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The Role of Subjective Perceptions and Objective Measurements of the Urban Environment in Explaining House Prices in Greater London: A Multi-Scale Urban Morphology Analysis

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Abstract: House prices have long been closely related to the built environment of cities, yet whether the subjective perception (SP) of these environments has a differing effect on prices at multiple urban scales is unclear. This study sheds light on the impact of people's SP of the urban environment on house prices in a multi-scale urban morphology analysis. We trained a machine learning (ML) model to predict people's SP of the urban environment around properties across Greater London with survey response data from an online survey evaluating people's SP of street view image (SVI) and linked this to house price data. This information was used to construct a hedonic price model (HPM) and to evaluate the association between SP and house price data in a series of linear regression models controlling location information and urban morphological characteristics such as street network centralities at multiple urban scales, quantified using space syntax (SS) methods. The findings show that SP influences house prices, but this influence differs depending on the urban scale of analysis. Particularly, a sense of 'enclosure' and 'comfort' are important factors influencing house price variation. This study contributes by introducing SP of the urban environment as a new dimension into the traditional HPM and by exploring the economic impact of SP on the house price market at multiple urban scales.

Keywords: house price; subjective perception; space syntax; street view image; machine learning

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1. Introduction

House price evaluation models constitute an important tool for informed decision-making in the housing market, and the physical characteristics of the urban environment have played a critical role in such models [1]. The assessment and modelling of house prices commonly include variables on such physical (i.e., objective) characteristics of the urban environment, and multiple features of the urban environment have been shown to affect house prices significantly, e.g., location information [2–4], properties of the street environment [5,6], walkability [7,8], or job and service accessibility [9]. Several studies have explored the impact of property attributes on house prices based on the hedonic price model (HPM), which was developed by Rosen [10] including four dimensions, i.e., house structure [11,12], location [3,13], environmental [14,15] and neighborhood attributes [16,17], the latter three of which are objective urban elements in a property's surrounds. In addition, multi-scalar properties of urban form, operationalized through a spatial network analysis approach, i.e., space syntax (SS) [18,19], have also been shown to capture location characteristics that influence house prices [20,21].

Although house price evaluation models that utilize objective urban features are widely researched and have a well-documented academic foundation, people's subjective perceptions (SP) of the urban environment are often overlooked. Humans perceive the urban environment, particularly at the neighborhood level (i.e., 'micro-scale'), which in turn influences their behavior and can lead to differing social outcomes [22]. For example, SP of the streetscape environment can influence people's sense of place [23,24], route choice [25,26], physical and psychological well-being [27,28], and quality of life [29]. At the street scale, less visible sky, denser buildings, and narrower streets increase people's sense of safety, which in turn affects their perception of the place [23,24]. Because these factors can influence people's house choices, people's SP may play a pivotal role in determining house prices [30–32]. At the urban design dimension, scholars have emphasised that aesthetic urban design elements and design thinking based on human urban perception contribute to the aesthetic image of cities and to the quality of the lived environment [33,34]. Therefore, a better understanding of people's SP of a place may provide critical insights into an overlooked influence of local house prices.

While substantial progress has been made in improving the inclusion of objective characteristics in house price models, research aiming to incorporate SP has been limited, particularly in the context of a multi-scale urban morphology analysis. This study proposes a method to add the SP of the urban environment into house price modelling based on street view image (SVI) analysis, computer vision (CV), machine learning (ML) and space syntax (SS) techniques to investigate whether people's SP significantly impacts house prices at multiple urban scales. It explores the economic impact of SP on the house price market in Greater London by incorporating SP as a new dimension of urban information into the traditional HPM. We used SVI data, online SP survey data, as well as CV and ML techniques to train a SP prediction model to obtain SP scores for all streets in London. The SP data obtained were formulated as part of the HPM, and ordinary least squares (OLS) regression models were used to explore the potential impact of SP on house prices. The location attribute in the traditional HPM (property's distance to the urban geographical center or the central business district) is replaced by more sophisticated urban street network analysis variables supported by SS urban network analysis [18,35], to explore the impact of SP on house prices at multiple urban scales, and how this potential impact might differ depending on various scales of analysis.

1.1. Objective Urban Dimensions in Traditional Hedonic Price Models

The hedonic price model (HPM) introduced by Rosen [10], is a commonly used method for estimating house prices. In HPM, house price is considered to be the value that buyers evaluate based on the intrinsic and extrinsic attributes of a housing unit, of which extrinsic attributes comprise physical elements of the urban environment [10,36]. The various attributes of the product category 'house' can be summarized in four dimensions: house structure, location, environment, and neighborhood characteristics [10]. The house price is defined as the function of these various attributes as independent variables [36]:

$$P = f(S_1, \cdots, S_n, L_1, \cdots, L_m, E_1, \cdots, E_z, N_1, \cdots, N_k) \quad (1)$$

where the S_n, L_m, E_z, N_k indicate the house structure, location, environment, and neighborhood attributes respectively.

Among the four house attribute dimensions, house structure attributes describe the internal spatial environment of a house property itself [11,37]. The remaining three dimensions of attributes are all descriptive of the external environment of the house and can be categorized as objective urban elements in the HPM. Location attributes have long been considered an essential characteristic of a house, traditionally represented by a "distance-value"-based urban economic model, relating land value to the distance from central marketplaces [38]. Environmental attributes, concerning the availability of amenities, are similarly an essential independent functional component in the urban environment [39,40]. Finally, neighborhood attributes depict the social and functional characteristics of a property's surrounding area, such as income, ethnicity, age [41], schools [16,17], metro stations, and other public infrastructures [42,43].

The role of location attributes in house price models has increasingly shifted from the traditional "distance-value" model to a calculation of more complex urban morphology-based variables such as street network centralities [20,44]. The traditional "distance-value"-based models have been criticized for being an oversimplified representation of property locations as they are solely based on the distance from the property to the central business district (CBD). Street network centralities, on the other hand, have been argued to be able to capture complex relational properties within a city's road network, which are a foundational component of the analytical theory called space syntax (SS) [18,35]. Scholars have utilize SS to capture urban morphological characteristics to describe the location of properties within the city to explore the impact of urban form on the house price market and to obtain more accurate house price models [20,44–46].

1.2. Subjective Perception as a New Urban Dimension Using Street View Images

People's subjective urban perception influences their value judgements on properties and hence constitutes a critical dimension for our understanding of the house price. Previous studies have relied primarily on objective urban element indicators to model house prices, and research on the relationship between subjective urban perceptions and house prices is at an early stage. For example, recent research on house prices in Shanghai [30,31,47] have made essential contributions to our understanding of people's SP of streetscapes on house prices, but more studies are needed. This study uses data science methods in conjunction with SS to add SP data to the traditional HPM multi-factor regression model to create a new SP factor dimension that will aid in understanding the impact of SP on house prices, as shown in Figure 1.

In general, SP of urban environments is measured through surveys and interviews [48] in which participants provide perception ratings to specific urban streetscape environments. Using such approaches, Ewing and Handy [49] identified five SP indicators, i.e., imageability, enclosure, human scale, transparency, and complexity. These SP indicators correlate with physical elements in street view imagery and are thought to capture people's SP of specific urban environment characteristics. In their study, they highlight three SP indicators that focus on comprehensive and holistic environment feelings, which are sense of safety, sense of comfort, and level of interest (see Table 1 for detailed definitions of these eight perceptual indicators). Research on house prices in Shanghai has preliminarily explored the impact of SP on house prices based on some of these perceptual indicators [30,50,51], but further validation is needed.

Large-scale surveys of SP in urban studies can be aided by using Google SVI data, CV and ML techniques. Numerous authors have combined these three computational technologies in conjunction with SVI data into an urban analysis workflow to evaluate (i) the quality of street environments [52–58], (ii) calculate the degree of greenery [53,59,60], (iii) construct a walkability index [53,60], or (iv) detect spatio-temporal evolution of urban environment [61]. This article builds on these recent developments and proposes a novel calculation methodology and dataset of city-wide SP outlined below.

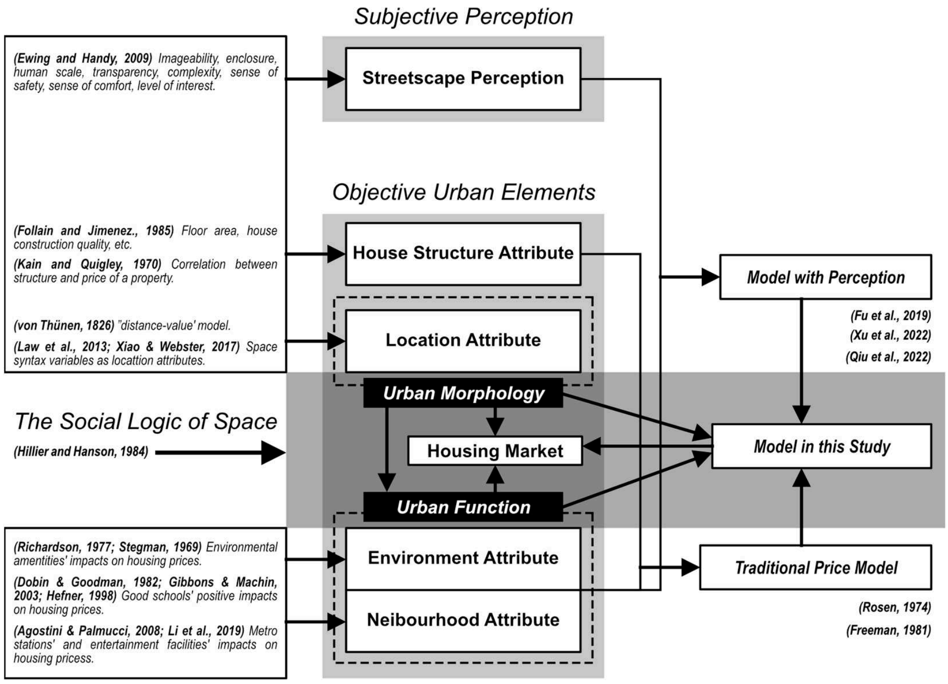

Figure 1. Conceptual framework and key literature [10,11,16–18,20,30,31,37–40,42–44,49,50].

Table 1. Definitions of urban perception variables.

Perception Variable	Scholars	Variable Definition
S1. Imageability	[62]	The potential of the urban environment to evoke a strong impression on observers and whether urban elements help people to memorize and recognize them.
S2. Enclosure	[63,64]	A sense of closure due to the blocking of views by vertical elements in the urban environment, with walls, trees, and other vertical elements creating varying degrees of boundaries.
S3. Human Scale	[63,65]	The extent to which physical attributes such as the size of buildings in the urban environment match the proportions of human size.
S4. Transparency	[66,67]	The extent to which people can see or perceive things beyond the edge of the street, such as walls, windows, landscapes, and other boundaries.
S5. Complexity	[66,67]	The visual diversity of a place, which depends on the diversity of the physical environment, such as the number and type of buildings, the number and type of landscape elements, and infrastructural settings, or the abundance of human activity.
S6. Sense of Safety	[68]	The level of fear people have of possible crime events within the urban environment.

Table 1. *Cont.*

Perception Variable	Scholars	Variable Definition
S7. Sense of Comfort	[69,70]	Commonly used to describe how comfortable people are in urban thermal environments. It is used to describe how comfortable people are when they visually perceive the urban environment in this study.
S8. Level of Interest	[71,72]	Frequently reflected in studies of urban point of interests describing how people like a place and how much they tend to visit it.

2. Materials and Method

Figure 2 illustrates the methodological framework of this study. First, using an online survey, this research collected information from 265 participants in London on their perception of 300 random SVIs based on eight SP indicators. Second, a semantic deep learning framework was used as the CV technique to extract the respective pixel ratios of over 30 physical streetscape elements in the SVIs. Third, ML models were trained to predict people's SP scores of London streets, using the pixel ratios of physical elements extracted from SVIs as the explanatory variables. In the fourth step, this study applied the best-performing ML model to predict SP scores for all streets in London. Subsequently, an HPM incorporated SP scores and quantified the extent to which SP influences house prices using OLS analyses. The impacts of SP on house prices were compared with the effects of multi-scale urban morphology and functional properties.

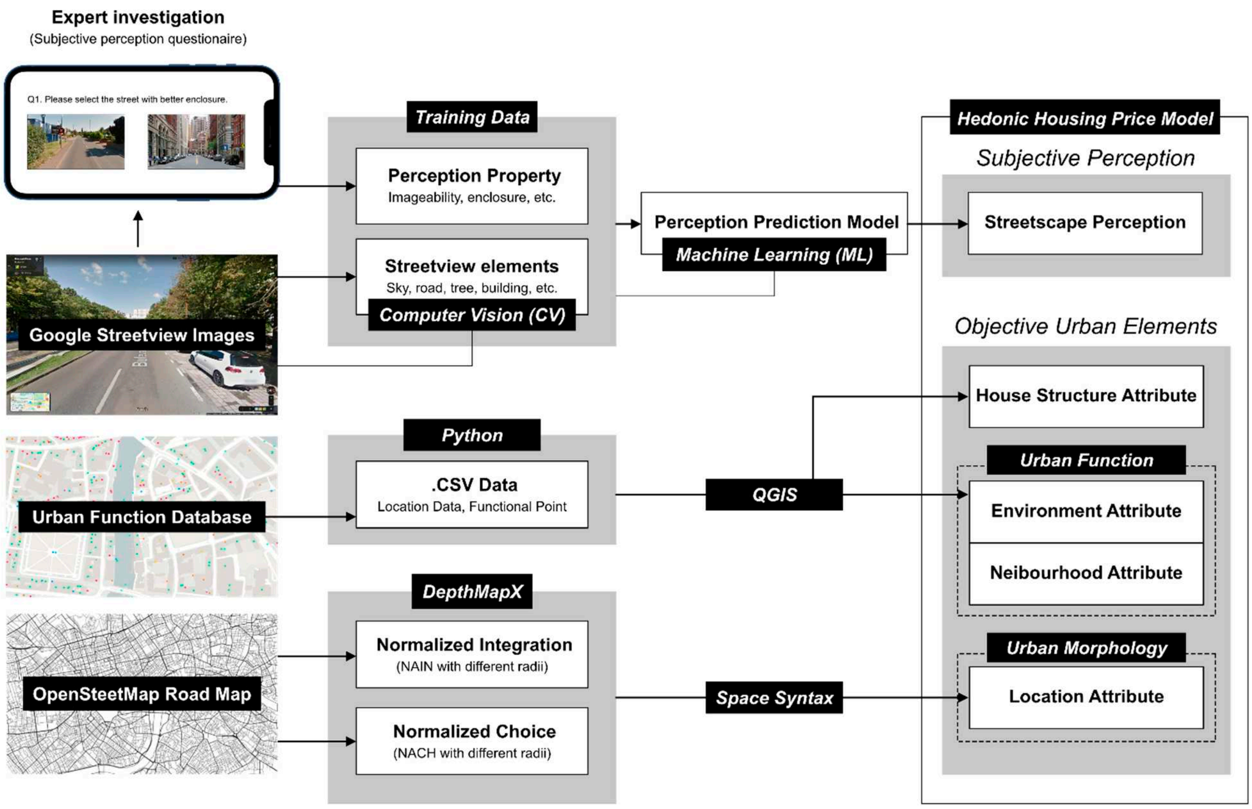

Figure 2. Research framework and workflow.

2.1. SVI, CV, and ML-Based Subjective Perception Data Collection

From an urban design perspective [49], people's experience of five design qualities of the street environment (imageability, enclosure, human scale, transparency, and complexity) and three types of people's overall perception of the streetscape (sense of safety, sense of comfort, and level of interest) were selected as quantitative indicators to represent people's SP of the urban environment. This study builds on eight parameters of [49] urban perception metrics, which constitutes a more comprehensive picture of the urban environment than previous studies incorporated—they used five [30] and six parameters [50] respectively.

Google SVI data provides a consistent data source for image-based descriptions of the urban environment and enables large-scale studies while requiring significantly low resources [73]. This data source has been proven to be consistent and reliable when compared against extensive empirical on-site surveys [73–75]. CV techniques allow researchers to extract and evaluate physical features in urban environments from SVI data, such as the sky, trees, or buildings. Coupled with ML techniques relatively small samples of such data can be used to predict global data [76], enabling indicator prediction for an entire city.

Using a geographic information system, this study sampled streetscape image points at 100 m intervals throughout London to obtain 70,059 streetscape images across Greater London from the Google Street View Static API. Figure 3 shows that each SVI is oriented directly towards the road to reflect the walking conditions on the street. Inspired by previous research on SP [31,77], an online questionnaire was designed to investigate and quantify people's SP of the street environment. The survey design is classified as exempt from ethics approval due to the use of non-sensitive information and the completely anonymous data-gathering process. Participants were provided with information on the type of data gathered and its research use and were asked to provide informed consent by accepting the survey terms prior to participation. Furthermore, participants could exit the survey at any time resulting in the deletion of their responses. Participants were asked to make a two-by-two comparison of images among 300 SVIs based on eight SP indicators. Participants were asked a total of eight questions corresponding to the SP indicators, as shown in Figure 4. Under each question, the online survey asked participants to perform five rounds of image comparison with two images in each round randomly selected from the pre-determined 300 SVIs. Participants would choose which of the two shown images best represents their perceptual experience. The TrueSkill algorithm [78] was used to convert participants' survey responses into a score ranging from 1–5 for each SVI, calculated based on the pairwise image comparison. Combined with the information from SVI segmentation by CV techniques, these scores are used as the training set for ML predicting the SP scores of streets, which were used to predict the SP scores of all other SVIs.

Participants numbering 265 took part in the survey, with a gender ratio of 1.17:1 (142 males, 123 females, and 12 others) and a predominant age distribution of 16–34 years. However, the sample does not constitute a representative sample of the London population. Young (16–24) participants are overrepresented, which constitutes a limitation of the study, and interpretations need to consider these limitations.

All participants had experiences of living in London, and approximately 80% were undergraduate and postgraduate students from a range of disciplines. The survey was more extensive and more diverse than previous studies, e.g., Ewing and Handy [49] who interviewed 10 planning experts, and Qiu et al. [30] who questioned 43 urban designers. The questionnaire avoids technical jargon, allowing participants to relate to the relevant SP variables without prior domain knowledge.

Figure 3. Study area, street view image sample, and Google's SVI camera setting.

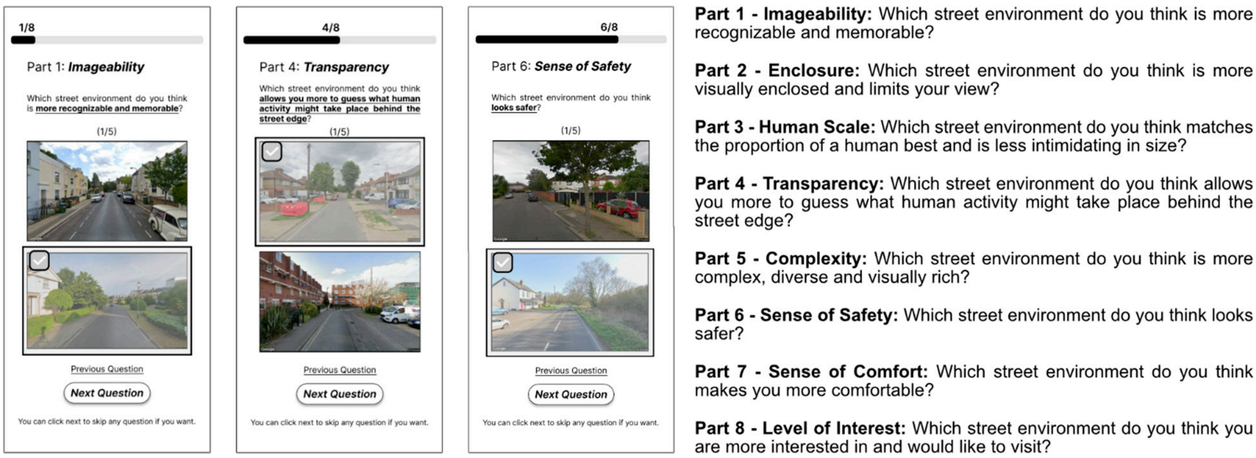

Figure 4. Survey website design and questions.

A deep convolutional neural network model, Pyramid Scene Parsing Network (PSPNet), was used to extract physical elements from SVIs. This model structure has been shown to be effective and accurate in SVI segmentation [79]. This method of quantifying the physical elements in the streetscape has begun to be used in a range of urban studies [32,80–82]. In this study, the PSPNet model was pre-trained based on the ADE20K database, a dataset of SVI data from 50 cities [83], and resulted in ratios of different physical elements in streetscapes in each image to the whole image, termed the view index [31]. The view index of a physical element i in each image is obtained through the following function:

$$V_i = \sum \frac{P_i}{P}, P = \{P_i | i \in \{sky,\ building,\ tree,\ etc.\}\} \quad (2)$$

where P stands for the total number of pixel points in the SVIs, while P_i represents the pixel number of certain physical element i. The set of visual indices of different physical elements is used to reflect the quantified objective reality of the streetscape through images.

ML algorithms have been used to study the SP of cities based on SVIs and are considered to be an effective means of predicting SP [84,85]. Following these examples and based on the dataset of SVIs, the Back-Propagating (backprop, BP) Neural Network was used to train a mathematical model that could predict people's subjective perceptual experience based on SVI visual index data. The BP neural network model was chosen because it featured the best predictive performance in pre-experiments compared to other ML models. Backpropagation and its application to neural networks were first proposed and further developed by Rumelhart et al. [86]. This multilayer perceptual model can cope with arbitrarily complex patterns for classification and provides sufficient multi-dimensional function mapping. As shown in Figure 5, in this study, the view indexes of 30 physical elements in a single SVI, e.g., V_{sky}, V_{wall}, V_{tree}, constitute the input layer. After the function calculation in the hidden layer, the output layer yields the scores of this image on eight subjective perceptual attributes, e.g., $S_{imageability}$, $S_{enclosure}$, $S_{human\ scale}$. The BP neural network model was used as a classifier to rate each SP variable of each SVI as an integer score ranging from 1–5 based on the information from the SVI segmentation. The data for the pre-trained model are derived from the results of the online perception survey based on 300 pre-determined SVIs and view indexes extracted from these images. Eighty percent of the data are used as a training set to build the BP neural network model, while 20% are used as a testing set to assess the model's accuracy.

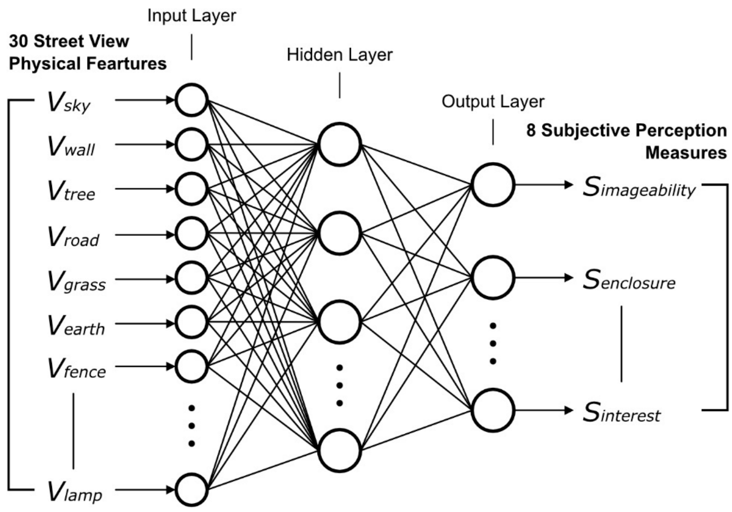

Figure 5. Algorithms diagram of Backprop Neural Network.

Accuracy, Precision, Recall, and F1 Score evaluate the prediction performance of a model. The best-performing model was then used to predict the SP scores for all 70,059 SVIs. The streetscape perception scores within 1 km of a property were averaged to represent the quality of the street environment in the property's neighborhood. However, it is acknowledged that what constitutes a neighborhood can vary in size and scale based on individual preferences. Descriptive statistics for the SP scores of the street environment around each property are presented in Table 2. In Figure 6, one can see that the SVIs are segmented according to physical features to obtain visual indices of different physical features. Subsequently, the subjective streetscape perception scores are predicted by the ML model.

Table 2. Descriptive statistics of all variables.

Variable	Description	Count	Mean	Std.Dev.	Min	Max	Data Source
PRICE	£/m^2, dependent variable	49,603	6793.59	3427.28	117.77	91,866.95	LR-PPD data
House Structure attribute							
H1_FLARA	Total floor area (m^2)	49,603	91.25	57.15	6.26	4373.00	EPCs data
H2_INSUP	House insulation performance	49,603	2.58	1.63	1.00	5.00	
H3_LIGTP	House lighting performance	49,603	3.69	1.52	1.00	5.00	
H4_HOTWP	House hot water performance	49,603	3.80	0.89	1.00	5.00	
H5_CO2EM	House CO_2 Emission	49,603	2.00	1.62	−1.40	66.00	

Table 2. *Cont.*

Variable	**Description**		**Count**	**Mean**	**Std.Dev.**	**Min**	**Max**	**Data Source**
	Description	Values	Count	Percent	Avg.Price	Avg.Area		Data Source
H6_FLLEV	Floor level	1: Low	15,959	32.17%	6908.76	65.03		EPCs data
		2: Mid	32,093	64.70%	6698.90	105.08		
		3: High	1551	3.13%	7571.03	74.85		
H7_PROTY	Property type	1: Detached	3464	6.98%	6123.85	174.60		
		2: Flat	24,841	50.08%	7539.41	67.13		
		3: Semi	7961	16.05%	5683.22	113.49		
		4: Terrace	13,337	26.89%	6244.62	101.24		
H8_MENER	Main energy source	1: Electricity	4626	9.33%	6602.96	63.06		
		2: Gas/LPG	38,167	76.94%	6409.88	97.83		
		3: Oil/Coal	101	0.20%	6684.66	100.98		
		4: Others	6709	13.53%	9111.52	73.11		
Subjective urban perception variable			Count	Mean	Std.Dev.	Min	Max	Data Source
S1_IMBLY	Perceived imageability		49,603	3.05	0.36	1.00	4.16	SVIs, Investigation data, ML results
S2_ENCLS	Perceived enclosure		49,603	2.86	0.46	1.50	4.65	
S3_HMSCL	Perceived human scale		49,603	3.06	0.26	1.00	4.29	
S4_TRANS	Perceived transparency		49,603	2.82	0.20	2.00	4.00	
S5_CMPLY	Perceived complexity		49,603	3.24	0.27	1.33	4.00	
S6_SAFTY	Perceived sense of safety		49,603	3.24	0.22	1.00	4.50	
S7_COFRT	Perceived sense of comfort		49,603	3.03	0.21	2.00	4.00	
S8_INTST	Perceived level of interest		49,603	3.09	0.17	2.00	4.33	
Objective urban perception variable			Count	Mean	Std.Dev.	Min	Max	Data Source
Location Attribute (Urban morphology)								
L1_D2CBD	Cost network distance to CBD		49,603	0.30	0.15	0.02	0.81	OS data
L2_POSDT	Postcode District		49,603	/	/	/	/	
M1_INT400	Space syntax-Integration[HH] (R400)		49,603	23.18	6.63	3.56	68.69	
M2_CH400	Space syntax-Choice (R400)		49,603	108.54	59.18	0.00	902.55	
M3_INT800	Space syntax-Integration[HH] (R800)		49,603	49.09	20.54	3.56	176.85	
M4_CH800	Space syntax-Choice (R800)		49,603	788.61	485.01	0.00	6399.87	
M5_INT2000	Space syntax-Integration[HH] (R2000)		49,603	155.50	88.85	3.56	575.72	
M6_CH2000	Space syntax-Choice (R2000)		49,603	11,141.62	7914.72	0.00	47,980.45	
M7_INT6000	Space syntax-Integration[HH] (R6000)		49,603	650.86	459.06	3.56	2148.27	
M8_CH6000	Space syntax-Choice (R6000)		49,603	272,714.0	249,841.4	0.00	1,552,460	
Neighbourhood and Environment Attribute (Urban Functional Property)								
F1_DENLS	Density of urban services (within 1 km)		49,603	341.28	384.77	0.00	5515.00	OS data
F2_DENWK	Density of workplace (within 1 km)		49,603	337.43	463.93	1.00	5880.00	
F3_DENAT	Density of attraction (within 1 km)		49,603	27.36	40.80	0.00	572.00	
F4_D2UDG	Distance to TfL station (km)		49,603	0.75	0.58	0.00	7.26	TfL data
F5_A2UDG	Accessibility to TfL station (within 3 km)		49,603	15.94	13.04	0.00	70.00	
F6_D2SCH	Distance to quality school (km)		49,603	0.56	0.40	0.00	6.94	Ofsted data
F7_A2SCH	Accessibility to quality school (within 3 km)		49,603	24.93	14.76	0.00	83.00	

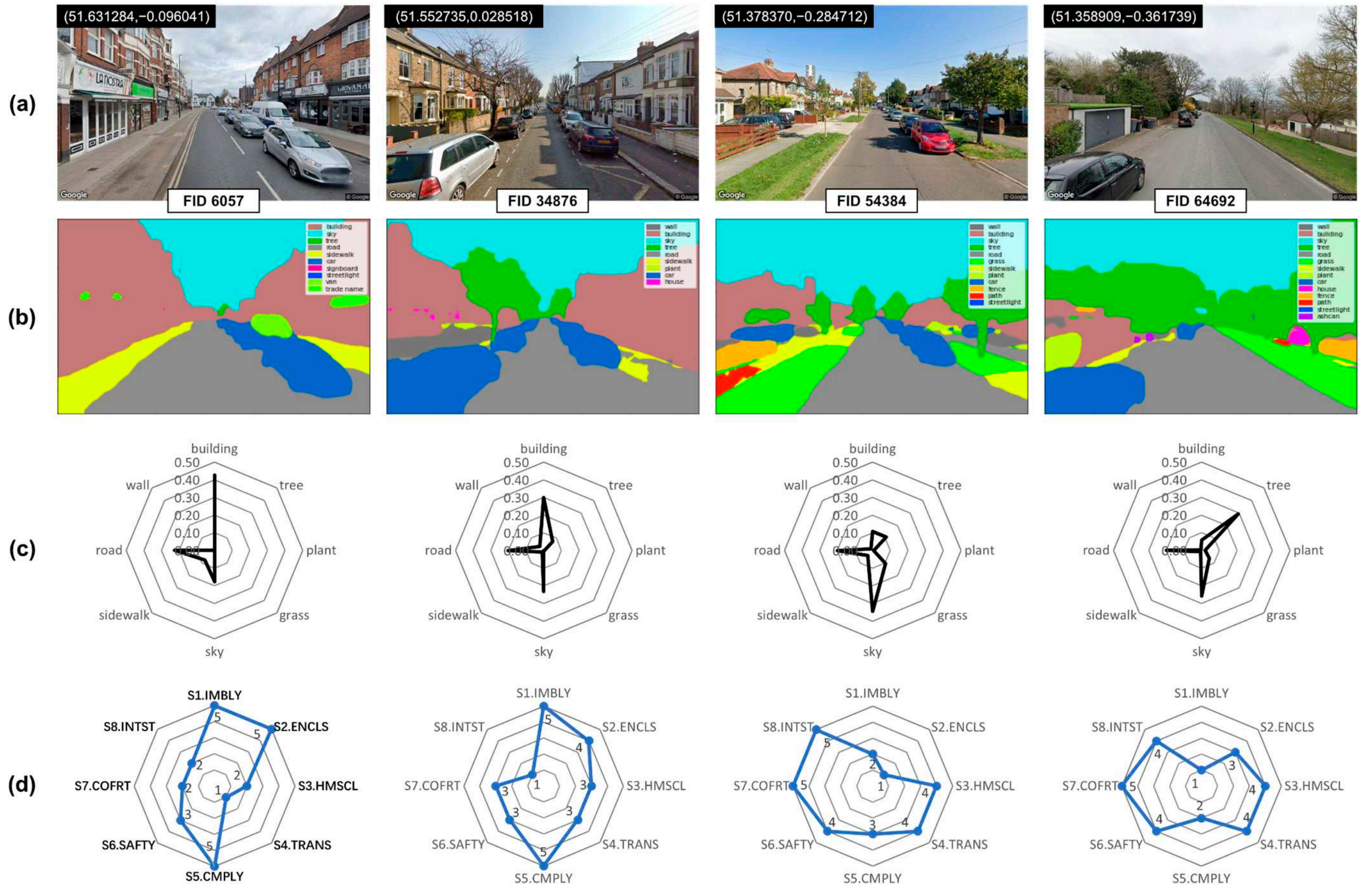

Figure 6. (**a**) Origin SVIs, (**b**) image segmentation results, (**c**) view indices calculated from SVIs, and (**d**) predicted SP scores. The radar charts present view indices from 0 to 0.5, while presenting perceptual scores from 1 to 5.

2.2. Hedonic House Price Model Architecture

2.2.1. Dependent Variable—House Price

We use house price information from two official open-source databases, i.e., the Land Registry Price Paid Data (LR-PPD) and Domestic Energy Performance Certificates (EPCs), compiled by Chi et al. [87]. The integrated database has had 18,575,357 property transaction records in England and Wales since 2011. We filtered the data spatially based on latitude and longitude coordinates for the Greater London area and temporally based on the transaction time for house prices since 2017 to remove the effects of time. A total of 49,603 property transaction data valid for this study were obtained. All independent variables were summarized to these 49,603 house price points and eventually placed into the regression equation for analysis (Table 2).

2.2.2. Model Architecture

Two sets of multiple linear regression (MLR) equations with house prices as the dependent variable were constructed, based on the most widely used Ordinary Least Squares regression (OLS) model in hedonic house price studies [21,31,50,88]. This model assumes that the target variable is linearly related to multiple predictor variables [89]. If k independent variables are selected for regression analysis with the house price variable, the OLS model can be expressed as follows:

$$T_{price} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + \varepsilon \quad (3)$$

where T_{hp} is the house price; $x_k (1 \leq i \leq k)$ are the k selected features from potential explanatory variables, which stand for factors in HPM, such as subjective attributes and neighborhood attributes; β_i denote the coefficients of the regression and ε denotes the random error. The standardized coefficients can be derived from the regression analysis and analyzed as the importance of the attributes in the regression equation. The OLS regression model can also generate R2 values to assess the model's overall performance in terms of the correlation between the dependent variable and explanatory variables.

2.3. Independent Variable Data in HPM

2.3.1. House Structure Variables

Although the house structure is not a traditional element of the urban environment, it is an essential component of the hedonic house price theory. Information on house structure was obtained from Domestic Energy Performance Certificates (EPCs), which include house floor area, number of floors, building type, and a range of energy performance variables such as energy source and insulation performance. Some of these variables are categorical and can be converted to continuous variables for regression analysis, as shown in Table 2.

2.3.2. Urban Morphology Variables

The location attribute is based on SS, a theory and method that conceptualizes space as a relational entity, which in turn can be represented and analyzed as a graph. Such a graph-based approach allows quantification of the spatial configuration (i.e., the part-to-whole relationship) of buildings and cities [90]. Previous research has shown that spatial configuration in buildings and cities has social impacts and drives human movement patterns and economic activity [91–94]. In the HPM, spatial configuration can be used to represent the location attributes of a property, while urban functions represent the neighborhood and environmental attributes of a property (see Figure 1).

Two variables in space syntax theory, i.e., integration and choice, can be generated at various distance radii allowing the incorporation of locational properties across multiple scales. Integration (or closeness centrality) measures the extent to which a street is likely to be chosen as a destination, while choice (or betweenness centrality) captures the likelihood of a street being chosen along a journey [18]. Both variables can serve as substitutes for the traditional "distance-value" model in hedonic house price evaluation [44]. This study calculated integration and choice values at multiple scales, from micro-scale urban morphological analysis to macro-scale analysis, including radii of 400 m, 800 m, 2000 m, and 6000 m, to replace the location attribute in traditional HPM. Space syntax-related urban form calculations were generatd using the space syntax toolkit in QGIS [95] and the shapefile of London's roads from Ordnance Survey (OS). Table 2 shows the descriptive statistics of urban morphology variables at a range of scales.

2.3.3. Urban Function Variables

The variables related to urban function are the neighborhood attributes in the HPM, as shown in Table 2. These variables are selected based on their wide use in the field. The density values of the main urban functions within a 1 km radius of each main house price point are calculated using OS points of interest data, which include urban services, workplaces, and attractions. In addition, the proximity of urban public transport and quality educational facilities has been shown to impact house prices positively [96,97]. Hence, this study obtained geographical data of underground and railway stations from Transport of London (TfL) and information on schools rated good or above from the official Ofsted school ratings database. The network distance from each property point to the nearest TfL station and school was calculated. Finally, the number of TfL stations and quality schools within a 3 km radius of each property was measured as a proxy for accessibility to these.

3. Results

3.1. Subjective Urban Perception Prediction

3.1.1. Accuracy of the Machine Learning Prediction Model

The prediction performance and model evaluation of the BP neural network model on the SP scores of the urban street environments are shown in Table 3. The model performed on average moderate or above for all subjective perceptual variables, with values greater than 0.5 based on a generally accepted rule of thumb evaluation criteria. The best-performing perceptual prediction models are models of 'imageability' (S1), 'human scale' (S3), 'transparency' (S4), 'sense of comfort' (S7), and 'level of interest' (S8), all with accuracy greater than 0.7, of which 'human scale' has the highest accuracy of 0.795. The prediction models for 'enclosure' and 'sense of safety' are less accurate at 0.643 and 0.652, respectively, while the model for 'complexity' has the lowest accuracy at 0.579. The accuracy of the SP model predictions in this study is relatively high, ranging from 0.58 to 0.80, which is a significant improvement compared to previous studies, with R2 of Verma, et al.'s prediction model [98] ranging from 0.20 to 0.66, and R2 of Qiu, Zhang, Liu, Li, Li, Xu and Huang's perception prediction model [30] ranging from 0.47 to 0.61.

Table 3. Performance of BP Neural Network predictions.

Perception	Accuracy	Precision	Recall	F1-Score	Criteria
S1. Imageability	0.710	0.731	0.725	0.721	Good
S2. Enclosure	0.643	0.630	0.666	0.629	Moderate
S3. Human Scale	0.795	0.785	0.780	0.779	Good
S4. Transparency	0.722	0.723	0.732	0.724	Good
S5. Complexity	0.579	0.628	0.613	0.613	Moderate
S6. Sense of Safety	0.652	0.657	0.664	0.659	Moderate
S7. Sense of Comfort	0.720	0.726	0.732	0.716	Good
S8. Level of Interest	0.711	0.737	0.724	0.729	Good

Evaluation criteria: >90% very good, 70–90% good, 60–70% moderate, <60% low.

A higher accuracy indicates fewer variations in survey scores, which in turn may imply that these SP dimensions can be better understood by respondents [5,30]. Imageability (S1), human scale (S3), transparency (S4), sense of comfort (S7), and level of interest (S8), all show higher levels of accuracy whereas complexity (S5) showed lower levels of accuracy, hinting towards a more ambiguous perception of the latter.

3.1.2. Spatial Heterogeneity of Urban Subjective Perception

Figure 7 shows the spatial distribution of SP prediction results, with clear spatial patterns for some SP variables. For the three SP variables of 'imageability' (S1), 'enclosure' (S2), and 'complexity' (S5), there is a strong tendency for the ratings to cluster geographically towards the city center, with enclosure being the most pronounced. This phenomenon can be explained by the high density of buildings in the city center, where the presence of buildings makes the street space more impressionistic and more enclosed and adds to the diversity and complexity of the urban space. For the three variables 'human scale' (S3), 'transparency' (S4), and 'sense of safety' (S6), the geographical distributions are reversed, with scores highly concentrated in the periphery of the city. The urban periphery, with fewer buildings and more greenery, is considered by respondents to have a 'human scale' (S3), 'transparency' (S4), and a 'sense of safety' (S6). The spatial distributions of 'sense of comfort' (S7) and 'level of interest' (S8) ratings are scattered across the research region, with interest scores being the most dispersed, suggesting that people's perceptions in these two SP dimensions are more complex.

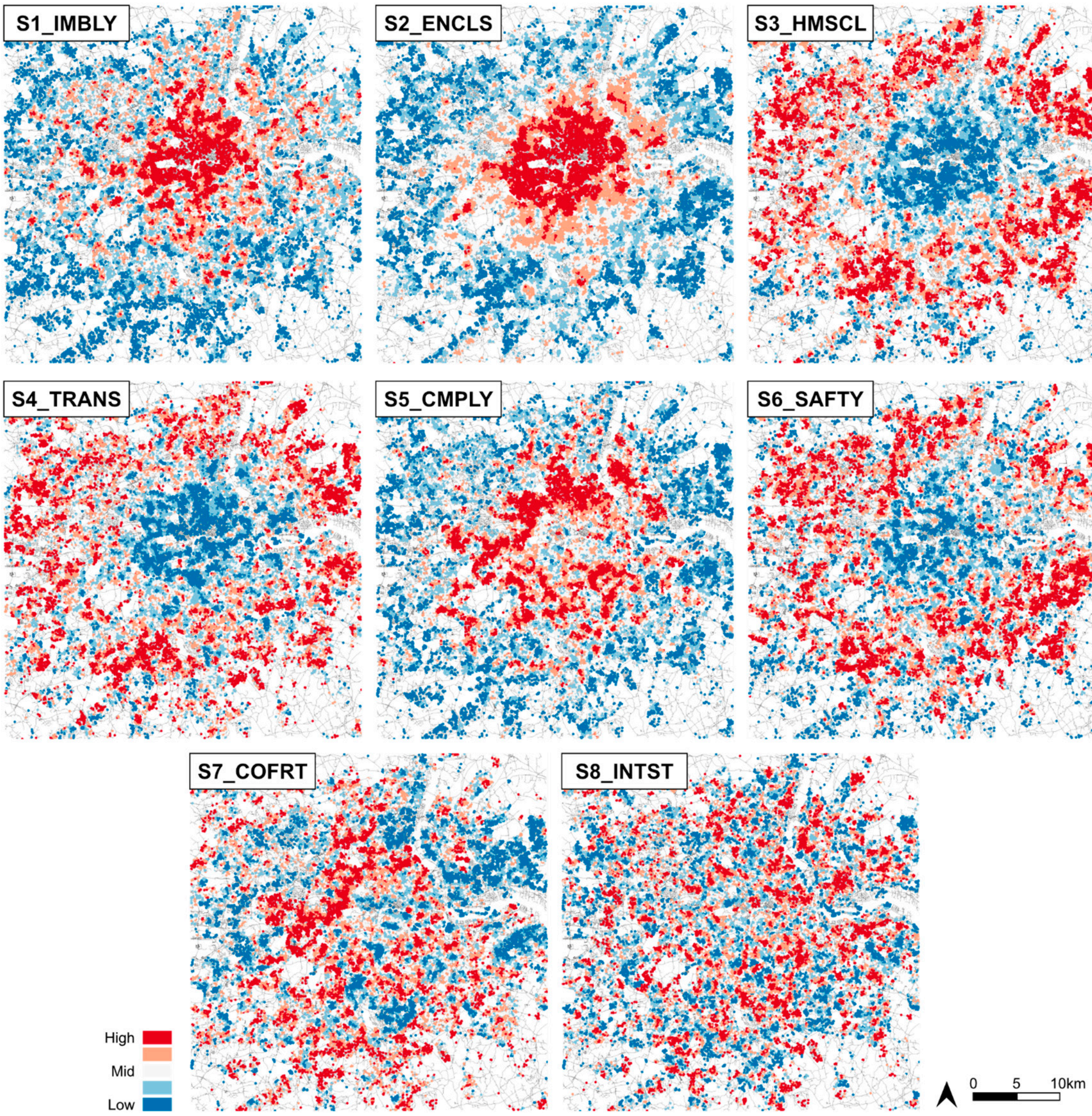

Figure 7. Spatial distribution of properties with SP scores.

3.2. Spatial Hedonic Price Model Result

3.2.1. Correlation of Each Attribute Group with House Prices

Table 4 shows the strength of the four attribute dimensions that make up the HPM in explaining house prices ($p < 0.01$). Location attributes, i.e., urban morphology attributes, are the strongest in explaining house prices (R2 = 0.427), followed by SP scores (R2 = 0.342) and neighborhood attributes (R2 = 0.339). The weakest influencing attribute group is the set of house structure attributes (R2 = 0.085).

Table 4. Model performance of each attribute group.

OLS Diagnosis	House Structure Attributes	Location Attributes (Urban Morphology)	Neighborhood Attributes (Urban Function)	Subjective Perception Scores
Adjusted R^2	0.085 ***	0.427 ***	0.342 ***	0.342 ***
Pr. (F-statistic)	0.000 ***	0.000 ***	0.000 ***	0.000 ***

*** $p < 0.01$ level.

3.2.2. Results of Regression Models with Multi-Scale Urban Morphology

The OLS model results are shown in Table 5, and the impact ranking of each of the five urban scale models is shown in Figure 8 respectively. The baseline model (Model 0) uses traditional location attributes, i.e., the property's network cost distance to the CBD (L1_D2CBD) and its postcode district (L2_POSDT). The other models (Model 1–4) apply different scales of integration and choice as location attributes of the HPM. Table 5 shows the regression model's performance and diagnostic outcomes. The adjusted R2 indicates a comparable association with house prices among the five models. When comparing Model 0 and Model 4, the overall performance of the two models is comparable after replacing the traditional location attributes with the urban morphology variables of space syntax (R2 = 0.496, R2 = 0.494). However, the integration variable in Model 4 (M7_INT6000, M8_CH6000) increases the models standardized coefficients, as shown in Figure 8. Such a result suggests that integration captures characteristics of the urban environment that influence house prices that traditional location attributes have been unable to represent.

Table 5. Regression with multi-scale urban morphology: results and diagnosis.

	Model 0		**Model 1**		**Model 2**		**Model 3**		**Model 4**	
Location Attribute	Baseline (L1, L2)		M1, M2 (R400)		M3, M4 (R800)		M5, M6 (R2000)		M7, M8 (R6000)	
Adjusted R^2	0.496	***	0.482	***	0.484	***	0.486	***	0.494	***
Pr. (F-statistic)	0.000	***	0.000	***	0.000	***	0.000	***	0.000	***
Variable	**Coef.**	**P > t**	**Coef.**	**P > t**	**Coef.**	**P > t**	**Coef.**	**P > t**	**Coef.**	**P > t**
CONSTANT		***		***		***		***		***
House Structure attribute										
H1_FLARA	−0.007		−0.009	**	−0.012	**	−0.014	**	−0.016	***
H2_INSUP	−0.009	**	−0.006		−0.001		−0.001		0.004	
H3_LIGTP	−0.039	***	−0.037	***	−0.036	***	−0.036	***	−0.035	***
H4_HOTWP	0.002		0.002		0.001		0.002		0.003	
H5_CO2EM	0.054	***	0.059	***	0.059	***	0.06	***	0.059	***
H6_FLLEV	0.068	***	0.062	***	0.063	***	0.062	***	0.066	***
H7_PROTY	−0.026	***	−0.02	***	−0.021	***	−0.021	***	−0.02	***
H8_MENER	0.122	***	0.135	***	0.136	***	0.134	***	0.137	***
Subjective urban perception variable										
S1_IMBLY	0.024	***	0.032	***	0.031	***	0.035	***	0.029	***
S2_ENCLS	0.135	***	0.157	***	0.16	***	0.164	***	0.125	***
S3_HMSCL	0.043	***	0.037	***	0.035	***	0.033	***	0.027	***
S4_TRANS	−0.022	***	−0.009	***	−0.009	***	−0.01	***	−0.017	***
S5_CMPLY	0.028	***	0.034	***	0.028	***	0.028	***	0.026	***
S6_SAFTY	−0.039	***	−0.051	***	−0.051	***	−0.052	***	−0.048	***
S7_COFRT	0.112	***	0.124	***	0.126	***	0.123	***	0.112	***
S8_INTST	−0.043	***	−0.044	***	−0.044	***	−0.041	***	−0.037	***
Objective urban perception variable										
Location Attribute (Urban Morphology)										
L1_D2CBD	−0.098	***	/		/		/		/	
L2_POSDT	0.136	***	/		/		/		/	
M1_INT400	/		0.115	***	/		/		/	
M2_CH400	/		−0.052	***	/		/		/	
M3_INT800	/		/		0.217	***	/		/	
M4_CH800	/		/		−0.14	***	/		/	
M5_INT2000	/		/		/		0.286	***	/	
M6_CH2000	/		/		/		−0.185	***	/	
M7_INT6000	/		/		/		/		0.324	***
M8_CH6000	/		/		/		/		−0.087	***

Table 5. *Cont.*

	Model 0		Model 1		Model 2		Model 3		Model 4	
Neighborhood Attribute (Urban Functional Property)										
F1_DENLS	0.135	***	0.111	***	0.088	***	0.087	***	0.102	***
F2_DENWK	−0.137	***	−0.177	***	−0.165	***	−0.164	***	−0.181	***
F3_DENAT	0.419	***	0.486	***	0.479	***	0.456	***	0.437	***
F4_D2UDG	−0.028	***	−0.019	***	−0.018	***	−0.021	***	−0.02	***
F5_A2UDG	0.048	***	0.044	***	0.046	***	0.041	***	0.009	***
F6_D2SCH	0.041	***	0.031	***	0.032	***	0.03	***	0.034	***
F7_A2SCH	−0.071	***	−0.039	***	−0.045	***	−0.067	***	−0.126	***

** $p < 0.05$ level, *** $p < 0.01$ level.

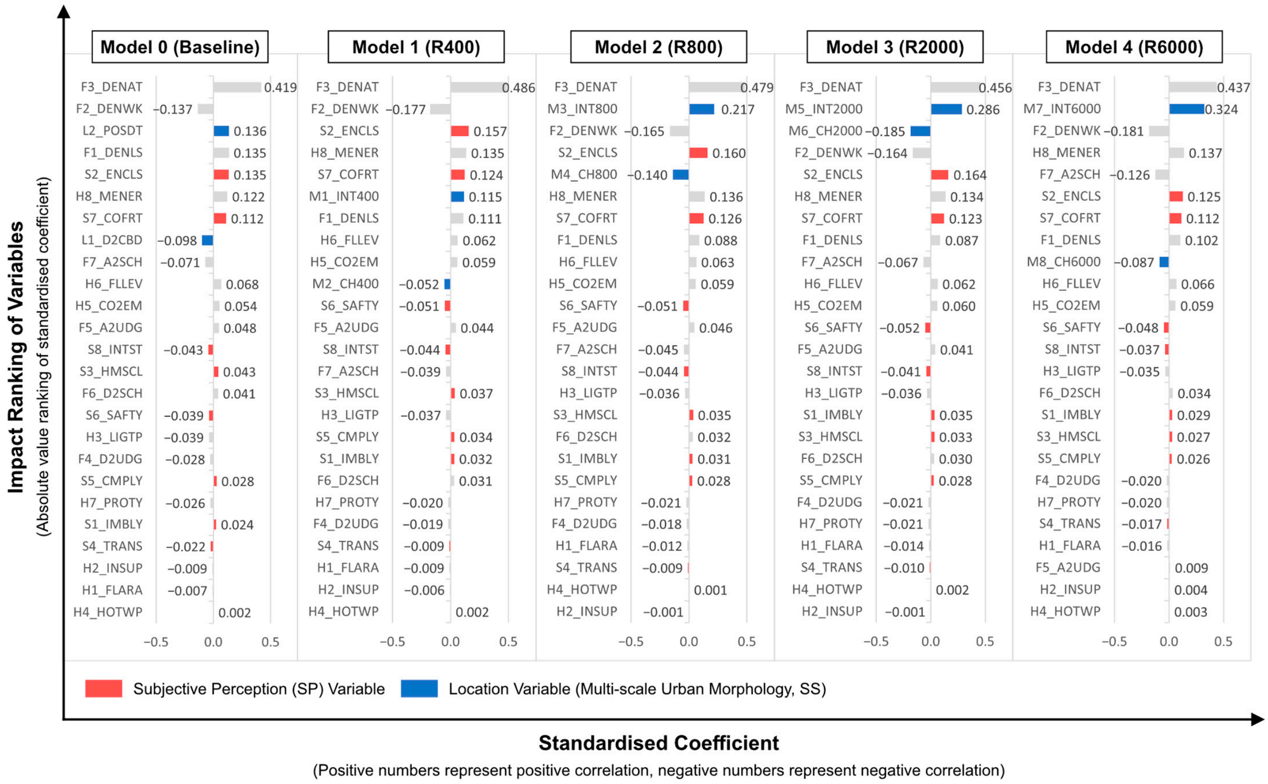

Figure 8. Impact ranking in models based on absolute standardized coefficients.

For models 1–4, while different scales of urban morphology are used as the location attribute, no significant change in R2 can be observed. Meanwhile, the density of attractions (F3_DENAT) exhibits the highest standardized coefficient among all models, implying that being close to functional opportunities has a greater influence on house prices than being closer to generic opportunities. Other important functional variables include the density of workplaces (F2_DENWK) and the density of urban services (F1_DENLS).

The models also show that the effect of people's SP varies depending on varying urban morphological scales. At a relatively large scale, i.e., a radius of 6 km (Model 4), the integration variable (M7_INT6000) can better explain house price variation, than the SP variables 'enclosure' and 'sense of comfort' (S2_ENCLS, S7_COFRT). The importance diminishes as the scale decreases (Model 2, Model 3) and eventually falls below some SP variables (Model 1). The choice variable has a similar trend in Models 1–3 but is not as noticeable as the integration value.

In terms of SP attributes, 'enclosure' and 'sense of comfort' can best explain house price variation, followed by 'safety' and 'interest', whereas 'imageability', 'transparency' and 'complexity' are the lowest. This result indicates that when holding other conditions equal, people's SP plays a role in shaping the house price market. Particularly areas featuring a sense of enclosure and which are also comfortable to live in tend to be more valued than other places.

4. Conclusions

The findings show that SP of the built environment has a significant effect on house prices. This effect is higher than neighborhood attributes (i.e., urban functions) or house structure attributes. However, our analysis has shown that location attributes (i.e., urban morphology) have a higher importance than SP attributes. This suggests that people's SP variables of the urban environment have significant impacts on house prices, above some objective urban environment attributes.

The HPM based on multi-scale urban morphology shows that when comparing urban morphological attributes with SP attributes, the smaller the scale of urban morphology (i.e., the more local the measure), the more important is the SP. Moreover, the larger the scale of urban morphology (i.e., the more global the measure), the more important are the urban morphological attributes. For the different SP variables, 'enclosure' (S2_ENCLS) and 'sense of comfort' (S7_COFRT) have more significant impacts on house prices than other variables. This study adds the SP dimension to the house price assessment model, helping to explore the impact of SP on house prices at different scales of urban morphology. Future related research could refer to such a framework using SVI data and SP surveys to incorporate people's SP of the urban streetscape near the property into house price assessment at multiple urban scales supported by SS techniques.

5. Limitation and Future Work

There are several limitations to this study. First, this study only used visual indices from SVI segmentation in building an SP prediction model. The prediction accuracy of this approach may be improved by increasing the quality and precision of SVI data extraction and expanding the volume of perception survey data: (i) more features, such as HSL histograms and Blob detection, may be added to complement the physical features presented by the SVIs; (ii) more field experiences and surveys may be added to the study to cross-validate the SP predictions and minimize the bias introduced by web image surveys. Second, in the SP survey, some participants' understanding of the concepts of SP may not accurately capture their perception. A better questionnaire design and question setting as well as a larger sample size could improve this limitation. Future research could involve a larger more representative sample including urban design professionals to provide a more accurate and efficient assessment of the street environment in images. In addition, VR technology and panoramic SVIs can be used in the perception survey sessions to provide participants with a more realistic environment and more accurate exploration of their SP. Finally, many studies have shown that spatial dependence and non-stationarity violate the basic assumptions of OLS regression. Due to spatial correlation effects, OLS regression models may be biased in their coefficients and report incorrect significance. More tests for OLS regression may be carried out, such as Moran's I and robust Lagrange multiplier (LM) tests, to see if lags and errors due to spatial correlation exist. Given there are spatial lags or errors in OLS regression models, other regression models that solve for spatial dependence may be introduced for more accurate multi-factor impact studies, including the Kelejian–Prucha's model (SAC) [99] and geographically weighted regression (GWR) [100]. These models can effectively manage spatial dependence and non-stationarity-related issues and achieve higher R2 values, thereby enhancing the models' precision and providing stronger data support for the paper's conclusions [51,55].

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