Landscape and Urban Planning 236 (2023) 104768

Contents lists available at ScienceDirect

Landscape and Urban Planning

journal homepage: www.elsevier.com/locate/landurbplan

Assessing differences in safety perceptions using GeoAI and survey across neighbourhoods in Stockholm, Sweden

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HIGHLIGHTS

- Citywide residents' safety perceptions are assessed with street view and deep learning.
- GeoAI-based safety perceptions express people's instant impressions of the built environment.
- Survey-based safety perceptions reflect residents' overall daily experiences of living areas.
- Citywide residents, not neighborhood residents, may feel economically vibrant places look safe.
- Elder people may underestimate the safety of their living places which may enlarge perception bias.

ARTICLE INFO

Keywords:
Safety perception
Built environment
Street view image
GeoAI
Perception bias
Ethics

ABSTRACT

The safety perception of the built environment, rather than the sheer number of crimes and incivility behavior, is a fundamental driver of public policies intended to improve urban safety. Traditional surveys often capture neighborhood residents' perceived safety, but may not fully reflect the perceptions of people who are unfamiliar with the area. In this study, focused on the city of Stockholm, Sweden, we develop a geospatial artificial intelligence (GeoAI) approach using street view images and recruiting locals to create a measure of citywide residents' safety perceptions. We compare the measures from the survey based on neighborhood residents' responses with those from the GeoAI approach to better understand the relationship between these safety measures. 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. 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. Regions that appear to be economically vibrant and have inner-city streetscapes are perceived as safe places from 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.

1. Introduction

Enhancing urban safety is essential for promoting social stability and building an inclusive and resilient environment (Ameen & 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 et al., 2020; Moore & Trojanowicz, 1988; UN-Habitat, 2019). 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

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https://doi.org/10.1016/j.landurbplan.2023.104768
Received 18 October 2022; Received in revised form 4 March 2023; Accepted 5 April 2023
Available online 19 April 2023

residents' safety perceptions, but they are expensive, labor-intensive, inefficient, and often restricted to smaller regions (Kang et al., 2020). 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., 2015; F. Zhang 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 & Ito, 2021; Kang et al., 2020). 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. They may be closer to dispositional safety perceptions and may be more reflective of individual factors of residents (Jackson, 2004; Solymosi et al., 2021). In comparison, GeoAI-based safety perceptions reflect the respondents' feelings of safety triggered by their visual perception of the environment and neighborhoods (Salesses et al., 2013), illustrating how a streetscape image connects to their idea of "safe" and "unsafe". Such perceptions might be impacted by situational context and may disappear shortly after leaving the environment (Fuhrmann et al., 2013; Jing et al., 2021). 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 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:

- measuring citywide residents' safety perceptions of the physical environment from street view images using the GeoAI approach in Stockholm.
- comparing the GeoAI-based safety perceptions of citywide residents with results from safety perceptions of neighborhood residents from the Stockholm Safety Survey.
- 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-fold: First, our study adds 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 for a greater focus on geoethical issues in GeoAI research.

2. Theoretical framework

2.1. Safety perceptions of people

Urban safety plays an important role in residents' settlement (Ceccato & Lukyte, 2011). People prefer to reside in a place that gives them a sense of safety and security, and protects them from risks and dangers (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 closely linked to crime victimization such as the intensity and distribution of criminal activities (Hale, 1996). Also, people's overall safety perceptions are deeply interconnected with a wide range of other anxieties and aspects of urban life (Lee, 2008), regardless of the actual risk of crime.

Research has illustrated that the physical environment and neighborhood conditions influence 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 & DePrince, 2020; May et al., 2010; Newman, 1972; Vrij & Winkel, 1991). Characteristics of the environment, (e.g., garbage on the streets and 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 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.

Our study contributes to the current literature on the multifaceted nature of safety perceptions. Research on fear of crime has traditionally considered complementary components of fear, one that is *dispositional* (fear as a trait) and another that is *situational* (fear as a state) (Gabriel & Greve, 2003). The former reflects inter-individual differences in the *tendency* to experience fear; whereas the latter refers to a transitory state of experiencing fear (Kappes et al., 2013). Gabriel & Greve (2003) also note that situational and dispositional safety perceptions influence each other. In our study, the survey-based safety perceptions may resemble a measure of dispositional of fear, or at least a direct product of it; while the GeoAI-based safety perceptions are associated with residents' situational feelings to visual cues of street view images, and might vanish in a short time. This study has a potential to offer a better understanding of how these two types of safety perceptions relate to and may differ from each other.

2.2. 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 perceptions of place (Dubey et al., 2016; Salesses et al., 2013; F. Zhang et al., 2018). A global dataset – MIT Place Pulse – was constructed which could reflect people's general perceptions of place (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., 2021). 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., 2021; 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 (e.g., biased) 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.

2.3. 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 use the 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 Fig. 1.

Perception bias refers to the mismatch between people's perception and real-world phenomena. Although people believe they are making impartial judgments, stereotypes often influence people's decisions unconsciously (JR, 2017). Perception bias 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., 2021), 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., 2021). Our work is different than this work since the two safety measures are collected differently; so 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 & 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 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

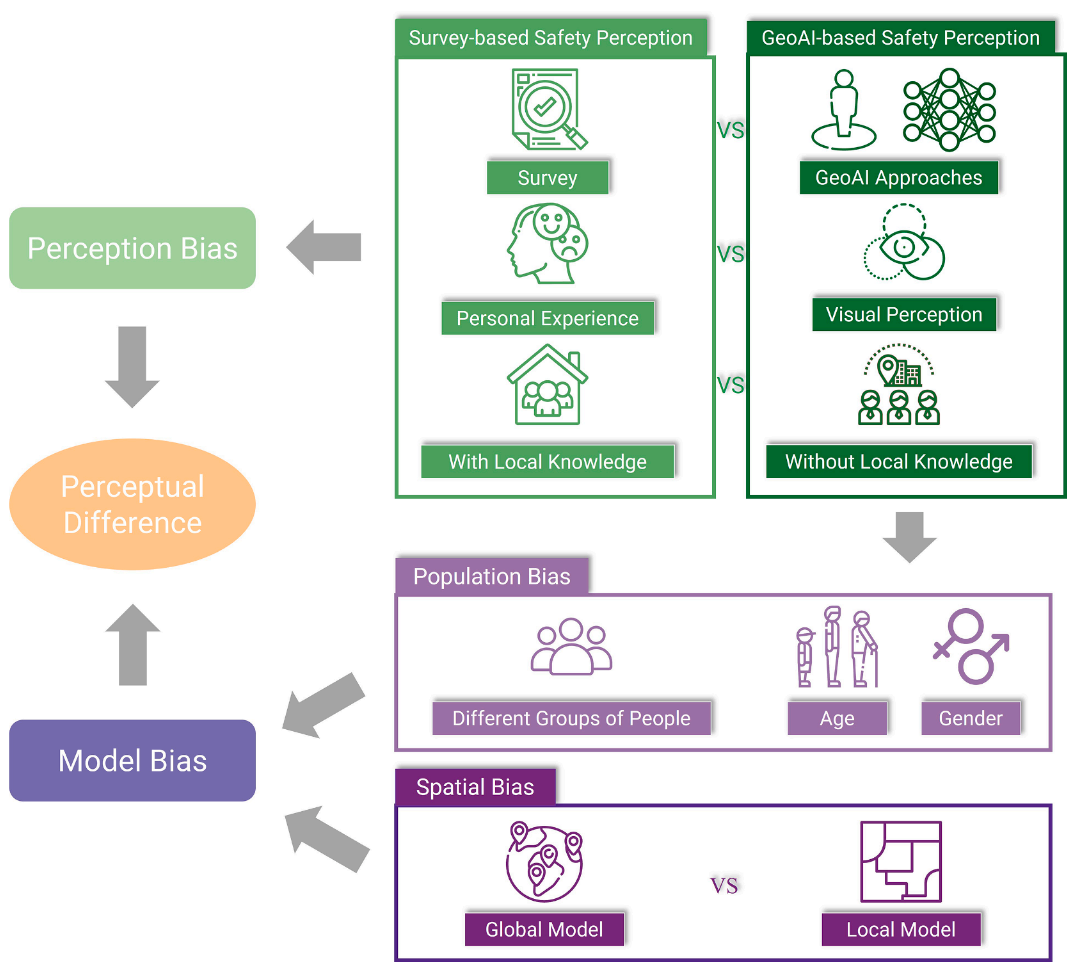

Fig. 1. The conceptual framework for understanding the perceptual difference in this study.

dataset to help monitor potential spatial bias. It should be noted that this paper mainly focuses on the 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).

3. Study area and datasets

3.1. 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*), a fine-resolution geographical unit in Sweden. In total, 419 base areas are adopted in this work. Fig. 2 shows the study area and base areas.

3.2. Datasets

We use 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 are downloaded. Each panoramic image contains a "panoid" as its unique identifier. Fig. 2 shows all panoids in Stockholm based on their latitude and longitude with an interval of 30 m. 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 large volume of street view images in Stockholm can represent the urban built environment comprehensively.

We use the Stockholm City Safety Survey of 2020 (Stockholm Stad Stockholm City, 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 are obtained from Sweco, a consultancy company that is responsible for Stockholm City's information service. Land use variables and urban facilities are 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.

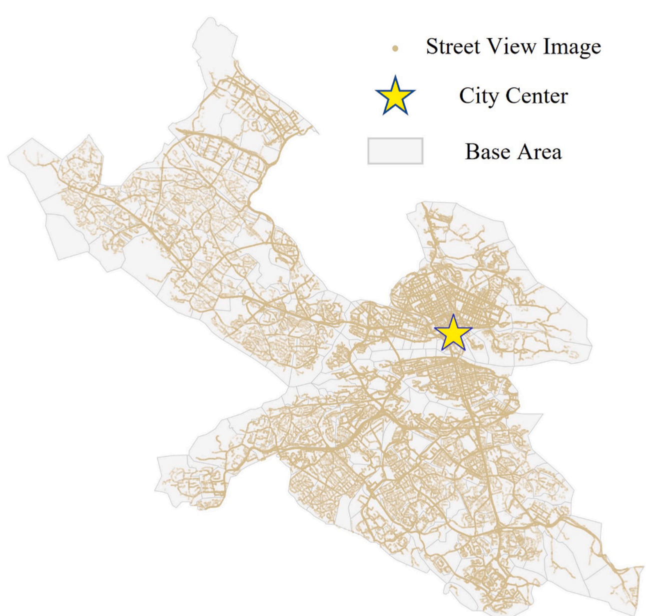

Fig. 2. The 419 base areas in Stockholm as the study area of this study.

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. Measuring safety perceptions and perception bias

4.1. GeoAI-based safety perceptions

Fig. 3 (a) shows the computational workflow to measure human perceptions using GeoAI approaches. First, an online survey is created based on a sample dataset of street view images; Local volunteers from the city of Stockholm are recruited to collect their safety perceptions in response to urban environments. Then, perceptual safety scores are inferred from participants' perceptions of street view images as a proxy of people's feelings of urban safety. Finally, a deep learning model is trained for predicting human perceptual safety patterns and applied to all street view images in Stockholm.

4.1.1. An online survey for collecting safety perceptions

Existing studies have suggested that recruiting local people may better reflect their perceptions of urban streetscape than using a global dataset (Yao et al., 2019). A localized online survey is launched to obtain human safety perceptions of Stockholm's urban environment. We randomly sample 4,953 street view images from the dataset. Then, we work with a surveying company to recruit participants who live in the city of Stockholm to collect the citywide residents' safety perceptions. The participants are sampled to be statistically representative of the population of each of the 6 main planning regions of Stockholm. Fig. 3 (b) shows the user interface of the created survey. Each participant is asked to provide their demographic information including age and gender for the survey for further analysis of potential population bias. Then, they are asked to make comparisons between a pair of two random street view images. Half of the participants are asked to respond to the question "Which place looks safe?", and the other half of participants are 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.

4.1.2. Perceived safety score calculation and deep learning model training

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. We follow the strategy that has been employed in the prior studies as their efficiency and accuracy has been proven (Dubey et al., 2016; Zhang et al., 2018). More technical details about the strategy for computing the GeoAI-based safety perceptions can be found in Appendix 1. The model produces a perceived safety score (ranging from 1 to 9, mean value is 5). The higher the score, the higher the perceived safety. It should be noted that we train the deep learning model to learn citywide residents' safety perceptions to ensure that we have sufficient training street view images. However, for each neighborhood, there might not be enough street view images.

Then, all street view images in Stockholm are input into the model to produce the safety scores. Fig. 4 shows several sample images, and the

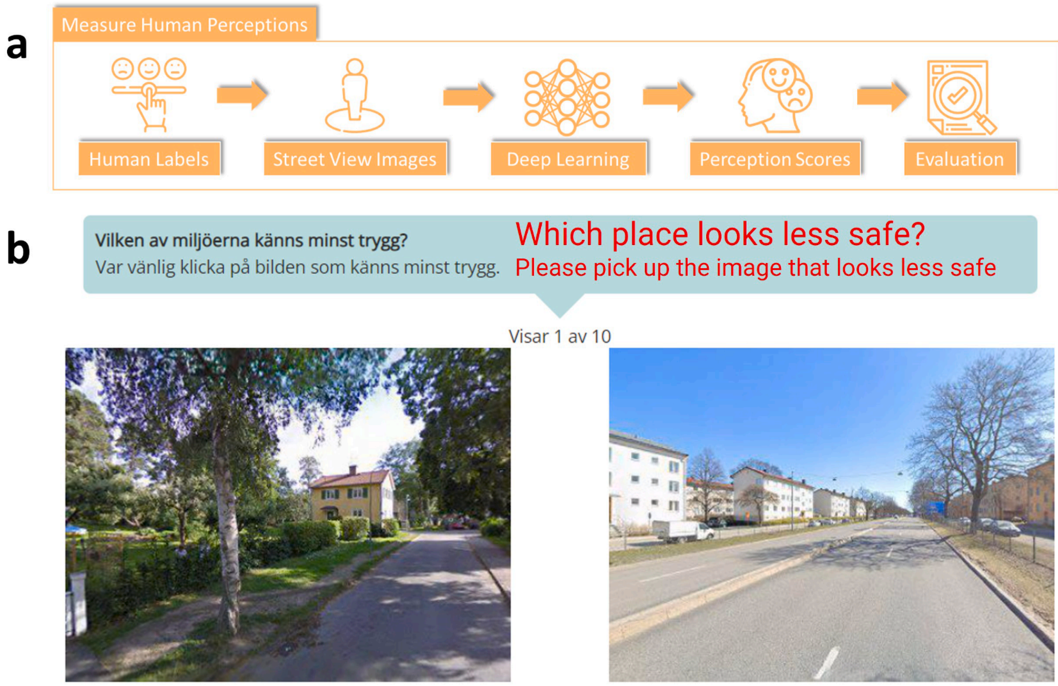

Fig. 3. (a) The computational framework to measure human safety perceptions; (b) A sample screenshot of the survey for collecting human safety perceptions by the citizens. The language of the platform is Swedish, with red text indicating translations into English. The question is "Which place looks safer/less safe?" Participants are asked to pick up the image that looks safe/less safe. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

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

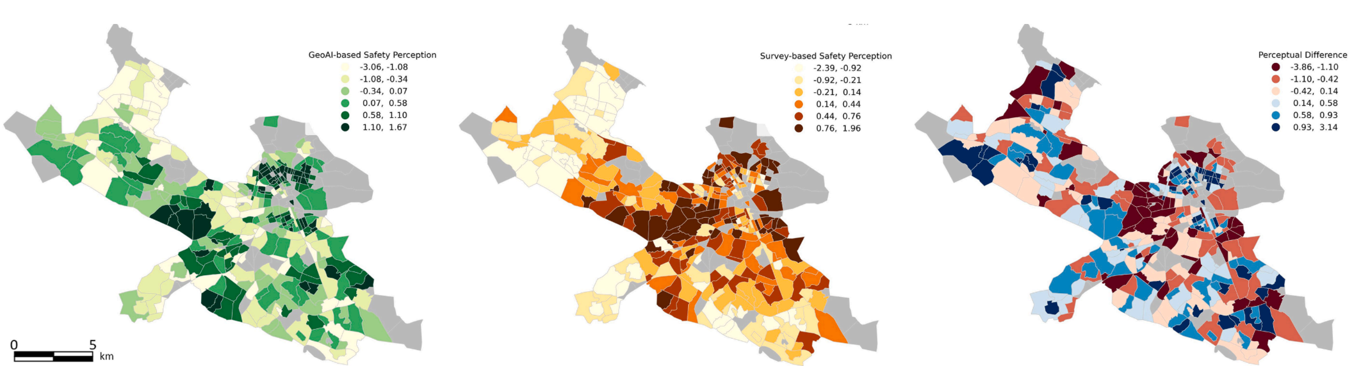

Fig. 5. (a) Distributions of safety perception scores with GeoAI approach in Stockholm. (b) Distributions of safety perception scores with the survey in Stockholm. (c) Distributions of perception bias in Stockholm.

built environment patterns are different in Fig. 4 (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 properly learns human safety perceptions. 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 Fig. 5(a).

4.2. Survey-based safety perceptions

To assess neighborhood residents' safety perceptions of their neighborhoods, we utilize the Stockholm City Safety Survey as a data source. More details about the metadata of the survey can be found in Appendix 2. 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. More details about the three questions and their processing procedures can be referenced in Appendix Table S1. The higher the score, the higher the perceived safety. 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 Fig. 5(b).

4.3. Perception bias

Here, we define perception bias *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 where they reside compared to citywide residents (i.e., residents in the same city who live in diffrent neighborhoods). These non-neighborhood residents may not know the place of the street view image and may rely on their "stereotypes" of the built environment elements, which may distort their judgments and produces perception bias. In a prior study by F. Zhang et al., (2021), 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:

$$PercepBias_i = S_{ci} - S_{ni} \tag{1}$$

where i refers to the computed base area. Fig. 5(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 1.

5. Modeling safety perceptions and perception bias

5.1. 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 are 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 Appendix Table S2). The two forms of safety perceptions and perception bias are used as dependent variables.

Table 1
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/km^2	0.00	27.85	274.25	54.42
Density of Street Lights/km^2	0.00	953.04	15,383.90	1,214.13
Density of Transport Stations/km^2	0.00	1.16	28.00	3.35
Density of Gas Stations/km^2	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

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 Fig. 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 environmental psychology/urban planning (Farrall et al., 1997; Fisher, 1996; 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 & 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 & Kelling, 1982). In other words, physical and social "incivilities" at a setting can trigger feelings of fear among the occupants of this setting. Building upon existing studies, we selected a couple of incivility factors in our study because they relate to Stockholm or they are related to the theory more in general (Ceccato & Haining, 2005; Ferraro & 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 S3, to ensure the robustness of our models. More detailed statistics of all variables used for the three-regression analysis are reported in Table 1.

5.2. GeoAI-based safety perceptions

Table 2 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 (R^2 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.

Table 2
Results of regression models, i.e., 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*
ρ		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

*p-value < 0.05.

First, the high quality of the neighborhood's visual appearance may contribute to people's positive safety perceptions (Cunningham & Jones, 1999; Schroeder & 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 & Block, 2011; Ceccato & Haining, 2004).

5.3. Survey-based safety perceptions

According to Table 2, 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 (R^2 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 & 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.

5.4. Safety perception bias

To compare the two measures of safety perceptions, we start by computing the correlation coefficients between GeoAI-based safety perceptions and survey-based safety perceptions. Pearson's correlation coefficient is 0.286, implying similar trends but also differences between the two safety perception measures at base areas. Also, Table 2 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 which 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 attractive for criminals as they may provide better crime opportunities for offenders (Brantingham & 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 are seen as places where more criminal activities happen from the perspectives of 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 2.

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 & Bamzar, 2016). Hence, regions with more populations that are older than 65 may express relatively lower neighborhood residents' safety perceptions than other groups, in which the perception bias might be enlarged.

Finally, the employment rate is negatively correlated with perception bias. Employment rates of the neighborhood likely cannot bedirectly inferred 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.

6. 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 3, the Pearson correlations are over 0.72 between any subgroups of the entire population. Results of the ANOVA test in Table 4 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.

7. Discussions

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

Table 3
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	14,260	10,000	13,710
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
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 (3) Safety perception score of females	0.638	0.528
(1) Overall safety perception score (2) Safety perception score of populations under 50 years old (3) Safety perception score of populations over 50 years old	0.096	0.908

7.1. 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" (J. Li & Nassauer, 2020) and Jeffery's Crime Prevention through Environmental Design (Jeffery, 1977). These theories suggest 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. Also, the environmental impressions in the citywide residents' safety perceptions are instant and more likely to capture a more temporary sense of safety; not dissimilar from the concept of situational fear (Jackson, 2004; Kappes et al., 2013).

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 regions that 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 & 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. Therefore, neighborhood residents' safety perceptions can as such be said to capture a form of dispositional fear, as it is shaped by individual long-term developmental processes (Jing et al., 2021; Kappes et al., 2013). 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.

7.2. 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. Moreover, we demonstrate that these factors reliably illustrate the safety perceptions of different residentsin the city. Our 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 & Love, 2015; Jeffery, 1977; Newman, 1972). Although planners may do little to change 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 such as survey 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 & 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.

7.3. 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 & 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, GeoAI methods can 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. We found that 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.

7.4. Limitations and future work

This study still has the 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. A prospective research topic involves carefully examining and testing the difference between dispositional and situational safety perceptions following existing criminology theories and principles. 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., 2021) and may be worth further exploration. Furthermore, we only investigated the associations between safety perceptions and land use as well as socio-demographic variables at the base area level. Various streetscape elements can be retrieved directly from street view images. Future research should investigate the relationships between safety perceptions and street features.

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.

8. 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.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

Acknowledgments

The authors would like to thank Cate Heine at the MIT Senseable City Lab who helped us preprocess the mobility dataset, Zhuangyuan Fan at the Hong Kong University who provide valuable discussions for explaining the safety perception results, and Timothy Prestby from the Pennsylvania State University who proofread the manuscript. This work is supported by the City of Stockholm, the Stockholm Chamber of Commerce, Newsec, and the members of MIT Senseable City Lab. The authors would like to acknowledge the financial support from the Senseable Stockholm Lab funded by City of Stockholm, KTH Royal Institute of Technology, the Stockholm Chamber of Commerce and Newsec, and in collaboration with MIT Senseable City Lab. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the funders.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.landurbplan.2023.104768.

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