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Is it safe to be attractive? Disentangling the influence of streetscape features on the perceived safety and attractiveness of city streets

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Abstract. City streets that feel safe and attractive motivate active travel behaviour and promote people's well-being. However, determining what makes a street safe and attractive is a challenging task because subjective qualities of the streetscape are difficult to quantify. Existing evidence typically focuses on how different street features influence perceived safety or attractiveness, but little is known about what influences both. To fill this knowledge gap, we developed a crowdsourcing tool and conducted a study with 403 participants, who were asked to virtually navigate city streets in Frankfurt, Germany, through a sequence of street-level images, rate locations based on perceived safety and attractiveness, and explain their ratings. Our results contribute new insights regarding the key similarities and differences between the factors influencing perceived safety and attractiveness. We show that the presence of human activity is strongly related to perceived safety, whereas attractiveness is influenced primarily by aesthetic qualities, as well as the number and type of amenities along a street. Moreover, we demonstrate that the presence of construction sites and underpasses has a disproportionately negative impact on perceived safety and attractiveness, outweighing the influence of any other features. We use the results to make evidence-informed recommendations for designing safer and more attractive streets that encourage active travel modes and promote well-being.

Keywords. Perceived safety, Perceived attractiveness, Streetscape features, Crowdsourcing, Street-level imagery

1 Introduction

Safe and attractive public spaces are essential to a city's vibrancy, as they encourage social interaction and physical activity through walking and cycling (Anderson et al., 2017; Stevenson et al., 2016; Traunmueller et al., 2015; Alfonzo, 2005). Since streets account for the majority of public space in cities, a growing body of literature focuses on identifying street design features that encourage active travel while also improving people's experiences and well-being (Harvey et al., 2015; Whyte, 2012; Adkins et al., 2012; Ewing and Handy, 2009; Mehta, 2009). Greenery, the density and mix of land uses along streets, the morphology and aesthetics of buildings, intersection density, good visibility and street lighting, and the quality and maintenance of sidewalks have been identified as essential characteristics of safe and walkable streets (Basu and Sevtsuk, 2022; Park and Garcia, 2020; Sallis et al., 2020; Ding and Gebel, 2012; Rydin et al., 2012; Ewing and Handy, 2009).

Aside from general streetscape characteristics, it is less clear how much each feature contributes to an overall sense of safety and attractiveness, and whether similar features have an equal influence on these perceived qualities. The subjective nature of perception, as well as the variety of conditions that influence it, makes determining these issues particularly difficult. Place perceptions vary among people of different ages, income levels, ethnic backgrounds, physical abilities, or past experiences (Barnett et al., 2017; Candeia et al., 2017; Cao, 2016; Traunmueller et al., 2015; Jim and Shan, 2013; Won et al., 2016), and getting a representative sample of people to participate in city-scale studies takes time and effort.

Ewing and Handy (2009) developed a conceptual framework that connects streetscape characteristics like sidewalk width and the number of trees to individual perceptions such as safety, comfort, and level of interest. Other empirical studies involving a small number of streets observed how people traversed and used the streets to identify characteristics such as street furniture and local stores that influence how people experience the urban environment and interact with other individuals (Whyte, 2012; Uslu et al., 2010; Mehta, 2009). More recently, a growing body of literature has investigated the relationship between urban characteristics and the perception of safety or attractiveness at the city scale using crowdsourcing and leveraging the availability of street-level imagery (Zhou et al., 2022; Biljecki and Ito, 2021; Bubalo et al., 2019; Candeia et al., 2017; Traunmueller et al., 2015; Salesses et al., 2013; Naik et al., 2014).

Typically, the streetscape features associated with perceived safety and attractiveness of city streets have been studied separately or assumed to be identical for both of these perceived qualities (Mouratidis, 2019; Mehta, 2014; Adkins et al., 2012; Borst et al., 2008). But, do streetscape features that promote safety impact a street's attractiveness, and vice versa? And how much influence does each feature have? What factors should be considered when designing streets to make them feel safer and more attractive? Disentangling the factors influencing how people perceive city streets as attractive and safe may help to inform design interventions that contribute to healthier, more walkable, and sustainable cities.

In this paper, we adopt a crowdsourcing approach to determining how different design features contribute to a street's overall sense of safety and attractiveness. We develop a crowdsourcing tool that allows participants to virtually navigate a set of city streets represented by panoramic street-level images. We use Frankfurt in Germany as a case-study city. Participants in the study are asked to rate the locations they visit along each street on a 5-point Likert scale based on how safe and attractive they appear. To compare the factors influencing participants' perceptions, we ask them to explain their ratings. Then we investigate which features influence the perceived safety and attractiveness of city streets and to what extent, while controlling for age and gender.

Our findings show that streetscape features that influence perceived safety and attractiveness have a high degree of overlap, highlighting key differences. Overall, perceived safety along city streets was found to be strongly related to human activity characteristics such as traffic and crowdedness, whereas attractiveness is primarily influenced by building aesthetics and the amenities and services offered along a street. We show that construction sites along a street or underpasses, more than any other feature, have a significant negative impact on a street's sense of safety and attractiveness. We also discuss the practical value of our tool and empirical findings for urban design.

The remainder of this paper is structured as follows. First, we present our research methodology and describe the data sources, as well as the demographics of the recruited participants. We then report the results of our analysis, followed by a discussion of the empirical findings and the practical value of our approach to urban design. The paper concludes with a summary of the main findings, an outline of the limitations, and suggestions for future lines of research.

2 Method

2.1 Collection of perceptions of safety and attractiveness along city streets

To collect data that capture how people perceive city streets, we use crowdsourcing and street-level imagery. Crowdsourcing is selected as a time- and labour-efficient practice that allows us to recruit participants at scale while controlling for an overall representative sample of participants in terms of demographic characteristics such as age, gender, or country of residence. Street-level images are selected since most streetscape characteristics could be visually observed and are, therefore, depicted in such images (e.g., the number of shops and trees, the width of the street, and the number of cars).

In particular, we developed a crowdsourcing tool in *AngularJS* that integrates three key characteristics. *(1)* City streets are depicted as a sequence of panoramic (360) street-level images. The distance between consecutive locations ranges from 20 to 25 meters (depending on the availability of the images) and, therefore, the images practically cover every part of the selected streets. In this way, we can study how participants' perceptions develop along the street and investigate to what degree the characteristics participants encounter along a street influence how they perceive it. *(2)* Participants have complete control over their experience and can explore the streets at their own pace. They can digitally traverse the streets (by moving from one image to another), turn their view, and zoom in and out. *(3)* The tool asks the participants to traverse a path (consisting of multiple streets) and to rate at least four locations along the path according to two questions: "how safe is this place in your opinion?" and "how attractive is this place in your opinion?". The provided ratings are based on a 5-point Likert scale (1 corresponding to very unsafe/unattractive and 5 to very safe/attractive). For a task to be completed, participants must visit each location on the entire path at least once. Moreover, the tool prompts the participants to explain their ratings further. To make each task time and labour efficient, the participants' input is asked every other time they provide a rating or when their ratings are at the extreme points of the rating scale (i.e., 1/5 or 5/5). This input can be used to capture what are the main characteristics that influence the participants' rating process.

The user interface we used to collect participants' input is shown in the upper part of Fig. 1. On the left side of the screen, participants see a street-level image and can turn their view and zoom in and out. Whenever they want to move to the following location, they can either click within the picture towards the direction they want to move or click on one of the two buttons named "BACKWARD" and "FORWARD" located at the bottom of the screen. Alternatively, they could also select to visit a specific location through the *birdview map*, located on the upper right side of the screen (Fig. 1). To provide a rating for a location,

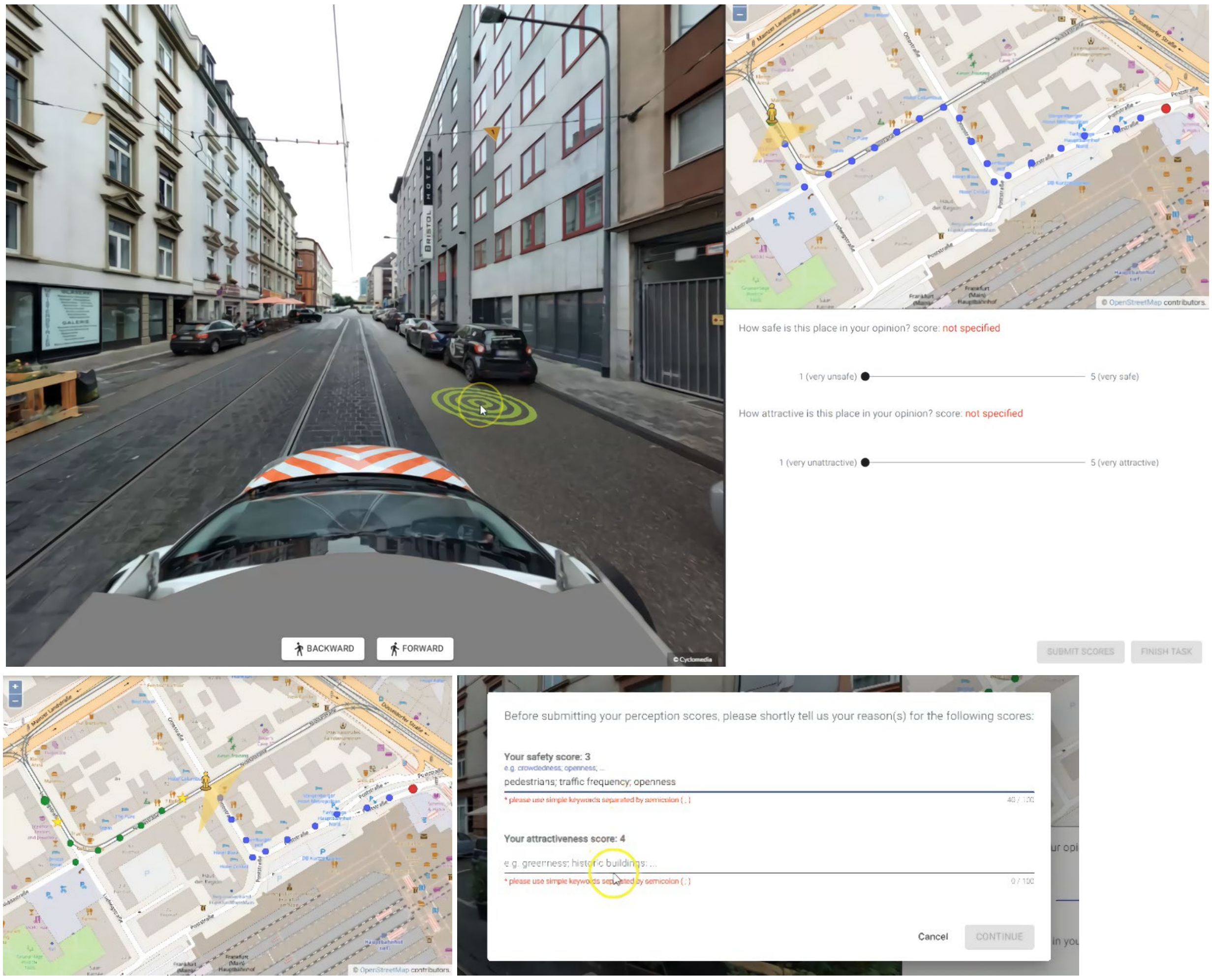

Figure 1. *Top*: The user interface of the crowdsourcing tool developed to capture how safe and attractive city streets are perceived. *Bottom left*: Example of the birdview map after 2 locations have been rated (marked with a star) and 9 locations have been visited (green points). *Bottom right*: Example of the panel in which participants provide their input to explain their ratings.

participants can adjust the sliders accordingly and then click on "SUBMIT SCORES". The locations for which they have already provided a rating will appear as a star on the birdview map (Fig. 1, bottom left). Fig. 1 (bottom right), also depicts the pop-up window that enables participants to provide an explanation of their ratings.

2.2 Identification of characteristics that influence the perceived safety and attractiveness of city streets

To identify the characteristics that influence how safe or attractive city streets are perceived, we first average the participants' ratings per location and then group the locations based on their average rating. In particular, according to our 5-Point Likert scale, each location has been rated by each participant as very unsafe/unattractive ($r = 1$), unsafe/unattractive ($r = 2$), neutral ($r = 3$), safe/attractive ($r = 4$), or very safe/attractive ($r = 5$). We calculate the rounded average of the participants' ratings per each location and group them accordingly as unsafe/unattractive ($r_{avg} \leq 2.5$), neutral ($2.5 < r_{avg} < 3.5$), or safe/attractive ($r_{avg} \geq 3.5$). Then, we process the text that accompanied the participants' ratings by first manually correcting spelling mistakes and merging closely related words (e.g., "road" and "street"). After that, we use the *NLTK* Python package[1] to remove stop-words, perform lemmatization, and look at the most frequently used words. In this way, we identify the characteristics participants most frequently describe when rating the perceived safety and attractiveness of city streets.

To further investigate how participants describe the characteristics that most frequently influence their perceptions, we convert the participants' input into a graph, similar to previous work that follows graph-based approaches to analyse textual data (Beliga et al., 2015; Abascal-Mena et al., 2015). First, for each word in each sentence we determine its *head* using *spaCy*[2], a Python Library that relies on dependency parsing (Honnibal and Johnson, 2015).

[1] https://www.nltk.org/
[2] https://spacy.io/

The head of a word determines the word's syntactic category (Vasiliev, 2020). As an indicative example, in the sentence "*Nice urban street with many cool shops and beautiful buildings*", the heads of "*urban*" and "*cool*" are the words "*street*" and "*shops*", respectively. Next, based on the *word-head* pairs, we construct a weighted graph where each word is represented by a node, and each *word-head* relationship is represented by an edge. The edges' weight reflects how often this pair occurs in our data. Then, we calculate the degree centrality of each node (i.e., how many other words it is connected to) to identify the characteristics that participants tend to describe most often. We examine the five nodes with the highest degree centrality scores, representing the five most discussed characteristics, and look at the 10 most frequent neighbours of those, representing the words most commonly used to describe these characteristics. In this way, we identify the words participants use to describe the characteristics they most frequently focus on when providing their ratings.

Furthermore, to investigate the degree to which streetscape characteristics influence the perception of safety and attractiveness, we look at the rate of change of the ratings along the streets. Particularly, we list all pairs of consecutive locations (distance of 20-25m) and calculate the absolute difference of each pair's ratings (for both perceived safety and attractiveness). A high difference implies that participants encountered within 20-25m characteristics that suddenly changed how they perceived the street. Then, we further examine the pairs of consecutive locations that exhibit the largest differences and based on the participants' input, we identify the characteristics responsible for these differences.

Lastly, we explore the linearity of the relationship between perceived safety and attractiveness and estimate their correlation.

3 Data

3.1 City Streets

We applied our methodology for 27 paths (500-750m each), each path consisting of multiple streets, covering areas in the centre and the outskirts of Frankfurt, Germany. To select the paths, we first randomly collected 2000 street segments in Frankfurt. Then, we selected 50 streets that are diverse in terms of socioeconomic aspects, such as the average size of the household, purchasing power, the number of retail stores, the rate of unemployment, and the dominant age group based on data from WIGeoGIS [3]. We used a location in the middle of each of the 50 streets selected as the origin of our paths. Next, we selected a set of destinations based on the locations of pharmacies (collected from *OpenStreetMap*) since they are described by a relatively uniform regional coverage throughout Frankfurt. Particularly, we calculated the 3 shortest paths (500-750m) from each of our 50 origin locations to each destination. Then, we obtained street-level imagery data from Cyclomedia[4], depicting the selected paths. We removed any overlapping paths and previewed them to ensure that the paths were clearly and consistently depicted through the street-level images. After these manual adaptations, we kept 27 paths represented by 753 distinct locations for our analysis.

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

3.2 Participants

We recruited 403 individuals through the Prolific platform, amongst which 94 do not share any personal information. The remaining 309 participants came from 54 (and currently reside in 12) different counties, 129 were male, and 178 were female (2 preferred not to say), and their ages ranged from 19-71 (with 79% of the participants' ages ranging from 19-40). Each participant was asked to rate three different paths. From these 403 participants, we received 7989 rating pairs of perceived safety and attractiveness and 19114 and 18232 words that were used to explain the ratings of safety and attractiveness, respectively.

3.3 Data and software availability

The data collected from the participants, after being aggregated, and the code used for the analysis are publicly available on GitHub [5]. The code used for developing the crowdsourcing tool can also be found on Github [6]. The street-level imagery obtained by Cyclomedia cannot be publicly shared due to the company's data-sharing regulations. The workflow underlying this paper was successfully reproduced by an independent reviewer during the AGILE reproducibility review. The corresponding report is published at https://doi.org/10.17605/osf.io/aqgxr.

4 Results

This section reports the results of our analysis. We present the characteristics that influence how safe and attractive people perceive city streets, explore the degree of this influence, and investigate the relationship between the ratings of perceived safety and attractiveness.

4.1 Characteristics that influence the perceived safety and attractiveness of city streets

Perception of safety. Starting with perceived safety, 6% of locations (44 locations) are considered on average as "very unsafe" or "unsafe" ($r \leq 2.5$), 50% of locations received ratings between 2.5 and 3.5, and 44% of locations are considered as safe or very safe ($r_{avg} \geq 3.5$, Fig. 2). Fig. 3 depicts the words participants most frequently used to explain their ratings. As observed, common reasons for a location to be considered unsafe revolve around

[4]https://www.cyclomedia.com/en
[5]https://github.com/MiliasV
[6]https://github.com/shahinsharifi/subjectivity

the high number of "*cars*" and "*graffiti*", the "*traffic*", and the existence of "*construction sites/building work*" (e.g., "*There is lots of construction, therefore, people do not visit this area for daily activities*"). Regarding the locations that were rated as safe, participants often mentioned that they "*have limited traffic*", look "*residential*", are "*open*", "*clean*", and "*busy*" and "*have people around*". Fig. 4 depicts as indicative examples the three locations that received the highest and lowest ratings regarding perceived safety. Furthermore, Table 1 presents the percentages of locations considered (very) safe/unsafe when controlling for the gender and age of the participants. We observe that male participants rated 11% of locations as unsafe and 50% of locations as safe, while female participants rated 9% of locations as unsafe and 47% of locations as safe. Thus, male participants appear to provide more extreme ratings than female participants. To control for age, we divide our participants into two age groups, including both male and female participants, with each group having a similar number of participants: 19-35 years old and 35+. The 19-35 group rated 8% of locations as unsafe and 45% of locations as safe, while the 35+ group rated 13% of locations as unsafe and 50% as safe. Therefore, in this case, the older participants seem to provide more extreme ratings.

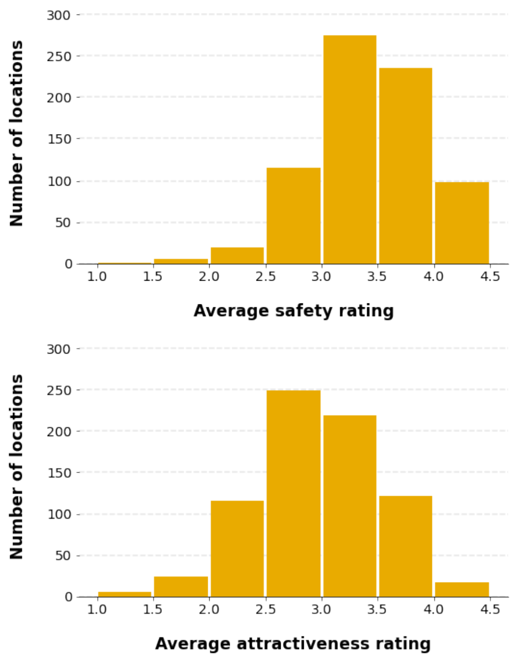

Figure 2. Histograms of the locations' average safety (top) and attractiveness (bottom) ratings.

Perception of attractiveness. Regarding attractiveness, the locations' average ratings present a higher variability than the ones for safety (Fig. 2). 24% of locations are considered "very unattractive" or "unattractive" ($r_{avg} \leq 2.5$) while most locations received a rating between 2.5 and 3.5 (57% of locations). The most frequent words participants used to describe (very) unattractive ($r \leq 2.5$) or (very)

Percentages of locations rated as (un)safe or (un)attractive				
	Safe	**Unsafe**	**Attr.**	**Unattr.**
Males	50%	11%	22%	31%
Females	47%	9%	22%	27%
19-35 y.o.	45%	8%	20%	26%
35+ y.o.	50%	13%	22%	37%

Table 1. Percentages of locations that were considered as (very) safe/attractive ($r_{avg} \geq 3.5$) or (very) unsafe/unattractive ($r_{avg} \leq 2.5$) when controlling for gender and age. The percentages of locations that received ratings higher than 2.5 and lower than 3.5 are not presented in the table.

attractive ($r \geq 3.5$) locations are depicted in Fig. 3. According to the participants, unattractive locations depict buildings that are "*ugly*", "*grey*", and "*dull*". Moreover, unattractive locations have "*graffiti*", "*lack of greenery*", and "*do not have many shops*". Similarly to the results about safety perception, participants mentioned the existence of construction sites as among the main reasons for considering a location unattractive. Oppositely, attractive locations were described as having "*trees*" and "*shops*" and being "*open*" and "*clean*". Buildings in attractive locations are often considered "*nice*", "*aesthetic*", or "*beautiful*" and the architecture of such locations is characterized as "*old*", "*modern*", or "*nice*". Fig. 4, depicts as indicative examples the three locations that received the highest and lowest ratings in terms of average attractiveness (bottom). Moreover, Table 1, includes the percentages of locations that are considered (very) attractive/unattractive when considering different gender and age groups. Overall, we observe that the percentage of locations rated as attractive is similar among the different gender and groups (20-22%). However, male and older participants appear to rate more locations as unattractive than female and younger participants.

Graph analysis of participants' input As explained in the *Methodology* section, we construct four graphs based on the words participants used to describe the locations they perceive as safe, unsafe, attractive, and unattractive. These graphs allow us to identify the characteristics participants most often mention when explaining their ratings and the words they use to describe these characteristics. Our results are well aligned with the results we present in Fig. 3. The 5 most mentioned characteristics are depicted in Fig. 5. As could be observed, "*building*" is among the five most mentioned characteristics in all four graphs, meaning that participants often describe the buildings along the street to explain why they rated a location as attractive, unattractive, safe, or unsafe. Regarding the locations that are considered safe, participants often characterize them as "*residential*". Other characteristics that participants mention to explain their ratings regarding safe/unsafe locations are the "*people*", "*traffic*", and "*car*".

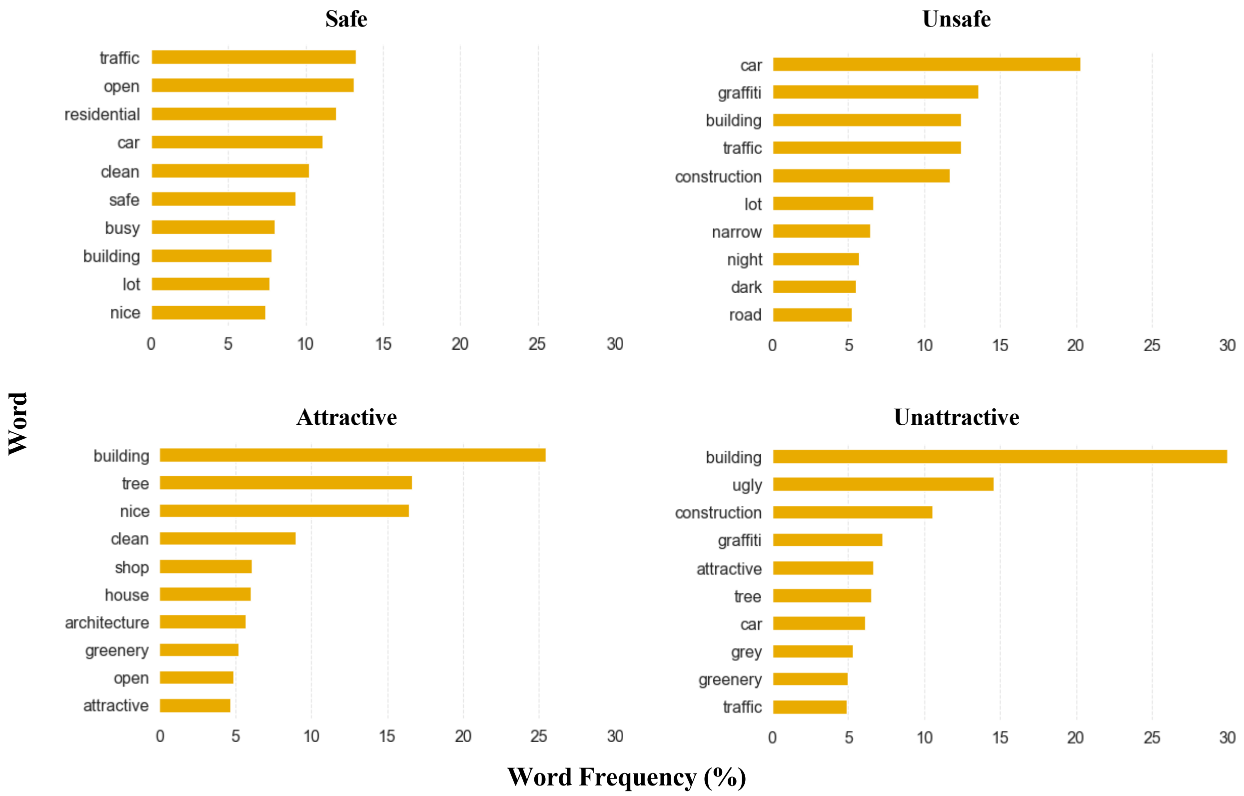

Figure 3. Most frequent words participants used to explain their ratings for the locations they rated as safe, unsafe, attractive, or unattractive.

However, these characteristics are not that frequently mentioned when participants explain their attractiveness ratings. Instead, participants frequently comment on the existence or absence of "*trees*" to explain why they consider a location attractive or unattractive. Therefore, trees appear to play a fundamental role in how attractive a location is perceived. When participants rate a location as attractive they also tend to explain their ratings by describing the "*shops*" and "*architecture*", while for unattractive locations they often mention "*graffiti*" as an important characteristic that influences their perception. Furthermore, the word "*construction*" is often used to describe why a location is rated as unsafe or unattractive.

We further examine the words most commonly used to describe the most mentioned characteristics by looking at the 10-nearest neighbours of these characteristics in our graphs. Table 2 presents an indicative example of the 10 most frequent words participants used to describe buildings in locations that are rated as safe, unsafe, attractive, or unattractive. As could be seen, participants often use different words to describe the buildings along a street depending on whether they rate perceived safety or attractiveness. For instance, to explain how buildings influence their perception of safety participants often mention the function of the buildings by using words such as "*residential*" or "*office*". For the safe locations, we could also see the word "*unattractive*" suggesting that some locations although perceived as safe they are also considered unattractive. For attractiveness, participants focus more on the aesthetics of the building using words such as "*colored*", "*high*", "*pretty*", "*tall*", "*big*", "*ugly*". Notably, in the case of unattractive locations, the word "*attractive*" is present. This, however, occurs because participants often mention that the buildings in this location "*are not attractive*". Similar results are found when looking at the words participants use to describe the other most mentioned characteristics.

Degree of influence To explore the degree to which streetscape characteristics influence perceived safety and attractiveness we look at how the collected ratings change as participants encounter different characteristics along the streets (example in Fig. 6). Regarding perceived safety, the absolute difference between the ratings of any two consecutive locations ($distance \leq 25m$) is less than or equal to 0.5 for 80% of the locations and less than 1 for 98% of the locations. The further apart two locations are located the more the ratings of perceived safety tend to differ (Table 3). For example, for the consecutive locations,

Figure 4. Examples of the three locations that received the highest and lowest average ratings in terms of perceived safety (top) and attractiveness (bottom).

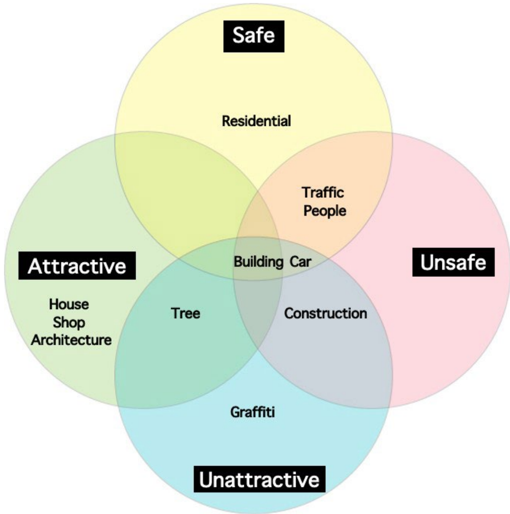

Figure 5. Five most mentioned characteristics based on the words participants used to describe the locations they rated as safe, unsafe, attractive, and unattractive.

Ten most frequent characterisations of "buildings" at locations rated as (un)safe or (un)attractive	
Sa	nice, office, modern, old, street, big, new, residential, car, unattractive
Uns	unattractive, site, nice, big, tall, closed, graffiti, construction, poor, bad
Attr	old, modern, tree, attractive, beautiful, pretty, colored, clean, ugly, historic
Unattr	ugly, high, unattractive, old, grey, big, plain, dull, attractive, tall

Table 2. The 10-nearest-neighbours of the word "building" according to the computed safe, unsafe, attractive, and unattractive graphs.

we observe an average difference of safety ratings equal to 0.25. This difference grows to 0.51 when considering locations within 260-325 meters. Similarly, the maximum difference between the ratings of different locations tends to increase the further apart those locations are from each other. To statistically evaluate this observation, we measured the global spatial autocorrelation of the safety ratings using Moran's I correlation coefficient. As expected, we identified a strong and significant spatial autocorrelation ($I = 0.63$, $z = 18$, $p = 0.001$) when looking at locations within a distance of 25m (i.e., using a 2-nearest neighbours connectivity matrix). This correlation weakens as the distance between the nearest locations we use increases. Thus, our results suggest that participants' perception of safety is spatially clustered. It does not increase or decrease steeply from one location to the next, but rather gradually, as participants move past the different locations.

The largest differences between the safety ratings of two consecutive locations range from 1.6 to 1.9 and are often explained by a single infrequently observed dominant characteristic. For instance, in one situation, the relatively high difference in the ratings was explained by the construction work that occurred when the pictures were taken. The participants described the first location (example A, location I in Fig. 7) as "*openness*", "*nice houses*", and "*good looking*" and the next (example A, location II in Fig. 7) as "*roadworks*", "*looks very dodgy, doesn't feel good*", and "*barriers and building materials in road, iron railings and barriers*". In another example, the first location is under a bridge (example B, location I in Fig. 7), received an average safety rating of 1.4, and participants described it as "*dark*", "*hidden*", "*sketchy*", and "*dangerous*". The next location (example B, location II in Fig.

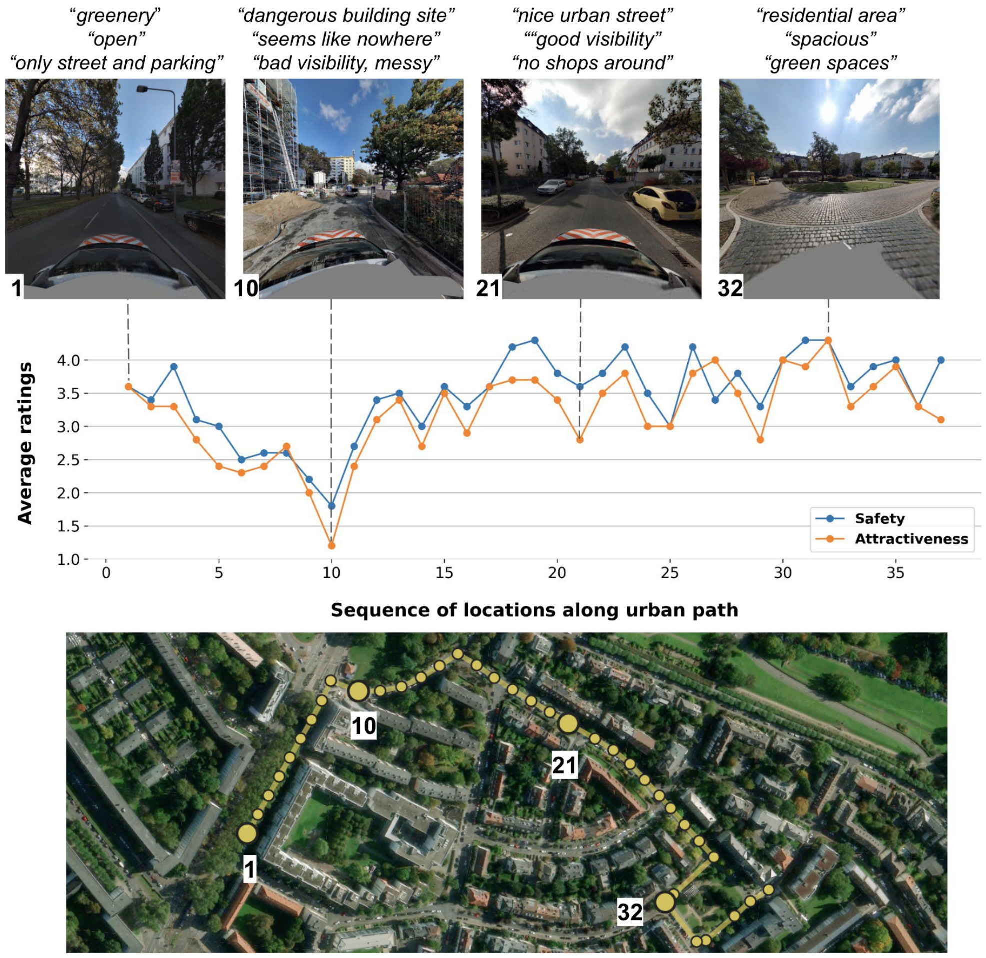

Figure 6. Indicative example of the perceived safety and attractiveness ratings of 37 locations along a path located in the Bornheim/Ostend district of Frankfurt, Germany.

7), located 20 meters away and shortly after the bridge, received a rating of 3.5 and was described as "*close to the public area*", "*well organised*", and "*well lit*". In most cases for which consecutive locations received ratings of a relatively high difference the comments of the participants revolve around a single dominant characteristic that made them suddenly feel unsafe (e.g., construction work, being under the bridge, graffiti, iron bars on windows).

Regarding the difference between the attractiveness ratings of consecutive locations, the results are similar to the ones about safety perception. In particular, this difference is less than 0.5 for 76% of the locations and less than 1 for 95% of the locations. The farther apart two locations are located, the more likely the attractiveness ratings are to differ (Table 3). Once again, to statistically evaluate our observation, we calculated Moran's I spatial autocorrelation coefficient for the attractiveness ratings and received similar results to the ones for the safety ratings: there is a strong and significant spatial autocorrelation ($I = 0.63$, $z = 18$, $p = 0.001$) that weakens as the distance between the locations we consider as neighbours increases. Therefore, as for the safety perception, the attractiveness of streets does not tend to change suddenly but rather gradually along streets. Relatively large differences in the attractiveness ratings were found only in particular situations, similar to the ones described above for safety perception.

Difference between the safety (and attractiveness) ratings of locations that are D-meters apart and located within the same path (Likert scale 1-5)

	Distance							
	20-25m		100-125m		180-225m		260-325m	
	Max. diff.	Avg. diff.	Max. diff.	Avg. diff.	Max. diff.	Avg. diff.	Max. diff.	Avg. diff.
Safety	1.9	0.25	1.8	0.47	2.5	0.47	1.9	0.51
Attr.	2.0	0.28	2.3	0.52	2.5	0.52	2.8	0.57

Table 3. Maximum and average ratings' difference between locations that are located within the same path and are D-meters apart (considering all 27 paths under study).

Relationship between safety and attractiveness perception. Since the normality test we performed on both the average ratings of safety and attractiveness indicated a normal distribution we used the Pearson correlation coefficient to calculate the correlation between the average ratings of safety and attractiveness. We identified a strong

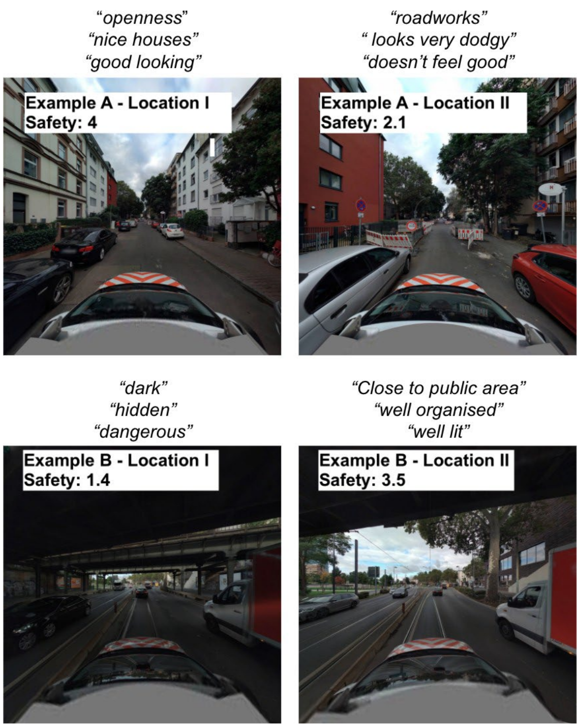

Figure 7. Indicative examples of consecutive locations with average safety rating differences larger or equal than 1.9.

positive and statistically significant correlation between the two ($r = 0.82$, $p < 0.005$) and computed the following linear fit (with $std_{error} = 0.023$, $R^2 = 0.66$):

$$attractiveness = 0.88 * safety - 0.07 \quad (1)$$

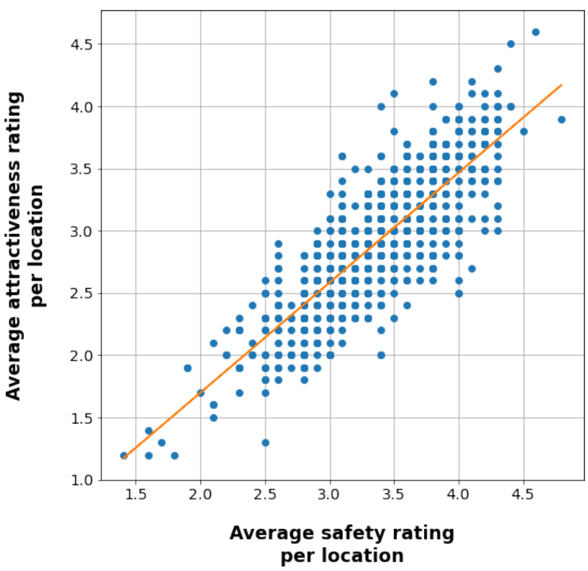

Figure 8. Linear regression between the average ratings of perceived safety and attractiveness of urban locations.

The linear regression model (Fig. 8) suggests that, overall, participants tend to rate urban locations higher in terms of safety than attractiveness. Also, while there are no locations that are considered at the same time unsafe ($rating \leq 2.5$) and attractive ($rating \geq 3.5$), 2% of the locations are perceived as safe and unattractive. According to the participants' input, the locations that are perceived as safe and unattractive seem to be located on quiet, residential streets without shops or other types of facilities. They are often described in terms of safety as "*narrow street*","*slow traffic*", having "*people around*", "*safe*", or "*residential*" and received ratings ranging from 3.5 to 4. In terms of attractiveness, the participants continuously emphasize the lack of shops (e.g., "*no place for shops*"). In certain cases, participants also mentioned "*Not a lot to look at aside from buildings, cars and wheelie bins*" and "*Not very appealing as a place to visit or place to be*".

5 Discussion

Our results highlight key similarities and differences in streetscape features that influence perceived safety and attractiveness. Furthermore, our method shows how crowdsourcing can be used to capture the elements of the built environment that influence how people perceive streets. In this section, we discuss our findings and make recommendations for the design of safer and more attractive streets that increase the probability of engaging in active travel.

Overall, our findings are consistent with previous research. According to our findings, the number of people and parked cars, the volume of traffic, and the presence of graffiti on city streets are among the factors that most frequently influence how safe a location is perceived to be, as suggested by other studies (Ramírez et al., 2021; Ewing et al., 2013). We also discovered that the presence of trees or green spaces influences the attractiveness rating of streets. A number of related studies support this finding, emphasizing the link between the presence of green spaces and attractiveness levels in urban areas (Basu et al., 2022; Quercia et al., 2014; Smardon, 1988). In line with Tobler's first law of geography (Tobler, 1970), crowdsourced safety and attractiveness ratings exhibit a strong and significant spatial autocorrelation, implying that nearby locations have more in common than distant locations. This also suggests that crowdsourcing can be used as an acceptable alternative to field observations, which may be more accurate but are also more expensive and time-consuming. Looking at the relationship between the ratings of perceived safety and attractiveness, we find a statistically significant and strong correlation between the ratings of perceived safety and attractiveness, similar to the one found in previous studies (Candeia et al., 2017; Salesses et al., 2013). Specifically, our calculated linear fit ($coef = 0.88$, $R^2 = 0.66$) aligns well with (Candeia et al., 2017)'s linear fit between perceived safety and pleasantness ($coef = 0.83$, $R^2 = 0.55$).

Our findings also provide new insights not previously found in the literature. We discovered that single, negatively perceived features, such as the presence of construction sites or underpasses, outweigh any other set of features in causing the most abrupt changes in safety ratings. Given that these features are uncommon, they can easily be overlooked by computationally-driven characterizations that rely on common feature patterns. The consistently found negative impact of temporary construction sites on people's perceptions should be taken into account when managing short-term construction projects. Our analysis shows that participants' explanations for safety ratings favour elements of potential human activity over street design features. When evaluating the perceived qualities of streets, participants emphasize traffic, cars, construction sites, and the presence of people more than general aesthetics and design features such as the architecture or the colours of the buildings. Notable exceptions to this include a street's "openness" (most commonly used to describe areas with a high percentage of open public space) and lighting (e.g., dark parts of streets are always considered unsafe). Overall, participants approach the question "How safe is this place in your opinion?" by assessing either the risk of accidents (e.g., the risk of crossing the street due to traffic) or the risk of crime (e.g., it feels safer if there are people around). When asking participants about their perception of safety, it is critical that they distinguish between these two scenarios and respond accordingly. We also discovered differences in the safety ratings from various demographic groups. Female and younger participants, in particular, appear to provide less extreme ratings, rating fewer locations as (very) unsafe or (very) safe than male and older participants, respectively. However, more research is needed to determine whether the differences in perceptions observed between different groups are due to how the city streets are perceived or how different groups use the Likert scale.

Regarding attractiveness, the ratings are more dispersed along the Likert scale than the safety ratings, with a higher frequency of both low (i.e., 1-2.5) and high (3.5-5) average ratings. In other words, the perception of attractiveness tends to be more sensitive to the characteristics along the streets than the perception of safety. Once again, sudden changes are usually caused by single negatively perceived characteristics that outweigh the influence of any other characteristic (e.g., a part of the street located un- der a bridge or the existence of windows that are covered by iron bars). When looking at the different demographic groups in terms of gender and age, we observe that while all groups identified nearly the same percentage of locations as attractive, male and older participants rated more locations as unattractive than female and younger participants, respectively. Thus, once again our findings highlight the variations in how different demographic groups perceive the urban environment. When rating the attractiveness of city streets, participants tend to focus on either the aesthetics (e.g., describing the architecture and how the trees make the street aesthetically appealing) or the opportunities (e.g., shops and parks) that are offered along the street. In some instances, the words participants used to explain the attractiveness ratings could be interpreted both as positive and negative. Notable examples of such words are the "old", which could be positively used as "old-fashioned" or negatively as "not well maintained", and the "crowded", which could imply vibrancy or overcrowdedness. Thus, even though the text participants provided was intended to explain the ratings, the ratings occasionally allowed for a richer understanding of the text. Overall, the combination of ratings and text proved to be necessary for interpreting our results.

The statistically significant and strong correlation between the ratings of perceived safety and attractiveness highlights the high overlap among the characteristics that influence the perception of safety and attractiveness of streets. However, our findings provide additional evidence that this relation is not entirely symmetric. While we observed that all places that are considered attractive are also considered safe, the opposite is not always true (i.e., some places are considered safe but unattractive). Based on our results, this mainly occurs in quiet, strictly residential streets with few amenities or shops.

Our analysis shows that greenery and shops are impor- tant factors in making a street attractive, but we found no significant evidence, contrary to widely held assumptions, that these features also make a street feel safer. This finding should be taken into account by built-environment professionals when planning and designing for improved streetscape qualities. To further support or refute similar findings, there is a need to invest in acquiring fine-grained data that capture the perceived qualities of streets. Our results also indicated variations in how different demographic groups perceive the streets and how individuals interpret the questions they are asked. Thus, when gathering people's opinions, special care should be taken to include a demographically representative sample of participants and to ask clear, concise, and understandable questions.

6 Limitations

We acknowledge several limitations of our work that could be addressed in future research. First, people's perceptions of city streets rely on a range of factors that go beyond the visually observable streetscape features such as the sounds or smells along a street, people's past experiences, or their familiarity with similarly looking streets (Basu and Sevtsuk, 2022; Tribby et al., 2017; Mehta, 2008). Thus, our work could be expanded to capture and combine additional factors. Second, the influence of streetscape features on people's perceptions could differ depending on the time of day, lighting conditions, weather, and season. Follow- ing our approach while including images that depict the streets under different conditions could allow for studying such differences. Third, studies have shown that crowdsourcing spatial information tasks often attract participants who are particularly interested in nature and landscapes (Bubalo et al., 2019). To better capture the opinions of the general public there is a need for developing or combining recruiting strategies towards including a more representative set of participants. Lastly, in our work, we studied streets coming from a single city. In the future, we aim to replicate our study in different cities to further investigate the generalizability of our insights and the influence the city selection has on our results. Despite these limitations, our study provides new insights into people's perceptions of city streets and presents a replicable time and labour-efficient crowdsourcing approach that can be easily enhanced with additional data and applied in other cities.

7 Conclusion

The design and structure of city streets can have a significant impact on the perceived level of safety and attractiveness. These, in turn, can encourage or discourage active travel and access to amenities, having an impact on people's well-being. Using a crowdsourcing approach, this study adds to the body of literature on measuring ur- ban design qualities by presenting empirically derived features that influence the perceived safety and attractiveness of city streets. Our findings suggest that the features that contribute to a street's perceived safety do not always overlap with those that contribute to its attractiveness, and vice versa. The number of people and parked cars, the volume of traffic, and the presence of graffiti all have an impact on the feeling of safety. In turn, the presence of green- ery, as well as the number and type of amenities along a street, are the primary contributors to the attractiveness of a street. We also provide evidence that certain character- istics, such as underpasses and construction sites, have a negative impact on both the perceived safety and attractiveness of city streets, outweighing the influence of any other set of characteristics. Further studies of cities with varying morphological characteristics, sizes, and densities that also represent non-European contexts should be carried out in order to develop more robust and universally applicable guidelines for the design of safer and more attractive streets. Nonetheless, our work demonstrates how crowdsourcing can be useful for built-environment professionals seeking to understand the factors that influence the perceived qualities of the urban environment using a tool like the one developed in this study. It presents an interesting future research direction in the measurement of urban design qualities, which can be incorporated into evidence-informed design standards for safer and more attractive cities that promote health and well-being.

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