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Human settlement value assessment from a place perspective: Considering human dynamics and perceptions in house price modeling

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ABSTRACT

A better formalization of place - where people live, perceive, and interact with others - is crucial for understanding socioeconomic environment and human settlement. The widely used hedonic pricing model for houses was proposed from the perspective of space, focusing mostly on static house structural information and objective built environment factors. However, the value of house settlement is not only determined by its spatial settings, but also varies from one place to another with different cultures, human dynamics, human perceptions and social interactions. In this work, we introduce a place-oriented hedonic pricing model (P-HPM) that incorporates human dynamics and human perceptions of places to understand human settlement. As an empirical study, we employ a large volume of house price data in Boston and Los Angeles, including detailed house and locational amenity information. Besides, we take the hourly number of visits to places as a proxy of human mobility patterns, and obtain human perceptions of places extracted from large-scale street-view images using deep learning. The results show that the P-HPM outperformed the traditional HPM significantly in these two cities. Moreover, through a geographically weighted regression analysis and the Monte Carlo test, we find that the impacts of the proposed place-related variables on house prices are stable across space. Our results provide new insights into the assessment of human settlement values by incorporating the role of place using multi-source big geo-data.

1. Introduction

Place, intertwined with human experience (Couclelis, 1992), is usually considered as where people live, perceive and interact with others, as pointed out by Tuan (1979) that “space infused with human meaning” in geography. Human mobility and perception are two important aspects of places. People carry out their everyday movements for shopping, working, educational, recreational and many other activities at different types of places (Chen et al., 2011; Goodchild, 2011; Seamon, 1980). They frame their behaviors by perceiving the world, which is coined as “sense of place” (Agnew, 2011; Harrison & Dourish, 1996). Researchers have argued that by depicting human dynamics and their perceptions of the physical settings, they can better understand and model the interactions between human and socioeconomic environments (Jorgensen & Stedman, 2011; Kang et al., 2020b; Liu et al., 2015; Shi et al., 2015; Sui & Goodchild, 2011; Xu et al., 2018).

As a “barometer” of human settlement and economic conditions, the research on house price has attracted much attention for decades. The hedonic pricing model (HPM) is one of the most widely used approaches in modeling housing prices (Rosen, 1974). Its hypothesis is that house values are determined by two components, namely housing attributes and locational attributes (Champ et al., 2003; Lancaster, 1966). In practice, housing attributes refer to the age of houses, the number of bedrooms, property area, etc. (Follain & Jimenez, 1985; Sirmans et al., 2006; Xiao et al., 2017); while locational attributes are represented by the accessibility to nearby facilities (hospitals, schools, parks, shops, detention basins, etc.) (Lee & Li, 2009; McLeod, 1984; Poudyal et al., 2009), distance to employment and work place (central business district (CBD), labor-market, etc.) (Bishop et al., 2019; Heikkila et al., 1989; Osland & Thorsen, 2008), and transportation accessibilities (Debrezion et al., 2011; McLeod, 1984). Besides, some research discussed the potential impacts of other factors related to housing attributes and locational amenities, including education status (Dougherty et al., 2009), crime rate (Gibbons & Machin, 2008; Lynch & Rasmussen, 2001), race

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ratio (Brasington et al., 2015), pollution (Bishop et al., 2019; Hui et al., 2007; Le Boennec & Salladarré, 2017), aesthetic views (Fu et al., 2019; Lindenthal, 2020), and noise (Day et al., 2007; Diao et al., 2016; Hui et al., 2007). Overall, the standard HPM has been proved effective and achieved great success in considerable fields and empirical studies, from real estate economy (Can, 1992; Diao & Ferreira Jr, 2010; Zheng & Kahn, 2008), urban planning (Debrezion et al., 2011; Pettit et al., 2020; Schläpfer et al., 2015), to policy making (Cebula, 2009; Lai et al., 2017).

However, the traditional HPM, derived mainly from a spatial perspective, may not fully characterize the human settlement comprehensively. Specifically, human settlements are only considered as a function of housing and locational attributes, which are static and objective whereas people's sense of place and place characteristics are overlooked (Agnew, 2011; Bishop et al., 2019; Boyd et al., 2015; Isard, 1956). In fact, the determinants of a house buyer's behavior for choosing a living place are not only the property and the physical environment settings of the house, but also relying on their unique social experience, perception of a place, and the vitality of a place. People live in "home" with interactions to their external social and physical environments, while not merely the "house" property. The "home" produces the society in which we live, while the "house" is only a physical unit of the spatial object (Easthope, 2004; Sack, 1997). Human think about the world from a place-based perspective. An examination of the social, psychological, and emotive meanings for individuals at places in housing studies enables us to gain insights into the people-environment interactions. However, all of these place-based aspects have not been examined extensively due to the absence of effective metrics and data.

The emergence of big data and volunteered geographic information (VGI) (Goodchild, 2007), along with state-of-the-art computing and analyzing techniques, provides new opportunities for capturing and depicting human mobility and perceptions of places. Various types of data sources have been used in understanding human dynamics. For example, by the utilization of taxi GPS data (Tang et al., 2015; Zhu et al., 2017), cell phone data (Gao, 2015; Kang et al., 2010; Peng et al., 2019; Ratti et al., 2006; Xu et al., 2015), and geotagged social media posts (Hu & Wang, 2020; Jurdak et al., 2015), researchers are able to capture fine-scale spatiotemporal human movement patterns at different places. Such information contribute to the global sense of place (Bissell, 2021), and can potentially reveal socioeconomic environment, such as land use type (Pei et al., 2014), commuting patterns (Yang et al., 2015), and urban vibrancy (Jia et al., 2019). Regarding human perceptions of places, abundant datasets about geo-tagged photos and street-view images, along with advanced machine learning techniques provide opportunities to obtain a more complete view about how people feel about the world through the analysis of their expressions, sentiments and emotions (Hu et al., 2019; Kang et al., 2019), and perceptions from the visual sceneries (Zhang et al., 2020; Zhou et al., 2014). The proliferation of the above-mentioned researches reveals the significance of embedding place-based human-environment interactions in solving socioeconomic problems and in planning for livable cities from a combination of humanistic perspective and using computational approaches.

To this end, we propose a conceptual framework which characterizes human settlement from a place perspective by highlighting people's sense of place and human dynamics. A place-oriented hedonic pricing model (P-HPM) that follows the conceptual framework is introduced. The P-HPM extends the traditional HPM by involving the notion of place from two aspects: human mobilities at places and human perceptions of places. More specifically, we take the hourly number of people's visits to a place as a descriptor of human mobilities, and the perceptual rating scores of a place's physical appearance captured in street-view images as a proxy of human perceptions. The contribution of this research is threefold: First, we propose a conceptual framework for human settlement value assessment from a place perspective, discuss how human mobilities and perceptions matter for determining house price modeling. Second, we introduce the P-HPM for modeling the house prices not only from static and objective perspectives of a property, but also by formulating dynamic human movement patterns and subjective human perceptions of places based on multi-source big geo-data and advanced machine learning approaches. Third, we compare the HPM and P-HPM to explore the impacts of place-related variables to illustrate how these determinants affect house prices and their spatial stationarities to the house prices. Our research provides humanistic insights into integrating place in human settlement value investigation. Such perspectives may benefit other fields of study not limited to urban planning, geography, and urban economics.

The remainder of the paper is organized as follows. Section 2 reviews the related literature on house price modeling and the understanding of human sense of place with big data and deep learning. In Section 3, we introduce the proposed framework of characterizing human settlement from a place perspective and the P-HPM model. In Section 4, we describe the datasets used in this research, including online house information, locational amenities, human mobility patterns, and perceptual rating metrics extracted from street-view images. Section 5 introduces the methods, including the factor analysis, spatial autoregressive model and geographically weighted regression (GWR). Section 6 presents the results of house price prediction in Boston and Los Angeles. We then discuss broad implications, policy making takeaways for urban planning, and limitation of this work and suggestions for future work on place-based housing price modeling in Section 7. Finally, we conclude this work in Section 8.

2. Literature review

2.1. Potential determinants for housing price modeling

Researchers from multiple domains, including economics, geography, urban planning, and policy, have conducted numerous studies on how various factors affect the price of properties. As suggested by the hedonic model, house prices are determined by housing attributes and locational attributes (Bartholomew & Ewing, 2011; Diewert et al., 2015; Mulley, 2014; Su et al., 2021). Also, neighborhood physical quality has been considered as an important factor on house prices (Hui et al., 2007). For instance, Freeman (1981) listed a set of environmental attributes that may matter for determining housing prices. Studies have shown that certain types of scenery such as ocean, lake, mountain, and greenery views (Benson et al., 1998; Luttik, 2000; Panduro & Veie, 2013; Rodriguez & Sirmans, 1994; Yang et al., 2021), are positively associated with housing prices; while other environmental factors such as air pollution and noise have negative impacts on property values (Chasco & Gallo, 2013; Chattopadhyay, 1999; Espey & Lopez, 2000; Harrison Jr & Rubinfeld, 1978; Wilhelmsson, 2000). Though the role of place in determining housing prices has been examined in literature, these studies mainly focus on the physical part (e.g., locations, and place settings) of the place, leaving the subjective part, i.e., sense of place underestimated. Human settlement values are seen as combinations results of these static and objective variables in these studies, and houses only serve as the basic unit to afford those environmental factors. Limited clue has been given to the senses and feelings that are evoked by the environment at places. Such sense of places, we believe, guide human behaviors, affect house buying decisions, may benefit our understanding of human settlement values following the "people-oriented" principle.

2.2. Understanding human sense of place with big data and deep learning

Understanding the relationships between people and places and examining the processes that shape those relationships are classic topics for geographers (Bissell, 2021; Tuan, 1979). Agnew (2011) suggests that *location*, *locale*, and *sense of place* are three components of place. Sense of place denotes those nebulous human meanings such as subjective feelings and perceptions, and human dynamics that evokes different emotions, experiences, identities attached to the place. Traditionally, in order to explore such relationships, geographers usually rely on questionnaires and surveys that are labor-intensive and time-consuming when conducting cognition experiments (Pliakas et al., 2017). With the support of geo-big data and advanced machine learning approaches, researchers are able to quantitatively measure the sense of place from human dynamics and human perceptions (Shaw & Sui, 2020). For example, Zhu et al. (2020) investigated place characteristics with the support of human mobility and perceptions at places. Gao et al. (2017) assessed the human cognition to different toponyms through multi-source social media data. Yao et al. (2019) evaluated human perceptions at local places from multiple aspects (e.g., safe, lively, boring). Wang et al. (2019) examined the linkages between perceptions and mobility. All these studies show potentials of using big data and machine learning for understanding human sense of place efficiently. In addition, existing studies have also show that big data and machine learning techniques may provide valuable insights for property price evaluation (Kang, Zhang, Peng, et al., 2020c; Law et al., 2018). Hence, it is possible to utilize these emerging data sources and powerful tools into empirical studies to support house price modeling and urban planning practices.

3. Framework

In this section, we first introduce two perspectives—the conventional method mainly from a space-based perspective vs. the proposed method from a place-based perspective—for human settlement value assessment. Then, following the conceptual foundations, we introduce a new place-oriented hedonic pricing model (P-HPM) which integrates human dynamics and human perceptions of place as additions to the traditional HPM for human settlement assessment.

3.1. Conceptual foundations

The determinants of homebuyer purchasing houses in traditional HPM are derived from their willingness to pay for a bundle of house characteristics (Lancaster, 1966). According to this, the physical infrastructure of a house, and the natural and built environments of a neighborhood are used for modeling human settlement values (Pred, 1984; Rosen, 1974). This approach can be seen from a space-based perspective where physical measurement matters.

Here, we argue that people live at "home" - a particular significant place located at one's house (Giuliani, 1991) - within which individuals experience social, psychological and emotive attachments (Easthope, 2004; Giuliani, 1991; Sack, 1997). When people buy houses, they are looking for a lively place or a neighborhood from which they can commute to work conveniently and a place that may enhance their social relationship or evoke their emotional feeling of home. For decades, researchers have differentiated the "house" and "home" from space and place respectively (Massey, 1992). Unlike researchers in real estate who may only focus on the fixed and measurable attributes, scholars who are concerned with home look beyond the house to consider the attached social relations and place-based landscapes. An understanding of human-environment processes enables practitioners to better explore how housing prices fluctuate and how the characteristics of places change across space and over time (Easthope, 2004; Pred, 1984; Shaw & Sui, 2020). Hence, a place-based perspective that considers how human think about the world may extend the traditional method to describe human settlement more comprehensively.

To formalize the linkage between house as a physical locality and home as a social and cultural construct, here, we mainly focus on two aspects - human dynamics and human perceptions. As a key component to the understanding of human dynamics, mobilities - people get to work places by a transportation mode, driving to home, or stop by grocery stores everyday through the same route - can evoke a unique sense of place (Cresswell, 2014; Seamon, 1980). The observed mobility patterns of people may reflect how they perceive and use the environment as different affordances of a place (Alazzawi et al., 2012;, Harvey et al., 1990; Scheider & Janowicz, 2014; Zhu et al., 2020). Other considerations of human dynamics may also involve spatial-social networks (Shaw & Sui, 2020). Apart from human dynamics, individuals invest their considerable emotions triggered by experiences and perceptions of environment to their home (Porteous, 1976). People may tend to live in a nice place. By watching the various landscapes at places, people have different experiences and visions to construct their local and regional environments, which can influence their sense of place (Rose, 1995; Tuan, 1979). Therefore, the understanding of how people feel about their home and their neighborhood may guide us a better learning of the value of a house and our human settlement.

Fig. 1 demonstrates the conceptual framework of human settlement assessment from a space-based perspective vs. a place-based perspective. The left part denotes the traditional perspective for human settlement assessment, which mainly focuses on the housing attributes and locational attributes; while the right part highlights the human dynamics and human perceptions of places. Besides the two, regarding a broader scope, we also believe that there could be more dimensions—such as social relations attached to a place–can be in the future work. Nevertheless, such an examination of "place" perspective in housing studies may help us gain insights into the relationship between a place and its economic value.

3.2. Place-oriented hedonic pricing model

The standard hedonic pricing model (HPM) is expressed as a multi-linear regression model:

$$P_H = \beta_0 + \beta_1 Struc + \beta_2 Loc + \varepsilon \tag{1}$$

where P_H represents the natural logarithm of estimated housing price, *Struc* denotes the structure attributes of houses, *Loc* is the locational attributes of the neighborhoods, whereas β_0, β_1, and β_2 are corresponding coefficients estimated in the model, and ε is the error term.

Extending from the classic HPM, here we propose a place-oriented hedonic pricing model (P-HPM), where human mobilities at places and human perceptions of places are added to the HPM model. The P-HPM can be expressed as follows:

$$P_H = \beta_0 + \beta_1 Struc + \beta_2 Loc + \beta_3 Vis + \beta_4 Percep + \varepsilon \tag{2}$$

where *Vis* represents the human visit patterns in places, and *Percep* refers the human perceptions at places. In the rest of this paper, human visit pattern-related variables are abbreviated as *mobility factors*, and human perception-related variables as *perception factors*.

4. Study area and data

4.1. Study area and spatial unit

Considering that factors impacting house prices may vary in different regions, we perform our experiments in two different metropolitan areas, the Greater Boston Area and the Greater Los Angeles Area (thereafter Boston and Los Angeles). The two areas, located at the east and west coasts respectively, are two of the most populous regions in the United States. These two areas have diverse groups of people, different spatial scales (the area of Los Angeles is about four times of that of Boston in this study), and different physical settings and urban structures (e.g., as pointed out by Boeing (2019), Boston has low orientation order while Los Angeles has high orientation order, both cities have similar network structures). All of these may influence housing market characteristics. Given these similarities and differences, conducting experiments at these two cities can assist illustrating the potential generalizability of the proposed model and the significance of the research findings. This study adopts census block groups (CBGs) as the spatial analysis unit. CBG is one of the fine-resolution geographical units in which the United States Census Bureau publishes sample demographics

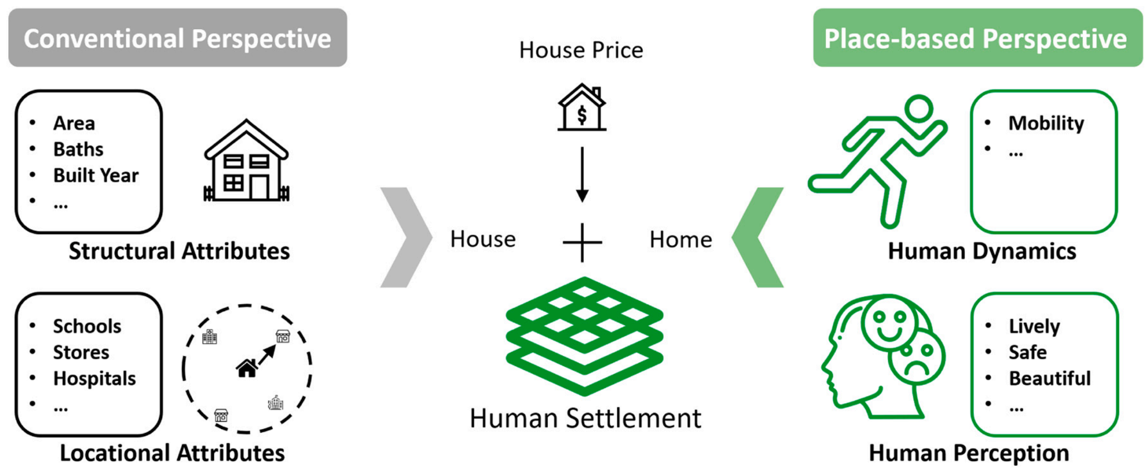

Fig. 1. Framework: conventional perspective (space-based) for human settlement estimation vs. place-based perspective for human settlement evaluation.

and socioeconomic data. Fig. 2 shows the study area with the road networks and mean house price distributions. In total 3964 CBGs at Los Angeles, and 944 CBGs at Boston are used in this study.

4.2. Data

There are four datasets used in this research: house information, locational attributes, human spatiotemporal visit data, and human perceptual measurements. House information is collected from an online real estate data platform. Locational attributes and human spatiotemporal visit data are obtained from a location big data company. Human perceptual measurements are extracted from street-view images. The first two datasets serve as the controlled variables in traditional HPM, while the other two datasets are employed as new independent variables that are discussed in the proposed P-HPM. All the aforementioned data were retrieved and computed for Boston and Los Angeles separately.

4.2.1. House attributes

House information was collected from the website of Redfin,[1] which is a popular real estate online platform. Seller agents and house owners post their house information on the website for sale, with an estimated house price provided by the system. The dataset contains the house location, the estimated price, and detailed structural characteristics of properties such as number of baths, stories, living area, etc. Detailed statistics are reported in Table 1. After data cleaning, 108,571 houses in Los Angeles and 94,892 houses in Boston remained for the further analysis. In Fig. 2A, the yellow dots denote the locations of the houses. Fig. 2B demonstrates the average price of the houses in each CBG (dollars).

4.2.2. Locational attributes

To construct the locational attributes of house properties, we retrieved points of interest (POIs) data from the SafeGraph database,[2] which provides detailed information for millions of places in North America. For each POI, it contains coordinates and a specific category code, which follows the standard rules according to the North American Industry Classification System (NAICS).[3] The following potential determinants of housing prices are selected and calculated as locational amenities based on existing literature, including the distances to the nearest schools, universities, natural parks, amusement parks, metro stations, and the number of bus stations within certain distance. It should be denoted that locational attributes are calculated at the property level, and are then aggregated to CBGs. Detailed statistics are reported in Table 1.

4.2.3. Visiting patterns

Visiting patterns of CBGs are also retrieved from the SafeGraph database. By tracking millions of anonymous mobile phone users' daily trajectories, the database provides the aggregated spatiotemporal visiting records of CBGs. We retrieved the total number of visits to a specific CBG, as well as the hourly visit counts which are represented as a 24-dimensional vector to show the dynamic visit patterns of CBGs. Considering that the absolute number of visits may vary in different CBGs because of the various population density, size of the CBG, etc., the ratio of the visits at each hour to the total number of visits are calculated as well. Hence, to illustrate the human movement patterns of CBGs, 49 variables are constructed, which contains the total number of visits, 24 hourly visits, and 24 ratio of hourly visits. Fig. 3A presents the spatial distribution of the total number of visits to different neighborhoods in the two cities.

4.2.4. Human perceptual measurements from street-view images

Street-view imagery captures the urban physical environment in detail from a similar view of human vision (Kang, Zhang, Gao, et al., 2020b; Liu et al., 2019; Zhang et al., 2019). In this work, we employ street-view imagery as the representation of physical settings of a place. To obtain human perceptions to street-view images, we train a deep convolutional neural network (DCNN) based on a large-scale human-image evaluation dataset, and predict the human perceptual scores for a large number of street-view images in Boston and Los Angeles using the DCNN.

We collected the street-view images through the Google Street View API.[4] To do so, a set of geo-referenced sampling points are first generated along the road network with an interval of 50 m. The road networks of Boston and Los Angeles are downloaded from the OpenStreetMap (OSM). For each sampling point, we then obtain four street-view images facing four directions at a particular location, which can depict the physical settings of a neighborhood comprehensively.

Given one street-view image, the DCNN is expected to output the perceptual score (ranging from 1 to 10) of the scene in the image. The model is trained based on the *MIT Place Pulse*[5] dataset (Dubey et al., 2016), which was initially collected through a large-scale online survey. On such a web-based platform, participants are asked to compare two

1 https://www.redfin.com
2 https://safegraph.com
3 https://www.naics.com/
4 https://developers.google.com/maps/documentation/streetview/intro
5 https://www.media.mit.edu/projects/place-pulse-1/overview/

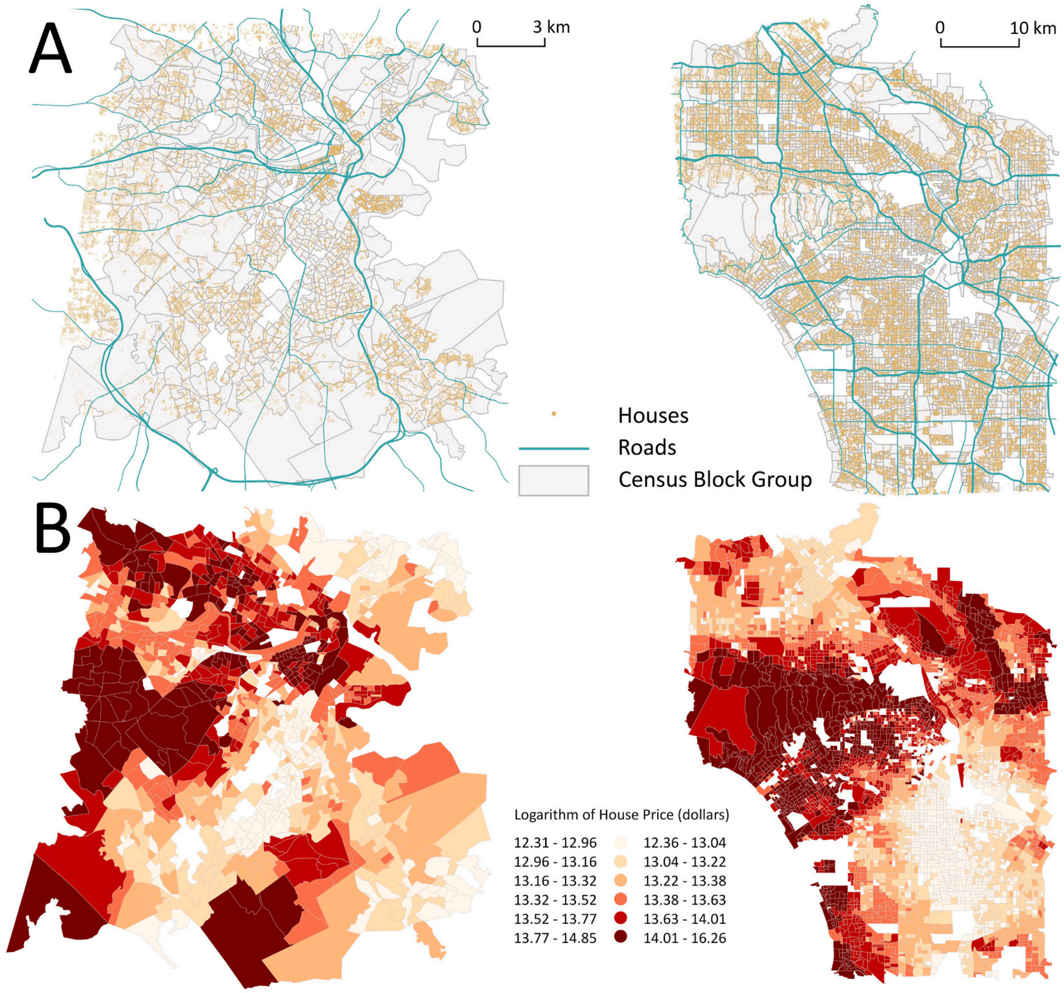

Fig. 2. Selected datasets and research area in Boston (left) and Los Angeles (right). A. Spatial distribution of houses as well as census block groups. B. Logarithm of average house price at each census block group.
Figure created with the Python library GeoPandas and Matplotlib.

Table 1
Detailed statistics for house attributes and locational attributes in Boston and Los Angeles.

Housing attributes	Boston		Los Angeles	
	Mean	Standard deviation	Mean	Standard deviation
Number of baths	1.7	0.5	1.9	0.7
Stories	1.7	0.4	1.2	0.3
House area (m^2)	149.1	62.9	146.5	56.2
Distance to universities (m)	1348.8	1015.8	1427.8	988.4
Distance to natural parks (m)	746.2	489.2	853.8	482.4
Distance to amusement parks (m)	1492.0	943.8	2603.1	1570.3
Distance to metro stations (m)	1353.5	1409.2	4477.7	4334.1
Number of bus stations nearby	30.8	14.7	17.8	12.8

street-view images and respond to questions such as “Which place looks more safe/beautiful/depressing/lively/wealthy/boring?”. For each time, only one perceptual dimension among the six appears in the question-answer interface, and users evaluate the images according to their perceptual preference by choosing one answer among the three options: “the left image”, “equal”, and “the right image”. In each trial, two images are randomly sampled from 110,998 street-view images collected from 56 cities among 28 countries in 6 continents. Launched since 2013 until 2016, more than 80,000 online volunteers have participated in the survey and contributed more than one million pair-wise comparisons. Considering the high diversity and vast volume of the image samples, the participants and their responses, we take this dataset as human's general perceptual preferences on urban scenes. Then, a deep learning model can be trained using this dataset to learn how people evaluate an urban scene.

Detailed description of the model configuration and the training process is elaborated in Zhang et al. (2018). The pre-trained DCNN model is then used to evaluate the street-view images of Boston and Los Angeles with six perceptual dimensions, namely, safe, lively, boring, wealthy, depressing and beautiful. Fig. 3C presents the samples of street-view image from Boston with different lively scores. Indeed, the content and settings of the scenes present their levels of lively, which demonstrates the effectiveness of the model.

At CBG level, the perceptual score of each unit is calculated by averaging all image-level scores. The reason we utilizes the average perceptual score is that the scenery may vary hugely even at a same location because of the camera views. An average value can potentially reduce the spatial non-stationarity and the standard deviation of scores to derive the common perception trend of a place. Fig. 3B shows the spatial distribution of average *lively* scores in Boston and Los Angeles, and Fig. 3C depicts sample street-view images with low, medium and

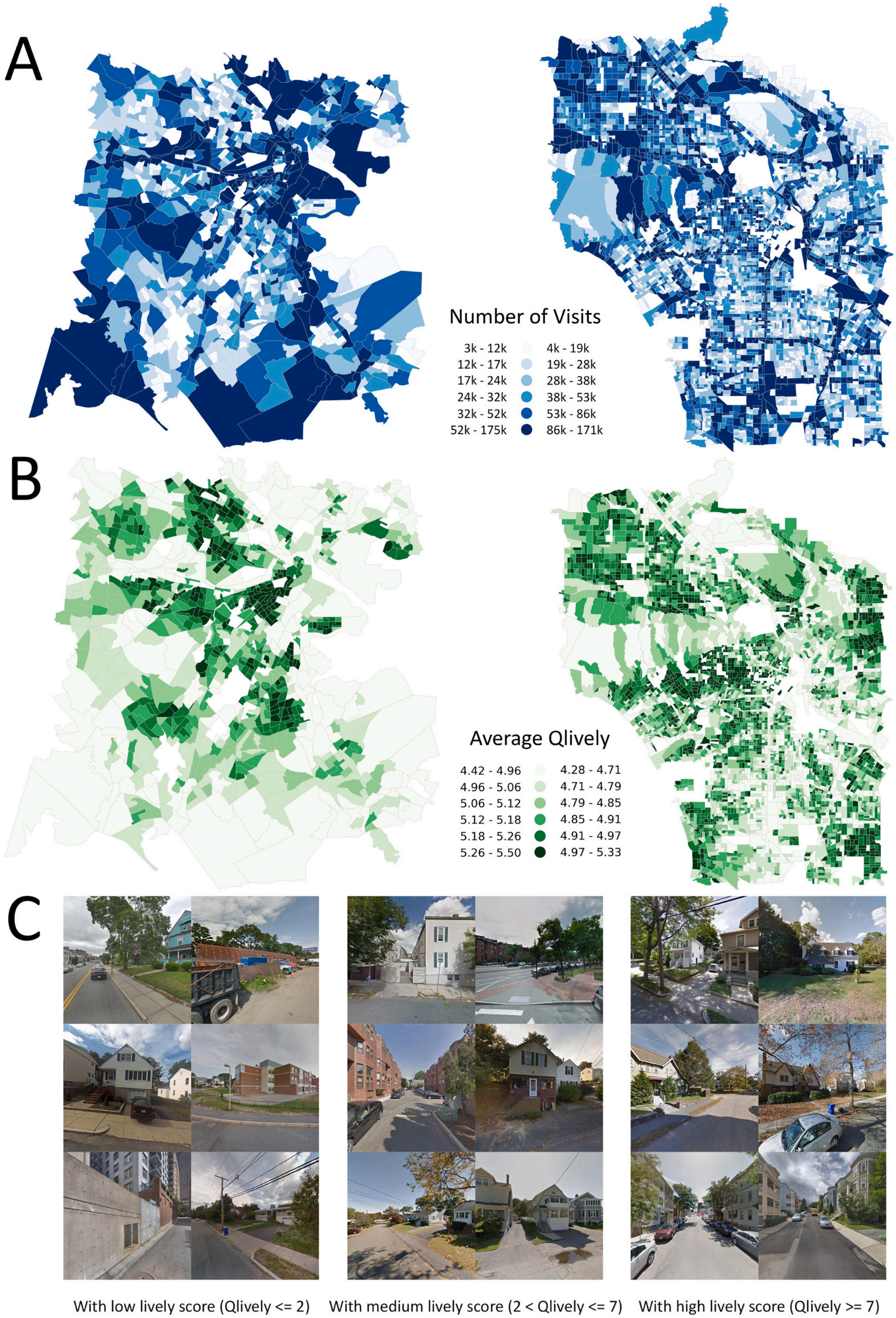

Fig. 3. Human visit patterns and perceptions at places: A. Total number of visits to CBGs. B. Average *lively* score calculated at each CBG. C. Examples of street-view images with different *lively* scores. Left: with low lively score. Medium: with medium lively score. Right: with high lively score.

high lively scores, respectively. However, it is worth noting that people with different social characteristic information such as gender, race, age, and education, may have different sense of place (Pánek et al., 2020). The examination of between-group differences in the sense of place would require additional individual-level data, which is not available in this study.

5. Methods

5.1. Factor analysis

High multicollinearity exists among variables in human mobility patterns and human perceptions of places because many variables tend to be closely correlated. For example, the number of visits to region at a specific hour t is highly related to the number at hours $t + 1$ and $t - 1$ (Gao, 2015). Places with beautiful scenery, may also make people feel lively and possibly safe. To deal with this issue, we perform the principle component analysis (PCA) with varimax rotation on the variables. The motivation is that house prices are influenced by a set of latent underlying variables, which may be represented as a linear combinations of place-related variables. By using PCA, the multicollinearity among place-oriented variables will be mitigated and the total number of place-related variables will be reduced to a small number of orthometric factors. These factors are the actual variables fed into the P-HPM.

5.2. Spatial autoregressive model

Socioeconomic variables often fluctuate synchronously over certain geographical areas, a phenomenon known as spatial autocorrelation. The spatial autocorrelation of house prices has been widely recognized in existing literature (Cohen & Coughlin, 2008; Krause & Bitter, 2012; Mueller & Loomis, 2008). To model the spatial dependence effect, we incorporate spatial autoregressive variables to our proposed P-HPM as a comparison. The typical spatial autoregressive lag model takes the following form (LeSage, 2015):

$$Y_i = \rho W Y_i + \sum_{k=1}^{m} a_k X_k + \varepsilon_i \tag{3}$$

where Y_i refers to the natural logarithm of average house price at location i; ρ is the coefficient of the spatial autocorrelation; a_k indicates the regression coefficient for the k^{th} independent variable; X_k refers to the k^{th} attribute of location i; m is the total number of attributes; and ε_i is the random error; W is a standardized spatial weight $n \times n$ matrix with zero diagonal that illustrates the spatial dependence. Here, the spatial weight matrix W is measured by the adjacency matrix. Any two adjoining regions that are not connected will be assigned with 0 in the corresponding element in the weight matrix, and 1 otherwise. By using this model, the nearby house values are included into the original ordinary-least-squares (OLS) model estimation and spatial dependency is augmented.

5.3. Geographically weighted regression and Monte Carlo simulation

In addition to spatial autocorrelation on house price that can be examined in spatial autoregressive models, we also consider spatial non-stationary effect in the P-HMP (Fotheringham et al., 1998). Typically, a multi-linear regression model with OLS coefficient estimation is used in HPM with the assumption of spatial stationarity, i.e., the relationships between house prices and determinants are static. However, such relationships might vary across space, and parameter estimates might exhibit significant spatial variations (Cao et al., 2019; Huang et al., 2010). GWR is designed to model these spatial variations of relationships. In Eq. (4), we present the typical form of a GWR model (Fotheringham et al., 2003).

$$Y_i = \alpha_{0(u_i,v_i)} + \sum_{k=1}^{m} a_{k(u_i,v_i)} X_{k(u_i,v_i)} + \varepsilon_i \tag{4}$$

where Y_i refers to the natural logarithm of average house price at location i with its coordinate to be (u_i, v_i); $\alpha_{0(ui,\ vi)}$ denotes the intercept; $a_{k(ui,\ vi)}$ indicates the local regression coefficient for the k^{th} independent variable; $X_{k(ui,\ vi)}$ refers to the k^{th} attribute of location i; and ε_i is the random error. By using this model, the derived coefficients can measure the spatial non-stationarity of impact factors that vary across different sub-areas.

A GWR model usually yields a better performance than an OLS model. However, instead of pursuing a higher model performance, in this work, the main purpose of using GWR is to test the significance of spatial non-stationarity—whether the relationships between house prices and the place-related variables vary across space. To evaluate the significance of the spatial non-stationarity, a Monte Carlo test is usually suggested to assess whether the set of local estimators show significant spatial variance so that results can be trusted or not. To do so, the standard deviation of all parameter estimates can be calculated at first. Under the null hypothesis, any permutation of (u_i, v_i) pairs among the geographical sampling location i are equally likely to occur. Second, the data is rearranged randomly in space by a large number of times. For each rearrangement, the standard deviation of the estimate in a GWR can be calculated. Hence, a distribution of the standard deviation of the randomization test can be built accordingly. Third, based on the distribution, a significant test can be performed to validate if the observed relationship between house price and an explanatory variable is spatial non-stationary (Brunsdon et al., 1998). It is important to emphasize that GWR and Monte Carlo simulation aim at examining whether effects of place-based variables on house prices are spatially stationary while spatial autoregressive models, in comparison, aim at taking spatial dependencies of house prices into account to identify the fix effects of place-based explanatory variables on house prices.

6. Results

In this section, we first present the results of factor analysis, which derives efficient components of mobility and perception variables for the regression models. Then, the standard hedonic pricing model and the proposed place-oriented hedonic pricing model are compared. Finally, we explore the spatial-nonstationarity of place-related variables in P-HPM.

6.1. Factor interpretation

6.1.1. Human mobility factors

As described in Section 4, for each CBG, a 49-dimensional vector is generated to represent the human movement pattern. It contains three parts: the total number of visits, 24 hourly visit counts, and the ratio of 24 hourly visits. Though some meaningful and measurable variables such as number of visits at daytime, number of visits at night can be used, they may have high multicollinearity. Thus, we conduct factor analysis with PCA to reduce the potential multicollinearity to generate the human mobility factors. The top principle components from PCA (e.g. PC1, PC2, …) are used as factors (e.g. *factor 1*, *factor 2*, …) to represent the transformed variables in factor analysis.

As illustrated in Table 2, the values are the correlation coefficients between the human mobility variables and the top three principle components from PCA (a transformation of the human mobility variables), indicating how well an original variable can be explained by the derived principle components. For instance, the value on the upper-left, 0.92, is the correlation coefficient between the variable "the total number of visits" and the new factor *factor 1* for Los Angeles. The last row in the table presents the cumulative proportion of the total variation that a principle component accounts for. For example, 0.53 indicates by only using *factor 1* (i.e., PC1), the total variation in the original 49 features of mobility factors can be explained by 53% for Los Angeles. Accordingly, the lower-right corner value, 0.91, means the total variation can be explained by 91% with the top three principle components (*factor 1* to *factor 3*). In other words, there is only a 9% loss in information with about 90% reduction in the number of the original mobility factors (from 49 to 3), for both Los Angeles and Boston. For interpretation convenience in later regression analysis, several factors are

Table 2
Factor loadings of mobility factors. For interpretation convenience, factor loadings with absolute value less than 0.30 are suppressed.

Mobility	Factor 1		Factor 2		Factor 3	
	Los Angeles visits at daytime	Boston[a] absolute number of visits	Los Angeles[a] visits at night	Boston[a] ratio of hourly visits at night	Los Angeles ratio of hourly visits at daytime	Boston ratio of hourly visits at daytime
Visit count	0.92	0.94				
0	0.63	0.93	0.61			
1	0.59	0.91	0.63			
2	0.56	0.90	0.65			
3	0.55	0.89	0.67			
4	0.62	0.91	0.66			
5	0.76	0.95	0.59			
6	0.84	0.97	0.48			
7	0.87	0.98				
8	0.88	0.98				
9	0.87	0.98	0.42			
10	0.87	0.98	0.42			
11	0.87	0.98	0.42			
12	0.87	0.98	0.41			
13	0.87	0.98				
14	0.88	0.98				
15	0.88	0.98				
16	0.88	0.98				
17	0.90	0.98				
18	0.90	0.98				
19	0.89	0.98	0.40			
20	0.87	0.98	0.47			
21	0.83	0.97	0.52			
22	0.77	0.96	0.56			
23	0.70	0.95	0.59			
0 Ratio	−0.70		0.63	0.88		
1 Ratio	−0.72		0.62	0.89		
2 Ratio	−0.72		0.62	0.89		
3 Ratio	−0.72		0.62	0.89		
4 Ratio	−0.71		0.63	0.89		
5 Ratio	−0.67		0.64	0.88		
6 Ratio	−0.65		0.63	0.80		
7 Ratio	−0.66		0.46	0.67		
8 Ratio	−0.63		0.52	0.69		
9 Ratio	−0.53		0.62	0.76	0.43	0.52
10 Ratio	−0.45		0.64	0.71	0.52	0.62
11 Ratio	−0.41		0.61	0.66	0.59	0.69
12 Ratio			0.57	0.59	0.64	0.74
13 Ratio	−0.42		0.57	0.60	0.63	0.73
14 Ratio	−0.49		0.53	0.62	0.61	0.71
15 Ratio	−0.55		0.43	0.66	0.53	0.60
16 Ratio	−0.64		0.50	0.72		
17 Ratio	−0.71		0.49	0.69		
18 Ratio	−0.74		0.53	0.80		
19 Ratio	−0.71		0.60	0.85		
20 Ratio	−0.70		0.63	0.88		
21 Ratio	−0.70		0.63	0.88		
22 Ratio	−0.68		0.64	0.87		
23 Ratio	−0.68		0.63	0.87		
Cumulative proportion	0.53	0.49	0.82	0.81	0.91	0.91

[a] Factors have multiplied with −1.

multiplied with −1 to get its reverse meaning (such as *factor 2* for Los Angeles, *factor 1* and *factor 2* for Boston). Factor loadings with absolute values less than 0.40 are suppressed.

For Los Angeles, *factor 1* is positively correlated with the absolute number of visits to each CBG (includes the total number of visits and 24 h hourly visits), while it is negatively correlated with the ratio of 24-hour visits. It should be noticed that the absolute number of hourly visits from 6:00 to 21:00 as well as the total visit number have higher loadings to the first principle component with higher coefficients (larger than 0.83), and the ratio of hourly visits from 9 to 15 o'clock have negative and smaller loadings as weighted values are greater than −0.55 compared with others. Hence, we consider the *factor 1* as "visits at daytime" for interpretation. *Factor 2* has negative loadings on all 49 mobility pattern vectors originally. To provide a better interpretation, all weights are multiplied with −1 to have positive loadings. The inverse factor will only be used and interpreted in later regression analysis. The weights of the hourly visits from 20 to 6 o'clock have strong and positive connections (with absolute values greater than 0.47) compared with other absolute number of visits, and the ratio of hourly visits from 19 to 6 o'clock and 9 to 11 o'clock also have higher positive loadings (with absolute values greater than 0.60). Therefore, *factor 2* can be summarized as the "visits at night". *Factor 3* shows that the ratios of hourly visits from 9 to 15 o'clock have large positive weights, it may primarily describe the "ratio of hourly visits at daytime".

In Boston, the case is different. The first principle component (*factor 1*) mainly describes the "absolute number of visits" after multiplying with −1. Because the absolute number of visits to each CBG has extremely high positive loadings (with all variables' values greater than 0.90), and the ratio of hourly visits have negative and less loadings (the coefficients of all variables are no less than −0.31). In comparison, the second principle component (*factor 2*) places the largest weights on the hourly ratio of visits after multiplying with −1 while have limited connections to the absolute number of visits. Noted that the ratio of hourly visits between 7:00 to 17:00 has smaller weights because their absolute values are less than 0.76 while others are higher than 0.80, we term the "ratio of hourly visits at night" for *factor 2*. In contrast, *factor 3* has positive high loadings on the ratio of hourly visits between 9 and 15 o'clock which is similar to the *factor 3* of Los Angeles. Therefore, we also summarize it as the "ratio of hourly visits at daytime".

6.1.2. Human perception factors

Similarly, we perform PCA on the six dimensional perception variables (safe, lively, boring, etc). Here, we select top two principle components as factors which explain 94% and 98% of total variation in original variables of Los Angeles and Boston respectively. Table 3 reports the results of factor loadings of the perception variables with absolute values larger than 0.30.

The factor analysis in two cities shows a similar trend. The first principle component (*factor 1*) fits common sense with positive high loadings on positive perceptions of places, including beautiful, lively, safe, and wealthy, while it has negative high loadings on negative perceptions of places like boring and depressing. Therefore, *factor 1* primarily describes "positive perception at places". The second principle component (*factor 2*) leans to the perceptions of lively, beautiful and boring places. It has negative high loadings on lively perception and positive high loadings on beautiful and boring perceptions, which can represent the degree of "unlively" at places.

6.2. Comparisons between HPM vs. P-HPM

Considering that house prices might be autocorrelated across space, we calculated the global Moran's I statistic (Cliff & Ord, 1981) of house prices in both cities. We found that house prices are highly spatially autocorrelated with Moran's I 0.86 in Los Angeles and 0.73 in Boston, and are statistically significant in both cities. Hence, it is necessary to model the spatial dependence in the P-HPM.

In sum, there are five (spatial) regression models with different independent variables built in two cities (Los Angeles and Boston) respectively:

Model 1. Standard HPM with housing attributes and locational attributes.
Model 2. P-HPM with added mobility factors only.
Model 3. P-HPM with added perception factors only.
Model 4. P-HPM with mobility factors and perception factors together.
Model 5. P-HPM with spatial lag variables.

Tables 4 and 5 report the results of Los Angeles and Boston respectively.

6.2.1. Hedonic pricing model

As the baseline model, model 1 presents the effects of housing attributes and location amenities variables on house prices. As expected, most of the housing attributes are significantly associated with house prices, and closing to a facility (including universities, natural parks in both cities, and amusement parks and metro stations in Los Angeles) leads to an increase in house prices. In terms of the performance of the standard hedonic pricing model, the R^2 is 0.684 in Los Angeles and 0.715 in Boston at the significance level of 0.05, suggesting that the HPM model can explain approximately 70% of the variation in house price of both cities. The following subsections explore the impacts of place-related variables in house prices which consider the Model 1 as the baseline.

Table 3
Factor loadings of perception factors.

Perceptions	Factor 1		Factor 2	
	Los Angeles	Boston	Los Angeles	Boston
	Positive perceptions at places		Unlively	
Beautiful	0.93	0.87	0.31	0.49
Boring	−0.91	−0.90	0.29	0.39
Depressing	−0.95	−0.97		
Lively	0.89	0.80	−0.39	−0.59
Safety	0.97	0.98		
Wealthy	0.96	0.98		
Cumulative proportion	0.88	0.84	0.94	0.98

Table 4
Estimation results of the five models in Los Angeles.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
	Hedonic model	Human mobility	Human perception	Place-oriented model	Spatial lag
Intercept	12.828*	12.802*	12.866*	12.866*	6.160*
Number of baths	0.004	0.009	0.013	0.015	0.010
Stories	0.009*	0.092*	0.079*	0.078*	−0.052*
House area	0.001*	0.001*	0.001*	0.0001*	0.000*
Distance to universities	−0.046*	−0.033*	−0.038*	−0.017*	−0.045*
Distance to natural parks	−0.070*	−0.059*	−0.063*	−0.048*	−0.377*
Distance to amusement parks	−0.015*	−0.012*	−0.012*	−0.007*	−0.039
Distance to metro stations	−0.015*	−0.015*	−0.017*	−0.013*	−0.096*
Number of bus stations nearby	−0.008*	−0.007*	−0.008*	−0.008*	−0.002*
Human activity PC1 (visits at daytime)		0.005*		0.012*	0.005*
Human activity PC2 (visits at night)		−0.020*		−0.019*	−0.007*
Human activity PC3 (ratio of hourly visits at daytime)		0.026*		0.026*	0.011*
Human perception PC1 (positive perceptions at places)			0.030*	0.037*	0.014*
Human perception PC2 (unlively)			−0.045*	−0.070*	−0.032*
Spatial lag coefficient					0.514*
R-squared	0.625*	0.657*	0.645*	0.684*	0.849*

p values are shown in parentheses.
* $p < 0.05$.

6.2.2. Mobility patterns

Model 2, Model 4, and Model 6 take mobility factors into consideration and present similar impacts. Table 4 reports the model results in Los Angeles. The first factor, "visits at daytime", has a positive effect on house prices, indicating that more visitors to a certain CBG at daytime is associated with higher house price of the CBG. *Factor 2* illustrates the "visit numbers at night". The negative coefficients indicate that more visitors to CBGs at night is associated with a lower house price. Accordingly, *factor 3* demonstrates that a higher ratio of visits at daytime will lead to a higher house price.

According to the results of factor analysis in Boston reported in Table 5, *factor 1*, which represents the "absolute number of visits", has

Table 5
Estimation results of the five models in Boston.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
	Hedonic model	Human mobility	Human perception	Place-oriented model	Spatial lag
Intercept	12.932*	12.918*	12.915*	12.896*	4.906*
Number of baths	0.532*	0.517*	0.526*	0.509*	0.308
Stories	0.102*	0.091*	0.090*	0.062*	0.001*
House area	0.000*	0.000*	0.000*	0.000*	0.000*
Distance to universities	−0.125*	−0.109*	−0.129*	−0.104*	−0.418*
Distance to natural parks	−0.203*	−0.184*	−0.172*	−0.132*	−0.521*
Distance to amusement parks	−0.024*	−0.029*	−0.002	−0.003	0.066
Distance to metro stations	−0.009	−0.011	−0.005	−0.010	−0.099*
Number of bus stations nearby	−0.002*	−0.001*	−0.004*	−0.004*	−0.001*
Human mobility PC1 (absolute number of visits)		0.005*		0.011*	0.006*
Human mobility PC2 (ratio of hourly visits at night)		−0.009*		−0.015*	−0.006*
Human mobility PC3 (ratio of hourly visits at daytime)		0.017*		0.024*	0.005*
Human perception PC1 (positive perceptions at places)			0.026*	0.041*	0.017*
Human perception PC2 (unlively)			−0.079*	−0.088*	−0.061*
Spatial lag coefficient					0.592*
R-squared	0.641*	0.658*	0.676*	0.715*	0.854*

p values are shown in parentheses.
* $p < 0.05$.

positive effects on house prices. In other words, the more visitors, the higher the house prices. In contrast, *factor 2* has negative coefficients on house prices. As *factor 2* mainly describes the "ratio of hourly visits at night", results suggest that more visitors to CBGs at night means lower property values. *Factor 3* indicates "ratio of hourly visits at daytime" and has positive coefficients. It means that high hourly ratio of visits at daytime have positive effects on house prices, while high hourly ratio of visits at night have negative impacts on house prices in Boston.

Overall, the results of mobility factors show that the number of visits to places is positively associated with the average house prices. In terms of time periods, the visits at daytime have positive effects on house prices; however, interestingly, more visits at night may have negative influences on house prices. It might because more visits at daytime reflect prosperous economic activities which have positive effects on house prices, while more night-time visits might be associated to nightlife and potentially increased crime rates which may have a negative impact on house prices (Gibbons, 2004).

6.2.3. Human perceptions at places

Model 3 and Model 4 involve human perception factors. Tables 4 and 5 show the coefficients of the five human perception-related loading factors and demonstrate their impacts on house prices. Since the *factor 1* indicates people's "positive perception", including beautiful, lively, safe and wealthy, it has positive correlation with house price, which is consistent with the sense that positive perceptions contribute to the house prices positively. The *factor 2* of human perception, which is indeed the representation of "unlively", is negatively correlated with house prices. It suggests that people tend to pay more for houses at CBGs with feelings of lively. In sum, CBGs with physical environment making people feel beautiful, lively, safe and wealthy show positive impacts on house prices significantly and vice-versa.

6.2.4. Overall comparison

In terms of the goodness-of-fit, our proposed model outperforms the traditional HPM with an increase of R^2 from 0.625 to 0.684 for Los Angeles and from 0.641 to 0.715 for Boston. When considering the spatial dependence into the model, there is no significant difference between the conclusions inferred from the Model 4 (using OLS) and the Model 5 (using spatial lag model), while the goodness-of-fit score increases significantly from 0.684 to 0.849 in Los Angeles and from 0.715 to 0.854 in Boston. It can be inferred that modeling spatial dependence can improve the prediction performance of human settlement valuation. Basically, all place-based variables' coefficients are statistically significant with *p*-value at 0.05 level. By controlling the housing and locational variables, place-related factors are indeed associated with property values.

6.3. Geographically weighted regression

To test whether the effects of variables to house prices are spatially stationary, we perform GWR and calculate the significance of the estimated coefficients through a Monte Carlo test. In detail, we perform the experiment 100 times which include 99 random perturbations of the data in space and one for the actual spatial arrangements of the data.

The p-values of all coefficients are reported in Table 6. The results show that the *p*-values of several locational attributes (e.g., distance to amusement parks and distance to metro stations) are smaller than 0.05; in comparison, the p-values of housing attributes, mobility factors and perception factors are larger than 0.05. This indicates that relationships between the locational variables used in traditional HPM and house price vary largely from place to place, and it is necessary to model the spatial heterogeneity of these variables. Nevertheless, the relationships between human mobility and perception factors, and house prices don't

Table 6
Results of geographically weighted regression-based place-oriented hedonic pricing model with Monte Carlo significance test.

Variables	Boston	Los Angeles
	p-Value	p-Value
Intercept	0.21	0.00
Number of baths	0.99	0.99
Stories	0.98	0.99
House area	0.36	0.99
Distance to universities	0.00	0.12
Distance to natural parks	0.16	0.99
Distance to amusement parks	0.02	0.00
Distance to metro stations	0.00	0.00
Number of bus stations nearby	0.72	0.20
Human mobility factor 1	0.73	0.99
Human mobility factor 2	0.99	0.99
Human mobility factor 3	0.99	0.99
Human perception factor 1	0.99	0.99
Human perception factor 2	0.97	0.99
R-square	0.921*	0.963*
Bandwidth (km)	0.735	1.43

show significant spatial variability, indicating that the impacts of human mobility and human perceptions are stable across the space.

7. Discussions

7.1. Patterns of place-based variables on housing values

The results demonstrate that place-related variables contribute to explain the variation of house prices significantly. We find that a larger number of visits to places, especially at daytime, have a positive effect on house prices, whereas more visits at night have a negative effect. The discovery might be resulted from the composite effect of multiple factors. For instance, high hourly daytime visits may reflect prosperous economic activities which can stimulate house prices; while high hourly night-time visits may link to nightlife districts and potentially increased crime rates which could suppress house prices (Gibbons, 2004). In addition, positive perceptions such as beautiful, lively, safe and wealthy, contribute to the higher house values significantly. Furthermore, the GWR model and Monte Carlo tests were employed to explore the spatial variation of the variables to house prices. The results explicitly show that the human mobility factors and perception factors contribute to house price modeling significantly but don't show significant spatial variation, which means their contributions to house prices are stable across space.

7.2. Integrating place-based insights for human settlement

It is also worth noting that our proposed P-HPM is not simply considering new objective neighborhood factors in the conventional HPM but we devote to highlighting the understanding of "sense of place" and integrating humanistic insights in evaluating the value of human settlement. On the one hand, researchers from the field of real estate usually treat housing prices as functions of a range of static factors while may ignore the human dynamic and perceptual perspectives. On the other hand, the concept of place that is central for humanistic geography is often missing in existing quantitative studies. The proposed conceptual framework makes explorations in bridging the gap by understanding how people move between places and how they perceive the "home". A house is no longer being treated as a physical unit, but a place intertwined with human mobility and perception. Results are also valuable for urban planners regarding urban infrastructure construction, as the relationships between human and environment are well addressed and formulated. We believe this study is just a start, as sense of place has gone beyond not only human mobility and human perception, but also social experience and emotion, place-based cognition, and cultural construct (Cantrill & Senecah, 2001; Kyle & Chick, 2007). Also, people's subjective sense of place may change and thereby influence their residential preferences. For instance, as illustrated by Bissell (2021), our sense of place is changing as well during the COVID-19 pandemic. Existing studies have shown that human mobility and connections decrease drastically since the start of the COVID-19 pandemic because of social distancing, work from home, etc.(Gao et al., 2020; Huang et al., 2021). Hence, the pandemic may rewrite our sense of place, mutate our preferences of residence, which may serve as one factor in housing price decision (Wang, 2021).

7.3. Implications for urban planning

For broader and practical applications in urban planning, the place-oriented perspective is expected to be integrated into current geographical modeling tools. Previous work has built solid foundations to achieve this goal (Chen et al., 2020; Lü et al., 2019; Wang et al., 2018). It also helps bridge the gap between the stated and revealed preferences of houses, as stated by Vasanen (2012). Our study provides insights in measuring such subjective place-related values with advanced AI tools that can deepen the understanding of residential preferences on housing choices. Introducing sense of place for urban planning is not only limited to local practices, but also for macro-scale investigation. Researchers are able to understand human perceptions and emotions for better modeling human-environment relationships at both global level and neighborhood scale (Hu et al., 2019; Li et al., 2021; Pánek et al., 2020). Understanding how people move around the city and its contribution to house price modeling is also critical as more fine-resolution human mobility datasets are increasingly available and openly accessible (Kang, Gao, Liang, et al., 2020a; Yilmazkuday, 2021). Though only two cities are selected in this work, projects in other area could also integrate these subjective place-oriented aspects for human settlement evaluation. Such a place-based paradigm may potentially benefit other research agendas beyond human settlement evaluation. With the development of quantitative measurements in various aspects of place, researchers and practitioners can examine the social, psychological, and emotive meanings for individuals at places, and better guide various applications such as the design of lively and safe neighborhoods, sustainable city planning, public transport infrastructures in the post-pandemic era (Bissell, 2021). Our studies also suggest that, instead of treating housing prices as combinations of a series of static and objective factors, it is necessary for planners and policy makers to take subjective and dynamic sense of places into account when implementing urban policies.

7.4. Limitations and potential improvements

Several limitations of this work are expected to be addressed in future work. As we collected house information and perceptual measurements from online platforms, data bias is a common concern for such crowdsourced information. Some of the housing attributes and locational attributes (e.g., number of baths, built year, distance to stores and schools) were collected at first, while were removed when conducting the experiments to eliminate the multicollinearity. Though we have made efforts in reducing the multicollinearity by materializing place-based variables as human mobility and perception factors using PCA, variables that are more meaningful and measurable can be used to enhance the interpretability of the model.

Besides, the perception of street-view images may vary person by person, i.e., places might be sensed differently because of the diverse demographic characteristics of residents. Here, we consider the average values computed by machine learning model at each neighborhood (i.e. CBG) as collective perceptual measurements. Therefore, more detailed data sources, for example, demographics of users (such as education, income), as well as more case studies in different countries are expected to help test the personalized sense of place in the proposed model.

Finally, as pointed by existing literature (Lee et al., 2016; Lieske et al., 2021), the results of hedonic models might be biased by the spatial scale and configuration, which is known as the modifiable areal unit problem (MAUP). Conducting empirical studies at fine scales (such as property level, neighborhood level) may capture more details influencing house prices, while might face more spatial variations. In comparison, coarser-level (such as zip code regions, counties) experiments may reflect general patterns of house price changes while lack of sufficient variations. Careful examination of the MAUP for the relationships between place-based variables and house prices at multiple scales and with different zones may deepen our understanding of the robustness of findings in future work.

8. Conclusions

In this research, we propose a place-based human settlement evaluation framework by incorporating two place-oriented components: human dynamics and human perceptions of places. Such a conceptual framework is derived from the humanistic thinking and highlights the role of the "people-centered" principle. Accordingly, a place-oriented hedonic pricing model (P-HPM) is developed which extends the traditional hedonic pricing model (HPM) from a place-centered perspective.

With the support of house instance-level datasets and machine learning approaches, a series of experiments are conducted in Boston and Los Angeles to demonstrate the effectiveness of the proposed model. We formulate the P-HPM by incorporating human movement patterns—computed from hourly visits of places based on millions of people's trajectories, and human perceptions of physical environments, which includes six dimensions of human perceptions of place extracted from large-scale street-view images using deep learning techniques.

Overall, this research demonstrates that by depicting how people move and their perceptions of place, we can better understand the physical and socioeconomic environments of a place. The proposed P-HPM involving human dynamics and human perceptions of places can effectively support the study of human settlement appraisal. In addition, the P-HPM shows its great potential for the infusion of place-based variables and humanistic perspectives in society for various fields such as real estate marketing, urban planning and management.

Declaration of competing interest

The authors declare that there is no conflict of interest.

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References

Agnew, J. (2011). Space and place. In *, 2011. Handbook of geographical knowledge* (pp. 316–331).
Alazzawi, A. N., Abdelmoty, A. I., & Jones, C. B. (2012). What can I do there? Towards the automatic discovery of place-related services and activities. *International Journal of Geographical Information Science, 26*(2), 345–364.
Bartholomew, K., & Ewing, R. (2011). Hedonic price effects of pedestrian-and transit-oriented development. *Journal of Planning Literature, 26*(1), 18–34.
Benson, E. D., Hansen, J. L., Schwartz, A. L., & Smersh, G. T. (1998). Pricing residential amenities: The value of a view. *The Journal of Real Estate Finance and Economics, 16*(1), 55–73.
Bishop, K. C., Kuminoff, N. V., Banzhaf, H. S., Boyle, K. J., von Gravenitz, K., Pope, J. C., … Timmins, C. D. (2019). *Best practices in using hedonic property value models for welfare measurement. Technical report, working paper*.
Bissell, D. (2021). A changing sense of place: Geography and COVID-19. *Geographical Research, 59*(2), 150–159.
Boeing, G. (2019). Urban spatial order: Street network orientation, configuration, and entropy. *Applied Network Science, 4*(1), Article 67.
Boyd, J., Ringold, P., Krupnick, A., Johnson, R., Weber, M., & Hall, K. M. (2015). Ecosystem services indicators: Improving the linkage between biophysical and economic analyses. In *Resources for the future discussion paper* (pp. 15–40).
Brasington, D. M., Hite, D., & Jauregui, A. (2015). House price impacts of racial, income, education, and age neighborhood segregation. *Journal of Regional Science, 55*(3), 442–467.
Brunsdon, C., Fotheringham, S., & Charlton, M. (1998). Geographically weighted regression. *Journal of the Royal Statistical Society: Series D (The Statistician), 47*(3), 431–443.
Can, A. (1992). Specification and estimation of hedonic housing price models. *Regional Science and Urban Economics, 22*(3), 453–474.
Cantrill, J. G., & Senecah, S. L. (2001). Using the "sense of self-in-place" construct in the context of environmental policy-making and landscape planning. *Environmental Science & Policy, 4*(4–5), 185–203.
Cao, K., Diao, M., & Wu, B. (2019). A big data–based geographically weighted regression model for public housing prices: A case study in Singapore. *Annals of the American Association of Geographers, 109*(1), 173–186.
Cebula, R. J. (2009). The hedonic pricing model applied to the housing market of the city of savannah and its savannah historic landmark district. *The Review of Regional Studies, 39*(1), 9–22.
Champ, P. A., Boyle, K. J., Brown, T. C., & Peterson, L. G. (2003). *A primer on nonmarket valuation* (vol. 3). Springer.
Chasco, C., & Gallo, J. L. (2013). The impact of objective and subjective measures of air quality and noise on house prices: A multilevel approach for downtown m adrid. *Economic Geography, 89*(2), 127–148.
Chattopadhyay, S. (1999). Estimating the demand for air quality: New evidence based on the Chicago housing market. *Land Economics*, 22–38.
Chen, J., Shaw, S.-L., Yu, H., Lu, F., Chai, Y., & Jia, Q. (2011). Exploratory data analysis of activity diary data: A space–time GIS approach. *Journal of Transport Geography, 19*(3), 394–404.
Chen, M., Voinov, A., Ames, D. P., Kettner, A. J., Goodall, J. L., Jakeman, A. J., , … DeLuca, C., et al. (2020). Position paper: Open web-distributed integrated geographic modelling and simulation to enable broader participation and applications. *Earth-Science Reviews*, 103223.
Cliff, A. D., & Ord, J. K. (1981). *Spatial processes: Models & applications*. Taylor & Francis.
Cohen, J. P., & Coughlin, C. C. (2008). Spatial hedonic models of airport noise, proximity, and housing prices. *Journal of Regional Science, 48*(5), 859–878.
Couclelis, H. (1992). Location, place, region, and space. *Geography's Inner Worlds, 2*, 15–233.
Cresswell, T. (2014). *Place: An introduction*. John Wiley & Sons.
Day, B., Bateman, I., & Lake, I. (2007). Beyond implicit prices: Recovering theoretically consistent and transferable values for noise avoidance from a hedonic property price model. *Environmental and Resource Economics, 37*(1), 211–232.
Debrezion, G., Pels, E., & Rietveld, P. (2011). The impact of rail transport on real estate prices: An empirical analysis of the dutch housing market. *Urban Studies, 48*(5), 997–1015.
Diao, M., & Ferreira, J., Jr. (2010). Residential property values and the built environment: Empirical study in the Boston, Massachusetts, metropolitan area. *Transportation Research Record, 2174*(1), 138–147.
Diao, M., Qin, Y., & Sing, T. F. (2016). Negative externalities of rail noise and housing values: Evidence from the cessation of railway operations in Singapore. *Real Estate Economics, 44*(4), 878–917.
Diewert, W. E., Haan, J.d., & Hendriks, R. (2015). Hedonic regressions and the decomposition of a house price index into land and structure components. *Econometric Reviews, 34*(1–2), 106–126.
Dougherty, J., Harrelson, J., Maloney, L., Murphy, D., Smith, R., Snow, M., & Zannoni, D. (2009). School choice in suburbia: Test scores, race, and housing markets. *American Journal of Education, 115*(4), 523–548.
Dubey, A., Naik, N., Parikh, D., Raskar, R., & Hidalgo, C. A. (2016). Deep learning the city: Quantifying urban perception at a global scale. In *European conference on computer vision* (pp. 196–212). Springer.
Easthope, H. (2004). A place called home. *Housing, Theory and Society, 21*(3), 128–138.
Espey, M., & Lopez, H. (2000). The impact of airport noise and proximity on residential property values. *Growth and Change, 31*(3), 408–419.
Follain, J. R., & Jimenez, E. (1985). Estimating the demand for housing characteristics: A survey and critique. *Regional Science and Urban Economics, 15*(1), 77–107.
Fotheringham, A. S., Charlton, M. E., & Brunsdon, C. (1998). Geographically weighted regression: A natural evolution of the expansion method for spatial data analysis. *Environment and Planning A, 30*(11), 1905–1927.
Fotheringham, A. S., Brunsdon, C., & Charlton, M. (2003). *Geographically weighted regression: The analysis of spatially varying relationships*. John Wiley & Sons.
Freeman, A. M. (1981). Hedonic prices, property values and measuring environmental benefits: A survey of the issues. In *Measurement in public choice* (pp. 13–32). Springer.
Fu, X., Jia, T., Zhang, X., Li, S., & Zhang, Y. (2019). Do street-level scene perceptions affect housing prices in chinese megacities? An analysis using open access datasets and deep learning. *PLoS One, 14*(5), Article e0217505.
Gao, S. (2015). Spatio-temporal analytics for exploring human mobility patterns and urban dynamics in the mobile age. *Spatial Cognition and Computation, 15*(2), 86–114.
Gao, S., Janowicz, K., Montello, D. R., Hu, Y., Yang, J.-A., McKenzie, G., … Yan, B. (2017). A data-synthesis-driven method for detecting and extracting vague cognitive regions. *International Journal of Geographical Information Science, 31*(6), 1245–1271.
Gao, S., Rao, J., Kang, Y., Liang, Y., Kruse, J., Doepfer, D., … Yandell, B. S. (2020). *Mobile phone location data reveal the effect and geographic variation of social distancing on the spread of the covid-19 epidemic* (arXiv preprint arXiv:2004.11430).
Gibbons, S. (2004). The costs of urban property crime. *The Economic Journal, 114*(499), F441–F463.
Gibbons, S., & Machin, S. (2008). Valuing school quality, better transport, and lower crime: Evidence from house prices. *Oxford Review of Economic Policy, 24*(1), 99–119.
Giuliani, M. V. (1991). Towards an analysis of mental representations of attachment to the home. *Journal of Architectural and Planning Research*, 133–146.
Goodchild, M. F. (2007). Citizens as sensors: The world of volunteered geography. *GeoJournal, 69*(4), 211–221.
Goodchild, M. F. (2011). Formalizing place in geographic information systems. In *Communities, neighborhoods, and health* (pp. 21–33). Springer.
Harrison, S. R., & Dourish, P. (1996). Re-place-ing space: The roles of place and space in collaborative systems. In *, vol. 96. CSCW* (pp. 67–76).

Harrison, D., Jr., & Rubinfeld, D. L. (1978). Hedonic housing prices and the demand for clean air. *Journal of Environmental Economics and Management, 5*(1), 81–102.
Harvey, D., et al. (1990). *The condition of postmodernity* (vol. 14). Blackwell Oxford.
Heikkila, E., Gordon, P., Kim, J. I., Peiser, R. B., Richardson, H. W., & Dale-Johnson, D. (1989). What happened to the CBD-distance gradient? Land values in a policentric city. *Environment and Planning A, 21*(2), 221–232.
Hu, Y., & Wang, R.-Q. (2020). Understanding the removal of precise geotagging in tweets. *Nature Human Behaviour*, 1–3.
Hu, Y., Deng, C., & Zhou, Z. (2019). A semantic and sentiment analysis on online neighborhood reviews for understanding the perceptions of people toward their living environments. *Annals of the American Association of Geographers, 109*(4), 1052–1073.
Huang, B., Wu, B., & Barry, M. (2010). Geographically and temporally weighted regression for modeling spatio-temporal variation in house prices. *International Journal of Geographical Information Science, 24*(3), 383–401.
Huang, X., Li, Z., Jiang, Y., Ye, X., Deng, C., Zhang, J., & Li, X. (2021). The characteristics of multi-source mobility datasets and how they reveal the luxury nature of social distancing in the us during the covid-19 pandemic. *International Journal of Digital Earth, 14*(4), 424–442.
Hui, E. C., Chau, C., Pun, L., & Law, M. (2007). Measuring the neighboring and environmental effects on residential property value: Using spatial weighting matrix. *Building and Environment, 42*(6), 2333–2343.
Isard, W. (1956). *Location and space-economy: A general theory relating to industrial location, market areas, land use, trade and urban structure*. MIT Press.
Jia, C., Du, Y., Wang, S., Bai, T., & Fei, T. (2019). Measuring the vibrancy of urban neighborhoods using mobile phone data with an improved pagerank algorithm. *Transactions in GIS, 23*(2), 241–258.
Jorgensen, B. S., & Stedman, R. C. (2011). Measuring the spatial component of sense of place: A methodology for research on the spatial dynamics of psychological experiences of places. *Environment and Planning. B, Planning & Design, 38*(5), 795–813.
Jurdak, R., Zhao, K., Liu, J., AbouJaoude, M., Cameron, M., & Newth, D. (2015). Understanding human mobility from twitter. *PLoS One, 10*(7), Article e0131469.
Kang, C., Gao, S., Lin, X., Xiao, Y., Yuan, Y., Liu, Y., & Ma, X. (2010). Analyzing and geo-visualizing individual human mobility patterns using mobile call records. In *2010 18th international conference on geoinformatics* (pp. 1–7). IEEE.
Kang, Y., Jia, Q., Gao, S., Zeng, X., Wang, Y., Angsuesser, S., Liu, Y., Ye, X., & Fei, T. (2019). Extracting human emotions at different places based on facial expressions and spatial clustering analysis. *Transactions in GIS, 23*(3), 450–480.
Kang, Y., Gao, S., Liang, Y., Li, M., Rao, J., & Kruse, J. (2020a). Multiscale dynamic human mobility flow dataset in the us during the covid-19 epidemic. *Scientific Data, 7*(1), 1–13.
Kang, Y., Zhang, F., Gao, S., Lin, H., & Liu, Y. (2020b). A review of urban physical environment sensing using street view imagery in public health studies. *Annals of GIS, 26*(3), 261–275.
Kang, Y., Zhang, F., Peng, W., Gao, S., Rao, J., Duarte, F., & Ratti, C. (2020c). Understanding house price appreciation using multi-source big geo-data and machine learning. *Land Use Policy*, 104919.
Krause, A. L., & Bitter, C. (2012). Spatial econometrics, land values and sustainability: Trends in real estate valuation research. *Cities, 29*, S19–S25.
Kyle, G., & Chick, G. (2007). The social construction of a sense of place. *Leisure Sciences, 29*(3), 209–225.
Lai, Y., Zheng, X., Choy, L. H., & Wang, J. (2017). Property rights and housing prices: An empirical study of small property rights housing in Shenzhen, China. *Land Use Policy, 68*, 429–437.
Lancaster, K. J. (1966). A new approach to consumer theory. *Journal of Political Economy, 74*(2), 132–157.
Law, S., Paige, B., & Russell, C. (2018). *Take a look around: Using street view and satellite images to estimate house prices* (arXiv preprint arXiv:1807.07155).
Le Boennec, R., & Salladarré, F. (2017). The impact of air pollution and noise on the real estate market. The case of the 2013 european green capital: Nantes, France. *Ecological Economics, 138*, 82–89.
Lee, J. S., & Li, M.-H. (2009). The impact of detention basin design on residential property value: Case studies using gis in the hedonic price modeling. *Landscape and Urban Planning, 89*(1–2), 7–16.
Lee, G., Cho, D., & Kim, K. (2016). The modifiable areal unit problem in hedonic house-price models. *Urban Geography, 37*(2), 223–245.
LeSage, J. (2015). Spatial econometrics. In *Handbook of research methods and applications in economic geography*. Edward Elgar Publishing.
Li, Y., Fei, T., Huang, Y., Li, J., Li, X., Zhang, F., Kang, Y., & Wu, G. (2021). Emotional habitat: Mapping the global geographic distribution of human emotion with physical environmental factors using a species distribution model. *International Journal of Geographical Information Science, 35*(2), 227–249.
Lieske, S. N., van den Nouwelant, R., Han, J. H., & Pettit, C. (2019). A novel hedonic price modelling approach for estimating the impact of transportation infrastructure on property prices. *Urban Studies, 58*(1), 182–202.
Lindenthal, T. (2020). Beauty in the eye of the home-owner: aesthetic zoning and residential property values. *Real Estate Economics, 48*(2), 530–555.
Liu, Y., Liu, X., Gao, S., Gong, L., Kang, C., Zhi, Y., Chi, G., & Shi, L. (2015). Social sensing: A new approach to understanding our socioeconomic environments. *Annals of the Association of American Geographers, 105*(3), 512–530.
Liu, Z., Yang, A., Gao, M., Jiang, H., Kang, Y., Zhang, F., & Fei, T. (2019). Towards feasibility of photovoltaic road for urban traffic-solar energy estimation using street view image. *Journal of Cleaner Production, 228*, 303–318.
Lü, G., Batty, M., Strobl, J., Lin, H., Zhu, A.-X., & Chen, M. (2019). Reflections and speculations on the progress in geographic information systems (gis): A geographic perspective. *International Journal of Geographical Information Science, 33*(2), 346–367.
Luttik, J. (2000). The value of trees, water and open space as reflected by house prices in the Netherlands. *Landscape and Urban Planning, 48*(3–4), 161–167.
Lynch, A. K., & Rasmussen, D. W. (2001). Measuring the impact of crime on house prices. *Applied Economics, 33*(15), 1981–1989.
Massey, D. (1992). A place called home. *New Formations, 17*(3), 3–15.
McLeod, P. B. (1984). The demand for local amenity: An hedonic price analysis. *Environment and Planning A, 16*(3), 389–400.
Mueller, J. M., & Loomis, J. B. (2008). Spatial dependence in hedonic property models: Do different corrections for spatial dependence result in economically significant differences in estimated implicit prices? *Journal of Agricultural and Resource Economics*, 212–231.
Mulley, C. (2014). Accessibility and residential land value uplift: Identifying spatial variations in the accessibility impacts of a bus transitway. *Urban Studies, 51*(8), 1707–1724.
Osland, L., & Thorsen, I. (2008). Effects on housing prices of urban attraction and labor-market accessibility. *Environment and Planning A, 40*(10), 2490–2509.
Panduro, T. E., & Veie, K. L. (2013). Classification and valuation of urban green spaces: A hedonic house price valuation. *Landscape and Urban Planning, 120*, 119–128.
Pánek, J., Glass, M. R., & Marek, L. (2020). Evaluating a gentrifying neighborhood's changing sense of place using participatory mapping. *Cities, 102*, Article 102723.
Pei, T., Sobolevsky, S., Ratti, C., Shaw, S.-L., Li, T., & Zhou, C. (2014). A new insight into land use classification based on aggregated mobile phone data. *International Journal of Geographical Information Science, 28*(9), 1988–2007.
Peng, H., Du, Y., Liu, Z., Yi, J., Kang, Y., & Fei, T. (2019). Uncovering patterns of ties among regions within metropolitan areas using data from mobile phones and online mass media. *GeoJournal, 84*(3), 685–701.
Pettit, C., Shi, Y., Han, H., Rittenbruch, M., Foth, M., Lieske, S., … Jamal, M. (2020). A new toolkit for land value analysis and scenario planning. *Environment and Planning B: Urban Analytics and City Science, 47*(8), 1490–1507.
Pliakas, T., Hawkesworth, S., Silverwood, R. J., Nanchahal, K., Grundy, C., Armstrong, B., … Lock, K. (2017). Optimising measurement of health-related characteristics of the built environment: Comparing data collected by foot-based street audits, virtual street audits and routine secondary data sources. *Health & Place, 43*, 75–84.
Porteous, J. D. (1976). Home: The territorial core. *Geographical Review*, 383–390.
Poudyal, N. C., Hodges, D. G., & Merrett, C. D. (2009). A hedonic analysis of the demand for and benefits of urban recreation parks. *Land Use Policy, 26*(4), 975–983.
Pred, A. (1984). Place as historically contingent process: Structuration and the time-geography of becoming places. *Annals of the Association of American Geographers, 74*(2), 279–297.
Ratti, C., Frenchman, D., Pulselli, R. M., & Williams, S. (2006). Mobile landscapes: Using location data from cell phones for urban analysis. *Environment and Planning. B, Planning & Design, 33*(5), 727–748.
Rodriguez, M., & Sirmans, C. (1994). Quantifying the value of a view in single-family housing markets. *The Appraisal Journal, 62*, 600.
Rose, G. (1995). Place and identity: A sense of place. In *A place in the world?: Places, cultures and globalization* (pp. 87–132).
Rosen, S. (1974). Hedonic prices and implicit markets: Product differentiation in pure competition. *Journal of Political Economy, 82*(1), 34–55.
Sack, R. D. (1997). *Homo geographicus a framework for action, awareness, and moral concern*.
Scheider, S., & Janowicz, K. (2014). Place reference systems. *Applied Ontology, 9*(2), 97–127.
Schläpfer, F., Waltert, F., Segura, L., & Kienast, F. (2015). Valuation of landscape amenities: A hedonic pricing analysis of housing rents in urban, suburban and periurban Switzerland. *Landscape and Urban Planning, 141*, 24–40.
Seamon, D. (1980). Body-subject, time-space routines, and place-ballets. *The Human Experience of Space and Place, 148*, 65.
Shaw, S.-L., & Sui, D. (2020). Understanding the new human dynamics in smart spaces and places: Toward a splatial framework. *Annals of the American Association of Geographers, 110*(2), 339–348.
Shi, L., Chi, G., Liu, X., & Liu, Y. (2015). Human mobility patterns in different communities: A mobile phone data-based social network approach. *Annals of GIS, 21*(1), 15–26.
Sirmans, G. S., MacDonald, L., Macpherson, D. A., & Zietz, E. N. (2006). The value of housing characteristics: A meta analysis. *The Journal of Real Estate Finance and Economics, 33*(3), 215–240.
Su, S., Zhang, J., He, S., Zhang, H., Hu, L., & Kang, M. (2021). Unraveling the impact of tod on housing rental prices and implications on spatial planning: A comparative analysis of five chinese megacities. *Habitat International, 107*, Article 102309.
Sui, D., & Goodchild, M. (2011). The convergence of GIS and social media: Challenges for GIScience. *International Journal of Geographical Information Science, 25*(11), 1737–1748.
Tang, J., Liu, F., Wang, Y., & Wang, H. (2015). Uncovering urban human mobility from large scale taxi gps data. *Physica A: Statistical Mechanics and its Applications, 438*, 140–153.
Tuan, Y.-F. (1979). Space and place: Humanistic perspective. In *Philosophy in geography* (pp. 387–427). Springer.
Vasanen, A. (2012). Beyond stated and revealed preferences: The relationship between residential preferences and housing choices in the urban region of Turku, Finland. *Journal of Housing and the Built Environment, 27*(3), 301–315.
Wang, B. (2021). How does covid-19 affect house prices? A cross-city analysis. *Journal of Risk and Financial Management, 14*(2), 47.

Wang, J., Chen, M., Lü, G., Yue, S., Chen, K., & Wen, Y. (2018). A study on data processing services for the operation of geo-analysis models in the open web environment. *Earth and Space Science, 5*(12), 844–862.

Wang, R., Liu, Y., Lu, Y., Yuan, Y., Zhang, J., Liu, P., & Yao, Y. (2019). The linkage between the perception of neighbourhood and physical activity in Guangzhou, China: Using street view imagery with deep learning techniques. *International Journal of Health Geographics, 18*(1), 1–11.

Wilhelmsson, M. (2000). The impact of traffic noise on the values of single-family houses. *Journal of Environmental Planning and Management, 43*(6), 799–815.

Xiao, Y., et al. (2017). *Urban morphology and housing market*. Springer.

Xu, Y., Shaw, S.-L., Zhao, Z., Yin, L., Fang, Z., & Li, Q. (2015). Understanding aggregate human mobility patterns using passive mobile phone location data: A home-based approach. *Transportation, 42*(4), 625–646.

Xu, Y., Belyi, A., Bojic, I., & Ratti, C. (2018). Human mobility and socioeconomic status: Analysis of Singapore and Boston. *Computers, Environment and Urban Systems, 72*, 51–67.

Yang, F., Jin, P. J., Cheng, Y., Zhang, J., & Ran, B. (2015). Origin-destination estimation for non-commuting trips using location-based social networking data. *International Journal of Sustainable Transportation, 9*(8), 551–564.

Yang, J., Rong, H., Kang, Y., Zhang, F., & Chegut, A. (2021). The financial impact of street-level greenery on New York commercial buildings. *Landscape and Urban Planning, 214*, 104162.

Yao, Y., Liang, Z., Yuan, Z., Liu, P., Bie, Y., Zhang, J., Wang, R., Wang, J., & Guan, Q. (2019). A human-machine adversarial scoring framework for urban perception assessment using street-view images. *International Journal of Geographical Information Science, 33*(12), 2363–2384.

Yilmazkuday, H. (2021). Stay-at-home works to fight against covid-19: International evidence from google mobility data. *Journal of Human Behavior in the Social Environment, 31*(1–4), 210–220.

Zhang, F., Zhou, B., Liu, L., Liu, Y., Fung, H. H., Lin, H., & Ratti, C. (2018). Measuring human perceptions of a large-scale urban region using machine learning. *Landscape and Urban Planning, 180*, 148–160.

Zhang, F., Wu, L., Zhu, D., & Liu, Y. (2019). Social sensing from street-level imagery: A case study in learning spatio-temporal urban mobility patterns. *ISPRS Journal of Photogrammetry and Remote Sensing, 153*, 48–58.

Zhang, F., Zu, J., Hu, M., Zhu, D., Kang, Y., Gao, S., Zhang, Y., & Huang, Z. (2020). Uncovering inconspicuous places using social media check-ins and street view images. *Computers, Environment and Urban Systems, 81*, Article 101478.

Zheng, S., & Kahn, M. E. (2008). Land and residential property markets in a booming economy: New evidence from Beijing. *Journal of Urban Economics, 63*(2), 743–757.

Zhou, B., Liu, L., Oliva, A., & Torralba, A. (2014). Recognizing city identity via attribute analysis of geo-tagged images. In *European conference on computer vision* (pp. 519–534). Springer.

Zhu, D., Wang, N., Wu, L., & Liu, Y. (2017). Street as a big geo-data assembly and analysis unit in urban studies: A case study using Beijing taxi data. *Applied Geography, 86*, 152–164.

Zhu, D., Zhang, F., Wang, S., Wang, Y., Cheng, X., Huang, Z., & Liu, Y. (2020). Understanding place characteristics in geographic contexts through graph convolutional neural networks. *Annals of the American Association of Geographers, 110*(2), 408–420.