyze how green spaces and the 5D built environment affect physical activity levels among the obese and standard-weight elderly populations in Lanzhou. Results indicate that green spaces significantly influence physical activity in both groups, with their effect surpassing other environmental and sociodemographic factors. Obese elderly individuals are more influenced by green space quality and accessibility, while standard-weight individuals are more affected by the overall quantity and coverage of green spaces. Obese individuals also rely more on street greening compared with their standard-weight counterparts. In addition, a diverse urban environment and appropriate public transportation distances are crucial for promoting physical activity among the elderly. Low temperatures inhibit physical activity more in obese elderly individuals. Our findings provide insights for policymakers, planners, and designers on optimizing green infrastructure to reduce obesity risks among the elderly in arid regions, ultimately enhancing the urban environment's effectiveness in promoting healthy aging.

Plain Language Summary This study investigates how the built environment affects physical activity levels among older adults in Lanzhou, a city in Northwestern China with an arid climate. Previous research has shown that physical activity can reduce the risk of obesity; however, most studies have focused on areas with mild climates. This study specifically examines how green spaces and other urban features influence physical activity among obese and healthy-weight elderly populations in Lanzhou. Results show that green spaces play a key role in encouraging physical activity for both groups, but the effect is stronger for obese individuals. Obese seniors are more affected by the quality and accessibility of green spaces, while those of standard weight benefit more from the overall amount and coverage of green areas. In addition, factors, such as diverse urban environments and easy access to public transportation, support physical activity. However, cold temperatures have a stronger negative effect on obese individuals. These findings offer valuable insights for urban planners and policymakers to improve green infrastructure and reduce obesity risks for the elderly in arid regions.

1. Introduction

The prevalence of obesity has dramatically increased globally over the past 40 years. Obesity has been defined as a body mass index (BMI) of >25 (Herrington et al., 2016); it may increase the risk for a series of chronic diseases and disabilities, affecting individuals across all age groups and socioeconomic backgrounds (Baum & Ruhm, 2009). For older adults, obesity is a major risk factor for health problems, such as diabetes, cardiovascular diseases, cancer, sleep apnea, nonalcoholic fatty liver disease, osteoarthritis, and other ailments (Ahima & Lazar, 2013). The World Health Organization (WHO) has declared obesity to be a major public health issue since 1997 (Harris et al., 2000). Obesity not only poses significant health risks to individuals, but also contributes to the strain on healthcare systems due to associated chronic diseases (WHO, 2024). Driven by the decline in fertility and the increase in life expectancy, the rapidly aging population has been posing serious challenges in China (Fang et al., 2015). According to the 2020 Report on the Nutrition and Chronic Diseases of Chinese Residents, the rates of obesity continue to rise among all age groups in urban and rural areas, with more than half of the adult

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population being either overweight or obese (Xia et al., 2019). Obesity in older people is closely related to various chronic diseases, such as cardiovascular diseases and type 2 diabetes, increasing medical and care pressures on the elderly (Chung et al., 2017). Obesity also increases the risk of disability in older individuals, affecting their daily living abilities and quality of life (Yelinfan & Peizhen, 2023). The prevalence of obesity among older people varies across different regions in China, necessitating the development of targeted obesity intervention measures for each area.

Reducing the risk of obesity has been a long-standing global challenge for governments and health departments. Engaging in regular physical activity (Blüher, 2019), for example, 150 min of moderate-intensity aerobic activity per week for adults, has been confirmed to significantly improve health condition and reduce the risk of obesity; however, one-third of the world's adult population do not meet this recommendation (WHO, 2020). WHO has developed four strategic objectives to provide a comprehensive framework for action to promote physical activity, namely, creating active societies, environments, people, and system, emphasizing the importance of supportive urban spaces for facilitating physical activity (WHO, 2019). Previous research has identified several built environment factors that benefit physical activity for urban residents, such as pedestrian-friendly infrastructure, proximity to recreational facilities, and safe neighborhood environments (Laddu et al., 2021). In addition, some scholars have found that land use diversity and street connectivity are associated with higher levels of physical activity (Cawley, 2014; Ewing et al., 2014; Frank et al., 2010).

The effect of green spaces on physical activity has long been a focal point of public health research, particularly regarding their influence on obesity among the elderly (Wolfenden et al., 2019). Numerous studies have indicated that green space can significantly promote outdoor physical activity for older adults and further reduce the risk of obesity and sedentary behavior (Cao, 2016). The frequency of using green spaces is linked to increased physical activity, for example, urban sprawl, parks, neighborhood squares, and community gardens may serve as public spaces for active travel, recreational exercise, and social interaction, helping older adults maintain regular physical activity and reducing the probability of obesity-related chronic diseases (Levy-Storms et al., 2018). Similar findings regarding the effect of green spaces on the health of older adults have been reported. Studies have confirmed that well-designed green spaces (e.g., pocket, central, and street parks), are positively correlated with physical activity levels and negatively correlated with obesity prevalence among older adults (Rioux et al., 2016; Veitch et al., 2022). Furthermore, the mental health benefits of green spaces should not be overlooked, because the environment provided by these spaces helps alleviate stress, improve quality of life, and support healthy lifestyles (Miralles-Guasch et al., 2019). Consequently, the positive correlation between green spaces and physical exercise suggests that increasing the availability of high-quality green spaces in urban environments offers a direct approach to obesity prevention (Veitch et al., 2022). However, findings regarding the relationship between green spaces and physical activity are inconsistent and largely influenced by differences in methods used to assess green space attributes. Some studies have evaluated green spaces based on their area or quantity, while others have focused on aspects, such as quality, facility availability, and accessibility (Loder et al., 2020). Such variations in measurement approaches can lead to divergent conclusions. For example, some studies have found that despite the presence of a large green space area, the lack of facilities, inadequate maintenance, or distance from residential areas may limit its effectiveness in promoting physical activity among older adults.

Although most studies in the Western context have confirmed the linear positive effects of the built environment on promoting physical activity among adults and older adults, such effects will be more complex in densely populated Asian countries, where several studies have found negative, nonsignificant, or nonlinear relationships between green spaces and obesity (L. Yang et al., 2024; Zang, Qiu, et al., 2022; Zang, Xian, et al., 2022). The complex results may be attributed to various factors, such as the social context of different countries, study design, the measurement of physical activity outcomes, and built environment variables (Sarkar et al., 2017; Yin et al., 2020). In cities such as Seoul, Tokyo, and Hong Kong, the extremely high population density and rapid urbanization have led to limited community green spaces (Nishigaki et al., 2020; Y. Yang et al., 2021). Some studies conducted in China have found that although green spaces theoretically provide opportunities for physical exercise, inconvenient transportation, lack of shaded areas, and overcrowding make the effective use of such spaces difficult for older adults, diminishing their potential benefits in engaging in physical activity, suggesting that simply increasing the quantity of green spaces and their exposure may not improve health outcomes for older adults (L. Yang, Ao, et al., 2021; Xu et al., 2022; Y. Yang et al., 2023).

However, only a few studies have examined the nonlinear effects of green spaces on physical activity among older adults (Wu & Kim, 2021). Nonlinear analysis is essential because it captures the complex, threshold-based relationships between green space attributes and physical activity that linear models may overlook (L. Yang, Ao, et al., 2021). For example, a small increase in green space area may initially have no significant effect on physical activity, but once a certain threshold is reached, its positive effect may amplify (P. Zang et al., 2023; Zhou & Lu, 2024). Moreover, attributes of green spaces, such as vegetation diversity and accessibility, may exhibit increasing or diminishing marginal effects on physical activity, which can only be effectively identified through nonlinear analysis (Zhou & Lu, 2024). Several existing studies have demonstrated the importance of nonlinear analysis in understanding the complex relationship between the environment and health behavior. For example, nonlinear models have revealed that an overly distant green space suppresses activity, while a suitably located green space significantly increases the frequency of outdoor activity (Zang, Qiu, et al., 2022; Zang, Xian, et al., 2022). These findings suggest that linear models, such as multiple linear regression, may underestimate or overestimate the effect of green spaces on health, while nonlinear approaches provide more comprehensive results (L. Yang, Liu, et al., 2021). Furthermore, nonlinear methods can reveal differentiated responses of individuals or groups to green space environments. For some people, a small improvement in green space may be sufficient to significantly enhance their frequency of outdoor activity, while for others, a large-scale green space intervention may be required to achieve similar effects (S. Yang et al., 2019). In addition, the environmental needs for physical activity differ between older adults with standard weight and those who are obese (Narsakka et al., 2022). Traditional nonlinear statistical models exhibit limitations. They rely on strict data distribution assumptions, experience computational issues in parameter estimation, lack good automatic feature selection, and struggle with high-dimensional data (Tong, 2012). Nonlinear machine learning methods excel because they handle complex relationships without such assumptions, perform feature selection efficiently, handle missing values better, and exhibit stronger generalization (Suykens et al., 2012). XGBoost stands out with its ensemble approach for improving performance and handling large data sets via parallel computing while providing feature importance. The Shapley Additive exPlanations (SHAP) approach helps by explaining model output, filling the interpretability gap of traditional models (Chang et al., 2022). In addition, SHAP has been used to interpret the output of the XGBoost model. SHAP values provide a clear and interpretable measure of feature importance, facilitating an understanding of the independent contribution of each green space attribute to physical activity behavior (Chen et al., 2023). By identifying the most influential factors that affect physical activity, SHAP enables a deeper understanding of how specific green space features affect regular-weight and obese older adults in a semiarid environment.

The actual effects of green spaces on different groups and their potential policy implications be comprehensively understood through nonlinear analysis. Despite the increased attention to the nonlinear effects of green spaces on physical activity among older adults, existing research lacks evidence regarding the specific environmental needs of obese older adults. In particular, no studies have yet compared the built environment requirements for older adults of standard weight versus those for obese older adults. Moreover, previous studies in China have primarily focused on temperate, subtropical, or tropical regions (Y. Yang et al., 2021). However, findings from Northern China have indicated that vegetation richness, suitable plant height, and comfortable urban outdoor temperatures contribute positively to physical activity and reduce psychological stress (Song et al., 2024; Zhou & Lu, 2024). Conversely, studies on semiarid regions remain relatively scarce, and their generalizability is limited, restricting the application of these findings under different climatic conditions. The arid and semiarid zones located in Northwestern China have vegetation characteristics that differ significantly from those of the aforementioned regions. These areas have received less attention with regard to the effect of urban green spaces in promoting physical activity. This research gap raises the question of whether such facilitating effects of urban green spaces on physical activity are still effective in these arid regions, and if yes, which green space attributes are the most crucial.

Lanzhou, the capital city of Gansu Province in Northwestern China, provides a unique context for studying the relationship between urban green spaces and physical activity among older adults (Tong & Shi, 2015). In contrast with more temperate and densely populated cities, such as Beijing and Shanghai, Lanzhou experiences a semiarid climate characterized by low precipitation and high temperature variability (Burbank & Jijun, 1985). This climatic condition poses specific challenges to the development and maintenance of green spaces, because water scarcity and extreme temperatures can limit the vegetation growth and usability of outdoor areas. In addition, Lanzhou serves as a major industrial hub, contributing to air quality issues that may deter outdoor physical activity. The city has undergone rapid urbanization in recent decades, resulting in increased population density and significant pressure on existing infrastructure, including green spaces (Ma et al., 2023). Despite these challenges, Lanzhou has implemented several urban planning initiatives that are aimed at expanding and enhancing green areas to promote public health (Yu et al., 2024). However, the effectiveness of these initiatives in fostering physical activity among the elderly, particularly in the semiarid context, remains underexplored. Furthermore, Lanzhou's socioeconomic profile, which is characterized by a mix of traditional lifestyle and modern economic pressure, influences residents' engagement in physical activity (Y. Wang et al., 2024). Cultural attitudes toward aging and health, coupled with economic disparities between urban and rural areas, necessitate a nuanced understanding of how green spaces can be optimized to support diverse populations. Simultaneously, recommendations on how to optimize green space characteristics in semiarid regions to encourage physical activity can be extended to other cities in similar climatic and socioeconomic contexts, such as parts of Central Asia, the Middle East, and even cities in southern Europe with a similar climate status.

To address current gaps in knowledge, the current study utilized physical examination data from 1,773 elderly residents in Lanzhou, China, to explore the nonlinear relationship between built environment characteristics and physical activity among regular-weight and obese older adults, with focus on the threshold effects of urban green space on physical activity. This study examines Lanzhou, a semiarid region that has been relatively underexplored in research on green spaces and physical activity among older adults. For the first time, this study compares the needs for urban green space between regular-weight and obese older adults, revealing differences in green space requirements across weight groups. In contrast with traditional studies that focus on the area and quantity of green spaces, this research employs the XGBoost and SHAP methods to examine the complex nonlinear effects of the multidimensional characteristics of green space, such as quality, accessibility, facilities, and climate, on physical activity. The insights gained from Lanzhou can inform urban planning strategies in similar climatic and socio-economic contexts, contributing to more effective obesity prevention measures for older adults across diverse Chinese cities.

2. Method and Data

2.1. Data

Individual data were collected from physical examination reports submitted by community health care centers in Lanzhou in 2021, including gender, age, weight and height information. The BMI was calculated using the following formula.

$$\text{BMI} = \frac{\text{mass}_{\text{kg}}}{\text{height}_{\text{m}}^2} = \frac{\text{mass}_{\text{lb}}}{\text{height}_{\text{in}}^2} \times 703 \tag{1}$$

where mass_{kg} is the weight of a person in kilograms, and $\text{height}_{\text{m}}^2$ is the square of the height in meters. The formula is also equivalent to the weight in pounds (lb) divided by the square of the height in inches (in), multiplied by 703.

Participants with a BMI of ≥24 were defined as the obese group, while participants with a BMI between 18 and 24 were considered the regular group. No participants had a BMI under 18. The study was reviewed and approved by the Ethics Committee, and all the participants were informed and consented to participate in the study.

Figure 1 shows the location of the participants who took part in the current study. Chengguan and Qilihe Districts have the most significant population and the highest percentage of older individuals among the eight counties and districts in Lanzhou. To ensure the diversity and representativeness of the sample communities, we utilized high and low economic status as criteria. In particular, we obtained transactional housing prices from the local communities through the Lianjia platform (https://lz.lianjia.com/xiaoqu/), calculated the median housing price, and designated communities with prices above the median as high socioeconomic status (SES) and those below the median as low SES. This approach further ensures the representativeness of the research sample communities (Figure 2). A total of 1773 valid data were obtained after removing missing data.

Given the sample grouping based on SES, considering other potential factors that influence obesity, particularly diet, is also important. Although diet is undoubtedly a key factor that influences obesity, its effect may be less pronounced in the elderly population, especially within the sociocultural context of this study sample. In many elderly communities, dietary habits tend to be relatively consistent, particularly in China, where urban–rural

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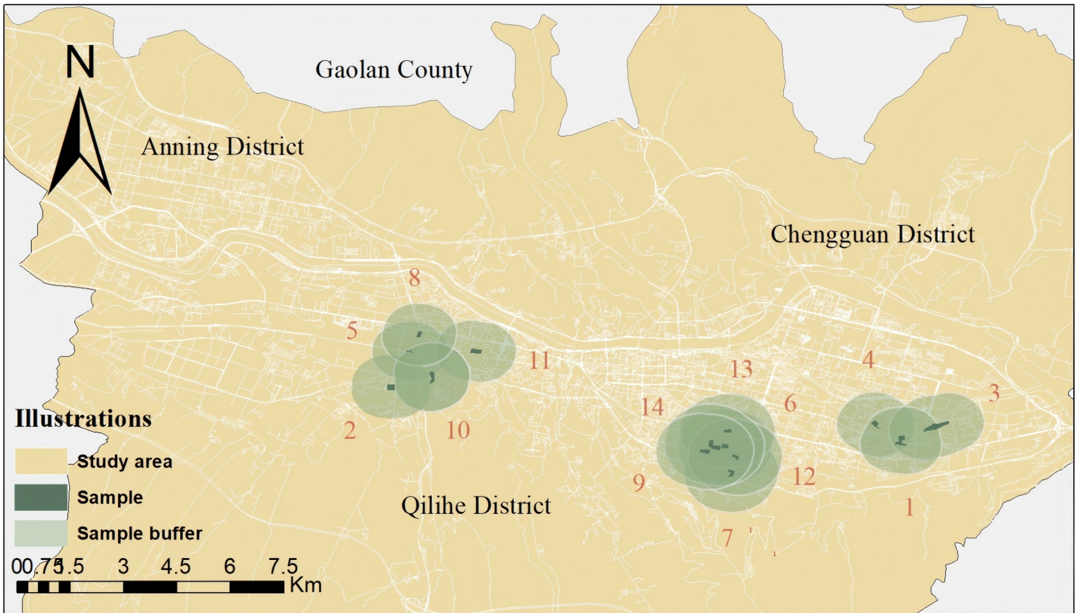

ID	Buffer name	Prices (Million)	Economic	ID	Buffer name	Prices (Million)	Economic	ID	Buffer name	Prices (Million)	Economic	ID	Buffer name	Prices (Million)	Economic
1	Feitian A	1.00	Low SES	5	Tielu Community	1.20	Low SES	9	Yiyuan	1.50	High SES	13	Qijian	1.70	High SES
2	Yanjiaping	1.10		6	Hejiazhuang	1.27		10	Locomotive factory	1.50		14	Renheng	2.00	
3	Feitian B	1.10		7	Hongshanxi	1.30		11	Jiangong community	1.50					
4	Zhumeng community	1.20		8	Huanglou	1.40		12	kangrui	1.60					

Figure 1. Research sample screening diagram.

differences and the shared dietary culture among older adults lead to similar eating patterns with low variability. Given this situation, although SES differences may account for some variations in obesity rates, the relatively uniform dietary patterns in our sample suggest that environmental factors are likely to exert a more significant effect on obesity levels than diet alone.

The selection of predictor factors was based on the existing literature and the empirical nature of the collected data (Calise et al., 2018; Nehme et al., 2016). Two sociodemographic variables, that is, age and gender, were obtained from medical examination records. In addition, following the 5Ds methodology for developing environmental assessments, 15 environmental variables were computed within the ArcGIS software framework. Built environment attributes were obtained from Gaode Maps (https://ditu.amap.com), and open-source data were accessed via the Google Earth Engine (GEE) platform (https://code.earthengine.google.com/). The geographic locations of the sample communities were accurately determined using the self-reported home addresses of the participants. For each community, a buffer zone with a radius of 1 km was established around the community center. This radius was selected based on the typical maximum walking distance for elderly individuals in their daily activity, enabling a more precise evaluation of the built environment that surrounded their residence. Within these buffer zones, two key green space variables—mean tree height and mean NDVI—were calculated using data from the ETH Global Canopy Height map at 10 m ground sampling distance and Landsat 8 Collection 2 (courtesy of the U. S. Geological Survey), respectively, as illustrated in Figure 2 (Lang et al., 2023). Descriptive statistics encompassing physical activity levels, built environment characteristics, and sociodemographic variables are summarized in Table 1.

To evaluate green space characteristics, several environmental and built environment variables were selected, including plant diversity and land use diversity. The calculation of these variables involved relatively complex methods, such as multi-layer spatial data analysis and the application of specific ecological indices. Plant diversity was quantified using the Shannon–Wiener Index, which integrates species richness and evenness across different green spaces. Additionally, semantic segmentation was carried out using YOLO8 to complete the statistics of vegetation types (P. Wang et al., 2024). The formula for the Shannon–Wiener diversity index is expressed as:

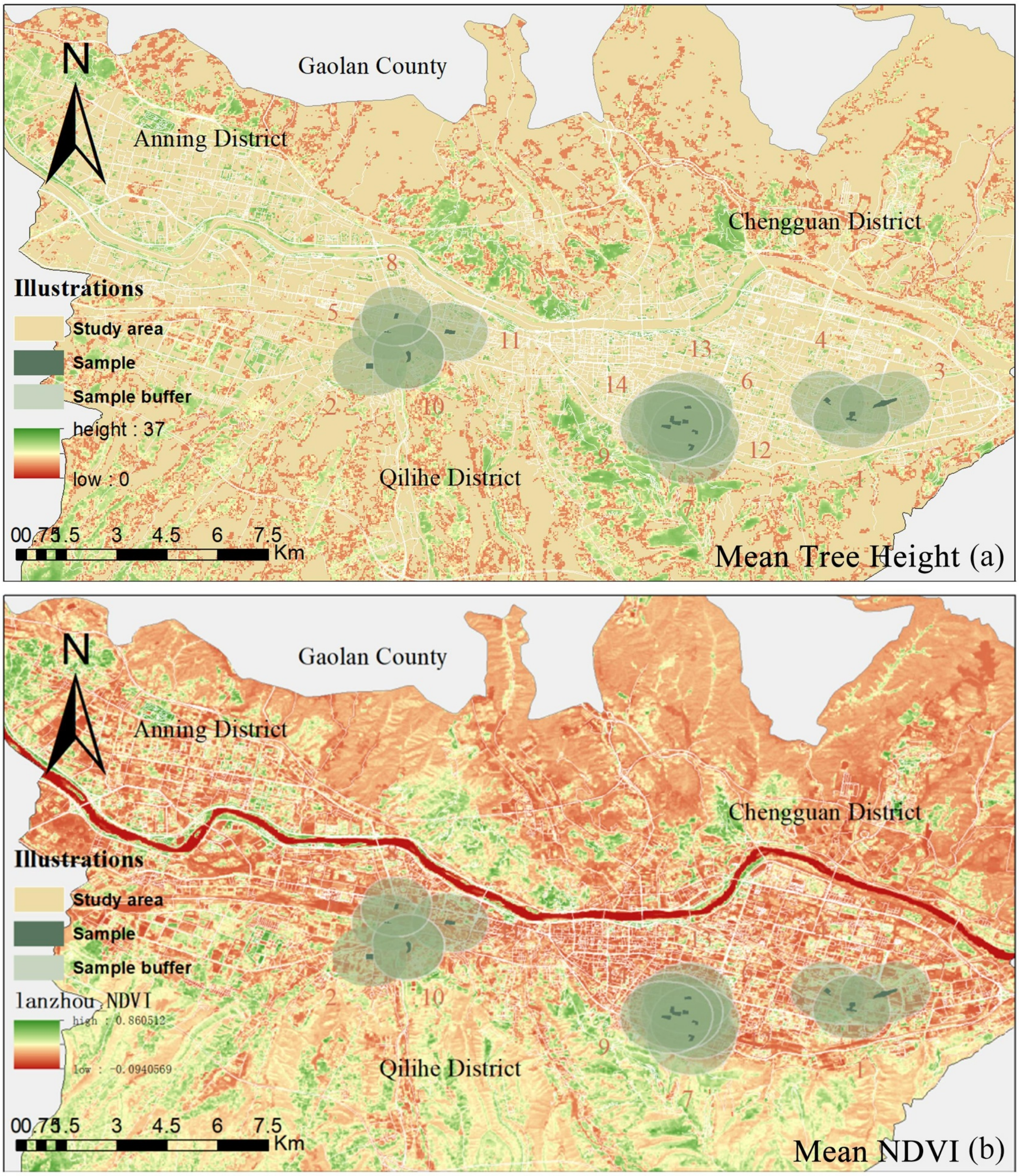

Figure 2. Mean Tree Height and Mean NDVI of study area, (a) Mean Tree Height, (b) Mean NDVI.

$$H' = -\sum_{i=1}^{S} p_i \ln(p_i) \tag{2}$$

where H′ denotes the Shannon–Wiener diversity index, *s* represents the total number of species, and pi is the proportion of individuals that belong to species *i* within the community. The following plant species were identified and included in the diversity assessment: potted plant, *Cinnamomum camphora*, *Salix spp*., *Acer palmatum*, *Sabina chinensis*, *Cycas revoluta*, *Ilex cornuta*, *Euonymus japonicus L. f. aureo-marginatus Rehd*., *Pleioblastus pygmaeus*, *Lagerstroemia indica*, *Ginkgo biloba*, *Malus domestica*, *Musa spp*., *Loropetalum chinense var*. *rubrum*, and *Citrus sinensis*.

Table 1
Descriptive Statistics and Descriptions of the Physical Activity Level, Built Environment Characteristics and Sociodemographic Variables

		Standard $N = 856$		Obesity $N = 917$	
Variable	Description	Mean	SD	Mean	SD
Predicted variable (dependent variable)					
Physical activity	Self-reported physical activity time	0.498	0.498	0.470	0.499
Predictor variables: sociodemographics (independent variable)					
Age	elderly adults aged 60–74 = 1, elderly adults aged 74–90 = 2, elderly adults aged ≥90 = 3	1.41	0.511	1.31	0.468
Gender	Male = 1, female = 2	0.40	0.489	0.450	0.497
Predictor variables: built environment (independent variable)					
Population density	The neighborhood's population density (unit: 100 persons per km^2)	0.071	0.009	0.071	0.010
Land-use density	Entropy for local land uses $H = -\left[\sum_{I=1}^{N} P_i \times \ln(P_i)\right]/\ln(N)$, where P_i represents the percentage of the ith land use, and N represents the total number of land-use categories. Seven land uses are studied ($N = 7$): residential, office, commercial, medical, entertainment, public services, and education	0.654	0.1239	0.651	0.117
Street connectivity	Total sidewalk length/total built-up area in a buffer zone (km/km^2)	1.951	0.388	1.940	0.396
Road intersection density	Within-community density at a street intersection (unit: 1 km^2)	25.726	6.237	26.767	6.614
Number of bus stops	The total number of bus stops inside a 1 km buffer zone	34.45	8.880	33.02	9.940
Bus stop distance	The shortest distance from the sample plot to the bus stop	115.373	113.089	132.323	107.652
Number of overpasses	The total number of overpasses inside a 1 km buffer zone	3.06	1.750	3.13	1.733
Predictor variables: green space (independent variable)					
Number of parks	The total number of groups inside a 1 km buffer zone	1.37	0.918	1.45	0.958
park distance	The shortest distance from the sample plot to the park	299.802	268.749	337.385	263.305
Streetscape green vision	Based on the zoning of the studied senior area, sampling sites are established by spacing all roadways inside the buffer zone at a constant distance of 50 m (static maps were purchased from the Baidu Maps developer platform, and a total of 29,000 BSV images were acquired; for each location point, four images were sampled at 90°, 180°, 270°, and 360° to represent a 360° panoramic image; the Baidu Street View-generated streetscape greenery was computed as follows: Green view index $= \sum_{i=1}^{4}$ Greenery pixels$_i/\sum_{i=1}^{4}$ Total pixels$_i$)	00.162	0.022	0.165	0.022
Mean NDVI	2021 all year average NDVI, extracted fusing GEE platform, ee.ImageCollection ("LANDSAT/LC08/C02/T1_L2"), Landsat-8 image courtesy of the U.S. Geological Survey	0.146	0.012	0.148	0.014
Plants diversity	Plant diversity at each streetscape green plant sampling site. A pre-trained data set and the Res-net deep learning framework were utilized to quantify the number of plant species	0.722	0.035	0.714	0.039
Mean Tree Height	Average tree height. ETH global canopy height 2020. EcoVision Lab, Photogrammetry and Remote Sensing, ETH Zürich	0.858	0.278	0.866	0.298
Mean LST	2021 all year average land surface temperature, extracted using GEE platform, ee. ImageCollection ("LANDSAT/LC08/C02/T1_L2"), Landsat-8 image courtesy of the U.S. Geological Survey	20.980	0.372	20.997	0.366
Total plants	The total amount of plants at each streetscape greenery sampling site (with grassland identified as a whole). Using a pre-trained data set and the ResNet deep learning framework to quantify the number of plants	1250.310	282.901	1233.90	291.173

Note. Built environment variables are measured in a 1 km buffer zone centered on the plot.

Land use diversity was assessed by integrating land use maps with population density data, considering built-up areas and open spaces. This integration facilitated a comprehensive evaluation of land use intensity and distribution within each buffer zone. Considering the methodological complexity involved in these calculations, detailed procedural descriptions are provided in the Table 1 for readers who are seeking an in-depth understanding of the processes. Descriptive statistics for all the variables, including physical activity levels, built environment

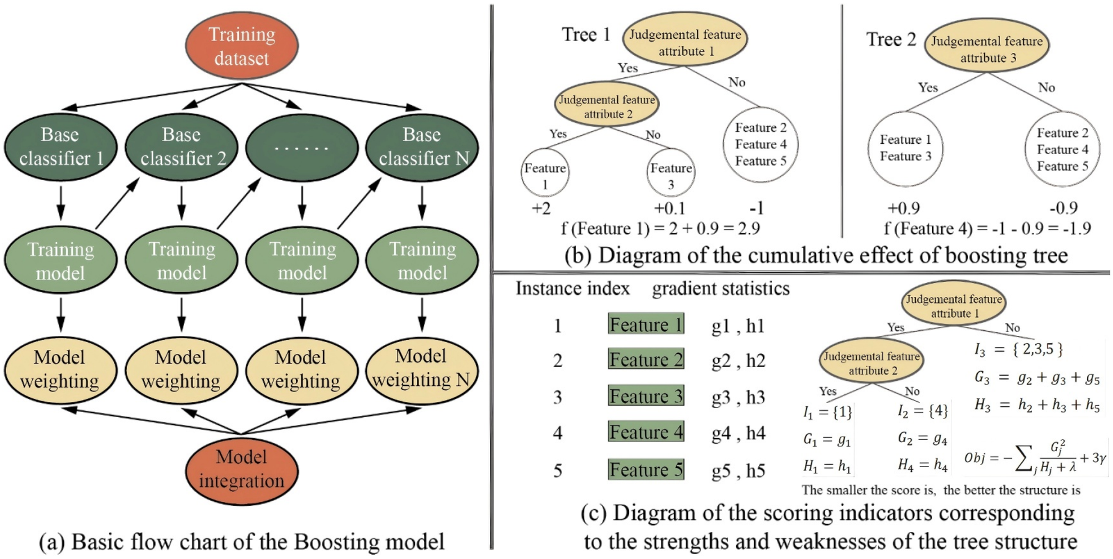

Figure 3. A XGBoost technique example.

characteristics, and sociodemographic factors, are compiled and presented in Table 1. Further statistical analyses were conducted to explore the relationships among these variables, employing appropriate multivariate techniques to account for potential confounders and interactions.

Before using XGBoost modeling, multicollinearity test was conducted to guarantee that no evident collinearity would exist between dependent and independent variables. All the variance inflation factor (VIF) values were lower than five.

2.2. Method

In this work, Figure 3 employs the XGBoost model, which is an outstanding machine learning technique. This algorithm has many advantages, including fast computation speed, scalability, and adaptability to numerical and categorical data. Furthermore, it can prevent overfitting in nonlinear models and is easy to interpret (Murphy, 2012). At present, the XGBoost model is frequently used in architecture and urban planning to elucidate the relationship between the built environment and travel preferences over time (Ding et al., 2018; H. Yang et al., 2022; L. Yang, Ao, et al., 2021).

Simultaneously, XGBoost is a boosting additive model, wherein each iteration only optimizes the submodel in the current step. where $f_m(x_i)$ is the submodel of the current step, and $F_{m-1}(x_i)$ is the first $m - 1$ fully trained and fixed submodel.

$$F_m(x_i) = F_{m-1}(x_i) + f_m(x_i) \tag{3}$$

$$\text{Obj} = \sum_{i=1}^{N} L\left[F_{m-1}(x_i) + f_m(x_i), y_i\right] + \sum_{j=1}^{m} \Omega(f_j) \tag{4}$$

The objective function is designed with a regularization term Equation 4. The regularization term $\Omega(f)$ represents the complexity of the submodel f and is used to control overfitting. XGBoost approximates the loss function by using a second-order expansion by applying the Taylor formula to approximate $f(x)$ Equation 5.

$$f(x_0 + \Delta x) \approx f(x_0) + f'(x_0)\Delta x + \frac{f''(x_0)}{2}(\Delta x)^2 \tag{5}$$

For the XGBoost loss function, we regard $F_{m-1}(x_i)$ as x_0, $f_m(x_i)$ as Deltax, and $L(\hat{y}_i, y_i)$ as a function of $\hat{y}_i$ in Equation 4, resulting in Equation 6.

$$\mathrm{Obj} = \sum_{i=1}^{N}\left[g_i f_m(x_i) + \frac{1}{2}h_i f_m^2(x_i)\right] + \Omega(f_m) \tag{6}$$

where $g_i = \partial L/\partial F_{m-1}(x_i)$, and $h_i = \partial^2 L/\partial^2 F_{m-1}(x_i)$. Here, L represents the loss function, which measures the quality of prediction. When $F_{m-1}(x)$ is determined, g_i and h_i can be easily calculated for each sample point i.

XGBoost's base classifiers support decision trees and linear models. To prevent overfitting, XGBoost sets tree-based complexity as a regularization term Equation 7.

$$\mathrm{Obj} = \sum_{i=1}^{N}\left[g_i f_m(x_i) + \frac{1}{2}h_i f_m^2(x_i)\right] + \gamma T + \frac{1}{2}\lambda\sum_{j=1}^{T} w_j^2 \tag{7}$$

where T is the number of leaf nodes of tree f, w is the vector of regression values output by all the leaf nodes, $||w||^2$ is the square of the $L2$ norm (magnitude) of the vector, and γ and λ are hyperparameters. For a regression tree, the more leaf nodes and the larger the output regression values, the higher the complexity of the tree.

We then search for the optimal tree structure based on the loss function. From Equation 7, $G_j = \sum_{i\in I(j)} gi$, $H_j = \sum_{i\in I(j)} h_i$, and G and H are both functions of j. λ and γ are preset hyperparameters, and G_j and H_j are determined by the loss function and the predicted results under a specific structure.

$$\mathrm{Obj} = \sum_{j=1}^{T}\left[G_j w_j + \frac{1}{2}(H_j + \lambda) w_j^2\right] + \gamma T \tag{8}$$

If the structure of a tree is determined, then the samples $(x_i,\ y_i,\ g_i, h_i)$ in each node are also determined, G_j, H_j, and T are determined. The regression value output by each leaf node should minimize the above expression, and then the weight w_j on each leaf can be solved. In this manner, we found our optimal tree structure and completed one iteration Equation 9.

$$w_j^* = -\frac{G_j}{H_j + \lambda} \tag{9}$$

Through the "model interpretation" package of SHAP, any machine learning model's output can be explained and an additive explanation model can be constructed, with all features considered as "contributors." For each predicted sample, the model produces a predicted value, and the SHAP value is the value assigned to each feature in that sample. Suppose the ith sample is x_i, the jth feature of the ith sample is x_{ij}, the model's predicted value for that sample is y_i, and the baseline of the entire model is y_{base}. Then, the SHAP value satisfies Equation 10.

$$y_i = y_{\mathrm{base}} + f(x_{i1}) + \mathrm{f}(x_{i2}) + \ldots + f(x_{ik}) \tag{10}$$

where $f(x_{ij})$ is the SHAP value of x_{ij}. Intuitively, $f(x_{i1})$ is the contribution value of the first feature in the ith sample to the final predicted value yi. When $f(x_{i1}) > 0$, the feature has increased the predicted value and exerts a positive effect; otherwise, the feature has reduced the predicted value and exerts a negative effect.

The partial dependence plot (PDP) generated by XGBoost modeling highlights the relationship between the predictor variables and the expected response (Pedregosa et al., 2012; L. Yang, Ao, et al., 2021). The formula is as follows:

$$\widehat{f_s}(x_s) = \frac{1}{N}\sum_{i=1}^{N}\hat{f}(x_s, x_{ic}) \tag{11}$$

where x_{ic} is the x_c value of the variable in the modeled data set, and N represents the total number of instances.

As indicated in Table 2, we compared the performance of three machine learning models, namely, random forest, gradient boosting decision tree, and XGBoost, based on key performance metrics, such as mean squared error (MSE), root mean squared error (RMSE), and mean absolute error (MAE). MSE measures the average of squared

Table 2
Comparison of Model Explanations for Random Forest, GBDT and XGBoost

	MSE		RMSE		MAE	
Model	Obesity	Standard	Obesity	Standard	Obesity	Standard
Random forests	0.252	0.251	0.502	0.500	0.497	0.497
GBDT	0.250	0.250	0.500	0.500	0.496	0.496
XGBoost	0.250	0.250	0.499	0.500	0.495	0.496

differences between the predicted and actual values, and a lower MSE indicates better model performance. RMSE, which is the square root of MSE, offers a more interpretable measure of prediction error in the same unit as the output variable, with smaller values indicating more accurate predictions. MAE calculates the average of the absolute differences between predicted and actual values, providing a direct measure of prediction accuracy without exaggerating large errors. Similar to MSE and RMSE, a lower MAE indicates better performance. The results demonstrate that XGBoost performs similarly to the other models in terms of these metrics but provides additional advantages in handling nonlinear relationships and complex interactions among variables, and thus, it is particularly suitable for the current study. Given its ability to model interactions and its robustness against overfitting, we chose XGBoost as the most appropriate model for this analysis.

We used the "sklearn" package in Python to build the XGBoost model by performing 10-fold cross-validation to fit and estimate the error, with 30% of each of the obese elderly population data set and the standard-weight elderly data set as the test set and 70% as the prediction set. The obese elderly cohort model has three established parameters (maximum tree depth: 10; minimum child weight: 4–6; learning rate: 0.01–0.1). A total of 1499 potential combinations were estimated, followed by a standard weight elderly cohort model with the same range of the three aforementioned parameters. The receiver operating characteristic (ROC) was used to evaluate model performance (Lee, 2019). After testing, the obese elderly group model ceased to grow at a maximum tree depth of 7, minimum child weight of 5, and a learning rate of 0.1, with an ROC of 0.70. With an ROC of 0.69, the standard-weight elderly group model ceased evolving at a maximum tree depth of 6, a minimum child weight of 4, and a learning rate of 0.1. Plots of the relative importance and partial dependence of environmental variables on the predictor variable (physical activity) were derived for both models for subsequent analysis.

3. Results

3.1. Relative Importance of Independent Variables

Figures 4a–4b compares key predictors in the XGBoost model by using physical activity as the outcome variable for obese and regular-weight elderly adults in Lanzhou. The relative importance of each factor is determined using absolute SHAP values, with the absolute value contributions summing to 1 and the relative contributions totaling 100% (L. Yang, Ao, et al., 2021). The results indicate that green space-related variables exhibit a significantly higher cumulative importance compared with built environment and social variables. In particular, green space factors, such as number of parks, distance to parks, streetscape green vision, and mean NDVI, account for 43.33% of the total importance in the obesity model and 42.42% in the standard model, highlighting the substantial influence of green space accessibility, greenery coverage, and vegetation diversity on promoting physical activity and reducing obesity risk in the obese and regular-weight elderly adult populations, and in surpassing the effect of other built environment and social factors.

The relative importance of other built environment characteristics is also significantly higher than sociodemographic characteristics. In the obese elderly group, population density exhibits the highest relative importance in the built environment at 8.39%, followed by mean land surface temperature (LST) (9.19%), streetscape green vision (8.36%), mean NDVI (8.19%), and number of parks (6.73%). Greening exposure significantly affects the physical activity of the obese elderly group, because the overall effect of green space is higher than those of the other environmental variables. In the standard-weight elderly group, mean LST and mean NDVI exert significant impacts on physical activity, ranking first (9.71%) and second (9.57%), respectively. The number of bus stations ranks third at 7.66%, demonstrating strong attraction, which is consistent with previous research result (Cheng et al., 2020). The greening metrics remain important for the standard-weight elderly group but are less important than for the obese elderly group. The importance of mean LST and mean NDVI around the community is higher than the other environmental variables in the obese and standard-weight groups.

3.2. Global SHAP

Figure 5 displays violin plots that reveal global SHAP summary charts, illustrating the SHAP distribution of 17 selected factors in the obese and standard-weight elderly groups within our data set, ranked by their SHAP values to highlight their effect on physical activity. These plots depict the distribution of SHAP values across various

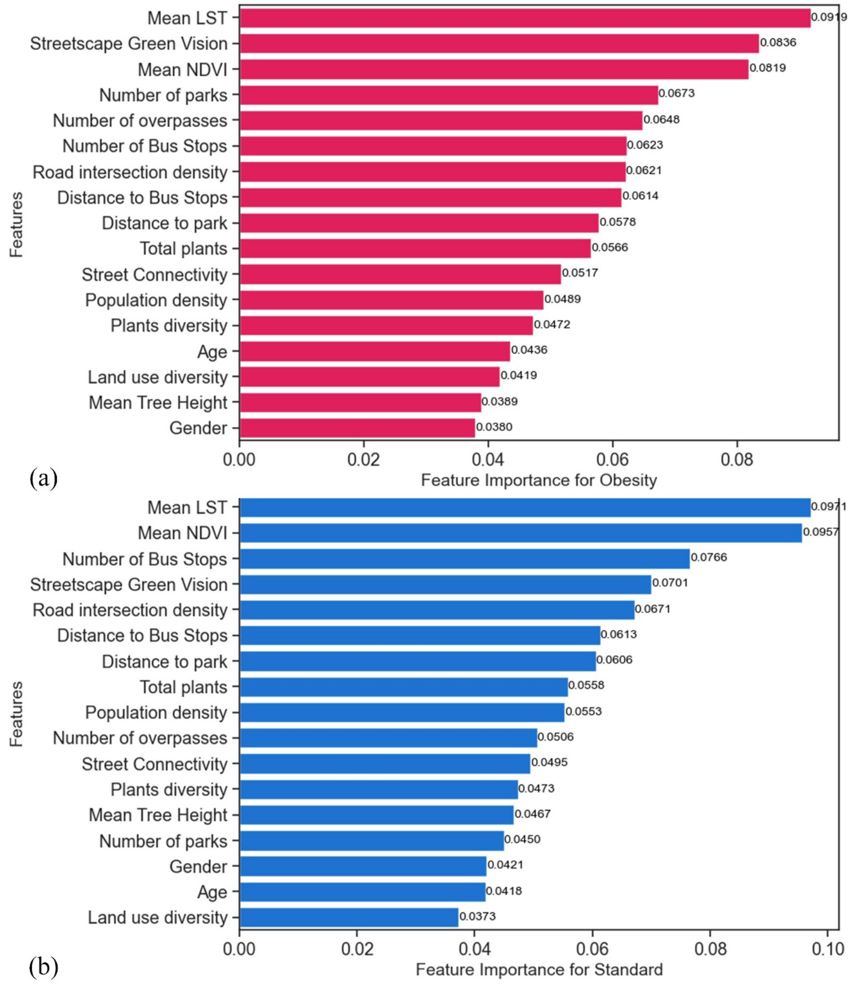

Figure 4. Predictor variables for the relative association between obesity and standard weight in the elderly population, (a) Feature importance for Obesity, (b) Feature importance for Standard.

features, with the horizontal axis representing the magnitude of each factor's SHAP value. Higher positive SHAP values for a feature indicate a more significant positive effect on physical activity. Each data point on the graph represents an individual sample, color-coded to reflect feature values, and vertically stacked to illustrate data density. The color gradients for each factor, which range from blue to red to represent low to high values, help elucidate how social factors, the built environment, and green spaces differently influence physical activity across the obese and standard-weight groups.

Figure 5 depicts a convincing trend that higher land use diversity, road intersection density, and mean LST are correlated with increased physical activity, suggesting that living in areas with smaller blocks, diverse land use functions, high population density, and suitable temperatures enhances the likelihood of elderly individuals engaging in physical activity. A decrease in the number of bus stops increases physical activity in the obese and standard-weight elderly groups, suggesting that residing in areas farther from public transport serves as an important reason for physical activity among these groups. The influence of green spaces on physical activity is more complex, as illustrated in the contribution plots of plant diversity, total plants, and streetscape green vision to physical activity. Although a higher streetscape green vision is generally beneficial, it does not imply a corresponding increase in the number and variety of street plants. For plant diversity, the largest global SHAP contributor, fewer street plant species contribute more variably to physical activity. Although some high values significantly boost activity in normal-weight elderly individuals, higher plant diversity does not notably benefit the physical activity of obese elderly individuals. The global SHAP contribution of total plants reveals that fewer plants correlate with higher physical activity in the obese group, with some minimum values also significantly

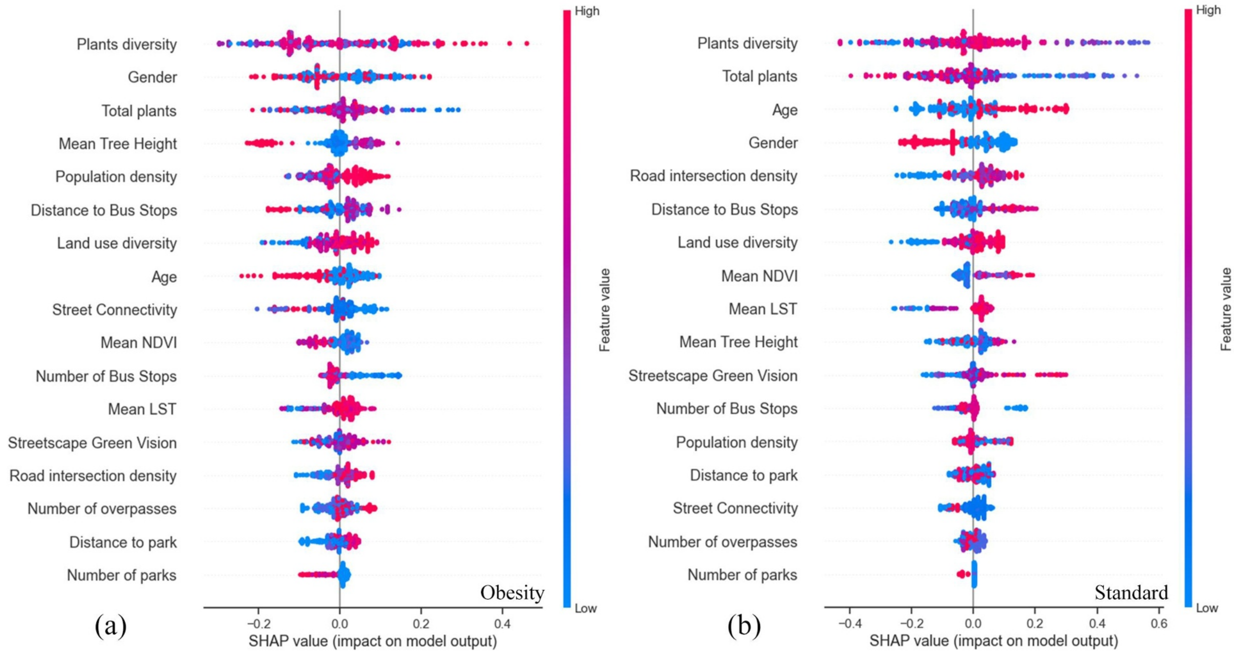

Figure 5. Global SHAP value of obesity and standard weight in the elderly population, (a) Obesity SHAP value, (b) Standard SHAP value.

enhancing activity in the standard-weight elderly group. Vertically, trees with medium to low height help increase physical activity. Horizontally, significant difference is observed in the relationship between mean NDVI and physical activity for the two groups, suggesting that abundant surrounding green space plays an important role in increasing physical activity in the obese elderly population but not in standard-weight individuals. Some scholars have also noted that sparse greenery will diminish the obese population's enthusiasm for daily travel and exercise, while normal-weight elderly individuals may also increase their activity in less green environments (Caili et al., 2024; Xiao, Miao, et al., 2022).

3.3. Nonlinear Relationship Between Physical Exercise and Green Space

Figures 6a and 6b illustrate the nonlinear relationship between plant diversity and total plants in the obese and standard-weight elderly groups. The red line is for the obese elderly group, while the blue line is for the standard-weight elderly group. Both graphs exhibit similar trends with spikes in the curve. The contributions of plant diversity and total plants to physical activity in normal-weight seniors are relatively stable, while changes in obese seniors are more pronounced. Plant diversity is generally positively correlated with physical activity. However, it is negatively correlated at below 0.65. Within the range of 0.65–0.70, plant diversity exerts a significant positive effect on the obese elderly group. A similar spike occurs in total plants at a value of 1000, where positive contribution to the physical activity of the obese elderly group peaks. The plots reveal that the values of plant diversity and total plants obtained from their respective spike intervals contribute the most to the SHAP values. Meanwhile, green space configurations with the optimal thresholds obtained from these intervals exhibit a significant and positive effect on enhancing the physical activity of the elderly.

Figures 6c and 6d depict the effects of mean NDVI and streetscape green vision on the physical activity of the obese and standard-weight elderly groups. The curve trends diverge in Figure 6c. When values exceed 0.15, an increase in mean NDVI boosts physical activity in obese seniors but reduces them in normal-weight seniors. The curves for streetscape green vision in both groups present a positive correlation. When the value exceeds 1.7, the red curve becomes steeper. This result suggests that more streetscape greening may exert a significant positive effect on the obese group. This finding can be attributed to the expansion of green space and street-level greening attracting physical activity among the obese elderly, while the overall low levels of green space and street greening are insufficiently attractive to those with normal weight.

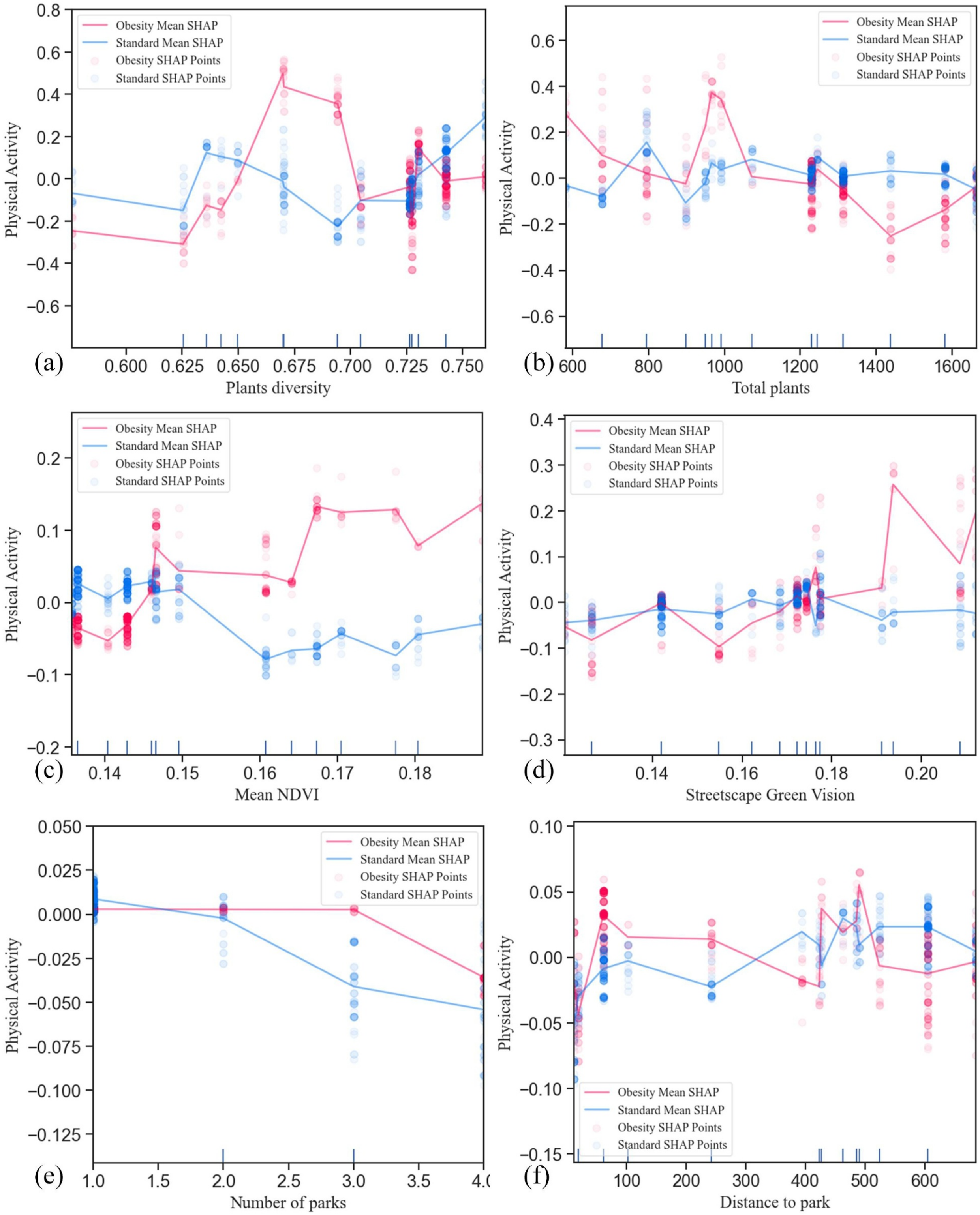

Figure 6. Association green space predictors and obese and standard weight elderly populations compared, (a) Plants diversity, (b) Total plants, (c) Mean NDVI, (d) Streetscape Green Vision, (e) Number of parks, (f) Distance to park. Obesity is defined as the group of older people with a physical activity ≥ 24 and the standard is defined as the group of older people with 18 ≤ physical activity < 24.

Figures 6e and 6f illustrate the nonlinear relationship between the number of parks and distance to parks for the obese and standard-weight elderly groups. Figure 6e indicates that the number of parks is negatively correlated with physical activity in Lanzhou. As the number of parks increases from 1 to 4, both groups exhibit a decrease in SHAP values, but the standard-weight group presents a more noticeable response. This result suggests that the presence of parks may play a more critical role in influencing the health outcomes of the standard weight group. The fitted curves in Figure 6f indicate a positive correlation between park distance and physical activity. At a distance of 100 m, the SHAP values for the obese group may exhibit some positive effects. A critical point exists at distances of 400–500 m, wherein positive contribution to the obese group is potentially maximized, while the positive effect on health diminishes beyond this range. This finding may be attributed to the increased walking time associated with greater park distance, boosting physical activity, particularly among the obese elderly group.

3.4. Non-Linear Relationship Between Physical Activity and the Built Environment

Figure 7 is a partial dependency plot that shows the nonlinear relationship between physical activity and other built environmental variables for the obese and standard-weight elderly groups. The red line is for the obese elderly group, while the blue line is for the standard-weight elderly group. Figure 7a depicts comparable physical activity and population density for the obese and standard-weight elderly groups, starting with a positive influence at 0.045, which indicates that lower population density may increase physical activity in the obese group. As population density increases, the red line dips near 0.06, becoming negative, and then rises again when density exceeds 0.075, suggesting that positive effect strengthens with increasing density; this finding is consistent with earlier research (Yin et al., 2020). Figure 7b illustrates the nonlinear effect of land use diversity on physical activity for the two elderly groups, with the images showing different shapes, with the obese elderly group depicting a decreasing trend in physical activity at a land use diversity of 0.6 and the standard-weight elderly group presenting an increasing trend at a land use diversity of over 0.7. The reason may be as follows: the higher the land use diversity, the easier for older people to perform their daily activity, resulting in more physical activity for obese older individuals who are more inclined to walk to their destinations (Hanibuchi et al., 2011).

Figures 7c and 7d illustrate the effects of street connectivity and intersection density on physical activity in the obese and standard-weight elderly groups. The smooth trend lines in Figure 7c is similar, showing a positive correlation with physical activity when street connectivity is below 2 and a negative correlation when it is above 2. Figure 7d shows different shapes. In the obese elderly group, physical activity are negatively correlated with intersection density that exceeds 25 pcs/km^2 and then dips when it passes 30 pcs/km^2. Meanwhile, in the standard-weight elderly group, physical activity decrease when intersection density is below 28 pcs/km^2 and increases when it is above 30 pcs/km^2. This result may suggests that increasing the number of intersections within a community can provide a richer road experience, helping the elderly group increase their daily activity (Koh et al., 2021). However, overly dense intersections can lead to more complex roads, reducing the inclination to travel of the obese elderly (Xiao, Chen, et al., 2022; Zenk et al., 2022).

Figures 7e and 7f show the threshold changes in the number of bus stops and distance to bus stops for the obese and standard-weight elderly groups. In Figure 7e, the overall physical activity of the normal-weight group is negatively correlated with the number of bus stops. For the obese elderly, a positive effect is exerted on physical activity when the number of bus stops is less than 20, while for the standard-weight elderly group, physical activity are negatively correlated with the number of stops when it exceeds 20. The fitted curves in Figure 7f exhibit a positive correlation trend between distance to bus stops and physical activity in the obese elderly group. The obese group's influence decreases as distance exceeds 300 m but remains positive, suggesting that longer distance from bus stops promotes activity among the obese elderly group while the boundary effect exists after 300 m (Rundle et al., 2007; Zang et al., 2021a, 2021b). This result may be attributed to a specific public transit distance significantly boosting physical activity among overweight elderly individuals who rely on public transport.

Figure 7g illustrates the relationship between the number of overpasses and physical activity in the obese and standard-weight elderly groups. Both smooth curves exhibit a U-shape, suggesting a positive correlation with physical activity when the number of overpasses is less than 2 and a negative correlation when it exceeds 2. This result suggests that an excessive number of overpasses increases travel difficulty for the elderly, with a more significant effect on obese individuals (Zang, Qiu, et al., 2022; Zang, Xian, et al., 2022). Figure 7h depicts a positive correlation between mean LST and physical activity in both groups. When mean LST is below 20.8, the

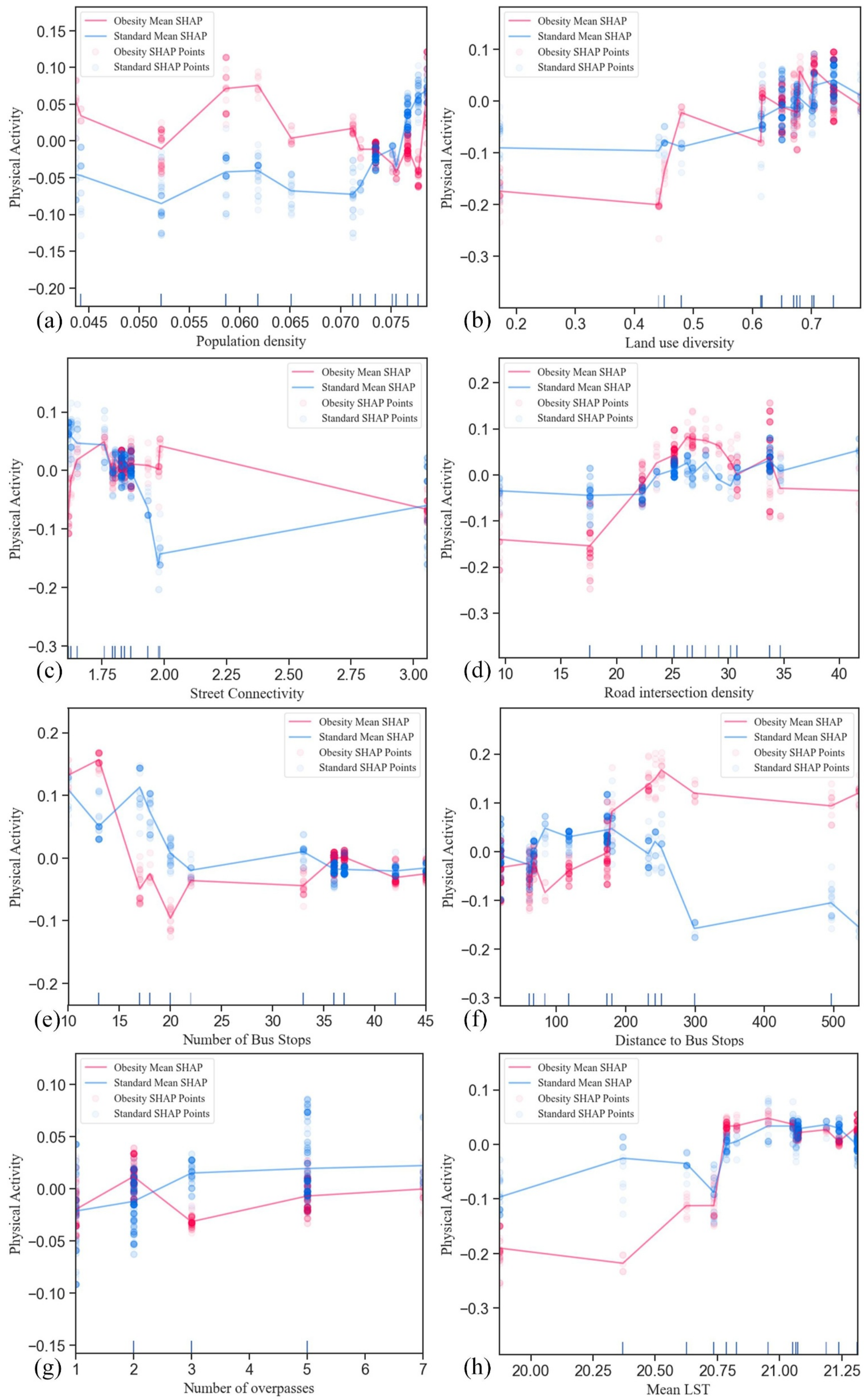

Figure 7. Association between built environment predictors and obese and standard weight elderly populations compared, (a) Population density, (b) Land use diversity, (c) Street Connectivity, (d) Road intersection density, (e) Number of Bus Stops, (f) Distance to Bus Stops, (g) Number of overpasses, (h) Mean LST. Obesity is defined as the group of older people with a physical activity ≥ 24 and the standard is defined as the group of older people with $18 \leq$ physical activity < 24.

correlation with physical activity is negative; when it is above 20.8, the correlation becomes positive. This result may be due to the generally colder climate in Lanzhou, which increases resistance to physical activity among the elderly, with overweight elderly individuals being more significantly affected by the low temperatures.

4. Discussion

As China enters a deeply aging society, promoting physical activity among the elderly can reduce the probability of obesity, maintain their independence, and thus, reduce societal medical pressure, ensuring the health and sustainability of a deeply aging society. Comfortable green spaces and 5D built environments are conducive to increasing the time that elderly individuals spend on physical activity. Using the XGBoost model to examine the nonlinear relationship between the physical activity time of standard-weight and obese elderly individuals in Lanzhou with green spaces and built environments, green spaces are determined to be more important to the elderly than 5D built environments. The quality of green spaces exerts a greater effect on obese elderly individuals than on standard-weight elderly individuals. An appropriate threshold range for green spaces is beneficial for obese elderly individuals to increase their physical activity, particularly vegetation diversity, which exerts a more significant effect on the elderly.

4.1. Major Findings

This study determines that green spaces exert a significant effect on physical activity among obese older adults, demonstrating distinct differences compared with their counterparts with standard body weight. First, the characteristics of green spaces, such as the visibility of street greenery, distance to parks, vegetation diversity, and average LST, exert a greater effect on promoting physical activity among obese older adults, while older adults with standard weight are more influenced by vegetation quantity and the number of parks; this result is consistent with the findings of other studies (Sallis et al., 2012). Moreover, the importance ranking of different green space characteristics varies significantly between the two groups, indicating different levels of dependence on environmental features. Lastly, obese older adults place greater emphasis on the quality and accessibility of green spaces, while those with standard body weight are more concerned with the overall amount and coverage of greenery.

Compared with previous studies, the current research highlights the importance ranking of different attributes within green spaces. In the obese elderly group, characteristics, such as street greenery visibility, number of parks, and average tree height, play dominant roles. This finding is aligned with previous conclusions that green spaces generally contribute to increased physical activity among older adults (Wolch et al., 2014); however, SHAP analysis further reveals the differential sensitivity of obese and standard-weight older adults to these features. Older adults with standard weight are more affected by number of parks and NDVI, while obese older adults rely more on visually accessible green spaces. In contrast with most previous studies that focused on linear relationships between the environment and older adults (Giles-Corti & Donovan, 2002; Zang et al., 2021a, 2021b), the current research highlights significant differences in how the same environmental characteristics affect different groups within varying ranges (L. Yang, Ao, et al., 2021). Although greater vegetation quantity is of higher importance for the standard-weight elderly group, the effect on obese individuals relies more on greenery's visual appeal and accessibility.

For green space variables, such as vegetation diversity, number of parks, and distance to parks, the current study finds a complex, nonlinear effect on physical activity among older adults (L. Yang et al., 2025). Vegetation diversity exerts the most significant positive effect on physical activity among obese older adults when it is between 0.65 and 0.70. This result is consistent with the findings from North America and Europe in which diversity and high-quality green spaces promote physical activity (Nguyen et al., 2021). The results further suggest that visual accessibility and overall quality of green spaces are key to promoting physical activity for obese older adults, while their influences on standard-weight older adults is less significant. The relationship between number of parks and physical activity among older adults exhibits a downward curve; that is, increasing the number of parks after a certain point reduces their effect on physical activity. This result may be due to the dispersal effect of having too many parks, failing to provide sufficient attraction for focused activity. This finding contrasts with those of other studies, which generally find a linear positive correlation between number of parks and physical activity, reflecting the complexity of different urban environments and population behavior patterns.

With regard to distance to parks, the results show that obese older adults benefit from moderate distances to parks (approximately 300–500 m), motivating them to engage in physical activity due to increased walking demand. For older adults with standard weight, proximity to parks better facilitates their daily activity. This result id partially aligned with previous research, which suggests that greater proximity leads to more frequent activity (Lu et al., 2018), but also demonstrates a different motivational distance for obese older adults, indicating a need for moderate challenges to boost their daily activity levels. Furthermore, the visibility of street greenery exhibits a significant positive effect on physical activity among obese older adults. When the street greenery visibility index exceeds a certain threshold (approximately 0.16), the physical activity of obese older adults significantly increases. This finding is consistent with conclusions drawn from studies in North America and Europe in which visually greener streets encourage more outdoor activity, particularly among populations with higher psychological stress (Besser et al., 2017). By contrast, older adults with standard weight exhibit a relatively lower dependence on street greenery, possibly due to their higher motivation to engage in physical activity and tendency to more actively seek out exercise opportunities (P. Zang et al., 2024).

With regard to the influence of the 5Ds on physical activity among older adults, the findings of the current study reveal similarities and differences compared with previous research. First, land use diversity exerts a positive effect on physical activity for obese older adults when it is within the range of 0.6–0.7. This result is consistent with findings that land use diversity can enhance activity levels among older adults (Van Cauwenberg et al., 2018). For older adults with standard weight, however, this effect also exhibits a positive correlation, which is in line with previous research, suggesting that they may engage in more daily activity in a functionally diverse environment (Barton, 2009; Xiao, Chen, et al., 2022). In addition, the number of bus stops has demonstrated a clear nonlinear relationship with the activity levels of older adults. A moderate number of bus stops can effectively promote physical activity among obese older adults, but an excessive number may reduce their activity frequency, possibly due to the complexity of navigating numerous stops. The convenience of transportation exhibits greater effect on physical activity for obese older adults, because bus stops that are farther away may increase their walking time, which can be beneficial for this group. This finding is in contrast with previous conclusions that closer bus stops are always better (Lu et al., 2018). In promoting physical activity among older adults, increasing distance to bus stops within a reasonable threshold can be beneficial.

4.2. Potential Role of Climate Zone in the Relationship Between Urban Greenery and Physical Activity

The current study compares the results of previous research, with particular emphasis on the positive relationships between green spaces and physical activity in temperate and subtropical regions (Li et al., 2016). Exploring why these relationships may be different in arid regions is also crucial. Previous studies in temperate and subtropical climates have shown that green spaces significantly promote physical activity due to more favorable climatic conditions, such as milder temperatures and abundant rainfall, which encourage outdoor activity (Zheng et al., 2018). By contrast, the results in arid regions are more varied, with some studies reporting weak or nonsignificant effects of green space on physical activity (Hogendorf et al., 2020). This discrepancy can be attributed to several factors that are inherent to arid regions. In arid climates, such as the semiarid region of Lanzhou, environmental conditions characterized by high temperature differences, water scarcity, and limited vegetation can reduce the attractiveness and usability of green spaces. The lack of adequate shade, coupled with seasonal extreme weather conditions, may discourage outdoor activity, particularly among the elderly (Richardson et al., 2012). By contrast, temperate and subtropical regions benefit from more moderate climate, which makes green spaces more conducive to year-round physical activity, leading to a more straightforward positive correlation.

In addition, the type of green space and its design may play a more significant role in arid regions. In Lanzhou and other semiarid areas, well-designed green spaces with sufficient shade, water features, and suitable vegetation are more likely to encourage physical activity (Xie et al., 2024). However, in areas where green space is poorly maintained or lacks the aforementioned essential attributes, the positive effects may be subdued. The nonlinear relationships observed in this study also suggest that the effectiveness of green space in promoting physical activity among older adults in arid regions may be contingent on the specific environmental features of these spaces, rather than their mere existence or size. This insight contrasts with findings from temperate and subtropical regions, where green space size and proximity to residential areas are frequently sufficient to promote physical activity.

4.3. Green Space Optimization Recommendations

Based on the current study, several practical recommendations for optimizing the accessibility and quality of green spaces in semiarid areas are made. First, green spaces should be located as close as possible to residential areas to ensure that they are accessible to older individuals on foot in less than 15 min, while improving the safety and accessibility of walking paths, especially for older people with mobility impairments. Second, given the temperature difference between day and night in semiarid areas, green space design should focus on providing facilities with adequate shade, while increasing the interest in green space by using a wide variety of water-saving and frost-tolerant plants to enrich plant species and efficient irrigation systems to ensure plant survival. To encourage physical activity among older adults, green spaces should provide diverse functional areas, such as fitness facilities, trails, and recreational spaces. In addition, community involvement in the design process is crucial. Understanding the needs of older adults and incorporating cultural and social elements can enhance the utilization of green spaces. Finally, ensuring the regular maintenance and safe design of green spaces can enhance their attractiveness and safety for the older population. Through these measures, the contribution of green spaces to the physical activity of older adults can be effectively enhanced, improving their health and quality of life.

4.4. Strengths and Limitations

The strengths of this study lie in its pioneering exploration of the relationship between physical activity and green spaces for the elderly in Lanzhou, a drought-prone area in Western China. The study uses physical examination data to calculate the BMI of the elderly, dividing them into standard-weight and obese groups. It is the first to discuss the nonlinear differences in green space needs for physical activity between obese and standard-weight elderly individuals. In the quantification of green spaces, deep learning techniques are employed to comprehensively quantify 3D green spaces from 2D and 3D perspectives, ensuring an accurate reflection of the entire environment.

Despite the progress made in exploring the relationship between green spaces and physical activity among older adults, this study has several limitations. First, data collection is limited to selected communities in Lanzhou that agreed to participate in the research, constraining the generalizability of the results. Second, this study primarily relies on the XGBoost model for analysis. Although this model excels in capturing complex nonlinear relationships, it exhibits limitations in causal inference. Another limitation of this study is that it does not consider the effect of diet on obesity and physical activity in older adults. Diet is a key factor in obesity, but the relatively homogenous dietary pattern of the older population in the sample of this study may have led us to underestimate the potential effect of diet. Moreover, although SHAP values provide an importance ranking of features, these conclusions are still based on correlation rather than causation. Future research can consider integrating structural equation modeling or other causal inference methods to enhance the interpretability of the results. Data collection should also be expanded to other regions, and longitudinal research designs should be used to validate the long-term effects of green spaces on the health of older adults. In addition, different forms of greenery, such as rooftop gardens or vertical greening, and their effects on older adults' health are worth further exploration. Such exploration will provide more diversified recommendations for urban planning, particularly on how to maximize the health benefits of green spaces when resources are limited.

5. Conclusions

This study provides important insights into the relationship between green space characteristics and physical activity among older adults, with focus on Lanzhou, a semiarid city in Northwestern China. The findings have broader implications for urban planning in similar semiarid and arid regions worldwide. Lanzhou's unique climatic and environmental conditions make it an ideal case for studying how these factors influence green space use by older adults. The results suggest that although green space quality and accessibility are crucial for promoting physical activity, these effects may differ depending on local environmental conditions. In cities that face similar challenges, these findings can inform strategies for designing green spaces that encourage more outdoor activity, particularly among elderly populations.

This study highlights several key aspects that contribute to our understanding of the relationship between urban green space and physical activity. First, the relationship was nonlinear, with significant effects emerging only after certain thresholds of green space quality and accessibility were met. This finding suggests that simply increasing the amount of green space may not be sufficient to improve physical activity levels. That is, the design and quality of these spaces are equally important. In semiarid regions such as Lanzhou, factors, including shading, water-efficient landscaping, and temperature regulation, play a significant role in making green spaces usable and attractive for physical activity, particularly during extreme weather conditions. This study also revealed that obese older adults experience different patterns of physical activity in relation to green space attributes compared with their non-obese counterparts. This finding suggests that urban planning should consider tailored approaches to green space design to meet the specific needs of different subgroups within the elderly population.

In conclusion, although the study is focused on Lanzhou, its findings have broader applicability to other semiarid and arid regions. These insights provide valuable guidance for urban planners in cities that face similar climatic and environmental challenges. Future research should continue to explore the interaction among green space characteristics, climate, and demographic factors to further refine strategies for promoting physical activity among older adults in diverse urban contexts.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

Data—The physical examination data of the elderly used in the research was obtained from Zenodo (Qiu et al., 2025a), after personal privacy was removed as the authors are prohibited from sharing personal—level physical examination data to protect sensitive personal information. The data set related to Land Surface Temperature (LST) was accessed through the Earth Resources Observation and Science (EROS) Center (Observation & Center, 2020). The data set related to tree height was obtained from Nature Ecology & Evolution (Lang et al., 2023). The data set related to Normalized Difference Vegetation Index (NDVI) was accessed from the Science of Remote Sensing (Crawford et al., 2023). The built—environment data from the Amap data set was retrieved as per (State Information, 2017).

Software—The Python 3.8 code for calculating the non—linear model was obtained from Zenodo (Qiu et al., 2025b) and is also publicly available on GitHub.

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