# Modelling link-level bike riding volumes in Greater Melbourne

Debjit Bhowmick<sup>1</sup>, Tanapon Lilasathapornkit<sup>2</sup>, Meead Saberi<sup>2</sup>, Sachith Seneviratne<sup>3</sup>, Trisalyn Nelson<sup>4</sup>, Kerry Nice<sup>3</sup>, Ben Beck<sup>1</sup>

<sup>1</sup>School of Public Health and Preventive Medicine, Monash University, Australia

<sup>2</sup> School of Civil and Environmental Engineering, Research Centre for Integrated Transport Innovation (rCITI), University of New South Wales, Australia

<sup>3</sup> Transport, Health and Urban Systems Research Lab, Melbourne School of Design, The University of Melbourne, Australia

<sup>4</sup> Department of Geography, University of California, Santa Barbara, USA Email for correspondence (presenting author): <u>debjit.bhowmick@monash.edu</u>

#### 1 Introduction

Robust bike riding demand models are critical for achieving long-term active transport and sustainability goals. Bike riding volumes are key to measuring ridership trends, prioritising interventions, and measuring risk exposure. We developed a robust model to estimate bike riding volumes on every street segment across Greater Melbourne, underpinned by a datadriven and locally specific route assignment. For our modelling, we implement an abridged four-step demand modelling approach integrated with a evidence-informed bike-riding route choice model (developed using GPS data from 20,000 bike trips in Greater Melbourne) to estimate current link-level bike riding volumes across Greater Melbourne, as this modelling approach allows for iterative expansion and improvement at different stages and on multiple fronts, thus making it ideal for long-term planning.

#### 2 Methodology

We used data from four waves (2012-14, 2014-16, 2016-18, 2018-20) of the Victorian Integrated Survey of Travel and Activity (VISTA) to derive the origins and destinations of trips, the types of trips, and number of trips occuring across Greater Melbourne at the population-level using the provided weights. For the development of a bicycling route choice model, we collected GPS data from a population-representative sample of 673 cyclists across Greater Melbourne who completed 19,782 cycling trips (corresponding to 35.6 million GPS points (Bhowmick et al., 2025). We used OpenStreetMap (OSM) to download a bikeable road network that underpinned our model and was used for assigning routes to cycling trips across Greater Melbourne. Links or street segments of the underlying bikable network were classified into different infrastructure classes to create features useful for the development of the bike riding volume model by spatially merging with multiple publicly available and proprietary datasets, such as motor vehicle volume, slope, and posted speed limits (link to GitHub repositories).

In VISTA data, we considered weighted bike trip legs made by adults that started and ended within the boundaries of Greater Melbourne to derive a population-level demand dataset. We assigned network nodes as origins and destinations to the bike trips based on Statistical Area 2 (SA2) and land use information. Our current model is not meant to be sensitive to mode choice decisions and only intends to generate appropriate bike riding volumes for 2019.. Using GPS data from around 20,000 bike trips, we created a locally tailored route choice model with the Path Size Logit (PSL) approach, which factors in route attributes like distance, bike infrastructure, slope, and traffic. After calibrating the route choice model, we applied it to generate route choice sets with associated probabilities to ultimately predict bike riding volumes across Greater Melbourne.

## 3 Results

We assess model validity by comparing the estimated link-level volumes with observed bike counts across 48 links. We used a matrix estimation approach to calibrate our model involving iterative weighting of bike trips to strategically reduce the difference between estimated and observed volumes. Our calibration resulted in significant improvement in model accuracy, with a Mean Absolute Error of 177 AADB (Annual Average Daily Bicycles), Mean Absolute Percentage Error of 25%, an R-squared value of 0.86 and a classification accuracy of 77%.

### 4 Discussion

The model reveals fairly representative link-level volume patterns, with high volumes assigned to popular corridors. However, the model's validation is still limited by the small number of bike count locations, mostly near the Melbourne CBD, highlighting the need for more diverse and widespread data collection to improve accuracy at links with low bike usage and varied infrastructure (Miah et al., 2022). Therefore, planned model improvements include incorporating more diverse bike count data, using more recent travel surveys, and exploring Reinforcement Learning for better route choice model parameters. Our modeling approach establishes a strong foundation for developing a robust, long-term link-level bike volume model, that allows for continuous expansion and iterative refinement. With the integration of an empirically formulated route choice model and plans to incorporate a novel mode choice utility functions incorporating psychological constructs of travellers, this model provides a solid foundation for accurately representing bike rider behavior and ensuring sensitivity to future infrastructure and policy interventions, thus establishing its relevance for long-term planning.

## 5 References

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