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The Impact of Built Environment in Shanghai Neighborhoods on the Physical and Mental Health of Elderly Residents: Validation of a Chain Mediation Model Using Deep Learning and Big Data Methods

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Abstract: As urban aging issues intensify, the impact of the built environment in urban neighborhoods on the physical and mental health of elderly residents has garnered increasing attention. Previous studies have demonstrated that the built environment is related to various health outcomes; however, most empirical research typically focuses on the objective physical environment, lacking measurements of subjective environmental perceptions. This study, using 24 neighborhoods in Shanghai as case studies, employed deep learning, big data methods, and surveys to collect 462 valid questionnaires from elderly residents. Structural equation modeling was applied to explore the relationship between the built environment and the physical and mental health of elderly residents, incorporating respondents' subjective perceptions, physical activity, and neighborhood relationships as chain mediation effects. The results indicate that although there is no direct relationship between the built environment and the mental health of elderly residents, the built environment positively impacts mental health through enhancing subjective.

Keywords: built environment; mental health; AMOS; deep learning

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1. Introduction

China has entered a stage of population aging. According to the seventh national census conducted by the National Bureau of Statistics in 2020 [1], the proportion of the population aged 65 and above in China is approximately 13.5%, reflecting an increase of about 4.6% compared to 2010. This gradually emerging aging trend has brought about unprecedented complexity and profound impacts across multiple levels of Chinese society, particularly posing severe and intricate challenges to the social structure, healthcare system, and social services. The health of elderly residents is influenced by various factors, traditionally classified into psychological, biological, and emotional categories, all of which are important in understanding the determinants of physical and mental health [2,3].

This study aims to investigate the relationship between the built environment and the health of elderly residents. Many studies have focused solely on the objective physical environment, while research on other non-physical factors has been relatively scarce [4]. This paper focuses on how subjective perceptions, physical activity, and neighborhood relationships mediate this relationship. However, subjective perception differs from concepts such as satisfaction; satisfaction refers to an individual's level of contentment with their environment, whereas subjective perception encompasses a broader range of emotional and cognitive responses, including perceptions of safety, aesthetic appeal, and comfort [5]. In this context, subjective perception refers to elderly residents' emotional and cognitive interpretations and evaluations of their surroundings, which may differ from objective measures of environmental quality. Therefore, examining how these non-physical factors affect the health of elderly residents is of significant practical importance and research necessity. This study helps to fill a gap in the existing literature and provides new perspectives and evidence for improving the physical and mental health of elderly residents.

In the context of neighborhood built environments, the declining physical functions and limited mobility of the elderly make neighborhoods the primary spatial units for their daily activities [6]. Scholars in geography and urban planning have discovered that factors such as street greenery visibility [7], building density [8], and road network density significantly influence the frequency of elderly participation in walking activities. Furthermore, different neighborhood environments can also affect the travel modes selected by the elderly [9].

In the fields of epidemiology, public health, and sports, research primarily focuses on the impact of the perceived built environment on leisure physical activity and total physical activity. This includes the total amount of leisure walking, moderate-intensity physical activity, and whether the total physical activity meets the recommended levels [10]. Despite variations in the measurement of physical activity across different disciplines, there is a general consensus that regular participation in physical activity can significantly improve the physical functions of the elderly, thereby effectively reducing the incidence of chronic diseases such as hypertension, hyperlipidemia, and heart disease [9].

Although the benefits of physical activity for the elderly are widely recognized, elderly urban residents exhibit more pronounced psychological issues such as depression and loneliness compared to the general population, often experiencing a psychological "island" effect [3]. It is imperative to recognize the significant role that the built environment of neighborhoods plays in promoting mental health.

Research by scholar Yue Yafei indicates that the proximity and concentration of basic service facilities in elderly residential areas affect their mental health. The mechanism of this influence varies between direct and perceived pathways. High concentration levels can negatively impact mental health through perceived pathways, including noise, insecurity, and environmental hygiene conditions [3].

For the elderly, the understanding of the built environment extends beyond its mere physical structure and functional assemblage, encompassing their subjective perceptions of the surrounding environment. Scholars have pointed out that the interrelationship between the objective built environment and subjective perceptions in influencing physical activity remains unclear [10]. This relationship involves not only the elderly's perceptions of buildings and spaces but also their subjective experiences and emotional responses to environmental elements, neighborhood atmosphere, and residential experiences [11].

Historically, various methods have been employed to assess perceptions of the built environment, with surveys being the primary method for evaluating subjective built environment perceptions (using a Likert 5-point scale) [12]. Fewer studies have used open-ended interviews for qualitative research [13]. Surveys have methodological drawbacks, such as being time consuming and labor intensive, requiring a large sample of participants, and being prone to errors during data collection, which can result in inaccurate information [14].

In recent years, advancements in deep learning technology have provided effective tools for the precise processing and element recognition of street view images in objective street indicator research. Image segmentation can divide street images into different regions in order to accurately delineate elements such as pedestrians, cars, lanes, buildings, and greenery, thereby enhancing the accuracy of street space composition analysis [15]. Additionally, object detection technology allows researchers to precisely locate and identify various objects in images, such as cars and pedestrians, providing reliable foundational data for the quantitative analysis of objective indicators [16].

The Massachusetts Institute of Technology Media Lab's "Place Pulse" project exemplifies this approach. By using large-scale street view image data collected through crowdsourcing, visitors to the online platform (http://pulse.media.mit.edu, accessed on 11 January 2024) evaluated the qualitative differences between pairs of images across various dimensions, forming a machine learning dataset [17]. Researchers Salesses and Naik used data from the Place Pulse project combined with street view images (SVI) and machine learning techniques to assign machine-generated scores for street attributes such as pleasantness, aesthetics, and safety.

Research on other non-physical factors, such as subjective perceptions and neighborhood relationships, is relatively scarce. Some literature has explored methods for obtaining subjective perceptions, innovatively using adversarial scoring, which can accurately rate large numbers of images based on perceptions. Nevertheless, utilizing objective environmental indicators and subjective perception indicators is only suitable for analyzing urban streets and cannot deeply analyze the changes in mental health among the target population.

Therefore, this study employs adversarial scoring methods (a deep learning artificial intelligence approach) to assess environmental perceptions of Shanghai's neighborhood built environment. It explores the impact of the built environment on the physical and mental health of the elderly, using neighborhood relationships and physical activity as chain mediators. This research aims to provide a basis for further adjustment and optimization of the structure, function, and quality of urban built environment elements [11].

2. Research Methodology

2.1. Research Framework

This paper first draws on the "Place Pulse" project from the MIT Media Lab, which employs a crowdsourcing method to collect street view images. On one hand, this approach gathers objective indicators of the built environment, while on the other hand, it evaluates the subjective environmental perception of streets through machine scoring. We draw upon WU's theoretical framework regarding the impact of the built environment on health, innovatively incorporating neighborhood relationships, physical activity, and subjective perceptions as mediating variables to develop a chain mediation model, and employing SPSS 26 and AMOS 24.0 to construct mathematical models, this study analyzes the underlying mechanisms and specifically explores the potential impact of the built environment on the physical and mental health of the elderly.

AMOS was selected as the analysis tool for structural equation modeling (SEM) because it effectively handles complex path relationships and offers a range of fit indices, such as CFI and RMSEA, to ensure model adequacy. Simultaneously, SPSS 26 was used for data management and basic statistical analysis, providing robust data cleaning and preprocessing capabilities, which are well-suited for the large-scale dataset in this study. Compared to alternative methods such as SmartPLS 4.0 and R i3863.1.1, AMOS 24.0 offers stronger theoretical validation capabilities, while SPSS features a user-friendly interface, making it easier to operate.

The framework of this paper constructs two models based on mental health and physical health, respectively. The basic paths of the models include:

Direct effect: Built environment—mental/physical health

L1: Built environment—subjective perception—mental/physical health

L2: Built environment—physical activity—mental/physical health

L3: Built environment—subjective perception—physical activity—mental/physical health

L4: Built environment—neighborhood relationships—mental/physical health

L5: Built environment—subjective perception—neighborhood relationships—mental/physical health

The basic hypotheses of the study include the correlation between objective indicators of the built environment and physical and mental health; the mediating roles of subjective perception, neighborhood relationships, and physical activity between the objective built environment and the physical and mental health of the elderly; and the significant chain mediation effect of neighborhood relationships and physical activity in the path of built environment—subjective perception—physical and mental health. The research model (Figure 1) aims to provide a scientific basis for the future design of age-friendly neighborhoods, encouraging social policymakers to pay more attention to and improve the living environment of the elderly, thereby supporting their healthy aging goals.

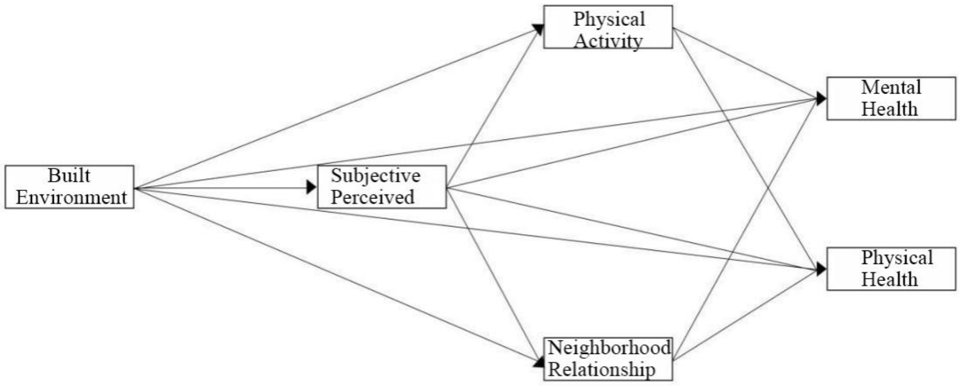

Figure 1. Research framework.

2.2. Geographical Scope of the Study

The study focuses on neighborhoods within the Inner Ring of Shanghai, specifically in the Pudong New Area, Xuhui District, Huangpu District, and Hongkou District. This study selects the Pudong New Area, Xuhui District, Huangpu District, and Hongkou District within Shanghai's Inner Ring as research subjects. These four districts exhibit significant differences in built environment characteristics, providing diverse perspectives for investigation. Six elderly communities were selected in each district, predominantly consisting of high-rise residential buildings and well-equipped neighborhoods that meet the living needs of older residents.

Pudong New Area is characterized by high building density and low greenery visibility, with convenient transportation facilities offering ample opportunities for social activities; however, this may also contribute to increased psychological stress among elderly residents. In contrast, Xuhui District combines historical culture with modern living, featuring moderate building density and higher greenery visibility.

Huangpu District, as a central area, has high building density and low greenery visibility; its bustling environment may pose challenges to social interaction for older adults. Conversely, Hongkou District exhibits tranquil community characteristics, with lower building density and higher greenery visibility, making it an ideal choice for elderly residents, where positive neighborhood relationships offer a supportive network.

The selection of these four districts encompasses a comparison between vibrant and serene environments, varying greenery visibility, building density, and road network density, thus facilitating a comprehensive exploration of the impact of built environments on the health of elderly residents and providing a scientific basis for policy formulation.

We employed a stratified sampling method to ensure the representativeness of different subgroups (e.g., neighborhoods) within the sample. The core principle of stratified sampling is to divide the population into several distinct subgroups (strata) based on specific characteristics and then independently sample from each stratum. This approach helps reduce bias in population estimates and improves statistical precision. In this study, elderly residents were stratified by their respective neighborhoods, ensuring that each community was adequately represented in the sample, thereby enhancing the accuracy of the results. This study selected a total of 24 communities, from which 20 participants were randomly sampled in each community, resulting in a total of 496 collected questionnaires. Missing data within the survey were addressed using insert method, e.g., multiple imputation or listwise deletion to ensure the robustness and completeness of the analysis while minimizing potential biases. After excluding respondents with missing health outcomes, the final dataset comprised 462 valid respondents.

2.3. Study Data

2.3.1. Study Roads

The street data used in the study were sourced from Open Street Map. These streets are considered important venues for daily social activities and are the focus of the study. During the data preprocessing phase, strict application of OSM attribute levels was used for filtering, excluding elevated roads, bridges, and internal residential roads. Additionally, the street samples were refined by segmenting them at intersections and removing sections within 0.5 m of intersections, within a 40 m buffer zone on either side of the centerline without building coverage, and segments shorter than 50 m.

After filtering and processing, 325 high-quality street samples were obtained. These street samples primarily ranged in length from 100 to 500 m, with an average length of 201 m. The widths of most streets ranged between 10 and 50 m, with an average width of 35 m. This data processing workflow ensured the representativeness and reliability of the street samples, providing a solid foundation for subsequent streetscape-related data collection and analysis.

2.3.2. Acquisition of Subjective Perception Data Using Street View Images and Deep Learning Methods

The images utilized in this study were extracted from Baidu Maps (https://map.baidu.com/, accessed on 15 December 2023) and assessed through a machine learning approach to evaluate the depiction of urban landscapes in street view imagery. To circumvent the limitations inherent in relying solely on color information for pixel classification (e.g., red, green, blue channels), we employed semantic segmentation techniques. This methodology allows for precise identification of various elements within the street view images, thus enhancing the accuracy and comprehensiveness of the evaluations [18]. Convolutional neural networks (CNNs), a form of deep learning model specifically designed for image processing, play a pivotal role in this context. Given that street view images often contain intricate details and complex scenes, CNNs are well-suited to extract features effectively and facilitate efficient information learning and extraction.

A human–computer adversarial scoring system was implemented to evaluate three aspects of the built environment: livability, aesthetic appeal, and safety. Given the visual characteristics and reliance on visual perception of the elderly, it is critical to consider that the human perception system predominantly depends on vision, which accounts for 83% of sensory importance. For the elderly, visual perception is particularly crucial, whereas hearing contributes 11%, smell 3.5%, touch 1%, and taste 1%. Consequently, the elderly's perception and understanding of their environment are largely visual. To address this, we utilized large-scale street view photographs and incorporated the AI-based scoring methodology proposed by Zhang [19], which leverages public perception for training purposes. The machine learning algorithms applied were based on the deep convolutional neural network (DCNN) ResNet model, utilizing data from the "Place Pulse" project conducted by the MIT Media Lab. This dataset comprises evaluations from 81,630 online participants, who performed 1,170,000 pairwise comparisons of 110,988 urban landscape images. Participants voted on which of two randomly presented street view images appeared more attractive, neutral, friendly, or distressing from an elderly visual perspective, thereby generating a comprehensive training dataset for model learning.

Second, each image sample i was compared with other images i'. The positive rate of image i along a certain perception indicator was calculated as $P_i = \frac{p_i}{p_i+e_i+n_i}$, and the negative rate was calculated as $N_i = \frac{n_i}{p_i+e_i+n_i}$. P_i and N_i represent the number of times image iii is selected or not selected in comparisons; e_i is the number of times image i is considered equal to another image. Picture i score: $M = \frac{10}{3}\left\{p_i + \frac{1}{p_i}\sum_{k1=1}^{p_i} p_{k1} - \frac{1}{n_i}\sum_{k2=1}^{N_{K2}} N_{k2} + 1\right\}$ [14].

Finally, the visual environment assessment scores were converted into an artificial intelligence scoring model. The evaluation model utilized five-fold cross-validation, training and validating the model using randomly generated sub-samples. This process resulted in a prediction accuracy of 0.79 for the evaluation model [17]. The assessment model, based on the trained DCNN deep learning model, automatically scored 101,006 street view images of Shanghai. The measurement of each street view perception at each sampling point was the average of the perception in four cardinal directions (0, 90, 180, and 270 degrees). For each residential area, we calculated the average street view perception for six perceptual indicators within a 1 km buffer zone for each sampling point [20]. This process involved averaging the scores of street view images per segment, with the segment's total score represented on a 10-point scale, with no specific units, indicating relative relationships. This scoring system reflects the perceived level of the built environment in the neighborhood, with higher scores indicating greater visual attractiveness (See Figure 2).

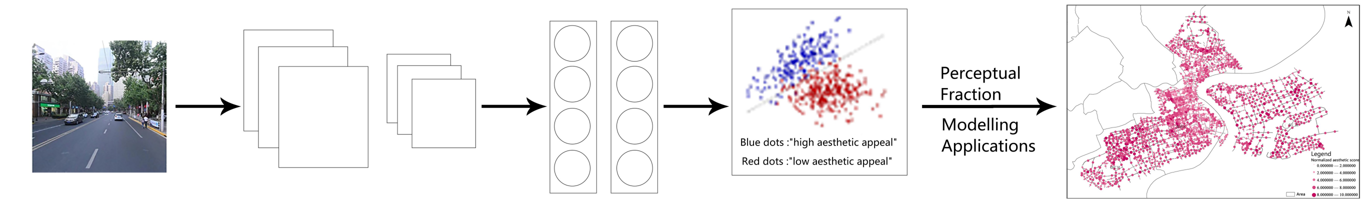

Figure 2. Analysis of street view images using deep learning.

2.4. Variable Selection

2.4.1. Explanatory Variables

According to the study by Zhu H [21], three objective indicators of the streetscape—"green view ratio, building density, and road network density"—were selected as explanatory variables for the built environment. The green view ratio, an indicator of the visual green environment, represents the proportion or coverage of green vegetation in the surrounding environment. Both the green view ratio and the level of urban management play crucial roles in shaping the overall street atmosphere. Numerous studies have demonstrated that variations in the green view ratio can have different effects on people's physiological and psychological perceptions [22]. The green view ratio data were obtained using semantic scene parsing, which is a key technology for object instance recognition and segmentation in natural images.

In this study, ADE20K scene parsing data and partial segmentation data were used for training, with the ResNet network serving as the encoder and PPM deepsup (which includes PPM and deep supervision techniques) as the decoder [17]. This technical framework effectively extracts features from the image environment, surrounding elements, and the image itself, enabling intelligent segmentation of objective elements within the scene. The model predicts corresponding class labels for each pixel, achieving an accuracy rate of 86% (see Figure 3). With this technical support, we interpreted the elements of Shanghai's street spaces, inputting image data from all points to identify and locate plants within street view images. We then calculated the proportion of pixels for each street point in four directions and averaged the results, presenting them as percentages (See Figure 4). From the Open Street Map (OSM) website, we sampled 500 m $\times$ 500 m units across four districts of Shanghai to obtain detailed data on road network length and ground floor area for surrounding streets. These data were then used to compute road network density and building density.

2.4.2. Mediating Variables

The mediating variables in this study include subjective environmental perception, neighborhood relationships, and physical activity. For subjective environmental perception, a human–computer adversarial scoring system was used to assess "livability, aesthetics, and safety", with a 10-point scale representing the relevance of these factors. According to Saelens, B.E., frequent social interactions help individuals gain positive psychological reinforcement and social support, thereby reducing the incidence and mortality rates of non-communicable diseases [23]. Highly integrated neighborhoods foster trustful neighborhood relationships and environments, promote the occurrence of healthy behaviors, and facilitate the dissemination of health information and norms [24]. Neighborhood relationships are primarily assessed by factors such as the number of friends in the neighborhood, frequency of friend interactions, and satisfaction with neighborhood relationships. As for physical activity, which is one of the key mediating variables, it involves the frequency and duration of travel and exercise among the elderly. By recording information such as exercise duration, intensity, and frequency, individual physical activity can be quantified.

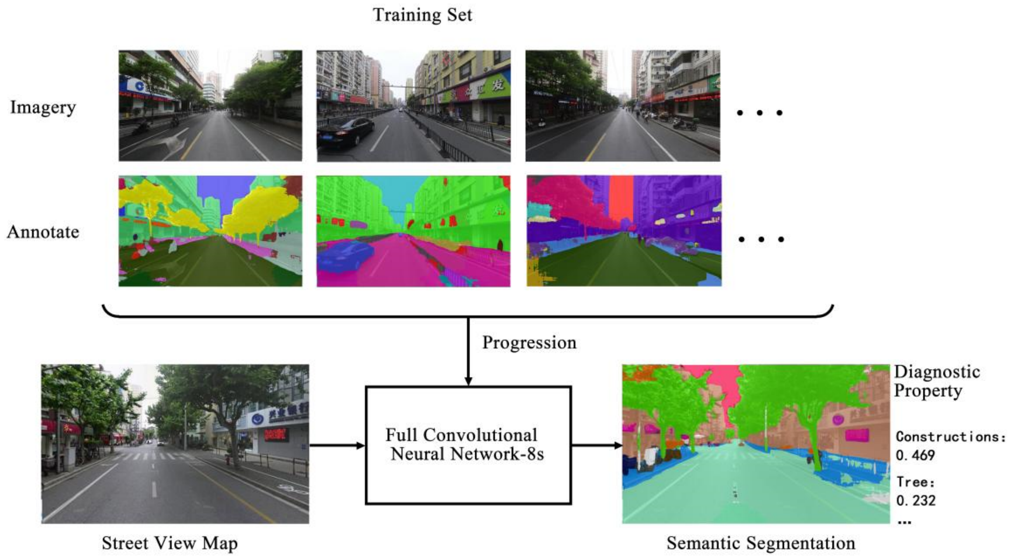

Figure 3. Semantic segmentation model analysis framework based on ResNet.

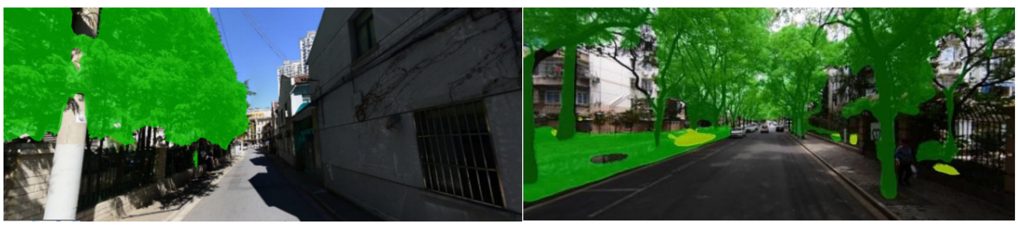

Figure 4. Segmentation of greenery via ResNet's streetscape semantic model.

2.4.3. Dependent Variables

The dependent variables in this study are psychological health and physical health. Psychological health is assessed through self-reported measures of residential happiness, travel-related happiness, and life satisfaction [3]. Physical health includes self-rated health, the number of chronic diseases, and the impact of physical health on travel activities [10].

Data for all variables were collected across eight streets in four districts of Shanghai. The surveys were conducted on weekdays from October 2023 to December 2023. A Likert five-point scale was used for all measures (see Table 1). The survey employed a combination of stratified and random sampling methods, with 60 residents sampled from each street, resulting in a final valid sample size of 462 responses.

Table 1. Potential variables and measurement methods in the research model.

Latent Variable	Observed Variable	Measurement Method
Neighborhood relationship	block friends	Number of frequent friends in the block: 1 (1–2 people)~5 (10 people or more)
	friend interactions	Number of interactions with friends on the block per week: 1 (0)~5 (7 or more)

Table 1. *Cont.*

Latent Variable	Observed Variable	Measurement Method
	Neighborhood satisfaction	Degree of satisfaction with neighborhood relations: 1 (very dissatisfied)~5 (very satisfied)
Physical activity	Trips per week	Daily trips per week: 1 (0)~5 (7 or more)
	exercises per week	Number of physical exercises per week: 1 (0)~5 (7 or more)
	Single trip time	Travel time: 1 (<30 min)~5 (more than 120 min)
	Single workout time	Single exercise time: 1 (<30 min)~5 (more than 120 min)
Mental health	Happiness of residence	Satisfaction with their own residential area as a place to live: 1 (very dissatisfied)~5 (very satisfied)
	Travel happiness	The degree of attraction of the residential area and its surrounding environment to their own travel: 1 (very dissatisfied)~5 (very satisfied)
	Life satisfaction	How satisfied you are with your life in the past year: 1 (very dissatisfied) to 5 (very satisfied)
physical health	Self-assessment of health status	Evaluation of their own health: 1 (very dissatisfied)~5 (very satisfied)
	Number of chronic diseases	Number of chronic diseases (diabetes, hypertension, etc.): 1 (more than 4)~5 (no chronic diseases)
	Travel impact degree	Effects of current physical conditions on participation in regular outdoor activities: 1 (very affected)~5 (not affected at all)

Note: "1 to 5" means using a 5-point Likert scale.

3. Research Results

3.1. Preliminary Data Analysis

After analyzing the characteristics of the sample, it was found that the respondents' ages ranged between 60 and 80 years. To ensure the accuracy of the model, reliability and validity tests were conducted on the scale data. First, Cronbach's Alpha coefficient was used to test the internal consistency reliability of the scale. The results showed that the overall Cronbach's Alpha of the scale was 0.874, with Cronbach's Alpha scores for the four subscales all exceeding 0.82 (see Table 2). According to the widely accepted standard of Cronbach's Alpha $\geq$ 0.70, the scale demonstrates good internal consistency and high reliability, making it suitable for further data analysis.

Table 2. Model data analysis table.

Variable	Object	Factor Loading	Cronbach's Alpha	AVE	C.R
Physical Activity	TLHD1	0.872	0.894	0.68	0.895
	TLHD2	0.813			
	TLHD3	0.788			
	TLHD4	0.825			
Mental Health	XLJK1	0.759	0.821	0.61	0.822
	XLJK2	0.796			
	XLJK3	0.781			
Neighborhood Relationship	LLGX1	0.848	0.852	0.664	0.856
	LLGX2	0.808			
	LLGX3	0.778			
Physical Health	STJK1	0.817	0.834	0.631	0.837
	STJK2	0.805			
	STJK3	0.760			

The composite reliability (C.R) of the latent variables was greater than 0.60, and the average variance extracted (AVE) was greater than 0.50, indicating that the model has good internal quality. The results showed that C.R values were all above 0.82, and AVE values were all above 0.6, proving that the scale has good convergent validity.

Pearson correlation tests were conducted for all endogenous (independent) and exogenous (dependent) variables, with results presented in Table 3. Significant correlations were found between the built environment, physical activity, neighborhood relationships, and psychological health, with correlation coefficients ranging from 0.3 to 0.7, indicating moderate correlations between the variables and no collinearity issues. However, physical health was significantly correlated only with physical activity and psychological health and not with the built environment, subjective perception, or neighborhood relationships.

Table 3. Pearson correlation analysis among latent variables.

Latent Variable	Subjective Perceived	Physical Activity	Neighborhood Relationship	Mental Health	Physical Health
Subjective Perceived	1				
Physical Activity	0.487 **	1			
Neighborhood relationship	0.431 **	0.215 **	1		
Mental health	0.518 **	0.490 **	0.436 **	1	
Physical health	0.143	0.370 **	0.213	0.487 **	1

** At level 0.01 (two-tailed), the correlation was significant.

3.2. Model Fit

Before analyzing the path impact factors, it is necessary to check the model fit indices for both models, as detailed in Tables 4 and 5. The Chi-square to degrees of freedom ratios (CMIN/DF) for both models are 3.255 and 3.285, respectively, both within the acceptable range of 1 to 5. The root mean square error of approximation (RMSEA) for both models is less than 0.08. The goodness-of-fit indices, including the goodness-of-fit index (GFI), adjusted goodness-of-fit index (AGFI), Tucker–Lewis index (TLI), normed fit index (NFI), and comparative fit index (CFI), all meet the standard criteria. These indicators and their reference values suggest that both models have good fit indices and are suitable for further analysis of the path impact factors.

Table 4. Goodness-of-fit index of mental health model.

Index of Model Goodness of Fit	CMIN/DF	AGFI	GFI	TLI	RMSEA	NFI	CFI
Fits the actual value of the index	3.255	0.887	0.921	0.931	0.07	0.923	0.945
An adaptive standard or critical value	1 < CMIN/DF < 5	>0.85	>0.9	>0.9	<0.08	>0.9	>0.9

Table 5. Goodness-of-fit index of the physical health model.

Index of Model Goodness of Fit	CMIN/DF	AGFI	GFI	TLI	RMSEA	NFI	CFI
Fits the actual value of the index	3.361	0.885	0.918	0.924	0.072	0.917	0.940
An adaptive standard or critical value	1 < CMIN/DF < 5	>0.85	>0.9	>0.9	<0.08	>0.9	>0.9

3.3. Chain Mediation Model Testing

Before testing the chain mediation model, it is necessary to perform correlation analysis for each path. According to the results of the psychological health model shown in Figure 5, the built environment has a positive but weak impact on psychological health (r = 0.14, p = 0.028). The built environment is significantly positively correlated with subjective perception, physical activity, and neighborhood relationships, with correlation coefficients of r = 0.67 (p < 0.01), r = 0.26 (p < 0.01), and r = 0.28 (p < 0.01), respectively. Additionally, subjective perception is significantly positively correlated with physical activity (r = 0.39, $p < 0.01$) and neighborhood relationships (r = 0.31, $p < 0.01$). Physical activity is significantly positively correlated with psychological health (r = 0.27, $p < 0.01$), and neighborhood relationships are significantly positively correlated with psychological health (r = 0.24, $p < 0.01$). In the physical health model shown in Figure 6, physical activity has a significant positive impact on physical health, whereas neighborhood relationships, subjective perception, and the built environment do not have significant effects on physical health.

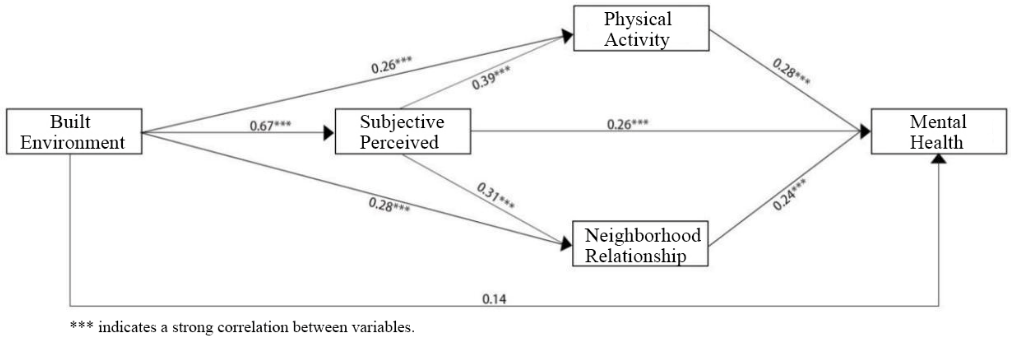

Figure 5. Analysis results of standardization coefficient of mental health model.

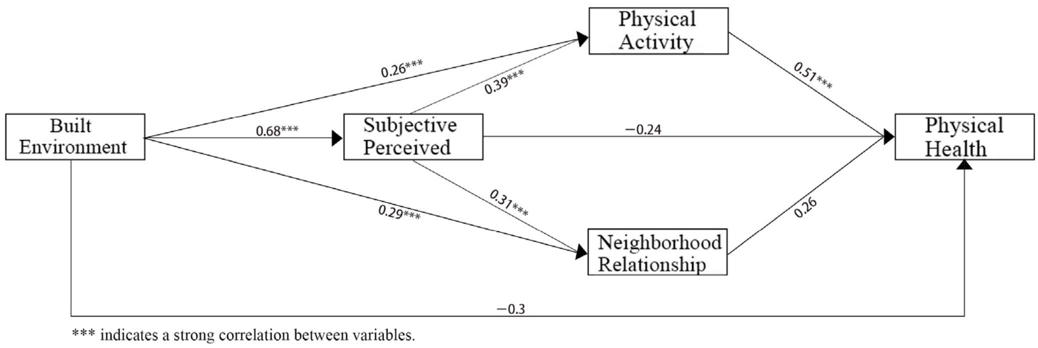

Figure 6. Analysis results of standardized coefficient of body health model.

To test the chain mediation model, Bootstrap methods were employed in the AMOS model to assess the chain mediation effects, with significance evaluated under a 95% confidence interval. The results for the psychological health model are shown in Table 6. The total effect is significant, with the built environment having a positive impact on psychological health. For the L1 path with subjective perception as a mediator, the mediation effect is 2.124 with a 95% CI of (0.856, 3.909). For the L2 path with physical activity as a mediator, the mediation effect is 0.89 with a 95% CI of (0.469, 1.568). For the L3 path with both subjective perception and physical activity as mediators, the chain mediation effect is 0.632 with a 95% CI of (0.287, 1.364). For the L4 path with neighborhood relationships as a mediator, the mediation effect is 0.888 with a 95% CI of (0.353, 1.748), accounting for 12.5% of the total effect. For the L5 path with both subjective perception and neighborhood relationships as mediators, the chain mediation effect is 0.844 with a 95% CI of (0.376, 1.726). The research results indicate that subjective perception as a mediator has a significant effect, accounting for 29.9% of the total effect. The mediation effect of physical activity is also significant, accounting for 12.5%, and the interaction between subjective perception and physical activity positively influences the effect, accounting for an additional 12.5%. Neighborhood relationships play a significant mediating role between the built environment and psychological health, accounting for 11.9% of the total effect. Additionally, the joint mediation effect of subjective perception and neighborhood relationships is significant, accounting for 8.9% of the total effect.

Table 6. Bootstrap analysis and its effect size for the significance test of mediating effect in the mental health model.

Parameter	Estimate	Lower	Upper
Total	7.107	4.105	9.116
L1	2.124	0.856	3.909
L2	0.888	0.353	1.748
L3	0.89	0.469	1.568
L4	0.844	0.376	1.726
L5	0.632	0.287	1.364

In the physical health model, the Bootstrap test for the chain mediation is shown in Table 7. The total effect is not significant, with a 95% CI of (−1.524, 1.095). However, physical activity as a mediator between the built environment and physical health has a significant effect, with a 95% CI of (1.007, 4.230). The chain mediation effect of subjective perception and physical activity is also significant, with a 95% CI of (1.256, 4.068).

Table 7. Bootstrap analysis and its effect size for the significance test of mediating effect in the body health model.

Parameter	Estimate	Lower	Upper
Total	−0.199	−1.524	1.095
L1	−0.686	−2.334	0.844
L2	0.077	1.007	4.230
L3	0.078	1.256	4.068
L4	1.727	−0.923	2.967
L5	1.261	−0.619	2.468

4. Discussion

4.1. Factors Affecting the Psychological Health of Elderly Residents in Neighborhoods

Analysis of the Psychological Health Model 1 (SEM) reveals that among the sample of elderly residents aged 60 to 80, the built environment variables positively impacted their psychological health through several significant chain mediation paths. The detailed findings are as follows:

4.1.1. Direct Effect: Built Environment → Psychological Health

Favorable built environment conditions, such as high green view rates, suitable building density, and road network layout, do not directly promote the psychological health of elderly residents. The psychological health model indicates that the positive impact coefficient of the built environment on psychological health is 0.142 ($p < 0.028$), which is a weak correlation. This suggests that the relationship between improvements in the built environment and the psychological health levels of elderly individuals is not substantial.

4.1.2. Mediating Effect of Subjective Perception

The structural equation model reveals a significant mediating effect of subjective perception between the built environment and the psychological health of elderly residents. The built environment indirectly influences psychological health by affecting residents' subjective perception. Subjective perception can effectively moderate the psychological health of the elderly [25], with the objective characteristics of the built environment exerting their effects through this mediating variable [26]. Some studies suggest that the natural aesthetics and livability of the environment have a significant impact on the psychological health of the elderly [27]. Research indicates that elderly residents who perceive their environment as aesthetically pleasing and comfortable experience improved mood states and reduced negative emotions, which effectively alleviates psychological distress. Additionally, moderate building density helps create compact and orderly neighborhood structures, reducing vacant land and idle spaces, thereby enhancing residents' sense of safety [28]. Furthermore, good road network density and building layout increase the suitability of the environment for elderly residents, making travel more convenient and living conditions more comfortable. In summary, optimizing the built environment can effectively promote the psychological health of elderly residents by enhancing their subjective perception.

4.1.3. Chain Mediating Effect of Subjective Perception and Physical Activity

Research findings indicate that physical activity plays a crucial mediating role between the built environment and the psychological health of elderly residents. Factors such as the duration, frequency, and type of physical exercise significantly impact psychological health [29]. As an important mediating variable, physical activity promotes the psychological well-being of elderly residents through various pathways. An enhanced built environment can encourage elderly individuals to engage more in physical activity. Previous studies have shown that individuals who actively participate in high levels of physical exercise have a lower likelihood of developing depression [30]. Regular physical activity effectively alleviates stress and anxiety, improves mood, and reduces the incidence of depressive symptoms [31], which positively impacts the psychological health of the elderly, consistent with earlier research [32]. Thus, optimizing the built environment to improve the quality of the surrounding environment and thereby promote physical activity indirectly enhances their psychological health.

In the L2 path, adding subjective perception and physical activity as chain mediators affecting elderly psychological health shows that a favorable neighborhood built environment increases elderly residents' willingness to travel. The objective characteristics of the built environment influence physical activity through subjective perception [26]. This chain mediating effect indicates that, although the built environment's direct relationship with psychological health is not prominent, enhancing subjective perception and increasing physical activity can indirectly provide greater health benefits.

4.1.4. Chain Mediating Effect of Subjective Perception and Neighborhood Relations

Previous social psychology research has explored the relationship between neighborhood relations and psychological health, indicating that a lack of strong neighborhood relations can negatively impact individual psychological well-being [29,33–35]. A favorable built environment provides residents with abundant natural landscapes and recreational spaces and creates opportunities for social engagement among residents. Increased building density and thoughtful layout enhance convenience and frequency of interactions, facilitating shared neighborhood activities and daily social exchanges. These interactions not only enhance neighborhood cohesion but also establish significant social support networks for the elderly, improving their emotional connections and sense of security. The research findings demonstrate that improving the built environment, which strengthens neighborhood relations, has a significant positive impact on the psychological health of the elderly [36]. In such supportive environments, elderly residents are more likely to participate actively in neighborhood activities, leading to meaningful social interactions that mitigate feelings of isolation, thereby reducing the risk of depression and anxiety. This dynamic contributes significantly to their overall psychological health [37].

Similarly, the chain mediation analysis including subjective perception and neighborhood relations reveals significant mediating effects. A well-designed built environment not only enhances residents' sense of security and comfort but also motivates greater involvement in neighborhood activities. Specifically, when elderly residents perceive their environment as safe, aesthetically pleasing, and conducive to social interaction, they are more inclined to engage in community events and activities. This heightened engagement fosters stronger connections with neighbors and encourages more frequent social interactions. This, in turn, boosts physical activity levels, which is known to further promote psychological well-being. Additionally, high rates of greenery and thoughtfully designed landscapes provide visual appeal, creating an atmosphere that enhances daily experiences of pleasure and relaxation. Such positive experiences lead to increased interactions with neighbors, which indirectly improves their psychological health by reinforces feelings of belonging and support.

The path analysis results indicate a significant positive correlation between the built environment and subjective perception, with a correlation coefficient of 0.29. In contrast, the correlation coefficient between subjective perception and psychological health is 0.26, which, while demonstrating some association, reflects a relatively weaker correlation. The findings suggest that elderly individuals may respond more readily to direct environmental perceptions—such as beautiful natural settings, safe neighborhood atmospheres, and accessible amenities—which can immediately enhance their emotional state and overall psychological health. Therefore, optimizing the built environment to improve subjective perceptions can significantly boost elderly psychological health more effectively than relying solely on neighborhood relations [38].

In summary, while the built environment does not directly impact psychological health, it can indirectly affect it through subjective perception, physical activity, and neighborhood relations. Both chain mediations significantly influence the psychological health of the elderly. Moreover, the Bootstrap test in the psychological health model shows that the direct effect of subjective perception (L1) is significantly greater than the indirect effect through neighborhood relations (L5). This suggests that direct environmental perception may be more immediate and effective in enhancing elderly psychological health compared to indirect effects via neighborhood relations. Elderly individuals may be more sensitive to direct environmental perceptions, such as beautiful natural landscapes, safe neighborhood atmospheres, and convenient travel conditions, which can immediately improve their emotional state and psychological well-being without needing the intermediary of neighborhood relations. Therefore, optimizing the built environment to enhance subjective perception can directly and more significantly improve elderly psychological health than through neighborhood relations.

4.2. Factors Influencing the Physical Health of Elderly Residents in Neighborhoods

The results show that while the direct effect of the built environment on physical health is not significant, physical activity can indirectly promote the physical health of elderly residents. Introducing subjective perception as a mediator reveals a noticeable chain mediation effect. This indicates that elderly residents' subjective evaluations of their environment's safety, aesthetics, and suitability not only influence their level of physical activity but also indirectly affect their physical health status. Therefore, neighborhoods with favorable built environments are more likely to encourage physical exercise among elderly residents, which benefits their physical health.

For instance, in Shanghai, our survey found that elderly residents in regular neighborhoods primarily engage in activities such as walking and dog walking. In contrast, in neighborhoods near hospitals, where many residents are ill, physical activity is limited to walking and sunbathing, with minimal engagement in aerobic exercises. Extensive evidence shows that physical activity and exercise are key factors affecting physical health [39]. Regular exercise can extend lifespan and reduce the risk of cardiovascular diseases, stroke, cognitive decline, osteoporosis, hypertension, dyslipidemia, obesity, and osteoarthritis, which is especially important for the elderly [40]. Through regular physical exercise, elderly individuals can maintain good physical function, improve cardiovascular and respiratory health, enhance muscle strength and bone density, and reduce the risk of falls and fractures [41].

Regarding the impact on physical health, the mediating roles of subjective perception and neighborhood relations between the built environment and physical health show relatively weak effects. Research indicates that although a favorable built environment can enhance residents' subjective perception and foster good social relationships, these factors do not exhibit significant mediation effects on physical health. This phenomenon may be explained by the fact that elderly individuals' physical health is more directly influenced by actual physical activity rather than through the indirect effects of subjective perception and social relationships [42].

4.3. Comprehensive Analysis of Influencing Factors and Policy Implications

This study underscores the complexity of subjective perception, particularly in the context of the second model. Although the path coefficient between subjective perception and physical health is negative (−0.24), its lack of statistical significance suggests that this relationship has not received adequate empirical support. This finding indicates that the influence of subjective perception on physical health may not be straightforward, necessitating further investigation into the underlying mechanisms of this relationship and the ways to effectively promote elderly health in diverse contexts.

Conversely, in the second model, the path coefficient for physical activity on physical health is 0.51***, significantly higher than the influence of physical activity on mental health in the first model (0.28***). This disparity highlights the pivotal role of physical activity in enhancing physiological health, suggesting that physical activity is not only a direct determinant of health promotion but also a critical variable influencing the health status of elderly individuals. Research indicates that increasing physical activity can effectively improve cardiovascular health, enhance muscle strength, and promote metabolic function, thereby reducing the risk of chronic diseases. Consequently, intervention measures aimed at promoting physical health should prioritize strategies to encourage elderly individuals to engage in regular physical activity.

Furthermore, the enhancement of physical activity is influenced not only by external environmental support but also by individual subjective perceptions. While the negative relationship between subjective perception and physical health in the second model lacks significant support, this outcome suggests that improvements in physical health may rely more on actual behavioral changes rather than enhancements in subjective feelings. This finding carries significant implications for health intervention practices: strategies aimed at promoting health among the elderly should focus on designing feasible activity programs to motivate elderly individuals to adopt more active lifestyles.

The findings of this study provide significant insights for urban planning policies. First, optimizing the design of the built environment is crucial, as the research demonstrates that the built environment significantly influences the subjective perception and health of elderly residents. Therefore, urban planning should prioritize the creation of livable public spaces, including safe walkways, accessible transportation facilities, and green areas, to enhance residents' subjective perceptions and, consequently, promote mental health and physical activity.

Second, fostering neighborhood relationships and community interaction is equally vital. Both models indicate that the impact of neighborhood relationships on health cannot be overlooked. Consequently, urban planning policies should encourage community engagement and the strengthening of neighborhood ties. Specific measures may include organizing community events, creating social spaces, and supporting volunteer services to enhance connections among residents and improve social support networks, thereby benefiting both mental and physical health.

Finally, investing in infrastructure that promotes physical activity represents an important strategy for enhancing the health of elderly individuals. The second model emphasizes the central role of physical activity in contributing to physical health. Thus, urban planning policies should focus on investing in fitness facilities, parks, and walkways, providing safe and accessible spaces for exercise to encourage elderly residents to engage actively in physical activities, thereby improving their health status and overall quality of life. By integrating these strategies, urban planning can effectively enhance the overall well-being of elderly residents.

4.4. Limitations and Future Directions

To address the gap in discussions on the impact of the built environment on mental health, this study selected four districts in Shanghai, including eight streets and twenty-four communities, to demonstrate the mediating roles of subjective perception, neighborhood relationships, and physical activity in the relationship between the built environment and overall health. However, there are still some limitations. First, the study's indicators for the built environment and methods for measuring physical activity were relatively singular, failing to comprehensively capture the diverse activities and environmental features experienced by elderly individuals in their daily lives. Future research could employ "wearable devices" such as accelerometers and heart rate monitors to gather more detailed data. Second, regarding the psychological health scale, due to the elderly residents' reluctance to participate in lengthy surveys, we used a Likert five-point scale for questionnaire measurement. This approach did not include broader methods like the General Health Questionnaire (GHQ), which might provide additional insights. Finally, this study did not consider individual differences, particularly for elderly residents who have recently moved into the community. This group may face unique challenges in adapting to new environments and establishing new social connections, which could significantly affect their physical activity levels and mental health. New residents may not yet have developed stable neighborhood relationships and social networks, potentially negatively impacting their overall well-being.

5. Conclusions

This study, using Shanghai neighborhoods as an example and selecting 24 neighborhoods as research objects, examines the impact of the built environment on the physical and mental health of elderly residents, as well as the chain mediation effects of subjective perception, physical activity, and neighborhood relationships. The study reveals three main findings: First, although there is no direct relationship between the built environment and mental health, enhancing subjective perception, improving neighborhood relationships, and increasing physical activity have positive impacts on mental health. Second, there is no direct relationship between the built environment and physical health, but increasing physical activity can positively affect physical health. Third, in the process of influencing mental health, the direct effect of subjective perception is more significant and may be more rapid and effective than the indirect effect through neighborhood relationships. This study also has some limitations. In the future, more objective environmental measurement indicators will be supplemented, and individual differences will be studied to further improve research methods and data collection techniques, providing scientific evidence for the development of healthy cities.

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