DATA-DRIVEN EVALUATION OF STREETS TO PLAN FOR BICYCLE FRIENDLY ENVIRONMENTS: A CASE STUDY OF BRISBANE SUBURBS

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Abstract. Empirical cycling data from across the world illustrates the many barriers that car-dependent cities face when implementing cycling programs and infrastructure. Most studies focus on physical criteria, while perception criteria are less addressed. The correlations between the two are still largely unknown. This paper introduces a methodology that utilises computer vision analysis techniques to evaluate 15,383 Google Street View Images (SVI) of Brisbane City against both physical and perception cycling criteria. The study seeks to better understand correlations between the quality of a street environment and an urban area's 'bicycle-friendliness'. PSPNet Image Segmentation is utilised against SVIs to determine the percentage of an image corresponding with objects and the environment related to specific cycling factors. For physical criteria, these images are then further analysed by Masked RCNN processes. For perception criteria, subjective ranking of the images is undertaken using Machine Learning (ML) techniques to score images based on survey data. The methodology effectively allows for current findings in cycling research to be further utilised in combination via computer visioning (CV) and ML applications to measure different physical elements and urban design qualities that correspond with bicycle-friendliness. Such findings can assist targeted design strategies for cities to encourage the use of safer and more sustainable modes of transport.

Keywords. Bicycle-friendly; Quality Streetscapes; Active Living; Visual Assessment; Computer Visioning; Machine Learning; SDG 3; SDG 11.

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1. Introduction

Australia is one of the highest carbon consumers in the world (Global Change Data Lab, 2020) where transport emissions comprise the third-largest contributor of greenhouse gas nationally (Department of Industry, Science, Energy and Resources, 2021). Private vehicles contribute to approximately 80% of transit activity across major cities such as Brisbane City (Australian Bureau of Statistics, 2018). Making the need for more sustainable transport in Australia vital to achieve key targets of the United Nations Sustainable Development Goals 11.2 and 3.6 (United Nations, 2021).

It is widely documented that cycling as part of a person's daily routine can reduce greenhouse gases associated with car usage, whilst also significantly improving physical and mental wellbeing (TNMT, 2021, Qja et al., 2011). Despite this, the uptake of cycling has been slow in Australian cities such as Brisbane.

Empirical cycling data from across the world illustrates the many barriers that car-dependent cities face when implementing cycling programs and infrastructure. This paper highlights how such findings can be further utilised and analysed at macro-scales, to identify and evaluate key factors that contribute to the overall bicycle-friendliness of cities such as Brisbane City. Through this methodology, targeted design strategies could be better informed to enable and encourage more cycling activity.

2. Literature Review

2.1. OBJECTIVE AND SUBJECTIVE MEASURES

Objective methods of analysis provide important findings into the general physical features required to enhance cycling environments and encourage more activity. It is becoming more prevalent, however, that physical elements alone fail to consider the subtle role that overall and underlying perceptions of an environment can have on levels of activity (Forbes-Mitchell and Mateo-Babiano, 2015, Osborne and Grant-Smith, 2017, Rossette et al., 2017, Winters et al., 2012).

Perceptions can be difficult to measure and will vary between demographics, however, studies such as Ewing and Handy (2009) have begun to successfully quantify subjective urban design elements and by doing so, effectively measure built-environment perceptions based on human behaviours.

2.2. COMPUTER VISION AND MACHINE LEARNING IN STREET MEASURES

A number of recent studies have demonstrated how the use of computer vision and machine learning (ML) in quantifying social science fundamentals can effectively predict, undertake and illustrate micro-urban analysis of environments at a macro scale (Naik et al. 2014, Qiu et al. 2021, Yin and Wang, 2016). Naik et al. (2014), for example, successfully measured perceived safety, utilising and converting survey data on urban perceptions to predict the perceived safety scores of streets across 21 cities worldwide (Qiu et al. 2021). Qiu et al. (2021) further measured four subjective, key urban design qualities and validated their associated scoring through objective points of interest data.

2.3. BIKEABILITY MEASURES

Much of existing literature on cycling either explores the quality and availability of physical infrastructure, perceptions of safety and risk, or local urban form, however, it remains unclear how these factors correlate at a macro-scale (Forbes-Mitchell and Mateo-Babiano, 2015, Osborne and Grant-Smith, 2017, Rossette et al., 2017, Winters et al., 2012).

Despite current data and research highlighting the common factors that encourage or deter cycling activity, further analysis is required to understand their correlations and affect in determining the bicycle-friendliness of an environment. Drawing from these methodologies and findings, our study utilises CV and ML technology to effectively evaluate Brisbane's cycling environment.

3. Methodology

3.1. CONCEPTUAL AND ANALYTICAL FRAMEWORK

Figure 1 illustrates the framework established to evaluate the bicycle-friendliness of a selected area, of which this study comprises 22 suburbs of inner Brisbane City.

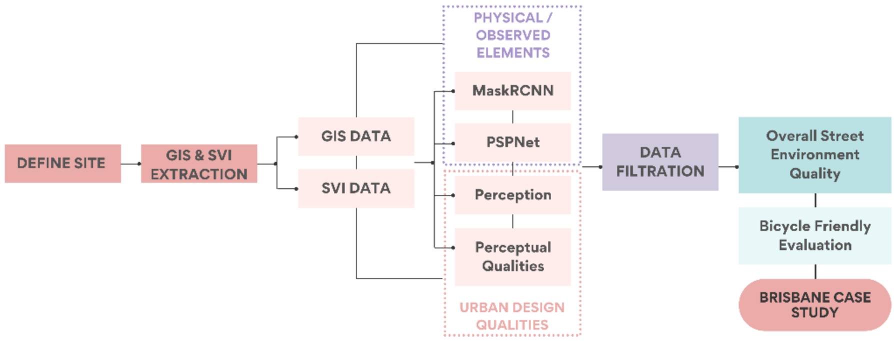

Figure 1. Conceptual Analytical Framework

3.2. OVERARCHING DEFINITIONS

3.2.1. Physical and Observed Elements

Most studies utilise objective quantities to measure varying cycling environments and draw conclusions about their qualities (Osborne and Grant-Smith, 2017). This study also identifies observed elements which may not be identified as easily through visual observation but can be evaluated through data collection and extrapolation.

Brisbane specific survey data and international research publications have identified several physical and observed elements as being influential in modal choice. Drawing from these findings, the below elements were selected for inclusion in the study's methodology.

- Collision Numbers: The number of road collisions reports involving bicycles
- Speed: The maximum speed that motorised vehicles can travel on the road
- Bikelane: The existence of bicycle lanes
- Sidewalk: The existence of footpaths
- Streetlight: The street lighting percentages
- Traffic Volume: The number of total vehicles including cars, trucks, motorcycles.

3.2.2. Urban Design Qualities

Personal perceptions of physical elements inform subjective individual measures relating to senses of safety, comfort, and pleasure (Ewing et al., 2006, van Hagen, 2019). A person's experience of a cycling environment can therefore be greatly influenced by senses of safety, where people 'dare to cycle' and senses of comfort and attractiveness where people are 'invited to cycle' (van Hagen, 2019). Research in the Netherlands has shown that attractiveness appears to be more important than speed, easiness, and comfort to the majority of bicycle riders (Van Hagen, 2019). Therefore, attractiveness is an important consideration which can lead to more subtle qualities of the built environment and urban design integrating with physical elements to achieve better bikeability. Existing guidance on designing bicycle infrastructure in accordance with principles of comfort and attractiveness include the consideration of perceptual qualities such as greenery, openness and aesthetics (Ewing et al., 2006, Ewing and Handy, 2009, Groot, 2016, Van Hagen, 2019). Drawing from such findings, the below urban design elements were selected for inclusion in the study's methodology.

- Visual Order: Based on the consistency of physical elements including arrangement of buildings, paving materials, broken glass, character and scale (Ewing et al., 2006, Ewing & Handy, 2009, Griew et al., 2013, Rundle et al., 2011, Qiu et al., 2022)
- Aesthetic (Imageability): Based on the distinctness in arrangement of physical elements and whether it captures emotions, impressions and/or attention (Ewing et al., 2006; Ewing & Handy, 2009; Ma et al. 2021; Qiu et al., 2021)
- Ecology (Greenness): Based on the proportionality between physical elements including vegetation and building facade (Ewing & Handy, 2009; Ma et al., 2021)
- Enclosure: Based on the proportionality between vertical height of physical elements and horizontal width of the space (Ewing et al., 2006; Ewing & Handy, 2009; Salesses et al., 2013; Dubey et al., 2016; Ma et al. 2021; Qiu et al., 2021)
- Complexity: Based on the diversity of physical elements including user numbers, architectural and landscape variety (Ewing et al., 2006; Ewing & Handy, 2009; Salesses et al., 2013; Dubey et al., 2016; Qiu et al., 2021)
- Human Scale: Based on the proportionality of between physical elements and humans and the speed that humans move (Ewing et al., 2006; Ewing & Handy, 2009; Salesses et al., 2013; Dubey et al., 2016; Qiu et al., 2021).

3.3. WORKFLOW

3.3.1. Obtaining Data

Quantum Geographic Information System (QGIS), Google Street View Imagery (SVI) and basic information was extracted from the local road data of Brisbane City, providing a series of points which each include a SVI, coordinates, street name, street type and the maximum speed limit. Additionally, two other datasets were used in the calculation of the street scores, that being the locations of existing cycle paths and historic locations of collisions between cyclists and other vehicles. Each SVI is assigned a score based on its locality to either one of these data sets.

3.3.2. Image Processing

Once the SVIs were extracted, a series of image processing was applied to further quantitate the images for analysis. Image segmentation was used to extract pixel ratios from SVIs of individual qualities, and Mask Region-Based Convolutional Neural Networks (Mask R-CNN) applied to count the number of specific objects. Subjective ranking of the SVIs could then be achieved according to various qualities through the use of ML.

The first process uses the pyramid scene parsing network (PSPNet) identifying the pixel ratios between each element in the image with a high accuracy, capable of distinguishing between streetscape elements such as trees, sky, roads, and buildings (Zhao et al., 2017). For this research, measuring of street lighting and sidewalks were later used in the evaluation as part of the objective analysis.

The second process used the Mask R-CNN, a powerful deep-learning framework with the task of instance segmentation (He et al., 2017, Qiu et al., 2021). This provides the objective analysis with a dataset of the number of vehicles and people in each SVI.

The final image processing was the application of ML in determining if an SVI portrays certain abstract qualities such as order, aesthetic, ecology, enclosure, complexity and human scale (Ewing et al., 2006, Ewing and Handy, 2009, Griew et al., 2013, Qiu et al., 2021, Qiu et al., 2022, Rundle et al., 2011). The ML process of comparing the elements and converting the preferences to street scores used Microsoft's skill based training system, Truskill algorithm, based on a series of surveys of 300 images from a number of university students, details of which can be found in Qiu et al., 2021. Once the images process was complete, the values assigned to each of the SVI were compiled for data manipulation. Further details of the scoring process can also be found in Qiu et al., 2021.

3.3.3. Compilation and Ranking

Each step of the image processing produces a set of data points linked to the SVI and its coordinates, these variables are filtered down to the following:

- Basic information: Coordinates, Road typology, Surface material, Maximum speed
- PSPNet: Streetlight, Sidewalk
- MaskRCNN: Volume of cars, trucks, busses, motorcycles and cyclists

- Subjective Scoring: Order, Aesthetic, Ecology, Enclosure, Complexity, Scale

For each of the variables, the scores are rated on a scale from Poor (0) to Good (5) through a process of scaling the current domain (Low_1, $High_1$) to the target domain (Low_2, $High_2$), otherwise known as reparameterization. These scores enable evaluation of overall street environment quality.

Achieving the reparameterized value (y), the following formula was used on the set of data, X:

$$For\ High_1, f(x) = \max\ \{x \in X\}$$
$$Low_1, f(x) = \min\{x\ \in X\}$$

From the reparameterized values, each variable is totalled and further reparameterized to a domain between 0 and 1, with 1 being the highest value in order to determine the SVI's 'cumulative street score' and effectively measure bicycle friendliness.

$$y = Low_2 + (x - Low_1) \times \frac{(High_2 - Low_2)}{(High_1 - Low_1)}$$

Finally, the model is further validated by comparing the 'cumulative street score' results with cycling activity data from the subject area (Brisbane City). Due to the vast amounts of data, a computational workflow is needed to manage each of the suburbs individually before assembling the data together again. The initial analysis of the site was computed in QGIS, which extracted the SVIs for image processing done in Python and produced numerous datasets which could be curated and cleaned in Rhino / Grasshopper for efficiency.

4. Results

Importantly, due to timing constraints attributed to the large amount of data requiring further validation with raw cycling activity data, the below results are preliminary. Nonetheless, figures 3 and 4 provide valuable insight into this model's ability to identify key correlations influencing an urban areas' bicycle-friendliness.

Figures 3 and 4 provide example street score results, illustrating the differences between a high street score, in terms of its physical and urban design elements, versus a low street score. Figure 2 below reiterates the model's bicycle-friendly evaluation method:

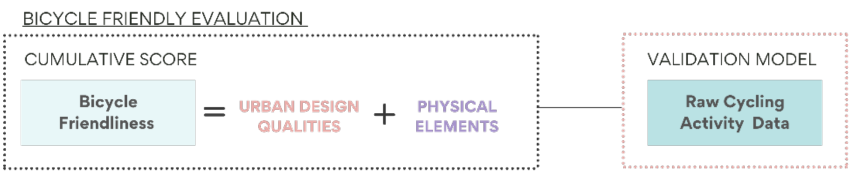

Figure 2. Bicycle-friendly Evaluation - Framework

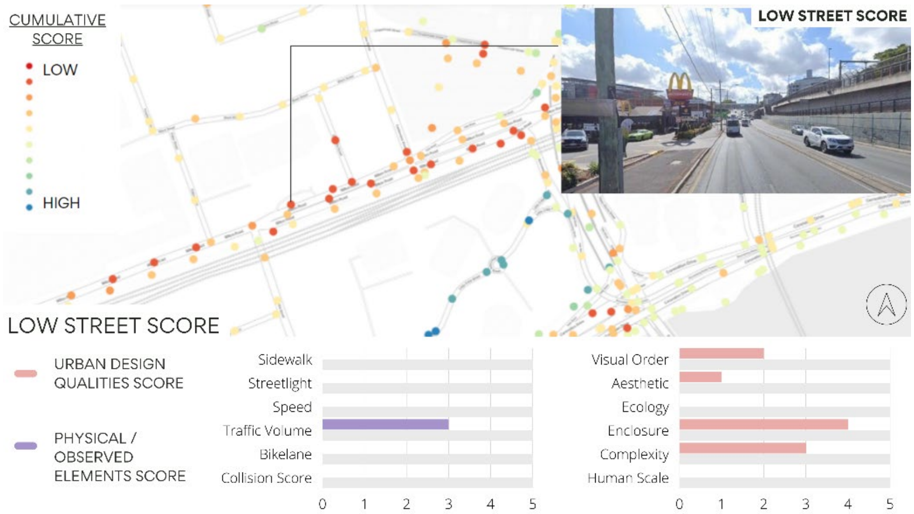

Figure 3. Bicycle-friendly Cumulative Street Score Results - Example Low Street Score

Figure 4. Bicycle-friendly Cumulative Street Score Results - Example High Street Score

Despite the above results being preliminary, we are already beginning to see trends hinting at a general lack of physical elements that could improve overall bikeability such as separated cycling lanes, sidewalks and lighting. Therefore, an immediate planning priority can be made in relation to implementing more cycling infrastructure.

Additionally, main roads which are identifiable by the higher speed limits, are alluding to a strong relationship with other physical and observed elements of higher collision numbers and vehicle activity. They also seemingly show a negative relationship with key urban design qualities such as scale, aesthetic (imageability) and ecology (greenness). Such an evaluation could assist engineers identify roads with high collision rates and implement varying safety measures to appropriately address these issues.

This model demonstrates how a number of key trends for Brisbane's overall bikeability at a macro scale can quickly be determined. Based on our preliminary street view analysis alone, results suggest SVIs resulting in a high (cumulative) street score typically score well among most urban design elements, despite not necessarily scoring well in physical elements.

5. Conclusion

From our preliminary findings, key factors that seem to be having the most influence in bicycle-friendliness in Brisbane City appear to be individual environment's relationship with traffic, where safety plays a key role (whether through separated bikelanes or calmer streetscapes), in hand with urban design qualities such as ecology (greeness) and human scale. A significant hurdle for Brisbane City's bicycle-friendliness is therefore not likely limited by just its lack of physical infrastructure, but also its lack of key urban design elements that ensure a space exudes a combined sense of safety, comfort and attractiveness.

5.1. EFFECTIVENESS OF PROPOSED MICRO-MACRO ANALYSIS FRAMEWORK

It is acknowledged that long-existing techniques in micro-urban analysis cannot be completely replicated at a macro-scale, however, whilst this method may not immediately replace existing techniques, it offers many benefits to planners and policymakers. Utilising and analysing SVI datasets, for example, allows for an analysis reflective of the pedestrian perspective, at varying urban scales and at a significantly lower cost than conventional methods.

5.2. LIMITATIONS AND NEXT STEPS

Limitations of this study are primarily associated with time and resource constraints, in addition to general limitations of computer-vision technologies, as detailed below.

5.2.1. Data Limitations

Firstly, elements informing the data collection were limited by time and resourcing, due mainly to limitations in developing necessary computerised scripts for undergoing and validating the analysis. Further studies could therefore benefit from incorporating additional cycling elements into the analysis, as well as validating the cumulative scores with cycling activity data.

The data analysis is also limited to visual senses that can be identified by imagery and GIS mapping data, of which perceptions may differ in reality. For example, the road may appear smooth in imagery but could be uneven in reality, which can influence perceptions of physical elements. Traffic volume data is also likely skewed by counts being derived from images of varying times of the day. Future studies may benefit from advances in technology associated with street view imagery.

Furthermore, limited by time and resourcing, Brisbane specific survey data was not collected or incorporated into the study and as such, subjective measures relied on existing research relating to perceptions and behaviours from around the world. Perception data from across the world may not accurately reflect perceptions of the local demographics of Brisbane City. Future studies could therefore benefit from undertaking additional surveys in their respective subject areas, to better align perception influences with local demographics.

5.2.2. Further Analysis

Using computer vision and machine learning techniques, a micro-level urban analysis of cycling environments can be undertaken at a macro-scale by combining objective and subjective measures of bikeability. By doing so, correlations between objective and subjective influences can be evaluated, and an insight into the overall bicycle-friendliness of urban areas demonstrated.

Future studies could establish additional scripts to incorporate missing bikeability elements and further analysis could be undertaken through additional surveying of human behaviours specific to the subject area and / or targeted design strategies to refine and validate the model's findings.

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