Understanding Human Perception of Place with Geospatial Data Science

by

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This dissertation is dedicated to

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ABSTRACT

This doctoral dissertation research is designed to advance our understanding of human perceptions of places using geospatial data science. Measuring human perceptions of places, such as how safe and lively a neighborhood is, is crucial for investigating the human sense of place and for furthering our knowledge of human-environment relationships. However, previous studies using interpretive approaches (e.g., interviews, questionnaires) to measure human perceptions of places face challenges such as high labor intensity, long update periods, and geographic scale limitations. Geospatial data science, including the usage of multiple sources of urban big data (e.g., street view imagery, human mobility) and the development of advanced geospatial artificial intelligence (GeoAI), provides unprecedented opportunities for researchers to not only model objective geographic phenomenon but also assess subjective human perceptions of places from a variety of dimensions (e.g., lively, safe, wealthy).

Here, we first introduce a computational framework to measure human perceptions of places from a data-driven perspective. We employ geocomputational approaches to assess human perceptions of places with large-scale street view images and advanced GeoAI approaches. By comparing with conventional interpretive approaches, we illustrate the effectiveness of geospatial data science for measuring human perceptions of places and acknowledge its potential biases and challenges. We then explore what and how various urban design and environmental factors may affect people's place perceptions to inform city developments. After that, we demonstrate how human subjective perceptions of place might be integrated into place-based spatial analytics and highlight the critical role of human place perception in understanding human-environment interactions. This dissertation is developed based on the author's three peer-reviewed journal articles and has been arranged as chapters 4, 5, and 6.

This work makes contributions to the broader fields of GIScience, geography, and urban planning. First, it shows how socioeconomic and environmental factors influence human

perceptions of places and reveals the complex interactions between human activities and the physical environment. Second, it provides insights and decision-making suggestions for urban planners and governments toward building safer, livelier, and wealthier communities and cities. Third, it illustrates how humanistic insights can be integrated into geospatial data science and offers insights for addressing ethical issues in the development of GIScience.

1 INTRODUCTION

I was born and raised in a tiny frontier town (Shihezi) in China, which I found to be a peaceful, quiet, and slow-paced place. I spent my last year of high school in Hengshui, a polluted, depressing, but still inspiring place. I then completed my undergraduate studies in Wuhan, a metropolis with over 10 million people and lots of skyscrapers, where I enjoyed the hustle and bustle of city life. After that, I continued my studies and conducted research in Madison, Wisconsin, a lovely, beautiful, leisurely city surrounded by the lake Mondota, and in Boston, a city rich in history and diversity. Each city has a unique landscape; each time I visit a new city, from the unfamiliar to the familiar, distinct emotions, memories, and perceptions flood my mind.

People have various perceptions of different places. No matter whether you are visiting a new place or a place you are very familiar with, the environmental settings of the place and your past experience intertwined with the place may evoke your unique emotions, influence your feelings of the place, and ultimately shape your place perceptions. Thus, how can we comprehend our perceptions of different places? How can we measure our subjective impressions of the environment? How can our perceptions of environments guide urban design and development? Motivated by these questions, I plan to provide a comprehensive exploration of our perceptions of place using advanced geospatial data science approaches to advance our understanding of human-environment interactions in this dissertation.

Chapter 1 provides a general introduction. In Sections 1.1 and 1.2, I will introduce the theoretical and methodological foundations, respectively. In Section 1.1, I will outline the concepts and roles of space and place, sense of place, and human place perceptions in geography and GIScience; I will also demonstrate the importance of examining human perceptions of place to gain a better understanding of sense of place for modeling human-environment relationships. Next, in Section 1.2, I will introduce geospatial data science, covering large-scale geospatial big data and advanced geospatial artificial intelligence (GeoAI); the geospatial data science workflow, a thorough overview of the technical foundation of this dissertation will be presented. The chapter goes on to outline the research gaps and proposes three major research questions along with their interrelations in Section 1.3. Finally, I will summarize the structure of this dissertation in Section 1.4.

1.1 Place, Sense of Place, and Human Perceptions

Space and *place* serve as two fundamental conceptions in defining the nature of geography about the *where* of things (Tuan, 1977; Agnew, 2011). Different from space, which focuses more on the abstract and objective settings of locations, place is always considered as intertwined with human experiences and various meanings (Lukermann, 1964; Tuan, 1979). As suggested by Agnew et al. (1987), there are three dimensions of place: (1) *location* — which refers to where an activity or object is located; (2) *locale* — which indicates the material settings where people conduct their everyday-life activities; (i.e., social relations) (Cresswell, 2014) and (3) *sense of place* — which denotes the nebulous human meanings — especially subjective and emotional attachment — of a place. Tuan (1977) argued that place is a way that we see, perceive, and understand the world (Cresswell, 2014). People frame their behaviors from experiences through which we get to know the world via emotion, perception, and cognition (Oakeshott, 1933; Gendlin, 1962; Tuan, 1979, 1990). In comparison, space has been seen as a “fact of life" that purely produces coordinates for human life (Tuan, 1977; Cresswell, 2014). The dichotomy of concepts between space and place has been examined by geographers for decades (McClay and McAllister, 2014).

To further clarify the concept of place and sense of place, I will use the contrast between *home* (a specific type of place) and *house* (from a spatial perspective) as an example. The house you lived in as a child may share similar spatial features (such as housing area, property values, and accessibility to facilities) with several other properties in the same neighborhood; however, the emotions evoked by this house are totally different from those evoked by other properties, given that it is the place — *home* — that affords your unique experience. It is a sense of place that condenses individual social relations, attitudes, and values; while not space, makes it appropriate to take a deep sleep in the bedroom but not in the street; to sit at our windows peering out in a relaxed and joyful way rather than being at other people's windows peering in; to take a rest when we no longer keep a brave front before the world (Tuan, 1975, 1977). Given the significance of the sense of place in understanding human-environment interactions, previous research has made comprehensive examinations of multiple aspects such as place attractiveness and place attachment (Low and Altman, 1992; Wilson, 1997).

Human perception of place, as well as its interactions with the environment, is an important aspect of human sense of place, and for decades has attracted scholars' attention from a wide variety of disciplines and fields, including but not limited to geography, urban planning (Lynch, 1964), environmental psychology (Downs and Meyer, 1978), and public health (Ulrich, 1979). For geographers, human perception is a critical component of the human sense of place, since it reflects our experience, attitude, worldview, and sociocultural ties with places (Cresswell, 2014; Lukermann, 1964; Tuan, 1990). Whether or not a place is perceived as a lively, safe, and beautiful community will surely affect how people experience it. Individuals' worldviews and behaviors are shaped by their experiences, which are in turn influenced by their surrounding environments (Downs and Meyer, 1978). Human geographers, or more specifically, researchers in the field of *perceptual geography*, argue that human behaviors serve as functions of people's feelings and perceptions of the world, indicating strong associations between perceptions of environment and behaviors (Downs and Meyer, 1978; Gold and Goodey, 1983, 1984; Tuan, 2003). Urban planners emphasize the practical values of individual perception to places by focusing on people's subjective feelings toward the environment from three perspectives, including identity, structure, and meaning (Lynch, 1964). Existing environmental psychology studies have also delved into

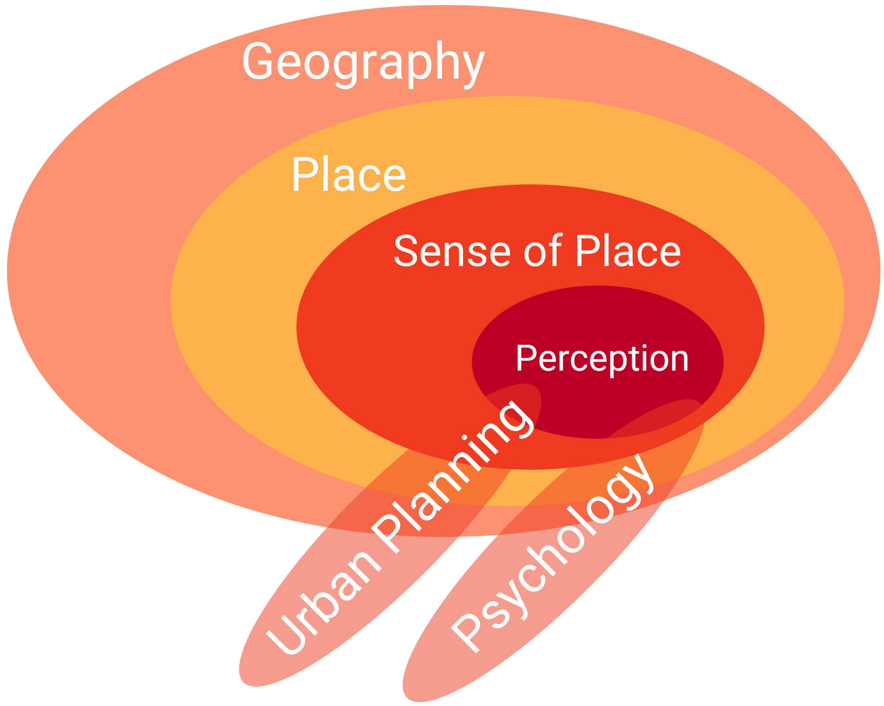

Figure 1.1: A conceptual framework to delineate the position of this study within the field and to demonstrate the relationships among key concepts: geography, urban planning, psychology, place, sense of place, and perception.

the significance of people's subjective perceptions and feelings about urban environments in mental health (Ulrich, 1979, 1984). Individuals can feel less depressed and stressed in a safer, greener, or more beautiful environment, which can have a restorative effect on patients by triggering affective reactions (Galea and Vlahov, 2005; Ulrich, 1984). Consequently, modeling human perceptions of place and examining the sense of place are crucial to advancing our knowledge of human-environment relationships.

This dissertation is building upon these solid theoretical foundations. Figure 1.1 clearly illustrates the position of this study. Informed by the aforementioned significance of studying human perceptions of place, the purpose of this dissertation is to model sense of place, understand human-environment relationships, and offer insights for enhancing human well-being and health and promoting sustainable city development practices.

1.2 Geospatial Data Science

This section begins with a concise introduction to geospatial data science. The fundamental elements and five steps of the geospatial data science workflow are outlined. The background of measuring human place perceptions using geospatial data science is then presented.

1.2.1 The Geospatial Data Science Workflow

It is now the era of big data. Every day, and even every second, people are generating numerous multi-source geospatial big data. Such huge volumes of geospatial big data bring us unprecedented opportunities to model the smart space and place, and to understand associated human behaviors and activities. Powered by advanced geospatial artificial intelligence (GeoAI) techniques, abundant geographic values can be extracted from geospatial big data which benefit individuals and society. Geospatial data science, which utilizes spatial data, develops geospatial techniques, and models geographic phenomena to support real-world decision-making, is playing an increasingly important role in geography and GIScience.

The rapid development of hardware such as location-aware devices, information and communication technologies (ICT), and sensor networks has revolutionized the paradigm for geospatial data collection. Governments, private corporations, and our users are generating huge amount of data every second, not only in terms of size and volume, but also by its variety and velocity (Thatcher et al., 2018). For example, when you use Twitter, you may post geotagged tweets. We can now track vehicles' mobility and trajectory because they are now equipped with GPS. We also have large-scale place data (i.e., points of interest) data that serves as the basic unit of mapping services. In addition, we now have street view images that can describe detailed urban environments. All of these geospatial big data sources provide us with unprecedented opportunities for modeling our digital world.

In this dissertation, the following types of datasets are primarily used, including but not limited to street view imagery, points of interest (POIs), human mobility, and demographic information from the US Census. Among them, street view imagery offers the key data source that allows us to measure human perceptions of place. A more detailed description of the street view imagery can be found in Section 3.2.

To process such huge volumes of geospatial big data, advanced geospatial artificial intelligence (GeoAI) techniques provide powerful tools to extract values from geospatial big data and support geospatial research (Janowicz et al., 2020). With the progress in artificial intelligence (AI), researchers adopt AI algorithms for geospatial knowledge discovery, geographic phenomena modeling, and human-environmental problem-solving, which is referred to as "GeoAI" research. Several advanced architectures were developed based on artificial neural networks and have been applied in geographic tasks, such as convolutional neural networks (CNNs) (Zhang et al., 2018), long short-term memory (LSTM), graph convolutional networks (GCNs) (Zhu et al., 2020), generative adversarial networks (GANs) (Kang et al., 2020a), and other machine learning algorithms including Markov random field (Kang et al., 2022), reinforcement learning (Rao et al., 2021b), federated learning (Rao et al., 2021a).

GeoAI has provided tremendous opportunities for geospatial research by utilizing advanced techniques, data, methods, systems, and services to support intelligent geographic information for a wide range of applications and tasks (Janowicz et al., 2020). GeoAI models including machine learning and deep learning are attracting more attention due to the following two reasons. First, compared with traditional GIS and geostatistics approaches, GeoAI techniques including machine learning and deep learning algorithms may achieve better performances in solving several complex geographical tasks such as object detection and segmentation from geotagged images (e.g., remote sensing images, social media photos, and street view images), geographic information retrieval, spatio-temporal geographic phenomena forecasting (e.g., human mobility, traffic flows). Second, GeoAI may be useful in assisting GIScientists to address several new spatial knowledge discovery tasks that existing GIS tools are unable to tackle, such as the creation of artistic maps and measuring human subjective perceptions of place. Given these advantages of GeoAI approaches, we leverage CNNs to process street view images, extract high-dimensional visual features, and measure human perceptions of place. A more detailed description of the computational framework is illustrated in Section 3.3.

The ultimate goal for geospatial data science is always to extract values from such promising geospatial big data with advanced GeoAI approaches, so that researchers and practitioners can better understand and model the world for the benefit of individuals and society (Thatcher et al., 2018). Hence, in addition to leveraging emerging geographic data sources and developing advanced algorithms, it is necessary to analyze geographic patterns, derive insights from large volume spatial data, and provide support for decision makings. It should be noted that the outcomes of geospatial data science should focus more on characterizing geospatial information, interpreting analysis results, making connections with theories, and establishing insights and communicating with users, rather than relying on algorithms and statistical correlations within datasets solely.

To summarize, geospatial data science can be regarded as a subfield of data science that uses geographic knowledge and AI approaches to extract meaningful insights from large-scale geographic data. Geospatial big data and GeoAI are the two fundamental technical components of geospatial data science. This interdisciplinary field has a broad range of applications and can be used to address challenges and issues across various domains, including but not limited to sustainability, public health, climate change, urban planning, and economics. A framework for illustrating the relationships between these components is presented in Figure 1.2. Its roots are in geography or geographic information science (GIScience), with a focus on spatial contexts (GISGeography, 2022). A general workflow of geospatial data science has been summarized as shown in Figure 1.3. The workflow contains five steps including data collection and management, model development, map-making and geovisualizations, spatial analysis, and implications for society and policy. Table 1.1 illustrates the definitions and research objects of each step, respectively. It should be noted that, researchers may gain insights from the final outputs of the fifth step *Implications for Society and Policy*. By allowing human-in-the-loop and interactions with AI, researchers can evaluate the effectiveness of geospatial data science in the support of decision-making, which in turn benefit the future usage of geospatial data science.

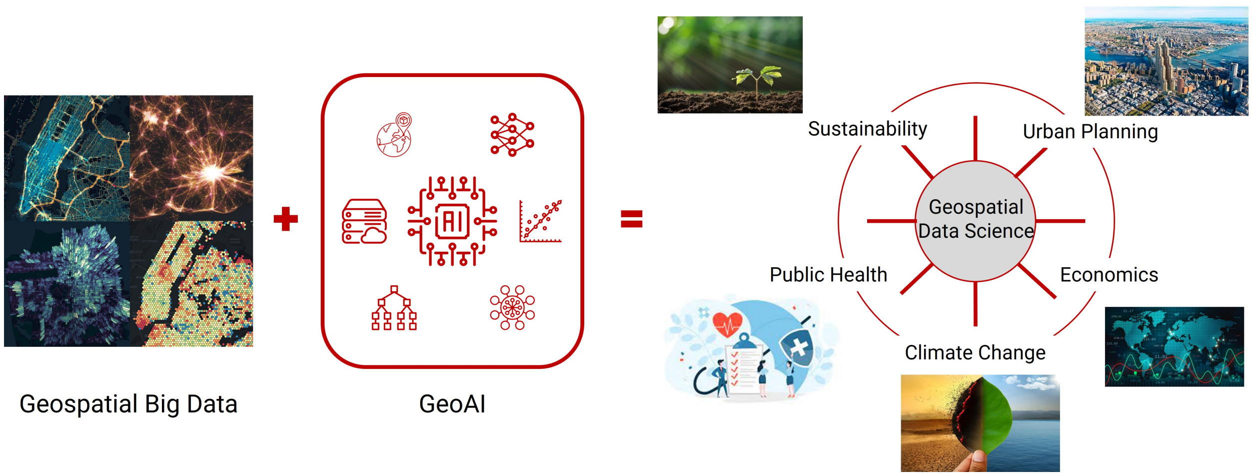

Figure 1.2: The conceptual framework of geospatial data science

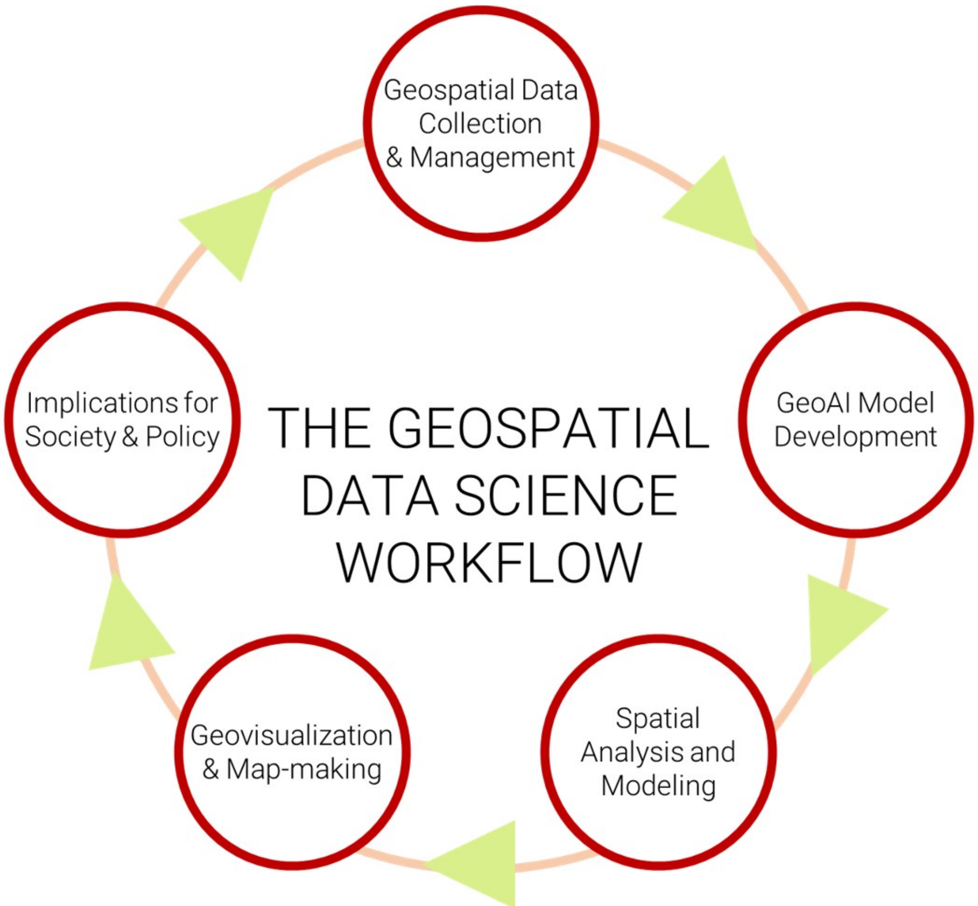

Figure 1.3: The workflow of geospatial data science

Table 1.1: Definitions of the five steps in the geospatial data science workflow.

Number	Step	Objective
1	Data collection and management	Capture large-scale geospatial data; store and maintain geospatial data with spatial database; use, manage, and share geospatial data.
2	Model development	Develop and deploy (spatial explicit) AI approaches to process and analyze geospatial data; perform and solve geographic tasks.

3	Map-making and geovisualizations	Create and design maps and geovisualizations to deliver geographic information and support decision-making.
4	Spatial analysis	Perform GIS and spatial statistics tools to analyze results; infer and discover geographic patterns to advance spatial knowledge.
5	Implications for society and policy	Derive insights for individual and society; provide policy suggestions for decision makers.

Despite the current success of geospatial data science in tackling a wide range of real-world problems and challenges, researchers and practitioners have growing concerns about the ethical issues of geospatial data science. Generally speaking, ethics refers to the rules of conduct regarding acceptable and unacceptable behavior within a particular social system (Siau and Wang, 2020). It is important to diagnose and prevent misuse of GIScience and geospatial data science by assessing their ethics. The ethical concerns are raised from two primary arenas: logical extensions to the existing Codes of Ethics governing GIScience (Nelson et al., 2022) and the ethical concerns about GeoAI raised by researchers outside of GIScience (e.g., researchers from computer science) (Jobin et al., 2019). Several notable unethical examples of AI and GIS include the awareness of using police surveillance and potential bias. For instance, AI may produce biased and even discriminatory results towards certain groups of people (Manyika et al., 2019). Therefore, it is crucial to develop trustworthy and responsible geospatial data science approaches by observing and mitigating bias, protecting human geoprivacy, and enhancing the explainability of geospatial data science models.

1.2.2 GeoAI-based Place Perception Measures

One remarkable advantage of geospatial data science is that researchers can model human subjective experiences such as perceptions and emotions, which were formerly thought to be challenging for GIS technology. For example, by combining street view images and deep convolutional neural networks, people's subjective perceptions of the built environment can be assessed to reflect their place perceptions (Dubey et al., 2016; Salesses et al., 2013; Zhang et al., 2018). A global dataset — MIT Place Pulse — was constructed that contains one million labeled images. Researchers have leveraged such a dataset to measure people's general place perceptions of streetscapes (Dubey et al., 2016). Participants were asked to rate street view images from six perceptual dimensions including *safe*, *beautiful*, *depressing*, *lively*, *wealthy*, and *boring*. The responses from volunteers to the street view images were seen as a proxy for their perceptions of the real-world scenery. Similarly, several other online surveys and platforms have been built to collect the multiple dimensions of human perceptions of the environment (Evans-Cowley and Akar, 2014; Yao et al., 2019; Kruse et al., 2021). Given its effectiveness, this dissertation also adopt such a computational approach, using the term *GeoAI-based place perception approaches* throughout the dissertation. More technical details are provided in Section 3.

In short, geospatial data science provides a solid methodological foundation for this dissertation. We adopts the geospatial data science workflow, combine geospatial big data and advanced GeoAI approaches, aim to measure human subjective perceptions of place, and gain insights to support decision-making in urban design and development and address problems between human and environment.

1.3 Motivations and Research Questions

In this section, I will demonstrate the motivations to conduct this dissertation, identify several research gaps that have not been adequately addressed or for which there is no existing literature, and then propose three research questions (RQs): RQ1, RQ2, and RQ3. The three RQs have taken into account both the depth and breadth of the subject of human perceptions of places. This dissertation seeks to bridge these multiple knowledge gaps by addressing the three RQs across the three experiments in Chapter 4-6. By setting the three RQs, we describe the main scope and the "boundary" of the research in the following paragraphs.

One important motivation of this research refers to the criticism that conventional GIS tools pay insufficient attention to human experiences (Shaw and Sui, 2020; Zhao, 2021), and may not be able to handle subjective human perceptions of places. To address these comments, several critical questions might be asked: How do we derive, conceptualize, and handle the vague place computationally? How do we integrate the concepts of places such as human sense of place, place perceptions, and other humanistic insights in GIS? The dissertation's aim is to partially provide some answers to these questions and to offer insights for multiple disciplines such as geography, urban planning, social science, public health, and computer science.

Traditionally, to measure human perception-environment interactions and evaluate human environmental perceptions, researchers from human geography and urban planning have used several interpretative approaches such as interviews, questionnaires, secondary resources, and mental maps (Cresswell, 2014; Montello, 2003). These traditional approaches have several challenges, such as high labor intensity and low cost-effectiveness, long update periods, and restriction to small-scale geographic areas, all of which makes performing experiments and analysis relatively complex and time-consuming. To overcome these limitations, several past studies have combined street view images and deep learning approaches to evaluate human perceptions of the environment from a data-driven perspective. These GeoAI-based place perception measurements are cost- and time-efficient and can cover a wider geographic area. A computational workflow using geospatial data science to measure human place perceptions is first proposed as a prerequisite for the experiments in Chapter 3. Despite its success, the ethical issues with this approach have not been thoroughly addressed or even recognized yet. It should be noted that the two data collection methods, namely traditional survey-based approaches and GeoAI-based approaches, follow different paradigms. Using traditional approaches, human perceptions of place might be derived from people's local experiences. While using GeoAI-based approaches, people's perceptions of place might be derived from people's general visual perceptions of the built environments. What are the relationships between these two measurements? Is there bias between the two and why? Furthermore, there may be potential model bias while training GeoAI-based place perception measurements. However, existing studies that have adopted GeoAI-based approaches either do not consider the difference between the two measurements or do not account for model bias.

Given these research gaps, we ask the following question RQ1:

RQ1: *What are the differences between the traditional approach and the geospatial data science approach in measuring human perception of place?*

To answer this question, I will assess and compare two forms of people's perceptions including the GeoAI-based perceptions and survey-based perceptions, to understand their perception bias and observe the model bias when training GeoAI approaches in Chapter 4. Based on the outcomes of Chapter 4, we will validate the effectiveness of the GeoAI-based approaches in measuring place perceptions, and have a better understanding of the characteristics of the GeoAI-based perceptions.

After demonstrating the efficacy of using geospatial data science to measure human perceptions of place, I am interested in how human place perceptions are shaped and may offer insights that could promote urban development. The human perceptions of place measured with geospatial data science are primarily derived from the built environments based on their urban visual characteristics. Researchers and practitioners in urban design and planning have identified a set of elements and principles in an effort to improve the urban quality that makes it comfortable for people to live in a place. Moreover, the colors of urban environments may have a psychological impact on human perceptions of place as well. However, how urban visual characteristics influence human perceptions has not been examined yet.

To bridge such a knowledge gap, we ask the following question, RQ2:

RQ2: *What and how do urban visual characteristics of built environments quantitatively associate with human perceptions of places measured by geospatial data science?*

To answer this question, I will first model urban visual characteristics, including Lynch's five elements of urban design (Lynch, 1964), urban design qualities of walking environments (Ewing and Handy, 2009), and colors. Then, by leveraging advanced explainable machine learning approaches including a causal discovery algorithm, this work reveals the complex relationships between human perceptions of place and urban visual characteristics in Chapter 5. The outcomes of Chapter 5 may allow us to better understand our subjective experiences and could guide future urban planning practices.

In addition to uncovering the driving factors of human place perceptions, I further explored how to leverage human place perceptions in spatial analysis. As mentioned above, traditional GIS approaches may have not paid sufficient attention to human experiences (Shaw and Sui, 2020; Zhao, 2021). Researchers conduct spatial analysis and modeling without considering place-based aspects such as the human subjective sense of place, due to the absence of effective data and measurements of human experiences. Even though a few prior researchers have employed geospatial big data to understand subjective human cognition of place and emotions in places, human experiences are viewed as functions of physical environments of place. Additionally, despite the fact that human geographers have emphasized the important role of "home" as a living place that condenses human social, psychological, and emotive experiences, existing housing-related studies only focused on the capitals of houses.

To bridge these research gaps, we ask the following question RQ3:

RQ3: *How do we integrate the human perception of place with geospatial data science including* *emerging data sources and advanced GeoAI into human settlement value assessment?*

To answer this question, we propose a conceptual framework that integrates human perceptions and human dynamics into modeling human settlement values from a platial perspective to measure "home" rather than "house" in Chapter 6. Unlike traditional place-related research that adopts a qualitative approach and incorporates philosophical theory for spatial modeling, or a bottom-up approach (O'Sullivan, 2017), our frameworks that integrate the measurements of human place perception with geospatial data science might be seen as a top-down view. We expect to offer new insights for the future GIScience and spatial analysis looking toward a place-oriented study.

1.4 Dissertation Structure

The dissertation will be structured based on an accumulation of three individual but interrelated articles by the author, which are Chapter 4, Chapter 5, and Chapter 6 (Kang et al., 2021). In addition, several materials by the author that are relevant to the dissertation contents appear in Chapter 3 (Kang et al., 2020b). The remainder of the dissertation is organized as follows.

Chapter 2 presents a comprehensive review of the background literature of this dissertation. Theoretical foundations of human perceptions of places are introduced; pioneer studies using geospatial data science for measuring human perceptions are summarized; and challenges and ethical issues in existing geospatial data science studies are discussed.

In Chapter 3, the general methodology of this dissertation is described, including street view imagery and measuring human perception of places with GeoAI models. The following three chapters focus on different RQs toward a comprehensive understanding of human perception of place.

Chapter 4 will present a study that compares the urban safety perceptions measured with geospatial data science and survey. We describe the spatial characteristics of perception bias and analyze its driving factors in the built environment. Model biases are also discussed that offer insights for addressing ethical issues in geospatial data science.

Chapter 5 will present a study that examines a variety of urban design elements and factors that may contribute to multiple dimensions of human perceptions. The relationships between urban design perceptions are delineated using explainable machine learning algorithms such as feature importance and a causal discovery algorithm. The results not only advance our understanding of human perceptions but may offer insights for future urban design.

Chapter 6 presents a study that proposes a place-oriented hedonic pricing modeling taking human perceptions and human dynamics into account for human settlement value assessment. The experiments show that human place perceptions matter, given that people tend to build up their "home" instead of merely purchasing a "house." Results approve the need for incorporating the sense of place in spatial analysis and emphasize the key role human perceptions have played in geospatial data science.

Finally, I summarize the conclusions of this dissertation, contributions to multiple subjects, and the broader implications of this dissertation. I also discuss several limitations and point out a few future directions that are worth exploring in Chapter 7.

2 LITERATURE REVIEW

Chapter 2 provides a comprehensive literature review on the major topics that are relevant to this dissertation. To illustrate the significance of understanding human perceptions of places, I first introduce how human place perceptions were traditionally studied in different fields using several interpretative approaches (e.g., surveys, questionnaires, and mental maps) in Section 2.1. Then, I talk about the explosive growth development of geospatial data science in recent years in Section 2.2 and demonstrate how it can be employed to study human sense of place, and help assess human perceptions of place in Section 2.3. Finally, I summarize several challenges in existing geospatial data science that motivate this dissertation, along with several ethical concerns in geospatial data science that require additional attention when measuring and analyzing human perceptions of place in Section 2.4.

2.1 Human Perceptions of Place

Researchers in geography, urban planning, environmental psychology, and public health have examined the interactions between human perceptions and the environment for decades. *Perceptual geography*, also known as *environmental perception*, is a specific research area mixed with geography, environment, and psychology with the belief that the way we perceive the world affects our human behaviors (Downs, 1970; Downs and Meyer, 1978; Ittelson, 1978; Bunting and Guelke, 1979). As a crucial component of the human sense of place, human place perceptions reflect our experience, attitude, and sociocultural ties, offering presentational, affective, and emotional meanings of place (Cresswell, 2014; Lukermann, 1964; Tuan, 1979; Burton, 1963; Burnett, 1976). As suggested by Solomon (1952), "we act and choose on the basis of what we see, feel, and believe; meanings and values are part and parcel of our actions. When we are mistaken about things, we act in terms of our erroneous motives, not in terms of things as they are." This clearly emphasizes the interconnections between human perceptions and behaviors.

Prior studies have made efforts to invest human perceptions of place towards a better understanding of human-environment interactions from both humanistic and empirical perspectives (Downs and Meyer, 1978; Bunting and Guelke, 1979). Geographers have investigated how human perceptions of landscape may influence their behaviors such as in settlements (Tuan, 1990; Blouet et al., 1975; Bunting and Guelke, 1979; Ittelson, 1978) and behaviors at shopping centers (Downs, 1970; Heinemeyer, 1967). Human reactions to hazards, termed *hazard perceptions*, ranging from natural hazards, such as floods, snow, drought, tidal waves, earthquakes, to man-made hazards such as pollution and traffic have also been studied to provide policy-making suggestions (White, 1974; Parker and Harding, 1979; Kasperson and Dow, 1993; Boufous et al., 2011; Nyimbili et al., 2018).

Another important stream of place perception research refers to the usage of the cognitive mapping approach (Downs and Stea, 1973; Gould and White, 2012). In Lynch (1964)'s seminal book, volunteers are invited to draw mental maps that reflect their subjective feelings toward the urban environment. As shown in Figure 2.1, the map shows how residents and workers in Boston perceive and recognize places in Boston. The three perspectives of urban imageability are emphasized including identity, structure, and meaning. Other researchers use cognitive mapping approaches and describe urban imageability as mixtures of visual perceptions and social meanings (Gulick, 1963; Bunting and Guelke, 1979; McCunn and Gifford, 2018; Rapoport, 2016).

In addition, prior studies from environmental psychology have also paid attention to the interactions between environments and human well-being (Ulrich, 1979, 1984; Araya et al., 2006). Researchers have explored the associations between people's subjective perceptions and feelings about urban environments and mental health (Evans, 2003; Galea and Vlahov, 2005). Individuals who have greater exposure to safer, greener, more open, or more beautiful environment may have a wide range of more favorable physiological outcomes such as reduced levels of depression and anxiety, less stress, and enhanced

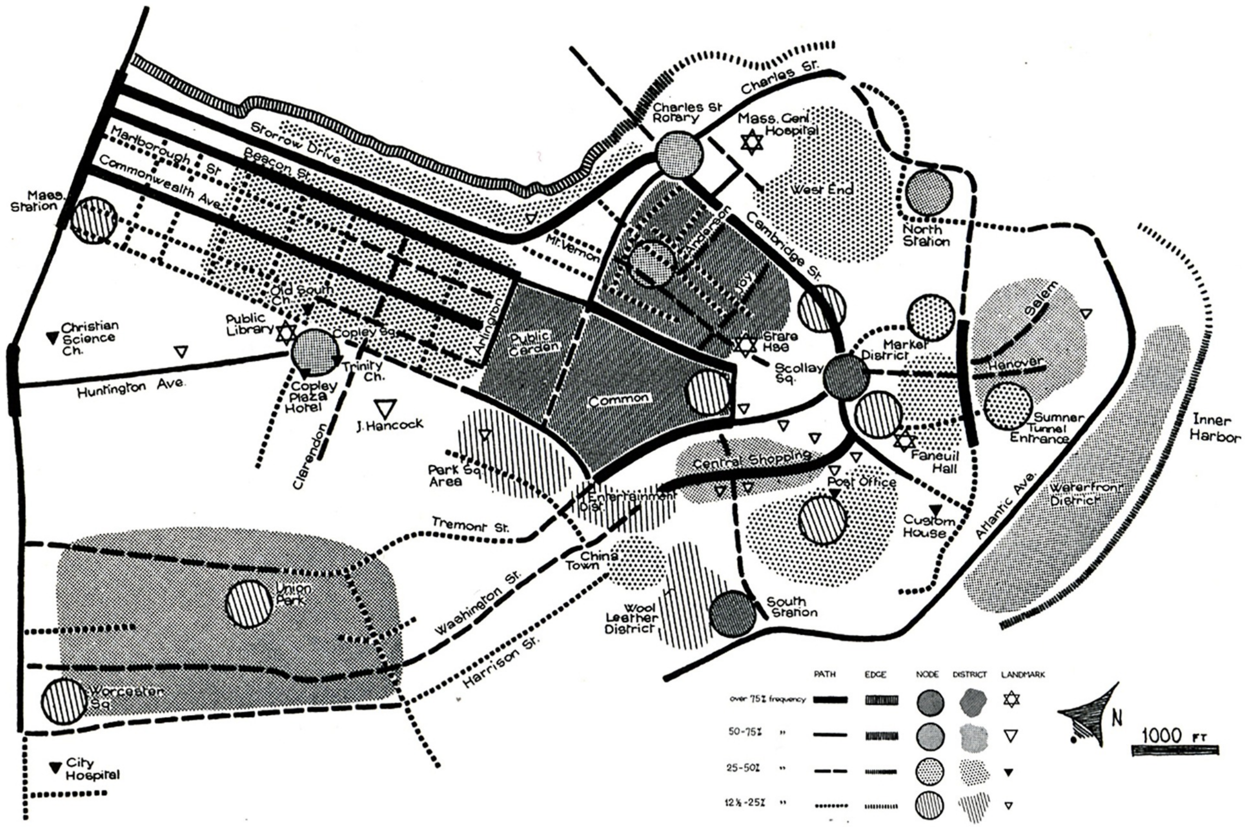

Figure 2.1: The Boston community map as expressed through verbal interviews. Source: Lynch, Kevin, *The Image of the City*, Figure 35 and corresponding legend, pp. 145–146, 1960. Copyright Massachusetts Institute of Technology, by permission of The MIT Press.

quality of life with better emotions (Galea et al., 2005; Ulrich et al., 1991; Lorenc et al., 2012; Ceccato, 2013; Svoray et al., 2018; Buxton et al., 2021). Hence, it is necessary to model human perceptions of built environments and examine the role of the sense of place in deepening our understanding of human-environment relationships. Results of the abovementioned studies provide insights for urban design to develop better living places and more health-conscious cities (Galea and Vlahov, 2005).

A prerequisite to understanding human place perceptions is to collecting the human sense of place data. Historically, researchers used interviews and questionnaires to collect data on different dimensions of human perception of places. Though these traditional approaches may encounter some challenges, such as being relatively labor-intensive and time-consuming, researchers have successfully investigated the associations between multiple dimensions of place perceptions (e.g., safety, lively, beautiful) and physical and socioeconomic environment. The following paragraphs present two main themes of studies, namely, urban safety perceptions, and perceptions of quality of life.

People's perception of urban safe environment plays an important role in choices of residents' settlement (Sundeen and Mathieu, 1976; Ceccato and Lukyte, 2011; Rastyapina and Korosteleva, 2016). People tend to live in a place that makes them feel safe from risk or danger. The feelings of security and fear of crime thereby play important roles in judging whether a place is safe or not, and are key components of human sense of place (Kaplan, 1979; Box et al., 1988; Van den Berg et al., 2019; Raco, 2007). Prior studies have established surveys to collect people's perception of safe places (Schroeder and Anderson, 1984; Stamps III, 2005), understand the fear of crime (Smith, 1987; Hale, 1996; Doran and Burgess, 2012), evaluate police performance (Priest and Carter, 1999; Huynh, 2022), and examine factors that stimulate people's fear (Schweitzer et al., 1999; Velasquez et al., 2021).

Another key dimension of human perception of place stems from people's pursuit of improving their quality of life. Prior studies have explored residents' subjective experience of neighborhood quality through survey and questionnaire to understand their satisfaction and platial attachments (Marans and Rodgers, 1975; Campbell et al., 1976; Connerly and Marans, 1985). Volunteers are recruited to collect their subjective experience that represent their feelings of living environment. Then, researchers made efforts in understanding the relationships between objective environments and subjective social and cultural factors (Seik, 2000; Marans, 2003; Lee, 2008b; Gabriel and Bowling, 2004; Huang et al., 2022; Plascak et al., 2021). The measurement of people's quality of life experience may provide supports for public policy implementation (Dahmann, 1985), urban design (Moser, 2009), and benefit individual settlement choice and well-being (Zehner, 1977; Marans and Stimson, 2011).

To summarize, prior studies have made great efforts in understanding the relationships between human perceptions of places and environments. All of the aforementioned studies offer solid theoretical foundations for this dissertation in terms of the significance of studying human perceptions of places. In parallel, geospatial data science including geospatial big data and GeoAI may provide cutting-edge techniques that better capture human environmental perceptions of place.

2.2 Geospatial Big Data and GeoAI

Geospatial Big Data and ***GeoAI*** are the two basic elements of ***Geospatial Data Science***. For every second, huge volumes of geospatial big data have been produced which present unparalleled opportunities to model smart spaces and places, and to better understand human behaviors and activities. For example, institutes such as NASA (National Aeronautics and Space Administration), USGS (United States Geological Survey) have produced petabyte-level high-resolution remote sensing images and topology maps (Sharwood, 2020); millions of points of interest (POIs), road segments, and street view images have been collected by several mapping companies. User-generated content (UGC), a form of content created by users of a system or a service and made available publicly on that system, also provides proliferate geospatial data foundations (Cha et al., 2009). UGC includes but not limited to geotagged social media posts, cell phone data, smart card data from transportation, GPS-enabled location services, and can be grouped into two categories (Gao et al., 2021). The first one is also known as volunteered geographic information (VGI) (Goodchild, 2007; Sui et al., 2012). Volunteers actively create geographic information and contribute to Web platforms so that both public and private sectors have access to the data, such as Wikimapia and OpenStreetMap (OSM). The second type of UGC refers to the socially constructed data such as data entries produced from various social media platforms and location services collected from smart phone applications. Such data might be produced by users unconsciously, but may have a higher accuracy as it is generated in the process of using the platforms with certain purposes (Harvey, 2013). For example, mobility and trajectory data, geotagged social media texts and photos, points of interest (POIs), where location information and geographic contexts are attached. The emergence of geospatial big data enables researchers to better observe, address, and tackle challenges and problems in urban environments towards sustainable city development (Martinez-Fernandez et al., 2012; Cheshire and Hay, 2017), which also foster the new paradigm in urban analytics and GIScience (Batty, 2019; Gahegan, 2020).

The integration of AI in geospatial studies can be traced back to 1980s (Smith, 1984; Couclelis, 1986; Openshaw and Openshaw, 1997). Recently, it has once again become a spotlight because of the rapid development of AI algorithms (such as machine learning and deep learning) in computer science. Back in 2012, the deep convolutional neural network (DCNN)-based approach achieved significant improvements in image object detection tasks (Krizhevsky et al., 2017). Later, AlphaGo (Silver et al., 2017), an intelligent system that uses advanced deep learning and reinforcement learning, beat the human championship in the Go game. Inspired by them, GIScientists started adopting deep learning approaches in the field of GIScience and made efforts in integrating spatial thinking to guide the development of AI (Janowicz et al., 2020). As suggested in Gao (2021), "GeoAI can be regarded as a study subject to develop intelligent computer programs to mimic the processes of human perception, spatial reasoning, and discovery about geographical phenomena and dynamics; to advance our knowledge; and to solve problems in human environmental systems and their interactions, with a focus on spatial contexts and roots in geography or geographic information science (GIScience)." In this dissertation, we will employ several advanced GeoAI approaches to measure human subjective perceptions of place with deep learning, machine learning, and causal discovery algorithms.

2.3 Geospatial Data Science for Sense of Place

The rapid development of geospatial data science, including geo-big data and state-of-the-art GeoAI approaches, offer unprecedented opportunities to model both objective geographic phenomena and understand subjective human experiences (e.g., perception, emotion, cognition) at place. As a methodological foundation for this dissertation, I summarize previous research that has used geospatial data science to model the human sense of place from multiple aspects. Specifically, I will offer a detailed literature review of human perceptions of place in Section 2.3.1, and then briefly introduce literature related to human emotions at place in Section 2.3.2 and human cognition of place in Section 2.3.3.

2.3.1 Measuring Human Perceptions of Place

To assess human place perceptions, researchers have employed large-scale street view imagery combined with advanced computer vision models to understand how people perceive environments (Salesses et al., 2013; Dubey et al., 2016; Zhang et al., 2018; Filomena et al., 2019; Biljecki and Ito, 2021). Street view images describe the urban streetscape including natural scenes and man-made landscapes with an angle of view similar to that of human vision. Based on street view imagery, researchers have recruited volunteers to collect their perceptions of streetscapes as proxy of place perceptions (Salesses et al., 2013; Liu et al., 2016; Evans-Cowley and Akar, 2014). For instance, the MIT Place Pulse image [1] that contains one million labeled street view images has been built to quantify human perception scores to streetscapes from six dimensions (safe, lively, boring, wealthy, depressing, beautiful), allowing a global-scale assessment of human place perceptions (Dubey et al., 2016). In addition to such global-scale human perception dataset, researchers have also created other survey platforms to collect a wide range of human perceptions depending on their research objectives (Ruggeri et al., 2018; Ye et al., 2019; Liu et al., 2022a; Shen et al., 2017; Yoshimura et al., 2020). Also, several studies have suggested that residents

[1] https://centerforcollectivelearning.org/urbanperception

with local knowledge, rather than relying solely on feelings toward visual cues of street view images, may more accurately reflect human sense of place, so it is necessary to recruit local residents to assess their urban perceptions of neighborhood and community where they live (Yao et al., 2019; Verma et al., 2020). Given that recruiting volunteers is generally not a cost-effective operation, an alternative solution is to use Amazon Mechanical Turk to accelerate the process of collecting human urban perceptions (Kruse et al., 2021; Ito and Biljecki, 2021). In this dissertation, we employ both the global-scale dataset and the local-scale dataset (introduced in Chapter 3).

After obtaining human subjective perceptions of place upon street view images, deep learning models are trained to learn people's place perception patterns. Multiple dimensions of human subjective perceptions of place have been evaluated. Researchers then employ the assessed human perceptions of place and analysed various environmental factors that may affect human place perceptions. Here, I summarize several dimensions of human perceptions and research topics that have been studied by existing studies.

Human safety perceptions have been extensively studied. Several studies have examined the effect of the built environments on human perception of safety, including class and uniqueness. Naik et al. (2014) proposed an algorithm to predict the perceived safety of a streetscape, while Porzi et al. (2015) predicted the perceived safety of a scene from street view images. Associations between urban greenery and perceived safety were investigated by Li et al. (2015b). Moreover, Compernolle et al. (2016) analyzed the associations between perceived safety and aesthetics of the environment and human behaviors, while Hollander et al. (2021) examined the relationship between perceived safety and transportation policy factors. Zhang et al. (2021a) analyzed the perception bias of the mismatch between perceived safety and criminal activities, while Sun and Lu (2022) investigated the associations between environmental inequalities and health-related elements such as perceptions of safety and beauty.

Aesthetics and visual quality are also important aspects in the field of urban design and planning. Quercia et al. (2014) investigated environmental factors that contribute to the perception of neighborhoods as beautiful, quiet, and/or happy, and Seresinhe et al. (2015) quantified the relationship between perceived environmental aesthetics and human health. Compernolle et al. (2016) analyzed the associations between perceived safety and aesthetics of the environment and human behavior, and Saiz et al. (2018) measured perceived architectural beauty from geotagged photos. Zhang et al. (2020) discovered the relationship between livability and beautiful places in cities, and Sun and Lu (2022) investigated associations between environmental inequalities and health-related elements such as perceptions of safety and beauty. Prior studies have also assessed the visual quality of the built environment. For instance, Ye et al. (2019) analyzed associations between the perceived visual quality of streets and environmental factors. Tang and Long (2019) analyzed variations between the perceived visual quality of urban spaces and physical environmental factors. Qiu et al. (2021) measured four dimensions of human perceptions to urban scenes including enclosure, human scale, complexity, and imageability. Xu et al. (2022) investigated the difference between objective and subjective measures of perceptions including greenness, walkability, safety, imageability, enclosure, and complexity. Guan et al. (2022) quantified human perception of scene complexity and analyzed its influencing visual, structural, and semantic factors. Qiu et al. (2022) estimated the role of urban design qualities such as enclosure, human scale, complexity, imageability, and safety in explaining housing prices.

Livability is a crucial component for improving human quality of life. Researchers have examined environmental factors that influence human livability perception. For example, Ruggeri et al. (2018) investigated the associations between perceived livability and environmental factors in cities, while Zhang et al. (2020) examined the relationship between livability and beautiful places in cities. Street view images have also been utilized to measure urban bikeability, i.e., whether the urban environments are appropriate for biking activities. Evans-Cowley and Akar (2014) examined environmental factors that influence the perceived bikeability of environments, and Ito and Biljecki (2021) assessed urban bikeability using human perceptions of the urban environment.

In addition to these studies, researchers have also examined other dimensions of human perceptions of the built environment, such as uniqueness (Salesses et al., 2013), quietness (Quercia et al., 2014), and happiness (Quercia et al., 2014; Xiang et al., 2021). Also, Kruse et al. (2021) explored environmental factors that influence perceived urban playability which refers to whether a place is appropriate for children to play, which may benefit their future growth. Urban green space is another key aspect of the built environment. Researchers have conducted experiments in understanding the associations between perceptions and urban green space. Fu and Song (2020) explored the relationships between perceived green space and greenery environment Xu et al. (2022) investigated the difference between objective and subjective measures of perceptions including greenness, walkability, safety, imageability, enclosure, and complexity

In addition, researchers have employed the Place Pulse dataset to measure the six dimensions of human perceptions. Wang et al. (2019c) analyzed the impacts of perceptions of the built environment on older health outcomes. Wang et al. (2019b) investigated associations between perceptions of the built environment and physical activities. Verma et al. (2020) predicted human perceptions of urban environment based on physical settings with street view images and audio clips. Kang et al. (2021) analyzed the associations between human perceptions and house prices. Yao et al. (2021) analysed the homogeneous geographic patterns of human perceptions. Zhang et al. (2021b) quantified the associations between human perceptions and urban scenes. Dai et al. (2021) analyzed the associations between the urban visual space and human perceptions. Zhu et al. (2020) investigated place characteristics with human mobility and human perceptions. Hu et al. (2022) quantified the relationships between shapes and amount of urban street trees and human perceptions.

Despite that measuring people's place perceptions using geospatial data science approach have been widely implemented to understand human-environment relationships, researchers have also noticed the limitations of such approaches. One notable limitation refers to the fact that place perceptions measured by geospatial data science approaches rely on people's visual perceptions of streetscapes (Quercia et al., 2014). However, human perceptions of place may also be influenced by their experiences attached to place which might be missed in the geospatial data science approach. Therefore, it is necessary to investigate the characteristics of such approaches which may guide the further spatial analysis. We made such explorations in Chapter 4.

2.3.2 Measuring Human Emotions at Place

Beyond human perceptions of place, a variety of important aspects of human sense of place have been assessed with geospatial data science, including human emotions and sentiments at place, as well as human cognition of place. Even if we merely examined human perceptions of place in this dissertation, the other factors are also key elements of human sense of place and may worth further exploration in the future. Here, I briefly introduce the recent advancements in measuring human sense of place including emotions and cognition.

Emotion is a mental state stored in our neurological system and is associated with human thoughts and feelings such as happiness, surprise, sadness. Human emotions are interconnected with surrounding environments by triggering a variety of feelings and experience. People also express their thoughts and feelings through sentiments (e.g., positive, negative, and neutral). The associations between human emotions and sentiments, and environment have been examined to enrich our understanding of places, which is termed "Place Emotion" studies (Kang et al., 2019; Huang et al., 2020a). Two forms of geospatial data have been used for evaluate human emotions and sentiments, namely, geotagged texts and geotagged images.

Prior studies have applied advanced text mining techniques with spatial analysis to estimate human emotions at places with geotagged texts collected from social media platforms such as Twitter and Weibo. Social media users share thoughts about their daily life, nearby events, and the surrounding environments. When users post status updates to social media, their emotions, sentiments, and opinions are also revealed through these posts, with which researchers have examined multiple factors that influence human emotions. For instance, Frank et al. (2013) investigated the relationships between expressed happiness and patterns of life from geolocated tweets. Mitchell et al. (2013) analyzed the distribution of emotions in the United States and explored potential socioeconomic factors that determine the emotions associated with a place. Yang and Mu (2015) detected depressed Twitter users and their spatial clusters in US metropolitan areas. Socioeconomic variables from the Bureau of the Census and climate risk factors were found to have an impact on the prevalence of depression but may vary seasonally in different regions (Yang et al., 2015b). High levels of air pollution were found to contribute to the urban population's reported low level of happiness in social media based on the analysis of over 210 million geotagged Weibo posts in China (Zheng et al., 2019). The variations of human emotions during the COVID-19 pandemic were assessed (Wang et al., 2022). A semantic-specific sentiment analysis was conducted on Web-based neighborhood textual reviews in the city of New York for understanding the perceptions of citizens toward their living environments (Hu et al., 2019).

In addition to geotagged texts, geotagged images have also attracted attention in recent years because of the rapid development of computer vision technologies and deep learning models, which can extract and analyze high-dimensional visual semantics from images. The geotagged photos uploaded to social media platforms may contain human facial expressions which could reflect human emotions. Researchers have assessed human emotions at places from facial expressions in geotagged images on social media platforms. For example, Abdullah et al. (2015) measured human sentiments from facial expressions and correlated with socioeconomic attributes of places. Kang et al. (2019) extracted human emotions from facial expressions in over 6million social media photos and explored the relationship between the physical environment and human emotions at different tourist sites. A positive correlation was found between the happiness score and the presence of natural environments such as water bodies and green vegetation in different types of place (Svoray et al., 2018; Kang et al., 2019). Li et al. (2021) mapped worldwide emotion distributions based on facial expressions to better understand the associations between human emotions and the built environment. Huang et al. (2020b) compared human emotions evaluated from online social media platforms and field survey to analyze the bias of emotions.

2.3.3 Measuring Human Cognition of Place

Besides human emotions at place, multiple aspects of human cognition of place has been evaluated as well. For example, Gao et al. (2017) assessed the human cognition to different toponyms through multi-source social media datasets to characterize vague place boundaries. Wu et al. (2019) proposed a fuzzy concept analysis-based approach that delineates the spatial hierarchies among different places and regions. Manley et al. (2021) measured human "cognitive accessibility" to understand people's perception of distance with multiple urban factors. All these studies offer insights of using geospatial data science for effectively understanding multiple aspects of human sense of place, and better modeling subjective human experiences towards the development of place-based GIS.

2.4 Challenges and Ethics in Geospatial Data Science

Despite its remarkable success in tackling a wide range of real-world geographic problems, geospatial data science is not without flaws, and challenges remain. In particular, there are two major challenges in the current geospatial data science: (1) inadequate attention was paid to human experiences; and (2) ethical considerations should be addressed throughout the development of geospatial data science, particularly GeoAI. The two challenges are introduced in Section 2.4.1 and 2.4.2, perspectively.

2.4.1 Insufficient Attention on Human Experiences

Researchers have argue that traditional GIS approaches have been criticized for failing to account for human experiences (Shaw and Sui, 2020; Zhao, 2021; Kwan, 2013). For decades, the development of GIS and spatial analysis methods primarily derives from a spatial perspective in modeling the space - in other words, geographic phenomena are purely treated as functions of spatial features (Isard, 1956; Tuan, 1979; Agnew, 2011; Shaw and Sui, 2020). For instance, human settlements by mixed effects of distances to various facilities; land use types in terms of transportation costs; human migration flows in terms of distances between origin to destinations. While formalizing place in the GIS context is relatively challenging (Sui and Goodchild, 2011). Although prior geospatial methods have been used in solving diverse complex real-world problems, manipulating and representing quantifiable objects in a spatial form successfully (Cresswell, 2014), place characteristics that may enable geographers to reasoning back to the social, economic, and political processes are usually overlooked (Agnew, 2011; Shaw and Sui, 2020). This dissertation serves as a pioneering work that attempts to integrate human experience and humanistic insights into geospatial data science. Inspired by theories from human geography and urban planning, we made efforts to conceptualize subjective human experience at place, which informs the development of GIScience.

2.4.2 Ethics in Geospatial Data Science

The ethics of AI is one of the most important issues for GeoAI and AI in general. Ethics refers to a set of principles or guidelines that help define what is good and right (Siau and Wang, 2020). In accordance with this idea, the ethics of AI refers to the precise rules that outline the moral duties and obligations of AI and its developers (Siau and Wang, 2020; Nelson et al., 2022).

The misuse of AI and unfair outcomes created by AI in recent years have sparked public concern, which has increased attention to the ethics of AI. For instance, a technique for superimposing faces called DeepFake has been abused to create pornographic or violent videos, leading to severe violations of privacy and portrait rights (Zhao et al., 2021). AI may produce discriminative results against certain groups of the population (Zuiderveen Borgesius et al., 2018).

Researchers from the computer science and robotics community have made efforts in defining moral behaviors of AI. Back in the 1950s, in the well-known friction *I, Robot*, Asimov (1950) introduced the Three Laws of Robotics: First Law, a robot may not injure a human being or, through inaction, allow a human being to come to harm. Second Law, a robot must obey the orders given to it by human beings except when such orders would conflict with the First Law. Third Law, a robot must protect its existence as long as such protection does not conflict with the First or Second Law. As suggested in Blanchard and Peale (2011), the three questions are asked when developing AI: Is it legal? Is it fair? How does it make me feel? Jobin et al. (2019) provides a comprehensive review of AI ethics guidelines in different countries which summarized a series of key ethical issues. In addition, the focus of ethical discussion in the GIScience community has gradually shifted from traditional GIS methods to GeoAI (Fu et al., 2019a; Nelson et al., 2022). Despite some preliminary discussions, a thorough overview of GeoAI ethics is currently lacking. Inspired by several ethical AI categorizations in the community of computer science (Jobin et al., 2019; Siau and Wang, 2020), here, I list several overarching ethical issues and principles that should be considered and addressed in GeoAI.

- *Transparency* and *Trust* refer to making the decision process of AI models more explainable to earn human trust. Current GeoAI technology is usually hard to understand, which is referred to as "black box" tools. The interpretability of GeoAI algorithms should be improved so that humans can monitor, direct, and regulate the activities of GeoAI agents, prevent them from harming society, and enhance trust between public and AI (Xing and Sieber, 2021).

- The second issue refers to *Justice*, *Fairness*, and *Equity* of AI. AI systems may become reliant on undesired sensitive features which produce discriminative decision-makings. Also, given that debiasing geographic data is an important step in GIS and GeoAI, it is necessary to examine, monitor, and mitigate various types of biases in geospatial data science (Janowicz et al., 2018; Zhang and Zhu, 2018; Ntoutsi et al., 2020).

- *Privacy* is another hot topic that attracts attention in the GIScience community. It is necessary to consider geoprivacy - an individual's rights to prevent the disclosure of individual identity at places and associated personal sensitive locations - and geospatial data security when developing GeoAI approaches (Gao et al., 2019; Rao et al., 2020).

- *Responsibility* refers to that GeoAI approaches should fulfills some social roles and meet certain responsibilities. It is necessary to be explicit about the decisions AI should make and who is responsible for the actions of GeoAI agents.

- *Beneficence* is another ethical issue that GeoAI approaches should consider. GeoAI approaches should be developed to advance social goods such as promoting human well-being, peace and happiness, improving economic opportunities and prosperity, and enhancing societal equality.

- Researchers should also develop *Sustainable* AI models. By increasing energy efficiency and minimizing the ecological footprint, environmentally friendly GeoAI systems should be designed, deployed, and managed (Strubell et al., 2019).

- Last but not least, *Solidarity* refers to taking democracy and civil rights into account when deploying GeoAI systems, especially for several potentially vulnerable persons and groups (Jobin et al., 2019)

Of these, *fairness, justice, and equity*, is a primary focus of this dissertation. As one crucial part of ethical issues for GeoAI, it often refers to biased or unbiased outcomes. We provide a summary of the various forms of bias not only from the machine learning, and the GIScience communities, but also from the psychology communities, as bias may have diverse facets in different fields.

In machine learning, AI bias refers to *the inclination or prejudice of a decision made by an AI system which is for or against one person or group, especially in a way considered to be unfair* (Ntoutsi et al., 2020). Given that AI systems are usually trained based on biased dataset, AI agents may produce discriminatory results against certain populations, such as gender bias (Larson, 2017; Zhao et al., 2017) and race bias (Xia et al., 2020). While in GIScience, bias is often relevant to data representativeness. The collected spatial data, though with relatively high spatial and temporal resolutions, may still not represent geographic phenomena accurately due to representation bias, population bias, etc (Zhang and Zhu, 2018; Liu et al., 2022b; Nelson et al., 2022). There have been several approaches for categorizing different forms of biases. Janowicz et al. (2018) discussed the three types of bias including data bias, schema bias, and inferential bias in knowledge graph data. Ntoutsi et al. (2020) identified three steps for fariness AI development: understanding bias, mitigating bias, and accounting for bias. Mehrabi et al. (2021) provide a comprehensive survey that discusses the AI bias and spatial bias. Liu et al. (2022b) followed their ideas and emphasized the five forms of bias that are relevant to geographic modeling.

In addition, psychology researchers have investigated different types of human bias to understand human cognitive behaviors which benefit people's mental health. In psychology, there are two major categories of biases: conscious bias - also termed explicit bias, as people aware their biased attitudes and behaviors; and unconscious bias, which exists in the subconscious and unintentionally affects people's attitudes and actions (Ruhl, 2021). Perception bias, a specific type of cognitive bias, occurs when we make decisions and judgement based on inaccurate assumptions and stereotypes that differ from real-world phenomena (Asana, 2021; Zhang et al., 2021a). Prior studies have made efforts in examining human perception bias at place with the support of geospatial data science to analyze the mismatch between urban safety and real-world criminal activities (Zhang et al., 2021a).

Here, I summarize several forms of bias that are relevant to this dissertation in Table 2.1:

Table 2.1: Summary of different forms of bias related to human perception of place with geospatial data science.

Form of bias	**Definition**
Measurement Bias	It refers to the bias arises from the way we create, select, and evaluate specific features (Suresh and Guttag, 2019). For instance, people may have different perceptions of street view images which may cause variations of choices and measurements.
Representation Bias	It refers to whether geographic phenomena are presented accurately. For instance, whether the collected geospatial data distribute across space evenly.
Aggregation Bias	It is relevant to the Modifiable Areal Unit Problem (MAUP). Different spatial units and aggregation approaches may produce diverse outcomes (Kwan, 2012).
Algorithmic Bias	It refers to the bias that is purely influenced by the algorithm such as certain optimization functions or consideration of certain subgroups of data. For instance, machine learning algorithms may prefer cities with greater populations and places with small populations are more likely to be ignored (Baeza-Yates, 2018; Liu et al., 2022b).

Table 2.1 – continued from previous page

Form of bias	**Research objective**
Evaluation Bias	It refers to the bias that arises during the evaluation process. For instance, evaluation metrics are usually performed based on the entire testing dataset. Given the spatial heterogeneity, outcomes of GeoAI models should be evaluated place by place.
Population Bias	It refers to the bias that arises when the characteristics and demographics of the population for which data are collected differ from the target population. For instance, place perception data collected from global volunteers may not reflect local residents' perceptions of place.
Perception Bias	It refers to the disparity between the subjective human perceptions of places and the real-world physical and socioeconomic environment (Zhang et al., 2021a).

Additionally, we employ several explainable AI approaches to support the *transparency* and *trustworthy* AI models in Chapter 5 by employing explainable AI approaches. For instance, we compute the feature importance, calculate the contributions of factors, and leverage a causal discovery algorithm to understand how urban design elements shape human perceptions of the built environment.

In conclusion, despite geospatial data science's enormous success in resolving a variety of geographic tasks, challenge remains. Multiple aspects of ethical issues including but not limited to bias and trust should be considered during the development of geospatial data science approaches. In this dissertation, we hope to assess these different challenges from multiple aspects throughout the measurement of human place perceptions in Chapter 4 and 5.

3 METHODOLOGY

In this chapter, I introduce the methodology of this dissertation including the theoretical framework, datasets and computational approaches for measuring human perceptions of place. More specifically, I first introduce the conceptual framework *Human-centered Geospatial Data Science*, a subset of geospatial data science that serves as the theoretical foundations of the approaches and techniques in Section 3.1. Then, the emerging geospatial data source, street view imagery, is demonstrated in Section 3.2. After that, in Section 3.3, I introduce the five-step computational workflow for assessing human place perceptions using geospatial data science. The methodology in Chapter 4-6 are built upon the datasets and methods introduced in this chapter, but the technical details may vary slightly in each chapter.

3.1 Human-centered Geospatial Data Science

This dissertation follows the Human-centered Geospatial Data Science framework. Human-centered geospatial data science is a subset of geospatial data science that focuses on human dimensions to understand human-environment interactions and ensure that GeoAI does not become a threat to humans. It has two missions:

1. Understand aspects of the human experience of place, including perception, emotion, behavior, creativity, and interaction;
2. Develop trustworthy and ethical geospatial data science approaches such as mitigating bias, protecting human geoprivacy, and enhancing the explainability of GeoAI models.

Such a conceptual framework is derived from post-positivism and humans are the focal point of this framework. The two missions emphasize the importance of advancing our knowledge of human-environment interactions and ensuring that geospatial technology is used ethically to protect humans. Figure 3.1 shows the conceptual framework of human-centered geospatial data science.

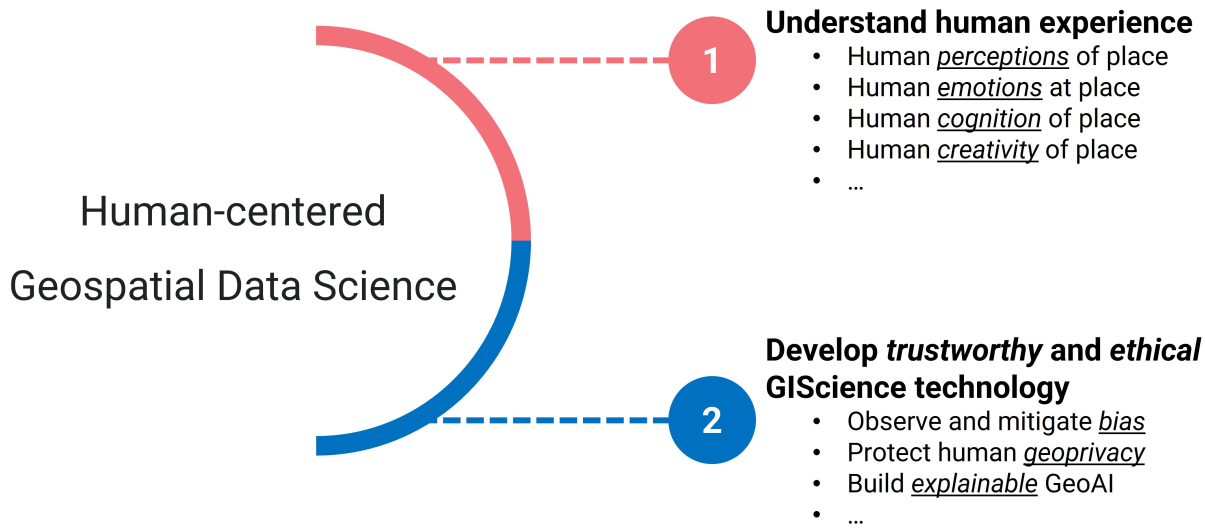

Figure 3.1: Two missions of human-centered geospatial data science: (A) Understand human experience; (B) Develop trustworthy and ethical GIScience technology.

In this dissertation, we follow this framework and place different emphases on the two missions, respectively. The entire topic of this dissertation contributes to the first mission, to understand human experience by measuring and analyzing human subjective perceptions of place. In parallel, we address ethical concerns throughout the usage of geospatial data science such as observing bias and building explainable GeoAI approaches, which work towards achieving the second mission.

3.2 Street View Images: The Principal Dataset

The street view imagery dataset is the primary dataset of this dissertation. We employ street view images to represent real-world landscapes where participants' perceptions of street view images are treated as proxies for their sense of place. Street view images refer to the scenery images that describe the urban streetscape with an angle of view similar to that of human vision. This kind of dataset can be accessed from web mapping services. Users are allowed to navigate the realistic scenery remotely through these interactive panoramic images, as if they were traveling in the real world (Anguelov et al., 2010; Badland et al., 2010). Google Street View (GSV)[1], launched in 2007, was the first service provider and is currently the most popular one. A great number of other mapping companies around the world now provide similar services, such as Bing maps[2], Baidu maps[3], and Yandex maps[4]. In addition to these mapping companies, Mapillary[5] provide street view services based on crowdsourced data, allowing users to contribute their own street view images.

In order to collect such images, GPS-equipped, drive-by sensing vehicles take panorama photos along road networks. By doing so, the coordinates are attached to each panorama photo. Researchers can thereby request and position various angles of view of the physical environment from online map services. For example, Figure 3.2 shows (A) the images from different angles that were used to construct the panorama image and (B) the panorama image. As shown in the images, the street view images capture objects in the urban streetscape at about eye-level.

Compared with traditional data sources, street view images have some inherent characteristics that render them as valuable data sources for urban environment auditing: high coverage and volume, relatively low data bias, cost-effectiveness and time effectiveness, and eye-level scenery (Wilson et al., 2015; Rzotkiewicz et al., 2018; Ibrahim et al., 2020; Biljecki and Ito, 2021). The following paragraphs discuss these advantages, respectively.

First, in terms of coverage and volume, large-scale street view images have been generated and stored by map service providers around the world. Google street view images has covered most cities in nearly 200 countries; Baidu street view images have covered all cities in China. The high coverage of street view imagery not only provides abundant information to characterize the urban environment comprehensively but also enables researchers to

[1]https://www.google.com/streetview/
[2]https://www.microsoft.com/en-us/maps/streetside
[3]https://www.google.com/streetview/
[4]https://yandex.com/maps/
[5]https://www.mapillary.com/

(A)

(B)

Figure 3.2: Two forms of street view imagery: (A) natural view; (B) panoramic view

evaluate and measure different urban scenery across countries on a global scale (Rundle et al., 2011; Yao et al., 2019; Zhang et al., 2019b). It is important to note that while street view images have extensive coverage and volume, a complete global dataset does not currently exist. There are still areas worldwide that remain unmapped or uncaptured, and thus, lack any available street view images.

Second, compared with volunteered geographic information (VGI) (Goodchild, 2007) and more broadly user-generated content (UGC) (Krumm et al., 2008), street view images have relatively higher quality and lower data bias in the urban environment. As a promising data source in the era of big data, all street view images follow the same standard rules and production workflow, and have uniform formats with a maximum image size of 2048*2048 pixels[6], which can guarantee the quality of images to a certain degree. Also, due to the fact that: (1) street view images are collected through uniform sampling along the streets in urban environments; (2) adjacent pictures may overlap in the description of scenery; (3)

[6]https://developers.google.com/maps/documentation/streetview/usage-and-billing

most regions in urban areas are covered by the street view imagery, there is less data bias when using street view images (Zhang et al., 2019c).

Third, street view images are low cost, easy to access, and easy to download. By using the API services provided by mapping companies, users can download freely available images in a short time. When requesting images, users customize the parameters of the images, including the location, time, camera angle, image size, etc., to collect street view images that fit their needs. Thus, it is possible for researchers to assess neighborhoods in a wide range of global contexts (Zeng et al., 2018; Li et al., 2015b).

Last but not least, street view images can capture the objective urban scenery from a human-perspective. Different from aerial photographs and remote sensing images that take photos from an overlooking view, street view images follow human perception to depict the urban environment by using a view angle similar to that of the human eye, and capture detailed objects in built environment more comprehensively (Li et al., 2015b; Wang et al., 2019a; Zhang et al., 2019c). In addition, the information contained in street view images enables the exploration of intangible aspects of urban life and people's perceptions of the environment (Zhang et al., 2018).

In this dissertation, we collected the street-view images through the Google Street View API[7]. To do so, a set of geo-referenced sampling points are first generated along the road network with a fixed distance interval. The road networks are downloaded from the OpenStreetMap (OSM)[8]. 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.

[7]https://developers.google.com/maps/documentation/streetview/intro
[8]https://www.openstreetmap.org/

3.3 Measuring Human Perception of Place

Several pioneers' work such as Salesses et al. (2013), Dubey et al. (2016), and Zhang et al. (2018) proposed a commonly used strategy to measure human perceptions of places with geospatial data science. Street view images are used to represent the built environments and deep learning approaches are trained to learn human place perception patterns. Such a strategy as well as its variations usually contains five steps as illustrated in Figure 3.3. First, participants are recruited to rate multiple dimensions of environmental perceptions based on a sample collection of street view images; Then, perceptual scores are inferred for each street view image, and used as a proxy for people's general perceptions of the surrounding environment; After that, a deep learning model will be trained to learn human perceptual patterns; Such a model can be applied to predict perceptual scores of any input street view images. Finally, the effectiveness of the deep learning approach for measuring human place perceptions is evaluated.

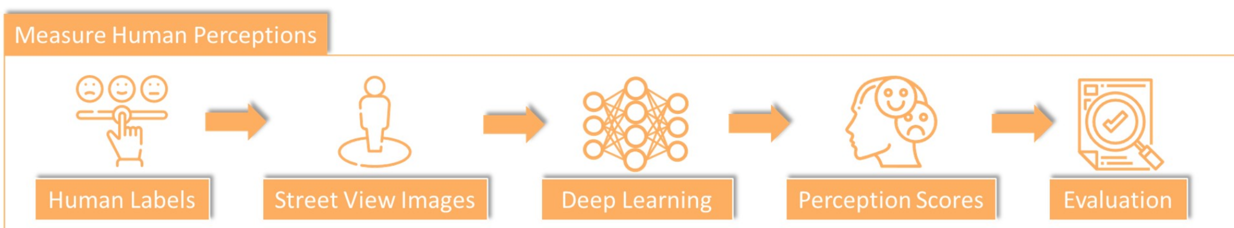

Figure 3.3: The workflow for measuring human place perceptions with street view images and GeoAI.

Street view imagery is used as the representation of physical settings of a place. Based on street view imagery, volunteers are recruited, and their perceptions of streetscapes in street view images are used as proxy of place perceptions. In this dissertation, two datasets are employed for assessing the human perceptions of place: a global-scale dataset, and a local-scale dataset in Stockholm, Sweden. The following paragraphs provide information on how these two datasets are generated.

3.3.1 A Global Dataset

The global-scale human place perception dataset refers to the MIT Place Pulse image[9]. It contains one million labeled street view images and aims to quantify human perception scores to streetscapes from six dimensions (safe, lively, boring, wealthy, depressing, beautiful). To construct such a large-scale dataset, a web-based platform was created, allowing participants to compare two randomly selected street view images and respond to one of the six questions. The questions have the structure “Which place appears X?” where X might be any of the following: safer, livelier, more boring, wealthier, more depressing, and more beautiful. For each time, 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, 81,630 volunteers have participated in the online survey and contributed 1,170,000 pairwise comparisons. Considering the high diversity and vast volume of the image samples, the participants and their responses, such a dataset has been used to reflect human’s general perceptual preferences on urban scenes at the global scale (Dubey et al., 2016; Zhang et al., 2018). All three chapters (Chapter 4-6) leverage such a dataset to measure multiple dimensions of human perceptions of the built environments.

3.3.2 A Local Dataset in Stockholm

Existing studies have suggested that recruiting local people may better reflect their perceptions of urban streetscape than using the global dataset (Yao et al., 2019). Therefore, in addition to the global dataset, we construct a local dataset in Stockholm, Sweden, to measure residents’ perceptions with a focus on safe. To do so, a localized online survey is launched to obtain human safety perceptions of Stockholm’s urban environment. We randomly sampled 4,953 street view images from the dataset. Then, we worked with a

[9]https://centerforcollectivelearning.org/urbanperception

Figure 3.4: A sample screenshot of the survey for collecting multiple dimensions of human perceptions of the MIT Place Pulse dataset.

surveying company to recruit participants who live in the city of Stockholm to collect the citywide residents' safety perceptions. The participants were sampled to be statistically representative of the population of each of the 6 main planning regions of Stockholm. Figure 3.5 shows the user interface of the created survey. Each participant was asked to provide their demographic information including age and gender for the survey for further analysis of potential population bias. Then, they were asked to make comparisons between a pair of two random street view images. Half of the participants were asked to respond to the question "Which place looks safe?", and the other half of participants were asked "Which place looks less safe?", to avoid the framing of the question influencing their responses. In both cases, participants need to pick up an image that best fits the question. Overall, 23,710 responses are collected from this survey. On average, each street view image is compared with other street view images 9 times. In Chapter 4, we use such a local dataset to measure residents' safety perceptions of the built environments in Stockholm.

Figure 3.5: A sample screenshot of the survey for collecting human safety perceptions by the citizens. The language of the platform is Swedish, with red text indicating translations into English. The question is "Which place looks safer/less safe?" Participants are asked to pick up the image that looks safe/less safe.

3.3.3 Training GeoAI-based Models with Deep Learning

Based on the pair-wise sample street view images, we can then train a deep learning model to predict people's perceptions from the abovementioned two datasets. Here, I will take the local dataset as an example to illustrate the training process of the deep learning model.

Given that the rating data collected from the survey were in the form of two-image comparisons, e.g., image A looks safer than image B, which cannot be input into the deep learning model directly. A perceived safety score is calculated for each image so that it can be fed into the deep learning model. Such a perceived safety score enables the quantitative comparison among all street view images. It also serves as the ground truth for the validation of the predicted perceived safety score. To do so, we use the following strategy that has been employed in several previous studies (Dubey et al., 2016; Zhang et al., 2018), as its effectiveness has been approved based on a global perception dataset Place Pulse. For each image i, the following two indices are computed: positive rate (P_i)

and negative rate (N_i).

$$P_i = \frac{p_i}{(p_i + n_i)} \tag{3.1}$$

$$N_i = \frac{n_i}{(p_i + n_i)} \tag{3.2}$$

where p_i indicates the number of times that the image i is picked as the "safer" image, while n_i indicates the number of times that the image i is not selected as the "safer" image. The sum of p_i and n_i equal to the total number of times that the image i is made comparisons. According to this, the perceived safety score S_i can be calculated following the equation:

$$S_i = \frac{10}{3}(P_i + \frac{1}{p_i}\sum_{k_1=1}^{p_i} P_{k_1} - \frac{1}{n_i}\sum_{k_2=1}^{n_{k_2}} N_{k_2} + 1) \tag{3.3}$$

where k_1 indicates the number of times that the image i is rated as the "safer" image, while k_2 indicates the number of times that the image i is not rated as the "safer" image. The perceived safety score S_i can be seen as the positive rate P_i corrected by the P_i' and N_i' of the images that it was compared with. If an image has a high positive rate P_i and its compared images also have a high positive rate P_i', such an image should have a higher S_i. The calculated perceived safety scores follow a normal distribution and range from 0.96 to 9.10. The average is 4.99, the median is 5.05, and the standard deviation is 1.22. To enhance the robustness of the safety score, we dropped the street view images that have less than 5 times comparisons from the entire dataset.

After obtaining the perceived safety score, two steps are performed for training the GeoAI models. First, we train a deep learning model that can learn human perceived safety of the environment. More specifically, a ResNet (He et al., 2016) model is employed as it has achieved high performance in a series of object detection tasks in computer vision. Then, we adopt the strategy of performing an image classification task. The deep learning model predicts one of the five categories of the perceived safety of each street view image rather than predicting the true perceived safety scores. Such a strategy achieves the balance between efficiency and accuracy. To be fed into the model, the street view imagery dataset is then randomly separated as a training dataset and a testing dataset in which the former counts on 80% of all sample street view images. The training procedure of the DCNN is performed on the training dataset, and the testing dataset is utilized for measuring the model's accuracy. Overall, the top 2 accuracy for the training dataset reaches 89.9% and 74.2% for the testing dataset. Models converged throughout the training process.

The output of the model is a five-dimensional vector that represents the probability of each category that the image may belong to. We then convert the output probability vector back to the predicted perceived safety score. The predicted perceived safety score has a similar distribution to the original perceived safety score. It ranges from 1.58 to 7.70, the mean is 4.95, the median is 5.04, and the standard deviation is 1.09. We also computed the MSE to test the difference between our model and the ground-truth safety perception scores. The MSE is 0.82, which indicates that the difference between the predicted safety perception score of a given street view image is no larger than 0.9. After that, we input all street view images in Stockholm into the model to produce the GeoAI-based safety perception scores. We then aggregate the GeoAI-based safety perceptions to the base area level by computing the mean values of all street view images inside a certain base area. Due to the spatial heterogeneity, we compute the standard deviation of the GeoAI-based safety perceptions in each base area which was 0.65.

To test the robustness of the model and the computational workflow, we input several street view images into the model to predict the safety scores. By doing so, we can validate the predicted results. Figure 3.6 shows several sample images, and the built environment patterns are different in Figure 3.6 (a) and (b), with the left regions perceived as "unsafe" while the right regions have higher safety perception scores. Results fit our common sense and indicate that the GeoAI approach learns human safety perceptions. The randomly selected images indicate that the deep learning model indeed learns human perception of safe patterns and may be transferred to other input street view images.

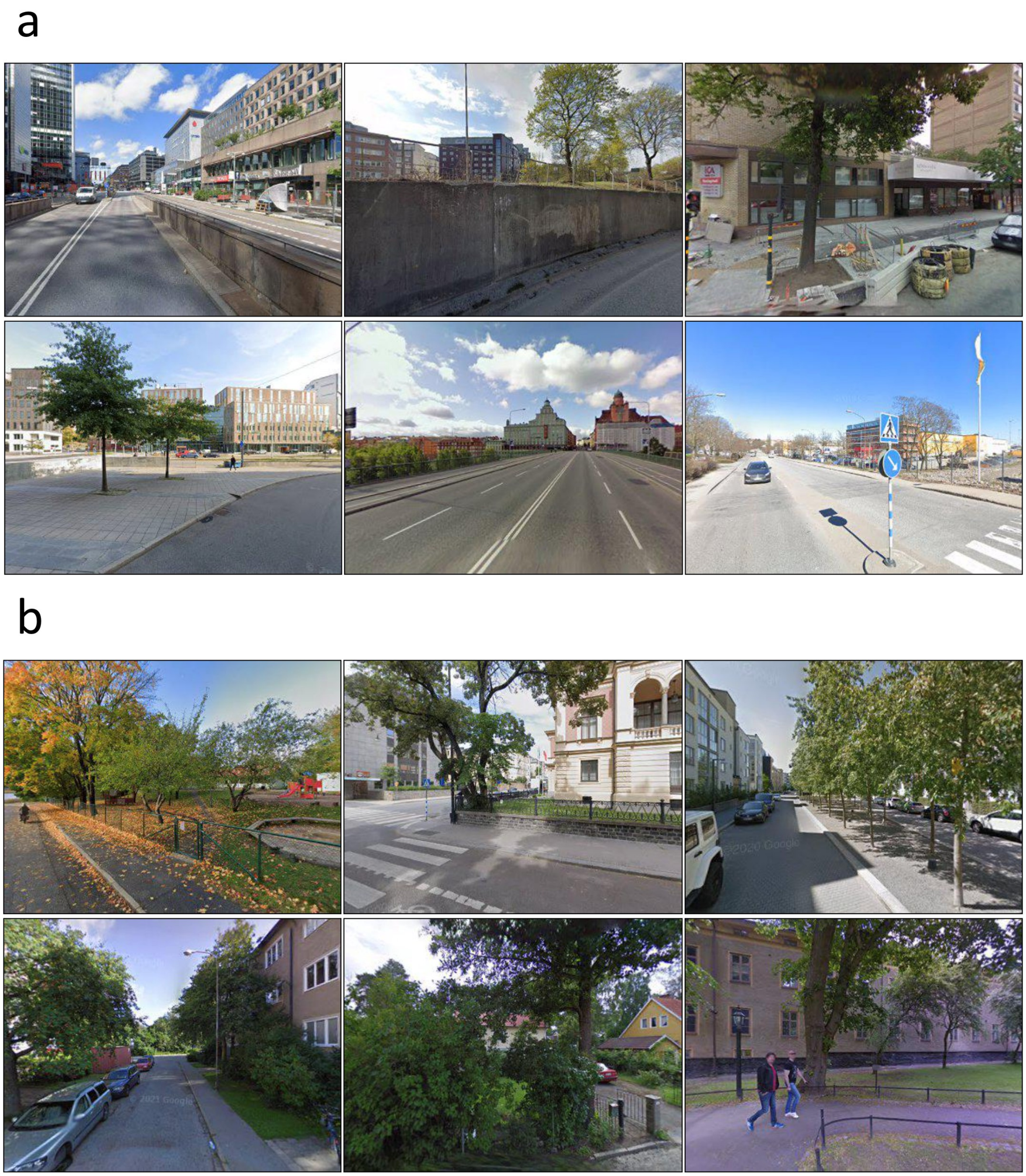

Figure 3.6: Sample images representing different perceived safety categories: (a) street view images labeled as 0 (unsafe);(b) street view images labeled as 4 (safe).

Similarly, a deep learning model can be trained using the global dataset to learn how people perceive an urban scene for the six dimensions. We employ the model trained in Zhang et al. (2018) to evaluate the street view images, and the output of each image is a vector contains six dimensions of perceptual scores, namely, safe, lively, boring, wealthy, depressing and beautiful. Such a model has a similar training process of our local dataset-based model. It should be noted that the global dataset-based model can classify each image into 10 categories rather than 5 in the local dataset-based model.

It should be mentioned, for further spatial analysis in this dissertation, the perceptual score of each spatial unit (CBG, street segment, base area) is calculated by averaging all image-level scores inside that unit. The reason we utilize the average perceptual score rather than the score of each image is that the scenery may vary hugely even at the 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. Despite that we aggregate perceptual scores to different spatial units, it is worth noting that people with different social characteristic information such as gender, race, age, and education, may have a 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. We investigate different groups of people's place perceptions to observe potential bias in Chapter 4.

4 MEASURING PERCEPTUAL DIFFERENCE OF SAFETY PERCEPTION

Chapter 4 provides an empirical study to investigate the RQ1: *What are the differences between the traditional approach and the geospatial data science approach in measuring human perception of place?* Specifically, we measure urban safety perceptions using two approaches by conducting an empirical study in Stockholm, Sweden: (1) a geospatial artificial intelligence (GeoAI)-based approach using street safety perceptions and recruiting locals to measure citywide residents' safety perceptions; (2) a survey-based approach that measures neighborhood residents' responses of their safety perceptions. By comparing the measures from the two approaches, we could better understand the human-environment relationships. We then model the two forms of safety perceptions and their disparities (i.e., perception bias) as a function of the city's land use and its socio-demographics. Results confirm that while the GeoAI-based measures better capture people's instant impressions of the built environment across the city, the survey-based measures reflect their overall daily experiences of specific areas. We found that regions that appear to be economically vibrant and have inner-city streetscapes are perceived as safe places from the visual appearance but are not always perceived as such by residents. Older adults tend to overestimate their likelihood of being victimized by crime, which may enlarge perception bias. The study concludes by critically assessing the potential ethical issues (e.g., spatial bias, population bias) in the proposed methodology and making suggestions for future research. This chapter also validates the effectiveness of the proposed computational framework and serves as the technical foundation of the dissertation.

4.1 Introduction

Enhancing urban safety is essential for promoting social stability and building an inclusive and resilient environment (Ameen and Mourshed, 2019). The consequences of crime, one of the primary threats to safety in cities, often go beyond immediate financial and personal losses: fear of crime and poor safety perceptions may also cause detrimental long-term effects on mental health and quality of life (Ceccato and Nalla, 2020; Moore and Trojanowicz, 1988). Hence, to create safer cities and communities, it is crucial to examine and understand how people perceive the safety of the built environment (Li et al., 2022).

Surveys and questionnaires have traditionally been used to assess residents' safety perceptions, but they are expensive, labor-intensive, low time-effective, and often restricted to smaller regions (Golder and Macy, 2011; Kang et al., 2020b). Geospatial Artificial Intelligence (GeoAI), the integration of advanced artificial intelligence with a special focus on geospatial studies, has brought breakthroughs in human-environment modeling (Gao, 2021; Janowicz et al., 2020). Prior studies have combined street view images that represent urban streetscapes and deep learning approaches to evaluate human safety perceptions of the environment. The associations between human safety perceptions, and several physical and socioeconomic variables in built environments such as green space and criminal activities have been investigated (He et al., 2017; Hipp et al., 2022; Khorshidi et al., 2021; Li et al., 2015a; Zhang et al., 2021a; Salesses et al., 2013; Ramírez et al., 2021). Such GeoAI-based methods are thought to cover a wider geographic area, have relatively limited data bias, and be cost- and time-effective (Biljecki and Ito, 2021; Kang et al., 2020b). Despite this, one drawback lies in the fact that safety perceptions evaluated by GeoAI approaches are usually derived from the people's general visual perceptions without considering the local context.

Therefore, this study has the potential to provide us with a more complete picture of safety perceptions by integrating GeoAI with traditional localized approaches, such as those measured via surveys. The two data collection methods differ in nature. Survey-based safety perceptions are gathered from reports of residents' feelings. They are derived from the experiences of locals and their knowledge of crime in the neighborhoods where they reside. In comparison, GeoAI-based safety perceptions reflect the respondents' feelings of safety triggered by visual perception of the environment and neighborhoods (Salesses et al., 2013), illustrating how that streetscape image connects to their idea of "safe" and "unsafe". Participants may not be familiar with the place depicted in street view images. In addition, there might be model bias (e.g., spatial bias, population bias) raised from a variety of sources during the training process of the GeoAI approach, which could influence the output safety perceptions and generate concerns of geoethics (Nelson et al., 2022). Some interesting questions that follow naturally are: what are the relationships between these two measurements? Do they differ and why?

To this end, we aim to assess and compare two forms of people's safety perceptions: (1) GeoAI-based safety perception: a GeoAI model is trained by using street view imagery and running a local survey that collects citywide residents' safety perceptions of the city of Stockholm, Sweden. (2) Survey-based safety perception: a localized survey is employed that harvests neighborhood residents' safety perception. We investigate what these safety perception indicators show, what factors contribute to explaining their geography, and how to understand the perceptual difference (i.e., the discrepancy between the two safety perceptions). This goal is achieved by:

1. Measuring citywide residents' safety perceptions of the physical environment from street view images using the GeoAI approach in Stockholm.

2. Comparing the GeoAI-based safety perceptions of citywide residents with results from safety perceptions of neighborhood residents from the Stockholm Safety Survey.

3. Explaining perceptual differences with base area-level characteristics including data on land use and physical and socioeconomic factors.

The major contributions and innovations of this study are three-folds: First, our study add to the international literature case studies by providing an example from Stockholm, a city in a welfare Nordic European context, and training a GeoAI model based on a localized dataset for tailoring citywide residents' safety perceptions. Second, as an empirical study, we compare safety perceptual differences between citywide residents with GeoAI and neighborhood residents with the survey; we provide clues for urban planners about the types of physical and socioeconomic environments in neighborhoods that "work" and those that "do not work" in terms of safety perceptions. Finally, by observing model bias including spatial bias and population bias which may enlarge perceptual differences, we advocate the needs to consider geoethical issues in GeoAI research.

4.2 Theoretical Framework

4.2.1 Safety perceptions of people

Urban safety plays an important role in residents' settlement (Ceccato and Lukyte, 2011; Rastyapina and Korosteleva, 2016). People prefer to reside in a place that gives them a sense of safety, security, and protects them from risks and dangers (Van den Berg et al., 2019; Low, 2004). Safety perceptions impact various aspects of quality of life, including mental and physical well-being, social cohesion, mobility, and accessibility in the city (UN-Habitat, 2019). As such, previous research has made extensive efforts in understanding people's perceptions of safety. First, fear of crime and other feelings of unsafety are very much linked to crime victimization such as the intensity and distribution of criminal activities (Hale, 1996). Also, our overall safety perceptions are deeply interconnected with a wide range of other anxieties and aspects of urban life (Lee, 2008a), regardless of the actual risk of crime.

Research has illustrated that the physical environment and neighborhood conditions matter for people's perception of safety. Places in a city can be perceived as safe or unsafe based on situational conditions such as the level of maintenance, lighting and visibility, the activity of people, and the ability to exert social control (Jacobs, 1961; Maier and DePrince, 2020; May et al., 2010; Newman, 1972; Ortigueira-Sánchez, 2017; Vrij and Winkel, 1991). Characteristics of the environment, e.g., garbage on the streets or groups of juveniles can be perceived as indicators of a community's inability to regulate people's behavior

(Gerber et al., 2010). However, while several studies have found significant impacts of these conditions on perceived safety, others have also found only trivial effects (Nair et al., 1993). As such, there is still a knowledge gap to be filled, and the extent of various elements in the built environment must be explored further to promote safer cities.

4.3 Measuring Safety Perceptions with GeoAI

Over the past few years, the emergence of large-scale geospatial big data and advanced Geospatial Artificial Intelligence (GeoAI) methods have provided unprecedented opportunities to handle a variety of geographic problems such as spatial phenomena modeling, geographic knowledge discovery, and human-environment understanding (Gao, 2021; Janowicz et al., 2020). Prior researchers have employed GeoAI to model various subjective place-based concepts, which were formerly thought to be challenging for GIS to assess. For example, by combining street view images and deep convolutional neural networks, people's subjective perception of the built environment can be assessed to reflect their place perceptions (Dubey et al., 2016; Salesses et al., 2013; Zhang et al., 2018). A global dataset – MIT Place Pulse – was constructed which could reflect people's general place perceptions (Dubey et al., 2016). Prior studies have already employed such a GeoAI-based strategy for measuring human safety perceptions at places (Moreno-Vera et al., 2021; Ramírez et al., 2021; Zhang et al., 2021a). Despite the effectiveness of using street view images and GeoAI approaches in observing the built environment, previous studies suggested that results obtained using GeoAI approaches may not be the same as those obtained using conventional approaches (Feng et al., 2021b; Helbich et al., 2019). Also, human perceptions measured with GeoAI approaches assume that participants' perceptions of street view images represent their place-based perceptions. However, visual perceptions may not fully reflect human perceptions of the environment and place. Incorporating the GeoAI-based perceptions in the spatial analysis may lead to incorrect and even unethical results. Hence, it is necessary to make a comparison between the GeoAI approach and the traditional surveys to learn about the characteristics of the GeoAI-based measures.

4.3.1 Perceptual difference: Perception bias and model bias

In this paper, we compare the two forms of assessed safety perception in cities: (1) GeoAI-based, and (2) survey-based safety perceptions. We term *Perceptual Difference* to indicate the potential disparity between the two safety perception measures. We suggest that two factors – perception bias and model bias – could be responsible for the perceptual difference. We provide a conceptual framework to examine perceptual differences from these two aspects, as shown in Figure 4.1.

Perception bias refers to the mismatch between our perception and real-world phenomena. Although people believe they are making impartial judgments, stereotypes often influence people's decisions unconsciously (Collaboration, 2017). It is prevalent in our daily lives as people's feelings of surroundings, such as political preferences (Badger et al., 2021) and safety (Zhang et al., 2021a), often differ from reality. A prior study has investigated the discrepancy between visually perceived safety and reported real-world crimes to understand the perception bias (Zhang et al., 2021a). Different from this paper, given that the two safety measures are collected differently, we define perception bias as the mismatch of perception between citywide and neighborhood residents.

Perception bias may not be the only factor that contributes to perceptual differences. Several model biases may arise during the training process of the GeoAI approach and enlarge the perceptual difference (Mehrabi et al., 2021; Zhang and Zhu, 2018). AI biases have gained attention in recent years. Some ethical researchers are concerned that the intelligent system may have undesirable features, which could lead to unfair decisions (Ntoutsi et al., 2020). Here, we identify two model biases: population bias, and spatial bias. Prior studies imply that different populations have a varied sense of place (Pánek et al., 2020). Consequently, it is necessary to analyze the safety perceptions of various

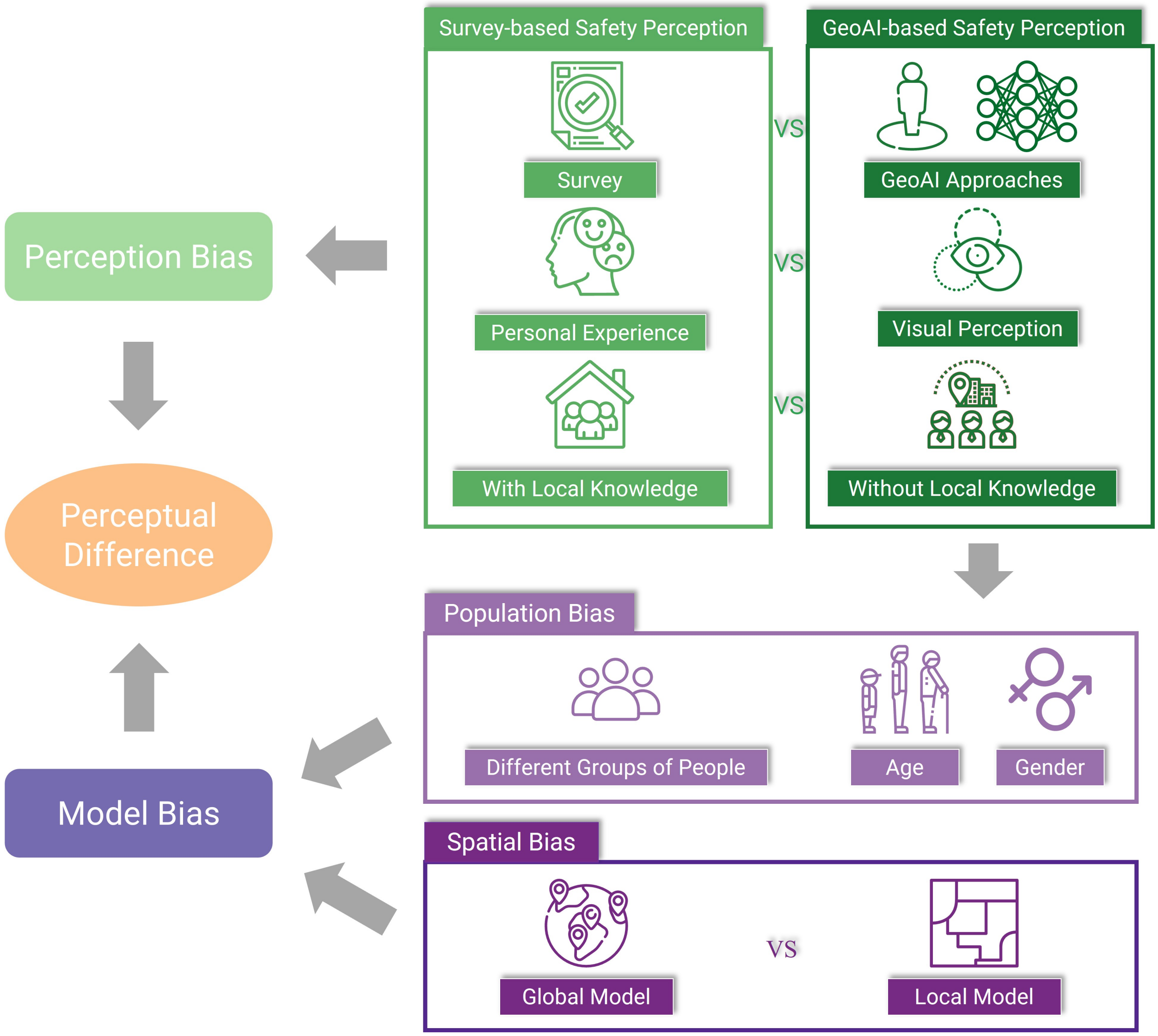

Figure 4.1: The conceptual framework for understanding the perceptual difference in this study.

populations. In addition, previous studies suggest that deep learning models trained on localized data better represent locals' perceptions (Yao et al., 2019). Therefore, our GeoAI-based safety perceptions are trained on a local dataset that only contains responses from citywide residents in Stockholm and is compared with the global MIT place pulse dataset to help monitor potential spatial bias. It should be noted that this paper mainly focuses on those model biases in GeoAI-based safety perceptions. However, the use of questionnaires and surveys to collect safety perceptions may also have bias issues such as social desirability bias, as participants may select responses that they perceive to be more socially acceptable than those that reflect their true thoughts (Grimm, 2010; Nederhof, 1985).

4.4 Study Area and Dataset

4.4.1 Study Area

Stockholm, the capital and largest city of Sweden, is selected as our study area. The basic spatial unit employed in this study refers to basområde (called base area) that is one of the fine-resolution geographical units in Sweden. In total, 419 base areas are adopted in this work. Figure 4.2 shows the study area and base areas.

4.4.2 Datasets

We uses four datasets: a street view imagery dataset, a survey of neighborhood residents' safety perceptions, a land use and socioeconomic variable dataset, and a cell phone-based mobility dataset. All datasets are aggregated to the level of base area for further analysis.

The street view imagery dataset provides eye-level panoramas of urban settings. Approximately one million street-view images between 2010 and 2021 were downloaded. More characteristics about street view images can be found in Section 3.2. Each panoramic image contains a "panoid" as its unique identifier. Figure 4.2 shows all panoids in Stock-

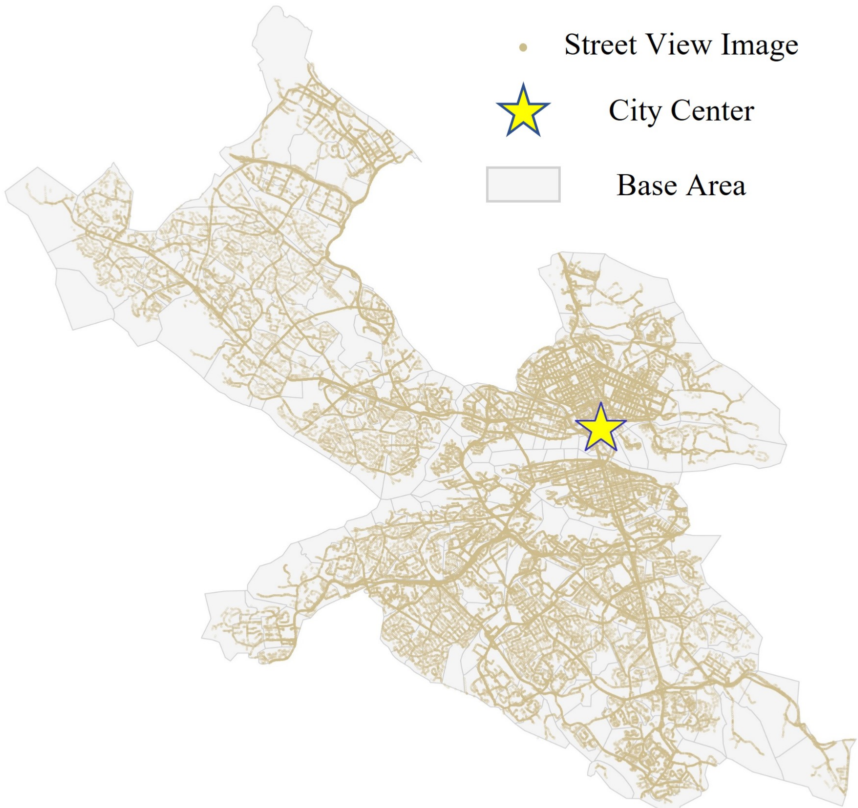

Figure 4.2: The 419 base areas in Stockholm as the study area of this study.

holm based on their latitude and longitude with an interval of 30 meters. On average, each base area contains 594 street view images. For one panoid, four street view images are collected to represent the different views of a place. Such a big volume of street view images in Stockholm can represent the urban built environment comprehensively.

We use the Stockholm City Safety Survey of 2020 (Stockholm stads Trygghetsundersökning 2020) to represent residents' safety perceptions of their neighborhoods. In total, 20,781 people over 14 years old who were registered as residents in Stockholm responded to the survey. The questionnaire posed questions on participants' safety perception and fear of crime in their residing neighborhoods.

We use multi-source socioeconomic and land use datasets to characterize the urban and social landscapes of Stockholm. Socioeconomic factors such as population by gender, age, country of birth, employment rate, and average annual income were obtained from Sweco, a consultancy company that is responsible for Stockholm City's information service. Land use variables and urban facilities were retrieved from Stockholm City's open data bank, Dataportalen, and OpenStreetMaps (OSM). The land use variables include the following seven types: commercial, residential, recreational, industrial, forest, nature reserve, and park. We have the following urban facilities and POIs such as bars, streetlights, bus stops, transport stations, and gas stations.

The mobility dataset is generated based on millions of anonymous cell phone users' activities during November 2019. The number of visitors in each hour during the weekdays and weekends is computed for each base area in Stockholm.

4.5 Measuring Safety Perceptions in Stockholm

4.5.1 GeoAI-based safety perceptions

We follow the computational workflow introduced in Section 3.3 to measure human perceptions using GeoAI approaches. Based on the rating data of citywide residents' safety perceptions, we train a deep learning model to learn safety perception patterns and predict safety perceptions from street view images. More technical details about the process for computing the GeoAI-based safety perceptions can be found in Section 3.3. The model produces a perceived safety score (ranges from 1 to 9, mean value is 5). The higher the score, the more the perceived safe. The outputs are then aggregated to area-level by computing the average values of all street view images inside a certain base area. Then, we standardize safety perception scores using the Z-score approach. The distribution of the citywide residents' safety perceptions in Stockholm with GeoAI is shown in Figure 4.3 (a).

Survey-based safety perceptions

To assess neighborhood residents' safety perceptions of their neighborhoods, we utilize the Stockholm City Safety Survey as a data source. The Stockholm City Safety Survey is conducted by the municipality of Stockholm. The survey contains questions pertaining crime victimization history, fear of being victimized, perceptions of personal safety, physical and social neighborhood disorders, etc. The survey has been conducted every three years since 2008. In this study, we utilized the most recent version of the 2020 responses. The total sample population consists of 40,000 citizens registered in Stockholm, aged 16-79. For the survey data collected in 2020, the total responses amounted to 20,781. On average, each base area has 55 responses. All responses were collected between March and May 2020. Three relevant questions are selected from the Stockholm City Safety Survey:

1. Have you during the past 12 months ever worried about becoming victimized of crime?
2. If you go outside late at night alone, do you feel safe or unsafe, or do you largely not go outside alone at night?
3. How safe or unsafe do you feel in your neighborhood?

We encode residents' responses to these questions as continuous values so they can be treated as dependent variables for further regression analysis. The three questions as well as their processing procedures are demonstrated in Table 4.1. Then, the safety perception score is computed based on the average value of three variables. The average values of all collected residents' safety perceptions are summed together to reflect the overall safety perceptions of their neighborhoods. We removed base areas that have less than 8 responses as their results might be more sensitive and may not be trusted. After aggregating the survey-based safety perceptions to the base area level, we also measured the standard deviation of the survey-based safety perceptions in each base which was 0.15. The higher the score, the more safety perception. Then, the neighborhood resident's safety perceptions are standardized using the Z-score approach to enable the comparison with GeoAI-based safety perceptions. The distributions of neighborhood residents' safety perceptions inferred from the survey in Stockholm are plotted in Figure 4.3 (b).

Table 4.1: The three questions and choices and their encodings.

Questions	Choices	Encoding
Have you during the past 12 months ever worried about becoming victimized of crime?	Yes, every day or almost every day	0
	Yes, once a week	1
	Yes, once a month	2
	Yes, a few times during the year	3
	No, never	4
If you go outside late at night alone, do you feel safe or unsafe, or do you largely not go outside alone at night?	I do not go outside alone at night due to other reasons	NA
	I do not go outside alone at night due to fear of being victimized of crime	0
	Very Unsafe	1
	Rather unsafe	2
	Rather safe	3
	Very safe	4
How safe or unsafe do you feel in your neighborhood?”	Very unsafe	0
	Unsafe	1
	Rather unsafe	2
	Safe	3
	Very safe	4

Perception Bias Calculation

Here, we define perception bias $\mathsf{PercepBias}$ in our context as the difference between the citywide residents' safety perceptions S_c measured with the GeoAI approach and neighborhood residents' safety perceptions S_n measured by the survey. Neighborhood residents have more local knowledge of their residing place. While citywide residents may not know the place of the street view image and rely on their “stereotypes” of the built environment elements, which may distort their judgments and produces perception bias. In a prior study by Zhang et al. (2021a), perception bias is classified into three groups, which may not quantitatively measure the impacts of factors on perception bias between citywide and neighborhood residents. Therefore, we compute the absolute differential values between the two forms of safety perceptions based on their standardized values:

$$\mathsf{PercepBias}_i = S_i - F_i \tag{4.1}$$

Table 4.2: Moran's I values and significance levels.

Variable	Moran's I index	p-value of I
GeoAI-based Safety Perceptions	0.37	0.0
Survey-based Safety Perceptions	0.44	0.0
Perception Bias	0.25	0.0

where i refers to the computed base area. Figure 4.3 (c) shows the distribution of perception bias in Stockholm, and there exist base areas where the two safety perceptions are similar and are different. Detailed statistics of the GeoAI-based and survey-based safety perceptions, and perception bias are illustrated in Table 4.3.

4.6 Modeling Safety Perceptions and Perception Bias

4.6.1 Understanding safety perceptions with (spatial) regression models

After characterizing the GeoAI-based and survey-based safety perceptions, three (spatial) regression models are employed to provide a comprehensive picture of safety perceptions including the ordinary least squares (OLS), spatial autoregressive (SAR), and spatial error models (SEM) (Fotheringham et al., 2000). The latter two were performed because geographic variables like safety perception measures often correlate with those in their nearby geographic areas, which is known as spatial autocorrelation (See the global Moran's I values in Table 4.2). The two forms of safety perceptions and perception bias are used as dependent variables.

The independent variables are inferred from the land use and socioeconomic datasets, and human mobility dataset. In addition, the distance from the base area to the center of Stockholm city (as shown in Figure 4.2) is also computed. The choice of these independent variables for the modeling of the safety perceptions follows more than seven decades of two main streams of research on fear (of crime) from criminology/sociology and on

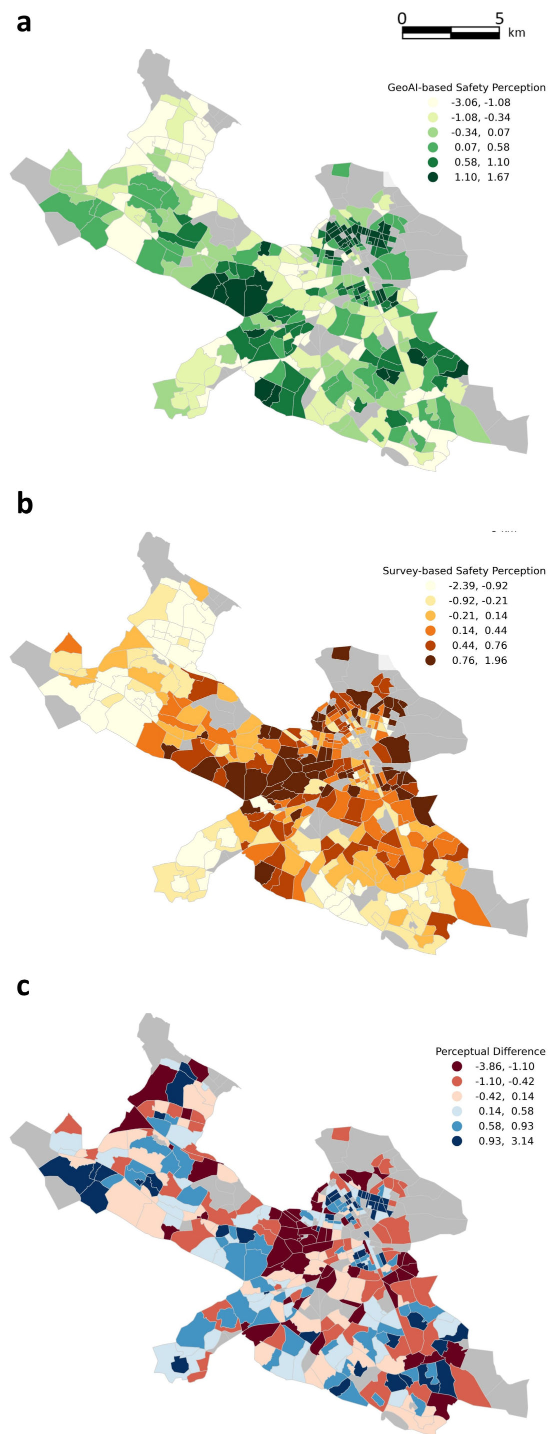

Figure 4.3: (a) Distributions of safety perception scores with GeoAI approach in Stockholm. (b) Distributions of safety perception scores with the survey in Stockholm. (c) Distributions of perception bias in Stockholm.

environmental psychology/urban planning (Farrall et al., 1997; Fisher and Nasar, 1992; Hale, 1996; Hart et al., 2022; Pain, 2000). For example, previous research has most commonly examined the relationship between safety perceptions and individual-level socioeconomic characteristics such as age and gender (Ferraro and LaGrange, 1988; Warr, 1985). Within these studies, it is reported that those who declare feeling the most unsafe, such as older adults, were less likely in reality to become a victim. We have also included environmental factors because research showed that a number of environmental characteristics of a setting may also produce fear (Newman, 1972). The level of maintenance of an environment can affect feelings of safety (Skogan, 1992; Wilson and Kelling, 1982). In other words, physical and social "incivilities" at a setting can trigger feelings of fear among the occupants of this setting. Built upon existing studies, we selected a couple of them in our study because they relate to Stockholm or they are related to the theory more in general (Ceccato and Haining, 2005; Ferraro and LaGrange, 1988; Newman, 1972). Several variables are dropped before input into the three (spatial) regression models because these variables are highly correlated and may cause high multicollinearity of the regression models. We also report the VIF values of all variables in Table 4.5, to ensure the robustness of our models. More detailed statistics of all variables used for the three-regression analysis are reported in Table 4.3.

Table 4.3: Detailed statistics for safety perceptions and land use and socioeconomic factors used for understanding safety perceptions

Variables	Min	Mean	Max	Std
GeoAI-based Safety Perceptions	-3.06	0.01	1.67	1.00
Survey-based Safety Perceptions	-2.39	0.00	1.96	0.84
Perception Bias	-3.86	0.01	3.14	1.12
Density of Bars / Km2	0.00	27.85	274.25	54.42
Density of Street Lights / Km2	0.00	953.04	15,383.90	1,214.13
Density of Transport Stations / Km2	0.00	1.16	28.00	3.35
Density of Gas Stations / Km2	0.00	0.29	16.98	1.34
Proportion of Commercial Areas	0.00	0.09	0.97	0.21
Proportion of Residential Areas	0.00	0.39	0.98	0.26
Proportion of Recreational Areas	0.00	0.00	0.16	0.02
Proportion of Forest Areas	0.00	0.12	0.78	0.15
Older Adults Population Rate	0.00	0.15	0.73	0.07
Foreign Born Population Rate	0.05	0.23	0.96	0.14
Employment Rate	0.12	0.80	0.97	0.09
Average Income	131,600	459,476	1,109,000	137,536
Visitors in Daytime	37	4,710	21,791	4,474
Distance to City Center (Km)	0.23	5.77	16.01	3.91

Table 4.4: Results of regression models, including ordinary least squares (OLS) regression, spatial autoregressive (SAR) model, and spatial error model (SEM), for GeoAI-based, survey-based safety perception and perception bias

	GeoAI-based Safety Perception			Survey-based Safety Perception			Perception Difference		
	OLS	SAR	SEM	OLS	SAR	SEM	OLS	SAR	SEM
Variables	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
CONSTANT	-0.0046*	-0.9059	-0.3495	2.0860*	1.4774*	1.9114*	-2.0906	-2.4029*	-2.1486*
Density of Bars / Km2	0.0041*	0.0035*	0.0033*	-0.0010	-0.0007	-0.0014	0.0051*	0.0042*	0.0049*
Density of Street Lights / Km2	-0.0002*	-0.0001*	-0.0001*	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001
Density of Transport Stations / Km2	0.0123	0.0037	0.0012	-0.0289*	-0.0320*	-0.0291*	0.0316	0.0356*	0.0302*
Density of Gas Stations / Km2	-0.0734*	-0.0840*	-0.0845*	0.0126	0.0123	0.0113	-0.086*	-0.0962*	-0.0943*
Proportion of Commercial Areas	0.9772*	0.8177*	0.7975*	-0.7560*	-0.5382*	-0.7560*	1.7332*	1.3661*	1.5036*
Proportion of Residential Areas	1.7845*	1.7069*	1.7993*	-0.1371	-0.0938	-0.0569	1.9216*	1.8030*	1.8398*
Proportion of Recreational Areas	-1.3315	-1.6259	-3.0562	-7.6788*	-6.2571*	-5.8654*	6.3473	4.6925	2.7892
Proportion of Forest Areas	1.7832*	1.5450*	1.1139*	0.0175	-0.0448	0.0336	1.7656*	1.5888*	1.1987*
Older Adults Population Rate	1.0865	1.1017	0.7990	-1.3670*	-0.9483	-1.2125*	2.4535*	2.0675*	2.0257*
Foreign Born Population Rate	-1.2775*	-0.5113	-0.6719	-2.3470*	-1.7039*	-1.9111*	1.0695	1.2145	1.0417
Employment Rate	-1.6068*	-0.6371	-1.0409	-0.6044	-0.4728	-0.5232	-1.0024	-0.1652	-0.6508
Average Income	0.0001*	0.0001*	0.0001*	0.0001	0.0001	0.0001	0.0001*	0.0001*	0.0001*
Daytime Visitors	-0.0001*	-0.0001	-0.0001*	-0.0001	-0.0001	-0.0001	-0.0001*	-0.0001	-0.0001
Distance to City Center (Km)	-0.0154	0.0060	-0.0225	-0.1030*	-0.0632*	-0.1070*	0.0876*	0.0707*	0.0854*
σ		0.3691*			0.3827*			0.3667*	
λ			0.5006*			0.3583*			0.4198*
(Pseudo) R-squared	0.517	0.558	0.501	0.441	0.483	0.438	0.346	0.395	0.337
Standard Error	0.710	0.664	0.662	0.626	0.602	0.610	0.927	0.872	0.877
AIC	750.885	728.236	729.946	679.950	661.462	667.956	933.099	914.027	917.838

Table 4.5: The VIF values of all variables in the three regression models.

Variable	VIF	Variable	VIF
Densiy of Bars / Km2	2.34	Proportion of Forest Areas	1.61
Densiy of Street Lights / Km2	1.45	Older Adults Population Rate	1.54
Densiy of Transport Stations / Km2	1.16	Foreign Born Population Rate	5.07
Densiy of Gas Stations / Km2	1.04	Employment Rate	3.53
Proportion of Commercial Areas	3.06	Average Income	2.19
Proportion of Residential Areas	1.66	Daytime Visitors	1.14
Proportion of Recreational Areas	1.05	Distance to City Center (Km)	2.09

4.6.2 Explain GeoAI-based safety perceptions

Table 4.4 reports the regression model results for GeoAI-based safety perceptions. Overall, the goodness-of-fits of all three models are over 0.50 with the SAR model performing best (R2 is 0.558). Most variables are significant (p-values smaller than 0.05) and can be trusted. Overall, the results are consistent with conclusions from existing literature and fit with our common sense. We summarize the associations between the safety perception of visitors and built environment variables from three aspects.

First, the high quality of the neighborhood's visual appearance may contribute to people's positive safety perceptions (Cunningham and Jones, 1999; Schroeder and Anderson, 1984). Areas with high proportions of residential, forest areas, more older adults, less foreign-born populations, higher average incomes, and fewer visitors may have a more peaceful, lively, and beautiful visual appearance from street view images, and are positively linked with higher safety perceptions. Second, regions with a high density of bars and high proportions of commercial facilities have positive associations with safety perceptions. Because these regions may be viewed as inner-city areas that have a relatively prosperous economy and business (i.e., economically vibrant places) according to the streetscapes. Also, it fits with the actual patterns in Stockholm as downtown areas are safer than those suburban areas. In addition, specific urban facilities such as gas stations may have negative impacts on human perceived safety, as gas stations have long been considered high-crime areas (Bernasco and Block, 2011; Ceccato and Haining, 2004).

4.6.3 Explain survey-based safety perceptions

According to Table 4.4, the neighborhood residents' safety perception results are different from that of citywide residents' safety perceptions. Overall, the goodness-of-fits of all three models are over 0.43 with the SAR model performing the best (R2 is 0.483). We summarize the associations between survey-based safety perceptions and built environment variables from two aspects.

First, base areas with a higher density of transport stations, and more commercial and recreational areas, have negative associations with the survey-based safety perceptions as they may attract more human activities. As suggested by prior studies, places with more human activities may have more criminal activities, thereby increasing neighborhood residents' fear of crime and reducing safety perceptions (Stucky and Ottensmann, 2009; Taylor et al., 1984; Wilcox et al., 2004). Another potential driver of neighborhood residents' safety perceptions refers to their local knowledge. Regions with more foreign-born populations have low safety perceptions, which indicates the inequality of safety perceptions between Sweden- and foreign-born populations. Areas with a higher number of immigrants (including human smuggling and illegal immigration) generally have higher crime rates and thereby may have negative impacts on human safety perceptions (besides creating or perpetuating social and cultural stigmatization) (Martens, 1997). Also, the distance to the city center plays a negative role in safety perceptions which is reflected by neighborhood residents' experiences and cognition.

4.6.4 Explain Safety Perception Bias

To compare the two measures of safety perceptions, we start by computing the correlation coefficients between the two at base areas. Pearson's correlation coefficient is 0.286, implying similar trends but also differences between the two safety perception measures at base areas. Also, Table 4.4 implies that physical and socioeconomic factors may contribute differently to urban safety perceptions, and GeoAI-based and survey-based safety perceptions have different emphases. Given such differences, we investigate what factors contribute to perception bias. We summarize the associations between perception bias and built environment variables from the following aspects.

First, from street view images, citywide residents may overestimate their safety perceptions of base areas with a higher density of bars, transportation stations, and proportions of commercial areas, as they look more economically vibrant and have similar streetscapes of inner-city regions. However, people living in these economically vibrant neighborhoods may have relatively low safety perceptions, as these regions might be considered crime attractors and generators, and provide better crime opportunities for offenders (Brantingham and Brantingham, 1995). Hence, the perception bias might be enlarged.

Second, people may perceive parts of the city as unsafe because they associate them or particular features in them with some degree of disorder (Skogan, 1992). For example, gas stations as places where more criminal activities happen from street view images (Bowers, 2014; Deryol et al., 2016). Therefore, regions with a higher density of gas stations may have a lower GeoAI-based safety perception and are negatively associated with perception bias as shown in Table 4.4.

Third, people may perceive areas with higher proportions of residential and forest areas as lively places as they have more residential buildings and greenness according to street view images (Hipp et al., 2022). Conversely, some types of residences in the periphery of the city, such as detached and semi-detached housing, experience a higher risk of residential burglaries (Bernasco et al., 2014). Hence, these regions may have higher GeoAI-based safety perceptions while the survey-based safety perceptions may be lowered, which enlarges perception bias.

Fourth, older adults tend to declare feeling unsafe because they overestimate their risk of being victimized compared with younger people because of their vulnerability (Ceccato and Bamzar, 2016). Hence, regions with more populations that are older than 65 may express relatively lower neighborhood residents' safety perceptions than other groups, in

Table 4.6: Correlations of perceived safety scores between responses from all participants and different groups of people across different population groups. All values are significant (p-value < 0.05)

	Male	Female	Populations under 50 years old	Populations over 50 years old
Number of Responses	9450	14260	10000	13710
Pearson Correlation (Safety Scores)	0.79	0.86	0.81	0.85
Pearson Correlation (Safety Category)	0.72	0.81	0.75	0.80

Table 4.7: ANOVA test results of comparison across different population groups

Groups		F-value	P-value
(1)	Overall safety perception score		
(2)	Safety perception score of males	0.638	0.528
(3)	Safety perception score of females		
(1)	Overall safety perception score		
(2)	Safety perception score of populations under 50 years old	0.096	0.908
(3)	Safety perception score of populations over 50 years old		

which the perception bias might be enlarged.

Finally, the employment rate is negatively correlated with perception bias. Employment rates of the neighborhood might not be inferred directly from streetscapes. While residents may have a better sense of employment rates and economic conditions of their living neighborhoods. Hence, the higher the employment rate, the higher the neighborhood residents' safety perceptions, and the perception bias is thereby reduced.

4.7 Observing Model Bias in GeoAI-based Safety Perceptions

We focus on two aspects of model biases in addition to perception bias: population bias and spatial bias. According to existing literature, different populations have varying human sense of place (Pánek et al., 2020). Motivated by this, we collect the gender and age information of participants in our survey. In addition to computing the perceived safety scores of the sampled street view images based on the responses of all participants, we also calculate the perceived safety scores based on the following categories of people only: male vs. female, and populations under vs. over 50 years old. We examined Pearson's correlation and conducted an ANOVA test to compare the perceived safety scores of each subgroup to those of the overall population. As shown in Table 4.6, the Pearson correlations are over 0.72 between any subgroups of the entire population. Results of the ANOVA test in Table 4.7 show that there are no significant differences among population groups. Consequently, it may be inferred that the population bias has minimal effects on the training dataset for the GeoAI approach for measuring citywide residents' safety perceptions.

Another potential refers to spatial bias. Existing studies have suggested that locally trained models may better reflect local people's perceptions. Our online survey only recruits citizens living in Stockholm to measure their safety perceptions. We further apply the global model from the MIT Place Pulse dataset to predict the perceived safety scores of those sample street view images used in the online survey. The results of the two models are compared by computing the mean squared error (MSE). The localized model has a lower MSE error of 0.82, whereas the global model's MSE is 1.86. Hence, it may be inferred that the localized GeoAI model performs better than the global model for capturing local people's safety perceptions.

4.8 Discussions

Here, we list several key takeaways from results that may inform research in multiple fields.

4.8.1 Factors influencing safety perceptions and perception bias

The modeling results of safety perceptions and perception bias indicate that the two approaches – the GeoAI and surveys place different emphases on safety perceptions. As illustrated in Section 5.2, citywide residents' safety perceptions measured by the GeoAI approach are associated with elements and scenarios in the built environment, such as the quality of neighborhood visual appearance, downtown/suburban city views and ecomically vibrant places, and specific facilities. These elements may be directly perceived from streetscape images. While other elements, such as socio-demographic factors, might not be apparent from streetscapes and thereby overlooked in the GeoAI-based safety perceptions. The associations between safety perceptions and built environment are consistent with several existing theories like "cues to care" (Li and Nassauer, 2020) and Jeffery's Crime Prevention through Environmental Design (Jeffery, 1977). It suggests that the perceptions of participants might be sparked by the visual cues from the streetscape. Their first impressions of environmental elements may help them determine whether these features are safe or not.

Comparatively, neighborhood residents' safety perceptions measured by the survey may include both safety perceptions inferred from the built environment and their living experience with local knowledge involved. For instance, as illustrated in Section 5.3, regions with more commercial activities and attract more outsiders, may have a similar streetscape with inner-city views, but may have negative associations on safety perception with local context considered (Stucky and Ottensmann, 2009; Taylor et al., 1984; Wilcox et al., 2004). Such knowledge might be obtained from the daily experiences of locals, rather than from visual clues in street view images. Similarly, different groups of people (e.g., older adults and foreign-born individuals) may have diverse safety perceptions that are not reflected in street view images, but may be captured more accurately by surveys with local contexts considered. Therefore, neighborhood residents' safety perceptions might reflect their long-term daily interactions and personal living experiences with place.

4.8.2 Implications for Urban Planning

We present a comparison between the two types of safety perceptions measured with different approaches. The characteristics of safety perceptions and their perceptual differences are described. Our study provides implications for urban planning studies in two aspects.

First, we provide a thorough examination of the associations between safety perceptions and physical and social environmental factors. The ultimate goal of urban planning is always to build communities that improve residents' quality of life and sense of security. The discoveries indicate that residents' perceptions of safety are influenced by a variety of physical and socioeconomic factors including land use, urban facilities, socioeconomic attributes, and human mobility, and how reliable are they to illustrate the safety perceptions of different residents in the city. The research's findings highlight the role of environmental design and elements in the built environment, which may benefit studies that adhere to the "Crime Prevention through Environmental Design" principle (Cozens and Love, 2015; Jeffery, 1977; Newman, 1972). Although planners may do little about the socio-economic conditions of neighborhoods, the findings of this study on the physical environment and safety may assist them in better planning new residential areas in the future.

Second, there has been a popular opinion that (Geo)AI-based systems could "replace" the traditional approaches in certain sectors. Nonetheless, some researchers have expressed their concerns regarding various ethical issues in these AI-based approaches, and have suggested that there is still a long way to go. How can these machines, for example, understand human safety perceptions (Shaw and Sui, 2020)? How accurate, reliable, and sensitive are these GeoAI methods? Can researchers trust these approaches in planning practices? Our study may be viewed as a satisfactory balance between the two perspectives. The GeoAI approaches bring opportunities for measuring safety perceptions that are not limited to local regions and are cost-effective. We also demonstrate that there are discrepancies between the GeoAI-based and survey-based safety perceptions. The GeoAI approach primarily focuses on the safety perceptions associated with built environments while overlooking personal experience. Given the advantages and disadvantages of both approaches, the promise of the GeoAI approach, and the proven effectiveness of traditional surveys, we suggest combining the two approaches in urban planning practices. Our study shows how advanced technologies may be incorporated into real-world practices to enhance the productivity of specific domains.

4.8.3 Implications for GeoAI Studies

In addition, our study provides insights into the development of GeoAI research. Despite GeoAI's significant success in tackling a wide range of geographic and urban challenges, ethical questions need to be considered before being used in real-world practices (Ntoutsi et al., 2020; Shaw and Sui, 2020). We demonstrate the value of domain knowledge in directing GeoAI study to problem-solving. Urban planning and criminology theories provide insights into the explanation of citywide residents' safety perceptions to ensure that the outcomes of the "black-box" models are robust and reliable. Hence, it is necessary to develop spatially explicit and theory-informed AI models rather than only use technology to solve problems. Although citywide residents' safety perceptions measured from the GeoAI approach may not "replace" the traditional survey approach at the current stage, the GeoAI method shows promise in measuring safety perceptions and may serve as a supplement to traditional approaches in planning practices. For example, examine the associations between the built and social environment, and analyze the temporal variations of safety perception on the urban environment day and night.

Also, we took attempts to monitor several model biases when performing the GeoAI approach. Model biases have minimal effects on the proposed GeoAI approach. Monitoring a variety of model biases is required for the development of trustworthy GeoAI systems. However, relatively few researchers have investigated this topic. Given that all approaches have pros and cons, it is vital to examine the characteristics and limitations of GeoAI approaches to better guide potential practical applications.

4.8.4 Limitations and Future Work

This study still has potential for improvement. One limitation relates to the notion of safety. There is no clear definition of safety when gathering safety perceptions; consequently, we treat participants' corresponding behaviors to represent the general public's safety perception. It may be necessary to measure safety perception from multiple aspects with more specific questions. Also, more variables might be involved in regression models such as the percentage of education and police stations to better explain the results. Several variables such as mobility-related factors play insignificant roles in this paper, which is inconsistent with prior studies (Zhang et al., 2021a) and may be worth further exploration. Another issue refers to the generalizability of the study. We primarily focus on the overall safety perceptions of Stockholm. Given the spatial heterogeneity, it is necessary to delve into various sub-regions and conduct a finer-resolution assessment. Also, more empirical research might be conducted across multiple cities. In addition, the model bias discussed in this paper is limited to those that exist in GeoAI approaches. It does not imply that traditional questionnaires and surveys are flawless. Our future work will also consider social desirability issues in questionnaires and surveys as a form of model bias.

4.9 Conclusions

In this research, we provide a comprehensive characterization of human safety perceptions in the city of Stockholm from two perspectives: (1) citywide residents' safety perceptions measured using the GeoAI approach that combines street view images and deep learning models, and (2) local neighborhood residents' safety perceptions measured using surveys. We examined the associations between the two safety measures and explored the perceptual differences by assessing perception bias and model bias. Results illustrate that the GeoAI-based safety perceptions may better express people's first impressions of the built environment, whereas survey-based safety perceptions condense and reflect residents' overall daily experiences in neighborhoods. In addition, we examined potential model bias that may influence perceptual difference. Despite the fact that safety perceptions may vary across multiple population groups, we discovered that such differences are not statistically significant. Also, it is necessary to use localized datasets that more accurately reflect locals' perceptions of GeoAI.

In summary, our contributions of this study include: First, we created a new measure of safety perceptions based on visual impressions of the environment using a GeoAI model in Stockholm, Sweden. Second, we were able to compare the similarity and discrepancy ("perception bias") between the citywide residents' and neighborhood residents' safety perceptions, one more capturing situational safety perceptions and the other measure close to dispositional safety perceptions. Third, we attempted to show patterns of "perception bias" by identifying factors that explained difference between the two forms of safety perceptions, and critically evaluated the "model bias" of the GeoAI approach.

Given the varying needs of potential audiences, we offer two insights: (1) For urban planners and policymakers, advanced GeoAI approaches can supplement traditional approaches and benefit real-world practices; (2) For GIScientists and computer scientists, the ethical issues should be considered during the development of advanced geocomputing methods.

5 UNDERSTANDING HUMAN PLACE PERCEPTION IN URBAN DESIGN

Chapter 5 provides an empirical study to investigate the RQ2: *What and how do urban visual characteristics of built environments quantitatively associate with human perceptions of places measured by geospatial data science?* Understanding how urban visual characteristics shape human perceptions of the built environment is vital for urban design and planning. Nevertheless, an explicit link between urban visual characteristics and human perceptions has not been comprehensively described yet. In this chapter, utilizing advanced machine learning algorithms and causal discovery techniques, we aim to provide a thorough investigation of the relationship between urban visual characteristics and human perceptions. We first quantify three aspects of urban visual characteristics by integrating street view images and network analysis. This includes the nodes and paths, which are the key components among the five urban design elements of Kevin Lynch's *The Image of the City*. Five dimensions of urban design qualities such as imageability, enclosure, human scale, transparency, and complexity, are also included in urban visual characteristics. In addition, we assess the significance of color (e.g., red, green, blue, hue, saturation, value, and colorfulness) in urban visual characteristics. After that, we conduct an empirical experiment in Los Angeles, employing advanced machine learning algorithms, notably XGBoost and causal discovery approaches, to model the complex associations between these variables. The explainable machine learning results including feature importance, SHAP (SHapley Additive exPlanations), and causal discovery indicate that certain urban visual characteristics have significant effects on how people perceive the built environment. More specifically, sky view-related enclosure, greenery-related human scale, complexity, as well as color hue are identified as the most influential urban visual characteristics on human perceptions. Overall, this chapter emphasizes the importance of understanding the relationships between urban visual characteristics and human perceptions and offers insights into the design of more aesthetically pleasing urban spaces. Our use of advanced machine learning algorithms, such as explainable XGBoost and causal discovery algorithms, demonstrates their effectiveness in modeling complex geographic phenomena.

5.1 Introduction

Imagining visiting a park, plaza, or bustling street in a vibrant city. People may experience a range of emotions when walking through the space that are shaped by various urban visual characteristics and design factors (Ewing and Handy, 2009; Pazhouhanfar and Kamal, 2014). For instance, as suggested in Lynch's seminal book (Lynch, 1964), there are five fundamental components of the visual qualities of the built environments including nodes, paths, districts, landmarks, and edges; Similarly, Ewing and Handy (2009) emphasizes multiple urban design qualities that may guide the development of liveable and visually appealing urban environments; Environmental psychologists pay more attention to the color of built environments, which can affect our cognitive performance and may benefit mental health (Tyrväinen et al., 2014). All of these urban visual characteristics can have a profound impact on our perceptions and behaviors, ultimately shaping our overall experience of a place (Ittelson, 1978). By analyzing the associations between urban visual characteristics and human perception of the urban environment, urban designers can make informed decisions to create built environments that are both functional and aesthetically pleasing, thereby enhancing the quality of the built environment, and promoting human well-being.

In recent years, researchers have made efforts to model the complicated associations between urban visual characteristics and human subjective perceptions of the built environment. On the one hand, the plethora of geographic data sources, such as street view images, has enabled researchers to create comprehensive and detailed representations of the built environment (Zhanga et al., 2023; Kang et al., 2020b). Researchers can properly represent the visual characteristics of the built environments by extracting a wide variety of objects, such as urban greenery (Li et al., 2015b), sky view (Gong et al., 2018), and vehicles (Gebru et al., 2017), from street view images. On the other hand, researchers can even evaluate subjective human perceptions of place, such as safety (Zhang et al., 2021a), liveliness (Kang et al., 2021), and beauty (Zhang et al., 2020), using advanced geospatial artificial intelligence (GeoAI) algorithms (Gao, 2021). Leveraging these powerful tools and techniques allow researchers to better model human-environment interactions, ultimately leading to the development of more livable, sustainable, and visually appealing cities.

Despite the success of recent research efforts, understanding the complicated relationships between urban visual characteristics and human subjective perceptions still face several challenges. One primary limitation is that these studies often concentrate on certain objects and elements within street view images rather than the entire landscape. For instance, while researchers have examined the associations between objects like buildings (Larkin et al., 2021), urban greenery (Li et al., 2015a), and roads (Larkin et al., 2021) and how they affect people's perceptions, these studies may only capture certain aspects of the complex associations between urban design and human perception, failing to account for the holistic and multi-dimensional nature of the built environment. It is worth noting that human perceptions may not be directly related to a single object of the built environment, and two places with similar objects may give people different perceptions based on their overall streetscapes. Consequently, rather than just considering street objects, it is necessary to examine the associations between urban design principles grounded by urban design and planning theories and human perceptions. In addition, color is an important element that may influence how we perceive the constructed world (Bruner et al., 1951). Psychologists have realized that human eyes are sensitive to different colors which may influence our perceptions (Haber and Hershenson, 1973). However, the explicit associations between color and human perception in the context of the built environments have not yet been adequately quantified.

Moreover, machine learning techniques have come under fire for being "black boxes" or difficult to be explained. Despite the high predictive accuracy that machine learning models can attain, the fundamental mechanisms that driving these predictions are often opaque and challenging to interpret. This lack of transparency may limit the practical applications of machine learning approaches, especially in fields such as urban design where stakeholders may require a clear understanding of how different design factors affect human perception. To address this issue, our study incorporates several explainable artificial intelligence (AI) approaches including feature importance, SHAP (SHapley Additive exPlanations) (Feng et al., 2021a), and causal discovery (Spirtes et al., 2000). In particular, we employ a novel machine learning approach called causal discovery, which is developed based on recent advances in causal inference and was recognized with the 2021 Nobel Prize in Economics (Nogueira et al., 2022). The causal discovery algorithm may help to identify causal relationships between different urban visual characteristics and human perceptions, enhancing the interpretability of our results. To the best of our knowledge, this work is the first to explore the application of causal discovery algorithms in urban studies.

To this end, this paper proposes a computational framework that utilizes multi-source geospatial big data to quantify urban visual characteristics from three aspects: nodes and paths, urban design qualities, and color. We further perform an empirical study in Los Angeles to explore the relationships between these urban visual factors and human subjective perception of built environments with advanced machine learning algorithms. We ask the following three research questions:

(1) How to quantify the urban design elements, urban design qualities, and color of built environments with multi-source geospatial big data?

(2) What are the relationships between urban visual characteristics and human perceptions of the built environment?

(3) How to integrate the causal discovery algorithm to identify the relationships between human perceptions and urban visual characteristics?

Specifically, we aim to investigate the associations between urban visual characteristics and human perceptions of the built environment through advanced explainable machine learning techniques, including XGBoost and a causal discovery algorithm. The ultimate goal is to enhance the understanding of complex human-environment relationships and to provide insights for urban planners and designers toward a more livable and sustainable city.

5.2 Literature Review

5.2.1 Urban Visual Qualities, Urban Design Qualities, and Color

To describe the associations between urban visual characteristics and human perceptions, we draw from multiple urban design and environmental psychology theories, including Lynch's urban design elements (Lynch, 1964), Ewing's urban design qualities (Ewing and Handy, 2009), and color (Bruner et al., 1951). The five fundamental components that contribute to urban design include nodes, paths, districts, landmarks, and edges. As suggested by existing studies, understanding the city's design elements has important implications for people's perceptions and behaviors. For instance, nodes, the focal points for urban activities, are positively associated with people's sense of orientation and wayfinding ability (Dalton and Bafna, 2003; McCunn and Gifford, 2018; Yoshimura et al., 2020). Similarly, paths, where people move through the city, can affect people's sense of distance, speed, and accessibility (Singh, 2016). Therefore, we take these two crucial aspects into account for our modeling. Also, Filomena et al. (2019) offers a computational framework for measuring the five urban design elements, which serves as the technical foundation of our work.

Ewing and Handy (2009) proposed a conceptual framework and examined multiple dimensions of subjective qualities of the urban street environment that are associated with walking behaviors. From the urban design literature (Ewing et al., 1996), five dimensions have been widely measured including urban design qualities such as legibility, coherence, complexity, and visual interest have also been found to affect people's perception of the built environment. Legibility refers to the ease with which people can understand and navigate an urban environment, while coherence relates to the extent to which different parts of the environment are connected and form a coherent whole (Salingaros, 2000). Complexity, on the other hand, refers to the richness and diversity of the urban environment, while visual interest pertains to the attractiveness and aesthetic qualities of the environment (Salingaros, 2000; Healey, 2006).

Finally, color is another important element that has been studied in relation to human perception. Psychologists have shown that color can influence people's emotions, behavior, and cognitive processes, and can also affect people's perception of space, distance, and size (Lin, 2004; Labrecque et al., 2013). Furthermore, color also plays a crucial role in shaping the perception of the built environment. Researchers have utilized street view images to explore the role of color in the built environment. For instance, based on street view images and machine learning approaches, Dai et al. (2021) have examined the associations between perceptions and blue-green spaces. Similarly, Quercia et al. (2014) examined the impact of different colors on people's perception of urban streetscapes to understand what factors contribute to a beautiful, quiet and happy environment. Results illustrate that green has strong associations with the three qualities. In summary, previous studies have shown that color is a significant factor in shaping human perception of the built environment.

5.2.2 Measuring Perception with Street View Images and Deep Learning

Over the past few years, researchers have utilized emerging large-scale geospatial big data sources (e.g., street view images, geotagged texts, human mobility data) and advanced Geospatial Artificial Intelligence (GeoAI) methods for spatial phenomena modeling, geographic knowledge discovery, and human-environment understanding (Gao, 2021; Janowicz et al., 2020). Specifically, prior studies have employed GeoAI to model various subjective human perceptions of place with street view images and deep learning approaches. The fundamental hypothesis is that people's perceptions of street view images are used as a proxy for their perceptions of places. For example, researchers have assessed people's subjective perception of the built environment from multiple dimensions such as safe (Dubey et al., 2016; Zhang et al., 2021a), lively (Kang et al., 2021), beautiful (Zhang et al., 2020), playability (Kruse et al., 2021), etc. These studies demonstrate the effectiveness of using street view images and GeoAI for measuring human subjective place perception. In this study, we follow this strategy to assess human perceptions of the built environment. Such a computational framework serves as the technical foundation of this study.

5.2.3 Advanced Causal Discovery Algorithms

Causal discovery aims to identify causal relations among a set of variables with automated procedures. The knowledge of these relations is useful for making predictions under interventions and performing interventions to reach desired outcome. Traditionally, causal relations can be identified by performing randomized experiments or interventions, which in many cases are expensive, challenging to implement, or ethically prohibited. Therefore, it is often necessary to identify causal relations by analyzing purely observational data (Spirtes et al., 2000), which has witnessed growing interest in past decades (Glymour et al., 2019).

Such causal discovery algorithms have been widely applied in many fields, such as biology (Neto et al., 2010; Zhang et al., 2012), economics (Koller and Friedman, 2009), and Earth system science (Runge et al., 2019). For example, these algorithms were applied in the field of biology to identify causal relations among phenotypes (Neto et al., 2010) and infer gene regulatory networks (Zhang et al., 2012). In climate search, causal discovery is applied to identify the relationships among different modes of atmospheric low-frequency variability in boreal winter (Ebert-Uphoff and Deng, 2012).

On the methodological side, causal discovery algorithms, broadly speaking, can be categorized into constraint-based methods and score-based methods (Glymour et al., 2019).

Constraint-based methods apply conditional independence tests to identify the undirected edges and then orient them with some rules (Spirtes et al., 2000), while score-based methods search for a causal structure that optimizes a certain goodness-of-fit measure. For these two classes of algorithms, some prominent examples are PC (Spirtes and Glymour, 1991) and GES (Chickering, 2002), respectively. As we will discuss in Section 5.3.4, we focus on constraint-based methods, specifically PC, in this work.

5.3 Data and Methods

This section outlines the methodology for investigating the associations between urban visual characteristics and human perceptions of the built environment. We first introduce three sets of variables for modeling urban visual characteristics and provide a detailed explanation of how they are quantified. Then, we present a computational framework for measuring human subjective perceptions of built environments, which enables us to further analyze their associations with urban visual characteristics. We then employ an advanced XGBoost model to investigate the relationships between urban visual characteristics and human perceptions, examining how multiple aspects of visual characteristics shape people's perceptions of the built environment. Finally, we employ multiple explainable AI approaches, including feature importance, SHAP, and a causal discovery algorithm to delineate the complex and multi-dimensional associations among the urban visual characteristics and human perceptions, further refining our understanding of the factors that shape human perception of the built environment. The computational framework of this study is demonstrated in Figure 5.1.

5.3.1 Nodes and Paths

Nodes and paths are key elements among the five basic components as suggested by Lynch's *The Image of City*. Nodes refer to those places where observers can enter, begin,

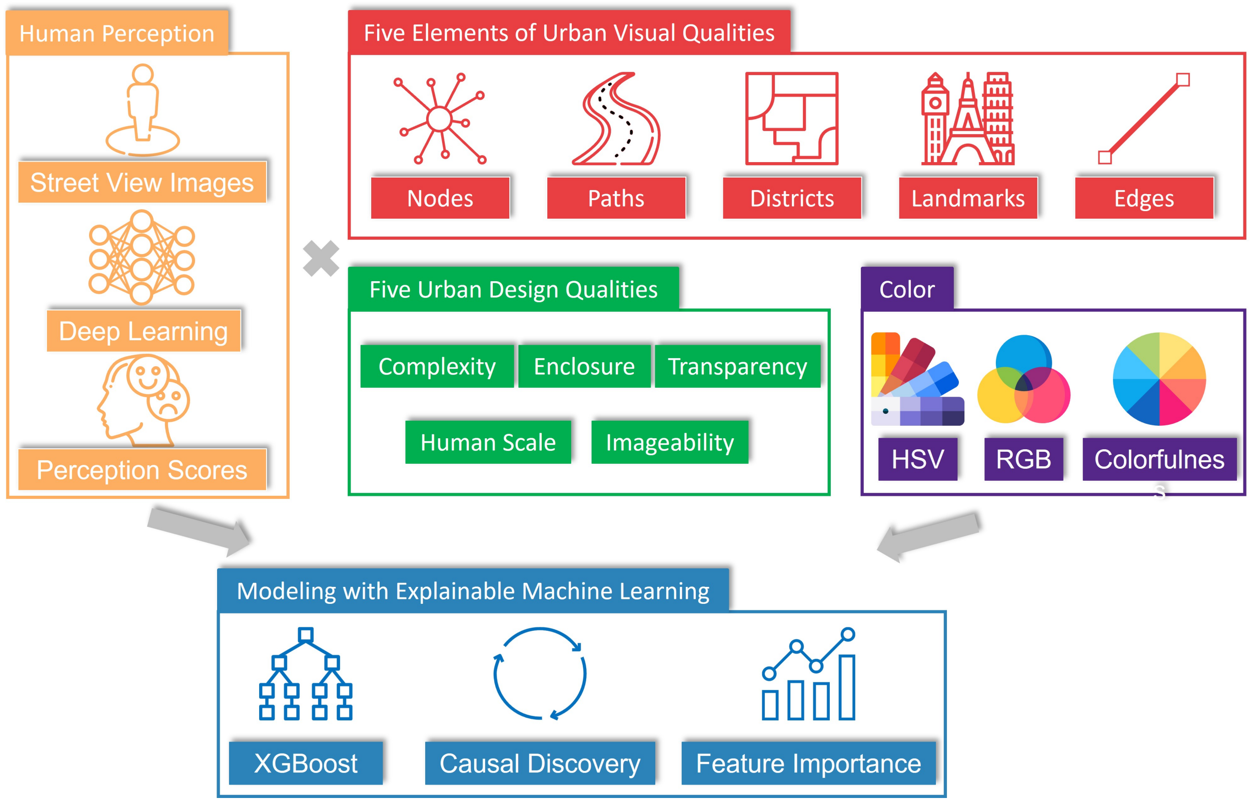

Figure 5.1: A computational framework of the study

or connect their travels. As suggested by Lynch (1964), junctions, places of a break in transportation, and a crossing or convergence of paths are nodes in the urban environment. While paths refer to those main channels that guide orientation and people's movement in the city. To model nodes and paths, this study examines the topological properties of street segments. Centrality is identified as one of the key factors that may influence people's perceptions and cognition of the built environments (Haq and Girotto, 2003), with central locations often becoming important nodes. Therefore, following Filomena et al. (2019), the study computes betweenness centrality to identify the most important nodes and paths that may affect human place perceptions. To do so, we compute the betweenness centrality of a node v in a connected road network graph with the following equations:

$$C_B(v) = \sum_{s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}} \tag{5.1}$$

where σ_{st} is the total number of shortest paths from node s to node t, and $\sigma_{st}(v)$ is the number of those paths that pass through node v.

Similarly, for a given road network, we treat each road segmentation as a vertex and each road intersection as an edge. By doing so, we compute the betweenness centrality of an edge u as:

$$C_B(u) = \sum_{s \neq u \neq t} \frac{\sigma_{st}(u)}{\sigma_{st}} \tag{5.2}$$

By focusing on the two key elements and using centrality as a measure, the study aims to gain a better understanding of how urban design qualities may shape human perceptions and behaviors in the built environment.

5.3.2 Five Urban Design Qualities

Urban design qualities refer to several perceptual qualities that may influence human subjective feelings of environments. Different urban design qualities can elicit different emotional responses from people and shape their perceptions of the space. According to Ewing and Handy (2009), physical features are key elements of urban design qualities that influence human perceptions. Here, we follow the five dimensions of urban design qualities that affect human walking environments defined in Ewing and Handy (2009).

As suggested in Kang et al. (2020b), both element-level and scene-level observations are necessary for modeling and representing the urban environment. Thus, we employed two types of approaches to extract physical objects and evaluate urban scenes from street view images, which we refer to as *element-level measures* and *scene-level measures*, respectively. To extract specific objects, items, and elements from street view images and compute *element-level measures*, we utilized the ADE20K dataset (Zhou et al., 2017), which is a widely used benchmark dataset for image semantic segmentation tasks that includes 150 object categories[1]. We then applied a state-of-the-art vision transformer architecture

[1] A list of the 150 object category of the ADE20K dataset can be found: https://github.com/CSAILVision/sceneparsing/blob/master/objectInfo150.txt.

implementation (Ranftl et al., 2021), which has outperformed previous deep convolutional neural networks, to process the images. The output of this deep learning model is a classification of each pixel of the street view image into one of the 150 object categories in the ADE20K dataset (Zhou et al., 2017). Based on this, we can compute the proportion of each object for a given street-view image. For an image i with $h \times w$ pixels where h is the height of the image and w is the width of the image, the proportion $\mathrm{Prop}_{i,m}$ of a certain object m in a given image can be computed as:

$$\mathrm{Prop}_{i,m} = \frac{\sum_{j=1}^{h} \sum_{k=1}^{w} \mathbb{1}(P_{i,j,k} = m)}{h \times w} \tag{5.3}$$

To further evaluate the semantic information of the streetscape scenes and infer *scene-level measures*, we utilized the Places-CNN classifier[2]. This classifier was trained on the Places Database, which includes over 10 million images. The output of Places-CNN is a classification of each street view image into one of 365 scene semantic categories such as bar, park, or plaza. By using this classifier, we can compute the probability of each street view image belonging to a specific scene category. For a street view image i, the output of the scene classifier is a 365-dimensional vector of softmax probability for scene categories:

$$C_i = [C_{i,1}, C_{i,2}, ..., C_{i,365}] \tag{5.4}$$

Also, the probabilities assigned to all scene categories add up to 1.

$$\sum_{m=1}^{365} C_{i,m} = 1 \tag{5.5}$$

After that, we followed the 5 urban design qualities including imageability, enclosure, human scale, transparency, and complexity, proposed in Ewing and Handy (2009), and identified certain physical attributes that are measurable with the element-level and

[2] A list of the 365 scene category of the Places dataset can be found: https://github.com/CSAILVision/places365/blob/master/categories_places365.txt.

scene-level measures using the state-of-the-art deep learning approaches. In the following paragraphs, we provide a detailed account of each of the five urban design qualities and their corresponding measures that we have developed.

Imageability pertains to the quality of a physical environment that triggers a vivid image in an observer's mind and is closely tied to the sense of place (Lynch, 1964; Gehl, 2001). A city that possesses high imageability is characterized by a well-structured layout, and distinctive parts, and can be instantly recognized by individuals who have visited or resided there. Here, we measure the imageability from the following three aspects:

1. Proportion of pixels classified as people: $Imageability_{people} = Prop_{i,13}$
2. Number of scenes that are courtyard, plaza, outdoor dinner, and park: $Imageability_{num\_scene} = \sum_{k=1}^{5} \sum_{m \in M} \mathbb{1}(t_{i,k} = m)$
3. Combined probability of street view images that are classified as courtyard, plaza, outdoor dinner, and park: $Imageability_{prob} = \sum_{m \in M} C_{i,m}$

It should be noted that m refers to the predicted scene, while M refers to the set of the categories of courtyard, plaza, outdoor dinner, and park.

Enclosure refers to the creation of outdoor spaces that have a room-like quality by treating the surrounding buildings as "walls" to enclose the space. Following the attributes listed in Ewing and Handy (2009), the following enclosure attributes are measured:

1. Proportion of pixels classified as building or wall: $Enclosure_{wall} = Prop_{i,1} + Prop_{i,2}$
2. Proportion of pixels classified as sky: $Enclosure_{sky} = Prop_{i,3}$

Human scale refers to the physical elements in the urban streetscape that match the size and proportions of humans. As suggested in Ewing and Handy (2009), the presence of smaller-scale features such as street greenery and street furniture are correlated with human scale. We define human scale with the following attributes:

1. Proportion of pixels classified as urban greenery including tree, grass, plant, and flower: $\mathit{HumanScale}_{greenery} = \sum_{m \in M} \mathrm{Prop}_{i,m}$
2. Proportion of pixels classified as street furniture including sidewalk, table, chair, sofa, armchair, seat, desk, and ottoman: $\mathit{HumanScale}_{furniture} = \sum_{m \in M} \mathrm{Prop}_{i,m}$

Transparency refers to the extent to which individuals can observe or perceive human activities beyond the edge of streets. Notable physical elements that influence transparency include windows and signs. Thus, we measure transparency with the following attributes:

1. Proportion of pixels classified as windows or signboards: $\mathit{Transparency} = \mathrm{Prop}_{i,9} + \mathrm{Prop}_{i,44}$

Finally, **Complexity** is defined as the visual richness of an urban environment. It is determined by the diversity of physical elements. A place with high complexity is characterized by a variety of built-environment elements. Hence, we define complexity with the following attributes:

1. Number of objects detected with the element-level measure: $\mathrm{Complexity}_{element} = \sum_{m=1}^{150} \mathbb{1}(\mathrm{Prop}_{i,m} > 0)$
2. $1-$ sum of squared softmax probabilities of place scenes: $\mathrm{Complexity}_{scene} = 1 - \sum_{m=1}^{365} C_{i,m}^2$

Quantifying the abovementioned aspects of urban design qualities allows us to have a comprehensive understanding of the interactions between human perceptions and the built environments.

5.3.3 Color

Color is widely considered to be the most significant and impactful visual cue in shaping our perceptual experience (Hill, 1996; Chen et al., 2022). Different color schemes can evoke diverse moods and emotions in people and thereby influence how people perceive the urban space (Hilbert, 1987).

We first represent the color information of a given street view image with two color models including RGB (red, green, and blue) and HSV (hue, saturation, and value). With RGB, each color is represented by an intensity value ranging from 0 to 255 for each of the three channels of red, green, and blue light. The HSV color model, on the other hand, represents colors in terms of their hue, saturation, and value. Hue refers to the actual color such as red, green, or blue represented by a value ranging from 0 to 360. Saturation describes how colorful a given color is compared to how much gray it contains, and value corresponds to the brightness or darkness of the color. Both saturation and value vary from 0 to 100 percent. In addition to the two color schemes abovementioned, we measured the colorfulness of street view images following Hasler and Suesstrunk (2003); Peng and JEMMOTT III (2018); Chen et al. (2022). This measure reflects the vividness or intensity of the colors in the image, with a more colorful image perceived as brighter and more distinct.

5.3.4 Explainable Machine Learning Algorithms: XGBoost and Causal Discovery

To unravel the intricate associations between urban visual characteristics and human perceptions, we employ cutting-edge machine-learning algorithms in this paper. Traditional statistical methods often struggle to detect non-linear patterns and relationships among variables and may face challenges such as the multicollinearity issue. Therefore, it is necessary to integrate advanced tools to have a more nuanced understanding of these complex interactions. XGBoost (Extreme Gradient Boosting) is a powerful decision tree-based machine-learning algorithm that is specifically designed to model non-linear relationships between variables (Chen et al., 2015). By leveraging the ability of XGBoost to identify complex patterns, we can model the associations between different urban visual characteristics and human perceptions with high performances.

Despite that advanced machine learning algorithms such as XGBoost have been widely used in various urban applications to effectively capture sophisticated human-environment relationships, such approaches have been criticized for their lack of explainability. Several approaches have been developed to evaluate the importance of variables in decision tree models such as feature importance and SHAP (SHapley Additive exPlanations) (Rifkin and Klautau, 2004; Kazemitabar et al., 2017; García and Aznarte, 2020). While these approaches have their advantages, they are considered shallow as they may not provide a deeper understanding of how the variables interact with each other to affect the outcome. It poses a challenge for interpreting the results and understanding the underlying mechanisms between urban visual characteristics and human perceptions. Uncovering the associations between the two is thereby crucial for informing design decisions and policy interventions.

To address this challenge, we employ causal discovery techniques in our study. Causal discovery allows us to discover the causal relationships between urban visual characteristics and human perceptions, which is crucial for understanding the underlying mechanisms that drive these relationships. In particular, we employed the PC algorithm (Spirtes et al., 2000) as it is one of the widely used causal discovery approaches.

As briefly discussed in Section 5.2.3, the PC algorithm is a constraint-based method that is based on conditional independence tests and consists of two phases. It relies on the Markov and faithfulness assumptions, which indicate that the conditional independencies in the distribution and the d-separating statements implied by the ground truth causal structure are equivalent (Spirtes et al., 2000). Furthermore, it also requires the causal sufficiency assumption, which implies that there is no unobserved confounder. In the first phase, PC starts with a complete undirected graph and iteratively performs conditional independence test to eliminate edge. Specifically, for each pair of variables X and Y that are adjacent, the algorithm determines if there exists a subset of variables **Z** in which all variables are either adjacent to X or Y such that X is conditionally independent of Y given **Z**. If such a subset exists, then the algorithm removes the edge between X and Y. After the first phase, the algorithm ends up with a skeleton with undirected edges. In the second phase, it orients as many edges as possible using some orientation rules, in order to determine the v-structures and additional directed edges (Meek, 1995). The result estimated by the PC algorithm is called a completed partially directed acyclic graph, which contains both undirected and directed edges. This is because the PC algorithm is only able to estimate the causal structure up to Markov equivalence class under the assumptions specified above (Spirtes et al., 2000). We use the implementation of PC through the `causal-learn` package available through `https://github.com/xunzheng/notears`, and adopt the Fisher-z test for the conditional independence test.

5.3.5 Study Area and Dataset

We selected downtown Los Angeles as our study area following the *The Image of the City*. Road network data is downloaded from the OpenStreetMap, which will be further utilized for measuring the betweenness centrality for quantifying nodes and edges, as well as downloading street view images. Figure 5.2 illustrates the study area as well as the road networks we downloaded. We then downloaded street view images based on their panoramic identifiers in the study area. Next, we employed our computational framework to compute the urban design qualities and color of each street view image. We also computed nodes and paths based on the centralities of each street. By doing so, we can identify the key hub points and intersections in downtown Los Angeles. Given that nodes and edges are computed at the street segment level, we aggregate all urban visual characteristics to the street level as well. The three aspects could provide a comprehensive picture of the urban visual landscapes.

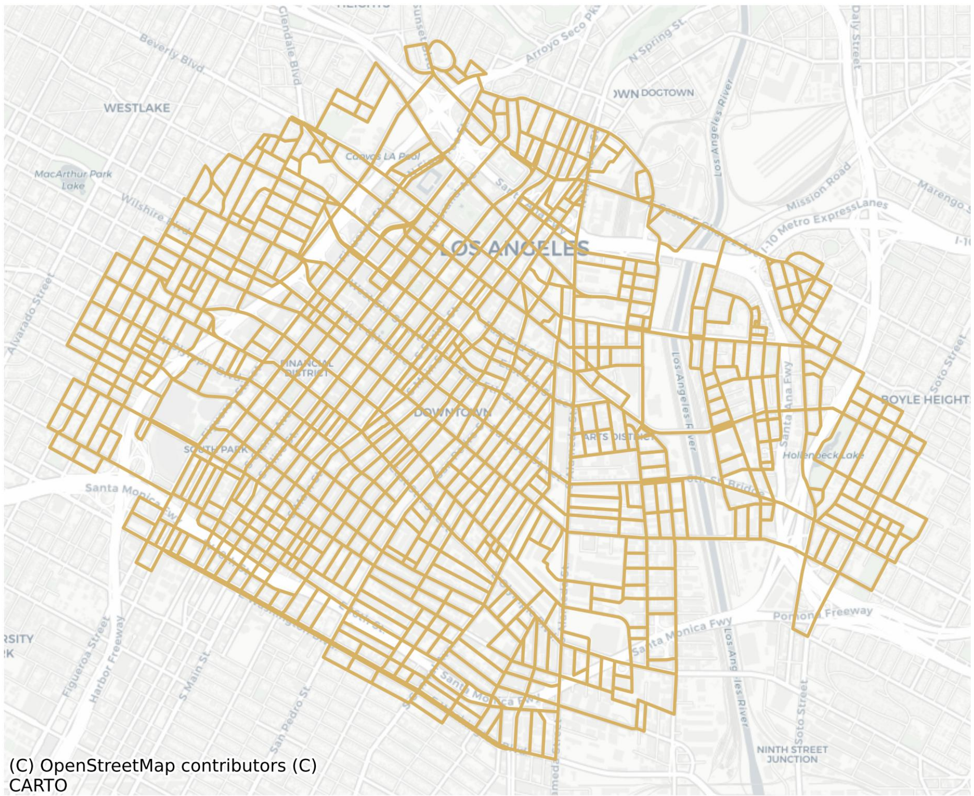

Figure 5.2: Road networks of the study area in Los Angeles

5.3.6 Correlation Urban Visual Characteristics

We start by computing the correlation coefficients between six dimensions of perceptions and urban visual characteristics. The results are depicted in Figure 5.3. Based on the results, the six dimensions of human perceptions can be categorized into two groups: positive human perceptions, which include beautiful, lively, safe, and wealthy, and negative human perceptions, which include boring and depressing. Overall, positive human perceptions demonstrate relatively consistent patterns, i.e., their signs of coefficients are approximately the same, and negative perceptions exhibit similar trends. However, we can also observe variations for each dimension of human perception. Nodes and paths have a relatively lower significance in comparison to urban design qualities and colors. Specifically, they have a minimal impact on human perceptions of beauty.

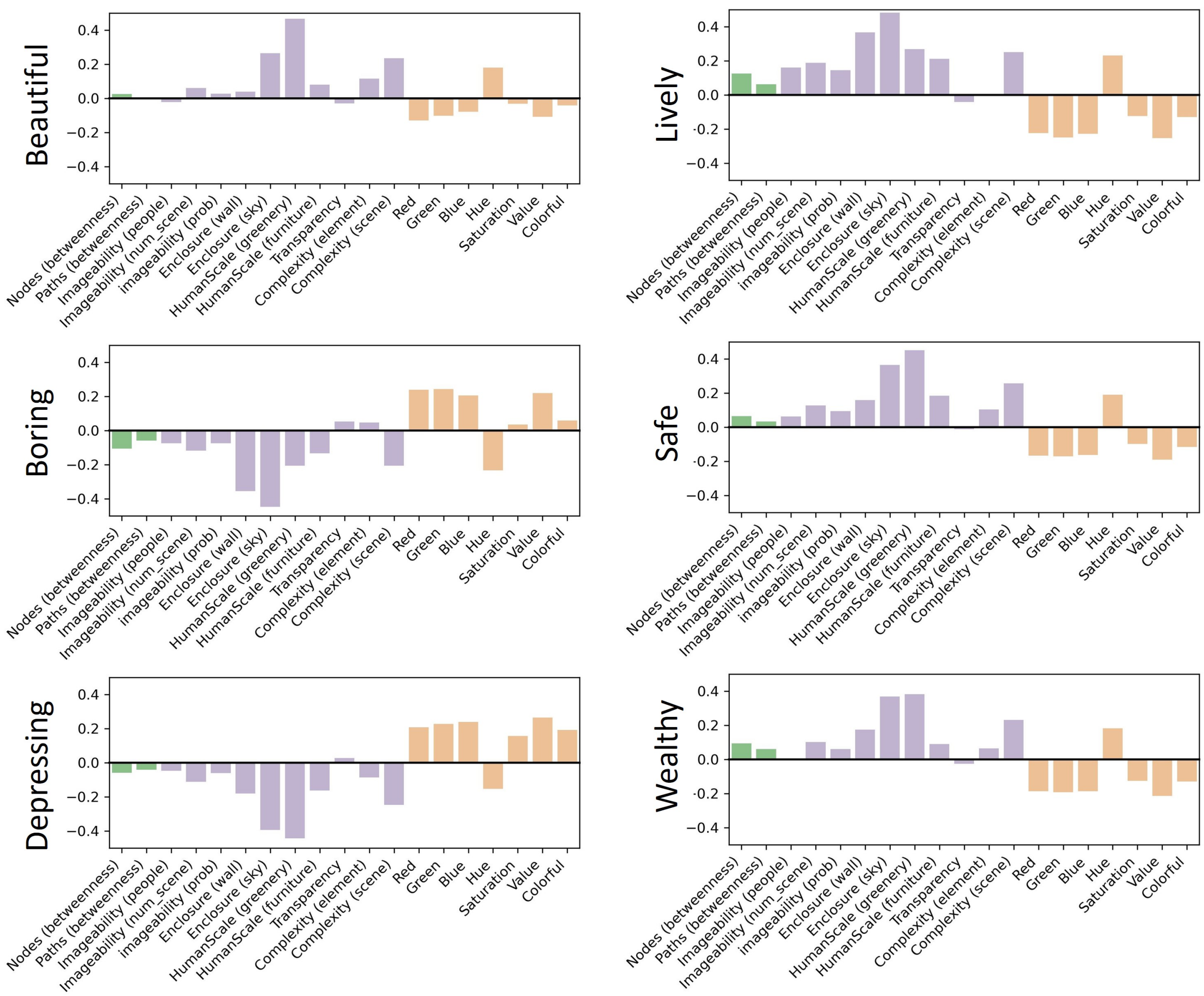

Figure 5.3: Correlation between human perceptions and urban visual characteristics

The correlation coefficients illustrate that urban design qualities play important roles in influencing human perceptions. In particular, $\mathit{Enclosure}_{sky}$, $\mathit{HumanScale}_{greenery}$, and $\mathit{Complexity}_{scene}$ were found to be among the most important factors. Results illustrate that the presence of sky and urban greenery are key factors in shaping human perceptions of the built environment. Also, the more complex a place is, the more positive the human perceptions of the built environment tend to be. While the role of $\mathtt{Enclosure}_{wall}$ may vary for different dimensions of human perceptions. For instance, $\mathtt{Enclosurewall}$ has relatively large correlation coefficients on human perceptions of boring and lively (with absolute correlation coefficients greater than 0.35), while has limited effects on human perceptions of beauty.

Regarding colors, the hue attribute has an opposite pattern compared to other color attributes in relation to human perceptions. Higher hue values are associated with higher human positive perceptions of built environments. While other color attributes have negative associations with positive perceptions. It is worth noting that the absolute values of correlation coefficients for hue and its relationship to human perceptions of beauty are relatively lower than for other dimensions of human perceptions.

5.3.7 XGBoost Modeling Result

We then perform XGBoost to model the complex associations between multiple dimensions of human perceptions and urban visual characteristics. Results of the cross-validation demonstrate that the predicted values reach a R^2 of 0.96 with a relatively low RMSE (Root Mean Square Error) of 0.04. Therefore, advanced machine learning can model the complex associations between human perceptions and urban visual characteristics with high accuracy.

We further examined the feature importance of these variables to understand what and how urban visual characteristics contribute to human perceptions. Figure 5.4 illustrates the top 10 most important variables that contribute to the six dimensions of perceptions. $\mathtt{HumanScale}_{greenery}$, $\mathtt{Enclosure}_{sky}$, hue, and $\mathtt{Complexity}_{scene}$ are all extremely influential in shaping human perceptions of the built environments as they rank the top 6 variables. It implies that urban greenery, sky, hue, and street complexity have the most impact on human perceptions.

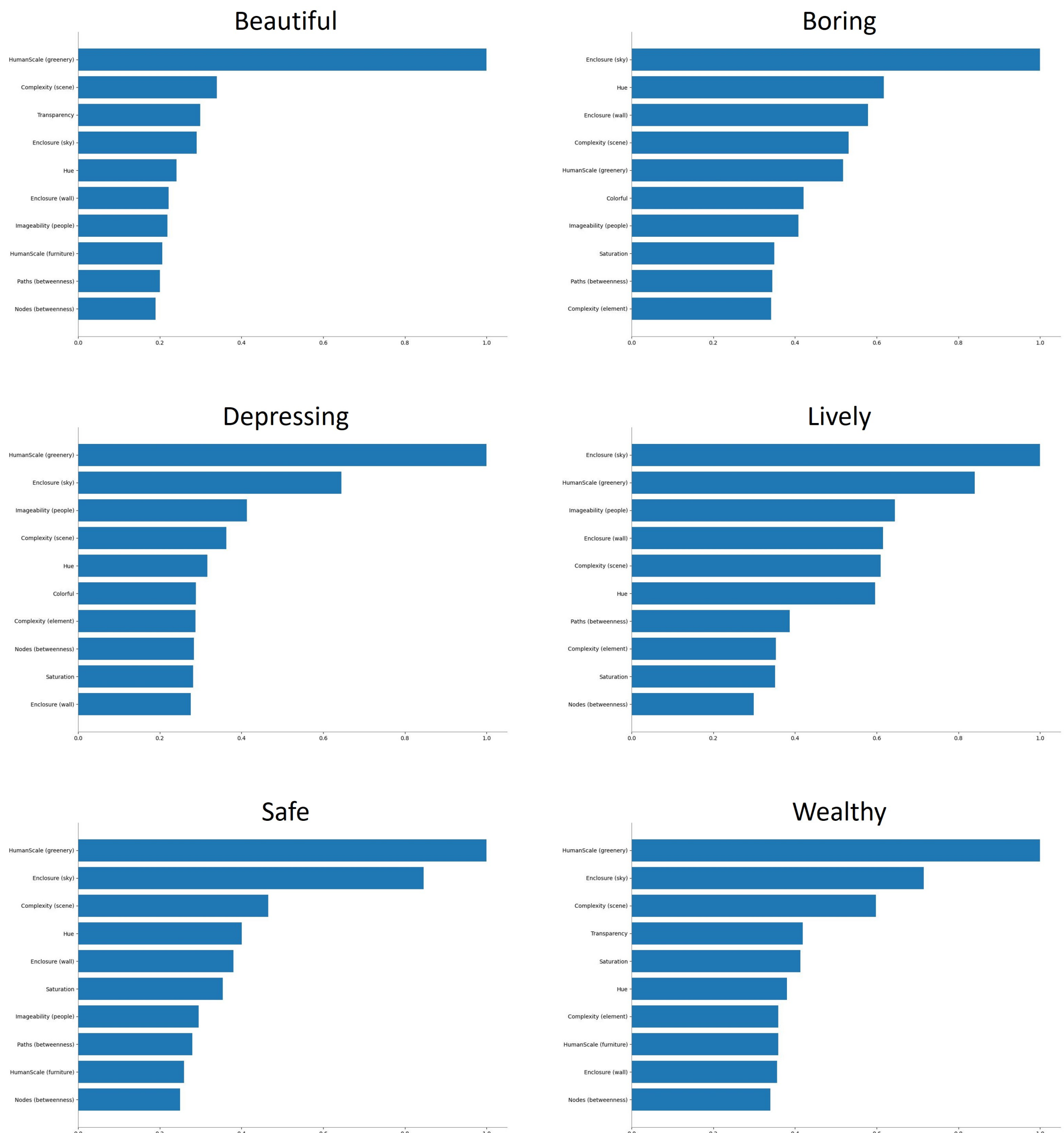

Figure 5.4: Feature importance of the XGBoost model for modeling perceptions

Given that variable importance measures may only reflect the absolute importance of the variables and not necessarily their positive or negative impacts on human perception, we employ a SHAP method to gain a deeper understanding of the complex relationships between human perceptions and urban visual characteristics. As illustrated in Figure 5.5, $\mathit{HumanScale}_{greenery}$, $\mathit{Imageability}_{people}$, $\mathit{Complexity}_{scene}$, $\mathit{Enclosure}_{sky}$, and hue are the most important features. They all have positive associations with positive human perceptions. In addition to $\mathit{HumanScale}_{greenery}$, $\mathit{Complexity}_{scene}$, $\mathit{Enclosure}_{sky}$, and hue, we found that $\mathit{Imageability}_{people}$ should be noted that people are also an important feature in influencing human perceptions.

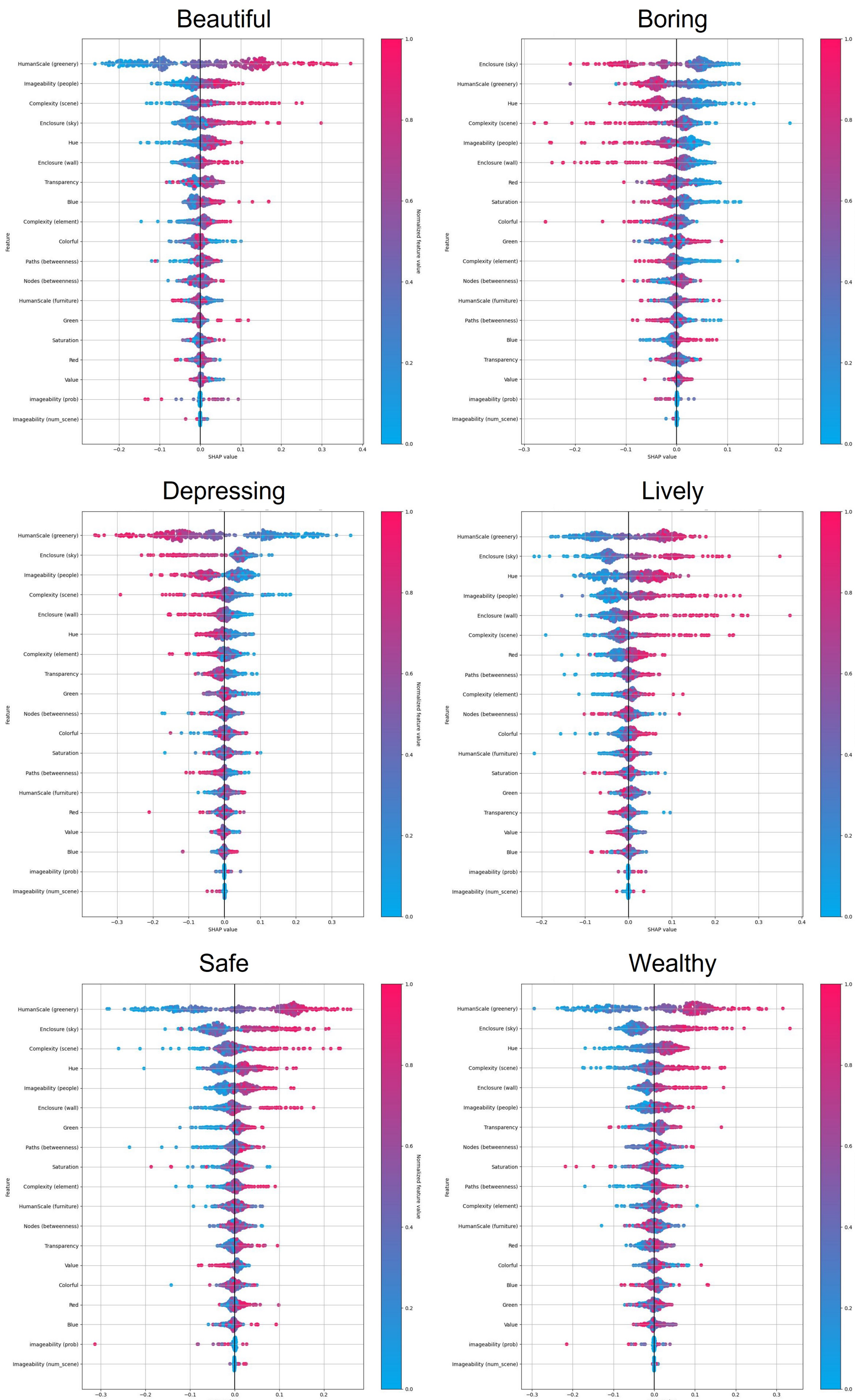

Figure 5.5: Explainable results of SHAP method

5.3.8 Causal Discovery Results

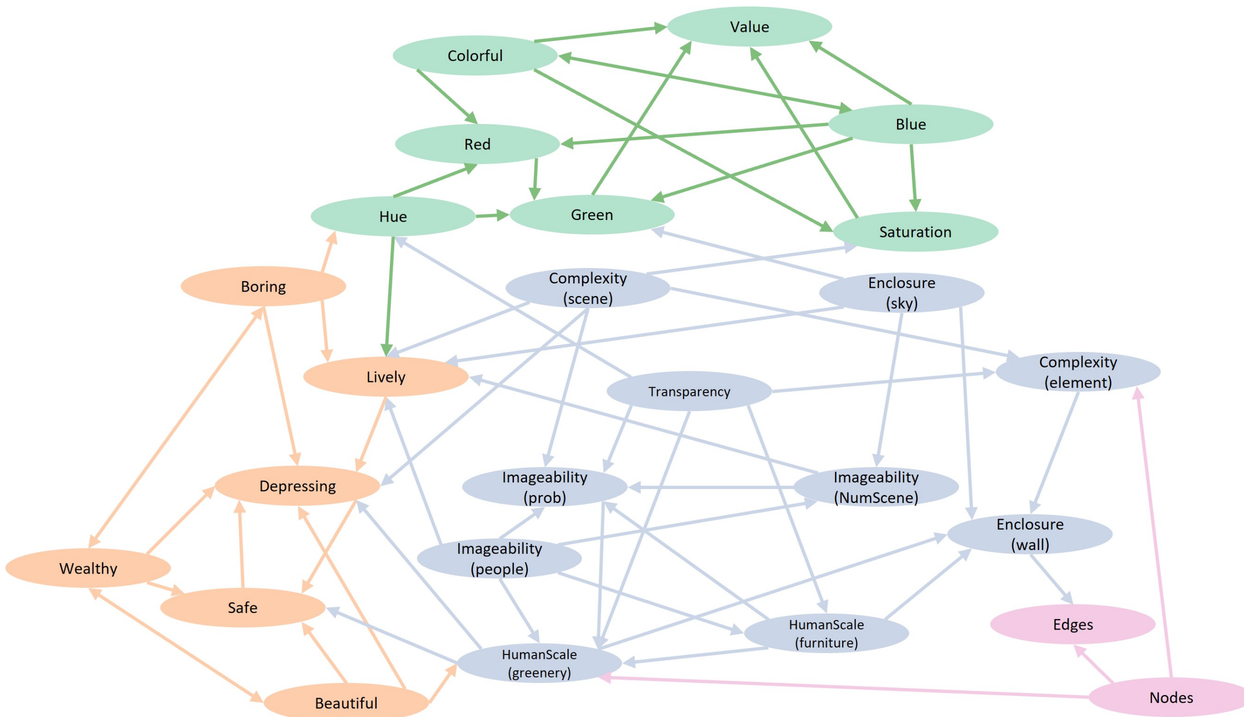

Figure 5.6: Results of causal discovery algorithm PC between perception and urban visual characteristics

Finally, we employed the PC algorithm, a causal discovery algorithm, to delineate the potential causal relationships between human perceptions and urban visual characteristics. As illustrated in Figure 5.6, several interesting patterns can be discovered. First, the six dimensions of human perceptions are inter-correlated with each other as they have connected edges. Similarly, in the same category of variables (e.g., nodes and paths, urban design qualities, and color), they are interconnected with other variables. Second, urban visual characteristics such as hue, $\mathtt{Imageability}_{\mathtt{people}}$, $\mathtt{Imageability}_{\mathtt{prob}}$, $\mathtt{Complexity}_{\mathtt{scene}}$, $\mathtt{Enclosure}_{\mathtt{sky}}$, and $\mathtt{HumanScale}_{\mathtt{greenery}}$ may determine the values of human perceptions of lively, depressing, and safe. It indicates that these variables may play a more important role in shaping human perceptions of built environments. The results are also relatively consistent with the results of correlation analysis and XGBoost.

5.4 Discussions

We list several takeaways from this paper.

5.4.1 Implications for Urban Planning

First, the results offer several implications for urban design and planning. The results reveal the complex relationships between human perceptions of the built environment and urban visual characteristic variables. The results emphasize the importance of incorporating green spaces ($\mathit{HumanScale}_{greenery}$) and more sky-view spaces ($\mathit{Enclosure}_{sky}$) into urban design and planning to enhance positive perceptions of the built environment. This can be achieved through the inclusion of parks, green roofs, and public spaces. Also, $\mathit{Complexity}_{scene}$ is positively associated with positive human perceptions, suggesting that designing urban spaces with a variety of architectural styles, ornamentation, and landscaping may lead to more positive perceptions of the built environment. This implies that urban planners and designers should aim to create visually engaging and aesthetically pleasing public spaces. Furthermore, this study emphasizes the need for a holistic approach to urban design and planning that considers the various dimensions of human perception rather than focusing on a single street element. By integrating human perceptions of the built environment into the design process, urban planners and designers may build more livable, sustainable, and enjoyable public spaces.

5.4.2 Implications for GIScience Studies

In modeling the complex relationships between human perceptions of the built environment and urban visual characteristic variables, the integration of advanced algorithms such as XGBoost, explainable machine learning, and causal discovery proved beneficial. The results suggest that XGBoost can model such relationships with high accuracy, and may be useful for future predictions of human perceptions of the built environments. Furthermore, the study is among the first to integrate causal discovery algorithms in GIScience and urban studies. This shows that causal discovery is a powerful tool for delineating the relationships among variables, providing insights into how urban design and planning decisions might influence human perceptions of the built environment. Also, the study highlights the importance of incorporating explainable AI approaches in GeoAI studies, as opposed to relying exclusively on model performance. The use of explainable machine learning enables researchers to have a deeper understanding of the interactions between variables and can guide urban planning decisions that consider the community's demands.

5.4.3 Limitations and Future Work

The limitations of this study are noted in this section for future improvement. First, in this paper, the analysis of Lynch's five elements of urban quality only considers two aspects, namely, nodes, and paths. Other factors such as edges, landmarks, and districts, could also play important roles in shaping human perceptions of the built environment. In the future, we will quantify the other three elements and provide a comprehensive investigation of their associations with human perceptions of the built environments. Second, the study was conducted in Los Angeles only, and the results may not be generalizable to other cities due to differences in demographics, urban layouts, and environmental factors. Further studies should be conducted in different cities to advance our understanding of human-environment interactions.

5.5 Conclusions

In this paper, we examined the associations between urban visual characteristics and human perceptions of the built environment by conducting an empirical study in Los Angeles. We employed advanced machine learning algorithms including XGBoost and PC, a causal discovery algorithm, to uncover the underlying mechanisms that drive these relationships. By quantifying the urban design elements, five urban design qualities, and colors, we show how these variables influence human perceptions. Our findings suggest that color hues, sky view, urban greenery, pedestrian, and places with complex scenes, are among the most significant factors that influence human perceptions. Results provide important implications for urban design and planning. By identifying the factors that most significantly impact human perceptions, designers and planners can prioritize the improvement of variables for creating a more visually pleasing urban environment. Furthermore, our use of advanced machine learning algorithms, notably, causal discovery techniques, highlights the importance of incorporating these tools into urban design research to gain a deeper understanding of the complex relationships between urban visual characteristics and human perceptions. Overall, our study contributes to the growing body of research on the impact of the built environment on human perceptions and provides insights into the design and planning of more livable and attractive cities.

6 ASSESSING HUMAN SETTLEMENT VALUE: A PLACE PERSPECTIVE

Chapter 6 provides an empirical study to investigate the RQ3: *How do we integrate the human perception of place with geospatial data science including emerging data sources and advanced GeoAI into human settlement value assessment?* Specifically, we introduce a place-oriented hedonic pricing model (P-HPM) that incorporates human dynamics and human perceptions of places to understand human settlement. Such a better formalization of place - where people live, perceive, and interact with others, can advance our understanding of the socioeconomic environment and human settlement. We argue that 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 that construct a *home*. To do so, a large volume of house price data are used 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. We demonstrate that human perceptions of places measured from geospatial data science could be incorporated into spatial analysis from a place-based perspective.

6.1 Introduction and Motivation

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 (Seamon, 1980; Goodchild, 2011; Chen et al., 2011). They frame their behaviors by perceiving the world, which is coined as "sense of place" (Agnew, 2011). 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 (Sui and Goodchild, 2011; Jorgensen and Stedman, 2011; Liu et al., 2015; Xu et al., 2018; Shi et al., 2015; Kang et al., 2020b).

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 (Lancaster, 1966; Champ et al., 2003). In practice, housing attributes refer to the age of houses, the number of bedrooms, property area, etc. (Follain and 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.) (McLeod, 1984; Lee and Li, 2009; Poudyal et al., 2009), distance to employment and work place (central business district (CBD), labor-market, etc.) (Heikkila et al., 1989; Osland and Thorsen, 2008; Bishop et al., 2019), and transportation accessibilities (McLeod, 1984; Debrezion et al., 2011). 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 (Lynch and Rasmussen, 2001; Gibbons and Machin, 2008), race ratio (Brasington et al., 2015), pollution (Hui et al., 2007; Le Boennec and

Salladarré, 2017; Bishop et al., 2019), aesthetic views (Lindenthal, 2017; Fu et al., 2019b), and noise (Hui et al., 2007; Diao et al., 2016; Day 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; Zheng and Kahn, 2008; Diao and Ferreira Jr, 2010), urban planning (Debrezion et al., 2011; Schläpfer et al., 2015; Pettit et al., 2020), 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; Isard, 1956; Bishop et al., 2019; Boyd et al., 2015). 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 (Sack, 1997; Easthope, 2004). 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; Xu et al., 2015; Kang et al., 2010; Ratti et al., 2006; Peng et al., 2019), and geotagged social media posts (Jurdak et al., 2015; Hu and Wang, 2020), 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., 2015a), 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 (Zhou et al., 2014; Zhang et al., 2020). 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.

6.2 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.

6.2.1 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 (Rosen, 1974; Pred, 1984). 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 (Sack, 1997; Giuliani, 1991; Easthope, 2004). 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 (Pred, 1984; Easthope, 2004; Shaw and 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 (Seamon, 1980; Cresswell, 2014). The observed mobility patterns of people may reflect how they perceive and use the environment as different affordances of a place (Harvey et al., 1990; Alazzawi et al., 2012; Scheider and Janowicz, 2014; Zhu et al., 2020). Other considerations of human dynamics may also involve spatial-social networks (Shaw and 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 (Tuan, 1979; Rose, 1995). 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.

Figure 6.1 demonstrates the conceptual framework of human settlement assessment from a space-based perspective vs. a place-based perspective. The left part denotes the

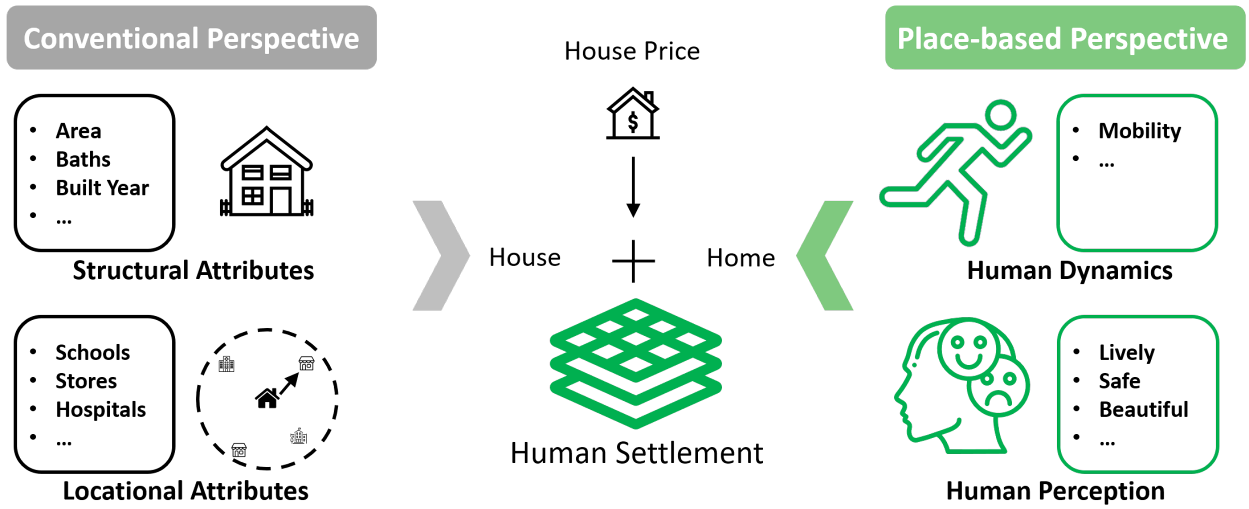

Figure 6.1: Framework: Conventional perspective (space-based) for human settlement estimation vs. place-based perspective for human settlement evaluation.

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.

6.2.2 Place-oriented Hedonic Pricing Model

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

$$P_H = \beta_0 + \beta_1 \mathrm{Struc} + \beta_2 \mathrm{Loc} + \epsilon \tag{6.1}$$

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:

$$P_H = \beta_0 + \beta_1 Struc + \beta_2 Loc + \beta_3 Vis + \beta_4 Percep + \epsilon \tag{6.2}$$

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*.

6.3 Study Area and Data

6.3.1 Study Area and Spatial Unit

Considering that factors impacting house prices may vary in different regions, we experiment on 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

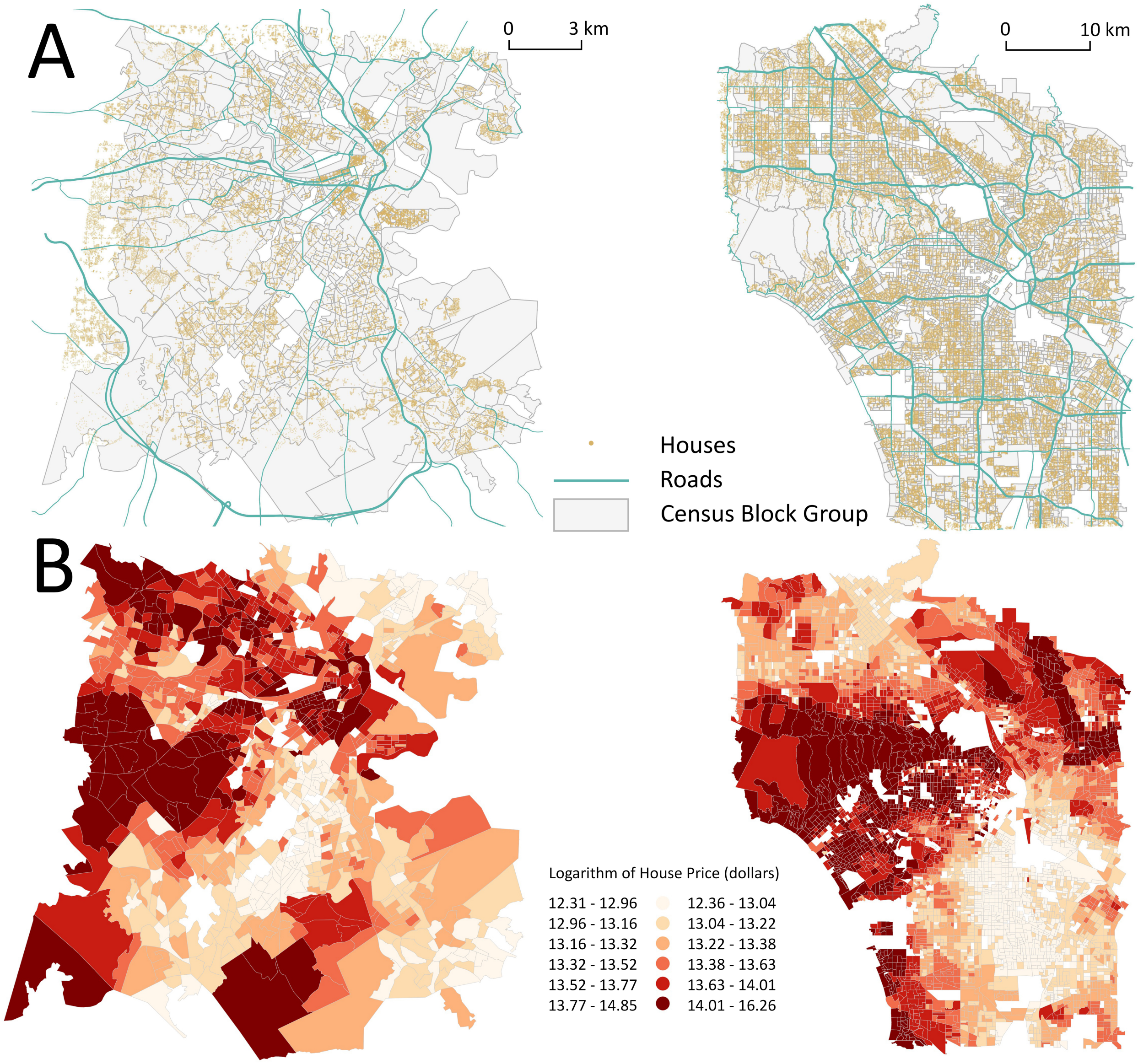

Figure 6.2: Selected datasets and research area in Boston (left) and Los Angeles (right). A. Spatial distribution of houses as well as census block groups. B. Logarithm of average house price at each census block group. (Figure created with the Python library GeoPandas and Matplotlib).

fine-resolution geographical units in which the United States Census Bureau publishes sample demographics and socioeconomic data. Figure 6.2 shows the study area with the road networks and mean house price distributions. In total 3,964 CBGs at Los Angeles, and 944 CBGs at Boston are used in this study.

6.3.2 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.

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 6.1. After data cleaning, 108,571 houses in Los Angeles and 94,892 houses in Boston remained for further analysis. In Figure 6.2A, the yellow dots denote the locations of the houses. Figure 6.2B demonstrates the average price of the houses in each CBG (dollars).

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. POIs are the primary venue for tracking place foot-traffic by SafeGraph, while CBG is one of the fine-resolution geographical units the United States

[1]https://www.redfin.com
[2]https://safegraph.com

Census Bureau used for publishing demographic and socioeconomic data. In total, there are more than 5 million POIs stored in the database, as well as more than 220 thousand CBGs retrieved from the ACS. The spatial density distribution of POIs across the Contiguous United States is mapped in Figure 6.3, which shows that places cluster in major cities and are generally located along streets. The more places, the brighter the region in the map.

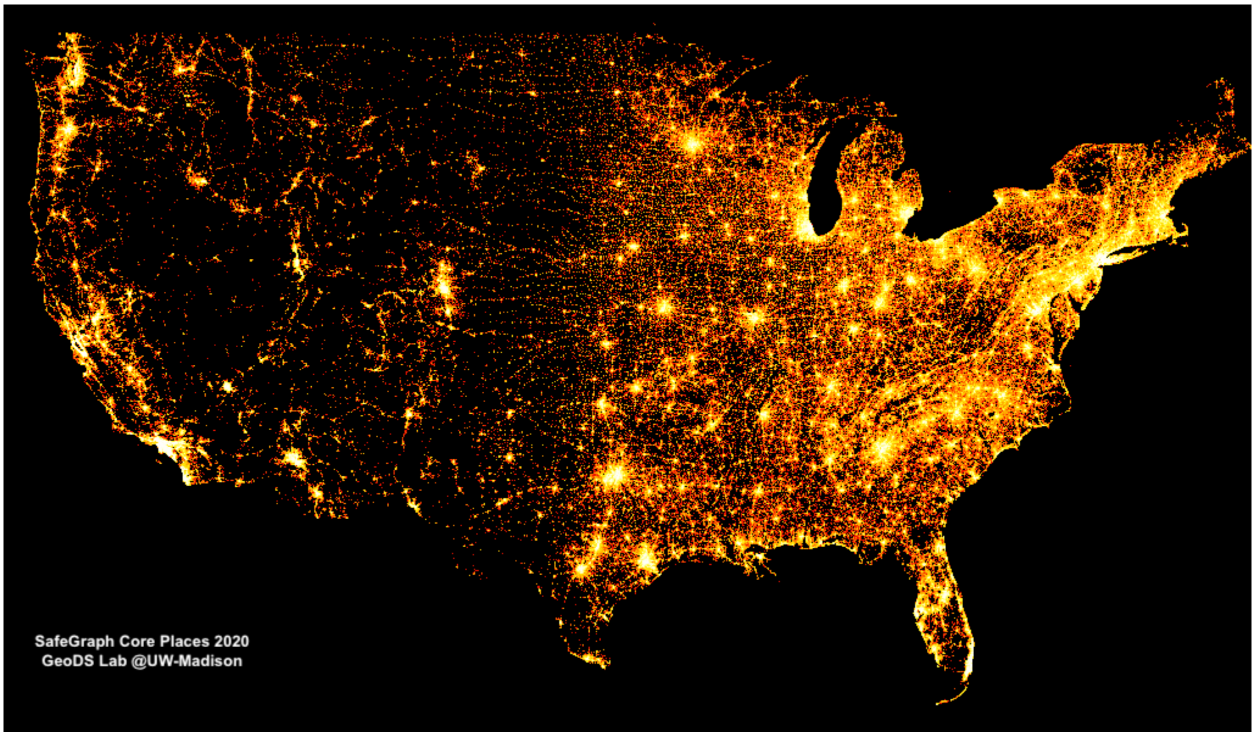

Figure 6.3: Spatial density distribution of places collected by SafeGraph across the whole United States; the visualization is created using the DataShader package, Python 3.7.

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

[3]https://www.naics.com/

calculated at the property level, and are then aggregated to CBGs. Detailed statistics are reported in Table 6.1.

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

Table 6.1: Detailed statistics for house attributes and locational attributes in Boston and Los Angeles.

Visiting patterns

Visiting patterns of CBGs are also retrieved from the SafeGraph database. To generate this dataset, millions of anonymous GPS pings collected from numerous mobile applications are tracked and then cleaned to remove noise. Then, users' home places are estimated and aggregated (e.g., at the level of a CBG), and those users' visits from home places to POIs are tracked. A home place of a user refers to his/her most common nighttime location during the last six weeks. For each day, GPS pings of each device are clustered and only those clusters during nighttime hours (6pm - 7am local time) are kept. The CBG with the most clusters in that day is recorded. Based on this, the most frequent CBG over the last six weeks that reflects the primary nighttime location is used as the "home location" for each user. By aggregating home places to CBGs, user privacy can be protected as no individual records can be traced and accessed (SafeGraph, 2020a).

Active users' visits to POIs are produced with a similar strategy. Using several clustering methods such as density-based spatial clustering for applications with noise (DBSCAN) (Ester et al., 1996), GPS pings are grouped together in which each cluster contains a set of potential POIs and associates with CBGs. The best place for a given cluster is classified by performing machine learning methods involving several entangled features. Thereby each user's visits from home place to various POIs and CBGs are identified (SafeGraph, 2020b).

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. Figure 6.4A presents the spatial distribution of the total number of visits to different neighborhoods in the two cities.

Human perceptual measurements from street-view images

Street-view imagery captures the urban physical environment in detail from a similar view of human vision (Zhang et al., 2019a; Liu et al., 2019; Kang et al., 2020b). 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 meters. 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.

[4]https://developers.google.com/maps/documentation/streetview/intro

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 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 pairwise 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. Figure 6.4C 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

[5]https://www.media.mit.edu/projects/place-pulse-1/overview/

the common perception trend of a place. Figure 6.4B shows the spatial distribution of average *lively* scores in Boston and Los Angeles, and Figure 6.4C depicts sample street-view images with low, medium and 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.

6.4 Methods

6.4.1 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.

6.4.2 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 and Coughlin, 2008; Krause

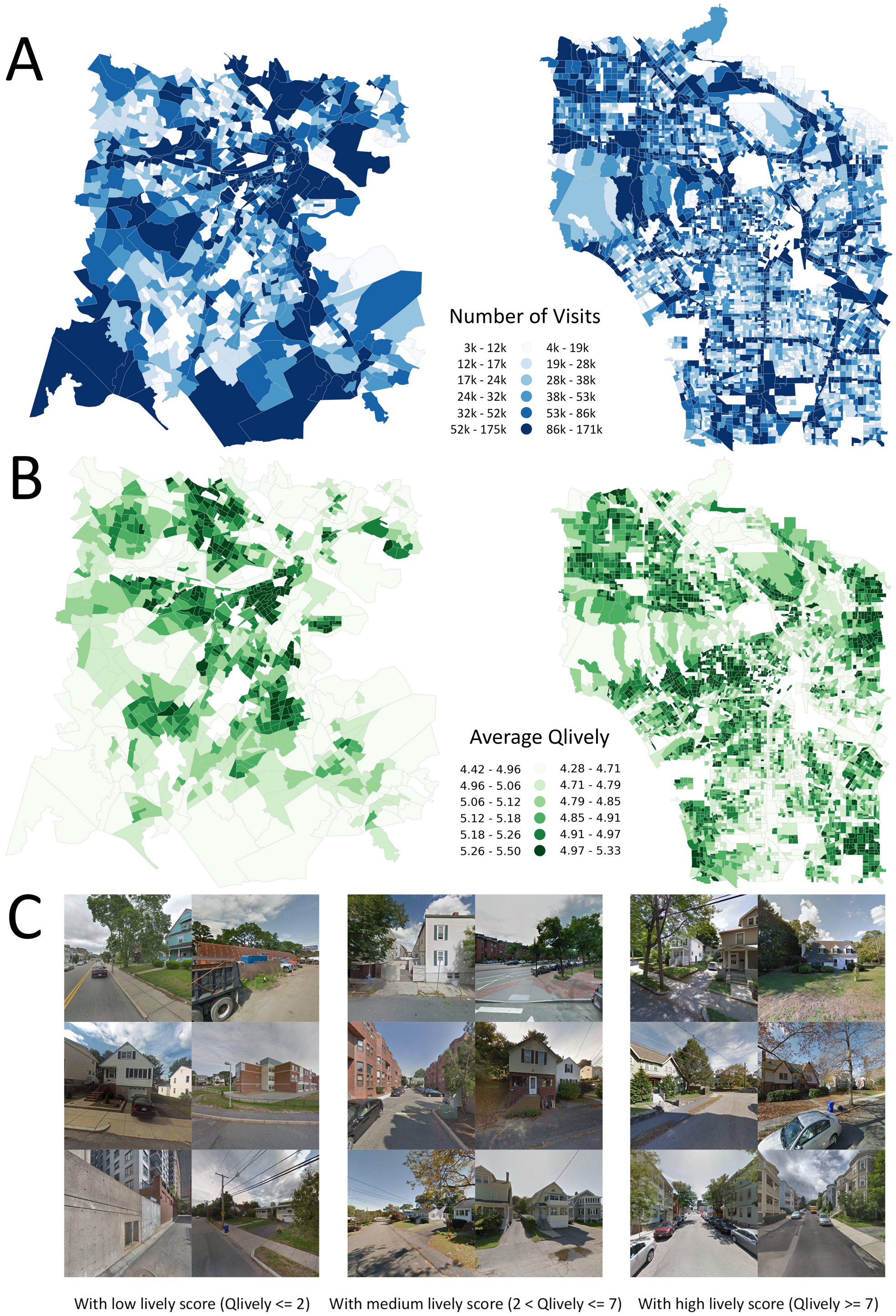

Figure 6.4: Human visit patterns and perceptions at places: A. Total number of visits to CBGs. B. Average *lively* score calculated at each CBG. C. Examples of street-view images with different *lively* scores. Left: with low lively score. Medium: with medium lively score. Right: with high lively score.

and Bitter, 2012; Mueller and 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):

$$Y_i = \rho W Y_i + \sum_{k=1}^{m} a_k X_k + \varepsilon_i \tag{6.3}$$

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.

6.4.3 Geographically Weighted Regression

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 (Huang et al., 2010; Cao et al., 2019). GWR is designed to model this spatial variations of relationships. In Equation 6.4, we present the typical form of a GWR model (Fotheringham et al., 2003).

$$Y_i = \alpha_{0(u_i,v_i)} + \sum_{k=1}^{m} a_{k(u_i,v_i)} X_{k(u_i,v_i)} + \varepsilon_i \tag{6.4}$$

where Y_i refers to the natural logarithm of average house price at location i with its coordinate to be (u_i, v_i); $\alpha_{0(u_i,v_i)}$ denotes the intercept; $a_{k(u_i,v_i)}$ indicates the local regression coefficient for the k^{th} independent variable; $X_{k(u_i,v_i)}$ 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 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 build 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.

6.5 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.

6.5.1 Factor Interpretation

Human mobility factors

As described in Section 6.3, 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 6.2, 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 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 24h 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 to 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".

Mobility	Factor 1 Los Angeles Visits at daytime	Factor 1 Boston* Absolute number of visits	Factor 2 Los Angeles* Visits at night	Factor 2 Boston* Ratio of hourly visits at night	Factor 3 Los Angeles Ratio of hourly visits at daytime	Factor 3 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

Table 6.2: Factor loadings of mobility factors. For interpretation convenience, factor loadings with absolute value less than 0.30 have been suppressed.
* Factors have been multiplied by -1.

Perceptions	Factor 1 Los Angeles	Boston	Factor 2 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 6.3: Factor loadings of perception factors.

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 6.3 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.

6.5.2 Comparisons between HPM vs. P-HPM

Considering that house prices might be autocorrelated across space, we calculated the global Moran’s I statistic (Cliff and 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.

Table 6.4 and Table 6.5 report the results of Los Angeles and Boston respectively.

Hedonic Pricing Model

As the baseline model, model 1 presents the effect 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.

Mobility Patterns

Model 2, Model 4, and Model 6 take mobility factors into consideration and present similar impacts. Table 6.4 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 6.5, *factor 1*, which represents the “absolute number of visits", has 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).

Human Perceptions at Places

Model 3 and Model 4 involve human perception factors. Table 6.4 and Table 6.5 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.

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.

Table 6.4: 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, $^{*}p < 0.05$.

Table 6.5: 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, $^*p < 0.05$.

6.5.3 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 6.6. 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 show significant spatial variability, indicating that the impacts of human mobility and human perceptions are stable across the space.

6.6 Discussions

6.6.1 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

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

Table 6.6: Results of geographically weighted regression-based place-oriented hedonic pricing model with Monte Carlo significance test.

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.

6.6.2 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 (Kyle and Chick, 2007; Cantrill and Senecah, 2001). 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).

6.6.3 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 (Wang et al., 2018; Lü et al., 2019; Chen et al., 2020). 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 (Li et al., 2021; Hu et al., 2019; 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 (Yilmazkuday, 2021; Kang et al., 2020a). 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.

6.6.4 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.

Also, the place-based variables might be inter-correlated with other variables such as land use type, socio-economic factors (e.g., income, unemployment rate) which may contribute to housing prices as well. In other words, human perceptions of places might be reflected by these factors, and then have impacts on housing prices. The current results only illustrate the associations between place-based variables and housing prices, rather than causal relationships. More experiments should be conducted to better revealing the complex relationships among these variables.

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., 2019), 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.

6.7 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.

7 CONCLUSIONS AND FUTURE WORK

7.1 Conclusions

Understanding the sense of place, a core concept in geography, is significant for modeling human-environment interactions. This dissertation specifically focuses on an important component of sense of place - human perceptions of place, and leveraged computational approaches with emerging data sources to understand it. To accomplish this, this dissertation first explored the characteristics of the computational approach — combining street view imagery and deep learning — to illustrate its efficiency and acknowledge the potential limitations. Then, using the proposed computational approach, we examined the relationships between urban design factors including the five elements of urban design, five dimensions of urban design qualities, colors, and human perceptions of built environments to obtain insights for guiding the future urban design and planning practices. Finally, we illustrate how data-driven human perceptions might be integrated into future spatial analysis starting from a place-oriented approach.

Chapter 4 compares the safety perceptions measured from the survey based on neighborhood residents' responses with those from the GeoAI approach to better understand the relationship among these safety measures in the city of Stockholm. We model the two forms of safety perceptions and their disparities (i.e., perception bias) as a function of the city's land use and its socio-demographics. The results demonstrate the characteristics of the GeoAI-based measures and explain how built environments contribute to safety perceptions and perception biases. The GeoAI-based measures tend to more express people's instant impressions of the built environment across the city, whereas the survey-based measures condense and reflect local residents' overall daily experiences of specific areas. Regions that appear to be economically vibrant and have inner-city streetscapes are perceived as safe places from visual appearance but are not perceived as such by residents. Older adults tend to overestimate their likelihood of being victimized by crime, which may increase perception bias. Furthermore, we assess the potential ethical issues (e.g., spatial bias, population bias) in the GeoAI-based approaches. This chapter validates the effectiveness of measuring human perceptions of place with geospatial data science, and illustrates its characteristics which may guide future practices.

Chapter 5 examines the associations between urban visual characteristics and human perceptions of the built environments by conducting an empirical study in Los Angeles. We employed advanced machine learning algorithms including XGBoost and PC, a causal discovery algorithm, to uncover the underlying mechanisms that drive these relationships. By quantifying the urban design elements, five urban design qualities, and colors, we show how these variables influence human perceptions. Our findings suggest that color hues, sky view, urban greenery, pedestrian, and places with complex scenes, are among the most significant factors that influence human perceptions. Results provide important implications for urban design and planning. By identifying the factors that most significantly impact human perceptions, designers and planners can prioritize the improvement of variables for creating a more visually pleasing urban environment. Furthermore, our use of advanced machine learning algorithms, notably, causal discovery techniques, highlights the importance of incorporating these tools into urban design research to gain a deeper understanding of the complex relationships between urban visual characteristics and human perceptions. This chapter offers a comprehensive investigation of how human perceptions are affected by urban design variables.

We conducted an empirical study in Chapter 6 to show how human subjective perceptions can be integrated into spatial analysis. We propose a place-oriented hedonic pricing model (P-HPM) that incorporates human dynamics and human perceptions of place to understand human settlement. Taking Boston and Los Angeles as examples, we take the hourly number of visits to places as a proxy of human mobility patterns and measure human perceptions of places from large-scale street view images using deep learning. The results show that positive perceptions have positive associations with house prices, and the P-HPM outperformed the traditional HPM significantly in these two cities. Moreover, through a geographically weighted regression analysis and the Monte Carlo test, the impacts of the proposed place-related variables including human place perceptions on house prices are shown to be stable across space. This chapter illustrates how human subjective experience could be involved in spatial analysis and offers insights by incorporating the role of place using multi-source big geo-data.

7.2 Research Contributions

As an interdisciplinary study, the contributions of this dissertation are multi-faceted. Here, I would like to discuss its contributions to different subjects, including GIScience, human geography, urban planning, and psychology.

There are three primary contributions to GIScience. First, we describe the characteristics of measuring human place perceptions with geospatial data science that may guide future usage of such computational frameworks in GIScience. We emphasize that GeoAI-based safety perceptions may better reflect people's first impressions of urban environments from the visual cues in street view images in Chapter 4. Second, we demonstrate the need to evaluate the ethics of geospatial data science. In Chapter 4, we examine the perception bias and model bias including spatial bias and population bias when measuring human perceptions of place, and illustrate that the localized dataset may better reflect residents' perceptions. We employed several explainable AI approaches (e.g., causal discovery) to promote the trustworthiness and transparency of GeoAI models in Chapter 5, which may better reveal the complex relationships between urban design elements and human perceptions. Observing and addressing ethical issues of geospatial data science approaches should become an important part of GIScience methods. Third, we illustrate how to involve human sense of place in spatial analysis. I propose *Human-centered Geospatial Data Science* in Chapter 3, and I demonstrate how to involve subjective human experiences including human dynamics and perceptions into spatial analysis by proposing the place-oriented hedonic pricing model. These observations highlight the significance of integrating human dimensions in spatial analysis.

For human geography, this dissertation shows that quantitative approaches may supplement existing qualitative approaches to understanding subjective human place perceptions, sense of place, and human experiences, as well as revealing complex human-environment relationships. Also, theories, ideas, and principles in human geography may guide the future development of human-centered geospatial data science.

We summarize two contributions to urban planning. First, our results advance our knowledge of the built environments and human perceptions of place. We have investigated a set of physical and socioeconomic environmental factors to explore how these variables contribute to different dimensions of place perceptions. The impacts of multiple aspects of factors including physical environment (e.g., land use), socioeconomic environment (e.g., demographic attributes), human activities, urban design qualities and color on human place perceptions were assessed. More importantly, the findings in Chapter 4 — 6 may guide future urban design and planning practices. For instance, the discoveries in Chapter 4 may help planning agencies to evaluate whether our framework could supplement perception collection. The findings in Chapter 5 may offer insights for benefiting human well-being through urban design (e.g., more green space) in planning practices. Chapter 6 may demonstrate how to involve place-based thinking in spatial analysis such as taking human subjective experience into account.

Finally, there are two major contributions to psychology. First, we demonstrate how to assess human perceptions of place, a psychological effect, using computational approaches. Using street view imagery and deep learning algorithms, multiple dimensions of human subjective perceptions (e.g., safe, lively, beautiful) of built environments may be measured. Such a computational approach could be exploited further to benefit perception studies in psychology, given that it can be expanded to measure not just human perceptions of place but also general human perceptions. Second, we delineate the associations between human perceptions and color in Chapter 5. The results of this dissertation may offer insights into explaining human perceptions through other psychological factors.

7.3 Broader Implications

The dissertation's broader implications are multifaceted:

In this dissertation, we have conducted interdisciplinary research. The theoretical foundations are built upon abundant existing literature in human geography, urban planning, and psychology. The advancement of GIScience and computer science offer solid methodological foundations. To finish this dissertation, I have collaborated with scholars from different fields. Understanding human perceptions of place is not a new topic, but combining advanced technologies offers new insights to advance our knowledge. Also, quantitative approaches were thought not appropriate to understand human subjective experiences such as place perceptions. However, our dissertation indicates a new paradigm of using quantitative measures to decode human perceptions of place. Therefore, it is necessary to conduct interdisciplinary research through collaborations with scholars from different domains, and GIScience might be leveraged to address problems not only in geography, but also outside geography.

The findings of this study can benefit society by improving quality of life in cities from multiple perspectives. This dissertation provides a deep understanding of people's perception-environment relationships, which can offer valuable insights into the construction of environmentally friendly and sustainable cities. For instance, discoveries in Chapter 4 may benefit reducing criminal activities and enhancing human sense of safety in cities; findings in Chapter 5 may guide future urban design and planning practices for built environments; discoveries in Chapter 6 may provide practical suggestions for building a more livable neighborhood that makes people feel comfortable. The results and discoveries could also help to achieve the United Nations' sustainable development goals (SDGs) including good health and well-being, and sustainable cities and communities.

This dissertation also has benefits for individuals. Investigating human sense of place and understanding its associated built environment factors may also help improve residents' quality of life. For instance, results in Chapter 4 and 6 may be useful for individuals' residential location decisions and choices on building a safe and comfortable living environment; examining the relationships between human place perceptions and built environments may also improve people's happiness and satisfaction in life. Furthermore, understanding perception-environment relationships may help treat people's mental health issues by reducing depression or relieving pressure and stress.

7.4 Limitations

I have acknowledged several limitations in each of the chapters (See 4.8.4, 5.4.3, and 6.6.4). In this section, I would reiterate two common limitations of this dissertation that need to be addressed in the future.

The first issue pertains to data quality, as geographic data is often associated with various uncertainties. Below, several data quality issues are listed for each data source. The street view imagery dataset may encounter issues such as blurred items and relatively low time resolution. Although previous studies have shown the effectiveness of using street view images to observe the urban environment, researchers have discovered that details of certain items (e.g., street lights, sidewalk continuity, and several small items) identified in street view images may not be reliable due to uncleared or blurred pixels that could affect the performance of measuring human place perceptions. Furthermore, it is important to consider the possibility of biases in the street view imagery dataset, including biases related to the time of day, lighting conditions, and the angle at which the images were captured. These biases are related to the data quality, have the potential to influence human perceptions of place, and should be taken into account when analyzing the data. Additionally, mapping companies do not update their street view images in real-time or frequently, and the images can only observe the scenery along the streets, making it challenging to analyze the variation of human place perceptions over time and within neighborhoods.

Regarding the human mobility datasets that we employed in this dissertation, both datasets were aggregated based on anonymous mobile phone data. The spatial bias (i.e., the representativeness) of the two datasets may influence the modeling results. While dynamic mobility flows are inferred from mobile phone applications by users, not everyone in the population has a mobile phone, and not everyone uses smartphone applications (for the SafeGraph data), especially elderly people and children. Given these differences in mobile phone usage, age groups and demographic composition might influence the estimated entire population's mobility flows.

Second, the human place perceptions measured and discussed in this dissertation are primarily referred to as "GeoAI-based place perceptions," since they only capture a portion of human place perceptions. As suggested in Chapter 4, these perceptions mainly reflect visual perceptions of the built environment. Participants often lack local knowledge of the places captured in the street view images and do not have emotional connections attached to places. Therefore, aspects such as daily life, experience, and routines are often lost in the perception measures. Additionally, the human place perception scores are based on aggregations of human perceptions to reflect the average of human perceptions. However, these perceptions may vary by individual based on their past experiences or socio-demographic groups (Pánek et al., 2020). Currently, human place perceptions may not reflect individual-level place perceptions. It is also important to note that the current perceptions may primarily reflect Western perspectives since most participants are from Western countries, and marginalized countries may have been underrepresented in the dataset.

7.5 Future Work

Giving the promise of using advanced computational approaches to understand human sense of place and advance our knowledge of human-environment relationships, here, I list several potential directions that may merit further exploration in the future.

7.5.1 Decoding Human Place Perceptions with Eye-Tracking Systems

The current GeoAI-based perception measures are computed based on human perceptions of an entire street view image from its visual clues. However, what triggers participants' place perceptions, such as certain objects, visual background, and layout of street view images, are still unknown. To better understand the process of how participants perceive the built environment, a possible solution is to combine the eye-tracking system to track participants' focus. An eye-tracking system (i.e., an eye-tracker) is a device that measures eye positions and eye movements. Using the eye-tracking system, researchers could record the point of gaze (i.e., where one is looking) of participants. Based on the results of the eye-tracking system, we may decode the process of human place perceptions to gain a better understanding of the underlying mechanisms of human perceptions of place. More importantly, the results may also guide explanations of GeoAI models. The results of the eye-tracking system could be leveraged to validate the explainability results (e.g., CAM) of GeoAI models.

7.5.2 Measuring Human Perceptions of Place with Soundscape

In this dissertation, measuring human place perceptions relies on street view imagery which reflects human visual perceptions of the built environment. However, human sense of place is not limited to visual perceptions and may also be derived from other human senses such as smell, touch, taste, and hearing, as well as daily experiences at a particular place. Thus, it is necessary to explore and incorporate other modalities of sensory data into

GeoAI-based place perception research. Recently, there have been emerging data sources that focus on the soundscape of places, such as geotagged acoustic datasets. Therefore, there is potential to develop soundscape-based GeoAI tools that process acoustic data and analyze the associations between sound-related place perceptions and the environment to build more hearing-friendly places. By combining multiple sensory modalities, such as visual and auditory perceptions, a more comprehensive understanding of human sense of place can be achieved. We may also employ multi-modal approaches to uncover new insights and improve the accuracy of GeoAI-based place perceptions.

7.5.3 Exploring the Impacts of Familiarity of Place on Perception

To enhance the accuracy of GeoAI-based place perceptions, it is essential to consider local contexts. Image perception may differ from one city to another. For instance, people may have differing perceptions of the same image if they know it is located in different cities. Therefore, it is crucial to include contextual information such as the place name. To achieve this goal, I intend to develop a new online survey system that incorporates participants' local knowledge when perceiving street view images. The survey will gather information such as the location of street view images, the toponym of the place depicted in the streetscape, and the socioeconomic environment of the neighborhood. Additionally, the survey will include a measure of participants' familiarity with the place, using a five-point Likert scale. By integrating local contexts, the performance of GeoAI-based place perceptions can be enhanced in terms of accuracy and efficiency.

7.5.4 Uncovering the Relationships between Mobility and Perception

Human mobility is a key component of human behaviors and dynamics. We have involved human mobility factors in spatial analysis in both Chapter 6 and Chapter 4. In Chapter 4, we examined how human mobility patterns contributed to human safety perceptions, and discovered there was limited impacts on human mobility patterns. In Chapter 6, we illustrated the impact of mobility patterns on house prices, and show that daytime visits and nighttime visits may have different influences on housing prices. However, the interrelationships between mobility-based variables and place-based variables were not examined. Therefore, due to the fact that the relationships between human mobility and place perceptions were not fully examined in both chapters, it is necessary to model the associations between human mobility and place perceptions. In addition to examining the human mobility patterns and place perceptions based on geospatial big data, I also plan to launch a new online survey and directly evaluate the impact of human mobility patterns on place perceptions. By doing so, the GeoAI-based place perception measurements could also be evaluated and validated.

7.5.5 Modeling Multiple Aspects of Sense of Place

Finally, it is necessary to have a more comprehensive investigation of sense of place by modeling the interrelationships among human perceptions, human emotions, and human cognition. Although this dissertation primarily focuses on human perceptions of place, the interrelationships among these three psychological components have yet to be fully understood. While there may be overlaps between these components, they have distinct emphases that necessitate further investigation. Examining the connections among these components and the environment is essential to comprehend the formation of sense of place. Furthermore, it is crucial to identify any elements that activate one component with limited effects on the others. Additionally, it is worth exploring whether any places have high perceptions but low emotions, or vice versa. Thus, a more comprehensive understanding of the relationships among the various components of sense of place warrants further exploration.

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