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What Makes a Place Safe? Assessing AI-Generated Safety Perception Scores Using Stockholm's Street View Images

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This article investigates what causes an urban environment to be perceived as safe using Stockholm, the capital of Sweden, as the study area. The study integrates AI-generated safety scores from street view images, image segmentation techniques and conventional and crowdsourced data using Geographical Information Systems (GIS) and regression models. After accounting for income, crime and other area characteristics, the models reveal that areas with lower safety scores primarily consist of areas with a relatively large percentage of roads in industrial and/or interstitial mixed residential areas. Conversely, higher safety scores are found in large but distinct combinations of buildings, vegetation and open sky, from detached single-family housing to inner city high-density built areas. To enhance safety in an area, good contextual knowledge of the area is fundamental to prioritize interventions in interstitial mixed residential zones where roads and highways may be the dominant features.

KEY WORDS: crime, built environment, street view images, safety perceptions, image segmentation, GSV, deep learning, regression models

INTRODUCTION

Large European cities are a blend of their architectural heritage and modern planning paradigms, reflecting multiple intertwined natural and man-made components (Hall & Falk 2013). Buildings, roads and vegetation are basic components, arranged in different ways reflecting a

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complex patchwork of planning ideals and spontaneous, organic growth. Inner city areas typically exhibit dense concentrations of buildings, whereas peripheral areas accommodate extensive portions of vegetation and open spaces interlinked by streets and roads (Pacione 2009; Sheikh & van Ameijde 2022). Although a large share of green areas and certain architecture and planning styles have traditionally been linked to safer environments (e.g. Poyner & Clarke 2013; Venter *et al.* 2022), international literature does not provide information on which components contribute to places that are perceived as (un)safe.

The UN-Habitat has advocated for cities to dedicate 'an average of 45% to 50% of urban land to streets and open public spaces' to foster a well-functioning, safe and prosperous city (UN-Habitat 2018: 4). While this guideline sets a quantitative target, it offers limited guidance on how these elements should be integrated to ensure a functional and safe city. One way to investigate the relationship between visible characteristics of the urban environment and people's perceptions of safety is to use methods that integrate street-view images and deep-learning models, enabling the evaluation of elements such as streets and buildings (Rundle *et al.* 2011; Alhasoun & González 2019; Kita-Wojciechowska & Kidziński 2019), the quality of green areas (Wang *et al.* 2021), but also elements linked to crime and safety (Naik *et al.* 2014; Zhanjun *et al.* 2022; Kang *et al.* 2023).

In this study, we begin by examining people's perceptions of safety in different types of urban environments. We ask them to indicate which images of the city make them feel safe. These images are from Street Views of Stockholm, Sweden. Using people's responses, we first create a human safety perception score based on ratings of images. Then, we train an AI model to learn human safety perception patterns which can then be leveraged to measure safety perceptions of citywide street-view imagery. Based on this, we created safety scores for each image over the whole city. Deep learning segments each pixel in the images into categories like trees, buildings and roads, helping researchers link specific objects to particular planning areas and, later, different levels of safety perceptions. We calculate the percentage of each object in the images to represent different types of urban environments in Stockholm's six planning areas. These areas have unique architectural characteristics following specific planning guidelines, such as million-home programs and single-family homes in the Garden Cities.

This article investigates what makes an urban environment perceived as safe, accounting for variations in land use and socioeconomic and other area-level characteristics, including crime in Stockholm, the capital of Sweden, as the study area. People's perceptions may be influenced by visual cues from the streetscape, where their initial impressions of environmental features help them assess whether these areas are safe. These environmental impressions are likely to shape the citywide residents' safety perceptions immediately and transiently, reflecting a more temporary feeling akin to the concept of situational fear (Jackson 2004; Kappes *et al.* 2013). By analysing people's responses, we train an AI model on citywide street-view imagery to generate safety scores for each image across the city. Such an AI model could learn human perceptual patterns and rate input street view images in a similar manner. We also extract elements of the urban environment in these pictures using techniques of image segmentation to extract their main components (buildings, vegetation and streets). Finally, we integrate AI-generated safety scores from street view images (the dependent variable), results from image segmentation techniques and both conventional and crowdsourced data (independent variables) into regression models using Geographical Information Systems (GIS) to assess how these factors combine to shape perceptions of safety.

This article draws on the theoretical concepts of situational fear and safety perceptions within the urban environment, grounded in environmental criminology and framed through the lens of Crime Prevention Through Environmental Design (CPTED). By integrating these frameworks, we highlight the role of environmental design in shaping safety perceptions and its

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potential impact on individuals' sense of safety in public spaces. In particular, the study seeks to address the following research inquiries:

1] Using information from Google Street View (GSV) images, how do buildings, vegetation and streets vary across the Stockholm municipality? Which areas exhibit notably high/low safety scores?
2] Which types of building areas are perceived as safer? Do areas with more vegetation tend to be perceived as safer? Are areas with a relatively high share of roads perceived as less safe?
3] How do these elements (buildings, vegetation and streets) combine to make an area safe?
4] What actionable recommendation(s) can urban planners make based on these findings?

Note that the primary aim of this study is not to examine crime or perceptions of safety about crime directly but rather to investigate how the image of urban environments influences people's safety perceptions. While crime is indeed a key factor influencing perceptions of safety, our focus is on understanding how urban design and planning—specifically, the physical and environmental aspects captured in 'planning areas'—shape subjective perceptions of safety, which may or may not align with actual crime rates. We aim to contribute to the growing field of environmental criminology by highlighting the broader factors influencing how people perceive safety in urban spaces, which is an important area of inquiry for understanding both social behaviour and crime prevention.

Since most studies have focused on specific elements of the urban environment, multidimensional approaches that consider physical, social and economic variables simultaneously are needed (Hipp *et al.* 2022a). Thus, this study aims to contribute to such a multidimensional approach and to inform local planners about the inherent quality attached to the choices of environments at the planning stage when new residential areas are built. In particular, we focus on three elements of the landscape: green areas/vegetation, buildings, streets and roads.

The article has six parts. First, the introduction, followed by section 2, presents the current knowledge on the built environment and safety perceptions and the potential of AI for urban studies. Section 3 introduces the research design, including the study area, data and methods. Section 4 presents the study's overall results, followed by a discussion in section 5. Finally, the article summarize our conclusions and offer recommendations for future research and practice.

THEORETICAL BACKGROUND

Safety perceptions and situational fear

Safety perception is used here as an umbrella term for 'declared perceived safety' based on individuals' responses to questions about the GSV images presented to them: a high perception of safety is when individuals feel safe upon viewing a streetscape, while a low perception indicates feelings of fear or unsafe. Personal factors (such as age and gender) may affect propensity to experience fear and the intensity of it, while an individual's sense of safety in a given moment is also based on situational factors, such as the surrounding environment and/or time of day (*see dispositional vs. situational fear*, Gabriel & Greve 2003). Safety perceptions related to GSV-images may better simulate situational fear (Kang *et al.* 2023), while on the other hand, both dispositional and situational fear influence each other (Gabriel & Greve 2003).

Given that both individual and environmental factors influence safety perceptions, the design and layout of urban spaces play a crucial role in shaping these perceptions. In the next section, we present the principles of Crime Prevention Through Environmental Design (CPTED).

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CPTED offers place-based strategies that aim to reduce crime and enhance safety by improving the physical and social environment.

Urban environment and CPTED

While its primary focus is on reducing opportunities for crime, CPTED also emphasizes the role of the physical environment in shaping overall perceptions of safety (Cozens *et al.* 2001). By designing urban spaces that are well-lit, have clear sightlines and include secure entry points, cities can foster a sense of security that goes beyond simply preventing crime (Crowe 2000). Moreover, well-maintained vegetation, such as trimmed hedges and trees, improves natural surveillance by enhancing visibility and contributes to a safer and more inviting urban atmosphere (Cozens *et al.* 2005). Understanding and applying these concepts is crucial for policymakers and urban planners who aim to create vibrant and safe cities. In this section, we explore how visible urban elements—such as vegetation, buildings and streets—affect safety perceptions, drawing on studies that use street-view images and deep learning techniques to analyse the relationship between urban design and safety perceptions.

Green areas

Vegetation in the form of trees, parks and other natural areas is generally linked to good quality urban environment. The greener a building's surroundings are, the fewer crimes there are; these results hold for both property crimes and violent crimes (Kuo & Sullivan 2001), but according to Venter *et al.* (2022), not for sexual crimes. The presence of nature in urban environments reduces the frequency of violent crime (Shepley *et al.* 2019). A recent literature review confirms that green areas had a decreasing effect on particular types of crime and that the presence of green areas positively affected perceived safety (Ceccato *et al.* 2020). Talen and Koschinsky (2014) suggested that the quality of the urban environment, social interactions and safety impacted residents' health. Evidence suggests a positive relationship between access to green or natural environments and people's perceived overall health (De Vries *et al.* 2003). More green space is linked to less stress in deprived communities (Ward Thompson *et al.* 2012). These findings underscore the important role that green spaces play not only in reducing crime but also in enhancing people's perceptions of safety and well-being in urban areas.

Buildings

Mixed-use developments, which combine residential, commercial and recreational spaces, tend to enhance safety by ensuring active surveillance and diverse activity patterns (Jacobs 1961). Buildings designed to enhance natural surveillance can reduce crime (Newman 1972), such as low-rise buildings with clear sightlines and windows facing streets, enable residents to monitor their surroundings, thus deterring criminal activities (Armitage 2013; Poyner & Clarke 2013). Conversely, Hipp *et al.* (2022b) finds that in disadvantaged neighbourhoods and for certain crime types, walls of buildings (providing low visibility) may have a much stronger negative relationship with crime than fences (high visibility). Studies have also shown that high-rise buildings, particularly in low-income areas, are often associated with higher crime rates than low-rise buildings. However, these features may depend on the context. Settings with high refuge qualities offer concealment for the potential offender, confirming that fear is higher in locations that offer good refuge for the potential offender but low prospects and escape for the user (Taylor & Harrell 1996). More recently, Lee *et al.* (2023) indicates that poor street or building maintenance, being adjacent to multi-family housing and being close to bus stops are consistently associated with both violent and property crime. This research highlights the significant role that building design and the type of development play in shaping people's safety perceptions, as features such as mixed-use layouts, low-rise buildings with natural surveillance and well-maintained spaces can foster a greater safety

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perception. Despite being highly context-dependent, there is international evidence that shows that high-rise buildings and poorly maintained areas may contribute to a sense of vulnerability and poorer safety perceptions.

Streets and roads

In her book, Jacobs discusses how the design and use of residential streets can be safe. She emphasizes the importance of 'eyes on the street', where continuous activity and the presence of people in public spaces contribute to a sense of safety (Jacobs 1961). Well-connected street layouts enhance safety by better-integrating street areas into neighbourhood networks and facilitating natural surveillance (Hillier 2004). Marohn Jr (2021) suggests poor street and road design in cities has dramatic effects on the lives of those who use them. Streets are made to create wealth, while roads connect points of activity. The author argues that too often, a mix of streets and roads can make places dysfunctional. More recent studies also confirm the relationship between the street network configuration and crime (Frith *et al.* 2017; Kim & Hipp 2020); however, such an effect seems to be moderated by the socioeconomic status of the street segment. Additionally, a high-density, diverse and fine-grained mix of activities that encourage human movement significantly contributes to the perception of safety and vibrancy in urban environments (Sheikh & van Ameijde 2022), while areas dominated by industrial uses or those with high road density may be perceived as less safe (Gehl 2013). In summary, the design and connectivity of streets and roads significantly shape safety perceptions, as well-connected, well-designed streets with active public spaces foster natural surveillance and a sense of safety, while areas dominated by high road density, industrial uses, or poor street layouts can contribute to feelings of insecurity and vulnerability. The nature of these environments—whether they encourage movement, interaction and visibility—directly influences how safe individuals perceive these areas to be.

AI, street view imagery and perceptions of the urban environment

Street view images and deep learning have been employed to assess and predict people's perceptions of urban environments (Salesses *et al.* 2013; Dubey *et al.* 2016). Street view images capture detailed urban streetscapes, offering valuable data sources to observe the urban built environment. Researchers have utilized deep learning methods to model and understand the environment captured in street view images. Recent studies have applied these methods to examine the impact of urban features on crime patterns and safety perceptions, revealing complex relationships influenced by factors such as street lighting, green spaces and other environmental characteristics (Zhang et al. 2018; Moreno-Vera et al. 2021; Zhang et al. 2021; Zhou et al. 2021; He and Li 2021; Hipp *et al.* 2022a). However, most of these studies were conducted primarily at the element level that focused on a few urban objects. This study explores the underlying process to examine how their associations are linked to different land use types and planning ideals.

STUDY AREA

The study area is Stockholm, the capital of Sweden and the largest city of the country and in Scandinavia, with a population of approximately 987,000 inhabitants (SCB 2023). The city's oldest section of the city is Gamla stan (Old Town), located on the original small islands of the city's earliest settlements and still featuring the medieval street layout. However, the city expanded outside its original borders in the fifteenth century. Norrmalm, now the central part of the shopping district of Stockholm, was originally a separate city but was incorporated in Stockholm during the early seventeenth century; all these areas constitute the section called 'A—Inner City' in Figure 1. During the nineteenth century, particularly up to the mid-twentieth

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century, Stockholm grew rapidly, with plans and architecture inspired by different styles. In the 1930s, modernism characterized the development of the city. During the 1950s, suburban development entered a new phase, which commenced in the early 1930s with the inauguration of the Stockholm metro. The modernist projects garnered international attention (part of D—'Subway city'). As the 1960s unfolded, suburban development continued. However, the prevailing aesthetic of that era led to substantial criticism of the industrialized and mass-produced apartment complexes, shown in the map in 'B—Large scale' and D—'Functionalism'.

As Figure 1 illustrates, the inner-city area is located in the east part of the city. The basic spatial unit employed in this study refers to basområde (called base area), one of the smallest units for statistical analysis used in Sweden (N = 419 areas).

DATA

We combined seven types of data sources into one dataset aggregated to the level of basområde: a street view imagery dataset, a citizen's panel survey, a land use and socioeconomic variable dataset, a cell phone-based mobility dataset, a crowdsourced records of graffiti and official police recorded data on total crime (Appendix A1).

Street view images contain approximately one million street-view images and were downloaded from Google. Each panoramic image contains a 'panoid' as its unique identifier and consists of four street view images to represent the different views of a location. All images were downloaded with around 50-m intervals among images. Such high density of images allows for fine-resolution assessments of safety perceptions across the whole city. An online survey was designed to assess people's perceptions of safety regarding the built environment. Participants were recruited through a citizen's panel of Stockholm (medborgarpanel) and were asked to select which image make them feel safe/unsafe using multiple pairs of street view images.

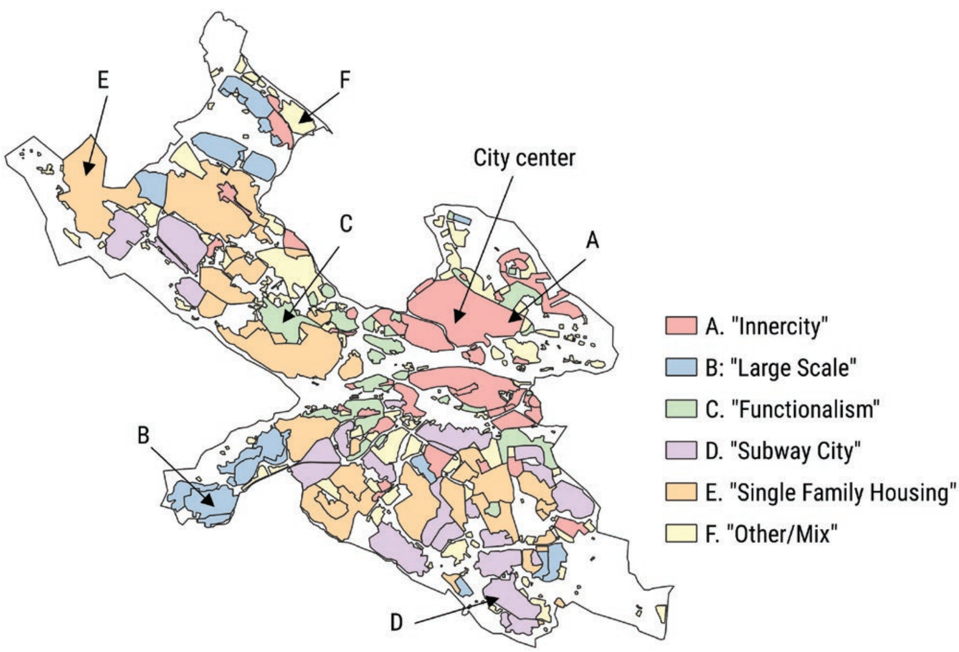

Fig. 1 The A–F planning areas in Stockholm, Sweden. Source: Stockholm municipality, 2021. The areas are aggregated from the "byggnadsordningen"-document (Stockholm municipality, 2020) based on similarities in the placement of buildings in relation to the street.

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Land use variables and urban facilities were retrieved from Stockholm City's open data bank, Dataportalen and OpenStreetMaps (OSM). The land use variables include commercial, residential, recreational, industrial, forest, nature reserve and parks. In order to estimate the population flow in these areas, we used aggregated measures from the cell phone data (Telia) generated based on millions of anonymous cell phone users' activities. For graffiti/physical damage, we used crowdsourced data from TyckaTill, a platform that helps people in Stockholm municipality to inform the local authority of problems needing attention, such as littering, inappropriate parking or abandoned vehicles and physical damage. The police recorded data on total crime comes from the Stockholm police authority headquarters from 2019 to 2020. A description of the dataset is found in Appendix A1.

METHODS

Measuring safety perceptions with street view images and deep learning

To measure human safety perceptions, we leveraged a strategy that integrates street view images and cutting-edge deep learning approaches. Such a strategy has already demonstrated its efficacy in Kang *et al.* (2023). It contains three phases: (1) We first hosted an online survey in Stockholm and recruited participants from local residents. The participants are asked to rate a sample dataset that contains around 5,000 randomly selected street view images. Each participant is asked to select one of the two randomly displayed street view images that answers the questions 'Which place looks safe/unsafe?'. By doing so, we can collect human safety perceptions in response to the built environment. The hypothesis is that people's responses to street view images are indicative of their safety perceptions of the built environment. This association arises from the fact that street-view images capture detailed landscapes of the built environment. In total, we received 23,710 responses from our participants, with each street view image undergoing comparison with nine other street view images. This ensures a comprehensive understanding of human safety perceptions of the built environment. (2) Based upon the collected safety perceptions, we then computed a safety score of each sample street view image representing the degree of people's safety within the urban environment. (3) After that, we trained an advanced deep learning approach that can learn people's safety perception patterns and thereby facilitate the prediction of human safety perception scores of any given input street view image. In particular, we used a ResNet architecture (He *et al.* 2016) to learn safety perception scores. The output perceived safety score ranges from 1 to 9 with an average value of 5. The higher the score, the safer the perceived safety in street view images. This model is then used to measure safety perception scores of all street view images (around one million) in Stockholm. It should be noted that before further utilizing such a method, we validated the model by calculating a series of metrics to validate the efficiency of the proposed approach. The Mean Squared Error of the safety perceptions between AI and the original human perceptions are compared and calculated with a value of 0.82, indicating the average error of safety perceptions is less than 1, which is highly aligned with human perceptions. More technical details can be found in Kang *et al.* (2023). After that, we associated each street view image with different land use types according to their coordinates and then computed the average safety scores for each land use and planning areas.

Identifying objects from street view images with deep learning

We further identified objects in street view images with advance computer vision approaches which enable us to examine the associations between elements in built environments and safety perceptions. In particular, we leverage a DPT model (Ranftl *et al.* 2021), which was developed based on a state-of-the-art vision transformer architecture, to identify objects from street view images. Such a model has been trained based on the ADE20K dataset (Zhou *et al.* 2016) and has outperformed previous convolutional neural networks in a variety of object detection tasks.

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The model could segment each pixel in street view images into 150 categories of objects such as trees, sky, roads, potentially allow researchers to further make associations between objects in urban environments and safety perceptions. Under this backdrop, for a given street view image, we compute the percentage of pixels of each object. For instance, given a street-view image i with a height of h and a width of w, the proportion Pim of an object m is:

$$P_{im} = \frac{\sum_{j=1}^{h} \sum_{k=1}^{w} 1\left(p_{jk} = m\right)}{h \times w}$$

where p_{jk} refers to a pixel of the street-view image i at h and w. By doing so, we could compute the percentage of each object m for all street-view images. A detailed list of the 150 categories of objects can be found at https://groups.csail.mit.edu/vision/datasets/ADE20K/. Based on the percentage of objects in street view images, we then compute the mean values of each object for each land use type to further interpret how different urban design and built environment objects may affect human safety perceptions. Figure 2 illustrates the process of image segmentation used in the study area.

Assessing areas using AI-safety perceptions scores

To determine whether the planning areas (which represent regions developed under different urban planning paradigms) in Stockholm differ significantly in terms of mean safety scores, an Analysis of Variance (ANOVA) can be used. ANOVA is a statistical method that allows us to compare the means of three or more groups to see if there are any statistically significant differences between them. In this context, the groups are the different planning areas in Stockholm and the variable of interest is the mean safety score for each area.

Fig. 2 An example of the image semantic segmentation to extract objects in street view images used in Stockholm.

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Modelling AI-safety perceptions scores

In order to assess whether and how AI-generated safety perception scores of residents are related to Stockholm's urban design styles, we used regression models controlling for land use and socio-economic and other area characteristics such as measures of graffiti and physical damage and official police data in each of the 419 areas. In order to test hypotheses about the statistical significance of different predictors, in particular, if a certain way of planning the city would explain the variation in the safety score, we initially used a normal linear model. The model is given by:

$$Y = X\beta + \varepsilon$$

where **Y** denotes the (N = 419) vector of AI-generated safety perception scores per basområde; **X** is an **N by p** matrix with $\boldsymbol{p}$ explanatory or predictor variables, including the constant term; $\boldsymbol{\beta}$ is the $\boldsymbol{p}$ vector of regression coefficients (including the intercept); and $\boldsymbol{\mathcal{E}}$ is the random error vector with mean $\boldsymbol{0}$ and variance $\boldsymbol{\sigma}^2\mathbf{I}$.

The Stockholm's urban design styles were implemented as dummy variables. Dummy variables are used to capture the categorical nature of independent variables in regression analysis. To incorporate this categorical variable into the model, we create six binary (0 or 1) one for each category from A to F urban design styles. If the basområde belongs to a particular category, the corresponding dummy variable is set to 1. If the basområde does not belong to that category, the dummy variable is set to 0. We used planning area A as the reference category (the one not represented by any of the dummy variables) to be the baseline for comparison. A positive/negative coefficient means that the presence of that category has a positive/negative effect on the dependent variable, assuming other variables are held constant.

In order to test for spatial autocorrelation in the residuals (Moran's I), the binary weight matrix was created based on neighbours sharing a common border. Based on the spatial diagnostics of the residuals of the OLS model, the lagged response and spatial error models were also fitted (Haining 2003: 312–16). To avoid multicollinearity problems in the regression model, a few variables were excluded when bivariate correlation analysis revealed strong correlations between independent variables. For example, we kept average income in the model and excluded unemployment, which was correlated with income. Another example is that we kept the periphery but excluded several other variables inversely correlated with distance, such as the proportion of bars. We are aware that this may not completely prevent multicollinearity because when using the lag model, multicollinearity could be introduced through the WX variable. They are correlated with X by construction, which worsens with higher lag terms.

In the spatial lag model, the endogeneity of the spatial lag term *Wy* is directly addressed in the likelihood function of Maximum Likelihood Estimation (MLE). Alternatively, in models with recognized endogeneity, the Instrumental Variables (IV) method can be used, where the spatially lagged explanatory variables *WX* serve as instruments to correct for the endogeneity of *Wy*. These techniques, developed in the 1990s by Kelejian and Prucha (1995), are also well-documented in the work of Anselin and Rey (1997).

The following discussion of results is divided into three parts. The first part reports the types of planning areas and the main components (buildings, roads and trees). The second part describes the geography of the AI-generated safety perception scores and how Stockholm is characterized regarding land use and other relevant characteristics. This provides background information for the results of the modelling that comes later. The third part discusses results from the OLS model and the lagged response and spatial error models, focusing on the categorical variables representing Stockholm's urban design styles (planning areas).

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RESULTS

How do buildings, vegetation and streets vary across Stockholm municipality?

The image segmentation of the Stockholm Street view images helps us characterize the environment of the planning areas. Table 1 reports the mean proportions of selected environmental characteristics in the street view images: buildings, trees, roads, sky, grass, sidewalks and cars.

Table 2 contains a comparison of mean proportions of the environmental features between the six planning areas, as well as a description of each area to better interpret the findings. For all areas in total, 'Building' followed by 'Tree', 'Road' and 'Sky' are the components with the highest mean proportion of the street view images in Stockholm (on average, around 20% of an image consists of these features). 'Grass', 'Sidewalk' and 'Car' are minor components but help better characterize the nature of certain components or combinations.

Images of locations in Area A stand out as having noticeably more built-up environments than all other areas (35% of images found in this area consist of buildings), which aligns with its designation of a more densely built inner city area. The average proportion of buildings here is over three times as high as in the more sparsely built environment of single-family housing zones (Area E). In contrast, Area A has the lowest proportion of visible sky, trees and grass, suggesting limited open spaces and green areas. As many as 9% of the images had no greenery visible. Both single-family (Area E) and multifamily housing areas in the periphery of the city centre (Areas B, C and D) have more greenery visible in street view images than the inner city (23–28% compared to 13%). The comparably less dense built environment in these areas may allow for more parks and integrated vegetation along the streets. Single-family housing areas have more vertical greenery in the form of trees, while low-level greenery, such as grass, is somewhat more common in large-scale multifamily neighbourhoods. While the higher proportion of visible sky in single-family housing areas compared to Areas C and D is expected, the similarly high proportion in Area B is more surprising, as it is characterized by residential high-rise complexes. One reason could be that the traffic-separated environments that characterize this area may have limited the ability to capture Street View images in residential areas.

The presence of the road network appears to be the most noticeable in Area F (on average, 23% of an image consists of roads) while having the least proportion of sidewalks (3%). This suggests that these environments are not designed for pedestrians but more for vehicle traffic. Areas F and E have significantly more visible sky than all other areas, while Area F still maintains many buildings and roads with a lower share of vegetation. Overall, it seems that the inner city is the most distinct from the average area in terms of the major components (Building, Sky, Tree), while the functionalistic and subway city-style neighbourhood seems to have the most balanced mixes of components (relative to the total averages). Notably, Area E and F have

Table 1. Mean proportion of urban components identified in Stockholm street-view images

Component	Mean (Range)	Std. dev
Building	0.22 (0–0.93)	0.17
Sky	0.18 (0–0.56)	0.09
Tree	0.21 (0–0.82)	0.13
Road	0.21 (0–0.44)	0.08
Grass	0.03 (0–0.44)	0.05
Sidewalk	0.04 (0–0.38)	0.04
Car	0.02 (0–0.27)	0.03

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relatively similar combinations of characteristics (greenery and roads being the main differentiating factors) yet differ in their respective descriptions.

Which areas exhibit notably high/low safety scores?

On average, the highest AI-safety perception scores can be found within areas classified as single-family housing (Area E), followed by the inner-city area (Area A) and areas characterized as functionalistic (Area C) (Table 3). Area F (Other/Mix) is notably the category that is

Table 2. Description of planning areas and graphical summary of mean proportion of components by planning area

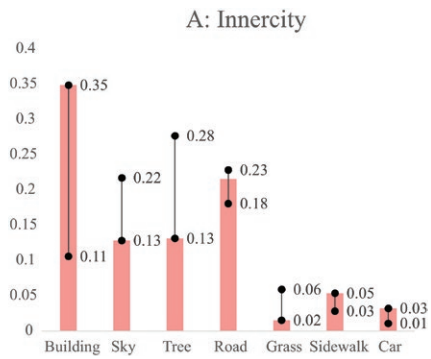
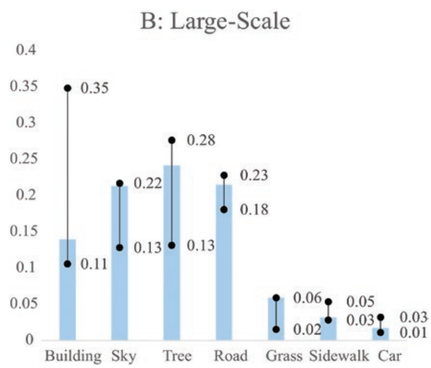
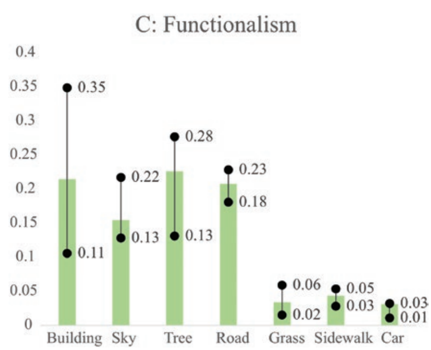
<table>
<tr><th></th><th>Description</th><th>Mean proportion of components</th></tr>
<tr><td>A—Innercity</td><td>Old town, dense city enclave, stone city, older suburb. Highly residential but areas with mixed land use, containing main transportation hubs and the Central Business District—CBD. Architectural style is mixed inspired by medieval and renaissance ancestry as well as Art Nouveau. From late 1990s, old industrial areas close to the inner city are being (re) built (densification) adopting a mix of modernistic and new urbanism styles (e.g. Hammarby Sjöstad and Stockholm Royal Seaport).</td><td></td></tr>
<tr><td>B—Large-scale</td><td>Large scale multifamily houses, Group-built detached houses (‘Storskalig stadsdel’). Pedestrian and vehicle traffic systems completely separate. Large-scale buildings/ terraced and semi-detached houses. The walkways go through the buildings or vegetation.</td><td></td></tr>
<tr><td>C—Functionalism</td><td>Stone City expansion around the inner city, multifamily houses and dense mixed city. ‘House-in-park’ (buildings freely located in a nature-like environment). Houses are often located far into the plot, with entrances facing inwards. Less clear division between streets and neighbourhood land. Walkways along streets.</td><td></td></tr>
</table>

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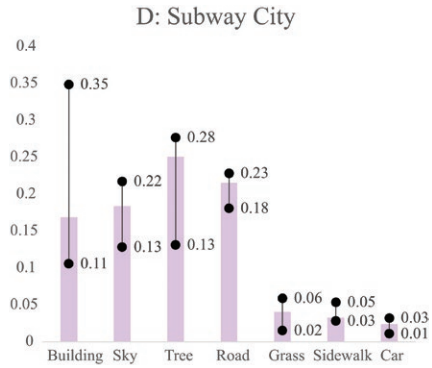
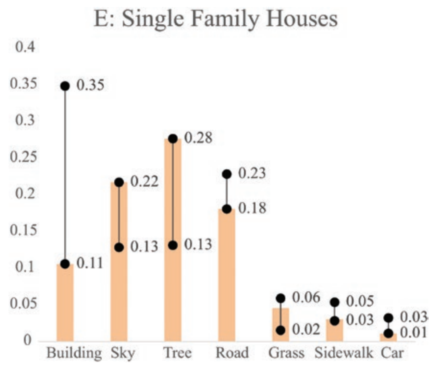
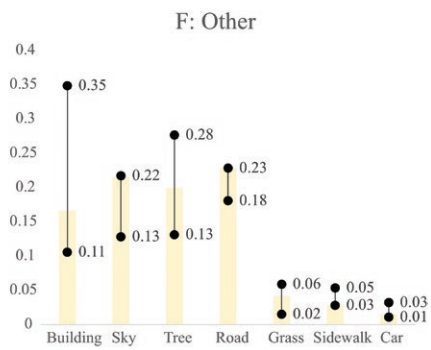
Table 2. Continued

	Description	Mean proportion of components
D—Subway city	Large-scale buildings in self-sufficient units along the metro line, community neighbourhood units, large-scale detached houses with a staircase in the middle and apartments around the metro line. Further development of 'house-in-park', some impact from older environments. Buildings are grouped around courtyards or parks. Entrances often turn inwards or away from the street. Walkways are both along streets and separate through parkland.	
E—Single family housing	Individual single-family houses, small cottage areas, garden cities ('Villastad'). Streets defined by bordering buildings, hedges, avenues. In the style of the Garden city movement, built between the wars, these areas include wide garden/courtyard faces the street; and they may include low blocks of apartments built during the 1940s.	
F—Other/ Mix	Areas with no distinct planning style underlying these residential areas. They tend to have large interstitial areas with industry, airport, harbour, fun-parks, residential areas with mixed land use ('Övrigt') located randomly across the city.	

associated with the lowest safety scores. An ANOVA analysis reveals that the planning areas are significantly different from each other in terms of mean safety score ($F(5, 195059) = 3940$, $p < 0.001$). See Appendix A2 and also Table 3.

Table 4 highlights some visual examples of typical environments with high and low safety scores by planning area. From the examples, images depicting residential areas, including greenery, are typically associated with high safety scores, while images depicting open spaces where roads dominate are perceived as less safe.

Over the years, the overall incidence of crime in the Stockholm region has tended to decline. However, there has been an increase in incidents of vandalism and confirmed cases of deadly

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Table 3. Average AI-safety perception score by planning areas

Planning area	N (Panoid images)	Mean safety score	St. Dev.
A—Innercity	64114	5.04	0.89
B—Large-scale	9331	4.57	0.71
C—Functionalism	20133	4.97	0.90
D—Subway city	33142	4.88	0.83
E—Single family housing	45860	5.26	0.76
F—Other/Mix	22485	4.37	0.85
Total	195065	4.96	0.88

violent crime since 2015 (Brå 2022). The districts located in the southwest and northeast periphery of the municipality exhibit significantly higher proportions of foreign-born residents, lower income levels and increased unemployment rates compared to both the municipality and the national averages. These areas are where some of the planning areas B and C dominate (Figure 3).

Modelling AI-safety perception scores in Stockholm

OLS regression analyzes the relationship between urban characteristics and AI-safety perception scores. This statistical method is chosen for its ability to estimate the linear relationship between independent variables (e.g. types of buildings, vegetation cover, road density) represented in the model by the different planning areas (A-F) and the dependent variable (AI-safety perception scores) after controlling for other area differences.

Results show that the Ordinary Least Square model explains about a quarter of the variation in the AI-safety perception scores (Table 5). This model controls for many variables that also turned out significant, such as bars and restaurants, parks, periphery, average income and total crime rates. Because there is an indication of the problem of non-normality of errors, the results were remodelled using the Natural log of the dependent variable (Square root was also tested with very similar results as the ones from the Natural Log), which are now shown in Table 1. Multicollinearity is under control. This is indicated by the multicollinearity condition, 11.80, where a value of 20 or above indicates a multicollinearity problem. The errors are homoscedastic (Koenker-Bassett) but with some indications of being nonnormal and Moran's I test shows spatial autocorrelation in the residuals. In this case, a common practice is to fit either a lagged response model or a spatial error model to handle the problem of autocorrelation in the residuals. These models explicitly account for spatial dependencies in the data and can provide more accurate parameter estimates. Failing to account for spatial autocorrelation can lead to biased parameter estimates and incorrect statistical inferences.

The lagged response model (second column) includes a lagged form of the response variable (W_AI safety score) as one of the independent variables. This variable is calculated by taking the sum of the observed and expected counts in the adjacent areas and dividing the sum of the observed counts by the sum of the expected count. If significant, it suggests that unaccounted spatial factors or spatial processes may be at play that influence the variable. When the lambda (λ) variable is found to be significant in the error model, as it is now, it indicates the presence of spatial autocorrelation in the error term of the model. This suggests that there are unaccounted spatial factors or spatial processes affecting the dependent variable that are not captured by the independent variables included in the model, which can lead to biased parameter estimates and incorrect statistical inferences, which is observed in this case. We also noticed that the lag model showed signs of multicollinearity, as evidenced by large coefficients compared to the OLS or

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Table 4. Examples of landscapes that were denoted as safe (high safety scores) and unsafe (low safety scores) for each category of urban design style

Urban design style	Safe	Unsafe
A—Inner city		
B—Large scale		
C—Functionalism		
D—Subway city		
E—Single family housing		

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Table 4. Continued

Urban design style	Safe	Unsafe
F—Other/Mix		

spatial error models, with some coefficients being nonsignificant. This suggests inflated standard errors. To address potential multicollinearity, we excluded certain variables after conducting a bivariate correlation analysis between the independent variables. However, this approach did not fully resolve the issue. Using instrumental variables (IV) for the spatial lag model could introduce further multicollinearity, particularly through the WX instruments, which are correlated with X by construction and become more problematic with higher lag terms.

Note that the spatial lag model performs better than the original OLS (R^2 increases from 26% to 46% and AIC values drop from −557 to −654), most likely because it takes care of a large share of the spatial autocorrelation on the residuals. The predictors that are significant in

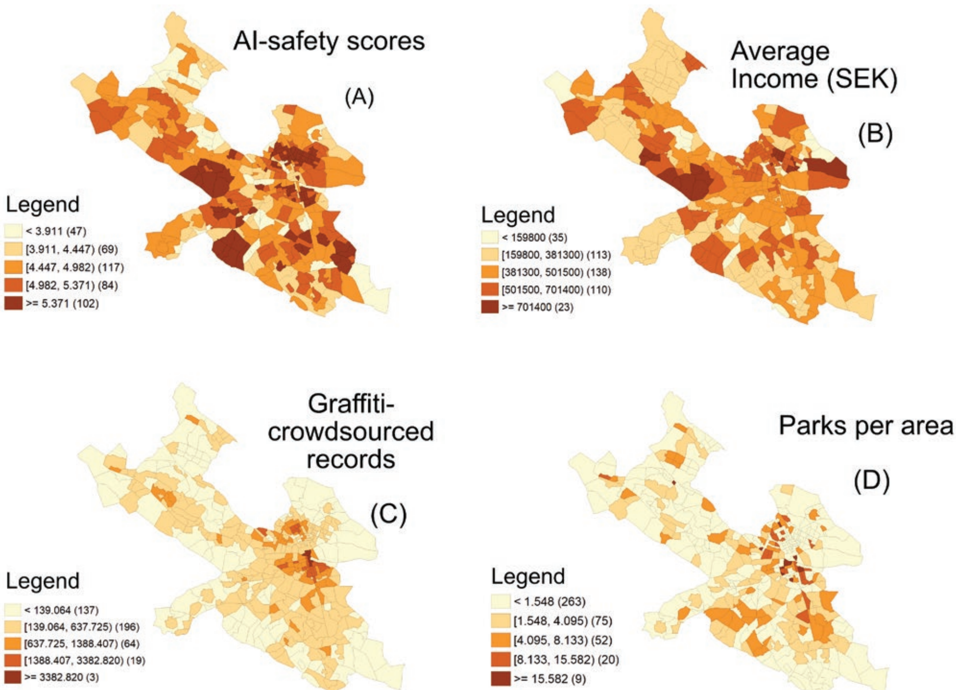

Fig. 3 Distributions of AI-safety safety perception scores (A), Average Income in SEK (B), Density of graffiti crowdsourced records (C) and parks per area (D) over the 419 base areas in Stockholm. Source: Authors.

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Table 5. Modelling results of OLS, lag and error models

Variable	OLS model		LAG model		Error Model	
	Coeff.	**Sig.**	**Coeff.**	**Sig.**	**Coeff.**	**Sig.**
Constant	1.4663	0.0000	0.5565	0.0000	1.5136	0.0000
Planning area B	0.0063	0.8379	0.0401	0.1240	0.0512	0.1442
Planning area C	0.3021	0.1807	0.0241	0.2028	0.0024	0.9159
Planning area D	**0.0600**	**0.0143**	**0.0522**	**0.0011**	0.0364	0.1821
Planning area E	**0.0780**	**0.0008**	**0.0556**	**0.0042**	**0.0474**	**0.0546**
Planning area F	**−0.0510**	**0.0005**	**−0.0420**	**0.0329**	**−0.0683**	**0.0053**
Bars & restaurants	**0.0026**	**0.0291**	**0.0003**	**0.0007**	**0.0003**	**0.0016**
Parks	**1.2280**	**0.0035**	**0.0035**	**0.0160**	**0.0042**	**0.0038**
Daytime visitors	−0.0243	0.7500	−2.2276	0.9735	−0.0002	0.9760
Periphery	**−0.0967**	**0.0189**	−2.563	0.1870	−0.0971	0.1699
Average income	**0.2604**	**0.0002**	**2.0999**	**0.0017**	**0.1636**	**0.0015**
Graffiti/Physical damage	9.4804	0.4422	8.6460	0.4057	1.8747	1.5034
Total crime rate	**−0.0003**	**0.1942**	**−0.0003**	**0.0845**	**−0.0003**	**0.0827**
W_AI safety score	-	-	**0.5923**	**0.0000**	-	-
Lambda	-	-	-	-	**0.6466**	**0.0000**
R-square	**0.2691**		**0.4652**		**0.4714**	
Autocorrelation—Moran's I	10.9088	0.000	-	-	-	-
Akaike info criterion—AIC	−557.335		−655.096		−654.590	
Multicollinearity condition number	11.1750		-		-	
Heteroskedasticity test	15.2397	0.2285	18.6057	0.0985	-	
Normality—Jarque-Bera	77.2431	0.0000	-	-	-	-

N = 419 areas. Y = Natural log of AI-safety perception scores.

the lag model are also significant for the two other models except for the planning area D and periphery. The spatial lag model performs slightly better than the error model, as seen in the AIC values. These two models are similar in statistical terms; we will therefore concentrate on discussing the results of both the spatial error and lag models.

The results show that three urban design categories significantly explained the variation of the log of AI-safety perception scores. As shown in the descriptive section, most of the high AI-safety perceptions scores coincide with those in areas classified as typical D—Subway city and E—Single-family housing. However, safety scores are inversely associated with planning area F, where no distinct planning style dominates, a large proportion of roads and highways, with large interstitial areas with industry, airport, harbour, fun parks and residential areas with mixed land use. Significant control covariates indicate areas associated with AI-safety perceptions of high/low safety scores. For instance, the log of AI-safety perception scores is associated with areas with high income, lively entertainment areas with bars, restaurants and parks, mostly areas that are located in inner city areas, which compose the urban design of planning area A. Regions with a high density of bars and commercial facilities are often perceived as safe, reflecting vibrant inner-city areas with a prosperous economy, as seen in that streetscape of Stockholm, where downtown areas are generally considered safer than suburban ones (Kang *et al.* 2023).

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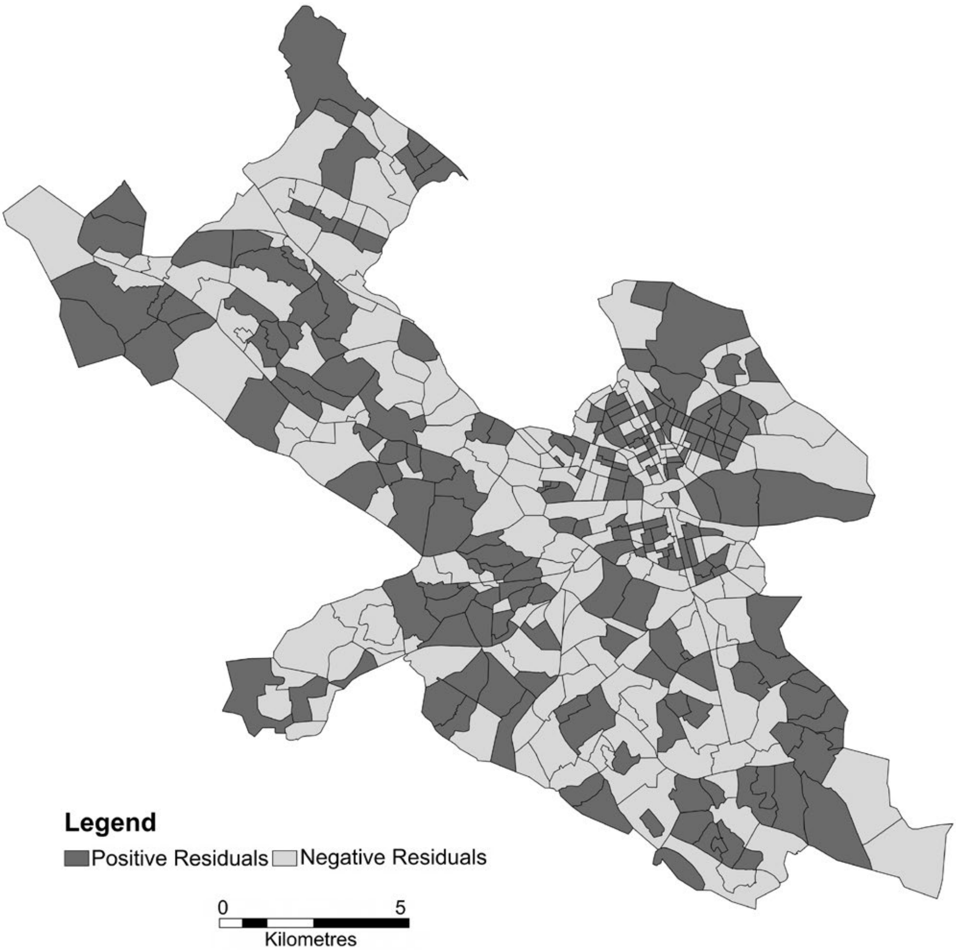

Fig. 4 Residuals of the spatial lag model for AI-safety perception scores.

Figure 4 illustrates the model's positive and negative residuals. Positive residuals on the map indicate locations where the model underestimates the AI-safety perception observed values, while negative residuals indicate locations where the model overestimates those observed values. The map can help identify future potential covariates that might be missing in the current model.

DISCUSSION OF RESULTS

In Stockholm, buildings, vegetation and streets vary significantly across different areas. The inner city stands out for its densely built environment, while peripheral areas offer a balanced mix of buildings, sky and vegetation, highlighting the diverse urban fabric of Stockholm. Images from Area A, a densely built inner city zone, feature a third of buildings, over three times higher than in single-family housing zones (Area E), with limited open spaces and greenery but concentrated in parks. In contrast, peripheral areas (B, C, D) and single-family zones (E) exhibit more greenery, with a fourth of street view images displaying vegetation compared to just a tenth in Area A. Area F, characterized by a noticeable road network (a fourth of images), contrasts with other areas due to its vehicular focus.

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The results from the modelling indicate that high AI-safety perception scores are predominantly found in areas classified as typical D—Subway city and E—Single-family housing. These findings suggest that pictures of these parts of the city constructed based on well-defined planning paradigms positively affect residents' perceptions of AI safety. In particular, the subway city's public transportation network and the single-family housing area's residential permeably connected with vegetation are the planning areas that are visually more appealing and scored highly by the population. Conversely, safety scores exhibit an inverse relationship in planning area F, characterized by its lack of a dominant planning style and significant land use mixture. The presence of roads, highways and large interstitial areas with mixed-use facilities such as industry, airports, harbours and residential zones detract from AI-safety perceptions. Further insights are obtained by the significant control covariates, particularly the association between AI-safety perception scores and high-income, lively entertainment areas. These areas, often located in inner-city zones corresponding to planning area A, include bars, restaurants and parks. These regions' vibrant social life and economic prosperity likely foster visual cues of a safe place, compensating for lacking qualities, such as access to green areas.

This finding underscores the challenges of maintaining areas with mixed land uses and diverse infrastructural elements, such as streets and roads. Our recommendation for urban planners and safety experts is that this methodology helps identify areas that need interventions. However, it is important to understand the area's layout, especially how the local street network works (Marshall & Garrick 2010; Hillier & Sahbaz 2012), green areas distribution and daily pedestrian activities in each area. In Stockholm, some areas with the lowest safety scores are close to highways, major roads and streets, meaning traffic safety was most likely in people's minds when they visually selected those images as unsafe. Identifying areas with high foot traffic near busy roads can guide the placement of barriers or fencing to protect pedestrians (World Health Organization 2023). Incorporating community feedback on the local design of these areas around the roads and streets can further refine these interventions, ensuring that they address the unique safety concerns and behaviours of the local population.

Examining such realistic depictions of streetscapes can advance our understanding of physical urban spaces. Additionally, advancements in Artificial Intelligence (AI), represented by the latest advancement in deep learning, have opened new venues for analysing such large-scale image datasets. By utilizing image segmentation, we can identify specific objects within the built environment, which can help urban planners assess and make changes in the built environment. Moreover, this approach also facilitates the exploration of human-environment interactions by examining the associations between human subjective perceptions in response to physical urban land use. In the future, we advocate for more integrations of such large-scale big data and methods in urban daily planning practices.

We have exemplified the potential of using street-view images and advanced deep-learning methods to support planning practices and urban decision-making. Street view images offer numerous opportunities in urban studies, as they could serve as a valuable resource to comprehensively decipher the built environment from a human eye-level perspective. Important to note that while creating a safe urban environment is a desirable planning outcome, the perceptions of the image of the urban environment—alone—cannot fully guarantee its quality (Gardiner 1978; Loewen *et al.* 1993; Cozens 2007; Hillier & Sahbaz 2012; Poyner & Clarke 2013; Brantingham & Brantingham 2017; Hipp *et al.* 2022a). A reason for this is that people's safety perceptions depend on the environment's functionality, the kinds of activities they generate and the people they attract, depending on the time of the day (Shaw & McKay 1942; Felson & Cohen 1980; Sandercock 2000; Pain 2001; Sampson & Groves 2017). For example, if the image of a park is combined with indications of drug use, people observing it will most likely describe it as unsafe. Another reason is that the quality of an environment depends not only on its appearance (as observed in the image)

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but also on how well the place is maintained (Kelling & Wilson 1982; Skogan 1992; Eck 2019). If the image of a newly constructed neighbourhood with well-designed public spaces and green areas shows signs of poor maintenance, such as litter, broken amenities, non-functional streetlights and poor landscaping maintenance, people may assess the area poorly (Iqbal & Ceccato 2016). Additionally, future work could examine how local social dynamics, media exposure, or demographic factors contribute to these perceptions and whether any other underlying variables influence the perceived-objective safety relationship.

Limitations

We also acknowledge several limitations when leveraging image segmentation to identify objects in built environments. It should be noted that we solely computed the percentages of objects in street view images to quantify their presence in built environments. However, the proportions of objects might be influenced by the viewpoints of the camera, potentially distorting the representation of objects (also suggested by Hodgen and Hipp (2024). Future studies might consider additional metrics, such as the absolute number of objects, to provide a more comprehensive assessment of the objects in the built environment. A step towards such a direction is considering how computer vision, together with cognitive psychology, can support research in getting 'the gist' of neighbourhood environmental design and explaining crime (see, for instance, Tucker *et al.* (2024)). Moreover, street view images are often taken during daylight hours and research shows that a park that feels safe and vibrant during the day might feel intimidating at night if it is poorly lit. Thus, data-permitting research should explore day-night variations of street-view images to understand better the temporal dynamics of urban environments and how they affect public perceptions of safety and usability. In the modelling, we recognize possible presence of multicollinearity in the Lag model as discussed in the results. Future studies should deal with any problems by manually code the WX variables and run a standard 2SLS model with Wy as the endogenous variable and the selected instruments.

While the six urban planning regions are distinct in character, analysing them at base area level could lead to a more generalized indicator of a neighbourhoods' urban planning style, missing certain nuances. This may be part of the reason for the relatively small (yet significant) differences between planning areas in terms of the perceived safety score. While future studies could investigate the use of smaller units of analysis, in the current study this was not feasible while controlling for neighbourhood-level factors.

Finally, how an environment is perceived depends on the eye of the beholder, namely the profile of the city users. This concept is grounded in the idea that different people experience urban spaces uniquely based on various personal, social and cultural factors (Loukaitou-Sideris 2005; Chowdhury *et al.* 2024). For instance, women more often experience sexual harassment in public environments (such as parks or on the way to public transportation) than men do, which may lead women to perceive images of isolated, secluded green areas as unsafe. Although we did not explore the relationship between city users and safety in this article, we recommend that this dimension be further explored in future studies. A commuter observing a park might appreciate its open layout and accessibility, while a parent with young children might find the park lacking in safety features and amenities and assess the area poorly.

CONCLUSIONS

This article states the following question: What makes an area safe? Using GIS and regression models to integrate AI-generated safety scores from street views, image segmentation techniques and conventional and crowdsourced data, the study shows that after accounting for differences in income, crime and other area characteristics, areas with higher safety scores feature a

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mix of buildings, vegetation and open sky, ranging from peripheral detached single-family housing to inner city high-density urban areas. The article also confirms the hypothesis that areas with lower safety scores primarily have a high percentage of roads located in industrial and/or mixed residential areas. At least in the case of Stockholm, interventions should be prioritized in interstitial mixed residential areas where roads and highways are prevalent. These findings can be important for researchers and planners to target these areas with good contextual knowledge to tailor the necessary changes. These findings can be relevant to other professionals in local and national governments worldwide who are attempting to integrate safety and long-term sustainable principles in new residential areas or maintain the existing ones. For future research, investigating residents' direct experiences and attitudes towards AI safety measures in diverse urban contexts would provide deeper insights into the role of buildings, vegetation and streets, guiding more tailored and effective urban planning strategies useful in other contexts.

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APPENDIX A1. DESCRIPTION OF THE DATASET

Type of data		Description	Year	Source	Variables in the model
1. Street view images	Approximately one million street-view images were downloaded from Google	Eye-level panoramas of urban settings. Each panoramic image contains a 'panoid' as its unique identifier and consists of four street view images to represent the different views of a location	2010–2019	Google	AI safety perception scores
2. Citizens panel survey	23712 based on street view images	Answers containing information about gender, whether they live alone or time of living in the area (medborgarpanel)	2021	NOVUS	Code for images: Safe and/or unsafe
3. Crime statistics	Total crime	Total violence, property crimes (including residential burglary, thefts, robberies and pickpocketing), drug related crimes and vandalism	2019–2020	Police authority headquarters	Total crime rates per 1000 inhabitants per basområden open space area (sq.km)

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Type of data		Description	Year	Source	Variables in the model
4. Land use data	Bars & restaurants	Location (x,y) of bars, nightclubs and restaurants	2020	Open geodata/ Stockholm municipality/ own calculation	Bars & restaurants—Proportion of bars and restaurants per basområden area
	Parks	Location (x,y) of parks			Parks—Proportion of parks per basområden area
	Periphery	Distance to city centre			Periphery—Distance to city centre (km)
	Planning areas	Boundaries of the six urban design styles			Dummy variables per basområden—Planning areas A, B, C, D, E and F
	Area	Area of basområde			Area (sq. km)
5. Crowdsourced data	Graffiti and physical damage 21,139 incidents	Location (x,y) of observed graffiti incidents	2019–2021	Stockholm municipality	Reported graffiti—recorded by population using the App TyckaTill or webpage
6. Mobility data	Daytime visitors	The cell phone data from the cellular company Telia was generated based on millions of anonymous cell phone users' activities (weekdays and weekends).	November 2019	Telia	Daytime visitors—The number of visitors aggregated by basområde.
7. Demographic, socio & economic data	Resident population	Count of population born abroad per neighbourhood unit	2020	SCB	Population was used as a basis for calculation of rates
	Income	The average income per neighbourhood unit			Proportion of unemployed population by basområde per workforce
	Unemployment	Count of unemployed population per basområde			Proportion of unemployed population by basområde per workforce

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APPENDIX A2. ANOVA ANALYSES—MEAN PROPORTION OF URBAN COMPONENTS IDENTIFIED FROM THE IMAGE SEGMENTATION BY PLANNING AREAS, WITH SIGNIFICANTLY DIFFERENT AREAS NOTED

Planning area	Building		Sky		Tree		Road		Grass		Sidewalk		Car	
	Mean (Range)	Sig. diff. areas	Mean (Range)	Sig. diff. areas	Mean (Range)	Sig. Diff. areas	Mean (Range)	Sig. Diff.	Mean (Range)	Sig. Diff. areas	Mean (Range)	Sig. Diff. areas	Mean (Range)	Sig. Diff. areas
A—Innercity	0.35 (0–0.93)	B**, C**, D**, E**, F**	0.13 (0–0.49)	B**, C**, D**, E**, F**	0.13 (0–0.71)	B**, C**, D**, E**, F**	0.22 (0–0.41)	C**, E**, F**	0.02 (0–0.41)	B**, C**, D**, E**, F**	0.05 (0–0.38)	B**, C**, D**, E**, F**	0.03 (0–0.27)	B**, C*, D**, E**, F**
B—Large-scale	0.14 (0–0.64)	A**, C**, D**, E**, F**	0.21 (0–0.37)	A**, C**, D**, E**	0.24 (0–0.62)	A**, C**, D**, E**, F**	0.22 (0–0.44)	C**, E**, F**	0.06 (0–0.39)	A**, C**, D**, E**, F**	0.03 (0–0.34)	A**, C**, E*, F**	0.02 (0–0.22)	A**, C**, D**, E**, F**
C—Functionalism	0.21 (0–0.67)	A**, B**, D**, E**, F**	0.15 (0–0.52)	A**, B**, D**, E**, F**	0.23 (0–0.7)	A**, B**, D**, E**, F**	0.21 (0–0.39)	A**, B**, D**, E**, F**	0.03 (0–0.44)	A**, B**, D**, E**, F**	0.04 (0–0.33)	A**, B**, D**, E**, F**	0.03 (0–0.24)	A*, B**, D**, E**, F**
D—Subway city	0.17 (0–0.73)	A**, B**, C**, E**	0.18 (0–0.48)	B**, C**, D**, E**	0.25 (0–0.68)	A**, B**, C**, E**, F**	0.22 (0–0.38)	C**, E**, F**	0.04 (0–0.39)	A**, B**, C**, E**, F*	0.03 (0–0.34)	A**, C**; E**, F**	0.02 (0–0.23)	A**, B**, C**, E**, F*
E—Single family housing	0.11 (0–0.59)	A**, B**, C**, D**, F**	0.22 (0–0.38)	A**, B**, C**, D**, F*	0.28 (0–0.82)	A**, B**, C**, D**, F**	0.18 (0–0.4)	A**, B**, C**, D**, F**	0.05 (0–0.37)	A**, B**, C**, D**, F**	0.03 (0–0.32)	A**, B*, C**, D**, F**	0.01 (0–0.22)	A**, B*, C**, D**, F**
F—Other/Mix	0.17 (0–0.9)	A**. B**, D**, E**	0.22 (0–0.56)	A**,C**, D**, E*,	0.2 (0–0.76)	A**. B**, C**, D**, E**	0.23 (0–0.41)	A**. B**, C**, D**, E**	0.04 (0–0.43)	A**. B**, C**, D*, E**	0.03 (0–0.35)	A**. B**, C**, D*, E**	0.02 (0–0.27)	A**. B**, C**, D*, E**
Overall city	0.22 (0–0.93)	-	0.18 (0–0.56)		0.21 (0–0.82)	-	0.21 (0–0.44)	-	0.03 (0–0.44)	-	0.04 (0–0.38)	-	0.02 (0–0.27)	-

* Significance level at 0.05 level, ** Significance at 0.01 level.

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