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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 using space syntax

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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 using space syntax

by

Sijie Yang

September 12, 2022

Supervisor: Kimon Krenz

A Dissertation submitted in part fulfilment of the

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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 using space syntax

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Abstract

House prices have long been considered to be closely related to the built environment of cities. The hedonic house price model is a well-known theoretical model that encompasses four dimensions: house structure attributes, location attributes, neighbourhood attributes and environmental attributes. In recent years, some scholars have used the urban morphology research tool space syntax instead of location attributes to study the built environment's impact on house prices at multiple scales. At the same time, subjective perception analysis of cities using street view images as a database has become a popular research trend in recent years and is considered to impact house prices.

This study investigates the impact of subjective urban perceptions on house prices in combination with other objective urban elements at multiple scales of urban morphology. In particular, subjective urban perceptions were assessed through street images, where a perception survey based on 300 street images was conducted among the population, and the results were subsequently used to build a machine learning model to predict street perception scores for areas around house price points across Greater London. The integration and choice values analyse the multi-scale urban morphology in the space syntax, combined with a number of other functional variables, to create the hedonic house price model, which is then placed in the OLS regression model for analysis.

The final results indicate that the impact of subjective perception on house prices is second only to location attributes and higher than neighbourhood attributes and house structure attributes. There is considerable differentiation in the impact at multiple scales of urban morphology. In the global analysis, subjective perceptions have a greater impact in the micro-scale urban morphology, which is higher than the location attributes, and a more negligible impact in the macro-scale urban morphology, which is lower than the location attributes, with 'enclosure' and 'sense of comfort' being more important than the other perception variables in influencing house prices. In the analysis of the four local areas, the study reveals that local urban form has a greater impact on house prices in the urban centres than in the city's peripheral areas, while the opposite trend is observed for the subjective perception variables.

Keywords

house price, subjective perception, urban morphology, space syntax, street view image

1. Introduction

1.1 Urban built environment and house price

Urban built environment refers to the space and settings constructed by humans for human activities in cities, which includes streets, parks, open spaces, etc. (CDC, 2015). It is also defined as the physical basis for day-to-day human life, work, and communication in cities (Roof & Oleru, 2008). The urban built environment is considered to have a wide range of impacts on human society in a series of dimensions, including community construction and isolation (Galster & Sharkey, 2017; Hanson & Hillier, 1987; Vaughan et al., 2005), public health (An et al., 2019; R. J. Jackson, 2003; Vaughan, 2018), human behaviour (An et al., 2019; Hillier & Hanson, 1984; Mahmoud, 2018) and more fields.

House price is considered to be the value that buyers evaluate based on the intrinsic and extrinsic attributes of a house unit, of which extrinsic attributes are mainly made up of various dimensions in the urban built environment (Freeman, 1981; Rosen, 1974). Multiple elements of the urban built environment have been shown to affect house prices significantly, including location (Alonso, 1964; Heikkila et al., 1989), street environment (Zhang & Dong, 2018), greenery (Ye et al., 2019), walkability (Boyle et al., 2014; Gilderbloom et al., 2015), etc. Some scholars have also studied the potential impact of the spatial attributes of urban road networks on house prices from an urban morphology perspective (Chiaradia et al., 2009; Law et al., 2013; Narvaez et al., 2012; Xiao & Webster, 2017), using the space syntax theory proposed by Hillier and Hanson (1984). They extend the relationship between urban morphology and the economy from the monocentric city model and the polycentric variants to a new dimension, the spatial dimension of a more complex urban network.

1.2 Subjective urban perception and objective urban elements in explaining house price

A series of studies has highlighted the importance of subjective perceptions and objective urban elements in the urban environment (Long & Baran, 2012; McCrea et al., 2006). These two dimensions are used to assess the social impact of many aspects of the urban environment, including community construction (Krupat & Guild, 1980), quality of life (McCrea et al., 2006; von Wirth et al., 2015), environmental quality (Chiarini et al., 2020; Zannin et al., 2003), etc. In particular, when it comes to house prices, people's subjective perception of the city has a strong complementary effect on house price assessment models based on objective elements in the urban environment (Qiu et al., 2022; Xu et al., 2022).

The urban environment, particularly the micro-scale neighbourhood environment, can affect human perceptions and behaviour, which ultimately has social effects. Subjective perceptions of the street environment can influence people's sense of place (Harvey, 2014; Yin & Wang, 2016), route choice (Ito & Biljecki, 2021; Miranda et al., 2021), physical and psychological well-being (L. E. Jackson, 2003; Wolch et al., 2014), and quality of life (Glaeser et al., 2018). For example, at the street scale, less sky, denser buildings, and narrower streets increase people's sense of safety, which in turn affects their perception of the place (Harvey, 2014; Yin & Wang, 2016). As a product of market economy, which is partly based on subjective value identity of people, people's subjective perceptions can also affect the house price (Chen et al., 2020; Fu et al., 2019; Qiu et al., 2022). Therefore, a better understanding of people's subjective perceptions of a place is critical to understanding local house prices.

Research on how objective urban elements affect house prices is comparatively well established. A number of studies have explored the impact of property attributes on house prices based on the hedonic price model, which was developed by (Rosen, 1974), in terms of four dimensions: house structure (Kain & Quigley, 1970; Sirmans et al., 2006), location (Heikkila et al., 1989; Osland & Thorsen, 2008), environmental (Brasington & Hite, 2005; Poudyal et al., 2009) and neighbourhood attributes (Dubin & Goodman, 1982; Gibbons & Machin, 2003), the latter three of which are objective urban elements. Urban morphology is another objective urban element, and its impact on house prices has become an important aspect of research (Law et al., 2013; Xiao & Webster, 2017).

1.3 Research gap

First, previous studies have relied primarily on objective urban element indicators to model house prices, and research on the relationship between subjective perceptions and house prices remains limited. There have been previous studies exploring the connection between streetscape visions and house prices (Ahmed & Moustafa, 2016; Law et al., 2019; Poursaeed et al., 2018), but they have mainly examined the physical features of streetscape scenes, rather than examining the real perceptions of people through surveys. Recent studies of house prices in Shanghai (Fu et al., 2019; Qiu et al., 2022) have made important contributions in terms of the effect of subjective perceptions on house prices, but more studies are needed to verify this effect.

Secondly, there is a lack of research on the relationship between subjective perceptions and multi-scale urban morphology in influencing house prices. Existing research on the impact of subjective perceptions on house prices has used simple models of urban form (Fu et al., 2019; Xu et al., 2022), examining the effects of geographic or network distance on people's behaviour, without attentions on the additional information contained in the city network at multiple urban scales. Several scholars have explored the impact of multi-scale urban morphology on house prices using space syntax theory (Law, 2018; Law et al., 2013; Xiao & Webster, 2017), but at the micro urban scale, i.e. the street environment scale, these studies have not been integrated with human subjective perception analysis. It is difficult to describe people's real experiences using objective data, and as subjective perception investigations can provide a more complete explanation of human behaviour (Lynch, 1960), further subjective perception studies need to be conducted in conjunction with multi-scale urban morphology data to explore their relationship in influencing house prices.

The third point is that there is still little research on how subjective perceptions combine with objective urban elements, including urban morphology and functional attributes, to influence house prices. The few existing studies have focused on the impact of subjective perceptions (Qiu et al., 2022; Xu et al., 2022), streetscape environments (Chen et al., 2020; Fu et al., 2019; Ye et al., 2019), multi-scale urban form (Chiaradia et al., 2009; Law, 2018; Xiao & Webster, 2017) and other functional attributes including schools, green spaces, etc. on house prices, while few studies have explored describing how they form an urban environment system that works together to affect house prices. Combining subjective urban perceptions and objective urban environments, a comprehensive system of judgement describing the house price market on the urban environment needs to be given.

1.4 Research questions and contributions

Based on street view images (SVI), computer vision (CV) analysis and machine learning (ML) techniques, we will investigate and measure people's subjective urban perceptions and attempt to explore three questions in conjunction with data and analysis at the dimensions of urban morphology and urban function:

(1) Does people's subjective perception of the urban environment have an impact on house prices? How does it influence?
(2) How do people's subjective perceptions, as a micro-scale urban experience, act on house prices in combination with different scales of urban form? Which has a greater impact on house price market?
(3) How do people's subjective perceptions interact with objective urban elements, including urban morphology and urban function, to affect house prices?

The contributions of this study are mainly falls on three dimensions: firstly, it further illustrates and verifies the potential impact of people's subjective perceptions on house prices. Secondly, it combines people's subjective perceptions at the micro-scale streetscape environment with a multi-scale model of urban morphology, in an attempt to explore how subjective and objective aspects act on house prices at multiple urban scales. In addition, the study further investigates how people's subjective urban perceptions and objective urban factors, including urban form and urban function, work together to refine the house price assessment model based on urban environment elements.

2. Literature Review

2.1 Hedonic price model (HPM) and house market

A variety of valuation methods exist for house prices, including some traditional methods such as the comparative method, which estimates the market value of a house by comparing the condition and price of various properties, and the profit method, which calculates the amount of capital a tenant can share with a landlord by estimating the gross profit of the business. In contrast, hedonic price model (HPM) is a more advanced and commonly used method of valuing house prices.

The theoretical basis for the hedonic price model is Lancaster's theory of consumer's demand (Lancaster, 1966). He argues that the utility of a composite good is not based on the good itself, but on its various homogeneous characteristics, its composite attributes. Further, Rosen proposed the related price theory, hedonic price modelling, where the total price of a good can be the sum of the prices of each homogeneous attribute, each of which itself has its own weight and implied price in the market (Rosen, 1974). In contrast to other approaches, the hedonic price model avoids the complexity of commodity characteristics by compressing multiple characteristics of a commodity into a single dimension (Rothenberg et al., 1991).

House is a product category that has many different characteristics, generally summarised as four dimensions: structure, location, environment, and neighbourhood characteristics (Ros. In the hedonic price model, different property indicators have different weights and collectively end up forming the house price market. The combination of these attributes ultimately has a determining impact on house prices, where house prices can be thought of as a function of various characteristics as independent variables (Freeman, 1981):

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

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

2.2 Subjective urban perception in the HPM

2.2.1 Subjective perception criteria for urban environment design

Subjective perceptions are measured mainly from surveys and interviews (Nyunt et al., 2015), and further perception ratings are given to the street environment. For subjective perceptions in micro urban environments, Ewing and Handy identified five urban design perception criteria through comparison surveys: imageability, enclosure, human scale, transparency and complexity. These subjective indicators were found to correlate with some of the physical elements in the streetscape images and are thought to provide a better description of people's subjective perceptions of the urban street environment (Ewing & Handy, 2009). Research on house prices in Shanghai has conducted a preliminary exploration of the impact of subjective perceptions on house prices based on these subjective indicators (Qiu et al., 2022; Xu et al., 2022). In addition, sense of safety in the urban environment, proposed by Naik and Brien (2013), was also investigated as an perception indicator in these studies.

These six perception indicators can be used to describe the subjective experience of the spatial attributes of the urban built environment, with different perspectives and definitions. Introduced by Lynch (1964), the first metric *imageability* is defined as the potential of the urban environment to evoke a strong impression on observers and whether urban elements help people to memorize and recognize them. Landmarks are considered to be a key component of imageability, as they create a distinctive visual image (Tunnard & Pushkarev, 1963). Secondly, *enclosures* describe 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 (Alexander, 1977; Cullen, 2012). The third indicator *human scale* refers to the extent to which physical attributes such as the size of buildings in the urban environment match the proportions of human size, with elements such as building details and street trees contributing to the establishment of human scale (Alexander, 1977; Hedman & Jaszewski, 1984). As the fourth indicator, *transparency* represents the extent to which people can see or perceive things beyond the edge of the street, such as walls, windows, landscapes, and other boundaries (Arnold, 1993; Jacobs, 1993). The fifth metric *complexity* means the visual diversity of a place, which depends on the diversity of the physical environment, such as the number and type of buildings (Jacobs & Appleyard, 1987), the number and type of landscape elements and infrastructural settings (Arnold, 1993; Jacobs, 1993), the abundance of human activity (Rapoport & Hawkes, 1970), etc. The effectiveness of these first five indicators in expressing people's subjective perceptions of the urban environment has been summarized and validated by Ewing and Handy (2009). On the basis of these five indicators, Qiu et al. (2022) propose adding the sense of safety indicator proposed by Naik and Brien (2013) to provide a more comprehensive description of people's subjective perceptions of the urban environment.

2.2.2 Computational techniques in streetscape perception investigation

Field investigation is a common way of collecting people's subjective perceptions of the urban environment, but it is only suitable for micro scale research and is difficult to implement on an urban scale (Dubey et al., 2016; Salesses et al., 2013). Google *street view images (SVI)* provide a way for observers to assess the urban street environment through online images, requiring significantly fewer resources for macro scale urban perception surveys (Griew et al., 2013). Subjective urban perception investigations through the SVI have proven to be consistent and reliable when compared to on-site surveys (75%-96.7%) (Griew et al., 2013; Kelly et al., 2013; Queralt et al., 2021).

Based on the SVI, *computer vision segmentation (CV)* techniques allow researchers to accurately extract and evaluate physical features in the SVI, such as the sky, trees, buildings, etc, which is used to assess the street environment quality (Dubey et al., 2016; Qiu et al., 2021; H. Zhou et al., 2019), calculate the greenery (Li et al., 2015; Ma et al., 2021; H. Zhou et al., 2019), construct a walkability index (Ma et al., 2021; H. Zhou et al., 2019), etc. These studies weighted and combined different physical feature indicators from CV analysis to express people's underlying subjective perceptions. Further, Qiu et al. (2022) used subjective perception investigation data of a small number of SVI samples to build a mathematical model based on CV-derived streetscape physical feature data by means of *machine learning (ML)*, linking people's subjective perception indicators to physical features in the SVI through equations, and used this model to predict people's subjective perception of other arbitrary streets in the city. The three computational techniques of SVI, CV and ML ultimately allow us to investigate and predict the subjective perception of all streets in a city from a small number of online images.

2.3 Objective urban elements in the HPM

2.3.1 Urban characteristics in traditional HPM analysis

Among the four dimensions, structure, location, environment, and neighbourhood characteristics, which are generally used by hedonic house price model related research (Sander et al., 2010; Wen et al., 2005; Won & Lee, 2017), structural attributes are used to describe the internal spatial environment of the house property itself, while the remaining three dimensions of attributes, location, environment and neighbourhood, are all descriptive of the external environment of the house and can be categorised as objective urban elements in the hedonic price model.

House structure attributes describe the physical structure of the interior of a property and are the easiest attributes to measure and perceive. Follain and Jimenez (1985) summarises the most popular structural attributes studied, including floor area, house construction quality, etc. A number of further studies have demonstrated the correlation between the internal structure of a house and the price of the property (Kain & Quigley, 1970; Sirmans et al., 2005), as well as its correlation with location attributes (Muth, 1971).

Location attributes of a property has long been considered an important characteristic of a house. The classical land use model proposed by Vou Thunen first relates value to distance from a central marketplace. A series of scholars have extended this “distance-value” model to a “spatially access-value” model, arguing that the transportation costs associated with distance are one of the trade-offs in the value of land (Alonso, 1964; Mills, 1972; Muth, 1971). A series of house price studies have found that the house price curve decreases with increasing house’s distance from the *Central Business District (CBD)* (Beckmann, 1973; Heikkila et al., 1989). Such a CBD-centred monocentric model considers employment accessibility to be an important factor in residential choice (Beckmann, 1973). The monocentric view has since been widely questioned by scholars from a number of perspectives, including the fact that the location of employment is not monocentric (Heikkila et al., 1989; McDonald, 1987; Steinnes, 1977) and that workplace accessibility has been overemphasised (Heikkila et al., 1989; Small & Song, 1992; White, 1988). Employment centres and welfare centres may be located outside the city centre, leading to complications in the house price hierarchy (Orford, 2017). It is thus evident that while location attributes are important, the factors that influence house prices are highly complicated.

Environmental attributes are similarly an essential functional component in the urban environment, although they are more concerned with the amenity and sustainability of the urban environment. A number of studies have used environmental attributes as independent indicators to evaluate house prices in the hedonic price model (Anderson & Crocker, 1972; Murdoch & Thayer, 1988). Environmental quality is critical in the assessment of environmental attributes, including air quality (Graves et al., 1988), water quality (Steinnes, 1992), noise comfort (Nelson, 1982; Schipper et al., 1998), greenery (Poudyal et al., 2009) and so on. A range of urban functional elements in the vicinity of a residential area can contribute to the quality of the neighbourhood environment. These elements are known as environmental amenities, such as rivers, open spaces, urban parks, etc., adding value to nearby properties (Richardson, 1977; Stegman, 1969).

Neighbourhood attributes depict the social and functional attributes of a property's immediate area. The social dimension includes the social status and demographic characteristics of the neighbourhood, including the income, ethnicity, age etc of the population, with higher income neighbourhoods considered to have higher quality, such as better quality of education and lower crime rates (Lochner, 2011). Functional dimensions include accessibility, density and quality of schools, metro stations and other public infrastructure. It is widely recognised that schools play an important role in influencing house prices and a range of studies have demonstrated that good characteristics of schools in different areas have a positive impact on house prices (Dubin & Goodman, 1982; Gibbons & Machin, 2003; Hefner, 1998). The good accessibility and high density of metro stations and entertainment facilities also have a beneficial effect on property prices (Agostini & Palmucci, 2008; Li et al., 2019).

In summary, it can be concluded that in the traditional HPM house price analysis, the objective urban environment elements can be divided into two components, the first is the urban spatial dimension, i.e. location attributes, the organisation of the city in the spatial dimension directly affects people's mobility at the physical level, the long distance to the CBD increases people's travel costs to the core area and enables house prices to become lower; The second is the social and functional dimension of the city, including neighbourhood attributes and environmental attributes, the social and functional resources of high-quality residential areas make house prices relatively higher in value.

2.3.2 Urban morphology in the HPM: from monocentric city model to space syntax

Urban morphology plays a crucial role in the urban economy and the location attributes of house in HPM analysis are part of urban morphology (Law et al., 2013; Webster, 2010; Xiao & Webster, 2017; Zhang et al., 2019). However, existing monocentric city model is an overly simplistic assessment of property location based solely on distance from the property to the CBD, which has limitations and ignores the complex connections and information in the urban grid. For the first time, Alexander introduces the concept of formal mathematics into the analysis of relevant urban morphology with regard to the network properties of cities (Alexander, 1965). More scholars have similarly discussed and studied urban morphology based on mathematical theories such as graph theory and

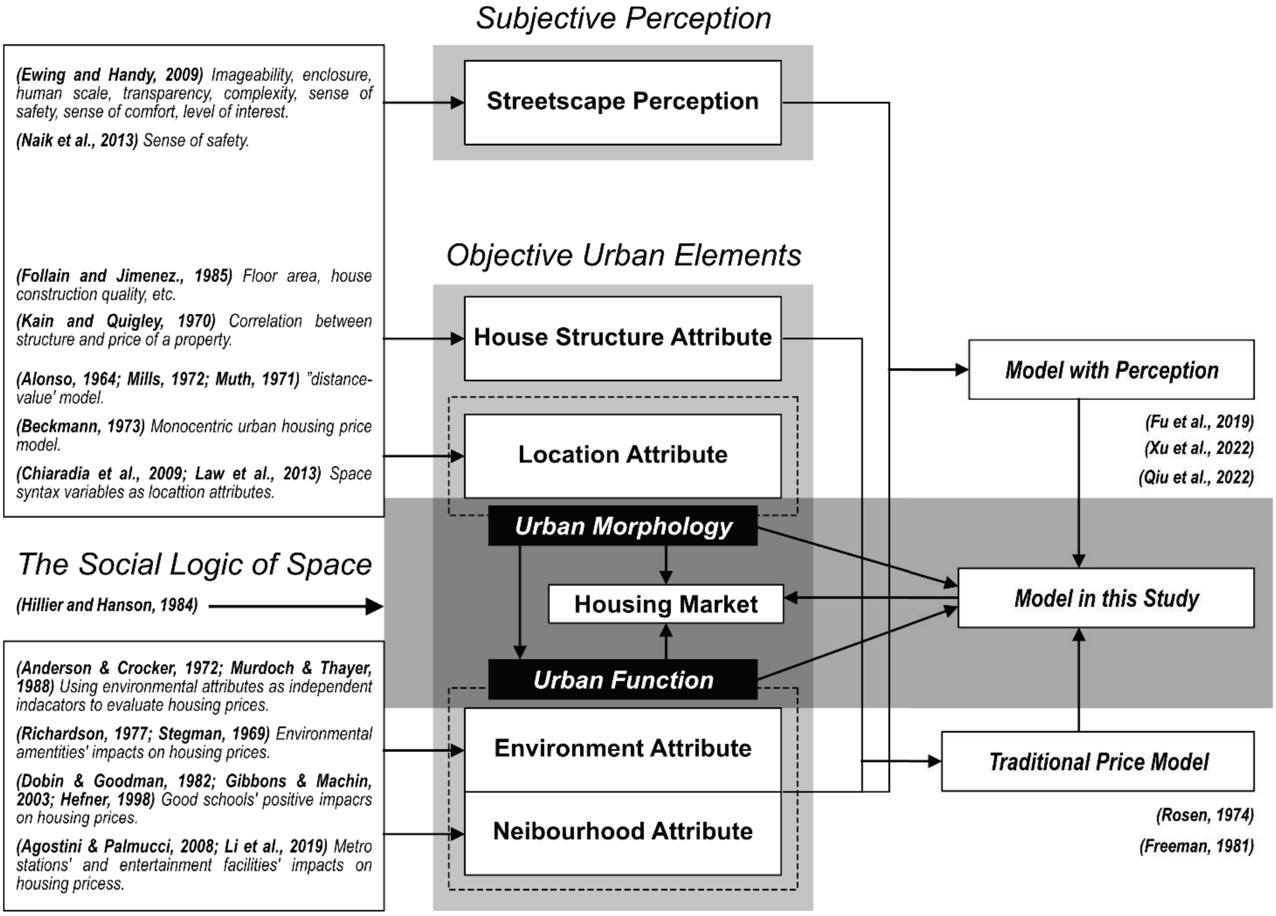


Fig. 1 Conceptual framework and key literatures

set theory. One of the most innovative and influential theories is the *space syntax* developed by Hillier and Hanson (1984).

Space syntax was introduced by Hillier and Hanson (1984) in their book *The Social Logic of Space*, and has since been refined and applied by scholars, culminating in the formation of a school of thought. Hillier and Hanson point out that the layout and structural form of space in cities and buildings, which they call *space configuration*, directs human movement patterns through the organization of physical space, and thus has potential effects on society. They have developed a series of mathematical indicators based on mathematical methods to describe the potential characteristics of spatial assemblages and to express the elements and potential information in the urban form through computer calculations (Hillier & Hanson, 1984).

Due to its superiority in expressing the properties of space composition in cities and buildings, space syntax has been used by many scholars to conduct research in a variety of space-related fields. In the urban and architectural study field, spatial syntax is used to conduct research in a number of dimensions such as spatial design (Karimi, 2012) , urban morphology (Karimi, 1997; Krenz, 2017, 2018; Yang & Hillier, 2007), spatial justice (Vaughan, 2007; Vaughan et al., 2005), spatial culture (Griffiths, 2016; Yang & Yang, 2022), building programme (Capillé & Psarra, 2014; Sailer et al., 2013), architectural narrative (Psarra, 2009), etc.

As part of the social impact of space configuration, house prices are also considered by some studies to have a high correlation with the space configuration of cities (Chiaradia et al., 2009; Law, 2018; Law et al., 2013; Narvaez et al., 2012; Xiao & Webster, 2017). After comparison with a variety of traditional location attributes, the integration and choice values in the space syntax are considered to be good ways to describe urban morphology and become an alternative to location attributes (Law et al., 2013). Space syntax variables based on varying radius sizes are used to study house price models at multiple scales of urban morphology (Chiaradia et al., 2009; Law, 2018; Xiao & Webster, 2017).

2.4 Conceptual framework: based on the social logic of space

Hillier et al. (1993) argued in the theory of '*natural movement*' that the functional distribution of the city is linked in some way to the urban form and eventually acts in conjunction with the urban morphology on the natural movement of pedestrians (Hillier et al., 1993). According to Hillier et al. (1993)'s theory, the distribution of urban functions is based on urban spatial form but is not completely causative, as urban functions form their own systems and have independent attractive powers from urban morphology. The attractiveness of the urban form, that is, the spatial characteristics expressed by the integration and choice values, is superimposed on the attractiveness of the urban functional system, both of which eventually effect the behaviour of pedestrians. In essence, the house price market is produced by human behaviour generated based on the objective urban environment, being influenced by urban morphology and urban function, which is aligned with the hedonic house price model (Hillier et al., 1993).

A methodology for studying the social impact of space has been developed in the field of space syntax (Hillier, 1996; Hillier & Hanson, 1984) as the basis for the theory of natural movement: firstly, space configuration, which is the particular organisation of space, needs to be studied in order to explore the intrinsic properties of space itself; the function of space and human behaviour should then be researched. Space configuration may have an impact on function and subsequently, together with function, influence human social behaviour. Such a theory reorganises and reinterprets the traditional hedonic house price model, where location attributes imply urban morphology and space grouping, while environmental and neighbourhood attributes are present in the model as urban functions, as shown in the Fig.1.

To conclude, more research is needed to support existing studies in the area of subjective perceptions' impacts on house prices. At the dimension of the impact of multi-scale urban morphology on house prices, there is some research, but it is still insufficient and has never been compared with the impact of subjective perceptions. This study attempts to construct a more comprehensive house price model based on subjective perceptions, multi-scale urban morphology, traditional hedonic house price models and the social logic of space theory, and to explore the impact of various factors on house prices (Fig.1).

3. Methodology

3.1 Research framework and study area

Fig.2 illustrates the main framework and workflow of this study. First, information from 200 participants in London was collected on their perception of 300 random street view images based on eight subjective perception measures using an online survey. Secondly, a semantic deep learning framework was used as the computer vision technique to extract the respective pixel ratios of over 30 physical streetscape elements in the street view images. Third, machine learning models were trained to predict people's subjective perception scores of London

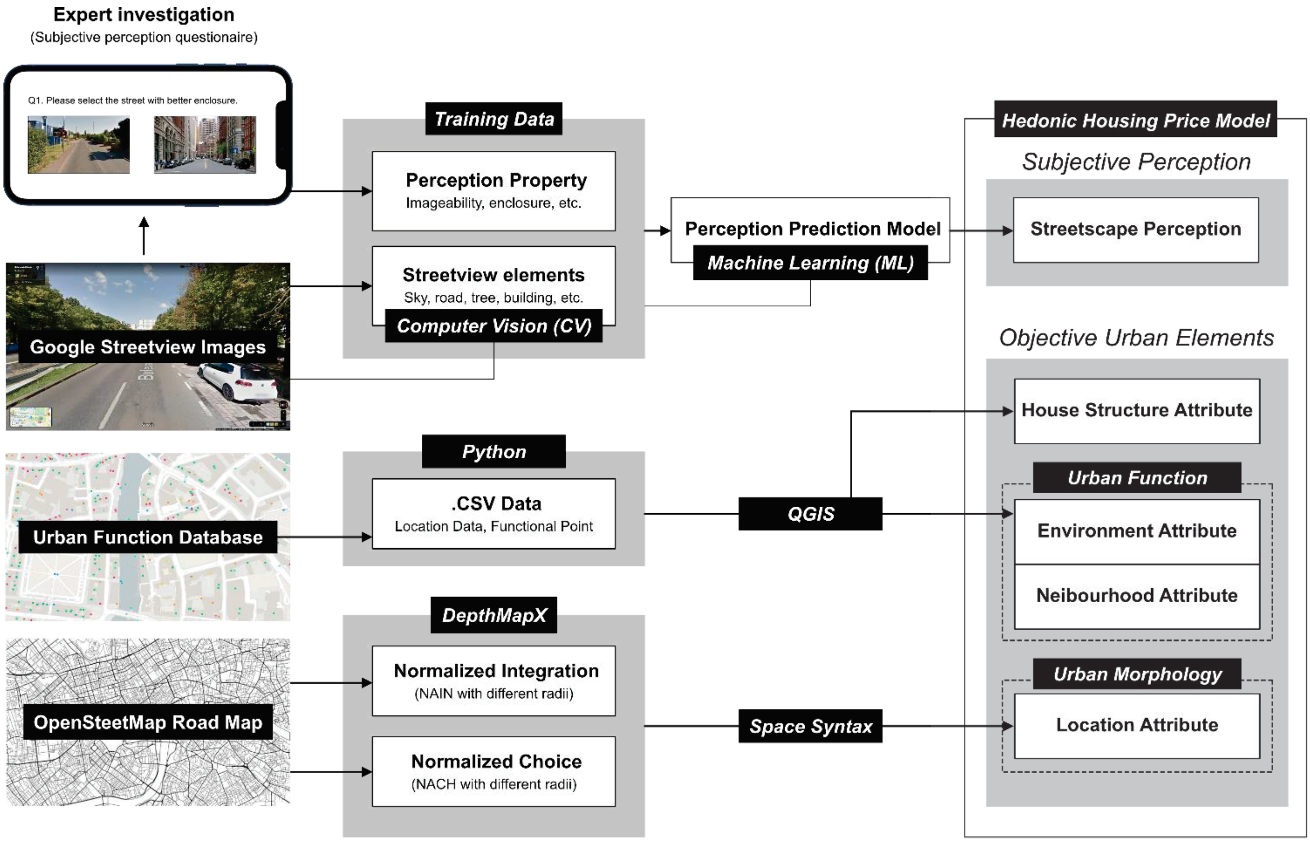


Fig. 2 Research framework and workflow

streets, using the pixel ratios of physical elements extracted from street view images as the explanatory variable. In the fourth step, the best performing machine learning model was applied to predict subjective perception scores for London streets, based on street view images. Subsequently, subjective street perception scores were incorporated to the hedonic price model and the extent to which subjective streetscape perception influences house prices was quantified regression models. The impacts of subjective urban perception on house prices were compared with the effects of multi-scale urban morphology and urban functional properties.

London is a cosmopolitan and financial centre for the UK and Europe as a whole, and is one of the most dynamic and expensive house markets in the region. A study of the factors influencing house prices in London can inform the house market conditions in other high-density metropolitan areas, as well as informing future urban design and urban development in London. Greater London has therefore been chosen as the main subject of this study (Fig.3).

3.2 Subjective urban perception scores

3.2.1 Downloading Google SVIs

Using QGIS, this study sampled streetscape points at 100m intervals throughout London, in order to obtain a total of 70,059 streetscape images across Greater London from Google Street View Static API through Python programming (https://developers.google.com/maps/documentation/streetview). Fig.3 shows that each street view image is oriented directly towards the road to clearly reflect the conditions of walking on the street. The walking distance of a person in a 15 minute living circle is approximately 1km, therefore street view images within a 1km radius around each property point are considered to reflect the characteristics of the street environment

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

around the property.

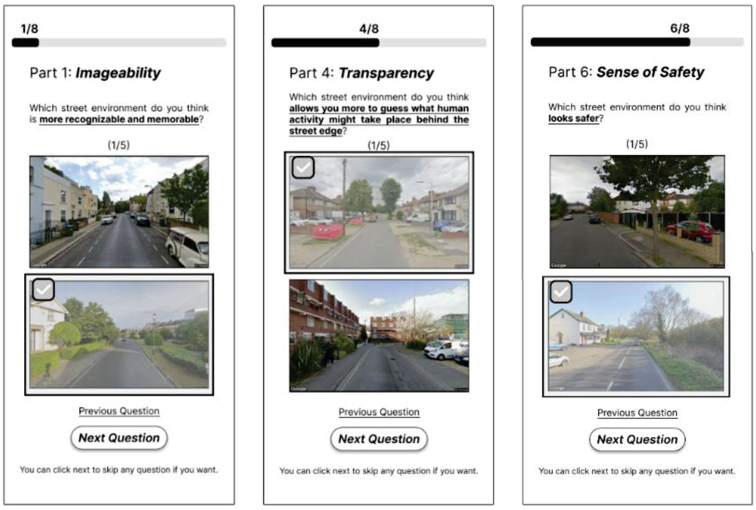
300 images were randomly selected from the acquired street view images for the subjective perception survey. The images were manually examined to confirm that they were all clear street view images and that they evenly encompassed the wide variation in Greater London's urban environment from the centre to the city periphery.

3.2.2 Investigating eight subjective perception measures

From an urban design perspective (Ewing & Handy, 2009), 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 subjective perception of the urban built environment. This framework of streetscape perception indicators has been accepted and found to be reliable by a range of urban studies. This study applies the urban perception metrics proposed by Ewing and Handy (2009) more comprehensively, building on previous studies, to eight parameters, compared to five parameters (Qiu et al., 2022) and six parameters (Xu et al., 2022) in previous applications.

Inspired by previous research on streetscape perception (Fu et al., 2019; Salesses et al., 2013), to investigate and quantify people's subjective perceptions of the street environment, an online questionnaire was designed, and participants were asked to make a two-by-two comparison of images among 300 street view images based on eight subjective perception indicators. A total of eight questions corresponding to the perceptual indicators were set in the questionnaire, and under each question participants were asked to perform five rounds of image comparison, with two images in each round randomly selected from the pre-determined 300 images of the street view, and participants would choose one of the two based on their own perceptual experience.

265 participants 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. All participants had experience of living in London and approximately 80% were undergraduate and postgraduate students from a range of disciplines. The survey was larger and more diverse than previous studies, where there are 10 urban planners in Ewing and Handy (2009)'s



Part 1 - Imageability: Which street environment do you think is more recognizable and memorable?

Part 2 - Enclosure: Which street environment do you think is more visually enclosed and limits your view?

Part 3 - Human Scale: Which street environment do you think matches the proportion of a human best and is less intimidating in size?

Part 4 - Transparency: Which street environment do you think allows you more to guess what human activity might take place behind the street edge?

Part 5 - Complexity: Which street environment do you think is more complex, diverse and visually rich?

Part 6 - Sense of Safety: Which street environment do you think looks safer?

Part 7 - Sense of Comfort: Which street environment do you think makes you more comfortable?

Part 8 - Level of Interest: Which street environment do you think you are more interested in and would like to visit?

Fig. 4 Survey website design and questions

research and 43 urban-related designers in Qiu et al. (2022)'s study. The questions in the survey were designed to avoid technical vocabulary as much as possible, making it easy for each participant to understand the relevant subjective perception variables. However, the sample does not constitute a representative sample of the London population. Young (16–24) and female participants are overrepresented. This constitutes an important limitation for the study, and findings need to be considered in light of the surveyed population

The TrueSkill algorithm (Herbrich et al., 2006) was used to convert participants' survey responses into a score ranking based on the pairwise street view image comparison. Under each subjective perception measure, TrueSkill modelled participants' preferences and choices of images into a competition and generated scores and rankings for 300 street view images. These scores, combined with the information from image segmentation, became the training set for predicting the subjective perception scores of streets, which were used to predict the perception scores of all other street view images.

3.2.3 Dissecting the physical elements in street view images

A deep convolutional neural network model called, *Pyramid Scene Parsing Network (PSPNet)*, was used to extract physical elements from street view images. This model structure has been shown to be effective and accurate in street view image segmentation (Zhao et al., 2017). This method of quantifying the physical elements in the streetscape has begun to be used in a range of urban studies (Chen et al., 2020; Gong et al., 2019; Lu, 2018; Zhou et al., 2021). After a PSPNet model is trained on ADE20K, a dataset of street view data from 50 cities (B. Zhou et al., 2019), it can efficiently identify physical elements in street space with high accuracy, and subsequently classify each pixel point in the image as a certain type of physical element, such as sky, building, tree, etc. In this study, PSPNet model was pre-trained based on the ADE20K database and ended up with ratios of different physical elements in streetscapes in each image to the whole image, which is called the *View Index* (Fu et al., 2019). The view index of physical element i in each image obtained by the calculation can be expressed as follows:

$$V_i = \sum \frac{P_i}{P}, P = \{P_i \mid i \in \{sky, building, tree, etc.\}\}$$

where P stands for the total number pixel points in the street view image, while P_i represents the pixel number

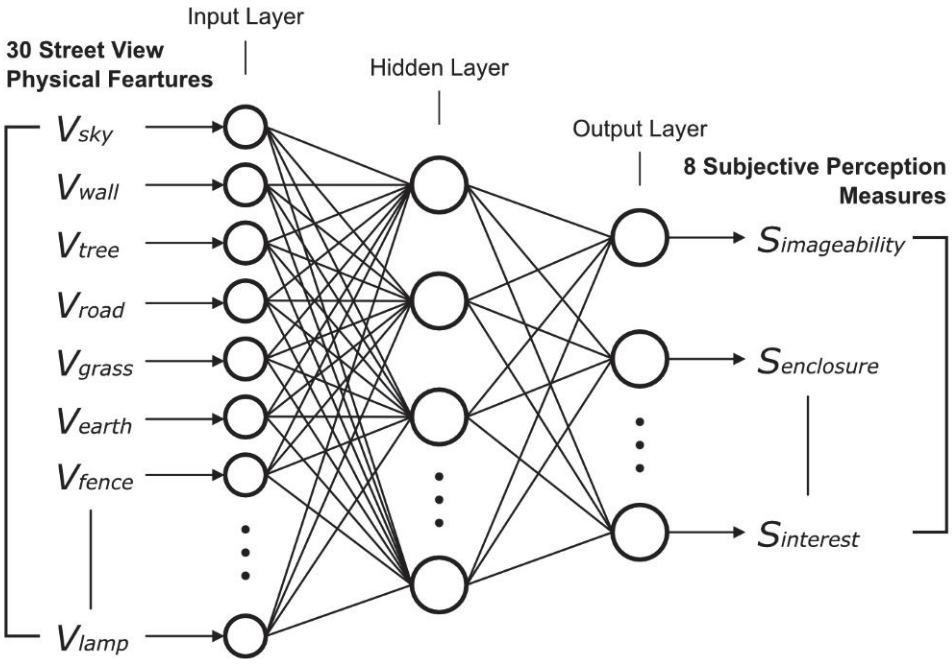


Fig. 5 Calculation diagram of BN Neural Network

of certain physical element i . The set of visual indices of different physical elements is used to reflect the quantized objective reality of the streetscape through images.

3.2.4 Predicting subjective perception scores with machine learning model

learning algorithms have been used to study the subjective perception of cities based on street view images and are considered to be an effective mean of predicting subjective perception: *Convolutional Neural Network* (CNN) was applied to predict urban safety (Fu et al., 2018; Porzi et al., 2015), while *Random Forest* (RF) algorithm has been used in a range of urban perception studies to predict urban perception scores (Qiu et al., 2022; Wang et al., 2019; Yao et al., 2019). Following these examples and based on the dataset of street view images, their perception survey scores, and their visual index information, the *Back-Propagating* (backprop, BP) *Neural Network* was used to train a mathematical model that could predict people's subjective perceptual experience based on street view image visual index data. Backpropagation and its application to neural networks was first proposed and further developed by Rumelhart et al. (1986). This multilayer perceptual model has the ability to cope with arbitrarily complex patterns for classification and provides sufficient multi-dimensional function mapping. It can be structurally divided into three parts: an input layer, a hidden layer, and an output layer. As shown in Fig.5, in this study, the view indexes of 30 physical elements in a single street view image, e.g., V_{sky}, V_{wall}, V_{tree}, are input in 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 final database, which holds the participants' ratings on eight subjective perceptual dimensions for 300 images, is divided into two parts, a training set and a validation set, according to 80% (240) and 20% (60). After building the mathematical model in the training set, the predictive performance of the model was evaluated in the validation set. The prediction performance of a model is evaluated by *Accuracy*, *Precision*, *Recall* and *F1 Score*, where accuracy represents the percentage of all samples that the machine learning classifier is correct on, precision indicates how the model performs in predicting a particular category, recall indicates the probability that the model detects a particular category, and F1 score is a combination of both precision and recall. In this study, the precision, recall and F1 score are calculated as macro-average values, which are the average values of all categories. All four parameters range from 0 to 1, with the closer to 1 the better the model performs in the prediction.

The best performing model was then used to predict the subjective perception scores for all 70,059 streetscape images. The streetscape perception scores within 1 km of a property were averaged to represent the quality of the street environment in the neighbourhood of the property. Descriptive statistics for the subjective perception scores of the street environment around each property are presented in Table 1.

The importance of view indexes of streetscape physical elements in the neural network prediction model is calculated by the permutation feature importance method (Breiman, 2001; Fisher et al., 2019), which reflects the importance of a feature in the model by measuring the magnitude of the prediction error of the model after permuting the data for that feature. For a single feature i, its importance FI_i in the prediction of the neural network model can be expressed as:

$$FI_i = \frac{s - s_i}{s_1 + s_2 + s_3 + \cdots + s_i}$$

$$s_i = \frac{1}{K}\sum_{k=1}^{K} s_{k,\,i}\,,\ i \in \{sky,\ building,\ tree,\ etc.\}$$

where s represents the original prediction score of the model, which is accuracy in this study, while $s_{k,\,i}$ is the prediction score of the model after the data for characteristic i have been permuted, and $s_{k,\,i}$ is finally averaged after K rounds of data permutation and calculation.

3.2.5 Verification and correlation analysis of subjective perception scores

Using streetscape images to evaluate the street environment is considered to be reliable, valid and consistent. Although this study did not use a field survey to check the consistency between subjective perceptions based on streetscape images and field perceptions. Four streetscape images were randomly selected and the segmentation results along with the prediction scores were presented to be evaluated manually.

Subjective perception variables can be highly correlated with each other and introduce multicollinearity. Therefore, crossed Pearson correlation matrix was plotted to examine the correlation level between the subjective perception variables, which helps to mitigate the problem of multicollinearity when selecting explanatory variables for the regression model.

3.3 Objective urban element variables

3.3.1 Urban morphology variables

Space syntax is widely used for the analysis and study of urban morphology (Krenz, 2017; Sun, 2013; Ye & Van Nes, 2014), where the integration and choice values are considered to be reliable descriptive variables for urban form, which can be alternatives to traditional location attributes. In this study, integration and choice values were calculated at multiple scales, from micro-scale analysis to macro-scale analysis, including radii of 400m, 800m, 2000m and 6000m. Space syntax related analyses were based on the space syntax toolkit in *QGIS* (QGIS.org, 2022) and shapefile of London roads from *Ordnance Survey (OS).* Table 1 shows the descriptive data of the calculated results of the urban morphology variables at a range of scales. A brief explanation of the integration and choice values is given below:

> *Integration* is considered to be one of the central concepts in space syntax, representing the extent to which a street is more accessible in an urban network (Hillier & Hanson, 1984). From a typological point of view, integration is calculated based on the minimum number of switches between different streets, which is the relative depth between two streets. This corresponds to angular and metric integration, with angular integration incorporating the change in angle between streets and metric integration including the distance between the midpoints of the streets (Hillier & Iida, 2005). Integration values can be calculated at multiple scales, including the global scale and the local scale (Hillier, 1996). The global scale calculation is based on the average depth of a street in relation to all other streets in the urban system, while the local scale calculation is based on the average depth of a street in relation to other streets within a fixed radius.
>
> *Choice* is defined as the extent to which a road is necessarily chosen by the shortest path in the process of traversing the urban network (Hillier et al., 1986). A street with a high choice value tends to be the one that is more likely to be traversed in the city. Like integration, choice can be calculated at multiple scales by selecting different radii for analysis.

3.3.2 Urban function variables

The variables related to urban function are the neighbourhood attributes and environmental attributes in the hedonic house price model, as shown in Table 1. These variables were selected based on the literature and the accessibility of the data. The density values of the main urban functions within a 1km radius of each of the main house price points are calculated, including living services, workplaces and attractions. These key functional data are provided by the POI database in *Ordnance Survey (OS)*. The proximity of urban public transport and good educational facilities is considered to have a positive impact on house prices. Therefore, 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 good school was calculated. In addition, the number of TfL stations and good schools within a 3km radius of each property was measured as the accessibility value for both functions.

3.3.3 House structure variables

Although the house structure is not a traditional element of the urban built environment, it is an important component of the hedonic house price theory and should be considered in order to create a standard model. Information on house structure was obtained from *Domestic Energy Performance Certificates (EPCs)*, which includes house floor area, number of floors, building type and a range of energy performance variables such as energy source, insulation performance etc. Some of these variables are categorical and can be converted to continuous variables for regression analysis, as shown in Table 1.

3.4 Hedonic price models

3.4.1 Dependent variable - the house price

The house price data came from two official open source databases, *Land Registry Price Paid Data (LR-PPD)* and *Domestic Energy Performance Certificates (EPCs)*, compiled by Chi et al (2021). The integrated database has 18,575,357 property transaction records of England and Wales since 2011. The data was filtered by two dimensions to match the needs of the research, 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 summarised to these 49,603 house price points and eventually placed into the regression equation for analysis (Table 1).

3.4.2 Model architecture

Three 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 (Fu et al., 2019; Law, 2018; Xu et al., 2022). This model assumes that the target variable is linearly related to multiple predictor variables (James et al., 2013). If k independent variables are selected for regression analysis with the house price variable, the OLS model can be expressed as:

$$T_{hp} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + \varepsilon$$

where T_{hp} is the house price; $x_k(1 = i \leq k)$ are the k selected features from potential explanatory variables; β_i denote the coefficients of the regression and ε denotes the random error. The standardised coefficients were derived from the regression analysis and analysed as the importance of the attributes in the regression equation.

(a) Firstly, four groups of independent variables - house structure attributes, location attributes, neighbourhood attributes and subjective perception attributes - were used as predictor variables to construct four models to examine the correlation between each attribute group and house prices, and the impact ranking of attribute groups on house prices.

(b) Secondly, the variables from the four attribute groups are integrated together for regression analysis to construct hedonic house price models. In order to carry out a multi-scale analysis based on urban morphology, five models were constructed, with the model using traditional location attributes (L1_D2CBD, L2_POSDT) as the baseline model and four models using multi-scale urban morphology attributes (400m, 800m, 2000m, 6000m) as the experimental models. The experimental results provide an understanding of the influence of each attribute on house prices at multiple urban scales.

(c) In the previous two steps of the study, the house price as the dependent variable encompassed property prices across Greater London, which was a global analysis. In the third step, Greater London will be divided into four regions by macro-scale space syntax integration values (M7_INT6000) in order to construct a local regional house price model. The independent variables integrate the four attribute groups, and micro-scale space syntax measures (M1_INT400, M2_CH400) are instead used as location attributes to build models under local urban morphology. The calculation results reflect the effects of different attributes on house prices within four different local areas.

Table 1 Descriptive statistics of all variables.

Variable	Description	Values	Count	Mean	Std.Dev.	Min	Max	Data Source
PRICE	£/m^2, dependent variable		49603	6793.59	3427.28	117.77	91866.95	Data from LR-PPD
House Structure attribute								
H1_FLARA	Total floor area (m^2)		49603	91.25	57.15	6.26	4373.00	
H2_INSUP	House insulation performance		49603	2.58	1.63	1.00	5.00	Data from EPCs
H3_LIGTP	House lighting performance		49603	3.69	1.52	1.00	5.00	
H4_HOTWP	House hot water performance		49603	3.80	0.89	1.00	5.00	
H5_CO2EM	House CO^2 Emission		49603	2.00	1.62	-1.40	66.00	
	Description	**Values**	**Count**	**Percent%**	**Avg.Price**	**Avg.Area**		**Data Source**
H6_FLLEV	Floor level the property locates	1: Low	15959	32.17%	6908.76	65.03		
		2: Mid	32093	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	24841	50.08%	7539.41	67.13		
		3: Semi	7961	16.05%	5683.22	113.49		Data from EPCs
		4: Terrace	13337	26.89%	6244.62	101.24		
H8_MENER	Main energy source	1: Electricity	4626	9.33%	6602.96	63.06		
		2: Gas/LPG	38167	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		49603	3.05	0.36	1.00	4.16	
S2_ENCLS	Perceived enclosure		49603	2.86	0.46	1.50	4.65	
S3_HMSCL	Perceived human scale		49603	3.06	0.26	1.00	4.29	
S4_TRANS	Perceived transparency		49603	2.82	0.20	2.00	4.00	Predicted by ML models based on perception survey and view indexes extracted from SVIs
S5_CMPLY	Perceived complexity		49603	3.24	0.27	1.33	4.00	
S6_SAFTY	Perceived sense of safety		49603	3.24	0.22	1.00	4.50	
S7_COFRT	Perceived sense of comfort		49603	3.03	0.21	2.00	4.00	
S8_INTST	Perceived level of interest		49603	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		49603	0.30	0.15	0.02	0.81	
L2_POSDT	Postcode District		49603	/	/	/	/	
M1_INT400	Space syntax-Integration[HH] (R400)		49603	23.18	6.63	3.56	68.69	
M2_CH400	Space syntax-Choice (R400)		49603	108.54	59.18	0.00	902.55	
M3_INT800	Space syntax-Integration[HH] (R800)		49603	49.09	20.54	3.56	176.85	Road map from OS calculated in QGIS
M4_CH800	Space syntax-Choice (R800)		49603	788.61	485.01	0.00	6399.87	
M5_INT2000	Space syntax-Integration[HH] (R2000)		49603	155.50	88.85	3.56	575.72	
M6_CH2000	Space syntax-Choice (R2000)		49603	11141.62	7914.72	0.00	47980.45	
M7_INT6000	Space syntax-Integration[HH] (R6000)		49603	650.86	459.06	3.56	2148.27	
M8_CH6000	Space syntax-Choice (R6000)		49603	272714.0	249841.4	0.00	1552460	
Neighbourhood and Environment Attribute (Urban Functional Property)								
F1_DENLS	Density of living service (within 1km)		49603	341.28	384.77	0.00	5515.00	
F2_DENWK	Density of workplace (within 1km)		49603	337.43	463.93	1.00	5880.00	Data from OS calculated in QGIS
F3_DENAT	Density of attraction (within 1km)		49603	27.36	40.80	0.00	572.00	
F4_D2UDG	Distance to underground and railway station (km)		49603	0.75	0.58	0.00	7.26	Data from TfL calculated in QGIS
F5_A2UDG	Accessibility to underground and railway station (within 3km)		49603	15.94	13.04	0.00	70.00	
F6_D2SCH	Distance to good school (km)		49603	0.56	0.40	0.00	6.94	Data from Ofsted calculated in QGIS
F7_A2SCH	Accessibility to good school (within 3km)		49603	24.93	14.76	0.00	83.00	

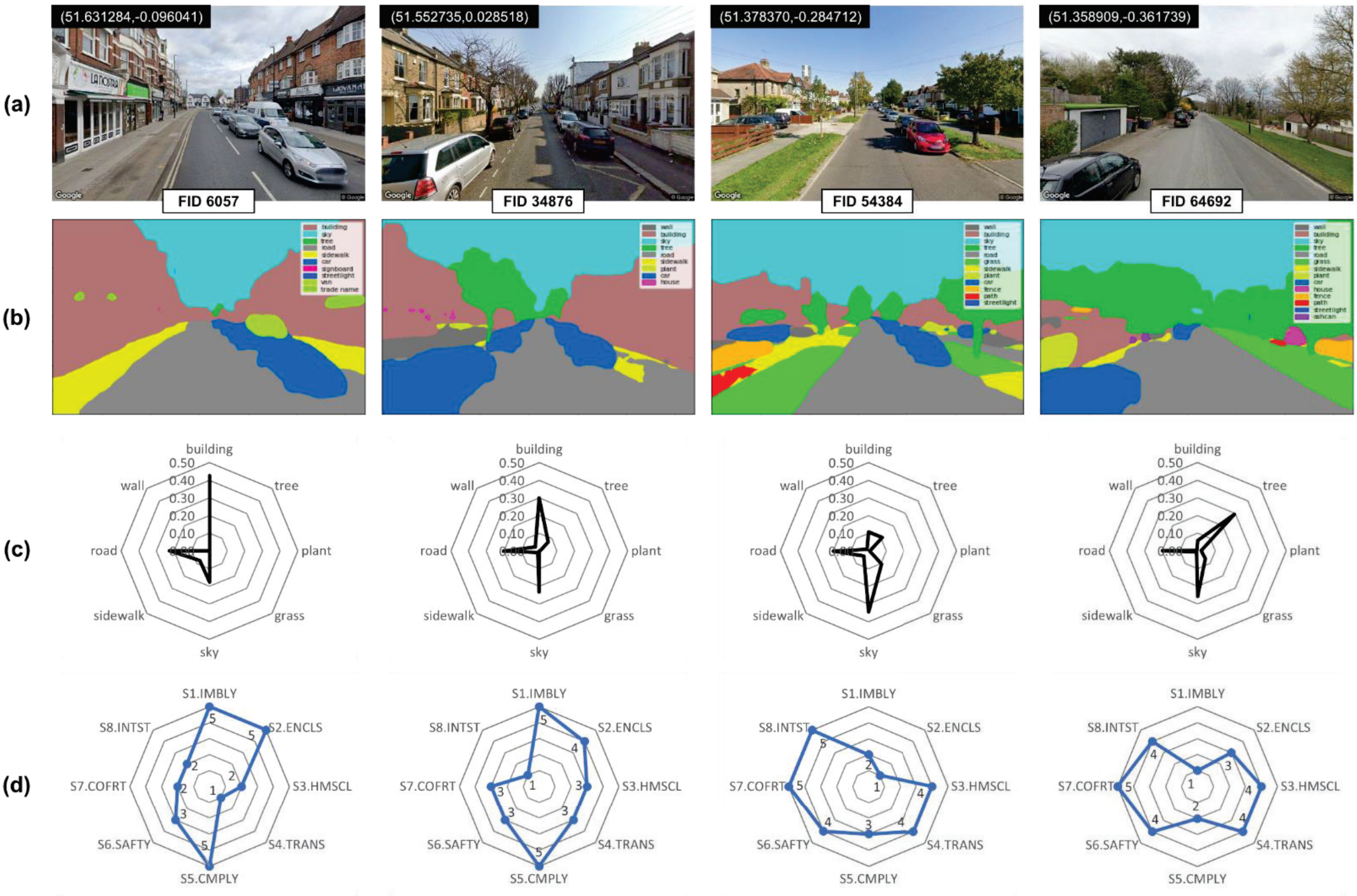


Fig. 6 (a) origin SVIs, **(b)** image segmentation results, **(c)** view indices calculated from SVIs, and **(d)** predicted subjective perception scores. The radar charts present view indices from 0 to 0.5, while presenting perceptual scores from 1 to 5

4. Results

4.1 Subjective Urban Perception Prediction

4.1.1 Verifying image segmentation and predicted subjective perception scores

Figure describes the final image segmentation results for some of the SVIs, the view indices of main physical elements, and the machine learning predicted subjective perception scores. The results of the image segmentation are shown in different colours in the Fig. 6 (b), and it can be seen that the segmentation is satisfactory, with elements such as the sky, buildings, roads and plants being clearly distinguished, and the corresponding view indices presented in the Fig. 6 (c).

It can be seen that in the first two images the buildings are more predominant, while in the second two images the plants and the sky are in greater proportion. This change in the proportion of physical elements in SVIs leads to a difference in people's subjective perceptions, as shown in the Fig. 6 (d). The first two images with a greater proportion of buildings have higher imageability, enclosure and complexity, perhaps due to the more complex and congested artificial environment, while the second two images with a greater proportion of plants and sky have a higher score on the perception of human scale, transparency, safety, sense of comfort and level of interest, due to the larger share of natural environment. Such an intuitive analysis shows that the results for image segmentation and subjective perception scores are broadly reasonable.

Table 2 Performance of BP Neural Network predictions.

Perception	Accuracy	Precision	Recall	F1-Score	Criteria (Allwright, 2022)
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

4.1.2 Accuracy of the machine learning prediction model

The prediction performance and model evaluation of the BP neural network model on the subjective perception scores of the urban street environments are shown in the Table 2. For all subjective perceptual variables, the model performed above moderate with an accuracy of greater than 0.5 based on Allwright (2022) 's 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 subjective perception model predictions in this study are relatively high, ranging from 0.58 to 0.80, which is a significant improvement compared to previous studies, with R^2 of Verma et al. (2020)'s prediction model ranging from 0.20 to 0.66, and R^2 of Qiu et al. (2022)'s perception prediction model ranging from 0.47-0.61. There are two main reasons that make this study more accurate than previous studies. Firstly, this study used a classification model rather than a regression model, and people's choices in the perception survey were transformed into a 1-5 rating system as the five categories in the machine learning model. Secondly, this study used a BP neural network model for training and prediction, which achieved a higher accuracy rate than models such as k-nearest neighbours algorithm (k-NN), random forest (RF) and support-vector machine (SVM).

Higher accuracy implies smaller variations in survey scores, reflecting the perception variables being more straightforward for people (Qiu et al., 2022; Zhang & Dong, 2018). In this study, for 'imageability' (S1), 'human scale' (S3), 'transparency' (S4), 'sense of comfort' (S7) and 'level of interest' (S8), people's perception of these variables with high levels of accuracy is more intuitive, whereas for variables with low levels of accuracy, such as 'complexity' (S5), people's perception is more ambiguous.

4.1.3 Feature importance in the prediction model

As can be seen from the Table 3 and Fig. 7, there are a total of 10 physical elements in the streetscape that have significant effects on people's subjective perceptions (from 'building' to 'fence'), with 'building' and 'tree' having the highest importance. These two elements also have the highest standard deviation values in the view indices in the streetscape database, at 17.50% and 13.97% respectively, indicating their view indices keep great changes across streetscape images. But such results differ from previous subjective perception studies of Shanghai (Qiu et al., 2022), where some physical elements such as the 'sky', 'person' and 'signboard' have significantly higher importance than they are in this study. Such differences may be due to city differences, and modelling studies based on larger, cross-city survey samples can be a new area for exploring the association between the physical elements of the streetscape and people's subjective perceptions.

Table 3 (a) Descriptive data summary of sample street view images and **(b)** Permutation feature importance in the BP Neural Network model.

(a) Descriptive summary				(b) Permutation Feature Importance in predicting subjective perception scores										
Sort	View Index	Mean	Std.	Sort	View Index	Sum	S1.IMBLY	S2.ENCLS	S3.HMSCL	S4.TRANS	S5.CMPLY	S6.SAFTY	S7.COFRT	S8.INTST
1	sky	21.03%	11.36%	1	building	0.958	0.114	0.126	0.128	0.123	0.102	0.122	0.116	0.127
2	road	21.72%	7.15%	2	tree	0.747	0.113	0.049	0.094	0.100	0.083	0.103	0.101	0.104
3	building	20.59%	17.50%	3	car	0.696	0.072	0.075	0.113	0.090	0.072	0.076	0.105	0.094
4	tree	14.82%	13.97%	4	sky	0.689	0.109	0.057	0.108	0.073	0.095	0.061	0.095	0.091
5	sidewalk	6.24%	5.60%	5	sidewalk	0.597	0.076	0.052	0.075	0.084	0.067	0.090	0.065	0.088
6	grass	3.80%	6.51%	6	grass	0.520	0.059	0.045	0.068	0.075	0.058	0.062	0.079	0.075
7	car	3.76%	4.93%	7	road	0.499	0.091	0.033	0.061	0.067	0.061	0.042	0.078	0.068
8	plant	1.93%	3.23%	8	wall	0.424	0.031	0.033	0.059	0.069	0.058	0.038	0.077	0.059
9	fence	1.56%	3.13%	9	plant	0.392	0.060	0.038	0.043	0.051	0.062	0.027	0.045	0.066
10	wall	0.97%	1.79%	10	fence	0.342	0.049	0.019	0.060	0.052	0.050	0.008	0.062	0.042
11	earth	0.55%	2.49%	11	earth	0.169	0.003	0.012	0.030	0.019	0.014	0.017	0.043	0.030
12	railing	0.25%	0.99%	12	signboard	0.165	0.016	0.020	0.019	0.035	0.024	0.019	0.023	0.009
13	van	0.16%	0.93%	13	van	0.130	0.009	0.022	0.020	0.010	0.021	0.007	0.017	0.024
14	person	0.15%	0.69%	14	streetlight	0.119	0.007	0.025	0.018	0.017	0.026	0.015	0.000	0.011
15	signboard	0.13%	0.40%	15	railing	0.115	0.003	0.020	0.004	0.023	0.021	0.016	0.017	0.011
16	ashcan	0.09%	0.32%	16	person	0.105	0.006	0.029	0.008	0.013	0.022	0.018	0.000	0.010
17	minibike	0.08%	0.59%	17	lamp	0.104	0.019	0.027	0.006	0.004	0.010	0.025	0.008	0.005
18	bridge	0.08%	0.98%	18	booth	0.103	0.018	0.029	0.008	0.004	0.009	0.023	0.008	0.003
19	streetlight	0.08%	0.19%	19	awning	0.103	0.018	0.024	0.008	0.005	0.012	0.023	0.008	0.005
20	bicycle	0.03%	0.24%	20	column	0.101	0.015	0.026	0.008	0.005	0.012	0.022	0.008	0.005
21	skyscraper	0.03%	0.32%	21	chair	0.101	0.016	0.028	0.009	0.005	0.011	0.023	0.007	0.002
22	water	0.02%	0.26%	22	bulletin board	0.100	0.015	0.030	0.010	0.003	0.009	0.023	0.005	0.004
23	awning	0.01%	0.09%	23	bridge	0.098	0.015	0.033	0.007	0.003	0.011	0.021	0.007	0.001
24	mountain	0.01%	0.08%	24	windowpane	0.098	0.017	0.029	0.008	0.004	0.009	0.022	0.007	0.003
25	bulletin board	0.00%	0.04%	25	mountain	0.097	0.015	0.024	0.007	0.004	0.012	0.025	0.005	0.005
26	column	0.00%	0.02%	26	ashcan	0.094	0.002	0.015	0.007	0.019	0.023	0.008	0.005	0.016
27	chair	0.00%	0.01%	27	water	0.093	0.005	0.025	0.004	0.015	0.018	0.013	0.002	0.011
28	windowpane	0.00%	0.01%	28	minibike	0.093	0.014	0.021	0.004	0.013	0.013	0.018	0.006	0.004
29	lamp	0.00%	0.00%	29	bicycle	0.079	0.006	0.015	0.003	0.006	0.009	0.022	0.002	0.016
30	booth	0.00%	0.00%	30	skyscraper	0.067	0.007	0.020	0.003	0.009	0.008	0.011	0.001	0.008

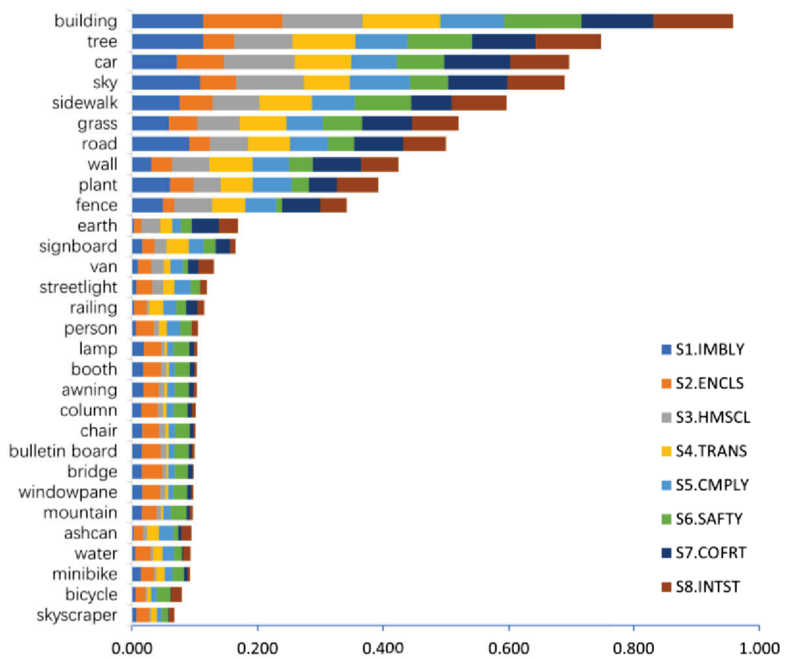


Fig. 7 Permutation feature importance in predicting subjective perception scores

Table 4 Pearson correlations of eight perception measures

	S1.IMBLY	S2.ENCLS	S3.HMSCL	S4.TRANS	S5.CMPLY	S6.SAFTY	S7.COFRT	S8.INTST
S1.IMBLY	1.000	0.125*	0.173**	0.098	0.351**	0.185**	0.145*	0.188**
S2.ENCLS	0.125*	1.000	-0.233**	-0.288**	0.187**	-0.072	-0.235**	-0.107
S3.HMSCL	0.173**	-0.233**	1.000	0.257**	0.130*	0.257**	0.309**	0.348**
S4.TRANS	0.098	-0.288**	0.257**	1.000	0.191**	0.235**	0.267**	0.219**
S5.CMPLY	0.351**	0.187**	0.130*	0.191**	1.000	0.331**	0.207**	0.224**
S6.SAFTY	0.185**	-0.072	0.257**	0.235**	0.331**	1.000	0.403**	0.301**
S7.COFRT	0.145*	-0.235**	0.309**	0.267**	0.207**	0.403**	1.000	0.429**
S8.INTST	0.188**	-0.107	0.348**	0.219**	0.224**	0.301**	0.429**	1.000

*. Correlation is significant at the 0.05 level (2-tailed). **. Correlation is significant at the 0.01 level (2-tailed).

4.1.4 Subjective variable correlation analysis

Previous studies have reported associations between subjective perceptual variables (Qiu et al., 2022; Zhang & Dong, 2018). We have produced a correlation matrix using Pearson's correlation coefficient in order to explore the degree of association between different subjective perceptual variables, as shown in Table 4. One can see that there is a relatively more pronounced correlation between the three sensory variables, 'sense of safety' (S6), 'sense of comfort' (S7), and 'level of interest' (S8), with Pearson's correlation coefficient reaching above 0.3. This can be explained as the three sense variables collectively reflecting people's common preferences for the street environment at a macro level. The correlations between 'human scale' (S3) and 'sense of comfort' (S7), 'human scale' (S3) and 'level of interest' (S8) both exceeds 0.3, suggesting the importance of human scale design for a good perceptual experience. 'Complexity' (S5), because of its correlation with 'imageability' (S1) and 'sense of safety' (S6), can be considered to be an important factor in shaping people's impression and safety sense of an urban space. In terms of negative correlations, 'enclosure' (S2) is negatively correlated with a number of variables, including 'human scale' (S3), 'transparency' (S4) and 'sense of comfort' (S5), implying that enclosure has a potential negative impact on people's perceived experience. The interaction of different subjective perceptual variables may be a new direction to explore people's perception of the urban environment. In this study, Pearson correlation coefficients above 0.6 are considered highly correlated and are, hence, removed in the following regression analysis.

4.1.5 Spatial heterogeneity of urban subjective perception

Fig. 8 shows the spatial distribution of subjective perception prediction results, with clear spatial pattern for some perceptual variables. For the three subjective perception variables of 'imageability' (S1), 'enclosure' (S2) and 'complexity' (S5), there is a strong tendency for the ratings to cluster geographically towards the city centre, with enclosure being the most pronounced. This phenomenon can be explained by the high density of buildings in the city centre, where the presence of artificial buildings makes the street space more impressionistic, 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 concentrate in the periphery of the city. The urban periphery, with fewer buildings and more greenery, is considered to have a better human scale, visual transparency and a better sense of safety. The spatial distribution

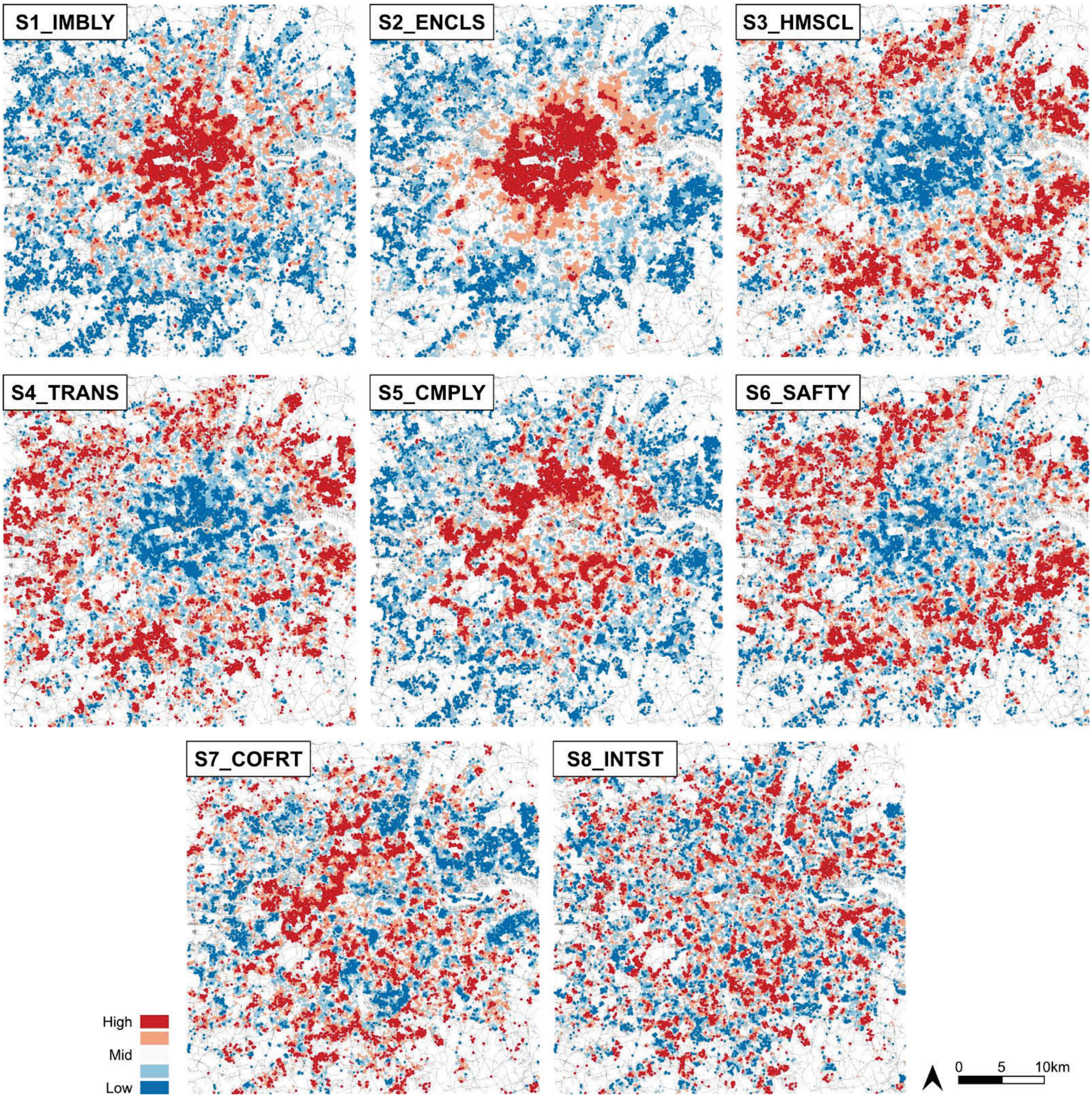


Fig. 8 Spatial distribution of properties with subjective perception scores

of ' sense of comfort' (S7) and 'level of interest' (S8) ratings is scattered across the research region, with interest scores being the most dispersed, suggesting that people's perceptions in these two subjective perception dimensions are complicated.

4.2 Description of objective urban environment

4.2.1 Clustering of house prices

Fig. 9 shows the geospatial distribution of house prices in the Greater London across the city, including the distribution of house price points and the average of house prices in postcode areas. Both graphs show a

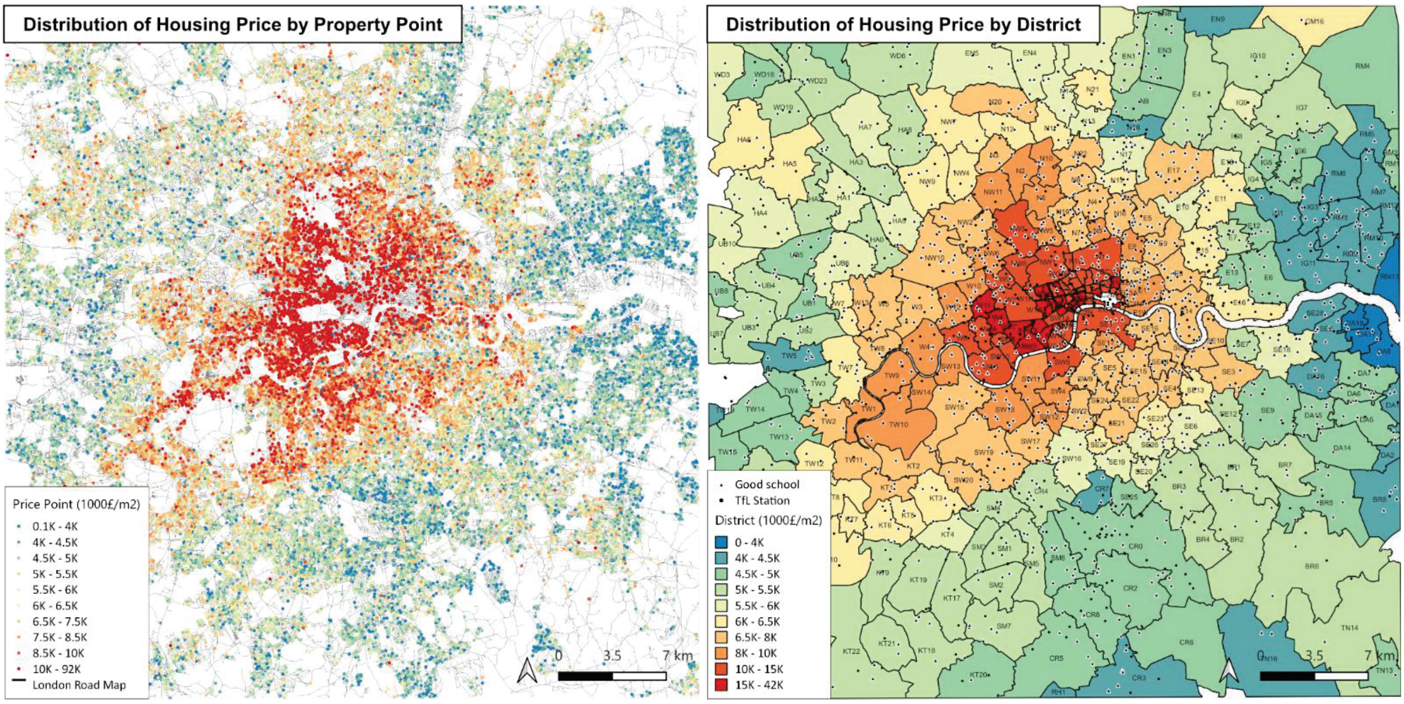


Fig. 9 Spatial distribution of house price data: **(a)** distribution by property units and **(b)** distribution by postcode districts

significant negative correlation between house prices and the distance from a property to the city centre: high-priced properties are concentrated in the city centre, while prices are generally lower in the periphery of the city. This implies that there may be strong spatial autocorrelation in the distribution of house prices, and the *local indicator of spatial autocorrelation (LISA)* is highly recommended for use in future studies to explore this dimension.

4.2.2 Representation of urban centres under multi-scale urban morphology analysis

The urban centres are represented differently under the analysis of multi-scale urban morphology with different radii. Fig. 10 presents the distribution of urban centres at four different scales (400m, 800m, 2000m, 6000m), including the results derived from integration and choice in space syntax analysis. The 400m and 800m analyses yielded urban centres at micro neighbourhood scale, the 2000m analysis produced urban centres at the meso city scale, and the 6000m analysis revealed urban centres at the macro city scale. It can be observed explicitly that at the analysis radii of 400m and 800m (M1_INT400, M2_CH400, M3_INT800, M4_CH800), both the integration and choice images present a dispersed polycentricity of the urban morphology. As the analysis radius expands, the dispersed local polycentric centres tend to integrate in the analysis images with radii of 2000m (M5_INT2000, M6_CH2000) and 6000m (M7_INT6000, M8_CH6000), leading to the formation of a macroscopic urban centre. This process of gradual geospatial change of urban centres as the radius of analysis increases was noted by (Hillier, 2009) and is referred to as '*pervasive centrality*'. Although integration and choice values reflect different spatial centrality attributes, with the former being people's destination centres and the latter being people's path selection centres, both relatively clarify the concept of pervasive centrality presented under multi-scale analyses.

In terms of urban morphology, this study validates Hillier (2009)'s theory of pervasive centrality, and identifies

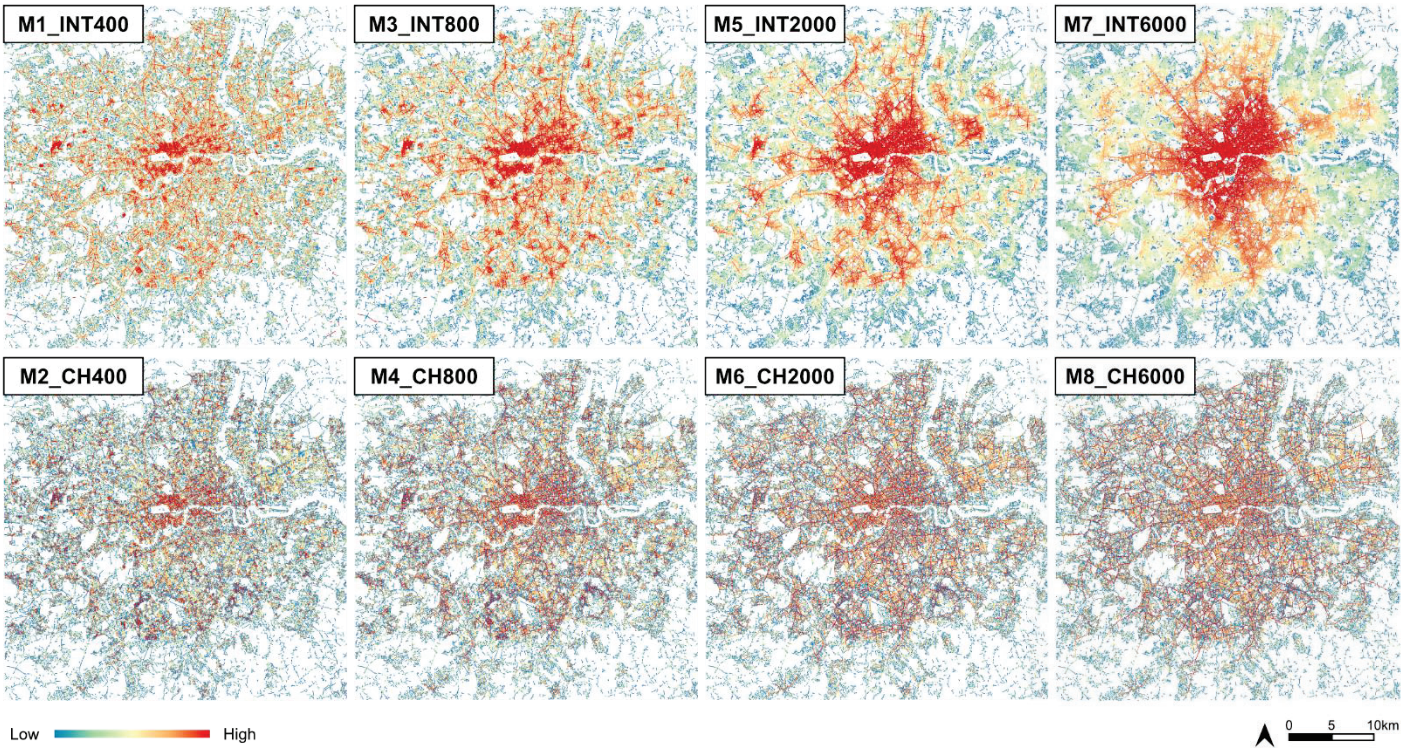


Fig. 10 Multi-scale integration and choice analysis with radii of 400, 800, 2000 and 6000 metres

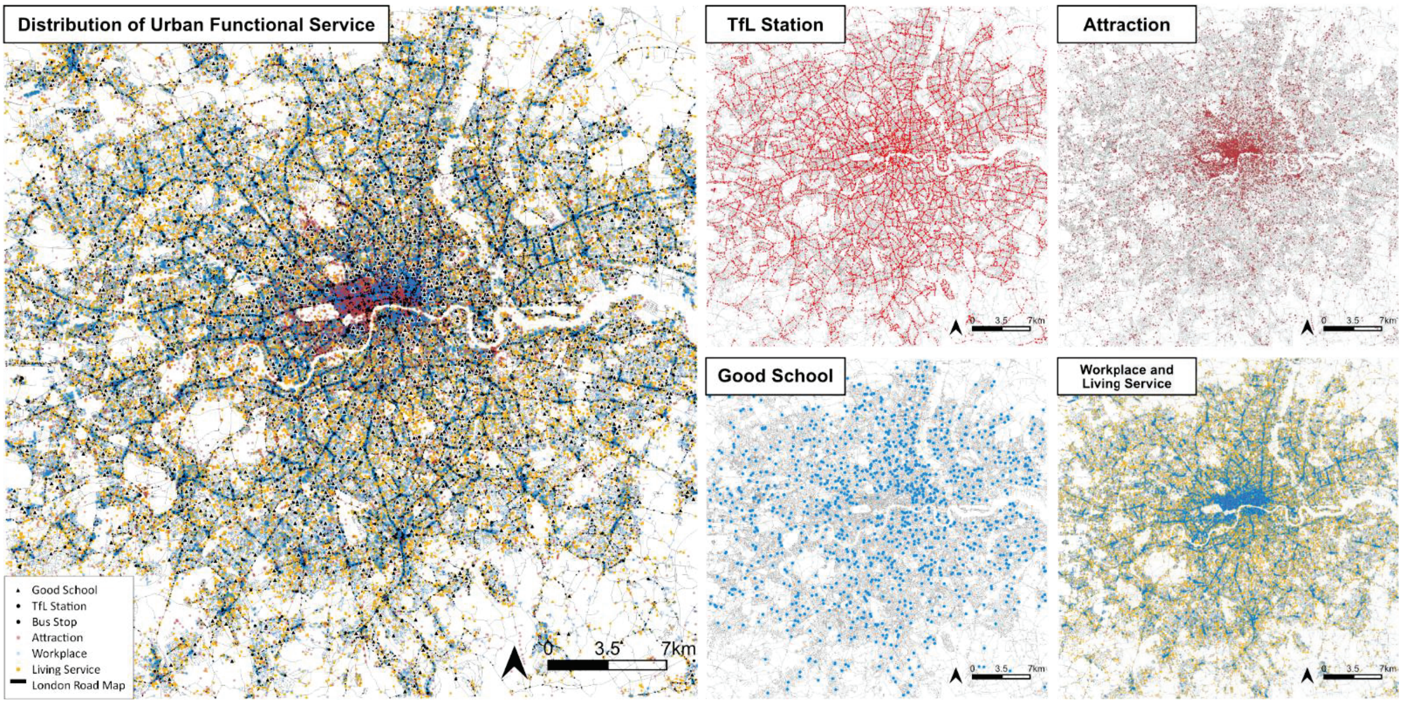


Fig. 11 Spatial distribution of urban functions

local urban centres, and global urban centres in the Greater London, which becomes an important morphological basis for our study of the impacts of subjective perception and objective urban environment on house prices under multi-scale urban form.

4.2.3 Aggregation of urban functions and its relationship to urban form

Fig. 11 shows the distribution of the main urban functions, which all tend to be centrally located, especially attraction, workplace and residential services. Transport of London (TfL) stations are mainly located along the road network, while the distribution of good schools is more sporadic compared to the other function categories. Such a centralised distribution is highly similar to the representation of house prices and urban spatial patterns, but the distribution of each function has its own independent system and distribution characteristics, which is a complicated system.

4.3 Spatial Hedonic Price Model Result

4.3.1 Correlation of each attribute group with house prices

Table 5 shows the strength of the four groups of attributes that make up the hedonic house price model in explaining house prices, with location attributes, i.e. urban morphology attributes, being the strongest in explaining house prices (R^2 = 0.427), followed by subjective perception scores (R^2 = 0.342) and neighbourhood attributes (R^2 = 0.339). The weakest influencing attribute group is the set of house structure attributes (R^2 = 0.085). All four sets of attributes passed the F-statistic test ($p<0.01$), confirming that they have significant effects on house prices.

Table 5 Model performance of each attribute group

OLS Diagnosis	House Structure Attributes	Location Attributes (Urban Morphology)	Neighbourhood 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***

4.3.2 Results of regression models with multi-scale urban morphology

OLS models integrating the four attribute groups were built, and a total of five models based on different scales of urban morphology attributes were constructed (Table 6, Fig. 12). The baseline model uses traditional location attributes, which are the property's network cost distance to the CBD (L1_D2CBD) and its postcode district (L2_POSDT). The other models apply different scales of space syntax urban morphology variables, integration and choice, as location attributes of the hedonic house price model. Table shows the regression model's performance and diagnostic outcomes. We can see from adjusted R^2 that all five models and house prices have good matching performances. While they do not reach great prediction levels, the significance is high enough to be used to investigate the importance of the impact factors. When comparing Model 0 and Model 4, the overall performance of the two models is similar after replacing the traditional location attributes with the urban morphology variables of space syntax (R^2=0.496, R^2=0.494), but the integration variable in Model 4 (M7_INT6000, M8_CH6000) improves the importance of the location attributes in the prediction model in terms of standardised coefficients, as shown in Figure. This suggests that the integration variable of space syntax in the urban morphology field better depicts the location attributes of properties and is a more efficient and valuable parameter for house price modelling.

For models 1-4, although different scales of urban morphology variables are applied on the location attribute dimension, there is no marked change in R^2, which is related to the important existence of neighbourhood attributes, i.e. urban functional properties. It can be seen that the density of attractions (F3_DENAT) has the highest absolute value of the standardized coefficient among all models, implying its great influence on house prices. Other more important variables include the density of workplaces (F2_DENWK) and the density of living services (F1_DENLS).

Table 6 Regression with multi-scale urban morphology: results and diagnosis

Location Attribute	Model 0 Baseline (L1, L2)		Model 1 M1, M2 (R400)		Model 2 M3, M4 (R800)		Model 3 M5, M6 (R2000)		Model 4 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 Arribute (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	***
Neighbourhood 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	***

At different scales of urban morphology, people's subjective perceptions have different importance in terms of house prices compared to location attributes. As can be noticed, in the analytical model at a larger scale of urban morphology in a radius about 6km (Model 4), the importance of integration values in explaining house prices is very pronounced (M7_INT6000), much higher than the main subjective perception variables (S2_ENCLS, S7_COFRT). The importance diminishes as the scale decreases (Model 2, Model 3) and eventually falls below

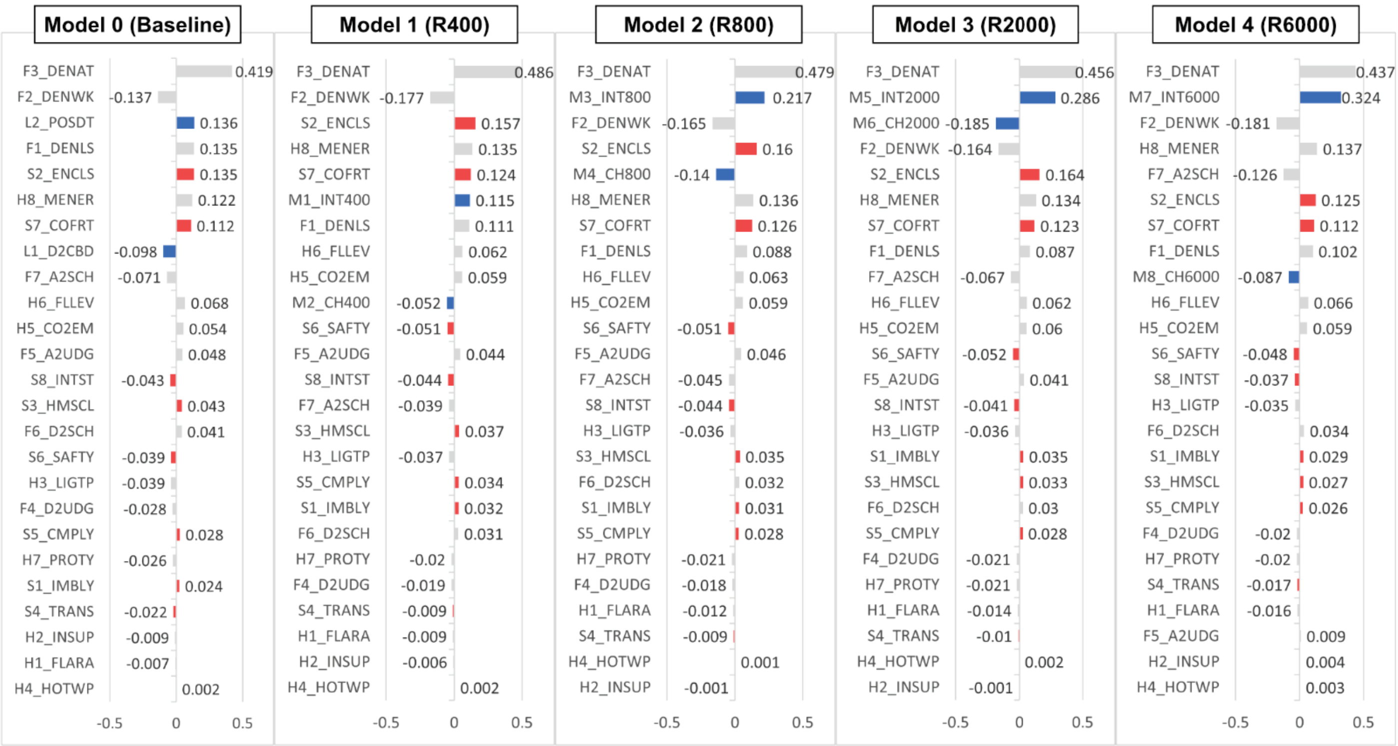


Fig. 12 Impact ranking in models based on absolute standardized coefficients

some of the subjective perception variables (Model 1). The choice variable has a similar trend in Models 1-3, but is not as noticeable as the integration value and is less important than integration in models.

In terms of subjective perception, 'enclosure' (S2_ENCLS) and 'sense of comfort' (S7_COFRT) are more important than other variables in the house price model, followed by 'safety' and 'interest'. 'imageability', 'transparency' and 'complexity' are the least important. This indicates people's subjective perceptual preferences in the house market, where other conditions being equal, properties that have a sense of enclosure but are also comfortable to live in tend to be more valuable.

4.3.3 House price model in specific urban areas

Property points are zoned according to urban morphology to explore the impact of subjective perceptions and objective urban environments on house prices within local areas. As seen in the previous global regression analyses, the integration value at radius 6 km can be a good descriptive parameter for houses' locations in the urban form and have a significant impact on house prices in the global scale, as shown in Fig. 12. Fig. 13 shows the results of the zoning of the Greater London according to the integration values (r = 6 km). The whole research area is divided into cells by hexagons with radius of 3km, and the zoning is determined by the average integration values within each cell. Four local zones were generated as the subjects of study for the house price modelling in specific local urban areas. The four groups of regions with integration values of 1400 to 2000, 1000 to 1400, 600 to 1000 and 200 to 600 are classified as Area 1, Area 2, Area 3 and Area 4 respectively, as shown in Fig. 13.

In the local area regression analysis models, the location attributes are local scale urban morphology variables, integration and choice at a radius of 400 m (M1_INT400, M2_CH400), and the effects of global scale urban morphology have been maximally eliminated by zoning based on global integration values. Table 7 shows the results of the multi-factor regression analysis of house prices in different local areas, where Model 1 becomes the baseline model reflecting the global picture, with local scale attributes (M1_INT400, M2_CH400) as its location

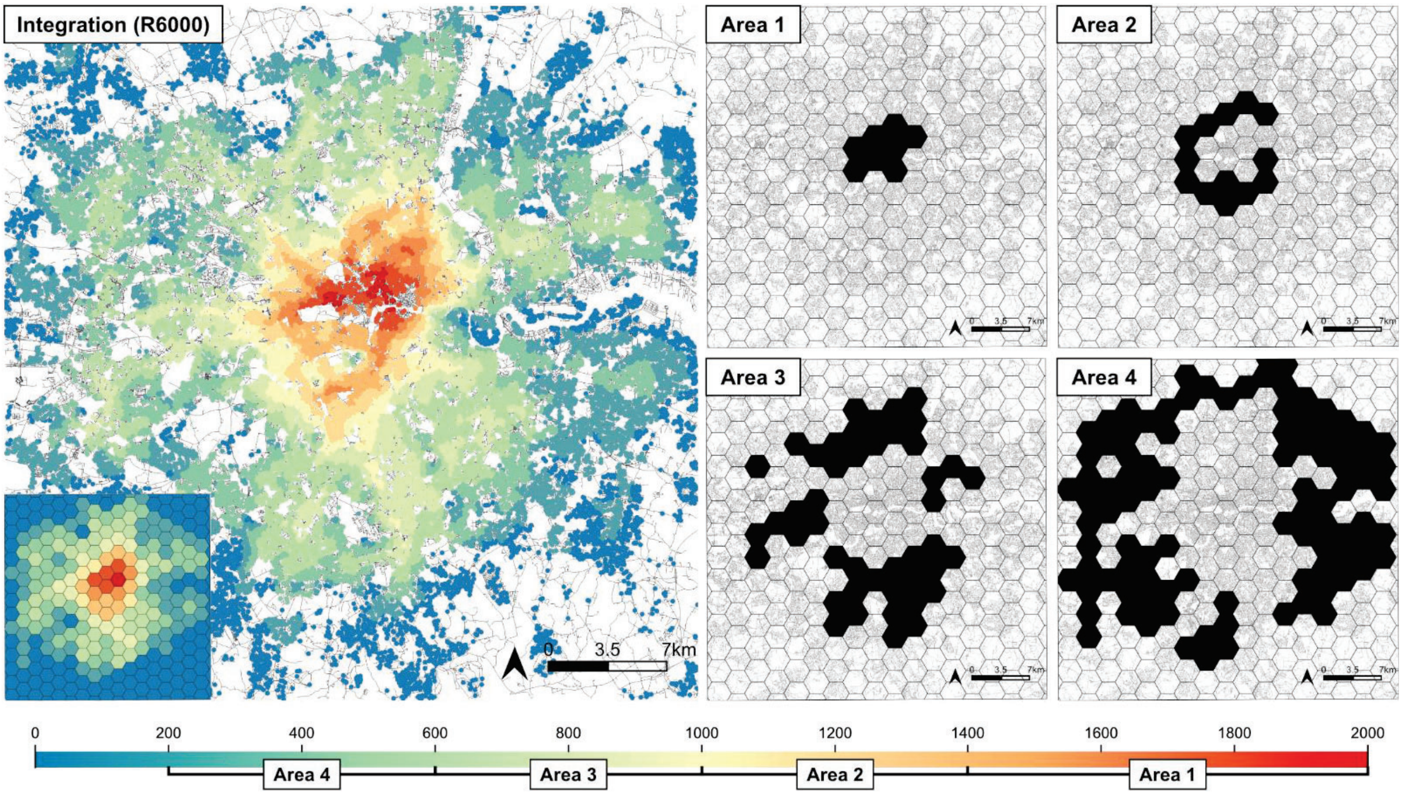


Fig. 13 Local research areas defined by regional average integration values

attribute. In terms of model performance, the regression models for the four local areas have R^2 of 0.383,0,281,0,243, and 0.305, which are reasonably poorer than the performance of the global regression analyses models, as the impacts of global morphology are removed.

Fig. 13 shows the feature importance ranking of attributes based on absolute standardised coefficients in Models 5-8. It can be seen that in the central areas (Area 1 and Area 2), the local urban form attributes, integration and choice in a radius of 400 m, still have important influences, especially in Area 2, where integration and choice have high absolute standardised coefficient values of 0.256 and 0.239. In the peripheral areas of the city (Area 3 and Area 4), the local urban form attributes have little influence, especially in Area 4, where they have no impact on house prices. This trend shows that in the central areas, the dominant location in the local urban morphology is still seen as an important resource in the house market, while in the peripheral parts of the city, the local location appears less important and house prices are still mainly influenced by the global urban morphology in terms of location attributes.

In contrast to the performance of local urban morphology attributes, subjective perception variables show a greater and more diverse influence on house prices in the peripheral urban areas, with two subjective perception variables having absolute standardised coefficients above 0.1 in Area 3 (S5_CMPLY, S7_COFRT), where the value of 'sense of comfort' reaches 0.243, and three in Area 4 (S2_ENCLS, S5_CMPLY, S7_COFRT), as shown in Table 7 and Fig. 14. In urban central areas, there is only one subjective perception variable with absolute standardized coefficient greater than 0.1, which is 'sense of comfort' in Area 1. It indicates that 'sense of comfort' is the single most influential factor in subjective perception on house prices in urban centres. This trend suggests that people's subjective perceptions of the street environment have a more important impact on house prices in the peripheral urban market than in the city centre, with 'complexity' becoming an increasingly important factor in addition to 'enclosure' and 'sense of comfort'. It can also be seen that the effect of subjective perceptions on house prices varies considerably across local urban areas, with complex patterns that need to be further explored in subsequent studies.

Table 7 Regression of specific local urban areas: results and diagnosis

	Model 1		Model 5		Model 6		Model 7		Model 8	
Location Attribute	Baseline (R400)		Area 1 (R400)		Area 2 (R400)		Area 3 (R400)		Area 4 (R400)	
Adjusted R^2	0.482	***	0.383	***	0.281	***	0.243	***	0.305	***
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	-0.009	**	0.178	***	0.040	**	-0.176	***	-0.198	***
H2_INSUP	-0.006		-0.005		0.003		0.019		-0.035	***
H3_LIGTP	-0.037	***	-0.032	**	-0.024	*	-0.049	***	-0.031	***
H4_HOTWP	0.002		0.037	**	0.023	*	0.025	***	-0.006	
H5_CO2EM	0.059	***	0.008		0.096	***	0.148	***	0.073	***
H6_FLLEV	0.062	***	0.026	**	0.089	***	0.111	***	0.169	***
H7_PROTY	-0.02	***	0.031	*	-0.026	*	-0.010		-0.104	***
H8_MENER	0.135	***	0.207	***	0.194	***	0.080	***	0.136	***
Subjective urban perception variable										
S1_IMBLY	0.032	***	0.049	**	-0.022		-0.042	***	-0.065	***
S2_ENCLS	0.157	***	-0.056	**	0.064	***	0.062	***	0.101	***
S3_HMSCL	0.037	***	0.020		0.056	***	0.005		0.033	***
S4_TRANS	-0.009	***	-0.020		0.095	***	-0.081	***	-0.061	***
S5_CMPLY	0.034	***	-0.054	***	0.046	***	0.138	***	0.123	***
S6_SAFTY	-0.051	***	-0.048	***	-0.006		-0.055	***	-0.023	***
S7_COFRT	0.124	***	0.153	***	0.016		0.243	***	0.141	***
S8_INTST	-0.044	***	0.026	*	-0.042	***	-0.060	***	-0.034	***
Objective urban perception variable										
Location Attribute (Urban Morphology)										
M1_INT400	0.115	***	-0.034		0.256	***	0.069	***	-0.019	
M2_CH400	-0.052	***	0.129	***	-0.239	***	-0.096	***	-0.002	
Neighbourhood Attribute (Urban Functional Property)										
F1_DENLS	0.111	***	0.102	**	0.074	***	-0.113	***	-0.083	***
F2_DENWK	-0.177	***	-0.032		-0.11	***	0.151	***	0.109	***
F3_DENAT	0.486	***	0.226	***	0.374	***	0.21	***	0.199	***
F4_D2UDG	-0.019	***	-0.001		-0.078	***	0.022	**	-0.026	***
F5_A2UDG	0.044	***	-0.101	***	0.122	***	-0.188	***	0.171	***
F6_D2SCH	0.031	***	0.177	***	0.056	***	0.024	***	0.074	***
F7_A2SCH	-0.039	***	-0.169	***	-0.248	***	0.118	***	-0.153	***

5. Discussion

5.1 Conclusion

The findings respond to each of the three research questions posed in the opening chapter: 1) whether there is an effect of subjective perceptions on house prices, 2) how subjective perceptions act on house prices in multi-scale urban morphology models in the global analysis, and 3) how subjective perceptions impact on house prices in local scale urban morphology models of different local areas.

In a separate regression model based on subjective perception variables and house prices, the subjective

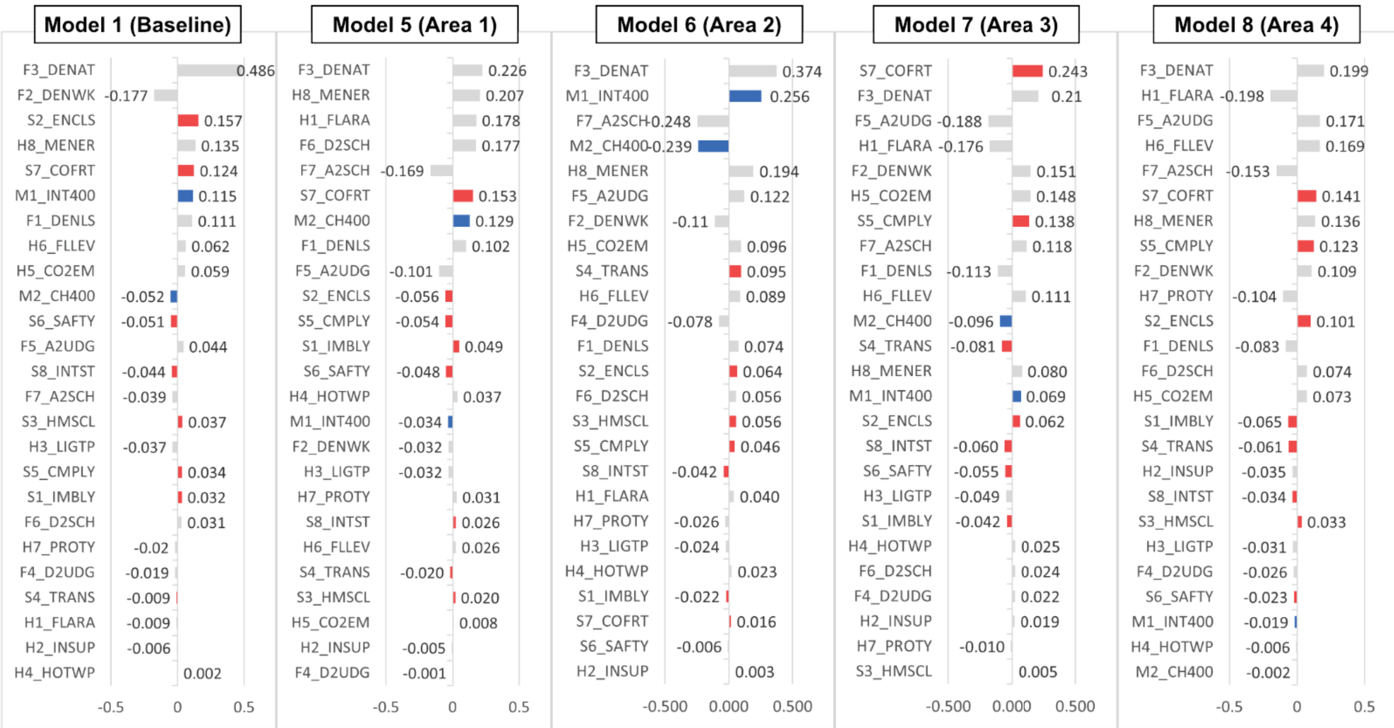


Fig. 14 Impact ranking in models based on absolute standardized coefficients.

perception attribute group has a significant effect on house prices, with an R^2 of 0.342, which is only lower than the location attribute group (urban morphology attribute) and higher than the neighbourhood attribute group (urban function attribute) and the house structure attribute group. This suggests that people's subjective perceptions of the urban environment have significant impacts on house prices, above some objective urban environment attributes.

The hedonic house price model based on multi-scale urban morphology shows that when comparing urban morphological attributes with subjective perception attributes, the smaller the scale of urban morphology, the more important the subjective perception is, and the larger the scale of urban morphology, the more important the urban morphological attributes are. Further, switching from global analyses to local analyses and dividing the Greater London into four zones based on integration values with a radius of 6km, it is found that local urban morphology (r = 400 m) is important for house price variances in the city central areas, while it has little or no effect on house prices in the periphery of the city; the effects of subjective perception variables on house prices show an opposite trend, with the overall impacts of subjective perception being weaker and more homogeneous in the city centre, while in the periphery of the city subjective perception variables have strong and diverse effects on the house market.

For the different subjective perception variables, ‘enclosure’ (S2_ENCLS) and ‘sense of comfort’ (S7_COFRT) have significant impacts on house prices in the global analysis; in the local area analysis, ‘sense of comfort’ continues to have an important effect on house price market, from the city central areas to the peripheral areas of the city, while ‘enclosure’ and ‘complexity’ (S5_CMPLY) tend to have more important effects on house prices in the periphery of the city compared they do in the city centre. Other variables have small effects on house prices or perform irregularities across scales and require further research.

5.2 Limitations and future work

There are several limitations to this study. Firstly, in building a subjective perception prediction model, this study only used visual indices obtained from street view image segmentation, the prediction accuracy of this approach may be limited, more features such as HSL histogram, Blob detection need to be added to complement the physical features presented by the street view images. More field experiences and surveys can be added to the study to cross-validate the streetscape perception predictions and minimise the bias introduced by web image surveys. Secondly, in the streetscape perception survey, some participants' understanding of the concepts of subjective perception may not be accurate, and better questionnaire design, question setting and a larger sample size could improve this. Future researches could involve urban design professionals to provide a more accurate and efficient assessment of the street environment in images. The third point is that a wide range of studies have shown that spatial dependence and non-stationarity violate the basic assumptions of OLS regression. Due to the presence of spatial correlation effects, OLS regression models may be biased in their coefficients and report incorrect significance. More tests for OLS regression should 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. If there are errors in OLS regression models, more regression models that solve for spatial dependence should be introduced for more accurate multi-factor impact studies, including the *Kelejian-Prucha's model (SAC)* (Kelejian & Prucha, 1998) and *geographically weighted regression (GWR)* (Brunsdon et al., 1998).

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