

Article

Quantifying Quality: Numerical Representations of Subjective Perceptions of Urban Space

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Abstract

The quality of urban space influences the sustainability of cities and the well-being of their inhabitants, but quantifying this attribute through numerical representations of urban conditions has proved difficult in urban planning. This article describes how integrating qualitative and quantitative datasets through analytical and generative methods can enhance the comprehension and evaluation of urban space quality. Focusing on the city of Sydney, Australia, the research employed a public survey to assess the urban conditions of 11 suburbs against key qualitative traits of beauty, comfort, safety and ambience. The data was analysed using image segmentation and geographical information systems, and correlations between the survey responses and the urban characteristics present in each image were calculated. The results include nine characteristics of urban spaces that reflect the listed qualitative traits and a percentile ratio for each urban condition that represents the perception of each trait, offering a comprehensive understanding of the determinants of the quality of urban spaces. The research contributes to ongoing efforts to improve the quality of life in urban environments by providing a highly specific and clear quantification of four highly subjective perceptions of urban space. The proposed quality measurement method represents a valuable tool for policymakers, urban planners and designers to use to inform decision-making and ultimately create more liveable, sustainable and inclusive cities.

Keywords: urban analysis; image segmentation; urban quality; image survey; quantifying quality



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1. Introduction

The quality of urban space (or urban quality) influences inhabitant satisfaction, comfort and sense of belonging, as well as sustainability and urban longevity [1]. Urban quality can be defined in multiple ways, including by environmental air quality [2], proximity to natural landscapes [3,4], transportation diversity and accessibility [5,6], public perception [7], and walkability, particularly for ageing populations [8]. Similarly, it can be assessed using various methods, including geographical information systems (GIS), surveys, site observations, remote sensing (satellite imagery and aerial photography), and environmental sensors [9,10].

Policymakers, city planners and designers who strive to improve urban quality need a clear understanding of its elements and means of assessment. Effective evaluation of

urban quality allows for targeted interventions that enhance living conditions, particularly in rapidly urbanising areas [11]. Quantifying urban quality enables systematic urban development, policymaking and resource allocation while fostering collaboration among decision-makers [12]. Refined methods of measurement of urban quality allow designers and policymakers to enhance inhabitants' urban experiences through informed decision-making [13].

A thorough examination of current methods of assessing urban quality highlights a wide range of approaches, each with distinct advantages and drawbacks. Research utilising street view imagery (SVI) has evaluated urban decay and disparities, but can suffer from perspective bias by prioritising vehicular views over pedestrian experiences [14]. The 5D + 3S model combines objective factors like density, diversity and accessibility with subjective insights such as safety and social interaction, creating a holistic framework for assessing street spaces. However, this model leans heavily on expert evaluation, which might restrict its adaptability in various urban environments [15]. Other methods use biosensors, including electroencephalographic and eye-tracking metrics, to analyse pedestrians' interactions with urban settings. While these techniques offer valuable insights into human perception, they struggle with scalability due to small sample sizes and high implementation costs [16]. Tools like Walk Score™ evaluate accessibility to local amenities but do not account for qualitative design aspects influencing the pedestrian experience [17].

Recent technical innovations have enabled new ways to measure urban quality. Object detection models can pinpoint physical characteristics indicative of urban decline, such as graffiti, broken windows and pavement cracks, enabling detailed analysis of urban inequality and temporal variations [14]. Metrics assessing the availability of green spaces and permeable surfaces can support urban resilience against flooding and improvement of well-being through access to nature [18,19]. Furthermore, urban design qualities such as imageability, human scale and transparency are based on measurable physical attributes, including façade continuity and street enclosure, providing a systematic method for evaluating street design [7,20,21]. Collectively, these metrics emphasise the complex nature of urban quality assessment.

The current research was based on the hypothesis that public perceptions of urban quality can be quantified effectively using simple data collection and analysis methods. The resulting datasets can be used in multi-objective optimisation algorithms, which are increasingly employed in urban design [22–27]. Accordingly, the authors developed a method of urban quality assessment that merges subjective survey data with objective spatial analysis through image segmentation and GIS processes. It emphasises pedestrian viewpoints and minimises reliance on SVI datasets or direct community involvement, providing a scalable, adaptable framework that reduces biases while capturing detailed metrics of urban quality. It aligns with recent advocacy for combining subjective perceptions with quantifiable physical characteristics to better guide urban planning and design. Moreover, it advances knowledge by pinpointing urban features such as greenery, shade and seating that improve perceptions of qualities like comfort and aesthetics, thus delivering actionable insights for enhancing urban spaces. Focusing on publicly accessible urban spaces (streets and plazas), the research examined how inhabitants define and experience urban quality daily. It created a numerical representation of subjective urban perceptions by identifying terms accessible to non-designers that shape urban experiences.

The paper presents a review of existing urban quality quantification methods, then introduces a new combined approach that was applied to 11 suburbs in Sydney, Australia. The results include correlations between subjective definitions and measurable characteristics. The paper concludes with a numerical framework for defining and quantifying

urban quality, applicable for assessing existing spaces and integrating the results into multi-objective optimisation models for future urban development.

2. Background and Context

2.1. *The Quality of Urban Space*

Urban quality affects inhabitants' satisfaction, comfort and sense of belonging, as well as the sustainability and lifespan of the urban environment [28]. It is determined not only by the physical environment but by how inhabitants perceive space and their experiences within it [29]. However, understanding the quality of urban space requires an examination of the experiences of both individuals and groups [30]. Key factors include tangible and intangible aspects of urban design, such as visual, auditory, and touch components [31], and accessibility, safety, comfort and beauty [32]. By examining these factors, researchers can better understand the underlying principles shaping urban environments and explore new opportunities for improving their quality. Furthermore, understanding the key components of high-quality urban spaces can inform sustainable design, promote environmentally friendly practices and reduce the impacts of climate change on communities [33].

2.2. *Determining Urban Quality*

Defining—and more specifically, quantifying—the quality of an urban space has been a continuous challenge for urban planners throughout the 20th and 21st centuries. Quantifying intangible urban qualities allows for an objective evaluation of the urbanscape, enabling estimation of the effectiveness of proposed urban planning and strategies. Moreover, urban designers and architects can utilise quantitative datasets to guide design decisions and facilitate communication and translation of ideas. Quantifying the quality of an urban environment gives policymakers and city officials a more in-depth understanding of its strengths and weaknesses and its impact on the economic development, health and well-being of citizens. It also enables the identification of neighbourhoods or communities that lack essential services, and guides interventions to prevent disparity and inequity.

Witten et al. [34] used the Community Resources Accessibility Index (CRAI) to identify how societal opportunities relate to the health and well-being of inhabitants via the physical environment and access to services and amenities. Their method enables datasets to be combined to measure and compare wealth or deprivation at local scale. However, the CRAI assumes a clear cultural identity, so may be difficult to implement in areas with substantial cultural mixing.

As noted earlier, recent technological advancements have made it possible to measure urban elements more efficiently and accurately. Physical site observation, employed by Cheung [35] and Liu [36], involves collecting data such as traffic flow, pedestrian density and activity patterns directly. This provides contextual understanding and immediate access to phenomena such as space usage throughout the day, but requires long periods in the field. To circumvent the limitations of physical observation, researchers have integrated GIS with SVI images, assisted computer vision and machine learning. Toohey et al. [37] utilised this combination to analyse infrastructure quality and availability for bicycle-friendly urban forms, while Ji et al. [38] utilised SVI and deep learning to assess human perception of the urban environment against defined attributes (e.g., 'safe', 'boring' and 'lively'). Digital methods enable the collection of larger sample sizes than physical observation, greatly enhancing efficiency and allowing for the analysis of larger areas. However, SVI can introduce biases by providing views primarily from vehicles rather than pedestrians, and large sample sizes require careful consideration of demographic variation. Andrienko and Andrienko [39] used interactive techniques and computational processing to analyse movement data from trajectories and bird's eye views. Their method can process

voluminous data but requires assumptions about the nature of people's interactions with urban space.

Koltsova et al. [40] conducted a literature review and expert interviews to create a list of urban design parameters at pedestrian scale, which they applied to a specific site. They constructed parametric 3D models to assist in urban analysis and the creation of design tools. Their research highlights the risk of developing a universal methodology of quantifying urban quality using a standardised method without consideration of site-specific characteristics.

In contrast to these large-scale digital methods, small-scale volunteer experiments capture intimate responses to the urban space. Hollander and Foster [41] used portable electroencephalographs to record participants' physiological and psychological responses as they walked through residential streets, allowing for the translation of human experience into quantitative datasets. Small sample size (driven primarily by time constraints) is a major limitation of this approach, but the data provides insights unobtainable from conventional large-scale methods.

Interestingly, quantification of urban quality has been attempted in diverse fields. Cucuzzella et al. [42] quantified urban quality for use in computer games, work that has potential for application to urban design. However, the authors' approach does not incorporate image-based surveying, which can be integral to understanding how people perceive and evaluate urban space. Such methods allow qualitative reactions to spatial environments to be captured and translated into measurable data, offering a more direct link between human perception and the quantification of urban quality.

Several studies (more closely related to the research presented herein) have examined the correlations between urban conditions and their subjective perceptions. Qiu et al. [43] tracked participants' eye movements when observing images of urban green sites. Gaze fixation may reflect heightened interest, but can also result from curiosity or confusion so does not always indicate positive perception. Similarly, glances may be associated with quicker processing of familiar or simple elements, not negative perceptions. The authors mitigated this problem by asking participants about the images directly. Other studies used large datasets to correlate subjective perceptions of urban space and characteristics. For example, Dong et al. [44] and Rossetti et al. [45] analysed SVI from the Place Pulse 2.0 dataset [46], using image segmentation to correlate subjective quality indicators and urban conditions. However, as noted previously, SVI does not adequately represent the pedestrian's perspective (partly due to its vehicle-based capture) and thus characterises urban spaces inaccurately. Despite their limitations, these models can successfully differentiate between characteristics of urban scenes and identify correlates of perception based on weighted attributes.

In recent years, the demand for evidence-based design strategies has grown as policymakers seek to improve the quality of spaces to create more enjoyable and healthy user experiences. However, there is no single optimal approach to quantitative analysis of the quality of urban space. Existing methods of qualitative analysis of urban space have varying advantages and limitations, but each contributes uniquely to a deeper understanding of urban environments. This paper proposes a new approach for quantifying quality in design, consisting of the analysis of site photos, image surveys, spatial analysis, and correlation of subjective and spatial data, as outlined below.

3. Methods

The aim of this study was to combine existing and new methods to improve understanding of the parameters that define subjective perceptions of the city. To do so, the following steps were taken:

1. Identify keywords to be used as representative of urban quality;
2. Collect images from the pedestrian's perspective (not SVIs) in multiple urban suburbs representing diverse urban typologies. Record the geolocation of each image taken;
3. Integrate the images and the keywords in an online survey and distribute them to the public to evaluate the images of urban spaces based on the qualitative keywords;
4. Analyse the survey responses and the data associated with each image (GIS, image segmentation);
5. Identify correlations between survey responses, image analyses and qualitative keywords;
6. Determine the numerical definition of each qualitative trait.

The primary goal of the process outlined above was the numerical quantification of subjective perceptions of urban space for use in either urban analysis or urban design and generation. As such, the clarity and relatability of the keywords used to represent urban quality were fundamental to the survey's success. Moreover, the keywords had to avoid design language that would be deemed too complex or designer-focused to ensure the respondents could assess the images against the keywords with clarity and minimal confusion. In this context, five keywords—Beauty, Comfort, Safety, Ambience and Character—were chosen, reflecting inhabitants' perceptions of the urban environment during day-to-day navigation. They were extracted from the literature [7,32,38], consultation sessions with a leading urban practice in Sydney that is currently involved in work related to quality assessment and place making (SJB), and urban qualities defined by the New South Wales (NSW) Government as part of its placemaking strategy [47,48].

Comfort in urban settings involves physiological and psychological aspects shaped by microclimatic conditions, physical layout and sensory experiences. Research highlights that comfort is not just about thermal or physical ease, but encompasses feelings of safety, accessibility, and relief from stress, all influenced by personal attitudes and environmental perceptions [49–51]. Beauty in urban spaces goes beyond visual appeal to encompass harmony between form, texture and social interactions. It represents a multi-sensory experience formed by the combination of spatial diversity, cultural expression and space upkeep. Scholars suggest that beauty is not strictly visual but also relational, reflecting how individuals connect emotionally with their environments [52]. Lastly, ambience refers to the sensory atmosphere of a location, influenced by light, sound, scent and spatial design. It is subjective yet grounded in concrete environmental features that trigger specific moods or emotions. Ambience is born from the lively interaction between the physical environment and human activities, resulting in a distinct sense of place that merges objective traits with personal experiences [53]. Collectively, these concepts create a comprehensive framework for assessing urban quality by merging concrete design aspects with intangible human perceptions.

The proposed method offers a systematic and data-driven approach to assessing urban quality, structured within a framework that is easily replicable and adaptable, enabling architects, designers and planners to assess and create spaces that meet the needs and preferences of their users. By identifying the relationships between subjective perceptions of design quality and objective spatial characteristics, the method offers insights into the key factors contributing to successful design outcomes. Moreover, the model presented herein is highly adaptable; the framework presented in Figure 1 can be applied with differing image locations, target audiences for the survey, and keywords.

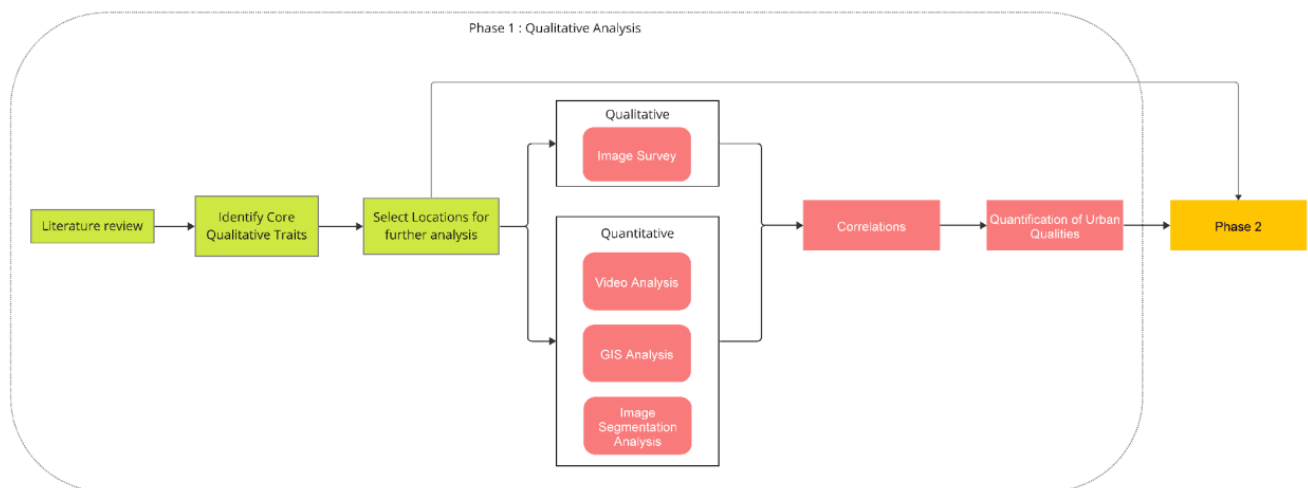


Figure 1. Method workflow for Phase 1 of the research. Phase 2 was an urban intervention in Sydney that used the findings of Phase 1, to be presented in a subsequent paper. The video analysis did not contribute to Phase 1 of the research (but did to Phase 2) and is not presented herein.

The proposed method differs from those in the literature in the following key respects:

- No direct community engagement, thereby enabling a large participant pool;
- No use of SVI—images were taken by the research team from the pedestrian’s view-point, minimising perspective bias;
- Quantification of urban quality via a combined ranking of images based on all traits, rather than independently on each assessed trait;
- Identification of key urban elements and their prevalence in the urban space, creating a design framework for urban proposals that target specific urban qualities.

3.1. Image Collection and Survey

The initial step in the proposed method entailed the collection and organisation of a comprehensive set of site photographs that showcase a diverse range of urbanscapes, building types, architectural styles and environmental contexts. To ensure broad representation, the research team visited 11 suburbs across Sydney (Figure 2), chosen for their unique characteristics and varied urban landscapes (Table 1). Photographs were taken on an iPhone, in Landscape format at eye level, across two weeks in October (Spring), between late morning and early afternoon in weather conditions that was clear with some overcast.

The field data was collated and organised into a comprehensive database. Photographs were grouped according to shared characteristics (including geographical location), facilitating the identification of themes and patterns within each group. Secondary attributes, such as building age or socio-economic context, were considered to ensure a thorough understanding of the various factors influencing design quality.

Following the organisation of images into groups to ensure a manageable dataset for analysis, a representative sample of images from each group was selected, totalling 174 images. A combination of qualitative assessments and quantitative measures, such as the frequency of specific design features or the prevalence of certain architectural styles, was employed to ensure that each group was well represented in the final selection. The resulting 174 selected images sufficiently ensured that the urban characteristics of all 11 suburbs were adequately represented.

Table 1. Demographic and urban typology details for each selected suburb ([54]). Note that Oran Park and Ed Park are new developments that increased inhabitation after the date of the census.

Location	Population	Density (People per Sq. km)	No. of Private Dwellings	Average No. of Vehicles per Dwelling	Ancestry (Top 3)	Location	Urban Typology	Median Dwelling Price, (Source: Realestate.com)
Rose Bay	9911	3767	4708	1.5	English, Australian, Irish	Eastern Suburbs	Low-rise single dwellings and some mid-rise walk-ups in a harbourfront setting	House: \$7 m Unit: \$1.7 m
Elizabeth Bay	4878	20,165	3840	0.7	English, Australian, Irish	Eastern Suburbs	Mostly mid-rise walk-ups, some new residential apartment buildings, in a harbourfront setting	House: \$- Unit: \$0.9 m
Surry Hills	15,828	11,651	9666	0.7	English, Australian, Chinese	City Fringe	Terrace housing, mid-rise walk-ups, residential apartment buildings, business and former industrial warehouses	House: \$2.1 m Unit: \$0.9 m
Zetland	12,622	4742	7466	0.9	Chinese, English, Australian	City Fringe	Predominantly medium to high-rise residential apartment buildings	House: \$1.8 m Unit: \$1 m
Maroubra	30,722	4996	13,598	1.4	English, Australian, Chinese	Eastern Suburbs	Mix of low-rise single dwellings with some mid-rise walk-ups	House: \$3.2 m Unit: \$1.1 m
Sydney CBD	16,667	5039	10,335	0.5	Chinese, English, Thai	Inner City	High-rise business and residential apartment buildings in a busy urban setting	House: \$- Unit: \$1 m
Haymarket	8305	10,169	3931	0.5	Chinese, Thai, English	Inner City	High-rise commercial and residential apartment buildings supported by high amount of retail floor space in low-rise shop fronts and mixed-use shopping centres	House: \$- Unit: \$0.95 m

Table 1. Cont.

Location	Population	Density (People per Sq. km)	No. of Private Dwellings	Average No. of Vehicles per Dwelling	Ancestry (Top 3)	Location	Urban Typology	Median Dwelling Price, (Source: Realestate.com)
Alexandria	9649	2012	5291	1	English, Australian, Irish	City Fringe	Terrace housing, residential apartment buildings, businesses, industrial warehouses	House: \$2.1 m Unit: \$0.9 m
Edmondson (Ed) Park	12,080	86	3797	1.9	Indian, Australian, Chinese	Western Suburbs	Terrace housing and residential apartment buildings with a mixed-use shopping centre in a greenfield development	House: \$1.2 m Unit: \$0.7 m
Oran Park	17,624	6	5612	2	Australian, English, Indian	Western Suburbs	Predominantly low-rise single dwellings in a greenfield development	House: \$1.1 m Unit: \$-
St. Marys	13,256	1143	3211	1.5	Australian, English, Filipino	Western Suburbs	Low-rise single dwellings and medium-rise residential apartment buildings in a traditional Australian high street	House: \$0.95 m Unit: \$0.6 m



Figure 2. Site locations in Sydney for image selection.

After selecting sample images, an anonymous online image survey was conducted to gather subjective data regarding aesthetic preferences, perceived functionality and overall satisfaction with the urbanscape showcased in each image. The survey was advertised through public channels (including LinkedIn, Instagram), email blasts to colleagues, industry contacts and school newsletter subscribers, and through posters displayed throughout the university campus. It was hosted on a public website and open between 7 November 2022 and 13 March 2023 (126 days).

The survey presented a series of images to participants, asking them to rate the spatial qualities of each image as ‘good,’ ‘bad,’ or ‘neutral’ with respect to the five qualitative traits (keywords) identified earlier (Figure 3). It also aimed to relate qualitative assessments to participants’ demographics, such as gender, age, cultural identity, and whether they resided in NSW. Participants could omit any information or skip entire sections, ensuring that their privacy was respected. Participants were encouraged to rate a minimum of 20 images to contribute meaningfully to the dataset.

Once the survey responses were collected, they were analysed using two key methods: First, the images were ranked based on each qualitative trait separately, identifying which images received the highest number of ‘good’ responses and which images received the highest number of ‘bad’ responses using a weighted scoring system based on the following equation. This ensured how many times an image received a response contributed to its weighted rank.

$$\text{Weighted Score} = (\text{no.of good responses} - \text{no.of bad responses}) \times \left(\frac{\text{Total no.of responses}}{\text{Total no.of views}} \right)$$

Secondly, the weighted scores for each trait were combined and ranked using the Pareto dominance method; primarily used in multi-criteria optimisation, Pareto dominance is a value that represents the optimal trade-off between two or more conflicting objectives [55]. Through this analysis, the highest ranked solutions comprised the Pareto Front and thus considered the highest performing images. Figure 4 is a simple graphical representation of how Pareto dominance is calculated on a problem with 2 variables.

Figure 3. Survey snapshot.

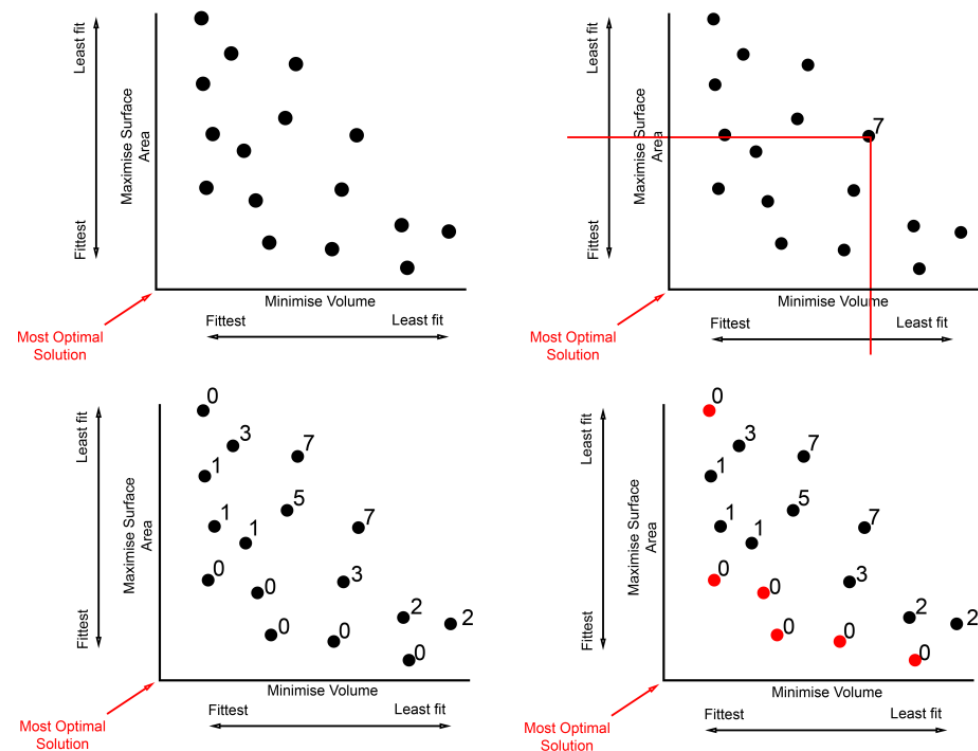


Figure 4. Description of the Pareto front using two objectives. The plotted solutions with a dominance value of 0 (highlighted in red) are part of the Pareto front.

3.2. Image Segmentation

Image segmentation involves dividing a digital image into multiple distinct regions or segments. By isolating objects or regions within an image, segmentation enables accurate analysis and understanding of complex visual data.

Pyramid Scene Parsing Network (PSPNet) and Region-based Convolutional Neural Network (R-CNN) were employed for robust image segmentation, object detection and analysis. PSPNet is a deep learning architecture designed for semantic image segmentation. It utilises a pyramid pooling module to capture multi-scale contextual information, enabling precise pixel-level classification and segmentation of objects within an image [56] is a

widely adopted framework for object detection and localisation. It generates a set of region proposals (potential object locations), then extracts features from these regions using a convolutional neural network, refining the proposed regions to accurately identify objects of interest [57]. Both models were sourced from the GluonCV model zoo [58], and were used as fixed, pre-trained models for feature extraction rather than as part of a supervised training workflow. PSPNet was pre-trained on the Cityscapes dataset [59], and R-CNN on the Pascal visual object classes dataset [60]. Figure 5 depicts PSPNet and R-CNN outputs for an image from the survey. PSPNet was the primary segmentation method; R-CNN was used selectively to assess traits that required object counts, such as the number of cars or trees in an image, rather than their proportional coverage.

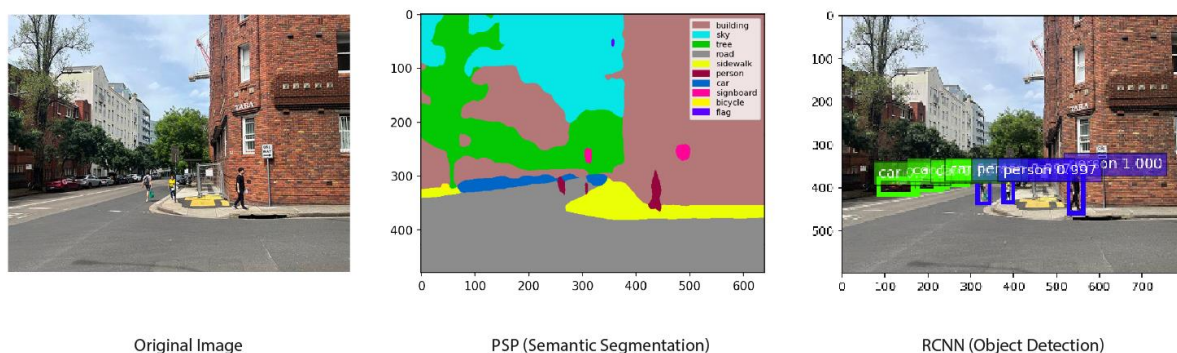


Figure 5. Example of the image segmentation setup.

3.3. Geographic Information System

GIS has revolutionised various fields, including urban planning, environmental management, and transportation [61]. One of the key benefits of GIS is its ability to integrate multiple layers of data in a common geographic framework. This integration facilitates comprehensive spatial analysis, allowing users to identify patterns, relationships and trends that might otherwise go unnoticed.

This study involved 106 GIS analysis categories, 50 spatial and 56 demographic (Appendix A, Table A1), that encompass a wide range of geographic factors. The spatial categories enable the examination and evaluation of physical environment and infrastructure aspects. The demographic categories facilitate socio-economic and population analysis, providing valuable insights into the relationship between spatial features and human characteristics.

Some locations extracted from the survey images were calculated at the point of image capture; others were calculated within 400 m of it. One of the benefits of calculating locations within a 400 m radius of the point of image capture is the ability to incorporate spatial context and variation, providing a more comprehensive representation of the environment. This improves understanding of the spatial relationships, distribution and diversity of local features, variations and patterns. However, and as observed in the results presented below, there is no certainty that the data collected from the allocated radius relates to the corresponding survey image.

4. Results

4.1. Survey

Two hundred and thirty-six individuals participated in the survey. They reported 42 cultural identities, 'Australian' being the most prevalent (Figure 6). NSW residents formed 56.4% of all participants. The 174 images received 5632 views and 4791 image submissions, giving an 84.9% submission rate. Although not the primary focus of this research,

a high-level analysis of the participant demographics reveals that despite the distribution of responses being relatively even across demographics, some clear tendencies emerge. Younger participants (18–34) are generally more positive across most traits, particularly for ambience and beauty; while older participants (50 and above) show a higher proportion of neutral responses across all traits and fewer positive ratings overall. Gender differences are subtle but consistent, with women reporting slightly higher comfort and safety levels than men. Participants located within New South Wales (NSW) showed marginally higher positive responses across all traits compared to those outside NSW. Table A2 (Appendix A) presents the complete results of the survey across the various demographics.

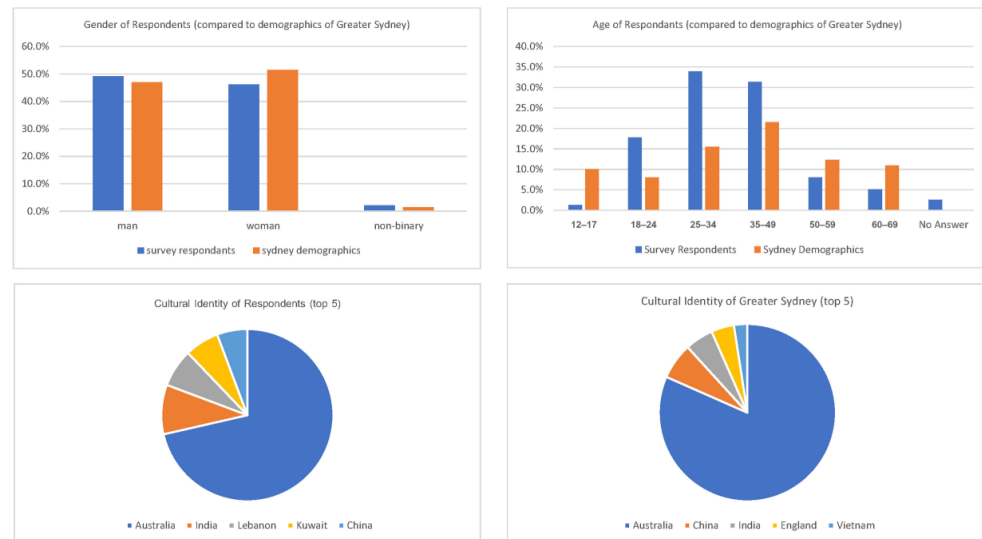


Figure 6. Age, gender and cultural identities of survey respondents compared to Greater Sydney demographics.

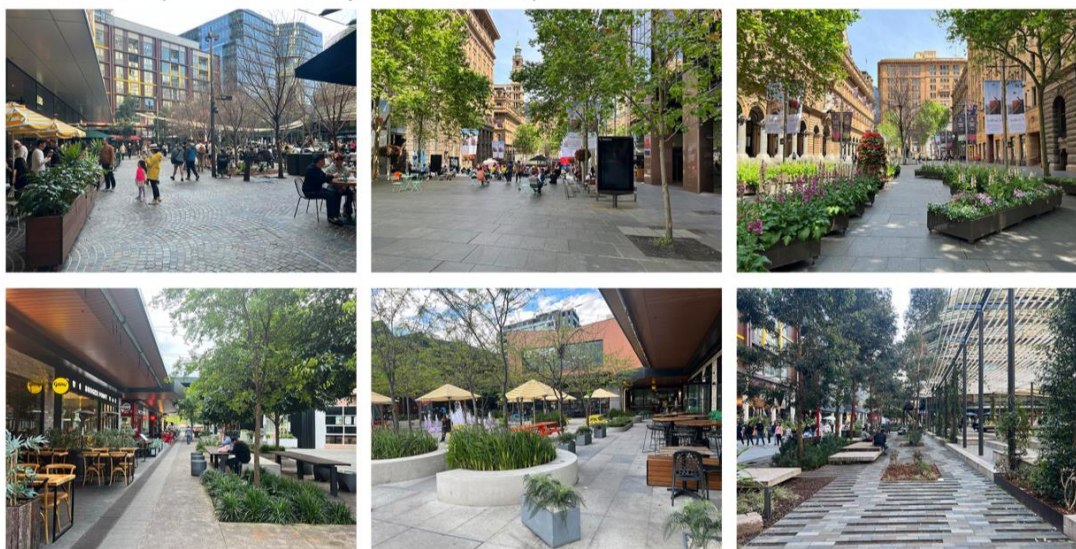
The highest ranked images for *ambience* were numbers 19 (Surry Hills), 90 (Ed Square), 34 and 41 (both Martin Place); for *beauty*, image 90 (Ed Square); for *character*, 35 (Martin Place); *comfort*, 118 (Ed Square) and 130 (Darling Square); for *safety*, 6 (Darling Square) and 29 (Martin Place). Conversely, the lowest ranked image(s) for *ambience* was number 30 (Oran Park); for *beauty*, 56 (Maroubra), 111 (Zetland), 30 and 83 (both Oran Park) received the equal highest number of ‘bad’ scores; for *character*, 56 (Maroubra), and for both *comfort* and *safety*, 166 (St Marys) (Figure 7).



Figure 7. Best (green) and worst (red) locations from the survey.

The Pareto ranking of the survey results yielded 6 images on the Pareto front for good and 8 images on the Pareto front for Bad (Figure 8), which reflected similar characteristics as the individual ranking for each trait presented in Figure 7. Further analysis was conducted on the survey images to identify which traits were in conflict (Figure 9). As can be observed, in most images, there is clear conflict between the traits; however, certain images demonstrate strong correlations, especially between ambience and beauty, and comfort and safety (respectively).

Pareto Front (non-dominated pareto solutions)



Most Dominated Pareto Solutions



Figure 8. Pareto Fronts for best and worst images.

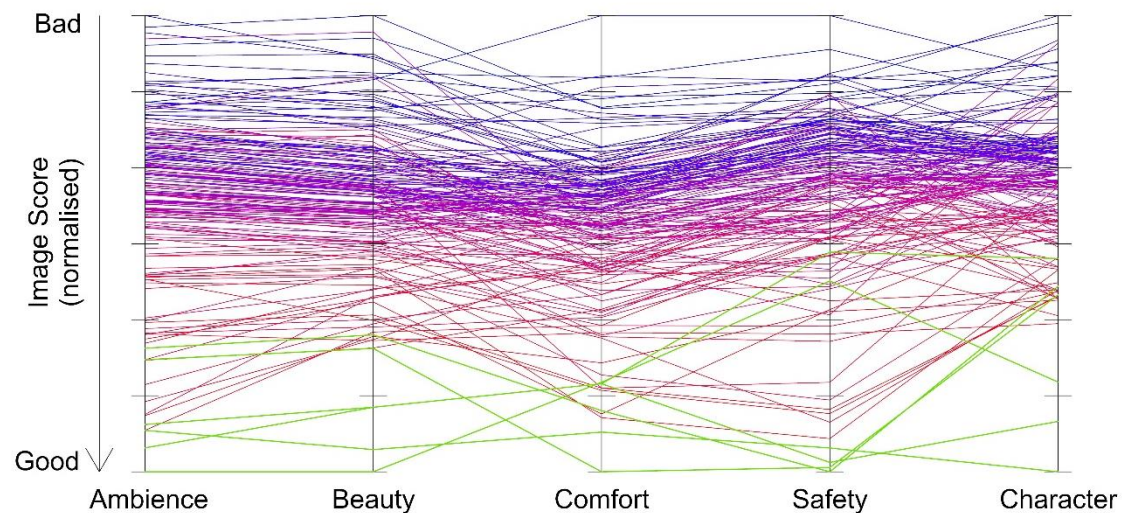


Figure 9. Parallel Coordinate plot showing the ranking of all 174 images across each qualitative trait. The blue to red colour gradient represents pareto ranking, in which blue is the worst pareto ranking and red is the best. The solutions highlighted in green are the images on the pareto front (dominance value of 0).

4.2. Image Segmentation

PSPNet successfully extracted a wide range of predetermined categories from the images and categorised them based on their percentage occurrence within each image, while R-CNN identified the number of objects within each image. Table A3 (Appendix A) shows the sample information that the PSPNet and R-CNN analysis extracted from the first 10 images. PSPNet accurately identified most urban elements, but struggled to distinguish between glass, windows, walls and buildings. The dominant elements present in most images are buildings, sky, trees, roads and footpaths. Skyscrapers were present in some images but were not captured, possibly because they were above the algorithm's height threshold and thus not identified as buildings. The R-CNN results show the number of items identified, with the dominant categories being people, cars and planter boxes. A few cows and horses were identified despite none being present (due to the algorithm confusing a bench at a certain angle with an animal); these errors were easily deleted from the results.

The scores for the highest and lowest-ranked survey images were correlated against the results of the image segmentation analysis for their locations, revealing distinct patterns). Notably, the presence of walls did not differentiate the ranked images: more walls were observed in negative Pareto fronts. This raises concerns about the ability of software to distinguish between walls and buildings. The low-ranked images exhibit a slightly higher mean proportion of sky, possibly indicating an imbalance in scene composition or a lack of relevant objects in the foreground. In contrast, high-ranked images include more trees, emphasising the positive contribution of greenery to visual aesthetics. Furthermore, high-ranked images exhibit significantly fewer roads and more footpaths, suggesting a preference for scenes with more open space and pedestrian-friendly elements.

The number of people in the scenes correlates positively with the quality of ranked images, contributing to their realism and appeal. However, a higher number of cars is correlated negatively with perceived quality. The composition of greenery in the ranked images varies greatly, with lower-ranked images containing a higher percentage of grass, indicating an overemphasis on open green spaces without a diverse urban context results in poorer quality. Conversely, high-ranked images feature a greater presence of plants, highlighting the importance of varied vegetation types. Notably, chairs and seating feature

strongly in the high-ranked images, while none are present in the low-ranked images. This observation suggests that seating elements improve perceived scene quality, implying comfort, human activity and interaction in urban scenes.

The correlations between image scores and image segmentation results provide valuable insights into the factors influencing urban quality. They have implications for refining urban scene generation algorithms to create more realistic and visually appealing scenes. Resolving the apparent limitations of software in recognising wall types and carefully managing the balance of visual elements would significantly enhance the quality of synthesised urban scenes.

Table 2 presents the correlations between the image segmentation data and pareto front solutions for the highest and lowest ranked images (the complete dataset can be found in Appendix A, Table A4). Additionally, Table 3 presents the statistical significance (p value) for the correlation between the ranked images and key urban characteristics. It shows statistically significant correlations for all characteristics except trees and walls. Consequently, in the final quantification of quality, additional image analysis was conducted to separate high canopy cover from low-level shrubbery and to differentiate between modern-building facades and traditional building facades.

Table 2. Image Segmentation Results and Correlation for the images on the Pareto Front for good (green) and bad (red).

	Image ID	Wall %	Building %	Sky %	Tree %	Road %	Sidewal %	Person %	Person (RCNN)	Car %	Car (RCNN)	Sign Board %	Street Light %	Grass %	Plant %	Chair %
Pareto Good	6	0.1	35	4.3	8.9	0	31.7	10	15	0.2	0	0	0.3	0	4	0.4
	29	0.0	25.3	2.7	33.6	0	35.1	2	5	0	0	1.8	0	0	0	0.1
	35	0.8	32.6	5.7	19.1	0	19.5	0	0	0	0	0.8	0.1	0	18.3	0
	90	0.3	19.3	3.2	24	0	22.0	1	3	0	0	0.3	0	0	10	0.7
	118	0.1	26.7	10.3	10.7	0	25.8	0	2	0	0	0	0	0	11.4	2.3
Pareto Bad	160	2.1	25	1	31.9	0	5.7	2	8	0	2	0	0	1.1	5.8	0
	3	5.4	7.6	20.4	20.8	3.5	15	0	1	0.2	1	0	0.1	8.2	2.7	0
	30	2.2	19.4	34.5	2.6	9.7	15.7	0	1	0	0	0	0	3.9	0.9	0
	36	0	58.8	8.9	0	3.2	15.5	0.4	2	12.5	6	0.5	0	0	0	0
	56	4.5	5.6	18.8	25.8	17.8	13.4	0	0	2	2	0	0.1	8.1	0	0
	62	0.2	23.6	22.5	10.5	3.7	24.3	0	1	1.2	1	3.5	0.3	0	9.4	0
	83	0	30.2	25.5	0.1	13.3	11.2	0	0	2.3	2	1.2	0.0	6.8	0.8	0
	166	1	5.5	37.7	2.1	18.8	17.6	0	0	4.7	11	0	0.1	3.4	0.9	0
	169	0	10	1.7	43.7	22.9	7.6	0	1	1.3	1	0	0	3.5	0	0

Table 3. The correlations between the ranked images and the urban characteristics, and their statistical significance. A p value of less than 0.05 is regarded as significant. Positive p values indicate a positive correlation (e.g., the more trees, the higher the image rank) while negative p -values indicate negative correlations (e.g., the more cars the lower the rank).

Urban Characteristic	Pearson Correlation	Significance (2-Tailed)
Wall	−0.030943	0.685239
Building	0.15084 *	0.046949
Sky	−0.330502 **	0.00000843
Tree	0.081612	0.284364
Road	−0.36007 **	0.00000106
Sidewalk	0.18112 *	0.016769
Person	0.429025 **	0.000000349
Person (RCNN)	0.475329 **	0.000000341
Car	−0.151289 *	0.04629
Car (RCNN)	−0.293913 **	0.00008274

** significant at the 0.01 level (2-tailed); * significant at the 0.05 level (2-tailed).

4.3. Correlations with GIS Data

Correlation analysis was performed to identify relationships between the spatial (GIS), demographic (GIS), image segmentation and survey data that may inform urban design. Python (v3.8) and Numpy (v1.19) were used to generate the correlation matrix shown in Figure 10. The colour represents the correlation value: red is positive, blue negative, with gradations of colour representing weakly positive or negative values.

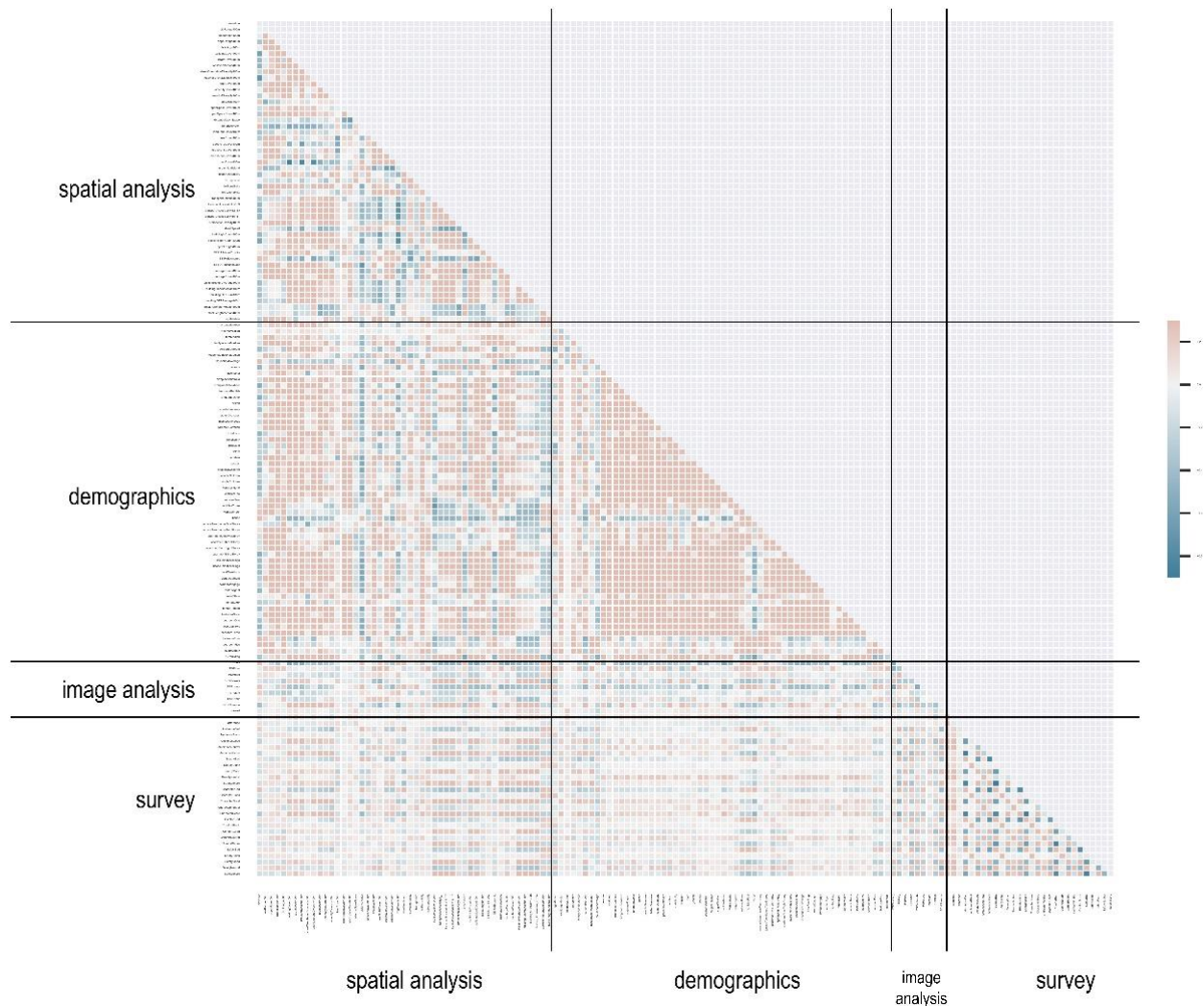


Figure 10. Correlation matrix of GIS data, demographics, image analysis and survey results. The figure is to be read based on colour; bright red and blue colours indicate strong positive (red) or negative (blue) correlations. Muted colours indicate weak correlations. For a detailed list of the spatial and demographic metrics used, please see Appendix A, Table A1.

The correlation matrix demonstrates very few positive correlations and few strongly negative correlations. Positive correlations are limited to approximately +0.2, but negative correlations extend to approximately −0.9. A number closer to 1 or −1 indicates a strong correlation. Most of the stronger correlations are between the spatial and demographic attributes. Strong correlations within the spatial and demographic datasets are plausible; for example, tree canopy cover and open space correlate positively because open spaces are likely to include mature trees. Conversely, spaces containing more buildings necessarily have fewer trees and less vegetation.

As the muted colours show, few strong correlations were detected between the image and survey results and the spatial or analysis data. Some strong negative correlations exist

between the attributes of the survey results, but this is due to the method of capturing data (as described in Figure 6). The lack of correlations between the spatial and demographic data and the image analysis and survey data could be attributed to multiple factors; some data may be inaccurate, incomplete or outdated. Moreover, the context in which the spatial and demographic analysis was performed does not likely relate to the method of subjective image analysis. The image survey asked respondents to rate a static image with a limited field of view. In contrast, the spatial and demographic analysis related to a much larger area, about which the image respondents may have had no understanding or context.

The urban context of the image survey was extremely varied. The images included street frontages, public open spaces and plazas, and different urban scales and contexts such as city centres and suburban locations. For example, the city includes tall buildings with no street setbacks and little tree cover, whilst suburban contexts consist of 1–2 storey buildings with deep setbacks and trees in gardens. This demonstrates that the methodology for identifying correlations between broad-scale spatial datasets and subjective image responses is invalid across multiple urban contexts when using a generic catchment area. A more refined approach to the catchment area is needed to ensure that strong correlations can be identified, but this requires a manual approach to analysis. This would likely make it unfeasible to perform on a large scale unless predefined boundaries can be used.

4.4. Quantifying Quality

The final step of this research was a secondary analysis of the highest-ranked images. The images were ranked according to their dominant values within the Pareto front (with the dominant value of 0 at the top) and plotted against the key dominant categories identified in the image segmentation and GIS analysis results. These urban quality categories include sky view factor, trees, low-level shrubbery coverage, public seating, shading (provided by trees, canopies and umbrellas), façade activation (including glass storefronts and restaurant/café street extensions), modern façade materials, traditional façade materials, and pavement material variations. Categories such as people and cars were omitted because they were not considered design factors (they indicate space use, but this can be identified through other categories). This analysis was conducted on ambience, beauty, safety and comfort. The fifth trait, character, was not included because the survey results indicated the respondents interpreted its meaning differently, giving an irregular and almost random pattern of responses.

To quantify the quality of urban space, the highest-ranked images were separated into ‘street’ images (images featuring a street) and ‘plaza’ images (images without a street). The analysis was conducted once for the street and plaza images combined and once with the street and plaza images separated. In the first run, the Pareto front images in the combined street and plaza set were analysed against the urban quality categories listed in the paragraph above. This process was repeated for each qualitative trait and their respective Pareto front images, with the average percentage for each trait calculated by multiplying the PSPNet quality percentage and the image’s normalised score on that trait (Table 4). The final score represents the average percentage of that urban quality category’s presence in the images for the qualitative trait. For example, an image with high *ambience* has an average of 3.14% sky view factor, 7.54% low-level shrubbery coverage, 22.34% trees, 1.30% seating, 24.15% shading, 11.18% façade activation, 16.03% traditional façade material, 83.97% modern façade materials, and three pavement variations.

Table 4. The urban and spatial characteristics that represent each quality category (street and plaza images combined).

Fitness Objective	Image ID	Location	Normalised Values	Quality Metrics											
				Skyview	Shrubs	Trees	Seating	Shading	Facade Activation	Glass (Facade)	Traditional Material (Facade)	Modern Material (Facade)	Material Variations (Pavement)	Traditional Facade Normalised	Modern Facade Normalised
Ambience	90	Ed Square	1	3.00	11.00	25.00	1.63	32.49	21.72	5.46	0.00	31.61	4.00	0.00	100.00
	160	Darling Square	0.95	0.95	7.60	29.45	3.71	27.51	1.25	1.37	0.00	20.01	6.00	0.00	100.00
	35	Martin Place	0.91	5.46	14.56	17.29	0.00	13.69	0.48	1.73	14.95	0.00	1.00	100.00	0.00
	19	Surry Hills	0.91	0.91	1.82	32.76	0.77	35.70	12.68	17.67	7.22	26.93	3.00	21.14	78.86
	6	Darling Square	0.9	5.40	2.70	7.20	0.38	11.34	19.79	12.19	0.00	37.60	1.00	0.00	100.00
	Average Percentage			3.14	7.54	22.34	1.30	24.15	11.18	7.68	4.43	23.23	3.00	16.03	83.97
Beauty	90	Ed Square	1	3.00	11.00	25.00	1.63	32.49	21.72	5.46	0.00	31.61	4.00	0.00	100.00
	35	Martin Place	0.81	4.86	12.96	15.39	0.00	12.18	0.43	1.54	13.31	0.00	1.00	100.00	0.00
	160	Darling Square	0.84	0.84	6.72	26.04	3.28	24.33	1.11	1.21	0.00	17.69	6.00	0.00	100.00
	6	Darling Square	0.76	4.56	2.28	6.08	0.32	9.58	16.71	10.29	0.00	31.75	1.00	0.00	100.00
	118	Ed Square	0.68	5.44	8.84	11.56	5.03	7.60	7.06	2.45	0.00	16.34	1.00	0.00	100.00
	Average Percentage			3.74	8.36	16.81	2.05	17.24	9.41	4.19	2.66	19.48	2.60	12.02	87.98
Comfort	118	Ed Square	1	8.00	13.00	17.00	7.39	11.18	10.38	3.60	0.00	24.03	1.00	0.00	100.00
	35	Martin Place	0.91	5.46	14.56	17.29	0.00	13.69	0.48	1.73	14.95	0.00	1.00	100.00	0.00
	173	Surry Hills	0.88	0.88	13.20	16.72	0.00	14.32	27.39	14.69	4.29	25.09	2.00	14.59	85.41
	130	Darling Square	0.87	6.09	4.35	6.09	0.22	5.93	3.65	6.98	1.54	32.24	1.00	4.56	95.44
	29	Martin Place	0.86	2.58	0.00	32.68	0.98	7.84	0.31	1.32	12.31	0.00	2.00	100.00	0.00
	Average Percentage			4.60	9.02	17.96	1.72	10.59	8.44	5.66	6.62	16.27	1.40	28.91	71.09
Safety	29	Martin Place	1	3.00	0.00	38.00	1.14	9.12	0.36	1.53	14.31	0.00	2.00	100.00	0.00
	118	Ed Square	0.99	7.92	12.87	16.83	7.32	11.07	10.28	0.36	2.85	0.36	1.00	88.89	11.11
	6	Darling Square	0.98	5.88	2.94	8.82	0.41	12.35	21.55	13.27	0.00	40.94	1.00	0.00	100.00
	35	Martin Place	0.95	5.70	15.20	18.05	0.00	14.29	0.50	1.81	93.65	0.00	1.00	100.00	0.00
	173	Surry Hills	0.93	0.93	13.95	17.67	0.00	15.13	28.95	15.52	4.53	26.51	2.00	14.59	85.41
	Average Percentage			4.69	8.99	19.87	1.77	12.39	12.33	6.50	23.07	13.56	1.40	62.97	37.03

This method was repeated for the street and plaza images separately to understand the effect of each urban quality on the two topographies (Table 5). The sky view factor percentages in street images that scored highly on *ambience* and *beauty* are slightly higher than in plaza images. In contrast, plazas have slightly higher low-level shrub coverage across all four traits. Tree percentages were substantially higher in the high-scoring *ambience* and *beauty* street images. Seating was at higher percentages in plazas than street images across all four traits. The percentage of shading in street images is similar across the four traits, but the plaza images have much higher percentages of shading for *ambience*, *beauty* and *safety* and higher percentages for comfort than the street images. The pavement variation score reveals that, for plaza images, images scoring high for *ambience* and *beauty* contain 2–3 variations but only 1–2 for *comfort* and *safety*, while street images feature 3–4 variations across all four traits.

The results presented above demonstrate the key urban metrics associated with each qualitative trait, showcasing how each quality is defined by its numerical representation of nine key urban characteristics. This quantification aims to define how *ambience*, *beauty*, *comfort* and *safety* can be measured and calculated accurately, thus serving as benchmarks for improving urban quality (Figure 11). Additionally, the quantified percentiles of the urban characteristics representing each quality can be used as part of analytic and generative processes. An example of an analytic process is an assessment of existing urban conditions in which the ‘performance’ of the urban space is evaluated against the four qualitative traits. An example of a generative process is the use of quantified metrics as in a model of design options that perform positively against the four qualitative traits.

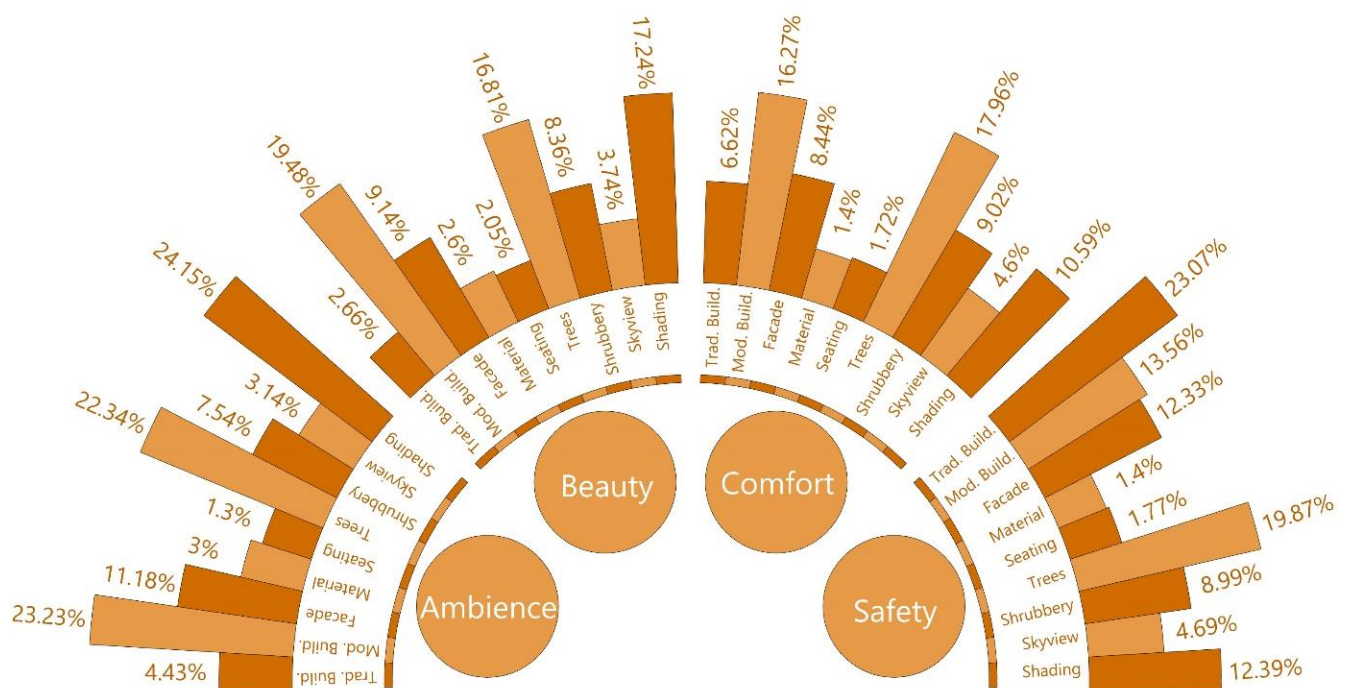


Figure 11. The quantification of ambience, beauty, comfort and safety. Each quality is defined through a percentile allocation of nine key urban characteristics extracted from the analysis of survey results and subsequent analysis.

Table 5. The urban and spatial characteristics that represent each quality for streets (top) and plazas (below).

Fitness Objective	Image ID	Location	Normalised Values	Quality Metrics											
				Skyview	Shrubs	Trees	Seating	Shading	Facade Activation	Glass (Facade)	Traditional Material (Facade)	Modern Material (Facade)	Material Variations (Pavement)	Traditional Facade Normalised	Modern Facade Normalised
Ambience	19	Surry Hills	1	3	11	25	0.85	39.23	13.93	19.43	7.93	29.59	4	21.14	78.86
	155	Rose Bay	0.79	21.33	5.53	18.96	0	5.4036	0	0	0	1.1771	4	0.00	100.00
	126	Zetland	0.77	4.62	3.85	40.04	0.1309	2.2946	0	0	0	4.5199	4	0.00	100.00
	28	Rose Bay	0.75	9.75	4.5	29.25	0	9.7425	0	0	0.375	0.795	4	32.05	67.95
	146	Surry Hills	0.66	0.66	3.3	20.46	0	1.6434	0	0.4356	27.9378	0	2	100.00	0.00
	Average Percentage			7.87	5.64	26.74	0.20	11.66	2.79	3.97	7.25	7.22	3.60	50.11	49.89
Beauty	19	Surry Hills	1	3	11	25	0.85	39.23	13.93	19.43	7.93	29.59	4	21.14	78.86
	28	Rose Bay	0.96	12.48	5.76	37.44	0	12.4704	0	0	0.48	1.0176	4	32.05	67.95
	146	Surry Hills	0.95	0.95	4.75	29.45	0	2.3655	0	0.627	40.2135	0	2	100.00	0.00
	126	Zetland	0.89	5.34	4.45	46.28	0.1513	2.6522	0	0	0	5.2243	4	0.00	100.00
	155	Rose Bay	0.86	23.22	6.02	20.64	0	5.8824	0	0	0	1.2814	4	0.00	100.00
	Average Percentage			9.00	6.40	31.76	0.20	12.52	2.79	4.01	9.72	7.42	3.60	56.71	43.29
Comfort	146	Surry Hills	1	1	5	31	0	2.49	0	0.66	42.33	0	2	100.00	0.00
	173	Surry Hills	1	1	15	19	0	16.27	31.13	16.69	4.87	28.51	2	14.59	85.41
	157	Surry Hills	0.96	5.76	1.92	20.16	0	2.9472	0	1.2192	5.184	38.1888	2	11.95	88.05
	59	Ed Square	0.87	16.53	6.09	3.48	0.5481	28.4055	29.3538	5.7159	0	22.3503	6	0.00	100.00
	38	Haymarket	0.86	0.86	0	16.34	1.0492	8.3506	0	0.2752	33.755	0.8686	4	97.49	2.51
	Average Percentage			5.03	5.60	18.00	0.32	11.69	12.10	4.91	17.23	17.98	3.20	48.93	51.07
Safety	38	Haymarket	1	1	0	19	1.22	9.71	0	0.32	39.25	1.01	4	97.49	2.51
	146	Surry Hills	0.97	0.97	4.85	30.07	0	2.4153	0	0.6402	41.0601	0	2	100.00	0.00
	59	Ed Square	0.87	16.53	6.09	3.48	0.5481	28.4055	29.3538	5.7159	0	22.3503	6	0.00	100.00
	173	Surry Hills	0.89	0.89	13.35	16.91	0	14.4803	27.7057	14.8541	4.3343	25.3739	2	14.59	85.41
	157	Surry Hills	0.8	4.8	1.6	16.8	0	2.456	0	1.016	4.32	31.824	2	11.95	88.05
	Average Percentage			4.84	5.18	17.25	0.35	11.49	11.41	4.51	17.79	16.11	3.20	52.48	47.52

Table 5. Cont.

Fitness Objective	Image ID	Location	Normalised Values	Quality Metrics											
				Skyview	Shrubs	Trees	Seating	Shading	Facade Activation	Glass (Facade)	Traditional Material (Facade)	Modern Material (Facade)	Material Variations (Pavement)	Traditional Facade Normalised	Modern Facade Normalised
Ambience	90	Ed Square	1	3	11	25	1.63	32.49	21.72	5.46	0	31.61	4	0.00	100.00
	160	Darling Square	0.92	0.92	7.36	28.52	3.588	26.6432	1.2144	1.3248	0	19.3752	6	0.00	100.00
	35	Martin Place	0.86	5.16	13.76	16.34	0	12.9344	0.4558	1.634	14.1298	0	1	100.00	0.00
	6	Darling Square	0.84	5.04	2.52	6.72	0.3528	10.584	18.4716	11.3736	0	35.0952	1	0.00	100.00
	41	Martin Place	0.81	8.1	0	12.15	2.1951	3.4344	10.9917	17.1153	3.2724	24.7617	1	11.67	88.33
	Average Percentage			4.44	6.93	17.75	1.55	17.22	10.57	7.38	3.48	22.17	2.60	13.57	86.43
Beauty	90	Ed Square	1	3	11	25	1.63	32.49	21.72	5.46	0	31.61	4	0.00	100.00
	35	Martin Place	0.92	5.52	14.72	17.48	0	13.8368	0.4876	1.748	15.1156	0	1	100.00	0.00
	160	Darling Square	0.77	0.77	6.16	23.87	3.003	22.2992	1.0164	1.1088	0	16.2162	6	0.00	100.00
	6	Darling Square	0.77	4.62	2.31	6.16	0.3234	9.702	16.9323	10.4258	0	32.1706	1	0.00	100.00
	Average Percentage			3.48	8.55	18.13	1.24	19.58	10.04	4.69	3.78	20.00	3.00	15.89	84.11
Comfort	118	Ed Square	1	8	13	17	7.39	11.18	10.38	3.6	0	24.03	1	0.00	100.00
	35	Martin Place	0.87	5.22	13.92	16.53	0	13.0848	0.4611	1.653	14.2941	0	1	100.00	0.00
	130	Darling Square	0.81	5.67	4.05	5.67	0.2025	5.5242	3.402	6.4962	1.4337	30.0186	1	4.56	95.44
	29	Martin Place	0.8	2.4	0	30.4	0.912	7.296	0.288	1.224	11.448	0	2	100.00	0.00
	Average Percentage			5.32	7.74	17.40	2.13	9.27	3.63	3.24	6.79	13.51	1.25	33.46	66.54
Safety	29	Martin Place	1	3	0	38	1.14	9.12	0.36	1.53	14.31	0	2	100.00	0.00
	118	Ed Square	0.99	7.92	12.87	16.83	7.3161	11.0682	10.2762	0.3564	2.8512	0.3564	1	88.89	11.11
	6	Darling Square	0.97	5.82	2.91	7.76	0.4074	12.222	21.3303	13.1338	0	40.5266	1	0.00	100.00
	35	Martin Place	0.93	5.58	14.88	17.67	0	13.9872	0.4929	1.767	15.2799	0	1	100.00	0.00
	171	Darling Square	0.85	0	1.7	4.25	0.816	70.65	21.0205	8.4745	8.4745	48.0845	1	14.98	85.02
	Average Percentage			4.46	6.47	16.90	1.94	23.41	10.70	5.05	8.18	17.79	1.20	31.50	68.50

5. Discussion

The presented research examines opportunities for quantifying qualitative characteristics in the urban space. The various methods used have been implemented before, but their combination and integration within a relatively simple, replicable and adaptable workflow (one that requires minimal use of advanced tools) for the purpose of the specific quantification of subjective perceptions through numerical representations was the key objective of this research. Through the combination of both user-driven (subjective) and data-driven (objective) approaches to data collection, and most importantly, the correlation between the two, the research presents a method by which highly subjective perceptions of the urban space—namely beauty, comfort, safety, ambience and character—can be quantified using definitions based on underlying physical characteristics. Although the first four keywords demonstrated clear patterns in the survey results, the fifth keyword, character, did not. This is likely due to the difficulty in defining character; although it may be clear in the urban design field, it is less so to non-designers. Due to this, the ‘character’ trait was removed from the final quantification.

The interplay of various physical and experiential elements, shaped by individual experiences and collective societal norms, underscores urban spaces’ complexity. This finding suggests that any methodology for quantifying urban space quality should be multidimensional and flexible, capable of capturing the full range of elements contributing to quality. Therefore, a survey is the primary step, serving as the foundation for all subsequent analysis. Moreover, an online survey using images from the pedestrian’s viewpoint (not SVI, which are from a vehicle’s viewpoint) is an efficient way to collect data on perceptions of urban quality and conditions. As such, the presented research is highly adaptable to different sites and/or assessment of urban space in relation to a specific function (such as running—[44]).

The GIS analysis generated primarily low positive correlations and a few strong negative correlations, mostly between spatial and demographic attributes. The correlation between image analysis and survey results in spatial and demographic analysis was minimal, likely due to the survey’s subjectivity and different scoring methods (GIS-based analysis being context-based on a suburban scale, while image analysis and survey were perspective-based on a pedestrian scale). Moreover, the survey results pertained to a specific static representation of an urban space (through an image), while the GIS analysis assessed its spatial conditions (within a 400 m boundary). Therefore, although the image may contain favourable urban qualities, its surroundings may not share those qualities. Although the comparison of the GIS-based and image survey data revealed few correlations, it illustrates the importance of maintaining scale and perspective in correlating data. It also demonstrates the difficulties in integrating spatial and subjective data, because the perspective of the space’s occupants is inherently different from that of urban designers and architects, calling for new methods that can examine spatial qualities through the lens of the occupants.

The research had several limitations, notably that the quantification of urban quality is heavily contingent on its definition. Academic literature, industry feedback and government initiatives were employed to identify the five selected qualities, but they do not incorporate environmental, demographic or cultural perceptions of urban space. Although some of this information may be inferred from the survey results, the objective of limiting the survey’s complexity also limited the depth of information that could be collected. Future researchers should incorporate an additional layer of subjective quality assessment, as presented in Mouratidis [62], in which unique pathways (e.g., travel, leisure, work, health) are mined for subjective perceptions.

Although the survey methodology was effective in capturing subjective views on urban qualities like ambience, beauty, comfort and safety, the lack of standardised definitions of these concepts across various cultural and demographic contexts risked variability in responses. For instance, concepts such as beauty may be understood differently due to cultural norms or personal preferences, as noted in studies of urban quality measurement frameworks [15]. Likewise, relying on static images for subjective assessments restrict the ability to consider dynamic urban factors like noise levels, pedestrian traffic patterns, or changes over time within urban areas [63].

The study's survey respondents presented a demographic imbalance, especially with respect to age. This discrepancy raises concerns about the applicability of findings regarding safety and comfort perceptions; older adults typically prioritise accessibility, available seating, and pedestrian infrastructure elements that younger people may regard as less important. This difference represents a problem for urban planning based on online survey methods, which inevitably cater to younger, more tech-savvy populations. To overcome this problem, future researchers could implement hybrid engagement approaches, complementing online platforms with in-person outreach at community centres to engage all age groups, mirroring practices in participatory GIS initiatives [64,65]. Such changes correspond with calls for intersectional methodologies that consider age, mobility and cultural identity in evaluations of urban quality.

Lastly, though the impact of demographic imbalances in survey participation was alleviated somewhat by the study's focus on creating a scalable framework rather than aiming for generalised conclusions about specific populations, researchers should consider how factors such as the underrepresentation of older adults may bias findings towards the perspectives of able-bodied individuals.

Future researchers should improve methodologies by integrating dynamic data collection methods (e.g., real-time sensors or participatory mapping) and broadening demographic representation to enhance inclusivity and robustness in assessing urban quality. They should embrace relational approaches that frame quantification within participatory, context-specific contexts. This could mean integrating dynamic data sources with collaboratively developed surveys that involve marginalised communities in creating quality metrics that reflect Participatory GIS principles. According to Mouratidis [62], urban quality is deeply interlinked with pathways like commuting and leisure that shape everyday experiences; similarly, Dong et al. [44] highlighted that assessments focused on specific activities provide deeper insights than generic benchmarks. Furthermore, adopting diverse interpretations of beauty and comfort, as Wan et al. [15] suggested, can minimise the biases present in existing measurement frameworks.

Ultimately, this study highlights a critical issue in urban analytics: the clash between technical precision and humanistic depth. As cities continue to implement algorithmic governance, it is crucial for scholars to critically examine whose perceptions are represented, how these perceptions are scaled, and for what purposes, thus ensuring that urban quality does not become yet another source of exclusion.

6. Conclusions

Current quantification methods either rely on small-scale community engagement, limiting scalability, or large-scale SVI analysis introducing perspective bias. The current research combined subjective and objective data collection methods to refine these systems while avoiding large-scale SVI and direct community engagement. The study's primary objectives were to quantify urban quality using specific, measurable characteristics at the neighbourhood scale, and develop a scalable and adaptable method applicable across diverse urban environments.

The results demonstrate that urban spaces with lower percentages of skyview, material variation in footpaths, a combination of traditional and modern buildings, and minimal traffic ranked higher across all traits (with variations between the traits). They also show that urban spaces with greater skyview, monotonous footpaths, high vehicular conditions, poor tree cover and shrubbery ranked poorly across all traits. The research demonstrates the numeric representation of subjective perceptions of urban space has two purposes—assessment of the quality of existing urban space, and the generation of new urban space of greater urban quality (phase 2 of this research used the findings presented herein to propose the transformation and improvement of an existing urban space in the City of Sydney. It utilised a multi-objective optimisation method that further demonstrated the utility of quantification in population-based algorithmic workflows [66]).

The research identified key attributes that define the quality of urban space correlated to each qualitative trait. The approach highlights the potential of combining subjective survey input with measurable physical characteristics in producing transferable and data-driven design frameworks. The survey serves as a foundational step, providing structured yet adaptable input that can support scalable, location-specific urban analysis. Its format—using imagery from a pedestrian’s perspective—enabled broad engagement and facilitated efficient data collection, without the need for extensive fieldwork.

The framework presented herein (Figure 12) is designed to be replicable across urban contexts, supporting analysis and design tasks that can benefit from measurement of perceptions of ambience, beauty, comfort and safety. As such, it offers a valuable tool for urban designers and researchers aiming to embed public perception more directly into the urban decision-making process.

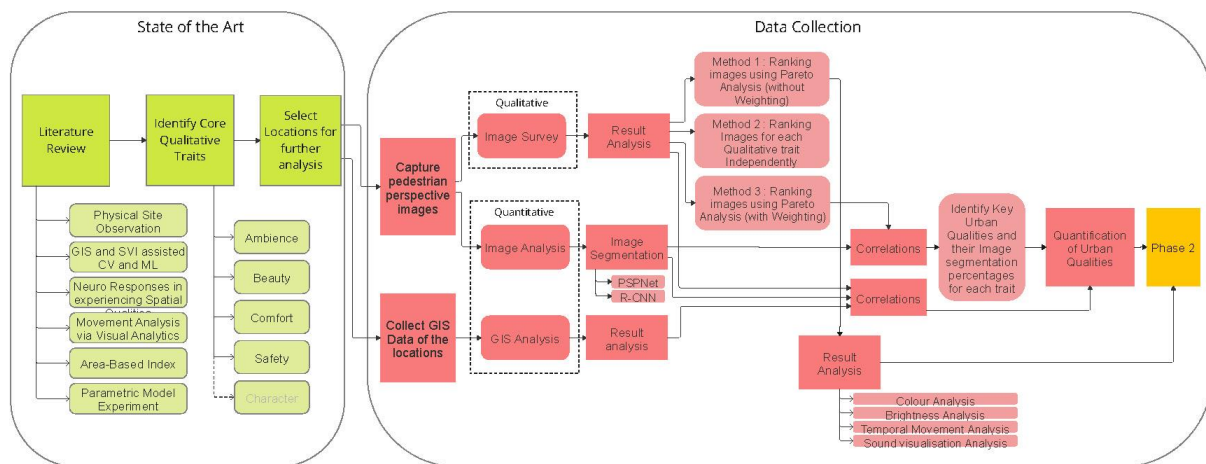


Figure 12. A detailed Pseudocode framework of the abstract workflow presented in Figure 1. Researchers and designers are encouraged to replicate this process for their own studies, making changes based on context as required.

Future work by the authors expands on the findings of this research across several fronts. First, Phase 2 of the study integrates the quantified metrics into a multi-objective evolutionary algorithm to propose an urban intervention in the City of Sydney [66]. Second, the role of colour in the highest- and lowest-ranked images is being further examined by identifying the dominant colours within each group and reconstructing the corresponding urban spaces using colour alone, through pavilions installed in public spaces across the city. Finally, the study is being extended to a new international context—one with markedly different environmental conditions, cultural background, demographics, and government regulations—to examine how the findings of this research translate across diverse urban settings.

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Institutional Review Board Statement: The study was conducted in accordance with the Australian Government’s National Statement on Ethical Conduct in Human Research, and approved by the Ethics Committee of University of Technology Sydney (Ethics Number: ETH22-7498, date: 7 November 2022).

Informed Consent Statement: Informed consent was obtained from all participants involved in the study. Prior to responding to the survey, participants consented to the publication/presentation of the results of this research in a variety of forums, and for the results of this research to be shared through open access (public) scientific databases, including internet databases.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Conflicts of Interest: Author Jordan Mathers and Marlin Hannam were employed by the company SJB. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Appendix A

Table A1. The spatial and demographic metrics used for the GIS correlation analysis. Although some of these metrics may be considered less relevant than others, the largest subset of data available for the selected sites was selected to ascertain any potential links between the survey results and the spatial/demographic analysis. The variables selected for analysis were based on the procurement of publicly available datasets to allow for replication of this study without the need to access data behind paywalls, and the method for calculation was based on the default calculation method located within the QGIS software (v3.22).

Spatial Metrics		
elevation	distanceWater	streetSpeed
eleRange400 m	landZoneCount400 m	trafficLightCount400 m
slopeMean400 m	treeCover400 m	trafficIncidentCount400 m
slopeRange400 m	tree3 to10 Cover400 m	cycleLength400 m
buildings400 m	tree10 to15 Cover400 m	SEIFAAdvanPlusDis
buildingCover400 m	tree15 PlusCover400 m	SEIFAEconomic
strataCover400 m	vegCover400 m	SEIFAEducationOcc
lotCoverMedian400 m	urbanHeatIsland	heritageCount400 m
streetOrientationDiversity400 m	heatVulnerability	heritageCover400 m
roadHeirarchyDiversity400 m	hviExposure	buildingHeightAverage100 m
roadCover400 m	hviSensitivity	buildingFloorsMedian100 m
amenityCount400 m	hviAdaptability	building GFASum100 m
amenityDiversity400 m	transportOptions400 m	building GFAAverage100 m

Table A1. Cont.

Spatial Metrics		
landArea400 m	transportAccessibility8_9	blockPerimeterMedian400 m
openSpaceCover400 m	transportAccessibility12_13	blockLengthMedian400 m
openSpaceCount400 m	transportAccessibility16_17	
distanceOpenSpace	intersectionDensity400 m	
Demographic Metrics		
ageMedian	buddhism	apartmentFourEightStorey
mortgageMedian	christianity	apartmentNineStorey
incomeMEdian	hinduism	occupiedDwellings
rentMedian	islam	unoccupiedDwellings
familyIncomeMedian	judaism	totalDwellings
personBedroom	secular	ownedOutright
householdIncomeMedian	coupleNoChildren	ownedMortgage
householdAverage	coupleChildren	rentedAgent
persons	singleChildren	rentedState
aboriginal	vehiclesNone	rentedCHP
birthplaceAustralia	vehiclesOne	rentedPerson
birthplaceElsewhere	vehiclesTwo	bedroomNone
languageEnglish	vehiclesThree	bedroomOne
languageOther	vehiclesFour	bedroomTwo
citizen	house	bedroomThree
parentsOverseas	terraceTownhouseOneStorey	bedroomFour
fatherOverseas	terraceTownhouseTwoStorey	bedroomFive
motherOverseas	apartmentOneTwoStorey	bedroomSix
parentsAustralian	apartmentThreeStorey	
Image Analysis		
PSP Building	PSP Road	PSP Plant
PSP Sky	PSP Sidewalk	RCNN CAR
PSP Tree	PSP Grass	RCNN Person
Survey Results		
No. of times image viewed	Beauty Good	Comfort Good
No. of times response submitted	Beauty Neutral	Comfort Neutral
Difference between views/submissions	Beauty Total Score	Comfort Total Score
Ambience Bad	Character Bad	Safety Bad
Ambience Blank	Character Blank	Safety Blank
Ambience Good	Character Good	Safety Good
Ambience Neutral	Character Neutral	Safety Neutral
Ambience Total Score	Character Total Score	Safety Total Score
Beauty Bad	Comfort Bad	
Beauty Blank	Comfort Blank	

Table A2. The distribution of perceived spatial qualities by participants’ demographics.

		Ambience				Beauty				Character				Comfort				Safety			
		Good	Bad	Neutral	-	Good	Bad	Neutral	-	Good	Bad	Neutral	-	Good	Bad	Neutral	-	Good	Bad	Neutral	-
Age	18–24	102	40	159	191	82	41	177	192	89	44	163	196	91	31	180	190	136	25	141	190
		21%	8%	32%	39%	17%	8%	36%	39%	18%	9%	33%	40%	18%	6%	37%	39%	28%	5%	29%	39%
	25–34	169	80	254	31	167	116	223	28	165	96	243	30	189	77	233	35	204	72	225	33
		32%	15%	48%	6%	31%	22%	42%	5%	31%	18%	46%	6%	35%	14%	44%	7%	38%	13%	42%	6%
	35–49	251	198	326	71	259	172	344	71	258	183	327	78	340	144	290	72	374	135	266	71
		30%	23%	39%	8%	31%	20%	41%	8%	30%	22%	39%	9%	40%	17%	34%	9%	44%	16%	31%	8%
	50–59	33	60	89	26	37	57	89	25	36	61	85	26	44	35	104	25	53	36	94	25
		16%	29%	43%	13%	18%	27%	43%	12%	17%	29%	41%	13%	21%	17%	50%	12%	25%	17%	45%	12%
	60–69	34	26	52	2	28	26	58	2	34	25	52	3	30	12	70	2	51	7	54	2
		30%	23%	46%	2%	25%	23%	51%	2%	30%	22%	46%	3%	26%	11%	61%	2%	45%	6%	47%	2%
Gender Identity	man	256	203	434	218	255	203	436	217	254	220	411	226	313	162	417	219	388	141	365	217
		23%	18%	39%	20%	23%	18%	39%	20%	23%	20%	37%	20%	28%	15%	38%	20%	35%	13%	33%	20%
	woman	337	202	451	103	323	210	459	101	334	189	463	107	386	139	463	105	434	136	419	104
		31%	18%	41%	9%	30%	19%	42%	9%	31%	17%	42%	10%	35%	13%	42%	10%	40%	12%	38%	10%
	non binary	8	10	1	0	8	11	0	0	9	8	2	0	14	4	2	0	12	6	2	0
		40%	50%	5%	0%	40%	55%	0%	0%	45%	40%	10%	0%	70%	20%	10%	0%	60%	30%	10%	0%
Cultural Identity	Australia	202	208	332	77	180	207	356	76	209	206	321	83	224	160	358	77	299	136	308	76
		25%	25%	41%	9%	22%	25%	43%	9%	26%	25%	39%	10%	27%	20%	44%	9%	37%	17%	38%	9%
	India	30	2	24	4	36	1	22	1	27	4	28	1	36	3	16	5	36	8	15	1
		50%	3%	40%	7%	60%	2%	37%	2%	45%	7%	47%	2%	60%	5%	27%	8%	60%	13%	25%	2%
	Lebanon	37	17	70	25	42	22	61	24	31	19	73	26	35	20	68	26	44	21	55	29
		25%	11%	47%	17%	28%	15%	41%	16%	21%	13%	49%	17%	23%	13%	46%	17%	30%	14%	37%	19%
	Kuwait	70	7	93	2	82	6	82	2	77	9	82	4	86	9	75	2	85	8	77	2
		41%	4%	54%	1%	48%	3%	48%	1%	45%	5%	48%	2%	50%	5%	44%	1%	49%	5%	45%	1%
	China	18	12	16	0	12	12	22	0	12	10	24	0	35	2	9	0	32	3	11	0
		39%	26%	35%	0%	26%	26%	48%	0%	26%	22%	52%	0%	76%	4%	20%	0%	70%	7%	24%	0%
In NSW	yes	299	271	458	236	270	263	499	232	308	248	469	239	339	203	486	236	423	181	428	232
		24%	21%	36%	19%	21%	21%	39%	18%	24%	20%	37%	19%	27%	16%	38%	19%	33%	14%	34%	18%
	no	290	133	422	85	303	149	392	86	274	161	401	94	355	96	391	88	395	94	352	89
		31%	14%	45%	9%	33%	16%	42%	9%	29%	17%	43%	10%	38%	10%	42%	9%	42%	10%	38%	10%

Table A3. A representative sample (from 10 images) of the Image segmentation results using PSPNet (percentile) segmentation and R—CNN (quantity) segmentation.

[illegible]

Table A4. The 174 images used in the survey ranked from best to worst based on Pareto dominance. The PSP results (and some RCNN result) are presented for each image. Each column is colour coded using a gradient from white (lowest value) to dark green (highest value).

Image ID	Wall	Building	Sky	Tree	Road	Sidewalk	Person	Person (RCNN)	Car	Car (RCNN)	Signboard	Streetlight	Bicycle	Grass	Plant	Bus	Chair
29	0.0%	25.3%	2.7%	33.6%	0.0%	35.1%	2.0%	5	0.0%	0	1.8%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%
6	0.1%	35.0%	4.3%	8.9%	0.0%	31.7%	10.0%	15	0.2%	0	0.0%	0.3%	0.0%	0.0%	4.0%	0.0%	0.4%
160	2.1%	25.0%	1.0%	31.9%	0.0%	5.7%	2.0%	8	0.0%	2	0.0%	0.0%	0.0%	1.1%	5.8%	0.0%	0.0%
35	0.8%	32.6%	5.7%	19.1%	0.0%	19.5%	0.0%	0	0.0%	0	0.8%	0.1%	0.0%	0.0%	18.3%	0.0%	0.0%
90	0.3%	19.3%	3.2%	24.0%	0.0%	22.0%	1.0%	3	0.0%	0	0.3%	0.0%	0.0%	0.0%	10.0%	0.0%	0.7%
118	0.1%	26.7%	10.3%	10.7%	0.0%	25.8%	0.0%	2	0.0%	0	0.0%	0.0%	0.0%	0.0%	11.4%	0.0%	2.3%
171	0.4%	52.7%	0.2%	3.5%	0.0%	24.7%	6.0%	12	0.0%	0	0.0%	0.1%	0.0%	0.0%	1.3%	0.0%	0.3%
146	0.0%	30.7%	1.3%	29.7%	0.4%	17.1%	0.0%	1	8.8%	4	0.0%	0.0%	0.0%	0.0%	5.0%	0.0%	0.0%
41	0.0%	34.5%	12.0%	14.6%	0.0%	30.9%	4.5%	7	0.0%	0	0.4%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%
19	0.0%	39.0%	0.2%	35.9%	3.0%	18.7%	0.1%	2	0.8%	4	0.2%	0.0%	0.1%	0.4%	1.6%	0.0%	0.0%
47	0.1%	39.9%	10.6%	13.5%	0.4%	24.2%	6.5%	17	0.4%	0	0.5%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
140	0.3%	4.3%	35.0%	17.4%	0.0%	2.0%	0.5%	2	0.0%	0	0.0%	0.0%	0.0%	3.9%	0.0%	0.0%	0.0%
130	0.0%	41.7%	7.4%	5.9%	0.0%	30.9%	4.8%	4	0.0%	0	0.0%	0.4%	0.0%	0.0%	5.4%	0.0%	0.0%
173	0.7%	33.5%	1.0%	18.4%	1.8%	18.9%	1.2%	4	1.2%	2	0.2%	0.0%	0.0%	0.0%	6.5%	0.0%	6.8%
38	0.0%	46.6%	0.7%	19.6%	3.0%	27.8%	0.4%	6	0.4%	0	0.0%	0.3%	0.0%	0.0%	0.0%	0.0%	0.0%
77	0.4%	11.8%	25.4%	15.8%	4.7%	10.1%	0.0%	2	3.0%	5	0.0%	0.1%	0.0%	7.3%	19.1%	0.0%	0.0%
155	0.5%	3.2%	27.1%	23.1%	28.8%	0.4%	0.1%	1	3.2%	3	2.1%	0.1%	0.0%	5.4%	0.4%	0.0%	0.0%
149	0.0%	32.0%	7.2%	12.9%	0.0%	35.2%	4.7%	11	0.2%	0	0.0%	0.9%	0.0%	0.0%	2.5%	0.0%	0.0%
126	0.0%	9.1%	6.8%	45.6%	0.3%	22.1%	0.1%	7	2.4%	3	0.0%	0.0%	0.0%	2.1%	6.1%	0.0%	0.0%
122	0.0%	51.6%	2.4%	7.0%	5.0%	27.4%	3.9%	9	0.0%	0	0.1%	0.0%	0.0%	0.0%	0.0%	0.5%	0.0%
66	0.0%	26.9%	13.9%	15.1%	0.0%	34.0%	0.8%	7	0.0%	0	0.0%	0.0%	0.0%	0.0%	1.2%	0.0%	3.0%
14	6.5%	5.2%	17.8%	30.9%	0.3%	20.2%	0.0%	0	5.2%	6	0.3%	0.2%	0.1%	3.4%	3.2%	0.0%	0.0%
34	0.0%	49.5%	4.8%	1.3%	0.0%	36.2%	3.7%	7	0.1%	0	1.5%	0.2%	0.0%	0.0%	1.0%	0.0%	0.0%
157	0.1%	43.2%	5.6%	21.6%	6.3%	11.7%	0.0%	0	6.7%	3	0.0%	0.0%	0.0%	0.0%	1.6%	0.0%	0.0%
152	0.0%	0.5%	18.5%	33.5%	3.7%	0.2%	0.0%	0	0.7%	2	0.0%	0.0%	0.0%	9.1%	14.5%	0.0%	0.0%
8	0.1%	45.3%	0.0%	6.9%	0.0%	30.4%	5.9%	9	0.1%	0	0.0%	0.0%	0.0%	0.6%	0.0%	0.0%	1.4%
161	0.0%	48.7%	4.6%	3.6%	0.0%	34.4%	6.2%	9	0.0%	0	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	1.3%
59	0.2%	22.4%	19.8%	1.2%	17.6%	14.8%	0.0%	0	0.0%	0	0.0%	0.2%	0.0%	0.4%	7.4%	0.0%	2.4%
84	3.9%	46.7%	0.5%	8.2%	6.2%	24.0%	6.6%	6	0.1%	0	1.3%	0.0%	0.0%	0.0%	0.0%	1.8%	0.0%
113	3.8%	1.8%	3.0%	45.6%	0.0%	2.1%	0.0%	0	2.2%	1	0.0%	0.0%	0.0%	0.0%	9.6%	0.0%	0.0%
150	0.0%	29.9%	4.8%	21.7%	0.0%	36.9%	1.7%	9	0.2%	0	2.7%	0.2%	0.0%	0.0%	0.9%	0.0%	0.0%
28	0.1%	2.0%	11.4%	41.6%	15.2%	2.9%	0.4%	3	1.8%	3	1.4%	0.3%	0.0%	4.2%	1.7%	0.0%	0.0%
154	0.0%	19.5%	4.0%	37.7%	7.1%	9.6%	0.1%	1	12.0%	6	1.3%	0.0%	0.0%	8.5%	0.0%	0.0%	0.0%
32	0.2%	6.2%	18.3%	28.3%	0.0%	0.2%	0.5%	3	0.0%	0	0.0%	0.0%	0.0%	6.8%	8.3%	0.0%	0.0%
131	0.0%	47.0%	0.7%	21.1%	0.1%	20.0%	7.1%	8	0.3%	0	1.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
80	0.0%	0.3%	25.8%	24.8%	11.0%	16.8%	0.0%	0	0.0%	1	0.3%	0.0%	0.0%	13.6%	0.0%	0.0%	0.0%
49	0.5%	52.6%	0.0%	1.8%	0.5%	17.1%	6.7%	5	0.6%	0	0.0%	0.0%	0.0%	0.0%	2.6%	0.0%	0.0%
172	0.2%	0.1%	20.3%	32.3%	7.7%	1.3%	0.0%	0	1.8%	3	0.0%	0.0%	0.0%	15.3%	3.9%	0.0%	0.0%

Table A4. Cont.

Image ID	Wall	Building	Sky	Tree	Road	Sidewalk	Person	Person (RCNN)	Car	Car (RCNN)	Signboard	Streetlight	Bicycle	Grass	Plant	Bus	Chair
81	0.0%	27.7%	18.1%	6.6%	0.8%	27.1%	1.0%	4	3.6%	5	4.3%	0.0%	0.0%	0.0%	3.0%	0.0%	0.0%
88	0.3%	0.5%	6.8%	52.1%	0.1%	0.0%	0.0%	0	6.8%	3	0.0%	0.0%	0.0%	10.2%	4.7%	0.0%	0.0%
11	2.7%	35.4%	9.9%	0.0%	0.0%	47.3%	1.1%	4	0.0%	0	0.1%	0.0%	0.0%	0.0%	0.0%	1.9%	0.0%
25	0.2%	36.6%	4.5%	19.5%	15.7%	13.7%	2.0%	2	5.5%	5	0.0%	0.0%	0.0%	0.0%	0.6%	0.0%	0.0%
142	0.0%	2.7%	34.2%	18.2%	9.8%	18.1%	0.0%	0	0.3%	2	1.2%	0.0%	0.0%	10.1%	4.1%	0.0%	0.0%
165	0.0%	48.3%	5.7%	18.7%	0.0%	9.9%	0.0%	0	5.2%	2	0.0%	0.0%	0.0%	0.0%	11.8%	0.0%	0.0%
89	0.0%	56.7%	7.9%	0.7%	7.2%	11.1%	0.0%	0	1.8%	1	0.1%	0.0%	0.0%	0.0%	14.4%	0.0%	0.0%
158	0.9%	15.1%	3.9%	36.4%	5.3%	12.9%	0.0%	1	10.1%	3	0.2%	0.0%	0.0%	8.8%	3.2%	0.0%	0.0%
164	12.1%	34.2%	1.9%	26.9%	6.8%	11.8%	0.3%	4	0.9%	4	1.2%	0.0%	0.0%	0.0%	0.6%	0.0%	0.0%
102	0.9%	10.4%	7.0%	22.8%	2.5%	45.8%	0.0%	0	0.3%	2	0.0%	0.2%	0.0%	0.0%	5.9%	1.2%	0.0%
51	0.0%	7.6%	34.9%	3.5%	11.7%	7.1%	1.4%	1	2.3%	3	0.0%	0.1%	0.0%	21.5%	4.4%	0.0%	0.0%
23	0.0%	34.9%	3.5%	19.9%	4.2%	26.4%	7.5%	7	0.9%	4	1.6%	0.4%	0.0%	0.0%	0.0%	0.0%	0.0%
61	0.1%	30.6%	22.6%	6.5%	1.7%	22.3%	0.7%	2	0.2%	1	4.3%	0.0%	0.0%	0.1%	5.9%	0.0%	0.0%
2	5.8%	4.6%	12.0%	40.2%	4.4%	16.8%	0.0%	0	1.3%	2	0.0%	0.0%	0.0%	8.3%	6.4%	0.3%	0.0%
106	0.3%	21.5%	25.4%	9.9%	3.5%	26.0%	0.0%	0	0.1%	1	0.0%	0.0%	0.0%	0.2%	8.3%	0.0%	0.0%
151	0.1%	14.1%	6.8%	35.8%	8.9%	13.6%	0.0%	0	5.0%	4	0.0%	0.0%	0.0%	0.0%	7.7%	0.0%	0.0%
60	4.2%	8.5%	32.0%	18.9%	0.1%	5.2%	0.0%	2	2.8%	3	0.0%	0.0%	0.0%	13.0%	11.7%	0.0%	0.0%
109	2.1%	28.6%	25.6%	8.6%	0.1%	23.2%	1.1%	1	0.2%	0	0.0%	0.5%	0.0%	0.0%	8.7%	0.0%	0.0%
33	0.2%	13.4%	16.1%	31.9%	0.5%	24.7%	0.1%	3	0.3%	0	0.0%	0.0%	0.0%	12.0%	0.0%	0.4%	0.0%
68	0.0%	16.9%	4.3%	43.0%	6.1%	20.9%	0.6%	3	0.7%	2	0.8%	0.0%	0.0%	0.0%	5.2%	0.0%	0.0%
31	7.2%	35.0%	2.0%	25.2%	1.4%	9.5%	0.0%	0	4.5%	5	0.1%	0.0%	0.0%	0.0%	13.9%	0.0%	0.0%
44	2.0%	0.3%	39.6%	15.8%	4.1%	33.4%	0.0%	0	0.0%	0	0.0%	0.1%	0.0%	1.4%	3.1%	0.0%	0.0%
123	4.8%	34.1%	22.3%	4.4%	5.9%	14.1%	0.0%	0	1.5%	3	0.0%	0.1%	0.0%	10.0%	0.0%	0.0%	0.0%
162	0.1%	18.6%	30.9%	12.5%	4.5%	1.2%	0.0%	1	0.4%	1	0.0%	0.0%	0.0%	25.1%	0.2%	0.0%	0.0%
132	1.2%	33.7%	3.4%	23.5%	2.6%	15.1%	0.1%	1	9.7%	2	0.0%	0.0%	0.0%	0.0%	3.1%	0.0%	0.0%
12	0.0%	37.6%	6.1%	10.0%	2.5%	31.8%	2.2%	9	0.3%	0	6.1%	0.0%	0.2%	0.0%	0.0%	0.0%	0.0%
40	0.0%	22.6%	36.7%	0.8%	5.6%	7.7%	0.0%	0	3.0%	3	0.0%	0.0%	0.0%	9.7%	8.4%	0.0%	0.0%
5	0.1%	20.4%	18.4%	12.6%	22.7%	5.5%	1.0%	5	2.4%	4	4.4%	0.0%	0.1%	0.2%	0.8%	0.0%	0.3%
108	0.0%	5.8%	22.6%	23.4%	7.1%	0.0%	0.0%	0	0.0%	1	0.0%	0.1%	0.0%	10.2%	0.7%	0.0%	0.0%
20	0.0%	68.8%	1.0%	1.3%	7.5%	17.3%	1.9%	3	2.3%	2	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
116	0.0%	15.2%	40.0%	2.3%	23.3%	5.2%	0.3%	1	2.4%	4	0.7%	0.4%	0.0%	0.0%	7.2%	0.0%	0.0%
125	6.7%	11.5%	20.0%	18.5%	0.6%	9.9%	0.0%	0	1.9%	4	0.0%	0.0%	0.0%	0.8%	29.4%	0.0%	0.0%
76	3.6%	8.9%	10.6%	39.1%	6.2%	0.0%	0.0%	0	8.4%	3	0.0%	0.0%	0.0%	0.0%	13.6%	0.0%	0.0%
170	0.0%	4.5%	7.7%	41.8%	1.5%	14.0%	0.0%	0	2.8%	3	1.2%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%
97	0.0%	7.2%	4.7%	28.1%	8.6%	28.8%	0.0%	1	0.6%	0	0.1%	0.1%	0.3%	0.0%	20.3%	0.0%	0.0%
85	2.4%	19.7%	16.9%	11.5%	11.0%	17.5%	0.0%	0	1.2%	4	4.5%	0.0%	0.0%	1.6%	0.2%	0.0%	0.0%
101	9.5%	30.9%	6.7%	12.7%	0.0%	23.0%	0.0%	0	0.0%	0	0.0%	0.1%	1.2%	0.7%	15.2%	0.0%	0.0%
18	3.0%	7.9%	10.8%	8.8%	10.1%	4.6%	1.2%	2	3.7%	3	6.0%	0.0%	0.0%	0.0%	0.0%	0.0%	1.1%
58	0.0%	20.3%	35.7%	2.3%	13.8%	8.2%	0.0%	0	8.9%	6	0.0%	0.5%	0.0%	0.0%	9.9%	0.0%	0.0%
120	3.7%	2.1%	3.9%	49.8%	0.4%	11.6%	0.0%	2	2.2%	2	0.0%	0.0%	0.0%	0.0%	7.0%	0.0%	0.0%

Table A4. Cont.

Image ID	Wall	Building	Sky	Tree	Road	Sidewalk	Person	Person (RCNN)	Car	Car (RCNN)	Signboard	Streetlight	Bicycle	Grass	Plant	Bus	Chair
45	0.9%	32.4%	0.1%	29.2%	7.6%	8.6%	3.0%	3	2.8%	3	1.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.2%
147	0.0%	7.6%	1.6%	55.1%	6.4%	8.1%	0.2%	0	4.7%	5	0.0%	0.0%	0.0%	0.0%	0.3%	0.0%	0.0%
121	9.0%	20.3%	20.7%	0.7%	9.4%	7.8%	0.8%	3	0.2%	1	0.5%	0.0%	0.0%	6.5%	4.8%	0.0%	0.0%
168	0.0%	36.2%	2.9%	29.3%	7.6%	0.3%	0.1%	1	1.7%	3	0.0%	0.0%	0.0%	0.0%	9.2%	0.0%	0.0%
141	0.5%	35.9%	7.6%	19.5%	9.8%	15.0%	0.0%	1	1.4%	2	0.0%	0.4%	0.0%	0.0%	0.0%	0.0%	0.0%
53	23.5%	17.1%	0.1%	28.1%	8.0%	12.5%	0.1%	1	8.3%	2	0.8%	0.0%	0.0%	0.0%	1.0%	0.0%	0.0%
16	1.5%	35.7%	0.6%	26.4%	9.0%	21.4%	0.0%	0	0.7%	2	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
138	0.0%	17.5%	27.9%	17.8%	27.6%	3.8%	0.0%	0	1.8%	3	0.3%	0.0%	0.0%	0.1%	2.6%	0.0%	0.0%
100	0.0%	0.5%	18.7%	36.3%	10.8%	21.7%	0.0%	0	0.1%	0	0.2%	0.0%	0.0%	4.7%	2.6%	0.9%	0.0%
9	10.7%	24.3%	4.2%	14.9%	1.3%	10.8%	0.0%	1	12.5%	3	0.2%	0.7%	0.0%	0.0%	9.7%	0.0%	0.0%
39	0.0%	35.7%	10.1%	10.7%	7.3%	34.5%	0.8%	8	0.0%	0	0.1%	0.2%	0.0%	0.0%	0.0%	0.0%	0.0%
91	2.9%	49.1%	0.2%	0.1%	3.0%	26.0%	5.0%	11	0.0%	0	0.8%	0.0%	0.0%	0.0%	0.9%	5.5%	0.0%
21	0.0%	8.9%	30.3%	6.7%	15.5%	10.8%	0.0%	0	1.4%	6	0.4%	0.1%	0.0%	8.7%	1.9%	0.0%	0.0%
111	1.7%	20.6%	34.8%	4.1%	11.2%	0.7%	0.0%	1	1.5%	1	0.3%	0.2%	0.0%	6.0%	11.2%	0.0%	0.0%
71	0.0%	25.2%	27.7%	3.5%	14.2%	14.7%	0.0%	0	2.0%	5	0.1%	0.6%	0.0%	0.0%	9.7%	0.0%	0.0%
50	0.2%	45.1%	1.8%	7.4%	16.7%	21.8%	0.1%	1	4.5%	5	2.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%
65	0.0%	51.9%	2.9%	6.3%	5.9%	28.4%	3.5%	8	0.4%	2	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%
37	0.0%	17.8%	3.3%	40.9%	3.5%	5.0%	0.0%	0	1.9%	2	0.4%	0.0%	0.0%	11.4%	5.1%	0.0%	0.0%
15	2.7%	13.6%	9.9%	43.3%	0.0%	22.4%	0.1%	1	0.1%	1	0.1%	0.0%	0.0%	5.9%	0.3%	0.0%	0.0%
110	0.0%	32.4%	3.9%	18.8%	3.2%	38.9%	0.0%	0	0.4%	1	0.7%	0.2%	0.0%	0.0%	1.1%	0.3%	0.0%
133	0.0%	27.3%	9.4%	21.4%	5.1%	23.3%	0.0%	0	1.2%	3	0.0%	0.0%	0.0%	1.7%	1.7%	0.0%	0.5%
119	3.4%	1.8%	14.5%	48.9%	0.5%	6.0%	0.3%	1	2.5%	3	0.0%	0.0%	0.0%	19.8%	0.0%	0.0%	0.0%
135	1.6%	5.3%	15.5%	31.3%	9.8%	6.8%	0.0%	0	0.7%	4	0.0%	0.0%	0.0%	4.9%	7.1%	0.0%	0.0%
115	3.4%	16.2%	34.0%	7.8%	3.7%	0.6%	0.0%	0	1.1%	1	0.2%	0.1%	0.0%	20.0%	2.8%	0.0%	0.0%
99	1.0%	2.0%	17.1%	38.6%	13.4%	1.0%	0.0%	0	0.3%	1	0.0%	0.0%	0.0%	12.5%	0.0%	0.0%	0.0%
159	0.0%	18.7%	6.8%	25.6%	10.0%	32.7%	0.4%	1	2.6%	6	0.0%	0.2%	0.0%	0.0%	1.2%	0.0%	0.0%
143	0.5%	11.9%	8.7%	39.6%	1.6%	16.8%	0.3%	2	5.1%	4	0.0%	0.0%	0.0%	0.0%	0.4%	0.0%	0.0%
86	0.0%	27.8%	8.9%	28.1%	6.5%	21.0%	0.0%	0	0.5%	1	0.0%	0.1%	0.4%	0.0%	5.4%	0.0%	0.0%
139	2.5%	6.0%	16.1%	39.3%	3.9%	0.0%	0.0%	0	3.0%	4	0.0%	0.0%	0.0%	3.0%	3.1%	0.0%	0.0%
144	0.0%	10.0%	11.6%	43.8%	4.7%	0.1%	0.0%	0	0.1%	1	0.0%	0.0%	0.0%	23.9%	0.0%	0.0%	0.0%
7	0.0%	2.9%	34.5%	14.5%	15.5%	8.8%	0.0%	0	3.8%	1	0.0%	0.0%	0.0%	1.8%	9.7%	0.0%	0.0%
105	0.0%	40.5%	12.6%	10.0%	1.2%	18.5%	0.0%	0	4.3%	3	0.0%	0.0%	0.0%	9.5%	1.3%	0.0%	0.0%
55	0.0%	55.2%	5.6%	0.3%	7.8%	21.6%	0.2%	4	5.3%	2	2.2%	0.5%	0.0%	0.0%	0.0%	0.0%	0.0%
27	0.0%	28.5%	13.5%	11.8%	19.3%	24.9%	0.1%	1	0.0%	0	0.3%	0.2%	0.0%	0.0%	0.0%	0.0%	0.0%
93	0.0%	1.4%	22.8%	30.4%	7.3%	3.1%	0.0%	0	1.0%	2	0.0%	0.0%	0.0%	16.8%	0.1%	0.0%	0.0%
114	0.0%	3.2%	29.1%	24.3%	11.6%	1.7%	0.0%	0	0.2%	2	0.3%	0.0%	0.0%	21.3%	0.1%	0.0%	0.0%
43	0.0%	42.9%	3.1%	22.6%	7.0%	9.4%	0.5%	2	0.5%	2	1.0%	0.0%	0.0%	0.0%	4.7%	0.0%	0.0%
163	0.0%	1.1%	30.9%	27.6%	12.4%	1.6%	0.0%	0	0.3%	2	0.5%	0.0%	0.0%	17.7%	0.3%	0.0%	0.0%
98	3.9%	4.6%	10.0%	41.9%	1.8%	5.8%	0.1%	0	8.8%	6	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%
67	4.5%	15.1%	3.0%	33.4%	8.7%	11.9%	0.0%	0	3.6%	5	0.0%	0.0%	0.0%	0.0%	19.4%	0.0%	0.0%
73	0.3%	26.9%	20.5%	5.9%	0.0%	1.6%	0.0%	0	0.5%	2	0.0%	0.0%	0.0%	5.3%	28.4%	0.0%	0.0%

Table A4. Cont.

Image ID	Wall	Building	Sky	Tree	Road	Sidewalk	Person	Person (RCNN)	Car	Car (RCNN)	Signboard	Streetlight	Bicycle	Grass	Plant	Bus	Chair
1	0.0%	23.0%	28.2%	1.0%	7.1%	10.3%	0.0%	0	2.0%	2	0.0%	0.1%	0.0%	8.7%	17.8%	0.0%	0.0%
10	2.7%	31.0%	1.8%	25.8%	0.9%	14.8%	0.1%	0	2.9%	2	0.0%	0.0%	0.0%	0.0%	18.7%	0.0%	0.0%
63	0.0%	42.9%	13.1%	10.1%	5.3%	26.6%	0.0%	0	0.3%	2	0.0%	0.1%	0.0%	0.0%	0.3%	0.0%	0.0%
0	0.0%	39.1%	13.8%	14.1%	26.2%	4.5%	0.5%	3	1.5%	3	0.3%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
124	0.0%	0.7%	12.2%	47.5%	4.7%	0.0%	0.0%	0	0.4%	1	0.0%	0.0%	0.0%	25.6%	2.8%	0.0%	0.0%
52	0.0%	54.9%	12.5%	7.7%	10.0%	11.1%	1.0%	4	2.5%	7	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
112	0.0%	28.3%	11.2%	22.8%	6.9%	24.0%	0.0%	0	1.8%	3	0.0%	0.0%	0.0%	0.0%	2.4%	0.0%	0.0%
137	0.4%	29.5%	4.6%	32.9%	12.8%	16.6%	0.0%	0	2.3%	2	0.0%	0.5%	0.0%	0.0%	0.0%	0.0%	0.0%
103	0.0%	25.0%	12.6%	11.1%	2.8%	33.9%	0.0%	0	0.5%	2	0.0%	0.1%	0.0%	0.0%	9.5%	0.7%	0.0%
104	1.9%	5.9%	33.6%	16.0%	8.5%	19.0%	0.0%	0	4.7%	7	0.1%	0.0%	0.0%	5.1%	0.0%	0.0%	0.0%
24	0.0%	46.5%	9.2%	15.3%	11.1%	10.2%	0.0%	0	2.8%	2	0.7%	0.5%	0.0%	0.0%	0.6%	0.0%	0.0%
134	0.0%	9.1%	7.9%	43.6%	12.8%	3.5%	0.3%	0	1.1%	4	0.0%	0.0%	0.0%	6.9%	5.3%	0.0%	0.0%
57	0.3%	40.0%	7.8%	25.8%	0.7%	12.4%	0.0%	1	12.4%	6	0.1%	0.0%	0.0%	0.0%	0.4%	0.0%	0.0%
94	0.0%	5.7%	25.6%	21.2%	7.5%	5.3%	0.0%	0	0.8%	4	1.1%	0.0%	0.0%	10.9%	7.6%	0.0%	0.0%
117	3.3%	33.3%	20.0%	2.8%	5.9%	19.4%	0.1%	0	3.4%	3	4.4%	0.1%	0.0%	0.0%	0.8%	0.0%	0.0%
87	0.0%	33.2%	16.6%	11.2%	0.2%	23.8%	0.1%	1	0.8%	3	0.0%	0.0%	0.0%	0.0%	14.1%	0.0%	0.0%
78	0.0%	34.5%	10.3%	13.0%	0.1%	23.4%	0.1%	2	3.9%	5	2.3%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
129	0.0%	3.0%	30.6%	25.9%	6.8%	0.0%	0.0%	0	1.6%	2	0.0%	0.0%	0.0%	22.0%	0.0%	0.0%	0.0%
4	0.6%	0.5%	26.7%	20.8%	8.6%	21.0%	0.0%	0	0.1%	0	0.3%	0.1%	0.0%	12.3%	2.7%	0.0%	0.0%
145	0.0%	40.1%	1.4%	30.4%	2.8%	14.3%	0.0%	0	10.6%	5	0.2%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
79	0.6%	5.7%	37.9%	8.7%	7.1%	1.0%	0.0%	0	0.2%	1	0.0%	0.2%	0.0%	20.8%	0.9%	0.0%	0.0%
74	0.0%	32.1%	18.3%	0.3%	14.1%	18.7%	0.0%	1	1.3%	4	0.0%	0.1%	0.0%	3.8%	2.0%	0.0%	0.0%
75	1.2%	8.4%	33.0%	10.8%	2.9%	22.1%	0.0%	0	6.3%	3	0.0%	0.0%	0.0%	5.9%	6.4%	0.0%	0.0%
95	0.0%	24.0%	15.9%	20.3%	13.6%	24.4%	0.0%	0	0.2%	0	0.0%	0.0%	0.0%	0.0%	1.2%	0.0%	0.0%
148	0.0%	46.7%	4.0%	15.0%	7.0%	21.7%	0.3%	3	2.6%	2	1.9%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
42	0.1%	2.0%	18.8%	26.9%	8.1%	25.8%	0.0%	0	2.1%	4	0.4%	0.2%	0.0%	8.9%	2.3%	0.0%	0.0%
128	0.0%	8.9%	18.7%	25.5%	8.8%	6.1%	0.0%	0	2.9%	3	0.0%	0.1%	0.0%	20.9%	0.0%	0.0%	0.0%
153	0.7%	3.1%	25.8%	28.5%	16.0%	21.0%	0.0%	0	1.8%	5	0.0%	0.0%	0.0%	0.5%	1.4%	0.0%	0.0%
48	0.0%	29.1%	30.6%	1.1%	7.5%	23.6%	0.0%	0	1.4%	3	0.6%	0.2%	0.0%	1.6%	3.7%	0.0%	0.0%
64	17.5%	15.8%	15.6%	2.0%	5.4%	24.2%	0.0%	0	7.2%	3	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
69	0.0%	35.9%	11.3%	10.8%	18.6%	22.8%	0.0%	1	0.0%	0	0.0%	0.2%	0.0%	0.0%	0.4%	0.0%	0.0%
82	0.4%	4.2%	16.8%	31.8%	7.1%	6.3%	0.0%	1	6.4%	3	0.0%	0.4%	0.0%	16.8%	0.0%	0.0%	0.0%
127	0.5%	3.9%	32.3%	19.1%	10.7%	3.4%	0.0%	0	0.5%	2	0.0%	0.0%	0.0%	13.3%	6.4%	0.0%	0.0%
136	0.0%	2.3%	30.8%	24.1%	16.6%	7.2%	0.0%	0	2.4%	3	0.1%	0.0%	0.0%	15.1%	0.0%	0.0%	0.0%
54	0.0%	32.0%	6.0%	24.8%	13.5%	21.4%	0.0%	1	1.5%	2	0.0%	0.0%	0.0%	0.3%	0.0%	0.0%	0.0%
26	1.3%	10.1%	5.4%	40.4%	4.3%	8.4%	0.0%	0	2.2%	4	0.1%	0.0%	0.0%	0.2%	15.5%	0.0%	0.0%
167	0.0%	17.6%	19.4%	19.4%	11.4%	21.3%	0.0%	0	2.6%	3	0.1%	0.0%	0.0%	0.2%	3.1%	0.0%	0.0%
107	8.6%	4.8%	40.0%	5.1%	1.0%	0.0%	0.0%	0	4.2%	5	1.3%	0.0%	0.0%	21.2%	0.7%	0.0%	0.0%
156	0.0%	45.6%	6.2%	20.3%	0.3%	4.5%	0.0%	1	10.4%	4	1.9%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
17	1.7%	15.1%	41.1%	0.4%	15.8%	14.8%	0.0%	0	0.0%	0	0.0%	0.0%	0.0%	7.4%	0.9%	0.0%	0.0%
96	1.4%	5.3%	27.4%	17.5%	12.1%	5.4%	0.0%	0	2.2%	6	0.0%	0.0%	0.0%	14.5%	3.8%	0.0%	0.0%

Table A4. Cont.

Image ID	Wall	Building	Sky	Tree	Road	Sidewalk	Person	Person (RCNN)	Car	Car (RCNN)	Signboard	Streetlight	Bicycle	Grass	Plant	Bus	Chair
72	0.0%	35.4%	15.3%	10.5%	12.4%	25.2%	0.0%	1	0.4%	1	0.0%	0.3%	0.0%	0.0%	0.5%	0.0%	0.0%
13	0.0%	69.7%	1.5%	0.4%	5.4%	21.4%	0.3%	3	0.0%	0	0.7%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
22	0.2%	2.6%	27.0%	13.5%	9.7%	3.1%	0.0%	0	6.1%	4	0.3%	0.0%	0.0%	5.5%	5.1%	0.0%	0.0%
70	0.0%	7.7%	33.8%	16.6%	5.2%	24.2%	0.0%	0	1.9%	4	1.2%	0.0%	0.0%	0.0%	8.8%	0.0%	0.0%
36	0.0%	58.8%	8.9%	0.0%	3.2%	15.5%	0.4%	2	12.5%	6	0.5%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
92	0.0%	23.3%	20.2%	14.5%	0.1%	27.0%	0.1%	1	5.2%	4	6.7%	0.2%	0.0%	0.0%	0.0%	0.0%	0.0%
62	0.2%	23.6%	22.5%	10.5%	3.7%	24.3%	0.0%	1	1.2%	1	3.5%	0.3%	0.0%	0.0%	9.4%	0.1%	0.0%
30	2.2%	19.4%	34.5%	2.6%	9.7%	15.7%	0.0%	1	0.0%	0	0.0%	0.0%	0.0%	3.9%	0.9%	0.0%	0.0%
46	1.8%	12.5%	37.4%	7.7%	16.2%	16.2%	0.0%	0	0.4%	3	0.0%	0.3%	0.0%	6.4%	1.1%	0.0%	0.0%
3	5.4%	7.6%	20.4%	20.8%	3.5%	15.0%	0.0%	1	0.2%	1	0.0%	0.1%	0.0%	8.2%	2.7%	0.0%	0.0%
166	1.0%	5.5%	37.7%	2.1%	18.8%	17.6%	0.0%	0	4.7%	11	0.0%	0.1%	0.0%	3.4%	0.9%	0.0%	0.0%
83	0.0%	30.2%	25.5%	0.1%	13.3%	11.2%	0.0%	0	2.3%	2	1.2%	0.0%	0.0%	6.8%	0.8%	0.0%	0.0%
169	0.0%	10.0%	1.7%	43.7%	22.9%	7.6%	0.0%	1	1.3%	1	0.0%	0.0%	0.0%	3.5%	0.0%	0.0%	0.0%
56	4.5%	5.6%	18.8%	25.8%	17.8%	13.4%	0.0%	0	2.0%	2	0.0%	0.1%	0.0%	8.1%	0.0%	0.0%	0.0%

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