Analysis of Perceived Safety, Urban Landscape Sense Perception

Subjects: Urban Studies

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Numerous studies in the field of urban planning show that the perception of qualitative traits such as safety is influenced by the visual components of the urban environment. Studies have proposed methods to predict citizens' subjective perceptions at the urban scale, which also includes the evaluation of the subjective safety perceptions of streets.

Keywords: perceived safety ; women ; urban science ; mobile phone data ; street view

1. Introduction

Since ancient times, safety has been the first requirement of city construction. A city must provide the best opportunities for everyone to develop in conditions that guarantee freedom and security, which is also an important goal of sustainable urban development [1]. Streets, as essential links between private space and public space, assume the functions of daily transportation, life, and cultural expression and are urban spaces with a high frequency of use [2]. Thus, more specifically, street safety is the primary objective of street space design as it directly affects the social activities of pedestrians. For example, a street that feels safe may have more people moving and walking around [3]; street safety may even have effects on mental health [4]. However, street spaces are designed more to serve vehicular traffic and pedestrian needs are often neglected, especially the most basic safety issues [5]. Therefore, it is particularly important to assess the safety perception of every street in the city.

2. Street Safety and Female Safety

Firstly, perceived safety needs to be defined. It is important to emphasise in advance that the definition of perceived safety is very broad, with some definitions being objective, such as crime and crash rates in the region [6][7][8], and some being subjective, such as people's perceived evaluations [9][10][11]. Researchers refer to some well-known streetscape perception studies to emphasise that this research refers to perceived safety in a broader sense related to types of human emotion [9][10][11]. More specifically, the place where perceived safety was evaluated in these studies was the street space.

Street safety means that the behaviours and state of others on the street are free from threats and violations and the safe conduct of all legitimate human behaviour on the street is guaranteed [12][13]. The safety perception of public spaces comes mainly from management services and the physical environment [14]. Traditionally, the most common method to ensure safety is maintenance and law enforcement, which means more police, monitors, tougher laws, etc.; in areas that are well policed and managed, crime and antisocial behaviour that threaten public safety are naturally rare. However, in today's increasingly complex urban systems, street safety by police and law alone is not enough [15]; in addition, the frequent presence of police systems can also create some unsafe feelings.

In addition, Crime Prevention Through Environment Design (CPTED) is an important component of the approach that this research seeks to explore. CPTED is designed to enhance the safety perception of pedestrians through the design of urban spaces [16][17], and it has been widely used to enhance urban safety in regions such as Europe and the USA [18]. Similarly, the concept of the "street eye" proposed by Jacobs [19] also emphasizes the impact of environmental design on the perception of street safety.

Every day, women globally are subjected to unwanted crimes and harassment while out and about [20], and those experiences may lead women to perceive less safety in public spaces, particularly in isolated and busy public spaces, which in turn may lead to more anxiety [21]. The danger of sexual harassment or physical assault (such as being robbed or mugged) is two to four times higher for women than for men, particularly in the young population, according to a 2004 report by the Department for Transport in the UK [22]. Women are more concerned about the safety of their daily routes than men. For example, "women choose a college in the bottom half of the quality distribution over a college in the top quintile to feel safer while travelling" [23]. In contrast, men give little thought to safety and are less constrained in their choice of colleges [23].

The WSA case points to the fact that women are both victims of space security issues and possibly the best guardians of space safety [24]. Cities such as Vienna, Berlin, and Vancouver have established women's advisory committees in their spatial planning or governance systems, using gender as one of the main perspectives in spatial policy making. These cities further practice urban development strategies that are safe and inclusive for all, so that the needs of all people, including women, are equally respected and taken into account [25][26]. Therefore, it is necessary to take a women's perspective on the safety of the streets.

3. New Data and Technology for Measuring Street Safety Levels

3.1. Street View Images and Deep Learning

Based on publicly available, geographically attributed data from street view images (SVIs) and a deep learning (DL) model, the visual elements in the SVIs can be objectively measured. On one hand, SVI is different from traditional planar datasets. Because the SVI provides a horizontal view of the street environment, close to the perceived sight level of pedestrians, it can be used as an alternative to live evaluation [27][28]; therefore, SVIs are an ideal data source for the human-centred evaluation of street spaces. On the other hand, SVI data are more easily available and have wider data coverage (e.g., publicly available at the urban scale) than traditional methods such as on-site audits [29][30][31]. This wide coverage can compensate for possible omissions in sample surveys or small-scale representative studies, making it possible to understand large-scale urban scenarios. In addition, with the development of Computer Vision (CV), the automatic extraction of SVI features has become possible, including measuring the percentage of greenery within the line of sight [32] and measuring the proportion of visual elements such as pedestrians, vehicles, traffic signs, the sky, and buildings [33][34][35][36].

3.2. Subjective Perception and Machine Learning

However, objectively quantified proportions of visual elements are not representative of pedestrians' overall perception of the street environment, and subjective frames perform better for perceptual qualities that are unfamiliar to people [37]. Gender differences in perceived safety have been demonstrated in small-scene studies in fields such as environmental psychology using image data. For example, Jiang et al. recruited volunteers to participate in a photo questionnaire survey [38]. The results of the study showed that men's perceived safety was generally higher than women's in all types of scenes; however, in scenes with complete urban functions and vegetation scenes, perceived safety was higher for both men and women, and the gender difference basically disappeared. Baran et al. used a VR experiment to allow volunteers to experience perceived safety in eight scenarios in a park [39]. The results of the study showed that, in seven scenarios, women had lower mean perceived safety scores than men, and the remaining one was the only environment in which men and women had the same mean perceived safety. These studies confirm the feasibility of using a virtual scenario (off-site) approach to evaluating scenario safety.

Furthermore, integrating crowdsourcing with artificial intelligence (AI) has become feasible for revealing large-scale public perceptions [10][40]. Naik et al. [11] used perceived safety information about urban areas online by MIT Place Pulse datasets, which asked volunteers to rank the perceived safety in SVIs of urban areas. These preferences were transformed into ranked safety scores and used as training data to develop ML models that could predict perceived safety scores for 21 different cities worldwide [11]. Similarly, many studies objectively measure subjective human perception by establishing statistical relationships between visual elements and perceptual scores, for example, openness [41], complexity [42], continuity [43], and psychological stress [44]. These studies provide an actionable framework for this research.

3.3. Simulation of Street Pedestrian Flows

Some studies calculate street accessibility through spatial syntax and further understand street accessibility as potential street pedestrian flow [45][46]. Spatial syntax studies the interaction between spatial networks and social activities and states that their interaction is based on the fact that humans will choose the most accessible paths in a spatial network [47]. This quantitative approach allows measuring the accessibility of streets (defined as the probability of a street space being traversed). The spatial syntax allows the simulation of urban street patterns related to the distribution of residents, identifying the most active urban street spaces and comparing them with residents' perceptions of street quality to provide data for future improvements in overall street quality [45][46].

With the proliferation of mobile phones and mobile Internet, mobile phone data offers the possibility of studying the movement of people on a large scale. Mobile phone data have the characteristics of high coverage and high holding rates, and the large sample size and rich information on individual spatio-temporal behaviour provides a new opportunity for the study of residents' commuting behaviour [48][49][50]. In addition, mobile phone data have user-based attributes that can further distinguish the gender population. Ahas et al. analysed urban residents' spatial and temporal distribution characteristics, including the commuting patterns of different populations, such as men and women [50]. Commuting is a regular social activity that can represent people's travel behaviour. The route from home and work to public transportation is a high-frequency purpose of street travel, and it should be the focus for safety because such a commute reduces mobile source air pollution and climate change. Thus, based on mobile phone data, it is possible to obtain the approximate location of each woman's home and workplace, simulate their likely walking paths during their commutes to work, and finally extrapolate the number of people on each street. Compared with the simulation results of spatial syntax, the simulation results based on mobile phone data can provide new perspectives that can help urban perception studies to further develop a more accurate evaluation.

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