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Nonlinear Associations Between Built Environment and Overweight: Gender and Marital Status Differences in Urban China

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Abstract

Overweight has become a major public health concern in China's rapidly urbanizing cities. Patterns of environmental exposure differ notably between men and women, both before and after marriage. This study examines how built environment characteristics influence the risk of overweight, with particular attention to nonlinear associations as well as variations by marital status and gender. Drawing on survey data from 2634 Shanghai residents, we applied extreme gradient boosting to model complex environment–health relationships. The results indicate that greenness, park accessibility, population density, and transit conditions are associated with overweight through nonlinear pathways, with threshold and plateau effects suggesting that benefits taper off, or risks escalate, beyond certain levels. These optimal ranges differ across gender–marriage groups: moderate density and green exposure were generally protective, but the effective ranges were narrower for women and unmarried individuals. Married men benefited more consistently, likely supported by healthier routines reinforced through spousal support, whereas married women showed weaker or even adverse effects, potentially due to greater family responsibilities. Overall, the findings reveal that overweight is shaped by socially differentiated nonlinearities in environmental exposures. Urban planning and public health policies should therefore optimize built environment attributes within effective ranges and tailor interventions to diverse demographic groups.

Keywords: overweight; built environment; nonlinear associations; gender–marriage heterogeneity; threshold effects; extreme gradient boosting

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1. Introduction

Overweight has become a pressing public health concern worldwide, substantially increasing the risk of cardiovascular disease, diabetes, and other chronic conditions. According to WHO data, approximately 2.5 billion adults, 43% of the global adult population, were overweight in 2022, underscoring its growing burden on healthcare systems [1]. In China, the prevalence of overweight has risen sharply in recent decades, driven by rapid urbanization and lifestyle changes [2]. This trend highlights the urgency of identifying the determinants of overweight to guide effective prevention strategies and public health interventions.

Among these determinants, the built environment has attracted increasing attention [3,4]. A well-designed urban form characterized by adequate density, diversity, and accessibility can promote physical activity and healthy dietary habits. By contrast, car-dependent environments with limited green space or abundant fast-food outlets tend to foster sedentary behaviors and poor nutrition, thereby elevating overweight risk [5,6]. Growing evidence suggests that features such as green space, population density, and public transport accessibility influence energy balance through both physical activity and dietary pathways, positioning the built environment as a key upstream determinant of overweight [7–9].

Behavioral factors are also central to understanding overweight [10]. Insufficient physical activity, prolonged sedentary time, irregular eating patterns, and frequent consumption of energy-dense foods are well-documented risk factors [11,12]. Additional lifestyle routines, including smoking, alcohol consumption, and sleep quality, further affect weight regulation [13,14]. Moreover, subjective life satisfaction has been shown to shape health-related behaviors: individuals with higher satisfaction are more likely to maintain healthier routines, whereas those with lower satisfaction may adopt sedentary or stress-related behaviors [15,16]. These findings emphasize that overweight cannot be explained solely as a matter of individual choice, but rather emerges from the interplay between behaviors, psychological states, and environmental conditions.

Despite notable progress, relatively few studies have examined population heterogeneity in these relationships [17,18]. The Social Determinants of Health framework highlights that demographic and social attributes shape how individuals perceive and interact with their environments [19]. Gender and marital status are particularly relevant, as they influence role expectations, lifestyle routines, and access to social support. Women often face structural and cultural barriers, such as household responsibilities and concerns about safety in public spaces, that restrict opportunities for exercise and limit their ability to benefit from green spaces and recreational facilities [20,21]. By contrast, men are typically more active in outdoor and recreational environments, although their higher rates of smoking and alcohol consumption may counteract some of these health benefits [22,23]. Marital status further complicates these dynamics: while marriage can provide protective resources through spousal support [24], it may also impose additional constraints, especially on women, due to greater family and caregiving responsibilities [25]. However, empirical evidence on how overweight is differentially linked to built environments and behavioral habits across gender–marriage subgroups remains limited. Addressing this heterogeneity is crucial for identifying vulnerable populations and designing more tailored interventions.

A further issue concerns the nonlinearity of environment–behavior–health linkages. Emerging evidence suggests that the effects of population density, green space, and transit accessibility on overweight often follow nonlinear patterns, with thresholds or optimal ranges beyond which benefits diminish or risks increase [26,27]. However, little is known about whether these nonlinearities apply uniformly across demographic subgroups. Incorporating gender and marital status into this discussion is particularly important, as these attributes not only shape behavioral practices but also condition how individuals access and benefit from environmental resources.

To address these gaps, we propose three hypotheses:

Hypothesis 1 (H1): *Nonlinear associations between the built environment and overweight vary across social groups, as lifestyle routines influence how individuals can access and benefit from environmental resources.*

Hypothesis 2 (H2): *Marriage provides spousal support that enables married men to adopt healthier lifestyles [24], thereby lowering their risk of overweight compared with unmarried men.*

Hypothesis 3 (H3): *Married women, constrained by limited opportunities for physical activity and greater family responsibilities imposed by social expectations [25], are more likely to face an elevated risk of overweight.*

This study drew on survey data from 2634 residents in Shanghai and applied XGBoost to examine how built environment, lifestyle, and socio-demographic factors are associated with overweight.

2. Literature Review

2.1. Built Environment and Overweight

The built environment is a key determinant of overweight, shaping both opportunities and constraints for healthy living. Core elements such as green space, population density, and transport accessibility influence physical activity, dietary behaviors, and psychosocial conditions, thereby affecting weight outcomes. Green space has consistently been shown to reduce overweight risk by providing venues for exercise, alleviating stress, and fostering social interaction [7–9]. Importantly, not only the presence but also the accessibility and quality of green areas matter, with some studies identifying threshold effects beyond which health benefits diminish [28,29]. Population density exerts mixed effects: moderate levels promote walkability and access to services, whereas very high density can reduce satisfaction, restrict recreational space, and increase sedentary time, thereby elevating overweight risk [30]. Transport accessibility also has dual implications. Proximity to transit supports active commuting and incidental walking [31], but long commuting times may reinforce sedentary behavior and reduce opportunities for exercise or healthy eating [32]. Taken together, these findings underscore that the built environment shapes overweight through both physical access and behavioral incentives, highlighting its importance as a modifiable factor in weight prevention.

2.2. Gender and Marital Status as Moderators of Overweight

Existing research highlights the important role of marital status and gender in shaping health outcomes. Marriage is frequently linked to protective effects, whereas divorce or widowhood elevates risks of morbidity and mortality, particularly among men [33,34]. In parallel, urban and public health studies emphasize the influence of the built environment on physical activity and obesity. Features such as neighborhood walkability, recreational facilities, and safety are positively associated with healthier lifestyles, though these associations often differ by gender [35].

While the built environment provides opportunities and constraints for health, its effects on overweight are mediated by behaviors and conditioned by gender and marital status. Behavioral factors, including physical activity, sedentary lifestyle, diet, sleep, smoking, alcohol use, and life satisfaction, directly shape overweight risk [36–39]. Regular exercise reduces risk by improving energy balance, whereas inactivity, poor diet, and inadequate sleep promote weight gain [40–42]. Smoking is sometimes associated with lower body weight but harms overall health, while alcohol consistently contributes excess calories [43,44]. In addition, life satisfaction influences weight regulation through stress, emotional eating, and motivation to maintain healthy routines [15,45].

These behaviors do not develop in isolation but are strongly shaped by socio-economic contexts [46,47]. Gender and marital status, in particular, influence both health behaviors and the use of the built environment, thereby reshaping daily routines and health outcomes [48,49]. Women often face structural and cultural constraints, such as safety concerns in public spaces or greater household responsibilities, that limit opportunities for physical activity and reduce their ability to benefit from urban green spaces, recreational

facilities, or walkable neighborhoods [20,50]. Men, by contrast, tend to report higher levels of physical activity but also greater engagement in risky behaviors such as smoking and alcohol consumption [22], which may offset the advantages of their more active use of parks, sports facilities, and other urban amenities [22]. These differences suggest that identical environmental or behavioral exposures may yield divergent outcomes by gender. Marital status adds another layer of complexity. Marriage is frequently associated with weight gain due to shared meals, reduced activity, and lifestyle adjustments, a phenomenon sometimes described as the "marriage market hypothesis" [25]. At the same time, married individuals may benefit from spousal support that fosters healthier routines, particularly among men [24]. Single, divorced, or widowed individuals often display different behavioral patterns shaped by social networks, stress, and economic stability [51]. When combined, gender and marital status create intersecting subgroups with distinct risk profiles. Married women, for example, may experience greater time constraints from household responsibilities, leaving them less able to take advantage of nearby parks, green spaces, or recreational facilities, even when such resources are physically accessible [50]. By contrast, men, especially single men, may be more vulnerable to unhealthy dietary patterns [24]. They are also more likely to use outdoor and recreational spaces actively while simultaneously frequenting fast-food outlets or bars, linking physical activity with riskier lifestyle habits [23]. These dynamics underscore that overweight is not simply the outcome of individual choices or environmental exposures but rather of social positions that mediate how people interact with and respond to them.

2.3. Nonlinear Effects and Subgroup Heterogeneity in Overweight

Despite a growing body of literature on overweight [22,46,47], conventional approaches often fail to capture the complex dynamics of its determinants. Traditional regression models typically assume linear and additive relationships between variables [31,52], thereby overlooking the threshold effects and nonlinear patterns that characterize the influence of the built environment on health. For example, the benefits of green space may plateau beyond a certain level, while the risks associated with population density may only emerge once critical thresholds are exceeded [30]. Similarly, lifestyle factors such as physical activity, sleep, alcohol consumption, and smoking have been shown to follow nonlinear trajectories, with optimal ranges rather than monotonic effects [53,54]. These lifestyle routines also vary substantially across demographic subgroups [43,55], meaning that the same built environment may produce divergent health outcomes depending on how it is used. Ignoring such nonlinearities and subgroup interactions risks obscuring vulnerable populations and generating oversimplified policy recommendations. Furthermore, comparative analyses across demographic subgroups remain limited. Recent advances in machine learning offer tools well-suited to address these complexities [27,56], providing more precise and context-sensitive insights into overweight risks.

3. Data and Methodology

3.1. Data Source

The data for this study were drawn from the project Spatial Structure, Social Structure, and Residential Satisfaction of Neighborhoods in Shanghai, jointly initiated by the Center for the Study of Social Transformation at Fudan University and the Center for Urban and Social Research at Tongji University. Neighborhood surveys were conducted between 2015 and 2017, and resident questionnaires between 2019 and 2021. Two structured questionnaires were employed. The neighborhood survey collected information on locational features, spatial structure, social composition, and governance, while the resident question-

naire covered demographics, occupation and life course, social capital, values and attitudes, housing, and self-rated health.

A five-stage probability-proportional-to-size sampling design was used to ensure representativeness. First, 30 subdistricts/towns within the Shanghai Outer Ring were selected based on location and the latest population data. From each, 4 neighborhood committees were chosen (120 total). Within these committees, 300–400 residential communities were sampled. In each community, approximately 60 households were contacted to obtain 20 completed interviews, yielding 3648 interviews in total (a 30% success rate). Finally, one individual aged 18–70 was randomly selected from each household using a Kish table. Neighborhood-level data were obtained from community committees and property managers, while resident-level data were collected through face-to-face household interviews, supplemented by field observations of greenery, facilities, and community activities. In total, 399 neighborhoods and 3630 residents were surveyed. After excluding incomplete or erroneous cases, 2634 valid samples were retained (Figure 1). In Figure 1, red squares denote the sampled neighborhoods, with their size corresponding to the boundary extent of each community.

3.2. Variable Description

The dependent variable in this study is the presence of overweight, defined as a body mass index (BMI) of 24 kg/m^2 or higher [57]. BMI is widely used in large-scale epidemiological research because it is simple to calculate, enables cross-study comparability, and is available in most survey datasets [58]. However, it reflects weight relative to height and does not capture body fat distribution or composition [59]. Alternative measures such as waist circumference, waist-to-hip ratio, or body fat percentage provide more direct assessments of central adiposity and metabolic risk, but these indicators were not available in the present dataset. Guided by the framework of health determinants, we examine both built environment attributes and individual behavioral habits as key explanatory factors of overweight. Built environment characteristics include the normalized difference vegetation index (NDVI) within a 1000 m buffer, distance to the nearest park, green view index (GVI) within a 1000 m buffer, total park area, population density, community green space ratio, and public transit travel time. Together, these variables capture greenery exposure, spatial accessibility, and mobility conditions, and are widely used in the literature to represent built environment features. Behavioral habit variables include monthly exercise frequency, alcohol consumption frequency, smoking frequency, sleep quality, and life satisfaction. These indicators are commonly employed to reflect individual lifestyle patterns and subjective health perceptions. In addition, several sociodemographic covariates were included: gender (male/female), age squared (continuous), marital status (married/unmarried), education level (categorical), and log-transformed personal income (continuous, in CNY).

3.3. Model and Analytical Approach

We employed extreme gradient boosting (XGBoost) to model associations between built environment and lifestyle attributes and overweight status. XGBoost is an advanced implementation of gradient boosting decision trees that integrates regularization, shrinkage, feature subsampling, and second-order optimization, thereby reducing overfitting and enhancing computational efficiency [60,61]. These properties make it particularly well suited for modeling complex, nonlinear relationships between environmental and behavioral factors and health outcomes in urban contexts [26,56].



Figure 1. Sample distributions.

Compared with traditional linear regression, XGBoost can flexibly capture nonlinear and interactive effects without assuming linearity, handle multicollinearity, and accom-

modate missing data [62]. It also performs robustly with moderate sample sizes and class imbalance, delivering strong out-of-sample accuracy. These strengths are especially relevant for built environment–health research, where predictors often interact across spatial, behavioral, and socioeconomic domains [63,64]. In this study, XGBoost allowed more accurate estimation of predictor importance and effect shapes than conventional regression, thereby improving interpretability and predictive power in multidimensional datasets.

Analyses were conducted in Python 3.11 using the XGBoost library. Data preprocessing involved variable cleaning, one-hot encoding of categorical predictors, and a stratified 75/25 train–test split. Class imbalance was addressed by setting the scale_pos_weight parameter according to the prevalence of overweight. The final model was configured with a binary logistic objective, 800 boosting iterations, a maximum tree depth of 3, a learning rate of 0.05, a subsample ratio of 0.8, and a column sampling ratio per tree of 0.8. On the test set, the model achieved an AUC of 0.529, accuracy of 0.530, sensitivity of 0.436, specificity of 0.599, and an F1-score of 0.440. Four subgroup models (female/male × unmarried/married) were fitted using identical parameters to assess heterogeneity in predictor importance and partial dependence curves across demographic strata.

We reported gain-based relative importance (RI) scores to quantify each predictor's contribution to loss reduction. Partial dependence plots (PDPs) were generated on quantile grids (5th–95th percentiles), with background data restricted to the same range to avoid extrapolation. Curves were smoothed using PCHIP for continuous features and LOWESS for ordinal behavioral variables, applying milder smoothing to built environment indicators and stronger smoothing to behavioral variables. Subgroup PDPs included 95% bootstrap confidence bands (B = 50) to capture uncertainty, enabling nuanced interpretation of nonlinear and threshold effects across domains [65].

4. Results

4.1. Descriptive Statistics

Table 1 summarizes the dependent variable and individual-level covariates. In our sample, 42% of respondents were classified as overweight, a proportion somewhat higher than the national average of approximately 34–35% reported in recent Chinese surveys [2]. Males represented 37% of participants, and 80% were married. On a four-point categorical scale of education level (1 = primary school or below, 4 = postgraduate or above), the sample mean was 2.35, suggesting that the typical respondent had completed education between the secondary and undergraduate levels. The mean value of log-transformed personal income was 10.20, corresponding to an annual income of approximately CNY 74,352. This figure is slightly above the 2019 average annual disposable income of Shanghai residents (CNY 69,442; Shanghai Municipal Bureau of Statistics, 2020). The higher average income likely reflects the inclusion of employed residents living in built-up districts, resulting in a sample with somewhat higher socioeconomic status than the general Shanghai population.

Table 1. Personal Characteristics.

	Mean (Tiesdell & Allmendinger)/%
Personal characteristics	
Overweight	
Yes	42%
No	58%
Sex	
Male	37%
Female	63%

Table 1. *Cont.*

	Mean (Tiesdell & Allmendinger)/%
Married	
Married	80%
Unmarried	20%
Education level	
Primary or below	3%
Secondary (Junior high/vocational high/general high/technical school)	62%
Undergraduate	33%
Postgraduate or above	3%
Age (years)	57.03 (13.89)
Log personal income	10.20 (1.70)

Table 2 presents the characteristics of lifestyle attributes and built environment variables in the study area. Regarding lifestyle, nearly half of respondents (48%) reported exercising daily, while smaller proportions exercised several times per week (18%), monthly (8%), or less frequently (8%); 18% reported no exercise at all. Most participants consumed alcohol less than once per week or not at all (81%), and 70% were non-smokers. Sleep quality was generally stable, with 86% reporting no deterioration, and life satisfaction was high, with 81% expressing satisfaction or strong satisfaction.

Table 2. Behavioral Habits and Built Environment Variables.

Variables	**Mean (Tiesdell & Allmendinger)/%**
Lifestyle attributes	
Exercise Freq	
No exercise	18%
≤1/month	8%
Several times/month	8%
Several times/week	18%
Daily	48%
Drinking Freq	
Former drinker	8%
<1/week or none	81%
1–2/week	5%
3–4/week	1%
Nearly daily	5%
Smoking Freq	
Non-smoker	70%
Non-smoker, passive smoke	8%
Former smoker	6%
Few cigarettes/week	2%
Daily (few)	10%
Daily (≥20/day)	4%
Sleep Quality	
Much worse than usual	2%
Worse than usual	12%
About the same	37%
As good as usual	49%
Life Satisfaction	
Very dissatisfied	2%
Dissatisfied	4%
Neutral	14%
Satisfied	54%

Table 2. *Cont.*

Variables	Mean (Tiesdell & Allmendinger)/%
Very satisfied	27%
Built environment	
NDVI (1000 m buffer)	0.16 (0.03)
Distance to nearest park (m)	651.01 (333.55)
Green View Index (1000 m buffer)	0.22 (0.06)
Park area within 1000 m (m^2)	78,102.14 (55,370.08)
Population density (persons/km^2)	37,744.85 (19,631.22)
Green space ratio (%)	26.89 (15.71)
Public transport accessibility (min)	4.18 (2.66)

With respect to the built environment, within a 1000 m buffer of participants' residences, the mean NDVI was 0.16, the mean GVI was 0.22, and the average park area was 78,102 m^2. The average distance to the nearest park was 651 m, while the mean green space ratio was 26.89%. Population density averaged 37,745 persons/km^2, consistent with the high-density urban form of the study area. Public transport accessibility was strong, with an average walking time of just over four minutes. Taken together, these indicators suggest that respondents lived in highly urbanized neighborhoods characterized by dense populations, moderate vegetation cover, convenient access to green spaces, and abundant public transportation options.

4.2. Feature Importance Comparison

Table 3 reports the RI of predictors for overweight in the total sample and across gender–marital subgroups. In the total sample, built environment factors contributed the largest share of predictive power (37.79%), followed by sociodemographic characteristics (35.57%) and lifestyle attributes (26.64%). At the individual level, gender (12.23%), education level (7.30%), and drinking frequency (5.75%) emerged as the strongest predictors, alongside built environment indicators such as distance to the nearest park (5.65%) and population density (5.54%).

Gender comparisons revealed that men's overweight risk was more strongly shaped by built environment factors (47.41–49.05%) than women's (47.00–48.24%), with population density, public transport accessibility, and green space ratio exerting greater influence in male models. Women's outcomes, by contrast, were more affected by sociodemographic and lifestyle factors, particularly education and income. Marital status also moderated predictor importance. Unmarried respondents, both male and female, showed greater reliance on built environment characteristics (male–unmarried: 49.05%; female–unmarried: 48.24%) than their married counterparts (male–married: 47.41%; female–married: 47.00%). Married groups gave greater weight to lifestyle factors such as drinking and exercise frequency, while unmarried groups were more sensitive to public transport accessibility, green space ratio, and education.

In the four-way subgroup breakdown, male–married participants were most influenced by built environment factors (47.41%), especially population density and NDVI, with drinking frequency as the leading lifestyle contributor. Male–unmarried participants exhibited the highest overall built environment share (49.05%), dominated by public transport accessibility and green space ratio, while drinking frequency ranked first across domains. Female–married participants were similarly shaped by built environment factors (47.00%), with the GVI as the top predictor, complemented by exercise frequency and sleep quality. Female–unmarried participants showed the strongest effect of education across all subgroups, alongside significant contributions from population density and park area within 1000 m.

Table 3. RI of predictors for overweight.

Variables Built Environment Variables	All Sample-RI, %	All Sample-Ranking	Male-Married-RI, %	Male-Married-Ranking	Male-Unmarried-RI, %	Male-Unmarried-Ranking	Female-Married-RI, %	Female-Married-Ranking	Female-Unmarried-RI, %	Female-Unmarried-Ranking
Total	37.79		47.41		49.05		47		48.24	
Park area within 1000 m (m^2)	5.37	10	6.72	8	6.86	6	7.07	4	6.87	4
Population density	5.54	6	7.18	2	6.33	11	6.84	6	8.48	2
NDVI (1000 m buffer)	5.46	8	7.06	3	6.83	7	6.55	10	6.48	10
Green space ratio	5.25	13	6.29	13	7.37	3	6.64	9	6.57	9
Distance to nearest park (m)	5.65	5	6.87	6	6.97	5	5.89	15	6.78	6
Green View Index (1000 m buffer)	5.41	9	7.01	4	6.62	9	7.57	1	6.37	11
Public transport accessibility (min)	5.11	16	6.3	11	8.08	2	6.45	11	6.69	7
Lifestyle attributes variables										
Total	26.64		33.71		32.84		31.49		29.13	
Exercise frequency	5.21	14	6.29	12	5.48	13	6.64	8	6.35	12
Drinking frequency	5.75	4	8.46	1	9.75	1	6.1	12	5.57	13
Smoking frequency	5.11	15	6.62	9	5.62	12	6.07	13	6.81	5
Sleep quality	5.3	11	5.95	14	6.74	8	6.7	7	5.02	15
Life satisfaction score	5.27	12	6.39	10	5.24	14	5.98	14	5.38	14
Sociodemographics variables										
Total	35.57		18.88		18.11		21.51		22.63	
Gender (1 = male)	12.23	1	0	16	0	16	0	16	0	16
Education level	7.3	2	5.15	15	4.42	15	7.5	2	8.72	1
Marital status (1 = married)	4.75	17	0	17	0	17	0	17	0	17
Log personal income	5.51	7	6.85	7	6.36	10	7.16	3	6.68	8
Age (squared)	5.78	3	6.88	5	7.33	4	6.84	5	7.22	3

4.3. Nonlinear Relationship Analysis

Full-sample partial dependence analysis revealed distinct and often nonlinear associations between overweight risk and built environment, lifestyle, and socioeconomic predictors (Figure 2). Both the green space ratio and GVI were positively associated with overweight, with risk increasing steadily and peaking at approximately 70–80% and 0.30, respectively. Park area within 1000 m and distance to the nearest park followed inverted U-shaped patterns: overweight probability peaked at ~100,000–175,000 m^2 for park area and ~700–900 m for park distance, with lower risks observed when park area exceeded 180,000 m^2 or distance reached 1100–1200 m. NDVI, population density, and public transit time displayed wave-like curves with clear inflection points. NDVI shifted from protective to risk-enhancing at ~0.18; population density minimized risk between 20,000 and 60,000 persons/km^2 but increased beyond 60,000 persons/km^2; and public transit time showed the lowest risk at ~12–14 min, whereas shorter times (6–8 min) were associated with higher risk. Lifestyle behaviors exhibited similarly complex associations. Smoking frequency and sleep quality both reduced risk up to moderate levels (around three to four times per week for smoking), after which the effect attenuated or reversed. Drinking frequency followed an inverted U-shape, with risk peaking at ~three times per week before declining at higher levels. Exercise frequency was consistently protective, with risk declining sharply until two to three sessions per week, after which the effect plateaued. Life satisfaction showed a positive association, with overweight risk rising sharply up to a score of three and stabilizing thereafter. Socioeconomic attributes produced comparatively stable associations. Gender was positively linked to overweight, with men at higher risk than women. Marital status exerted a protective effect, as married individuals consistently exhibited lower risk compared with their unmarried counterparts. Education level was inversely associated with overweight, suggesting that higher educational attainment reduces risk. By contrast, personal income displayed fluctuations without a clear monotonic trend, while age (squared) showed a nonlinear trajectory with oscillating risks across age groups rather than a consistent directional effect.

Subgroup heterogeneity was also evident in lifestyle behaviors (Figure 3). For drinking frequency, female subgroups displayed relatively flat risk curves, while male–married individuals experienced a decline at the level of former drinker but an increase at three to four drinks per week. Male–unmarried individuals showed little variation across drinking levels. Smoking frequency revealed more distinct thresholds. Among men, an inflection point emerged at non-smoker with passive smoke exposure, after which overweight risk declined consistently. Among women, divergence appeared at the level of former smoker: female–married individuals exhibited increasing risk, whereas female–unmarried individuals showed decreasing risk. Sleep quality also highlighted subgroup-specific thresholds. Male–married individuals maintained relatively stable risk up to about the same as usual, followed by a modest increase, whereas male–unmarried individuals displayed a steady upward trend across the entire scale. In contrast, both female subgroups faced higher risk once sleep quality reached as good as usual, with the increase steeper for female–married than for female–unmarried individuals. Exercise frequency produced contrasting effects by marital status. Married subgroups demonstrated a consistent decline in overweight risk with greater exercise frequency, while unmarried subgroups displayed an inflection at daily exercise, beyond which risk rose. Life satisfaction revealed further divergence. Male–married individuals experienced reduced risk once satisfaction reached satisfied, with male–unmarried individuals showing a similar decline only at very satisfied. By contrast, female–married individuals exhibited a continuous rise in risk with increasing satisfaction, whereas female–unmarried individuals showed a marked decline between neutral and satisfied.

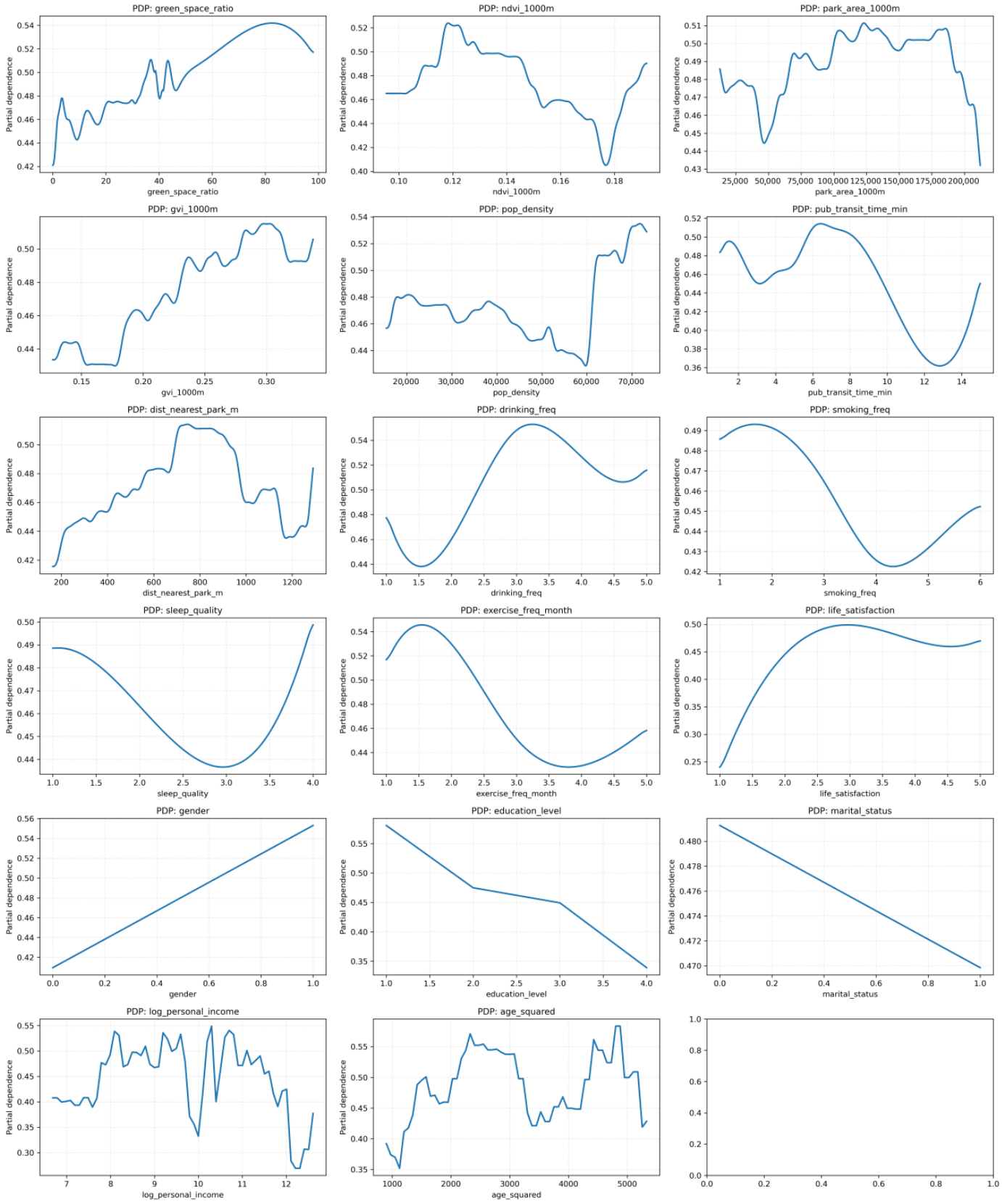


Figure 2. Nonlinear Relationship Analysis of All Samples.

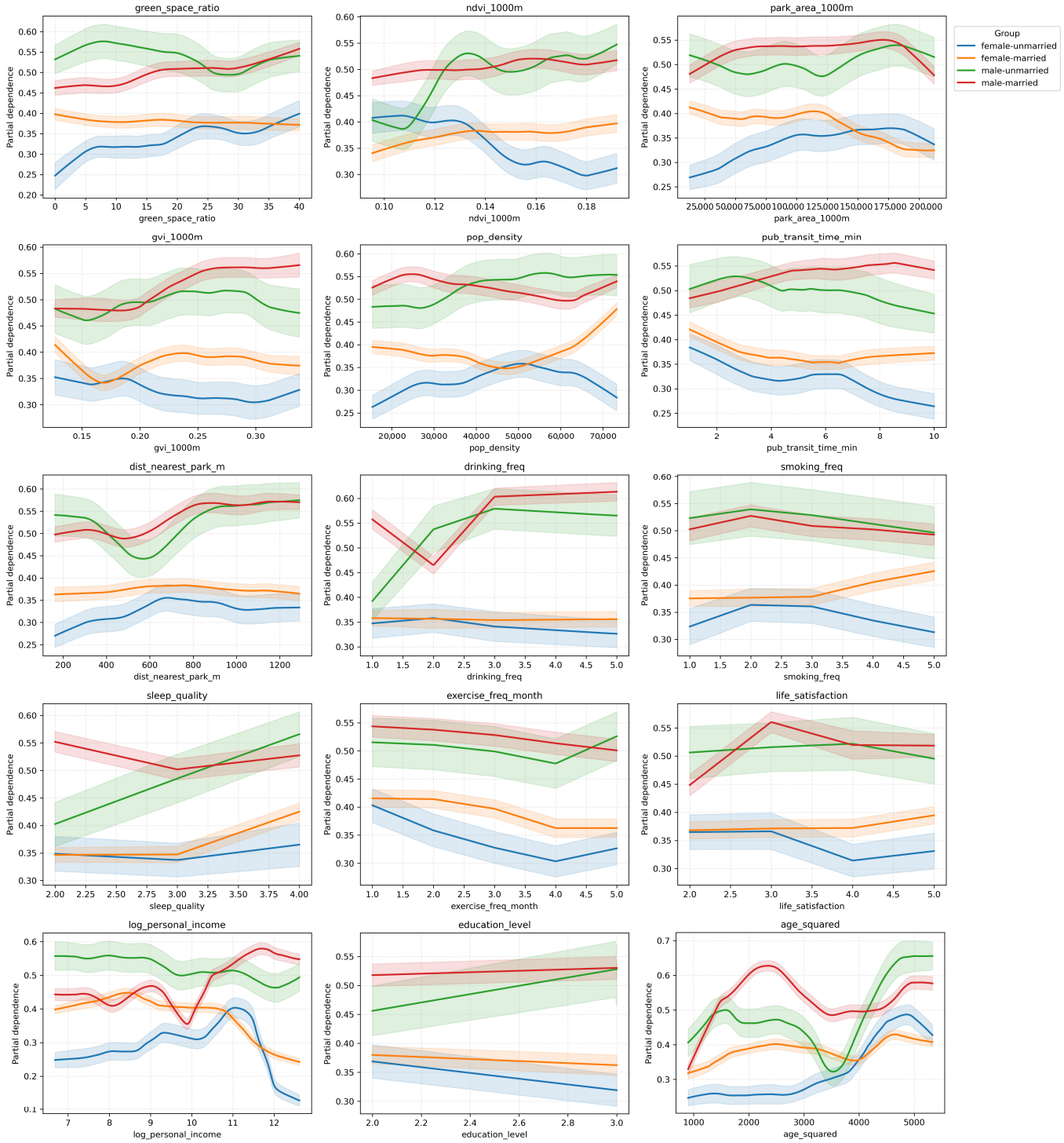


Figure 3. Nonlinear Relationship Analysis of Subgroup Sample.

4.4. Robustness Check

To assess robustness, we compared feature importance rankings from XGBoost with SHAP explanations (Figure 4). Both methods consistently identified gender, age, and personal income as the most influential predictors, underscoring their stability in explaining overweight risk. NDVI also ranked highly across approaches, confirming the importance of greenness exposure. However, the two methods differed in emphasis: SHAP attributed relatively greater importance to behavioral and green space attributes, such as exercise frequency, sleep quality, green space ratio, and GVI, reflecting their nonlinear contributions

at the individual level. In contrast, XGBoost highlighted variables such as park area and population density, which serve as frequent splitting criteria in tree construction.

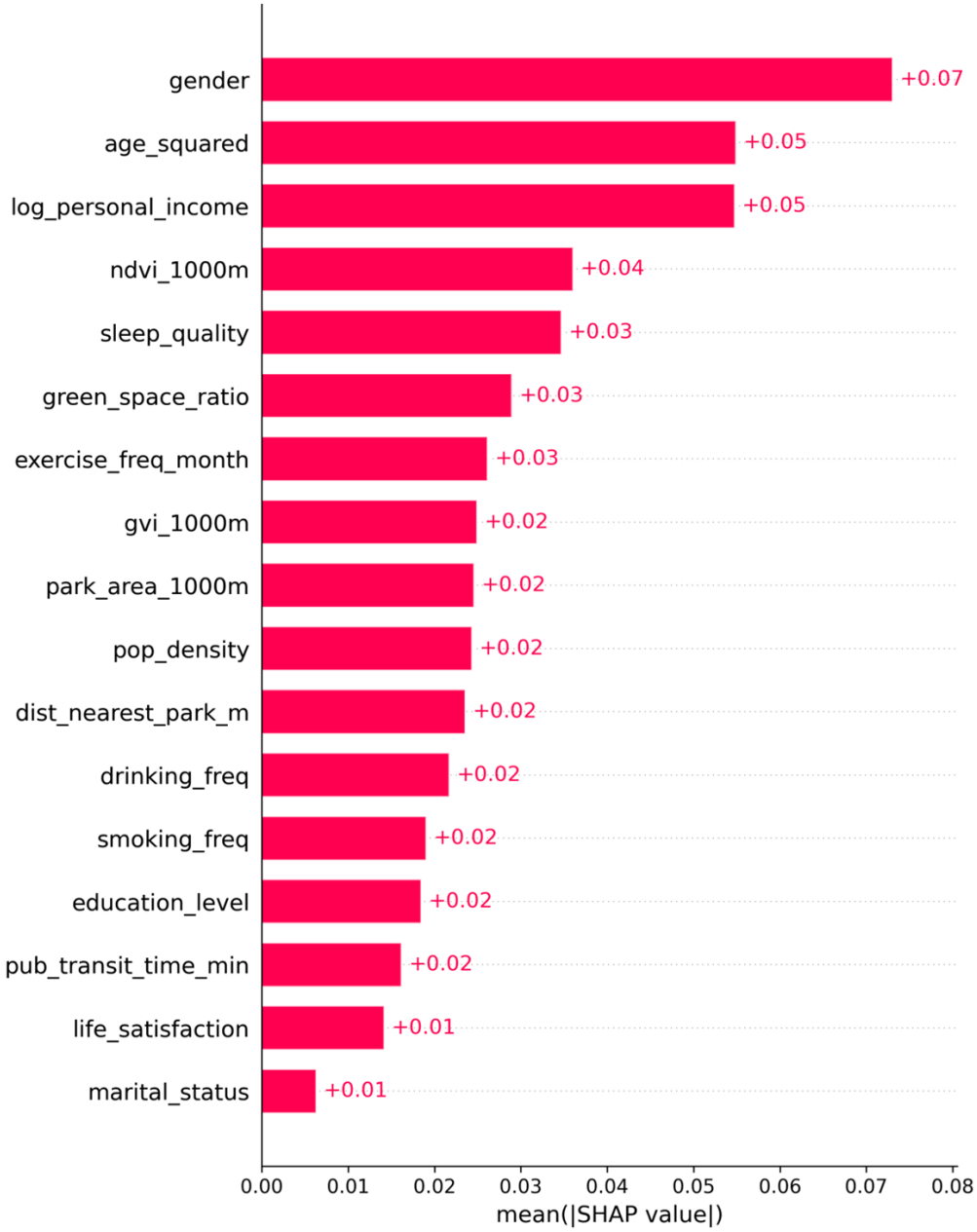


Figure 4. SHAP summary bar plot.

The SHAP value distributions further validated the direction of the main effects (Figure 5). Male gender was consistently associated with higher overweight risk, whereas higher income, more frequent exercise, and better sleep quality were protective. Smoking frequency also showed a negative association, though this should be interpreted cautiously as it reflects body weight outcomes only and does not imply broader health benefits. Several predictors displayed nonlinear or threshold-like patterns, including NDVI, green space ratio, GVI, park area, and distance to the nearest park, as well as behavioral factors such as drinking frequency, exercise frequency, and sleep quality. By contrast, life satisfaction and marital status exerted only weak and unstable effects. Taken together, the convergence of key determinants across methods and the presence of theoretically plausible nonlinearities strengthen confidence in the robustness of the results.

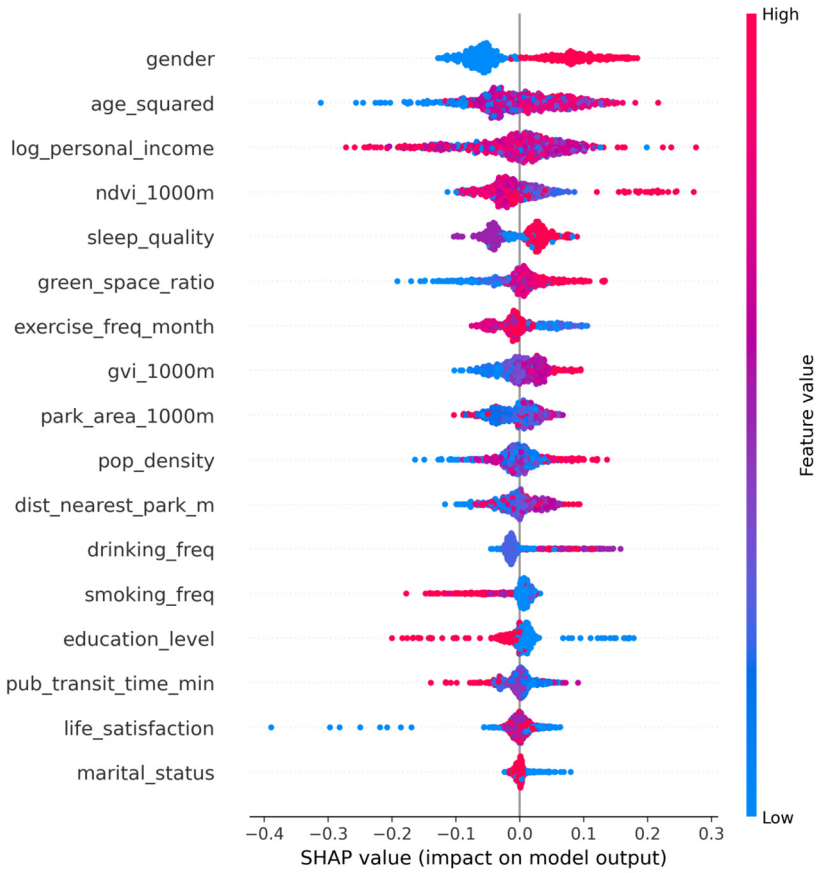


Figure 5. SHAP beeswarm plot.

5. Discussion and Limitation

First, our findings support Hypothesis 1, which posits that built environment attributes, including greenness (NDVI, GVI), park accessibility, population density, and public transport proximity, exhibit nonlinear associations with overweight risk, and that the optimal ranges vary across subgroups. NDVI was protective up to ~0.18 before reversing to risk-enhancing, consistent with diminishing returns of greenness [66]. Population density followed a U-shaped pattern, with the lowest risk at ~20,000–60,000 persons/km^2 and increased risk beyond 60,000, suggesting that density, like greenness, operates within an optimal range [30]. Subgroup analyses revealed distinct thresholds: park accessibility benefits diminished earlier for unmarried men, whose risk was more strongly linked to alcohol consumption, while GVI remained protective up to ~0.15 for unmarried men and ~0.17 for married women. These patterns demonstrate that "optimal ranges" are socially differentiated, shaped by gendered lifestyles and marital status [53–55]. Evidence from green exercise research further supports this interpretation, showing that brief exposures to natural environments produce the largest gains in self-esteem and mood, with benefits that diminish but persist under longer or more intensive engagement [67]. Overall, our findings highlight that built environment effects operate through threshold-dependent mechanisms, underscoring the need to target effective ranges rather than assuming that "more is always better."

Second, our findings support Hypothesis 2, which posits that married men are more likely to maintain healthier lifestyles and therefore face a lower risk of overweight compared with unmarried men. Overall, men exhibited a higher probability of overweight than women, consistent with prior research [68,69], as shown in Figure 2 (full sample) and Figure 3 (subgroups). Within male subgroups, however, marriage played a protective role: married men maintained healthier routines and thus experienced lower overweight

risk relative to their unmarried counterparts. Lifestyle factors contributed most strongly among married men (33.71%), the highest of all subgroups, with drinking frequency ranked first (RI = 8.46), followed by exercise and sleep quality. Although unmarried men were even more sensitive to alcohol (RI = 9.75), their overall lifestyle contribution (32.84%) was slightly lower. In contrast, women displayed smaller lifestyle contributions (31.49% for married, 29.13% for unmarried), indicating stronger influence from socio-demographic and environmental conditions. These patterns suggest that marriage reinforces healthier behaviors and amplifies the benefits of favorable environments, consistent with prior evidence of spousal support shaping men's diets and health practices [24,70]. Importantly, such protective effects also extended to the built environment, where married men responded more stably and beneficially to greenness and park accessibility [25].

Third, our findings support Hypothesis 3, showing that married women face a higher risk of overweight. Subgroup analyses indicated that unmarried women consistently displayed the lowest risk. For instance, their overweight risk declined with higher NDVI and longer public transport walking time, whereas risk in other groups either plateaued or increased. By contrast, married women exhibited weaker protective effects from exercise and sleep quality, and in some cases even experienced rebound risks at higher levels of NDVI. These outcomes reflect how gendered social roles condition health behaviors: unmarried women often have more discretionary time for outdoor activity and may engage in healthier routines to manage body shape [21], while married women face role overload and reduced autonomy in lifestyle choices, limiting the benefits of protective behaviors [71]. These findings emphasize the need for urban planning and public health interventions that alleviate time constraints and provide safe, accessible environments tailored to women with family responsibilities.

This study has several limitations. First, the cross-sectional design precludes causal inference between built environment attributes and overweight. Second, BMI was partly self-reported, and the dataset lacked detailed measures of diet, food environments, and occupational activity, which may introduce residual confounding. Third, the sample was drawn from urban neighborhoods in Shanghai, so the findings may not be generalizable to rural settings or cities with different social and environmental contexts. Despite these limitations, the study provides novel evidence on nonlinear and socially differentiated associations between built environments and overweight.

6. Conclusions

This study drew on survey data from 2634 residents in Shanghai and applied XGBoost to examine how built environment, lifestyle, and socio-demographic factors are associated with overweight. The analysis revealed nonlinear relationships characterized by thresholds and plateaus rather than simple linear trends. Key built environment attributes, greenness, park accessibility, population density, and transit proximity, all displayed "optimal ranges," though in distinct nonlinear forms: population density and NDVI followed U-shaped patterns with clear minimum-risk points; park accessibility showed an inverted U-shaped association with a peak protective interval; and transit proximity exhibited oscillating patterns with a specific low-risk range.

The central contribution of this study is to demonstrate that these nonlinear associations are socially differentiated. Gender and marital status condition daily lifestyles and mediate how built environment features influence overweight risk. Subgroup-specific thresholds and turning points highlight the need for contextualized health planning. Characteristics of green space in Shanghai, such as fragmentation, small scale, and limited accessibility [72], may partly explain subgroup differences, while East Asian cultural norms

and gendered household roles [73] further magnify the interaction between marriage, lifestyle, and health.

Overall, the findings underscore the importance of socially differentiated strategies in overweight prevention. In high-density cities like Shanghai, planning should maintain greenness and density within effective ranges and improve access to fragmented, small-scale green spaces. Public health measures should also address subgroup vulnerabilities, such as alcohol-related risks among men and time constraints faced by women with caregiving responsibilities. By identifying subgroup-specific thresholds and turning points, this study provides empirical evidence to inform more precise and equitable urban health planning, showing how cultural context, gender, and marital status shape the benefits of environmental exposures.

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