Quantifying urban environments: Aesthetic preference through the lens of prospect-refuge theory

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ABSTRACT
Prospect-refuge theory suggests that people prefer environments that offer both prospect, the ability to scan for resources, and refuge, a safe place to hide. Urban planners, architects and researchers alike have had a tendency to use prospect-refuge theory research on natural scenes to inform on the design of urban environments. Despite the large body of prospect-refuge theory research, the degree to which prospect and refuge impact preference in urban environments remain unclear. Here, we aim to first evaluate the relationship between prospect, refuge and preference for urban scene images. Secondly, we aim to evaluate the contributions of visual features and streetscape quality ratings to subjective ratings of prospect and refuge in order to create proxy values of prospect and refuge. Finally, we aim to understand how the proxy values impact preference for urban scenes, and if the proxy values created replicate the relationship between subjective measures of prospect, refuge and preference. First, we used participant ratings of prospect and refuge to predict participants’ preference for 552 images of urban street scenes. Higher ratings of both prospect and refuge predicted greater image preference. We next used principal components analysis to summarize these images’ low- and high-level visual features as well as participant ratings of streetscape qualities, such as walkability and disorder. Visual feature and streetscape quality principal components predicted prospect and refuge ratings in this first image set, providing “proxy measures” for prospect and refuge. In an independent set of 1119 images from Talen et al. (2022) for which prospect and refuge ratings were not available, we asked whether these proxies for prospect and refuge predicted preference. Findings replicated the effect that more refuge in an image predicts more preference. However, the proxy measure of prospect did not predict preference. In summary, our results show that refuge ratings do relate to preferences in urban environments, which extends prospect-refuge theory to more urban environments. Future work is needed to understand if prospect has different implications in more urban environments.

1. Introduction

The creation and design of optimal urban spaces has long intrigued architects, urban planners, and researchers alike. Crafting such urban environments requires an understanding of what underpins the environmental preference of city-dwellers and why certain features of urban spaces influence individuals to inhabit those spaces. Recognizing what features motivate preference can lead to a more informed and sustainable approach to urban design.

Aesthetic preference is a “like-dislike” affective response that arises when viewing a scene containing elements that increase likelihood of survival (e.g. areas offering safety and essential resources; Kotabe et al.,...
1.2. Visual features on aesthetic preferences

Researchers have long been theorizing the underpinnings of environmental preference. One such theory is prospect-refuge theory, coined by Jay Appleton (1975). Prospect-refuge theory is defined as an evolutionary preference for environments that offer safety (refuge) while also having the ability to survey your surroundings for resources, potential threats, and other organisms (prospect; Egner et al., 2020; Dosen & Ostwald, 2016; Ramanujam, 2006; Appleton, 1975; Appleton, 1984; Appleton, 1996, pp. 66–67). By evolutionary, Appleton (1975) does not necessarily posit a genetic predetermination of preference, but rather a psychological bias cultivated over time based on the adaptive advantages of environments that confer survival - i.e., environments with ideal prospect and refuge. Prospect-refuge theory also accounts for individual experience, as individuals tend to perceive their environment through the lens of what that environment can provide for, or afford, to them (Mumcu & Duuml, 2016; Gibson, 1986; Norman, 2013). Gibson (1986) and Norman (2013) both offer a comprehensive framework to understand human-environment interactions through the concept of affordances (e.g., a tree stump can afford sitting). Through this lens, an environment can afford an individual prospect and refuge. For example, Appleton (1975) suggests that a more preferable environment can afford the opportunity to scan for resources and threats and a safe place to hide, as it caters to a high likelihood of survival (Ramanujam, 2006). Appleton (1975) implies that experience gained in discerning aspects of the environment can afford prospect and refuge can be passed down from generation to generation, hence the theory being coined as evolutionary.

Understanding how individuals discern the adequacy of prospect and refuge in an environment, and how prospect and refuge impact preference can inform on crafting optimal environments for pedestrians. A meta-analysis examining environmental preference through prospect-refuge theory supports the efficacy of prospect on preference over refuge in urban environments, however, the degree to which prospect and refuge impact preference for an environment remains unclear (Dosen & Ostwald, 2016). Surprisingly, studies of prospect-refuge in architecture commonly refer to results pertaining to natural environments over urban environments (Dosen & Ostwald, 2016). In addition to measures of prospect and refuge, prospect-refuge theory has expanded to include measures of visual complexity and mystery (a sense of discovery for information gathering) in order to account for more nuance in human perceptions of environments (Berman et al., 2014; Kardan et al., 2015; Ibarra et al., 2017; Zhang et al., 2018, Rossetti et al., 2018). For example, Zhang et al. (2018) used deep learning based semantic scene segmentation to extract high-level features from images and place them into over 150 categories to observe how these object categories predict ratings of how safe, lively, beautiful, wealthy, depressing, and boring a scene is, using the MIT Place Pulse dataset (http://pulse.media.mit.edu/). Rossetti et al. (2018) created a causal model of how the extracted higher-level features in each category predicts pedestrian ratings of safety, liveliness, beauty, wealth, depression and boredom to create a map of Santiago, Chile that shows these predicted pedestrian ratings for each of its areas.

The assessment of low- and high-level features has been previously examined to underpin aesthetic preference (Kardan et al., 2015; Coburn et al., 2019; Berman et al., 2014; Valtchanov & Ellard, 2015; Camgoz, Yener, & Güvenç, 2002; Ibarra et al., 2017). For example, hues with high levels of saturation and brightness are more preferred when assessing foreground and background color relationships (Camgoz, Yener, & Güvenç, 2002). Quick judgments of aesthetic preference were more related to low-level features associated with naturalness, such as an increase in non-straight lines, lower hues (yellows and greens), and more diversity in levels of saturation (Kardan et al., 2015; Ibarra et al., 2017; Zhang et al., 2018, Rossetti et al., 2018). Additionally, slower, more deliberate judgments of aesthetic preference indicated the presence of higher-level semantic content that lead to preference for a natural image versus an urban one, suggesting that the presence of low-level features and higher-level semantic content in natural images help individuals make aesthetic judgments (Kardan et al., 2015; Ibarra et al., 2017; Kotabe et al., 2016; Schertz et al., 2018, 2020; Akcelik et al., 2022). For example, increases of the color green may indicate an abundance of vegetation and other elements of naturalness in a scene, which people tend to strongly prefer (Zhuang et al., 2021; Berman et al., 2014; Barnes, 2013, pp. 261–287; Berto, 2005; Kaplan, 1995). Higher-level features are suggested to mediate the impact of low-level visual features on preference and perceived naturalness in a combination of natural and urban images (Berman et al., 2014; Ibarra et al., 2017; Korab et al., 2016; Oliva & Torralba, 2006; Schertz et al., 2020), essentially positing that low-level features make up higher-level features. For example, brightness, a low-level feature, has a more positive impact on preference when in the presence of vegetation, a higher-level feature (Akcelik et al., 2022; Ibarra et al., 2017). Brightness may enhance perception of vegetation, allowing an individual to assess both the availability of resources (prospect), and safety (refuge) in a natural environment, which may impact subsequent preference (Akcelik et al., 2022; Appleton 1975, 1983; Zajonc, 1980). Urban spaces promoting safety, comfort, and privacy can lead to a higher environmental preference (Appleton, 1996, pp. 66–67; Cushing & Miller, 2019). Previous research has suggested that availability of social cohesion and support, the ability to gather information, and space novelty impact urban environmental preference (Dosen & Ostwald, 2016; Kaplan & Kaplan, 1989; Chavis & Wandersman, 2002).

1.1. Prospect-refuge theory & environmental preference

Generally, visual features are rapidly processed along the ventral visual stream, beginning in primary visual cortex (V1), through the ventral surface (areas V2 and V4) and eventually projects into the inferior temporal cortex of the brain (Hebart & Hesselmann, 2012; Grill-Spector & Weiner, 2014; Ungerleider & Mishkin, 1982; Mishkin & Ungerleider, 1982). Visual features are rapidly processed along the ventral visual stream, whereas high-level features, defined as objects that carry semantic information in a scene (e.g. sidewalks, traffic lights, or cars; Zhang et al., 2018; Hunter & Askarnejad, 2015; Schertz et al., 2020; Ibarra et al., 2017), are processed more anteriorly in the visual ventral stream (e.g., inferior temporal cortex, anteromedial temporal cortex, parahippocampal place area; Clarke et al., 2013; DiCarlo & Cox, 2007; Creem & Proftt, 2001; Conway, 2018; Milner, 2017; Tyler et al., 2013). Brightness, a low-level feature, has a more positive impact on preference when in the presence of vegetation, a higher-level feature in each category predicts pedestrian ratings of safety, liveliness, beauty, wealth, depression and boredom to create a map of Santiago, Chile that shows these predicted pedestrian ratings for each of its areas.

1.2. Visual features on aesthetic preferences

Visual features can be defined as a measurable property of a whole image or object within an image (Weinman, 2013), and have been categorized into low- or high-level visual features based on where the observed features are processed in the brain (Peirce, 2015; DiCarlo & Cox, 2007; Grill-Spector & Weiner, 2014; Ungerleider & Mishkin, 1982; Mishkin & Ungerleider, 1982). A higher-level feature is a complex feature that an individual can come to recognize after processing a large number of lower-level features. Higher-level features have been shown to impact preference, meaning that these features can influence how people judge an environment. For example, brightness, a low-level feature, has a more positive impact on preference when in the presence of vegetation, a higher-level feature (Akcelik et al., 2022; Ibarra et al., 2017). Brightness may enhance perception of vegetation, allowing an individual to assess both the availability of resources (prospect), and safety (refuge) in a natural environment, which may impact subsequent preference (Akcelik et al., 2022; Appleton 1975).
Urban design researchers have established five objective, empirically valid measures of perceptions of urban environments that measure walkability (Ewing & Handy, 2009; Ewing et al., 2006; Talen et al., 2022). The five urban design qualities that were agreed upon by urban design experts as objectively measurable are as follows: imageability, transparency, enclosure, complexity, and humanscale (Table 1). Talen et al. (2022) includes an additional streetscape quality to examine besides the five urban design qualities and walkability: disorder. The concept of disorder at the street level can be split into two categories: semantic disorder or visual disorder, the former referring to a physical representation of a rule being broken (i.e., a broken window, litter), and the latter being a configuration of low-level features that are perceived as disorderly and influence rule-breaking behavior (Kotabe et al., 2016; Wilson & Kelling, 1982).

1.4. Research aims

Broadly, the purpose of this paper is to understand the extent to which prospect and refuge impact urban environmental preference. Specifically, the aims of this paper are to (1) elucidate the impact of prospect and refuge on preference, (2) to observe which low-and high-level visual features and urban design/streetscape qualities predict ratings of prospect and refuge, and (3) to test whether proxies of prospect and refuge generated from low-and high-level visual features and streetscape quality ratings predict scene preference. Aims (1) and (2) will be investigated in Study 1, and aim (3) will be investigated in Study 2. This work can help researchers and urban planners alike pin-point various quantifiable features of the environment that can promote prospect and refuge, which could inform the creation of highly preferred urban environments.

2. Study 1- understanding ratings of prospect & refuge

2.1. Methods

2.1.1. Materials

2.1.1.1. Sidewalk view images. The image set used was collected by Talen et al. (2022). The image set consists of 552 sidewalk view images obtained from the Google Street View API, covering approximately 138 blocks within Chicago, and were chosen based on selection criteria including but not limited to the availability of a sidewalk view, the presence of at least one commercial use, and absence of anti-pedestrian land uses such as parking lots (Study 1 in Talen et al., 2022).

2.1.1.2. Ratings of preference & urban design/streetscape qualities. Talen et al. (2022) obtained ratings of aesthetic preference and urban design/streetscape qualities from 558 participants total who were non-experts in urban design (Talen et al., 2022). The urban design/-streetscape qualities (Table 1) were measured in separate studies. These measures were previously established by Ewing et al. (2006) to have the potential to influence pedestrian perceptions of and preference for an urban environment at the street level. Ratings in Talen et al. (2022) were obtained by asking participants to choose four images that best represented the quality being tested from 12 possible images. The ratings of urban design/streetscape qualities and preference were calculated as follows (Talen et al., 2022):

Choice Probability Rating (perceptual quality i, image j) = \[ \frac{\text{number of clicks on image } j \text{ for perceptual quality } i}{\text{total number of participants in group}} \]
Talen et al. (2022) conducted split-half correlations to check consistency across participants which suggest that ratings for urban design qualities and preference were indeed consistent across participants (see Talen et al., 2022 for more information).

2.1.1.3. Ratings of prospect & refuge. For this present study, ratings of prospect and refuge were collected from new participants through Cloud Research Connect (https://www.cloudresearch.com/) using a similar survey paradigm to that of Talen et al. (2022). A total of 120 participants rated the 552 Google Street View images, with 60 participants rating images for prospect and another 60 participants rating refuge (see Table 2 for participant details). Two participants were omitted from ratings of prospect, due to their data not recording upon completion of the study. Each participant was presented with all 552 images in the image set, with 12 images shown at a time situated in a 4x3 matrix. Participants were instructed to select four images that were most representative of either prospect or refuge (see Table 2 for the prompts). The survey instructions for prospect and refuge were derived directly from prospect-refuge theory (Appleton, 1975; Dosen & Ostwald, 2016). Final ratings of prospect and refuge were then computed via choice probability (see choice probability formula in section 2.1.1.2 and Talen et al., 2022).

2.1.1.4. Visual feature extraction

2.1.1.4.1. Low-level visual features. The low-level visual features that were extracted from each image were spatial and color features. The color properties of low-level features are calculated using the Hue, Saturation and Value model using the built in functions in the MATLAB image processing toolbox (MATLAB and Image Processing Toolbox Release 2012b; The MathWorks, Inc., Natick, Massachusetts, United States, 2022). These features are hue, standard deviation of hue, saturation, standard deviation of saturation, brightness, and standard deviation of brightness (see Berman et al., 2014 for additional information). The spatial properties of low-level features are entropy, straight edge density and non-straight edge density (see Fig. 1 for a demonstration of low-level feature extraction).

2.1.1.4.2. High-level visual features. A deep-learning scene segmentation algorithm trained on the Cityscapes Dataset (https://www.cityscapes-dataset.com/), Google DeepLabv3 (Chen et al., 2017; see Fig. 2 for a demonstration), was applied to the 552 images in order to extract high-level features from each image. Google DeepLabv3 outperformed other models in the PASCAL 2012 semantic segmentation measure of accuracy and efficiency in visual data categorization (Chen et al., 2017). This deep learning algorithm assigns each pixel of an image to the following high-level feature categories: road, sidewalk, building, wall, fence, pole, traffic light, traffic sign, vegetation, terrain, sky, person, rider, car, motorcycle, bicycle, and unlabeled (features that could not be categorized into the presented object categories). Then, the algorithm creates a percentage of each category present in the image, which is the present study’s measure of high-level features within an image. This approach to scene segmentation enabled precise pixel class labeling and quantification of object categories in images (see Fig. 2).

2.1.2. Analyses

2.1.2.1. Prospect & refuge predict preference. Ratings of prospect and refuge were input in a regression model predicting preference in order to understand how these measures impact ratings of preference. Prospect and refuge ratings were standardized using the base R scale () function (version 3.6.2; R Core Team, 2023). Linear regression was performed using the base R lm () function (version 3.6.2; R Core Team, 2023).

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Table 2
Participant Demographics for the Replication study. This table outlines how many participants took each study, the mean age and standard deviation of age. This table also outlines the instructions presented to the participant when shown the 4x3 image matrix.

<table>
<thead>
<tr>
<th>Study</th>
<th>Total Participants</th>
<th>Mean Age</th>
<th>SD Age</th>
<th>Survey Instruction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prospect</td>
<td>58</td>
<td>35.69</td>
<td>9.67</td>
<td>Select 4 images that could allow you an open view to scan for resources, threats, and other people.</td>
</tr>
<tr>
<td>Refuge</td>
<td>60</td>
<td>39.32</td>
<td>10.64</td>
<td>Select 4 images that could provide you a safe place to hide.</td>
</tr>
</tbody>
</table>

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Fig. 1. Low-level features extracted from a single scene/image. a) the image pre feature extraction; b) extracted brightness/color value; c) extracted color saturation; d) extracted straight edges (purple) and non-straight edges (green); e) extracted hue measures from the original image. From Schertz and Berman (2019), reprinted with permission. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)
2.1.2.2. Principal component analyses for low- & high-level features & streetscape qualities. To account for potential multicollinearity within the streetscape qualities and low- and high-level visual features, principal components analyses (PCA) were performed on these measures. All the streetscape qualities were placed in their own PCA, with low- and high-level features placed in their own separate PCA. The top three PCs that had passed the Kaiser (K1) criterion and accounted for the most variance were retained for each PCA of visual features and urban design/streetscape qualities. Before we conducted each PCA, the data frames for low- and high-level features as well as the streetscape qualities were mean-centered using the base R `scale()` function (version 3.6.2; R Core Team, 2023). The PCA was computed using the function `principal()` from the R package, ‘psych,’ (version 2.3.9; Revelle, 2023), employing varimax rotation to increase the interpretability of the top three PCs for both the visual features and streetscape qualities.

Fig. 2. Google DeepLabv3 Scene Segmentation. A representative image from the 552 images analyzed in this study, depicted before and after processing with the Google DeepLabv3 scene segmentation algorithm. Objects categorized by Google DeepLabv3 are highlighted via color overlays: purple for roads, pink for sidewalks, green for vegetation, and red for cars. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Fig. 3. Top 5 and Bottom 5 Images with the Highest and Lowest Prospect & Refuge Ratings. This figure depicts the images with the highest and lowest ratings of prospect and refuge in Study 1’s imageset (552 Google Streetview Images). A) The top 5 images with the most prospect; B) the bottom 5 images with the least prospect; C) The top 5 images with the most refuge; D) The bottom 5 images with the least refuge.
2.1.2.3. Low- & high-level visual features & streetscape qualities predict prospect & refuge. Bi-directional stepwise regression was employed using the base R `step()` function (version 3.6.2; R Core Team, 2023) to address how visual features and streetscape qualities predict ratings of prospect and refuge. Bi-directional stepwise regression tests each predictor variable in separate regression models and makes a decision to either include or exclude predictor variables to reduce overfitting and to aid in model selection. The visual feature and urban design/streetscape quality PCs were standardized using the base R `scale()` function (version 3.6.2; R Core Team, 2023) before they were input in the stepwise regression. Three total stepwise regressions were performed to identify the predictors for prospect and refuge using visual features and urban design/streetscape quality PCs both separately and in tandem. The model with the lowest AIC value and highest $R^2$ value was chosen to best represent prospect and refuge, respectively.

2.1.2.4. Exploratory analysis of the relationship between prospect, refuge, naturalness & preference. An exploratory analysis was conducted to elucidate the relationship between prospect, refuge, naturalness and preference. To address this, prospect, refuge and the PC associated with the extent of naturalness in an image (visual feature PC1) were placed in a linear regression model, using the base R `lm()` function (version 3.6.2; R Core Team, 2023).

2.2. Study 1 - results

2.2.1. Prospect & refuge predict preference

Ratings of prospect and refuge from the first image set (see Fig. 3 for the images with highest and lowest ratings of prospect and refuge) significantly predicted ratings of preference. This regression model had an $R^2$ of 0.19 and an adjusted $R^2$ of 0.18 ($p < 0.001$) suggesting that prospect and refuge ratings accounted for approximately 18.5% of the variance in preference ratings. Prospect positively and significantly predicted preference, with a beta estimate of 0.083 (95% CI [0.032, 0.134], $p < 0.001$). Preference also significantly and positively predicted refuge, with a beta estimate of 0.017 (95% CI [0.002, 0.032], $p < 0.001$). When comparing the impact of prospect and refuge ratings on preference, refuge in an urban image bears more weight on preference than that of prospect in an urban image.

2.2.2. Principal component analyses for low- & high-level features & streetscape qualities

2.2.2.1. Visual feature principal components analysis. The low- and high-level visual features extracted from our first image set were placed in a PCA and the top three PCs were retained as summary features. Fig. 4A shows the variance explained by each visual feature PC. These PCs accounted for 14.6% (PC1), 12.35% (PC2), 9.08% (PC3), accounting for 36.03% of the variance in all visual features in the sample total (Fig. 4A).

The loadings of each PC were visualized to facilitate interpretation (Fig. 4B). Features with a correlation value of ± 0.3 to the overall PC score were considered as the features that best represent their respective PC (Tavakol & Wetzel, 2020; see Fig. 4B). The features that best represent PC1 are saturation ($r = 0.61$), the contrast in saturation ($sdSat; r = 0.59$), straight edges (StraightED, $r = -0.551$), non-straight edges (NonStraightED; $r = 0.861$), building ($r = -0.711$), pole ($r = -0.36$), vegetation ($r = 0.827$), and terrain ($r = 0.652$). These correlations show that PC1 mostly represents a the extent of an image containing features of naturalness, as low-level features saturation, contrast of saturation and non-curved lines (Kardan et al., 2015), alongside high-level features, vegetation and terrain, that are all strongly and positively associated with PC1 and have all been previously associated with naturalness (Kardan et al., 2015; Berman et al., 2014; Ibarra et al., 2017; Akcelik et al., 2022, Fig. 4A).

The features that best represent PC2 are brightness (Lum; $r = 0.802$), contrast in brightness (sdBright; $r = 0.565$), contrast in hue (sdHue; $r = 0.73$), entropy (degree of randomness; $r = 0.327$), straight edges ($r = -0.38$), road ($r = 0.589$), sidewalk ($r = -0.383$), vegetation ($r = -0.369$), and sky ($r = 0.908$; Fig. 4B). These correlations suggest that PC2 represents a luminous open view, with an abundance of road and sky, with a high contrast in both hue and brightness, all of which are strongly and positively correlated with PC2 (Fig. 6A).

The features that best represent PC3 are saturation ($r = 0.311$), brightness ($r = 0.334$), contrast in saturation ($r = 0.37$), contrast in brightness (sdBright; $r = 0.578$), entropy ($r = 0.651$), straight edges (StraightED; $r = 0.47$), road ($r = 0.4$), pole ($r = 0.477$), traffic lights ($r = 0.311$), traffic signs ($r = 0.351$), and unlabeled elements in the scene ($r = 0.451$; Fig. 4B). These correlations with PC3 suggest that PC3 is representative of an urban street corner (Fig. 6A).

2.2.2.2. Streetscape qualities principal components analysis. We next performed PCA on the streetscape qualities (see Table 1) extracted from the first image set. The top three PCs were retained to act as predictors for our regression model. Fig. 5A shows the variance explained by each streetscape feature PC. These PCs accounted for 37.56% (PC1), 26.79% (PC2), 18.06% (PC3), accounting for 36.03% variance total (Fig. 5A).

Using the same criteria as for the visual feature PCs, the urban design/streetscape qualities that best represent PC1 are walkability ($r = 0.916$), imageability ($r = 0.931$), and complexity ($r = 0.703$; Fig. 5B). These correlations show that PC1 represents an image containing higher user ratings of walkability, imageability and complexity (Fig. 6C).

The streetscape qualities that best represent PC2 are complexity ($r = 0.627$), transparency ($r = 0.895$), and disorder (Disorder; $r = 0.837$; Fig. 5B). These correlations suggest that PC2 represents a more complex, transparent and disorderly image, with all representative streetscape qualities strongly with PC2 (Fig. 6C).

The streetscape qualities that best represent PC3 are Enclosure ($r = 0.766$), and humanscale (Humanscale; $r = 0.867$; Fig. 5B). These correlations suggest that PC3 represents a more enclosed image where the elements in the image are proportionally scaled to the size of a human, with both streetscape qualities strongly with PC3 (Fig. 6C).

2.2.2.3. Visual features & streetscape qualities predict prospect & refuge

2.2.2.3.1. Visual feature PCs and streetscape quality PCs predict prospect. A bidirectional stepwise regression was employed to elucidate the best fit relationship between (1) low- and high-level feature PCs and prospect, (2) streetscape quality PCs and prospect and (3) both low- and high-level feature PCs and streetscape quality PCs and prospect. We used three different feature sets to predict prospect to understand which model best represents prospect ratings. The model with the lowest AIC to reduce overfitting and the highest $R^2$ to reduce underfitting was chosen to best predict prospect ratings. The model containing both visual features and urban design/streetscape qualities was the chosen model. The other two models (visual features predicting prospect, and urban design/streetscape qualities predicting prospect) can be viewed in the supplementary materials section (Supplementary Table S1 and Supplementary Table S2, respectively).

The chosen model for predicting prospect ratings contained both visual feature and streetscape quality PCs, which had a multiple $R^2$ of 0.451; Fig. 4B). These correlations with PC3 suggest that PC3 is representative of an urban street corner (Fig. 6A).

Table 3

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Estimate</th>
<th>Std. Error</th>
<th>t</th>
<th>p</th>
<th>95% CI LL</th>
<th>95% CI UL</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>0.335</td>
<td>0.007</td>
<td>47.49</td>
<td>&lt;0.001</td>
<td>0.321</td>
<td>0.349</td>
</tr>
<tr>
<td>Prospect</td>
<td>0.017</td>
<td>0.002</td>
<td>2.247</td>
<td>0.025</td>
<td>0.002</td>
<td>0.032</td>
</tr>
<tr>
<td>Refuge</td>
<td>0.083</td>
<td>0.007</td>
<td>11.16</td>
<td>&lt;0.001</td>
<td>0.069</td>
<td>0.098</td>
</tr>
</tbody>
</table>
0.45, an adjusted $R^2$ of 0.45 (p-value < 0.001) and an AIC value of $-2158.37$ (Table 4). This stepwise regression included all six PCs predicting prospect ratings. The other models with just the visual feature PCs and just the urban design/streetscape PCs had AIC values of $-2058.19$ and $-1893.59$ respectively and $R^2$ values of 0.43 and 0.11, respectively (Supplementary Tables S1 and S2).

In the selected model, visual feature PC1 (naturalness) negatively predicted prospect, suggesting that more naturalness in an image decreases prospect. Visual feature PC2 (a bright, open view) positively predicted prospect, suggesting that more bright, open views in an image increases prospect. Visual feature PC3 (an urban street corner) negatively predicted prospect (albeit with a smaller beta coefficient), suggesting that an increase in features that make up an urban street corner in an image decreases prospect ratings.

Streetscape quality PC1 (more walkable, more imageable, more complex) positively predicted prospect (Table 4). This suggests that a more walkable, imageable and complex image increases prospect. Streetscape quality PC2 (a more complex, transparent and disorderly image) did not predict prospect ratings (Table 4). Streetscape quality PC3 (more enclosed and proportional to humans) was negatively predictive of prospect, suggesting that a more enclosed and human-scaled image decreases ratings of prospect.

2.2.3.2. Visual feature PCs and streetscape quality PCs predict refuge. We repeated the analyses above using visual and streetscape quality PCs to predict refuge. The model containing both visual features and urban design/streetscape qualities was chosen as the model for predicting refuge. The other two models (visual features predicting refuge, and urban design/streetscape qualities predicting refuge) can be viewed in the supplementary materials section (Supplementary Tables S3 and S4, respectively). The chosen model for refuge contains only the first two visual feature PCs and all three urban design/streetscape quality PCs.

The chosen model for predicting refuge contained both visual features and urban design/streetscape quality PCs, which had a multiple $R^2$ of 0.6134, an adjusted $R^2$ of 0.6099 (p-value < 0.001) and an AIC value of $-2058.19$ (Table 5). The chosen model included the first two visual feature PCs and all three urban design/streetscape quality PCs to predict ratings of refuge. The other models with just the visual feature PCs and just the urban design/streetscape quality PCs had an AIC of $-2453.75$ respectively and an $R^2$ of 0.32 and 0.48, respectively (Supplementary Tables S3 and S4).

Visual features PC1 (naturalness) negatively predicted refuge, which suggests that more naturalness in an image would decrease ratings of refuge in urban environments. Additionally, visual features PC2 (a bright, open view) negatively predicted refuge, suggesting that an increase in bright open views within an image will result in a decrease in
Fig. 6. Images with the top five highest and lowest scoring images (552 Google Street View image set; see Study 1 of Talen et al., 2022) for visual feature (low- and high-level) PC1, PC2 and PC3, and streetscape quality PC1, PC2 and PC3. A) The top 5 images for low- and high-level PC1, PC2 and PC3. B) The bottom 5 images for low- and high-level PC1, PC2 and PC3. C) The top 5 images for streetscape quality PC1, PC2, and PC3. D) The bottom 5 images for streetscape quality PC1, PC2, and PC3.
Urban Design/Streetscape Quality PCs Predicting Refuge Ratings.

"Streetscape quality PC3 (more enclosed and proportional to enclosed and human-scaled image would increase ratings of refuge. A transparent and disorderly image was indicative of an increase in refuge ratings."

Refuge ratings.

Streetscape quality PC1 (more walkable, more imageable, more complex) was positively predictive of refuge, suggesting that a more walkable, imageable and complex image confers ratings of refuge. Streetscape quality PC2 (more complex, more transparent, more disorderly) was positively predictive of refuge, suggesting that a more complex, transparent and disorderly image is indicative of an increase in refuge ratings. Streetscape quality PC3 (more enclosed and proportional to humans) was positively predictive of refuge, suggesting that a more enclosed and human-scaled image would increase ratings of refuge.

2.2.4. Exploratory analysis of the relationship between prospect, refuge and naturalness

The purpose of this exploratory analysis was to see the impact of prospect, refuge and naturalness (visual feature PC1) on preference. Prospect was weakly and negatively correlated with naturalness (r = –0.14; Supplementary Fig. S2) and refuge had a near zero correlation with naturalness (r = –0.06; Supplementary Fig. S2). We conducted a linear regression using prospect, refuge and naturalness as a predictor of preference. Research has shown that naturalness is a significant predictor of scene preference (Coburn et al., 2019; Meidenbauer et al., 2020) and we wanted to examine if prospect and refuge were still reliable predictors of preference when naturalness was also included in the model. Prospect, refuge, and naturalness all positively predicted preference, with a multiple R² of 0.58, an adjusted R² of 0.58 (p-value <0.001) and an AIC value of –2347.91 (Table 6).

2.2.5. Study 1 summary

This study asked whether ratings of prospect and refuge predicted preference, and what visual features and urban design/streetscape qualities predicted ratings of prospect and refuge themselves. We found that both prospect and refuge were positively predictive of preference, however, refuge had a stronger effect on ratings of preference than that of prospect (Table 3). We also found that all visual feature and urban design/streetscape PCs predict prospect, accounting for approximately 45% of the variance in prospect ratings (Table 4). Visual feature PC2 (bright, open views) had the most impact on prospect ratings, where it positively predicted prospect. The second most impactful predictor of prospect was urban design/streetscape quality PC1 (complex, imageable and walkable), which also predicted greater prospect. Additionally, we found that ratings of refuge are made up of the first two visual feature PCs and all urban design/streetscape quality PCs, accounting for approximately 61% of the variance in refuge ratings (Table 5). Both visual feature PCs (PC1 - naturalness; PC2 - bright open views) negatively predicted refuge, while all three urban design/streetscape PCs positively predicted refuge ratings (PC1 - complex, imageable, walkable; PC2 - complex, transparent, disorderly; PC3 - enclosed, humanscale). Of the three urban design/streetscape PCs, PC1 had the most impact on refuge ratings (Table 5). In our exploratory analysis, we added visual feature PC1 (naturalness) to a model of preference that also included prospect, and refuge (Table 6). Prospect, refuge and PC1 accounted for approximately 58% of the variance in preference, with all three predictors positively predicting preference ratings (Table 6). These results indicated that prospect and refuge had effects on preference that were independent of naturalness.

3. Study 2 - proxies for prospect & refuge

3.1. Methods

Our aim for this study was to determine if we could replicate the relationship between prospect, refuge and preference in study 1 by creating proxies of prospect and refuge using quantifiable visual features and urban design/streetscape qualities. For this study, we generated proxies of prospect and refuge in an additional image set used in Talen et al. (2022) that did not contain direct measures of prospect and refuge. Visual features (low- and high-level) were extracted from the study 2 image set using the same extraction methods as study 1. Urban design/streetscape quality PC1 (naturalness) to a model of preference that also included prospect, and refuge. Prospect, refuge and PC1 accounted for approximately 58% of the variance in preference, with all three predictors positively predicting preference ratings (Table 6). These results indicated that prospect and refuge had effects on preference that were independent of naturalness.

### Table 4
Stepwise Regression Summary Table for Low- & High-Level Visual Feature PCs & Urban Design Quality PCs Predicting Prospect Ratings. Multiple R² = 0.45; adjusted R² = 0.45; AIC = –2158.37.

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Estimate</th>
<th>Std. Error</th>
<th>t</th>
<th>p</th>
<th>95% CI LL</th>
<th>95% CI UL</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>0.341</td>
<td>0.006</td>
<td>56.88</td>
<td>&lt;0.001</td>
<td>0.329</td>
<td>0.352</td>
</tr>
<tr>
<td>Visual PC1</td>
<td>-0.058</td>
<td>0.008</td>
<td>-7.38</td>
<td>&lt;0.001</td>
<td>-0.073</td>
<td>-0.043</td>
</tr>
<tr>
<td>Visual PC2</td>
<td>0.123</td>
<td>0.007</td>
<td>18.13</td>
<td>&lt;0.001</td>
<td>0.109</td>
<td>0.136</td>
</tr>
</tbody>
</table>

### Table 5
Stepwise Regression Summary Table for Low- & High-Level Visual Feature PCs & Urban Design/Streetscape Quality PCs Predicting Refuge Ratings. Multiple R² = 0.61; adjusted R² = 0.61; AIC = –2616.

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Estimate</th>
<th>Std. Error</th>
<th>t</th>
<th>p</th>
<th>95% CI LL</th>
<th>95% CI UL</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>0.341</td>
<td>0.004</td>
<td>85.92</td>
<td>&lt;0.001</td>
<td>0.332</td>
<td>0.347</td>
</tr>
<tr>
<td>Visual PC1</td>
<td>-0.018</td>
<td>0.005</td>
<td>-3.51</td>
<td>&lt;0.001</td>
<td>-0.028</td>
<td>-0.008</td>
</tr>
<tr>
<td>Visual PC2</td>
<td>-0.056</td>
<td>0.005</td>
<td>-12.40</td>
<td>&lt;0.001</td>
<td>-0.064</td>
<td>-0.047</td>
</tr>
<tr>
<td>Streetscape PC1</td>
<td>0.072</td>
<td>0.005</td>
<td>15.06</td>
<td>&lt;0.001</td>
<td>0.063</td>
<td>0.081</td>
</tr>
<tr>
<td>Streetscape PC2</td>
<td>0.048</td>
<td>0.005</td>
<td>10.32</td>
<td>&lt;0.001</td>
<td>0.039</td>
<td>0.057</td>
</tr>
<tr>
<td>Streetscape PC3</td>
<td>0.015</td>
<td>0.004</td>
<td>3.402</td>
<td>&lt;0.001</td>
<td>0.006</td>
<td>0.023</td>
</tr>
</tbody>
</table>

### Table 6
Regression Summary Table for Naturalness, Prospect & Refuge Ratings Predicting Preference. Multiple R² = 0.58; adjusted R² = 0.58; AIC = –2347.912.

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Estimate</th>
<th>Std. Error</th>
<th>t</th>
<th>p</th>
<th>95% CI LL</th>
<th>95% CI UL</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>0.334</td>
<td>0.005</td>
<td>66.241</td>
<td>&lt;0.001***</td>
<td>0.325</td>
<td>0.344</td>
</tr>
<tr>
<td>Prospect</td>
<td>0.037</td>
<td>0.005</td>
<td>6.827</td>
<td>&lt;0.001***</td>
<td>0.026</td>
<td>0.048</td>
</tr>
<tr>
<td>Refuge</td>
<td>0.097</td>
<td>0.005</td>
<td>18.023</td>
<td>&lt;0.001***</td>
<td>0.086</td>
<td>0.108</td>
</tr>
<tr>
<td>Visual Feature PC1</td>
<td>0.117</td>
<td>0.005</td>
<td>22.809</td>
<td>&lt;0.001***</td>
<td>0.107</td>
<td>0.127</td>
</tr>
</tbody>
</table>

3.1.1. Materials

3.1.1.1. Sidewalk view images. The second image set was taken by Talen et al. (2022), where 1119 eye-level street images were taken via mobile phone. Further details regarding the selection criteria of these images...
can be found in Study 2 of Talen et al. (2022).

### 3.1.2. Analyses

#### 3.1.2.1. Creating & testing proxies of prospect & refuge

After understanding how visual features and streetscape qualities were related to prospect and refuge ratings, we used the models generated from the stepwise regressions from study 1 to create proxies of prospect and refuge in study 2. We created these proxies for the second image set from Talen et al. (2022; see Study 2), which does not contain ratings of prospect and refuge. To do so we projected the visual feature and streetscape scores of the 1119 images in the second image set into the PC space defined on the first set of images (the original 552 Google Street View images). The transformation was performed by taking the dot product of the factor loadings of each PC and the second image set’s extracted low- and high-level visual features and urban design/street-scape quality ratings.

#### 3.1.2.2. Creating proxies to predict preference

We generated three proxies each for prospect and refuge: one using visual features, one using streetscape ratings, and one using both. These proxies were computed using one of the stepwise regression formulas with the highest R² and lowest AIC, alongside the variables that best predicted prospect and refuge ratings from those regression models. Each proxy for prospect and refuge was then placed into a linear regression model to predict preference.

### 3.2. Study 2 - results

#### 3.2.1. Prospect & refuge proxies predict preference

We next asked whether these proxies for prospect and refuge could predict participant preference in an image set without direct ratings of prospect and refuge. To do so we transformed our second image set’s visual features and streetscape qualities (see Study 2 in Talen et al., 2022) into the PC space defined with image set 1. Transformation was accomplished by computing the dot product of the visual feature and streetscape quality PC loadings from the first image set and their respective visual features and streetscape quality ratings from the second image set. Then, using the intercept and beta estimates from the stepwise regressions, three proxies were created from each of the stepwise regressions conducted to predict prospect and refuge. This section will cover the proxies made from the models that had the highest R² and the lowest AIC value for predicting prospect and refuge from Study 1.

The prospect and refuge proxies made with the chosen stepwise model (lowest AIC, highest R²) for both visual feature and streetscape qualities were placed in a linear regression model that predicted preference, with the model having an R² of 0.30 and an adjusted R² of 0.30 (p-value <0.001; AIC = 4911.31; Table 7), which accounts for approximately 30% of the variance in preference. The prospect proxy did not predict preference (Table 7). The refuge proxy was able to predict preference positively, with increases of the refuge proxy in an image resulting in increased ratings of preference (Table 7).

### 3.3. Study 2 summary

The goal of this study was to generate proxies of prospect and refuge using visual features and urban design/streetscape qualities in an image set that did not contain direct ratings of prospect and refuge. Using the chosen models representing prospect and refuge from study 1, we created proxies of prospect and refuge for study 2 images. We then ran an additional regression model to see if proxies of prospect and refuge predicted preference similarly to that of measured prospect and refuge ratings. We saw that, despite the image sets being taken in different seasons and with different cameras, the study 2 image set’s visual feature and urban design/streetscape quality PCs looked similar to that of the study 1 image set (Fig. 7). Importantly, only the refuge proxy predicted preference in the study 2 image set. While the positive relationship between the refuge proxy and preference replicated that observed in study 1, the relationship between the prospect proxy and preference did not replicate. There are a number of possibilities for this discrepancy. First, the relationship between preference and measured refuge ratings was much stronger than that of the relationship between measured prospect ratings and preference (see study 1), so the relationship between prospect and preference may be weaker and more variable. Both the visual features and urban design/streetscape qualities were fairly predictive of both prospect (R² of 45%; Table 4) and refuge (R² of 61%; Table 5). However, comparatively, the visual features and urban design/streetscape qualities did not account for as much variance in prospect as refuge.

Additionally, we created proxies of prospect and refuge for the first image set (552 Google Street View images from study 1) to compare to the proxies we created for study 2. We observed the same effects of the proxies created for study 1 image set on preference as the study 2 proxies on preference (i.e., positive effect of refuge and no effect for prospect (Supplementary Fig. S1)).

### 4. Discussion

Prospect-refuge theory suggests that individuals prefer environments that confer their survival: prospect, to scan for resources and threats, and refuge, to safely hide away (Appleton, 1975; Dosen & Ostwald, 2016). Analyzing how prospect and refuge impact urban environmental preference is key for informing pedestrian-centered urban design.

Supporting predictions of prospect-refuge theory, in study 1, we found that human prospect and refuge ratings predict preference, such that images with higher prospect and refuge ratings are more preferred. Refuge had a larger effect on preference than prospect. These results run counter to a meta-analysis of environmental preference that suggests efficacy of prospect shaping preference, with more neutral findings for refuge in urban environments (Dosen & Ostwald, 2016). The difference in findings could be attributed to a variety of factors. First, the meta-analysis conducted consisted of only three quantitative studies (Dosen & Ostwald, 2016) and many of the studies had small sample sizes (i.e., most studies only had 20 participants; Dosen & Ostwald, 2016). For direct measures of prospect and refuge in study 1, we collected data from a total of 118 participants (58 for prospect, 60 for refuge; Table 2), and used data from 558 participants from Talen et al. (2022) where we created proxies of prospect and refuge. Another difference comes from how prospect was defined. In prior work from the meta-analysis, prospect was defined as a place associated with openness, unobstructed views, and ability to discern ease of movement (Nasar, 1988; Dosen & Ostwald, 2016; Loewen, Steel, & Suedfeld, 1993; Mumcu & Duuml, 2010). In our study, prospect was defined as an open view to scan for resources, threats and other people (Table 2; Appleton, 1975; Appleton, 1984). These differences in definitions could have led to differences in the relationship between prospect and preference.

When looking at the images associated with the highest prospect.

### Table 7

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Estimate</th>
<th>Std. Error</th>
<th>t</th>
<th>p</th>
<th>95% CI</th>
<th>LL</th>
<th>UL</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>0.18</td>
<td>0.01</td>
<td>14.72</td>
<td>&lt;0.001</td>
<td>0.16</td>
<td>0.21</td>
<td></td>
</tr>
<tr>
<td>Visual Features &amp; Streetscape Proxy</td>
<td>−0.01</td>
<td>0.01</td>
<td>−0.56</td>
<td>0.57</td>
<td>−0.03</td>
<td>0.01</td>
<td></td>
</tr>
<tr>
<td>Visual Features &amp; Streetscape Refuge</td>
<td>0.35</td>
<td>0.02</td>
<td>17.14</td>
<td>&lt;0.001</td>
<td>0.31</td>
<td>0.39</td>
<td></td>
</tr>
</tbody>
</table>
Fig. 7. Images with the top five highest and lowest scoring images (1119 image set; see Study 2 of Talen et al., 2022) for visual feature (low- & high-level) PC1, PC2 and PC3, and streetscape quality PC1, PC2 and PC3. A) The top 5 images for visual feature PC1, PC2 and PC3. B) The bottom 5 images for visual feature PC1, PC2 and PC3. C) The top 5 images for streetscape quality PC1, PC2, and PC3. D) The bottom 5 images for streetscape quality PC1, PC2, and PC3.
ratings (Fig. 3), images are more open and contain a larger field of view, possibly due to the increase of road, sky and distance between objects. Additionally, there are other elements in each image that signal resource availability, such as storefronts, other people, cars and more. Then, when looking at the bottom five images for refuge ratings (Fig. 3), we only see bright open views, and an absence of elements that could signal resource availability. The top five refuge ratings (Fig. 3) depicts the fronts of buildings and nature that could cause an individual to feel enclosed (Cushing & Miller, 2019; Singh, 2016), while also providing a more open field of view. Seeing a degree of prospect in the highest rated images for refuge made sense, as both prospect and refuge ratings were correlated ($r = -0.327; p < 0.001$; Supplementary Fig. S2), providing support for the notion that prospect and refuge are not mutually exclusive (Appleton, 1975; Dosen & Ostwald, 2016; Ramanujam, 2006).

Our exploratory analysis showed that prospect, refuge and naturalness (visual feature PC1), all predicted preference, with naturalness having the most impact on preference (Table 6). The beta estimates of both prospect and refuge increased relative to the first analysis predicting preference in study 1, in addition to prospect becoming more significantly, and positively, predictive of preference. The positive prediction of preference via naturalness is not particularly surprising, as it supports previous research that has found that increased naturalness is associated with increased preference (Coburn et al., 2019; Herzog, 1989; Kaplan, 1987; Kaplan et al., 1972; Meidenbauer et al., 2020). Accounting for the effect of naturalness in prospect-refuge theory studies may help to disentangle the relationships between prospect, refuge, and preference.

For our second aim, we observed which low-and high-level visual features and urban design/streetscape qualities predict ratings of prospect and refuge. All visual feature PCs and urban design/streetscape quality PC1 and PC3 were predictive of prospect ratings. Visual feature PC2 (bright open views) and urban design/streetscape PC1 (complex, imageable, and walkable) were the only positive predictors of preference, which suggests that increases in bright open views that are also complex, imageable and walkable increase prospect ratings.

For predicting refuge ratings, the chosen model (the model with the highest $R^2$ value and AIC value; see Table 5) contained visual feature PC1, visual feature PC2 and all three urban design/streetscape PCs all predicted greater refuge. Interestingly, visual feature PC1 represented the extent to which an image contained features of naturalness, negatively predicted refuge ratings. Previous research has also theorized that benefits associated with interacting with nature, such as improvements in working memory, a decrease in violent and/or aggressive behavior, and increases in positive affect and stress reduction could possibly explain a variety of evolutionary environmental preference theories, including prospect-refuge theory (Appleton, 1975; Cushing & Miller, 2019; Dosen & Ostwald, 2016; Ramanujam, 2006; Razani et al., 2018). However, vegetation, which is also associated with naturalness and increased preference (Herzog, 1989; Kaplan, 1987; Purcell & Lamb, 1998), has also been suggested to be perceived as less safe, and can increase fear of crime in urban environments depending on context (Xuo & Sullivan, 2001; Andrews & Gatersleben, 2010). For example, high-levels of vegetation within an urban area can impede prospect and have the capability to allow more social danger, with threats using vegetation as a place to hide and potentially attack from, as opposed to the same in a rural context (Andrews & Gatersleben, 2010; Fisher & Nasar, 1992; Michael et al., 2001). Overall, increased naturalness in an image could possibly signal more danger in an urban context, which could cause the decrease in refuge ratings.

When looking at images associated with the five highest ratings of refuge (Fig. 3), we can see that natural elements (e.g. trees) exist within the images, but do not dominate them. The presence of trees in the images could possibly provide a sense of enclosure that does not feel entrapping or threatening (Cushing & Miller, 2019; Talen et al., 2022). More vegetation present within an image seems to elicit preference as long as it is not obstructing open views, or creating a sense of social danger (Andrews & Gatersleben, 2010; Fisher & Nasar, 1992; Michael et al., 2001). The high refuge-associated images were also taken in the daytime and seem well-lit, which could be due to the images not being dominated by trees, which can obstruct lighting (van Rijswijk & Haans, 2018). Previous findings have found that lighting availability in an urban environment made people feel more safe (van Rijswijk & Haans, 2018), which could be another reason these images are highly associated with refuge (Fig. 3).

For our final aim, we evaluated whether proxy measures of prospect and refuge could predict preference in a second image set (without direct measurements of prospect and refuge). In study 2, the proxy for refuge predicted preference ratings, replicating the relationship between measured refuge and preference in study 1. The proxy for prospect did not predict preference, which did not replicate the relationship between measured prospect and preference from study 1 (Table 7). We also computed proxies for prospect and refuge for the original image set used in study 1 (552 Google Street View images), and predicted preference for that image set using those proxies. For both image sets, we found that only the refuge proxy was positively predictive of preference ratings, while the prospect proxy, across both image sets, did not have an effect on preference.

The lack of replication of the relationship between measured prospect and preference could possibly be due to prospect having a more complex relationship with visual features and streetscape qualities in urban environments compared to refuge ratings. When comparing the images associated with the highest measured prospect ratings (Fig. 3) to images associated with the study 1 prospect proxy, (Supplemental Fig. S1), we can see both groups contained bright, open views with little obstructions, and a high degree of road and sky in the images. However, what the former had that the latter didn’t was the presence of storefronts, people, cars, and traffic signs. The presence of these features could be due to the fact that our definition of prospect included the ability to scan for resources (Table 1). The proxy calculated does not contain a measure of resource availability, which could explain the prospect proxy’s lack of effect on preference. Visual features and urban design/streetscape qualities alone may not be enough to truly replicate prospect ratings (~45% of the variance; Table 4), in comparison to refuge ratings (~61% of the variance; Table 5). Future research is needed to see what underpins the concept of prospect in an urban environment. A possible future direction could focus on a more detailed quantification of urban affordances when evaluating prospect ratings (Appleton, 1975; Gibson, 1986; Mumcu & Düuml, 2010; Norman, 2013). By applying Clark and Uzzell’s methodology for measuring affordances, a machine learning model could be developed to create a more nuanced prospect proxy for urban images.

The studies conducted in this manuscript are not without limitations. First, the respective image sets in both studies 1 and 2 differ. The image set used in study 1 was taken with the intent to display these photos on a 360-degree view using a camera mounted on a car (Google Street View images, https://www.google.com/streetview/how-it-works/). The second image set used in study 2 (taken by Talen et al., 2022) was taken using a mobile phone camera. Both image sets have the possibility of being slightly distorted due to the differences in the lenses used and the camera itself, which can affect how the visual features are extracted. Additionally, the image set used in study 2 was taken in a different season than that of the image set used in study 1, which could impact how the visual features were extracted (e.g., differences in brightness, vegetation etc). Another limitation of this study is that our definition of prospect included the concept of “scanning for resources” as opposed to solely defining prospect as “an open view.” While the definition of prospect is “an open view to scan for resources” (Appleton, 1975, 1984), this may also signal to the participant to evaluate resource availability in addition to prospect. Finally, the proxy values of prospect and refuge created in study 2 included the streetscape/urban design ratings, which are more subjective than objective and may not entirely generalize to every single urban environment due to individual differences in
perception of urban environments.

Overall, this work provided partial support for prospect-refuge theory in urban environments with refuge ratings providing strong and consistent effects of predicting environmental preference and more equivocal effects for prospect. This work has also provided insight on what quantitative (i.e., low- and high-level features) and experiential elements (urban design/street-scape qualities) are related to ratings of prospect and refuge in urban environments. More research is needed to understand which particular visual features and urban design/street-scape perceptions relate to the other components of prospect-refuge theory, mystery and complexity, and how those features are weighted for prospect and refuge ratings in more urban vs. more rural/natural contexts. Additional research in this area has implications for providing urban planners, architects and researchers alike with information on how to design urban environments in order to garner the most aesthetic preference from their inhabitants.

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CRediT authorship contribution statement

Gaby N. Ackelik: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. Kyoungh Won Choe: Supervision, Resources, Methodology, Data curation, Conceptualization. Monica D. Rosenberg: Writing – review & editing, Supervision, Project administration, Methodology. Kathryn E. Schertz: Writing – review & editing. Kimberly L. Meidenbaur: Writing – review & editing. Tianxin Zhang: Conceptualization. Nakwon Rim: Investigation, Data curation. Riley Tucker: Writing – review & editing. Emily Talen: Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization. Marc G. Berman: Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envp.2024.102344.

References


