Investigating associations between built environments and cycling behaviour using street view imagery and Strava Metro data: A case study in City of Sydney, Australia

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Abstract. Cycling, recognized as a healthy and environmentally beneficial mode of active transport, has gained widespread acceptance and become increasingly popular. Its prevalence is profoundly influenced by the built environment, highlighting an emerging need to explore the associations between built environment factors and cycling behaviour. With the advancement of artificial intelligence, an increasing number of scholars assess the perception of the built environment using street view imagery (SVI), analysing these perceptions in conjunction with survey data. However, the usage of real-world cycling data in assessing the built environment remains limited. In our study, we explore the relationship between the built environment and cycling behaviour by correlating image segmentation analysis results of SVI from the City of Sydney with real-world cycling data from Strava Metro Data (SMD). A multivariate Poisson regression model was applied for this research. Research findings indicate a positive correlation between cycling frequency and factors such as street greenness, presence of bike lane, traffic lights, and on-street parking, while cycling frequency is negatively associated with sky openness, enclosure, street curbs, and traffic sign frame. Therefore, to build a better cycling-friendly city, urban planners and designers should focus on factors that encourage cycling and positively influence cycling behaviour. Moreover, the novel and reliable approach of integrating SVI with real-world cycling data has potential for measuring eye-level built environments in future cycling-friendly city studies.

Keywords: cycling behaviour; street view imagery; built environment; Strava Metro data.

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adfa, p. 1, 2011.

1 Introduction

Urban development dominated by automobiles is increasingly exacerbating climate changes. Concepts such as walkable cities (Southworth, 2005a) and 15-minute living circles (Shanghai Planning and Land Resources Administration, 2016) have been proposed to encourage sustainable mobility. The objective of these concepts is not only to bring positive health benefits to individuals but also to reduce carbon footprints and mitigate global warming. Cycling, as a mode of green transportation, obtained more attention in recent years, both in developed and developing countries. It plays an important role on promoting human well-being and constructing sustainable cities, as it not only benefits on risk reduction of diseases such as diabetes, cardiovascular and certain cancers, but also alleviates urban traffic congestion and minimizes air pollution (Lee et al., 2012). Nevertheless, according to WHO (2010), there has been a significant decline in cycling rates in developing countries over the past few decades, attributed to urbanization, and rates continues to be low in developed nations. Therefore, promoting active transport such as cycling has become an essential approach when adopting green and sustainable city development agenda.

Cycling behaviour is influenced by many factors, including sociodemographic characteristics, meteorological conditions, air quality, and physical built environment is considered as one of the most essential aspects. Many scholars have reached a consensus on this issue, asserting that it can provide insights for urban design and planning policies, thereby promoting the construction of cycle-friendly cities (Lu et al., 2019). For instance, Bai et al. (2023) analysed the impact of built environment factors on cycling behaviour in urban greenways, revealing that street-level greening are positively correlated with cycling frequency. Yang et al. (2019) demonstrated that the presence of cycling infrastructure is a related built environment factor affecting cycling behaviour. While many studies have explored the impact of the built environment on cycling behaviour, comprehensive research examining the relationship from the perspective of street-scale environmental factors is scarce. Most studies either explore the impact of one or a few street environmental factors on cycling behaviour or use large-scale factors such as vegetation cover, land use, and architectural design (Bai et al., 2023). In this study, 23 street environment features are extracted from SVI to comprehensively explore the associations between these features and cycling behaviour. We aim to answer the following research question: what are the associations between built environment characteristics and cycling behaviour? How can we further improve cycling frequency and experience in the urban renewal process based on this information?

2 Literature review

2.1 Street view images in urban cycling research

Urban cycling research has increasingly been accorded paramount attention among the public and governments. Many studies are dedicated to developing urban bikeability scores to assess the construction of cycling-friendly cities, while pyramids of studies focus on exploring the relationship between the built environment and cycling behaviour (Koh and Wong, 2013; Tran et al., 2020). The use of Geographic Information System (GIS), in conjunction with census data and government open-source geographic information such as land-use data and Normalized Difference Vegetation Index（NDVI), has become prevalent in pinpointing objective measures of built environment (Yang et al., 2019). However, the use of such meso-scale data leads to limitations in the scale of research. Recent advancements in computer vision technologies, coupled with the extensive increase in the spatial coverage of SVI, have gradually contributed to the field in urban mobility (Ito and Biljecki, 2021). In these studies, only a few environmental factors derived from SVI are considered, often combined with other meso-scale data for cycling assessments. For instance, Tran et al. (2020) used only three out of twelve environmental factors derived from SVI, and although Gu et al. (2018) relied solely on SVI for data source, which only examined three environmental factors from SVI for consideration with urban bikeability. Most previous research has combined perceptual data collected from interviews or questionnaires with built environment factors to explore the relationship between cycling behaviour and environmental factors, as they are widely used methods to gather human's perceptual data (Yang et al., 2019). However, it is notable that the disadvantages of interviews and questionnaires, such as time-consuming, labor-intensive, and the limitations on small sample sizes, can adversely affect the research outcomes.

2.2 Objective & Subjective Measures

Numerous studies have delved into urban walkability and bikeability by analysing the objective factors of the built environment (Winters et al., 2016). Objective factors refer to the permanently present elements within the static street environment. The status quo of street infrastructure has been utilized in many previous studies and is considered as a significant objective factor in exploring cycling behaviour (Arellana et al., 2020; Cain et al., 2018). Cain et al. (2018) revealed that the quality of built environment, such as the presence of bicycle facilities and sidewalks, significantly impacts human's physical activity behaviour. Arellana et al. (2020) considered nine factors related to street facility construction, including the presence of bike lanes, sidewalks, curbs, trees, and others, to develop an index for assessing urban bikeability. Additionally, subjective factors, typically referring to individuals' perceptions of their environment, also play a crucial role in the study of urban mobility. Most research integrates subjective with objective factors to investigate cycling behaviour (Koh and Wong, 2013). As mentioned in the previous section, this non-observation data is usually collected through time-consuming interviews and questionnaires. However, in the study by Ito and Biljecki (2021), they demonstrated that data obtained solely from the SVI could be utilized to comprehensively assess urban bikeability from both subjective and objective perspectives. Moreover, urban greenness, spatial enclosure, and street congestion are three common subjective factors obtainable from SVI, which have been employed in numerous studies to evaluate human's perceptions of streets (Gu et al., 2018; Tran et al., 2020; Zhou et al., 2019).

2.3 Summary

In summary, there are notable gaps in urban cycling behaviour research that merit emphasis. Firstly, current research primarily focuses on correlational analysis using data collected from interviews and questionnaires with data from the SVI, with less exploration given to the integration of real-time cycling data. However, real-time cycling datasets, such as bike-sharing datasets and the Strava Metro Dataset (SMD), which contain more detailed data on bicycle usage frequency can enhance our understanding of built environment factors that influence cycling (Griffin and Jiao, 2015; Sun et al., 2017). Secondly, the majority of data derived from SVI represents only a minor portion of the environmental factors selected for previous studies, suggesting that the use of SVI is not yet exhaustive. Thirdly, Australia, exhibits a vibrant cycling culture with a sizable population of cyclists, complemented by its robust infrastructure and 'sunny climate'. While a few studies have utilized the Strava data to analyze urban cycling behavior in Australia, such research combining the active transport data with SVI to investigate the influence of built environment factors on cycling behavior in the country is relatively rare. Therefore, this pilot study aims to validate the built environment factors affecting cycling behaviour in the central area of Sydney, Australia, by utilizing real-time cycling frequency data from SMD and a more comprehensive set of subjective and objective environmental factors obtained solely from SVI. The study further explored whether different built environment factors impact cyclist behaviour for different cycling purposes, by comparing the associations on commute cyclist and those on leisure cyclist.

3 Methods and Materials

3.1 Study Area

The city of Sydney is located in the central core area of the Greater Sydney. According to Australia Bureau of Statistics (2022), This city encompasses an area of 2506.6 hectares and has a population of 224,331. As the CBD area of Sydney, nearly half of the top 500 companies have their main offices, and the headquarters for almost 80 percent of the international and national banks operating in Australia. The City of Sydney with the most complex road network and built environment is the busiest city in Australia. Therefore, the City of Sydney was selected for this pilot study.

3.2 Methodology

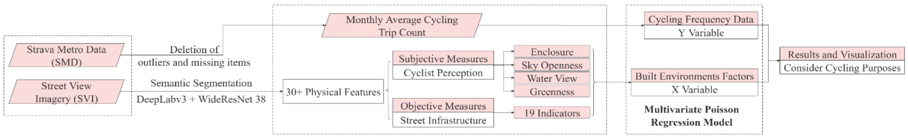


Fig. 1. Research framework and methodology

Firstly, this study used SVI as the only data source to evaluate 23 factors under two categories. Cyclist perception includes greenness, water view ratio, sky openness, and enclosure. Street infrastructure as objective measures consists of 19 indicators including bike lanes, bike rack, rail track, on-street parking, sidewalk, crosswalk, curb cuts, traffic lights, traffic sign, traffic sign frame, street lights, junction box, surveillance, potholes, manhole & catch basin, signage, banner, street amenities and utility pole & pole. At the meanwhile, for the SMD, missing and aberrant data were eliminated. Subsequently, we processed the cycling activity data into an average monthly cycling frequency, as we are unable to depict the distinct monthly scenarios and monthly variations using SVI. Finally, a Multivariate Poisson Regression model was applied to explore the associations between built environments and cycling behaviour.

3.3 Data collection

3.3.1 Street View Images Data

This study relies on the API of Google Street View (GSV) to retrieve information on SVI, as its widespread reach and superior quality across Australia. 11,618 SVI sampling points were generated with 50-m spacing along the street network in City of Sydney (data of street network were obtained from OpenStreetMap). For each location point, we could obtain unique panorama images by using GSV API. However, significant image distortion of panorama images can impact the segmentation results (Yu et al., 2019). Therefore, we collected images (640 x 640 pixels) with four headings of 0°, 90°, 180°, and 270° for each sample point and then merge them to mitigate this limitation. In this study, we collected 46,472 images from four directions and joint the images with 11,618 panorama images in total. After filtering out some irrelevant images, 9,301 panoramic street view images were subjected to image segmentation.

3.3.2 Strava Metro Data

The data of cycling frequency was obtained from Strava Metro Data (SMD). Strava (San Franciso, CA, USA) comprises both web-based and app-based formats to allow users to track their daily activities including, running, walking, cycling, etc. GPS enabled smartphone collect location points, time data, demographic data, and purposes of cycling that are subsequently aggregated as Big Data within SMD.

Currently, students and researchers worldwide have access to request cycling data from Strava free of charge. We have applied for and acquired the monthly cycling data of the year 2023 in the City of Sydney. This research contains aggregated and de-identified data from Strava Metro. Based on the descriptive analysis of the dataset (Table 1), there are total 24,502 road segments with 71,143,145 trips in the SMD in 2023. 66% of cycling journeys are undertaken for leisure purposes, while 34% are motivated by commuting needs. The majority of cycling activities are concentrated in the morning and evening, accounting for 58% and 23% of total journeys, while midday and overnight cycling trips together comprise only 19%. From a demographic perspective, 86% of cycling activity participants are male, with the primary age groups involved being those between 35 to 54 years old and 18 to 34 years old. In addition, after excluding cases lacking complete data for all twelve months, we conducted a temporal analysis (Fig. 2). It was noted that cycling activities progressively increased from January to March. A notable decline from April to July, marking the period with the lowest frequency of cycling activities within the year. This was followed by a steady resurgence in cycling frequency, despite a slight reduction observed in November.

Table 1. Descriptive Analysis of Strava cyclists data

Strava Metro Data of City of Syndey 2023				
Total Segment Count			24,502	
Total Trip Count			71,143,145	
Commute Trip Count			24,391,075	(34%)
Leisure Trip Count			46,792,780	(66%)
Trip Count by Time	Morning	Midday	Evening	Overnight
	58%	17%	23%	3%
Cycling Participation by Gender	Male	Female	Unspecified	
	86%	12%	2%	
Cycling Participation by Age	18-34	35-54	55-64	65+
	32%	51%	14%	4%

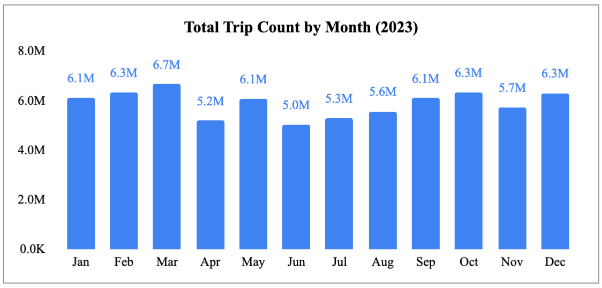


Fig. 2. shows the total trip count by month

4 Data Processing & Analysis

4.1 Information extraction from SVI

Deeplabv3 model pre-trained with ADE20K dataset is widely used by urban researcher for image semantic segmentation, as it can segment 150 categories, the most labels up to now (Gong et al., 2023). Nevertheless, Mapillary Vistas dataset lies in its global coverage and diversity of the trained images, including street images from Australia. Moreover, it specializes in segmenting labels of street infrastructure, such as bike lanes, curbs, and potholes, which are elements not achievable by ADE20K segmentation. Consequently, for the task of segmentation, we have chosen the In-Place Activated BatchNorm (IPAB) model, which has been trained on the Mapillary Vistas dataset using WideResNet38 and DeepLabv3, developed by Bulo et al. (2018). Several cyclist perception indicators such as eye-level greenness, water view factor, and sky openness can be quantified by the proportions of vegetation, water, and sky in the image. Moreover, the measurement of enclosure can be calculated by using the ratio of vertical objects to horizontal features and a higher value of enclosure denotes a more compact spatial configuration (Bai et al., 2023; Zhou et al., 2019a). In terms of street infrastructure indicators, we utilised binary values to quantify them, as calculating the pixels of street infrastructure elements like streetlights, bike lanes, and street amenities is not meaningful, scoring 1 if present in the image and 0 if absent (Ito and Biljecki, 2021).

4.2 Cycling Frequency Data & Spatial Process

Firstly, to mitigate the impact of the temporal dimension on the results, we utilized the monthly average trip count per segment as the data for cycling frequency. For instance, some segments lack cycling frequency data for all 12 months; hence, using the total number of trips as the dependent variable would be inaccurate. Secondly, it is necessary to correlate the cycling frequency data with the image segmentation data for statistical analysis. Spatially, the monthly average cycling frequencies obtained from SMD are based on data from 30,332 road segments, while the results of image segmentation are based on data from 9,301 street view points. We employed a Near analysis tool in ArcGIS Map to spatially link the data from these two layers, resulting in 7,775 corresponding data points. Finally, after excluding outliers and eliminating missing values, over 6,204 data points were used for the final statistical analysis.

4.3 Statistical analysis

After completing the data processing, we initially employed scatterplot analysis for a preliminary investigation of several variables, aiming to better understand the characteristics of the data and the relationships between each variable. Variables of street infrastructure were all binary data. Thus, it is not meaningful to analysis their correlation. Fig. 3 illustrated that there are no significant linear relationships either among the selected independent variables or between the independent and dependent variables.

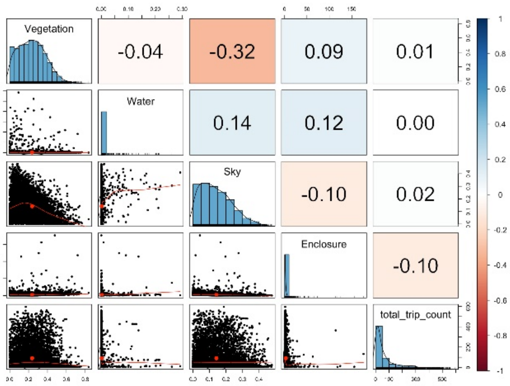


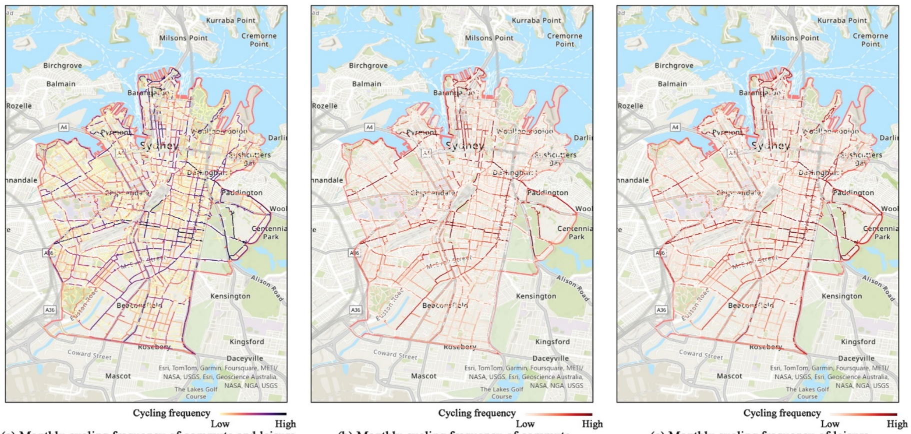
Fig. 3. Correlation matrix of variables

Furthermore, a correlation matrix (Fig. 3) based on Pearson's correlation coefficient was computed, which further substantiated the absence of multicollinearity among the independent variables. According to previous studies (Bai et al., 2023; Wang et al., 2020), this research utilized a multivariate Poisson regression model to explore the impact of built environment factors on cycling frequency, given that cycling frequency is a count variable. Moreover, the cycling frequencies on commute and leisure individually tested within two separate regression models to investigate variations in cycling purposes.

5 Results and Discussion

5.1 Spatial Distribution of Cycling Frequency

Fig. 4 demonstrates the spatial distribution information of different cycling purposes. From an overall perspective on cycling frequency distribution, it is evident that the majority of higher frequency cycling routes are located on primary roads, while secondary and tertiary roads exhibit lower cycling frequencies. This could suggest that cyclists prefer to select primary roads for their wider lanes and better street infrastructure. In comparison between cycling frequencies for commuting purposes and leisure activities, leisure cycling is more frequent, aligning with the data (Table 1) showing that leisure constitutes the main purpose of cycling activities (66%). Furthermore, in terms of spatial distribution differences, cycling for commuting purposes is more frequent in central urban areas, particularly near public transport stations. Although there are some overlapping hotspots for both purposes, streets with higher cycling frequencies for leisure purposes are predominantly located around urban green spaces and waterfront areas.



(a) Monthly cycling frequency of commute and leisure (b) Monthly cycling frequency of commute (c) Monthly cycling frequency of leisure

Fig. 4. Spatial distribution of cycling frequency (a) cycling frequency of both commute and leisure cyclist (b) commute cycling frequency and (c) leisure cycling frequency

5.2 Spatial Distribution of Cycling Perception Indicators

Fig. 5 illustrates the spatial distribution of four cycling perception indicators including vegetation view (VV), sky openness (SO), water view (WV) and enclosure (ENS) based on image segmentation analysis. The central area of the City of Sydney shows lower VV and SO, which can possibly be attributed to the area being the center of Sydney's skyscrapers. The high-density development results in reduced levels of greenery and limited sky exposure. Moreover, the distribution of VV and SO appears to be similar, suggesting a potential linear relationship between these two factors, consistent with findings in the correlation matrix (Fig. 3). Regarding water view, it is distinctly noticeable that areas with high waterfront visibility predominantly lie near coastal zones and around water features within green spaces. Highly enclosed areas are primarily found in the city's central area. As you move away from the city centre, the sense of enclosure tends to lessen, a pattern that may be related to the density of urban development.

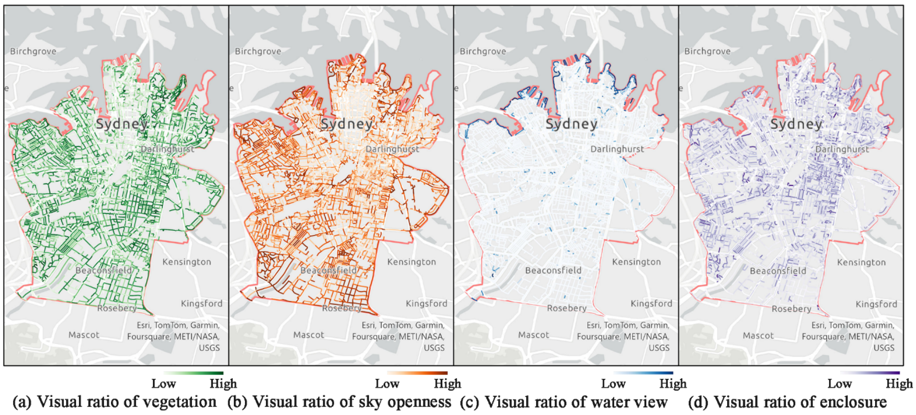


Fig. 5. Spatial distribution of four different cycling perception indicators (a) vegetation view (b) sky openness (c) water view and (d) enclosure

5.3 Correlation between built environments and cycling behaviour

We applied multivariate Poisson regression analysis in R Studio to explore the relationship between built environment factors and cycling behaviour (Table 2). For perception indicators, our results suggest that the visibility of vegetation positively influenced cycling frequencies regardless of the rider's purpose. Previous studies have also found that exposure to greenness was positively associated with the frequency of cycling (Bai et al., 2023; Wang et al., 2020). Views of water were strongly positively correlated with leisure cycling in the City of Sydney, while they had a weak negative correlation with cycling for commuting purposes. This finding indicates that water bodies are more attractive leisure cyclists, who prefer to cycle around waterfronts. A clear sky was consistently associated with lower frequencies of cycling. This phenomenon could be due to the fact that a wide-open sky often results in higher temperatures from greater sun exposure, whereas cyclists may prefer to ride in cooler conditions (Meng et al., 2016). The enclosure aspect showed a negative relationship in cycling frequency, indicating that streets that are more enclosed may deter cycling. In terms of street infrastructure, the presence of bike lanes and traffic lights was positively correlated with cycling frequencies, particularly commute cyclists, as these features tend to make the streets safer. Cyclists are more likely to use bike lanes because such infrastructure can enhance their perceived safety (Rita et al., 2023). However, features such as curb cuts and large traffic sign frames had a negative effect on cycling frequency, although less significant. This can be explained by the fact that large sign frames often exist on highways or expressways, which restrict cycling activities. In addition, our regression results also indicate that advertisements in signage and banner were positively associated with cycling frequencies. The abundance of street advertisements may serve as an indicator of an urban street's vibrancy, which could potentially attract a greater number of cyclists.

Table 2. The associations of 24 built environments and cycling frequency with different purposes

Model predictor	Model 1: Total cycling frequency	Model 2: Commute cycling frequency	Model 3: Leisure cycling frequency
	Coef. (p-value)	Coef. (p-value)	Coef. (p-value)
Cycling perception indicators			
Vegetation	0.009 ***	0.006 ***	0.010 ***
Water	0.042 ***	-0.067 *	0.061 ***
Sky	-0.014 ***	-0.018 ***	-0.012 ***
Enclosure	-0.647 ***	-0.577 ***	-0.685 ***
Street infrastructure indicators (presence of ...)			
Bike.Lane.True	0.135 **	0.259 ***	0.073
Bike.Rack.True	0.142 *	0.146 .	0.142 *
Rail.Track.True	0.125 .	0.200 **	0.085
On.Street.Parking.True	0.199 ***	0.201 ***	0.200 ***
Sidewalk.True	0.095	0.060	0.104
Crosswalk.True	0.065	0.090 .	0.052
Curb.Cut.True	-0.097 **	-0.103 *	-0.096 **
Traffic.Light.True	0.350 ***	0.360 ***	0.347 ***
Traffic.Sign.True	-0.020	-0.002	-0.028
Traffic.Sign.Frame.True	-0.346 *	-0.499 **	-0.287 *
Street.Light.True	0.042	0.065	0.034
Junction.Box.True	-0.006	0.003	-0.011
Surveillance.True	-0.172	-0.177	-0.172
Pothole.True	-0.051	-0.151	-0.003
Manhole.Catch.Basin.Ture	-0.041	0.006	-0.064 .
Signage.Ads.True	0.271 ***	0.275 ***	0.274 ***
Banner.Ads.True	0.117 *	0.152 *	0.099 .
Street.Amenities.True	-0.071 *	-0.067 .	-0.073 *
Utility.Pole.True	0.420 *	0.774 **	0.298 .

Coef. = Coefficient; p-value: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

6 Conclusion and Future Research

This study is a pilot study to explore the association between built environments and cycling behaviour in Australia by using real-time cycling frequency data and street-view data. The findings indicate that vegetation showed a significant positive correlation with cycling frequency both on commute purpose and leisure purpose. In contrast, sky openness and enclosure were negatively associated with cycling behaviour. Furthermore, street infrastructure indicators such as presence of bike lane, on-street parking and traffic lights were three key factors have positive influence on cycling behaviour in that they increase frequencies, while the presence of traffic sign frame and curbs showed negative impacts on it. Therefore, urban planners and policymakers should pay more attention to these key subjective and objective environmental factors to promote a better cycle-friendly cities.

Several limitations needed to be presented. First, our segmentation utilized pre-trained IPAB models on old Mapillary Vistas dataset, which have a limitation on categories (66 labels) extracted from images. Second, some limitations on the cycling data such as the absence of personal and economic data about cyclists restricts the range of our statistical evaluation. Third, as a pilot study of City of Sydney, future investigation could explore the comparison among other Australian cities. In future research, the new Mapillary Vistas dataset, featuring 124 labels capable of capturing more comprehensive street information, along with a more powerful model like One-former, can be utilized for segmentation tasks. Additionally, this study did not include several variables, such as urban density, road width, and land-use data. Future studies should consider incorporating these variables. Furthermore, spatial heterogeneity and the non-linear relationship between built environments and cycling behaviour should also be taken into account in future research.

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