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# Environmental and social influences on cycling adoption: A socio-ecological mode choice analysis in Greater Melbourne

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ABSTRACT

Cycling is widely recognised as a sustainable and health-enhancing mode of transport; however, its adoption remains low in many urban areas due to safety concerns and infrastructure limitations. This study considers the multiple levels of influence on individual behaviour. Adopting a social ecological framework, it examines how traffic stress, social norms, and family influences shape cycling uptake in Greater Melbourne. It focuses on the impact of lowering residential speed limits to 30 km/h and expanding low-stress cycling networks. The study uses the Victorian Integrated Survey of Travel and Activity, a household travel survey data and a multinomial logit model to evaluate how reducing the Level of Traffic Stress (LTS), combined with social and family reinforcement, influences mode choice behaviour.

The results indicate that speed reductions significantly lower the proportion of high-LTS road segments from 45% to 30%, leading to a 49.6% increase in cycling adoption in the model with LTS alone and from 27.85% to 88.37% in models incorporating social and family influences. The findings highlight that infrastructure improvements alone are insufficient; family and social support are crucial in reinforcing cycling behaviour and mitigating infrastructure constraints. These insights highlight the need for an integrated ecological approach combining infrastructure, behavioural strategies, and policy interventions to promote cycling.

## 1. Introduction

Cycling is widely recognised as one of the most sustainable and health-enhancing urban transport modes. It provides numerous environmental, economic, and social benefits, including reduced greenhouse gas emissions, lower urban congestion, and improved public health outcomes (Pucher and Buehler, 2017; Logan et al., 2023; Handy et al., 2014). As a zero-emission mode of transport, cycling plays a crucial role in climate change mitigation and supports more liveable urban environments (Pucher et al., 2010; Piatkowski and Bopp, 2021). Despite these advantages, its adoption remains relatively low in many cities, necessitating targeted interventions to improve cycling conditions and increase ridership.

Several factors affect cycling uptake, including infrastructure limitations, safety concerns, and social and behavioural influences. Research highlights that cycling participation is closely linked to the quality of infrastructure, particularly the availability of low-stress environments that enhance safety and comfort (Mekuria et al., 2012; Rérat and Schmassmann, 2024; Chataway et al., 2014). The Level of Traffic Stress (LTS) framework is widely used to assess cycling conditions, with evidence showing that lower-stress environments encourage greater ridership (Yannis and Michelaraki, 2024; Pucher and Buehler, 2016; Jafari et al., 2025b). Recognising the need for safer road environments, Infrastructure Victoria recently recommended lowering local street speed limits to 30 km/h to enhance pedestrian and cyclist safety, particularly in areas frequented by children and communities (Infrastructure Victoria, 2025). This policy aligns with global and nation-wide best practices, where speed reductions have successfully mitigated road trauma and improved conditions for active transport (Yannis and Michelaraki, 2024; Pearson et al., 2025).

Beyond infrastructure, social factors also play a crucial role in shaping cycling behaviour. Social influence, also known as subjective norms, including peer and family encouragement, has significantly impacted cycling uptake (Willis et al., 2015; Kim et al., 2018). These findings align with the socio-ecological model of travel behaviour, which

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conceptualises mode choice as the outcome of interactions between individual, social, and environmental influences rather than solely built-environment conditions (Giles-Corti and Donovan, 2003). However, despite growing recognition of these social dimensions, infrastructure-based mode choice models have been extensively studied; the interaction between infrastructure, social, and family influences, however, remains underexplored. It creates a gap in understanding how physical and social environments work together to support the uptake of cycling. To address this gap, this study adopts a socio-ecological model that jointly incorporates individual, household, social, and built-environment determinants into the cycling mode-choice analysis. The conceptual model guiding this study is presented in Fig. 1. We analyse how residential speed limit reductions and the resulting changes in LTS influence cycling mode choice, and how these effects differ in the presence of social and family cycling influences.

In summary, this study makes two key contributions. First, it integrates a socio-ecological perspective into active transport mode-choice analysis, capturing individual, household, social, and built-environment attributes of cycling behaviour together. Second, it examines the impact of a speed limit reduction intervention as a policy-level factor within the socio-ecological framework on LTS and cycling mode share, identifying how both social and family factors reinforce responses to improved low-stress conditions and shape cycling mode choice. To address these contributions, the study answers the following research questions:

- How does high LTS impact cyclists' mode choice and behaviour?
- How do social norms and family influences impact cyclists' mode choice?
- What is the potential increase in cycling ridership when residential LTS is reduced and family and regional social influence are enhanced?

The remainder of this paper is structured as follows. Section 2 provides a detailed review of the literature on socio-ecological models, cycling infrastructure, LTS, and the role of social and family influences in cycling adoption. Section 3 outlines the methodology used to examine the impact of speed limit reductions and social and family factors on cycling mode choice. Section 4 presents the results of the models. Section 5 discusses the results and provides policy recommendations. Finally, Section 6 concludes the paper and provides directions for future research.

## 2. Literature review

### *2.1. A socio-ecological approach for bicycle mode shift*

A socio-ecological framework provides a multi-level perspective for understanding cycling behaviour by recognising that individual attributes, social influences, the built and natural environment, and broader policy settings together shape travel decisions (Jafari, 2022). Originally proposed by social ecologist Daniel Stokols (Stokols, 1996), the approach builds on ecological theories emphasising the reciprocal relationships between individuals and their environments. Adopted in public health and physical activity research (Giles-Corti and Donovan, 2002) to examine multiple levels of influence on individual behaviour (Sallis et al., 2015), this framework has since been applied in numerous health-related active transport correlate studies (Giles-Corti and Donovan, 2003; Heesch et al., 2015; Yang et al., 2019). Prior research demonstrates that cycling behaviour is influenced by socio-demographic and psychological factors (Aldred et al., 2016), social support and norms (Willis et al., 2015), built environment characteristics such as density, connectivity, and cycling facilities (Pucher et al., 2010; Jafari et al., 2025b), natural environmental conditions including slope and weather (Gao et al., 2018), and transport and planning policies (Buehler and Pucher, 2021). The socio-ecological framework, therefore, offers a comprehensive approach to studying cycling, recognising that cycling behaviour emerges from interactions between individuals and their physical and social environments rather than being solely determined by travel time or cost.

Despite growing recognition of this perspective, many empirical cycling studies continue to focus primarily on individual and built-environment factors. While there has been an increasing use of infrastructure quality measures, such as LTS, few studies have adopted a social-ecological framework that integrates social and family influences alongside objective street-level stress indicators. This is despite the literature clearly highlighting the role of social norms, support, and household cycling culture in shaping travel behaviour.

Addressing this gap, the present study applies the socio-ecological framework to jointly account for individual characteristics, social factors (i.e., household and neighbourhood cycling exposure), and built-environment factors (i.e., infrastructure-related stress). As illustrated in Fig. 1, the conceptual framework used in this study organises the key correlates into four interconnected layers: individual, social, physical, and policy, extending the framework adopted by Jafari (2022) to explicitly bridge social norms and objective cycling stress conditions.

Grounding our study in the socio-ecological framework enables a more holistic interpretation of cycling behaviour, consistent with calls in the literature to incorporate behavioural, individual, social, physical environmental, and structural influences in active travel research (Giles-Corti and Donovan, 2003; Ogilvie et al., 2011; Götschi et al., 2017). This approach recognises the interplay between individual, social, and environmental influences.

### *2.2. Cycling infrastructure and level of traffic stress*

The availability and quality of cycling infrastructure are key determinants of cycling uptake, with multiple studies highlighting that well-designed facilities can significantly increase ridership (Pucher and Buehler, 2017; Fishman, 2016; Tiwari et al., 2025c). Infrastructure elements such as segregated cycle lanes, shared pathways, and dedicated cycling signals enhance safety and convenience, encouraging more individuals to choose cycling as a primary mode of transport (Crane et al., 2016; Goodman et al., 2014; Parker et al., 2013). However, beyond dedicated cycling infrastructure, the broader urban environment fundamentally shapes cycling behaviour, including road design, traffic speeds, and land-use characteristics.

A key framework for assessing cycling conditions is the LTS approach, which classifies road segments based on their stress levels for cyclists (Mekuria et al., 2012). Mekuria et al. (2012) categorised streets into four stress levels based on key factors such as speed limits, road width, number of traffic lanes, and the presence of cycling infrastructure. LTS 1 represents low-stress environments, often associated with separated bike paths or quiet residential streets, while LTS 4 marks high-stress conditions, typically multi-lane arterial roads without dedicated cycling facilities. Cervero et al. (2019) refined the LTS framework by integrating UK Census commute data with road network attributes to classify stress levels, incorporating impedance measures to assess deviations from low-stress cycling routes.

In a recent study, Jafari et al. (2025b) developed an LTS-based classification framework for Greater Melbourne, assigning LTS values to all road segments using OpenStreetMap data. The LTS classification done by Jafari et al. (2025b) was based on cycling infrastructure, speed limits, road hierarchy, and traffic volumes. They found that a significant portion of Melbourne's urban network consists of LTS-3 and LTS-4 roads, disproportionately affecting cycling accessibility in outer-suburban areas. This highlights the limitations of current urban transport networks in supporting widespread cycling adoption. Fig. 2 provides an overview of the LTS levels classified in Jafari et al. (2025b).

Research consistently shows that cyclists prefer routes classified as LTS-1 or LTS-2, which provide low-stress environments with minimal interactions with motor vehicles (Lowry et al., 2016). Conversely,

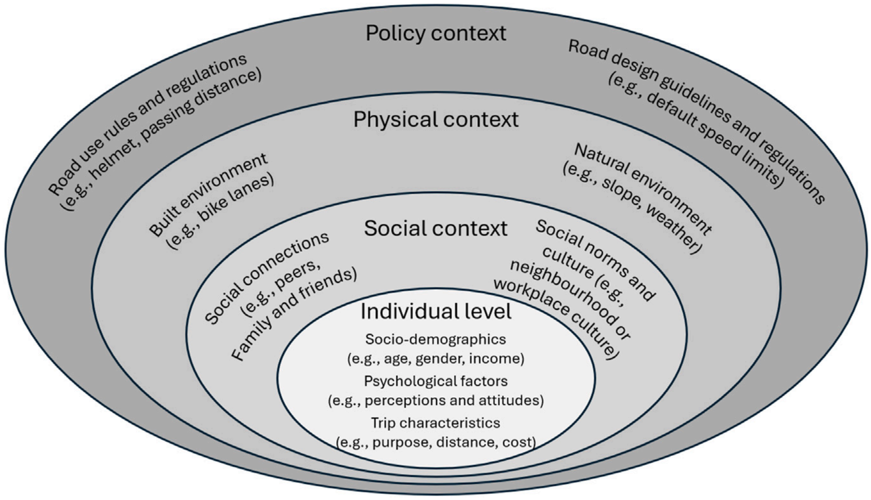



**Fig. 1.** A socio-ecological framework of factors affecting active transport.

| Road Type | Traffic Volume (vehicles/day) | Speed Limit (km/h) ≤ 30 km/h | ≤ 40 km/h | ≤ 50 km/h | ≤ 60 km/h | > 60 km/h |
|---|---|---|---|---|---|---|
| **Off-road Paths** | | | | | | |
| All path types | Any | LTS 1 | LTS 1 | LTS 1 | LTS 1 | LTS 1 |
| **Separated Cycle Lanes** | | | | | | |
| All road types | Any | LTS 1 | LTS 1 | LTS 1 | LTS 2 | LTS 4 |
| **On-road Cycle Lanes** | | | | | | |
| Local, tertiary and secondary roads | ≤ 10,000 | LTS 1 | LTS 2 | LTS 2 | LTS 3 | LTS 4 |
| Local, tertiary and secondary roads | > 10,000 | LTS 2 | LTS 2 | LTS 3 | LTS 3 | LTS 4 |
| Primary roads | Any | LTS 2 | LTS 2 | LTS 3 | LTS 3 | LTS 4 |
| **Mixed Traffic** | | | | | | |
| Local roads | ≤ 750 | LTS 1 | LTS 2 | LTS 2 | LTS 3 | LTS 4 |
| Local roads | ≤ 2,000 | LTS 1 | LTS 2 | LTS 3 | LTS 4 | LTS 4 |
| Local and tertiary roads | ≤ 3,000 | LTS 2 | LTS 3 | LTS 3 | LTS 4 | LTS 4 |
| Local and tertiary roads | > 3,000 | LTS 3 | LTS 3 | LTS 4 | LTS 4 | LTS 4 |
| Secondary and primary roads | Any | LTS 3 | LTS 3 | LTS 4 | LTS 4 | LTS 4 |

**Fig. 2.** Levels of Traffic Stress classification framework.
*Source:* Jafari et al. (2025b).

routes classified as LTS-3 or LTS-4, characterised by high traffic volumes and higher speed limits, serve as deterrents to cycling, particularly for less experienced riders (Yannis and Michelaraki, 2024; Pucher and Buehler, 2016). Furth (2017) found that even a single high-stress segment in a route can discourage cyclists, particularly those who are less confident or risk-averse. Cervero et al. (2019) found that a 10% increase in LTS 1 and LTS 2 road segments led to a 0.65% and 0.73% rise in bicycle commuting, respectively. This concept of continuous low-stress connectivity aligns with the findings of Cabral et al. (2019), who demonstrated the value of low-stress network expansion in improving access to key destinations.

Speed limit reduction has gained significant interest in recent years as an effective and low-cost strategy to create safer environments for bicycle riders and other vulnerable road users. Studies show that reducing residential speed limits to 30 or 40 km/h significantly increases the proportion of low-stress routes while reducing high-stress cycling environments (Lowry et al., 2016; Yannis and Michelaraki, 2024). Yannis and Michelaraki (2024) reported that introducing 30 km/h speed limits in cities led to a 23% decline in road crashes, along with a 37% decrease in fatalities and a 38% reduction in injuries. Recently, Jafari et al. (2025b) quantified the impact of speed limit reductions on LTS, demonstrating that implementing a 30 km/h speed limit on residential streets could convert a substantial number of LTS-3 and LTS-4 roads to LTS-1 and LTS-2, thereby increasing the proportion of the road network classified as low-stress. However, that study did not examine behavioural responses such as mode shift, focusing instead on changes in network-level stress exposure. It also did not consider the influence of social norms on mode choice. The study showed that high LTS negatively influences cycling mode choice, reinforcing the need for targeted interventions to improve cycling conditions. Mertens et al. (2017) found that individuals residing in neighbourhoods with a higher prevalence of streets with speed limits below 30 km/h were more likely to use cycling as a mode of transport. Additionally, lowering speed limits from 50 km/h to 30 km/h has been found to reduce noise levels by up to 40%, enhancing urban liveability (Vienneau et al., 2015). Additional interventions such as traffic calming measures, including speed humps and road narrowing, further enhance cyclist safety and comfort, making cycling a more viable transport option (Pucher and Buehler, 2012).

### 2.3. Social and family influence on cycling behaviour

While infrastructure plays a fundamental role in shaping cycling adoption, social and family influences also significantly affect individuals' decisions to cycle (Tiwari et al., 2025b). An active cycling community within a region increases the visibility and normalisation of cycling, encouraging higher participation rates (Willis et al., 2015). Studies indicate that regions with higher existing bicycle modal shares tend to experience sustained growth in cycling adoption, as new cyclists feel more comfortable in an environment where cycling is already a common practice (Dill and McNeil, 2013). Goel et al. (2022) found that cities with higher cycling mode shares exhibit more balanced

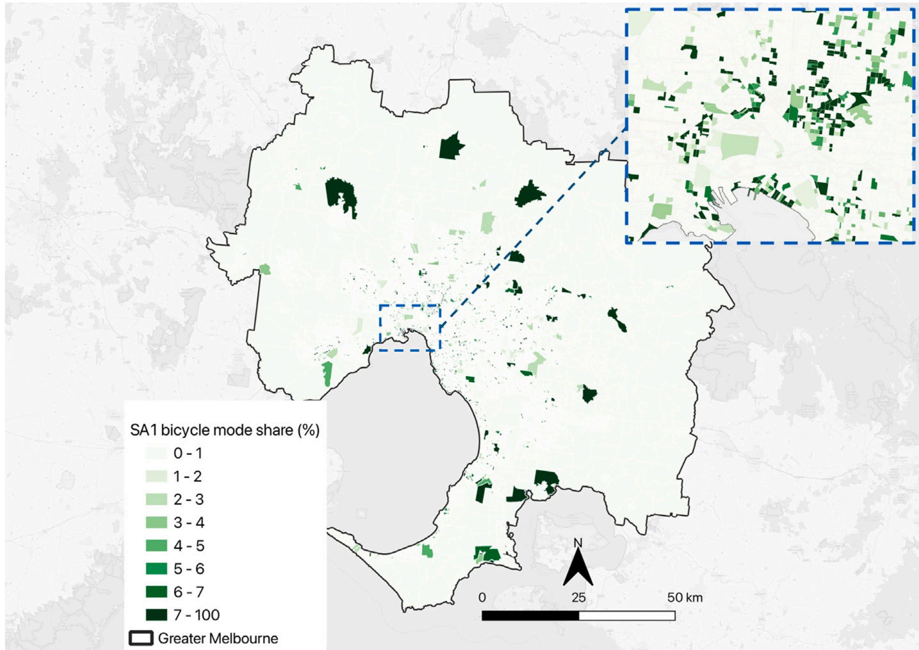



**Fig. 3.** Bicycle mode share in Greater Melbourne in VISTA shown at the SA1 level (basemap from OpenStreetMap).

gender and age representation, indicating that visible participation by peers and community members may serve to normalise cycling, thereby reinforcing social influence in travel behaviour. Research also highlights that in regions where cycling is viewed as a practical and socially accepted mode of transport, individuals are more likely to integrate cycling into their daily routines (Willis et al., 2015; Si et al., 2020).

Family influence is also key, as household mobility habits strongly affect individual travel behaviour (Tiwari et al., 2025a). Research has shown that individuals with a cycling partner or family member are more likely to adopt cycling as a regular mode of transport (Geus et al., 2008). The perceived approval or expectation from significant others further increased the likelihood of individuals choosing to cycle, as highlighted by de Bruijn et al. (2005). A study by Sherwin et al. (2014) found that many new cyclists cited family members as a major influence in their decision to cycle. Similarly, Kaplan et al. (2015) demonstrated that social encouragement, particularly from close relatives and friends, has a direct impact on cycling frequency and purpose. Cycling behaviour is also shaped by how individuals relate to social norms, with identity and self-perception influencing their willingness to adopt cycling as a mode of transport (Murtagh et al., 2012). Additionally, Wang et al. (2018) found that individuals were more inclined to cycle when they believed that their social circles valued and endorsed cycling as a sustainable transport choice.

While infrastructure and social and family influence encourage cycling uptake, their combined effects remain underexplored, as cycling-friendly infrastructure and social influence can create a self-sustaining loop of increased ridership and normalisation of cycling (Gutiérrez et al., 2020). However, the extent to which social and family influences moderate the relationship between LTS and cycling adoption remains unclear. Therefore, this study integrates LTS analysis and its impact on mode choice with social and family factors to model their combined impact on cycling adoption.

## 3. Methodology

### 3.1. Study area

Greater Melbourne, the capital city of Victoria, Australia, has an estimated population of approximately 5 million residents (Australian Bureau of Statistics, 2021). The metropolitan area spans around 10,000 square kilometres, and projections indicate that its population will nearly double by 2050, reaching approximately 9 million (Department of Environment, Land, Water and Planning, 2017). This anticipated demographic growth necessitates comprehensive planning in transport and housing policies to accommodate the increasing demand for urban infrastructure.

Melbourne exhibits a predominantly monocentric urban structure, with a dense central core surrounded by expanding suburban areas characterised by lower population densities and car-oriented development. The metropolitan transport system is multimodal, consisting of an extensive Public Transport (PT) network of trains, trams, and buses, complemented by a growing network of cycling and walking infrastructure. Despite ongoing investments in sustainable transport, private vehicles continue to dominate daily travel, accounting for approximately 72% of all trips, while active modes such as walking and cycling together account for around 18% (16% walking and 2% cycling) according to the VISTA (Victorian Department of Transport, 2018). Over the past decade, the city has undergone a gradual shift in modal transportation, with an increasing emphasis on active modes, driven by substantial investment in cycling infrastructure. Nonetheless, significant spatial disparities exist, with inner-city areas demonstrating higher uptake of sustainable modes compared to outer suburbs, where longer travel distances and limited PT options reinforce car dependency.

The Australian Bureau of Statistics (ABS) employs a hierarchical classification system for census data, Statistical Areas. For instance, SA1 units typically represent suburbs in urban regions, with populations averaging 400 residents. Fig. 3 presents the bicycle mode shares in each SA1 identified in VISTA. It can be observed that Greater Melbourne's urban structure exhibits a monocentric pattern, with a significant number of bicycle trips concentrated in the Central Business District (CBD). This centralisation creates substantial pressure on transport infrastructure, particularly on networks facilitating access to the CBD. Although cycling constitutes a relatively minor share of total commuter trips, accounting for approximately 1.6%, this number remains higher than the national average of around 1% (Australian Bureau of Statistics, 2022), with participation being significantly higher in inner-city areas.

Fig. 4 illustrates a section of Greater Melbourne's baseline network used in this study, highlighting variations in speed limits. The inner

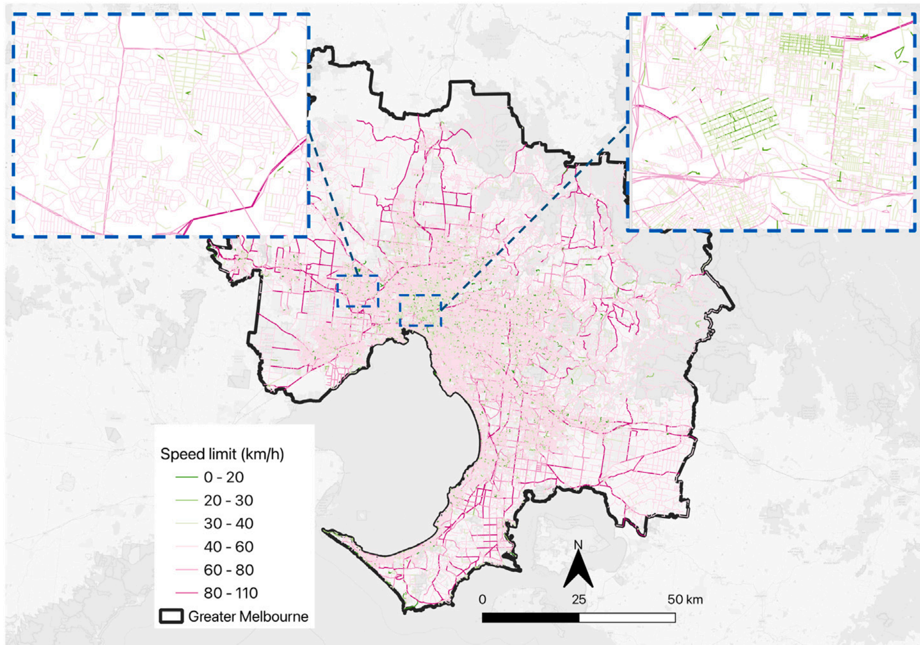



**Fig. 4.** Greater Melbourne's baseline road network with the current speed limits from OSM (basemap from OpenStreetMap).

areas of Greater Melbourne, where streets with speeds of 30–40 km/h are more common, contrast with the outer suburban network, where roads with speeds of 50 km/h and higher are dominant. The road network was sourced from Open Street Map (OSM) and processed using the algorithm developed by Pemberton and Jafari (2024), which identifies cycling infrastructure and attributes such as cycleway type, road hierarchy and posted speed limits. Using this processed data, the LTS classification framework proposed by Jafari et al. (2025b) was applied to classify each road segment into one of four LTS levels.

For this study, two scenarios are considered: (1) a Baseline (actual speeds from OSM) and (2) a Scenario with residential speed limits reduced to 30 km/h (RSS-30).

### 3.2. Data source

This study used the VISTA 2012–2020,[1] which is a household travel survey conducted by the Victorian Department of Transport and Planning. The survey collects detailed information on participants' travel behaviour by recording trip and activity data for a designated survey day. The data includes trip origins and destinations, primary modes of transport, trip purposes, and departure and arrival times, providing valuable insights into travel patterns and transport demand across the region. The detailed properties of the data are shown in Table 1.

### 3.3. Correlation and multicollinearity

Understanding the relationships between the variables is essential in mode choice modelling, as it helps identify dependencies that may impact the robustness and interpretability of the model. Multicollinearity occurs when two or more explanatory variables in a regression model are highly correlated, leading to unstable parameter estimates and inflated standard errors (Daoud, 2017). The Variance Inflation Factor (VIF) is commonly used to quantify the severity of multicollinearity. VIF for a given variable $X_i$ is calculated as:

$$VIF(X_i) = \frac{1}{1 - R_i^2} \tag{1}$$

where $R_i^2$ is the coefficient of determination from regressing $X_i$ on all other explanatory variables. Typically, a VIF value greater than 5 suggests moderate multicollinearity, while values exceeding 10 indicate severe multicollinearity that should be addressed by removing or combining variables.

### 3.4. Mode choice models

Three mode choice models were developed using VISTA 2012–2020, based on the Multinomial Logit Model (MNL) with walking, cycling, driving, and PT as alternative modes to understand travel behaviour and mode preferences. Each model specification was designed to assess the influence of different factors on cycling behaviour. Following the socio-ecological model shown in Fig. 1, variables were selected to represent key influences across different layers: individual socio-demographic and trip characteristics, social norms indicators (family and neighbourhood cycling influence), and physical environment attributes using LTS. While policy variables are not explicitly included as attitudinal factors, the framework is complemented by a policy scenario analysis later in the study. This structure allows assessment of how factors across multiple levels jointly relate to cycling mode choice and enables comparison between models with and without social-influence variables.

#### 3.4.1. Assigning a valid route to trips from the travel survey

The R5 routing engine via the 'r5r' package in R was used to estimate travel times for all modes except cycling. R5 integrates OSM data and General Transit Feed Specification (GTFS) files with the Round-Based Public Transit Routing (RAPTOR) algorithm used for PT routes (Pereira et al., 2021). Driving and walking routes were calculated using speed limits and walkable paths, respectively.

The cycle routing process involved mapping trip origins and destinations MeshBlock (MB) centroids from the VISTA dataset to the nearest LTS-1 or LTS-2 nodes. A network-based routing algorithm

[1] VISTA is an ongoing survey of household travel activity in Victoria, where all members of surveyed households are asked to complete a travel diary for a single specified day. https://discover.data.vic.gov.au/dataset

**Table 1**
Summary statistics and definitions of variables based on different trip purposes.

| Variable | Definition | Mean | SD | Trip purpose | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | Work | Education | Pick Up/Drop Off | Shopping/Social | Other |
| **Available Mode Choices** | | | | | | | | |
| Cycling | 1 if selected; otherwise 0 | 0.015 | – | 0.019 | 0.032 | 0.006 | 0.012 | 0.018 |
| Driving | 1 if selected; otherwise 0 | 0.774 | – | 0.701 | 0.619 | 0.903 | 0.810 | 0.772 |
| PT | 1 if selected; otherwise 0 | 0.085 | – | 0.135 | 0.183 | 0.008 | 0.055 | 0.123 |
| Walking | 1 if selected; otherwise 0 | 0.126 | – | 0.145 | 0.166 | 0.083 | 0.124 | 0.087 |
| **Age Groups** | | | | | | | | |
| 1–17 | 1 if selected; otherwise 0 | 0.192 | – | 0.030 | 0.815 | 0.269 | 0.130 | 0.192 |
| 18–30 | 1 if selected; otherwise 0 | 0.137 | – | 0.192 | 0.132 | 0.064 | 0.129 | 0.111 |
| 31–45 | 1 if selected; otherwise 0 | 0.251 | – | 0.294 | 0.031 | 0.325 | 0.219 | 0.225 |
| 46–60 | 1 if selected; otherwise 0 | 0.241 | – | 0.314 | 0.015 | 0.231 | 0.236 | 0.240 |
| >61 | 1 if selected; otherwise 0 | 0.179 | – | 0.170 | 0.008 | 0.111 | 0.285 | 0.234 |
| **Individual Characteristics** | | | | | | | | |
| Sex | 1 if male; otherwise 0 | 0.486 | 0.500 | 0.520 | 0.498 | 0.418 | 0.456 | 0.428 |
| License | 1 if license; otherwise 0 | 0.762 | 0.426 | 0.940 | 0.225 | 0.723 | 0.832 | 0.754 |
| Working | 1 if working; otherwise 0 | 0.573 | 0.495 | 0.834 | 0.112 | 0.489 | 0.517 | 0.488 |
| **Household Characteristics** | | | | | | | | |
| Bike Ownership | Avg. no. of bikes | 1.432 | 1.729 | – | – | – | – | – |
| Car Ownership | Avg. no. of cars | 1.834 | 0.979 | – | – | – | – | – |
| Weekly Income | Mean household income (AUD) | 1975.31 | 1404.54 | – | – | – | – | – |
| **Overall Trip Distribution by Trip Purpose** | | | | **35.2%** | **9.6%** | **22.4%** | **32.3%** | **0.5%** |

was employed to select the lowest impedance path for each trip. The impedance-based routing model followed the methodology proposed in previous research (Jafari et al., 2025b), wherein the road network was represented as a graph, with nodes corresponding to intersections and edges representing road segments. Each edge was assigned an impedance score, and the impedance score was calculated as the segment's length multiplied by an LTS factor, reflecting the cyclist's willingness to take minor detours to avoid high-stress segments. Impedance penalties were also applied at intersections based on the highest-stress incoming link, with additional costs added for unsignalised intersections to account for crossing difficulty. After assigning impedance values, the algorithm employed the shortest-path function in igraph, utilising impedance as the weight to ensure that the chosen route minimised exposure to high-stress links rather than merely minimising distance. Upon determining the optimal path, the model calculated key outputs, including total route length, the percentage of the route falling within each LTS category, and deviation from the absolute shortest path. The model allowed cyclists to deviate up to 15% from the shortest route to maintain lower stress conditions, aligning with empirical evidence that cyclists prefer slightly longer but safer routes. For a detailed description of the assumptions and calculation procedure used in estimating travel times, refer to Appendix.

### 3.4.2. *Assigning a travel cost for trips from the travel survey*

Travel costs were determined using a fixed fare for PT trips and driving costs based on fuel prices and travel distances. According to VISTA data for 2012–2020, PT users in Greater Melbourne averaged two daily trips, with a daily maximum fare cap of AUD 8 (a flat fare of AUD 4 per trip). Driving costs were based on distance-based fuel consumption rates per the Australian Transport Assessment and Planning (ATAP) guidelines[2] and average fuel prices in Victoria from 2012–2020, as reported by the Australian Institute of Petroleum.[3] For a detailed description of the assumptions and calculation procedure used in estimating travel costs, refer to Appendix.

[2] https://www.atap.gov.au/sites/default/files/pv2_road_parameter_values.pdf

[3] https://aip.com.au/aip-annual-retail-price-data

### 3.4.3. *Mode choice model specification*

Routed trips from the travel survey were used to estimate the mode choice model parameters for Greater Melbourne. Trips with valid routes for all four modes, driving, PT, walking, and cycling, were selected, resulting in a final dataset of 66,223 trips. These four modes were used as the choice alternatives in the models, with driving serving as the reference mode.

Across all models, the following independent variables were considered: (i) travel time for all modes, (ii) travel cost for driving and PT, (iii) fraction of high-stress LTS segments for cycling (Model 1 (Eq. (2)) and Model 3 (Eq. (4))), (iv) household member cycling behaviour (family influence) for cycling (Model 2 (Eq. (3)) and Model 3), (v) regional cycling mode share (social influence) for cycling (Model 3), (vi) number of cars and bikes in the household for driving and cycling, respectively, (vii) if the trip purpose is work, for driving, cycling, and PT.

Fig. 5 presents a schematic overview of the mode choice model and the subsequent mode assignment process.

**Model 1: Base model with LTS**

The first model ($U_{ij}^{(1)}$) serves as the base model, incorporating standard mode choice determinants such as travel time, travel cost, and household vehicle ownership. Additionally, it considers the influence of the LTS, which is shown as a high-stress road segment. The inclusion of LTS aims to assess how infrastructure conditions affect cycling uptake. The utility function for this model is formulated as follows:

$$U_{ij}^{(1)} = \mathrm{ASC}_j \cdot x_5 + \beta_{\mathrm{TT},j} \cdot T_{ij} + \beta_{\mathrm{money}} \cdot C_{ij} \cdot x_3 + \beta_{\mathrm{LTS}} \cdot P_{\mathrm{LTS},ij} \cdot x_2 + \beta_{\mathrm{BA}} \cdot \mathrm{NB}_i \cdot x_2 + \beta_{\mathrm{CA}} \cdot \mathrm{NC}_i \cdot x_1 + \beta_{\mathrm{W}} \cdot \mathrm{W}_i \cdot x_4 \quad (2)$$

where:

$U_{ij}^{(m)}$ : Utility of individual $i$ choosing mode $j$ under Model $m$,
$\mathrm{ASC}_j$ : Alternative-specific constant for mode $j$,
$T_{ij}$ : Travel time for mode $j$ for individual $i$,
$C_{ij}$ : Travel cost for mode $j$ for individual $i$,
$P_{\mathrm{LTS},ij}$ : Fraction of the total length of the lowest-impedance route for cycling that consists of high-stress road segments for individual $i$,
$\mathrm{NB}_i$ : Number of bikes in the household of individual $i$,
$\mathrm{NC}_i$ : Number of cars in the household of individual $i$,

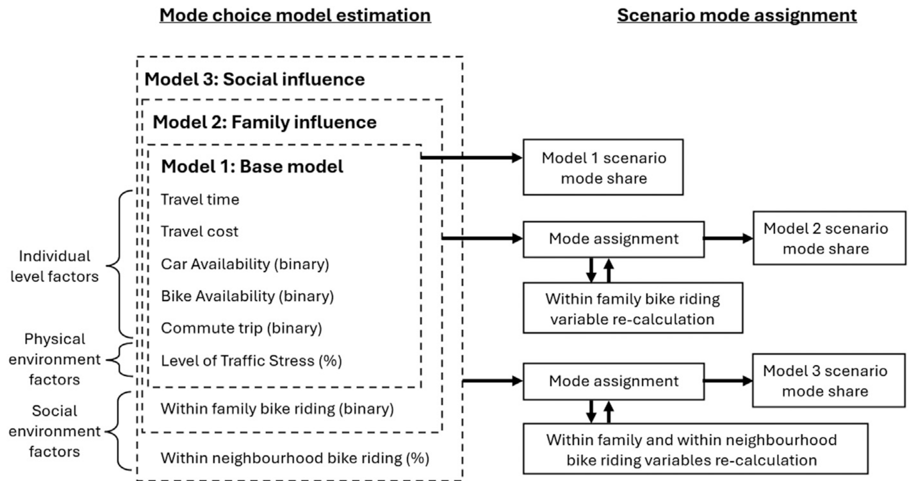



**Fig. 5.** An overview of the mode choice model and mode assignment approach.

$W_i$ : Binary variable = 1 if individual $i$ is on a work trip, 0 otherwise,
$x_1$ : Binary variable = 1 if $j$ is driving, 0 otherwise,
$x_2$ : Binary variable = 1 if $j$ is cycling, 0 otherwise,
$x_3$ : Binary variable = 1 if $j$ is driving or PT, 0 otherwise,
$x_4$ : Binary variable = 1 if $j$ is driving, cycling, or PT, 0 otherwise,
$x_5$ : Binary variable = 1 if $j$ is cycling, PT, or walking, 0 otherwise.
$\beta_{TT,j}, \beta_{money}, \beta_{LTS}, \beta_{BA}, \beta_{CA}, \beta_{W}$ are the coefficients to be estimated.

**Model 2: Model with LTS and family influence**
Building upon Model 1, the second model ($U_{ij}^{(2)}$) introduces family influence, shown as a binary variable representing whether any household member has a cycling trip. This model extends the base model to recognise if household members' cycling behaviour can impact individual mode choices. The utility function for this model is formulated as follows:

$$U_{ij}^{(2)} = \text{ASC}_j \cdot x_5 + \beta_{TT,j} \cdot T_{ij} + \beta_{money} \cdot C_{ij} \cdot x_3 + \beta_{LTS} \cdot P_{LTS,ij} \cdot x_2 + \beta_{family} \cdot F_{cyc,i} \cdot x_2 + \beta_{BA} \cdot \text{NB}_i \cdot x_2 + \beta_{CA} \cdot \text{NC}_i \cdot x_1 + \beta_W \cdot W_i \cdot x_4 \quad (3)$$

where the new terms are defined as:

$F_{cyc,i}$ : Binary variable = 1 if any household member of individual $i$ has a cycling trip, 0 otherwise,
$\beta_{family}$ : Coefficient capturing the marginal effect of household-level cycling behaviour on the individual's cycling choice.

All other variables and notation are as defined in Model 1.

**Model 3: Model with LTS and family influence and social influence**
The third model ($U_{ij}^{(3)}$) expands upon Model 2 by incorporating social influence, represented by regional cycling mode share. This addition captures the effect of a broader community cycling culture on individual travel decisions. Both the family influence ($F_{cyc}$) and social influence ($S_{cyc}$) variables are included as contextual indicators to capture associative relationships with cycling behaviour rather than causal effects. The utility function for this model is formulated as follows:

$$U_{ij}^{(3)} = \text{ASC}_j \cdot x_5 + \beta_{TT,j} \cdot T_{ij} + \beta_{money} \cdot C_{ij} \cdot x_3 + \beta_{LTS} \cdot P_{LTS,ij} \cdot x_2 + \beta_{social} \cdot S_{cyc,i} \cdot x_2 + \beta_{family} \cdot F_{cyc,i} \cdot x_2 + \beta_{BA} \cdot \text{NB}_i \cdot x_2 + \beta_{CA} \cdot \text{NC}_i \cdot x_1 + \beta_W \cdot W_i \cdot x_4 \quad (4)$$

where the new terms are defined as:

$S_{cyc,i}$ : Regional cycling mode share in the SA1 region of individual $i$,
$\beta_{social}$ : Coefficient representing the effect of regional cycling prevalence on an individual's likelihood of cycling.

All other variables and notation are as defined in Models 1 and 2.

### 3.4.4. *Mixed logit model specification*

The Mixed Logit (ML) models extend the MNL models by allowing specific coefficients to vary randomly across individuals, capturing unobserved preference heterogeneity. Models 1 to 3 were expanded accordingly, treating three explanatory variables, $\beta_{LTS}$, $\beta_{social}$, and $\beta_{family}$, as random parameters to reflect individual-level variation. All other attributes were estimated as fixed parameters, implying consistent effects across individuals similar to those in the MNL models.

The random coefficients are specified as follows:

$$\beta_{LTS} = \bar{\beta}_{LTS} + \sigma_{LTS} v_{LTS}^i, \quad \beta_{social} = \bar{\beta}_{social} + \sigma_{social} v_{social}^i, \quad \beta_{family} = \bar{\beta}_{family} + \sigma_{family} v_{family}^i, \quad (5)$$

where:

- $\bar{\beta}_\bullet$ Mean coefficient across individuals,
- $\sigma_\bullet$ SD across individuals,
- $v_\bullet^i \sim \mathcal{N}(0,1)$ Standard normal random draws.

The probability that individual $i$ chooses mode $j$ is given by the integral of the logit formula over the distribution of random parameters:

$$P_{ij} = \int \frac{\exp(U_{ij})}{\sum_k \exp(U_{ik})} f(\boldsymbol{\beta}^i \mid \bar{\boldsymbol{\beta}}, \boldsymbol{\sigma})\, d\boldsymbol{\beta}^i \quad (6)$$

where $f(\boldsymbol{\beta}^i \mid \bar{\boldsymbol{\beta}}, \boldsymbol{\sigma})$ represents the joint probability density function of the random coefficients. This formulation allows the model to relax the independence of irrelevant alternatives (IIA) assumption and to account for preference variations that cannot be observed directly.

### 3.4.5. *Model comparison using the likelihood ratio test*

To evaluate whether the ML models offer an improved representation of observed travel mode choices relative to the MNL models, a likelihood ratio (LR) test is conducted. The ML model extends the MNL model by allowing for random taste heterogeneity across individuals, making the LR test a standard and appropriate approach for comparing the two specifications (Vuong, 1989).

Let $LL_{MNL}$ and $LL_{ML}$ denote the log-likelihood values at convergence for the MNL and ML models, respectively. The LR test statistic is defined as

$$LR = -2\left(LL_{MNL} - LL_{ML}\right), \quad (7)$$

which follows an asymptotic chi-square distribution with degrees of freedom, denoted by $df$, equal to the difference in the number of estimated parameters between the two models.

A statistically significant LR statistic indicates that the extended ML model provides a significantly better fit to the data. A non-significant LR result indicates that the MNL model adequately represents observed choice behaviour.

### 3.5. Calculating the elasticities for each mode

In addition to estimating the mode choice coefficients, elasticities were calculated to measure the sensitivity of the probability of choosing a mode concerning changes in its attributes, normalised for the variables' units. Following the approach used by Train (2009), the elasticity of the probability $P_{ni}$ of choosing mode $i$ with respect to an attribute $z_{ni}$ is given by:

$$E^{z}_{n,i} = \frac{\partial P_{n,i}}{\partial z_{n,i}} \cdot \frac{z_{n,i}}{P_{n,i}} = \beta_z \cdot z_{n,i} \cdot (1 - P_{n,i}) \quad (8)$$

Where:

- $\beta_z$ is the estimated coefficient of attribute $z$ from the mode choice model,
- $z_{n,i}$ is the value of attribute $z$ for individual $n$ and mode $i$,
- $P_{n,i}$ is the predicted probability of individual $n$ choosing mode $i$.

The elasticity $E_{iz_{ni}}$ quantifies the percentage change in the probability $P_{ni}$ resulting from a 1% change in the attribute $z_{ni}$. This measure is beneficial for evaluating the relative impact of different mode attributes on individual mode choices.

### 3.6. Mode shift estimation as a result of reducing speed limits

The mode shift analysis was conducted iteratively as shown in Fig. 5. Consistent with the socio-ecological model in Fig. 1, this stage operationalises the policy context layer by testing a real-world intervention: reducing residential street speed limits to 30 km/h (RSS-30) and reclassifying the road network LTS accordingly.

Model 1 estimated the modal shift under the RSS-30 scenario, providing initial mode choice probabilities. Using these probabilities, travel modes were assigned for all individuals. Consistent with the socio-ecological model in

Next, Model 2 was applied, where the mode assignment was updated iteratively. In each iteration, new cyclists are identified and $F_{\text{cyc},i}$ was updated accordingly. The mode choice probabilities were then recalculated, and modes were reassigned. This iterative process continued until the system reached a near-equilibrium state, meaning that the number of individuals changing modes between iterations became negligible.

Subsequently, modes were assigned using Model 3, where both the family influence ($F_{\text{cyc},i}$) and the social influence ($S_{\text{cyc},i}$) were updated iteratively. In each iteration, newly identified cyclists were incorporated into the influence variables, after which $F_{\text{cyc},i}$ and $S_{\text{cyc},i}$ were recalculated and modes were reassigned. This process continued until a near-equilibrium state was reached.

Finally, the mode shares obtained after convergence were compared with baseline conditions to determine the net change in cycling and other modes resulting from the RSS-30 intervention.

## 4. Results

### 4.1. Descriptive statistic results

Table 1 describes the VISTA trips and travellers in the final dataset used for the mode choice modelling. The table provides a summary of the sample's demographic and trip characteristics to contextualise the modelling dataset. The choice model parameters were estimated using home-based survey trips to non-recreational destinations in Greater Melbourne from the VISTA 2012–2020 dataset. Driving was Greater Melbourne's most utilised mode of transport, accounting for 77.4% of all trips. Walking and PT were less frequently chosen, with mode shares of 12.6% and 8.5%, respectively. Cycling had the lowest share, representing just 1.5% of trips. Trip purposes were classified into work, education, pick-up and drop-off, shopping and social, and other categories. Work-related trips were the most frequent, comprising 35.2% of all trips, followed by shopping and social trips, which accounted for 32.3%. Education trips were less common at 9.6%, while those categorised as 'other' had the lowest share at 0.5%.

The 31–45 age group had the highest proportion of travellers, accounting for 25.1%, followed by the 46–60 age group at 24.1%. The 18–30 age group had the lowest representation at 13.7%. Males comprised 48.6% of travellers. A majority held a valid driving license, and 57.3% were employed. Household car ownership was higher than bicycle ownership, with an average of 1.83 cars per household compared to 1.43 bikes. The mean weekly household income was AUD 1975.31, with a high SD indicating a broad range of income levels among VISTA travellers.

Table 2 presents the correlation matrix highlighting key relationships among the variables used in the models. The model incorporates the following variable: travel time for mode $j$ ($T_j$), travel cost for mode $j$ ($C_j$), fraction of the high LTS road segment ($P_{\text{LTS}}$), regional cycling mode share in the SA1 ($S_{\text{cyc}}$), household cycling participation ($F_{\text{cyc}}$), number of bicycles in the household (NB), number of cars in the household (NC), and work trip indicator ($W$).

Travel times across different modes exhibit strong positive correlations. For example, the correlation between $T_{\text{car}}$ and $T_{\text{bike}}$ was 0.942, while the correlation between $T_{\text{bike}}$ and $T_{\text{walk}}$ was 0.999. This suggests that individuals experiencing longer travel times by one mode will likely encounter longer travel times across other modes. Such high correlations raise concerns regarding potential multicollinearity, which can lead to unstable coefficient estimates in the discrete choice model if they are used together in the utility of a single mode. However, since these variables are used in the utility functions of different modes, multicollinearity should not pose an issue in the mode choice models. Cost variables also exhibit moderate correlations. The correlation between car travel cost ($C_{\text{car}}$) and PT cost ($C_{\text{pt}}$) was 0.456, indicating that higher costs in one mode tend to be associated with higher costs in another.

A moderate negative correlation was observed between household vehicle ownership ($NC$) and bicycle modal share ($S_{\text{cyc}}$), with a coefficient of −0.120. This indicates that areas with higher car ownership tend to have fewer bicycle trips. Conversely, the correlation between the total number of bicycles in a household ($NB$) and bicycle modal share ($S_{\text{cyc}}$) was 0.238, suggesting that regions with greater use of cycling also tend to have households owning more bicycles.

The relationship between $P_{\text{LTS}}$ and $S_{\text{cyc}}$ reveals important insights into how infrastructure conditions impact cycling adoption. The correlation between $P_{\text{LTS}}$ and $S_{\text{cyc}}$ was negative (−0.062), suggesting that areas with lower traffic stress tend to have a higher share of bicycle trips. This suggests that improved cycling infrastructure and reduced traffic stress levels encourage more individuals to opt for cycling as a mode of transport. Similarly, the weak negative correlation (−0.014) between $P_{\text{LTS}}$ and household cycling participation ($F_{\text{cyc}}$) suggests that while infrastructure plays a role in influencing cycling adoption, household-level factors such as bike availability and social norms may have a more direct impact. The correlation between $S_{\text{cyc}}$ and $F_{\text{cyc}}$ was 0.306, indicating a moderate positive relationship. This suggests that households are more likely to have at least one member who cycles in areas where cycling is more common. This reflects the reinforcing nature of social norms in transportation choices: households in cycling-friendly environments are more likely to engage in cycling due to the availability of infrastructure and cultural

**Table 2**
Pearson correlation matrix.

| | $T_{car}$ | $T_{PT}$ | $T_{bike}$ | $T_{walk}$ | $P_{LTS}$ | $C_{car}$ | $C_{PT}$ | $NC$ | $NB$ | $W$ | $S_{cyc}$ | $F_{cyc}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $T_{car}$ | 1.00 | 0.942 ** | 0.754 ** | 0.941 ** | −0.043 ** | 0.958 ** | 0.407 ** | 0.110 ** | −0.067** | 0.387 ** | −0.066 ** | −0.044 ** |
| $T_{PT}$ | 0.942 ** | 1.00 | 0.767 ** | 0.772 ** | −0.001 | 0.773 ** | 0.587 ** | 0.150 ** | −0.024 ** | 0.308 ** | −0.097 * | −0.050 ** |
| $T_{bike}$ | 0.754 ** | 0.767 ** | 1.00 | 0.999 ** | −0.035 ** | 0.989 ** | 0.445 ** | 0.114 ** | −0.068 ** | 0.401 ** | −0.075 ** | −0.048 ** |
| $T_{walk}$ | 0.941 ** | 0.772 ** | 0.999 ** | 1.00 | −0.030 ** | 0.990 ** | 0.452 ** | 0.115 ** | −0.067 ** | 0.398 * | −0.077 * | −0.048 ** |
| $P_{LTS}$ | −0.043 ** | −0.001 | −0.035 ** | −0.030 ** | 1.00 | −0.037 ** | 0.013 ** | 0.007 | −0.002 | −0.024 ** | −0.062 ** | −0.014 ** |
| $C_{car}$ | 0.958 ** | 0.773 ** | 0.989 ** | 0.990 * | −0.037 ** | 1.00 | 0.456 ** | 0.116 * | −0.065 ** | 0.394 ** | −0.075 * | −0.047 ** |
| $C_{PT}$ | 0.407 ** | 0.587 ** | 0.445 ** | 0.452 ** | 0.013 ** | 0.456 ** | 1.00 | 0.075 ** | −0.001 | 0.116 ** | −0.044 ** | −0.024 ** |
| $NC$ | 0.110 ** | 0.150 ** | 0.114 ** | 0.115 ** | 0.007 | 0.116 * | 0.075 ** | 1.00 | 0.159 ** | 0.082 ** | −0.120 ** | −0.027 ** |
| $NB$ | −0.067 | −0.024 ** | −0.068 ** | −0.067 ** | −0.002 | −0.065 ** | −0.001 | 0.159 ** | 1.00 | −0.101 ** | 0.082 ** | 0.238 * |
| $W$ | 0.387 ** | 0.308 ** | 0.401 ** | 0.398 * | −0.024 ** | 0.394 ** | 0.116 ** | 0.082 ** | −0.101 ** | 1.00 | 0.017 ** | −0.016 * |
| $S_{cyc}$ | −0.066 ** | −0.097 * | −0.075 ** | −0.077 * | −0.062 ** | −0.075 * | −0.044 ** | −0.120 ** | 0.082 ** | 0.017 ** | 1.00 | 0.306 ** |
| $F_{cyc}$ | −0.044 ** | −0.050 ** | −0.048 ** | −0.048 ** | −0.014 ** | −0.047 ** | −0.024 ** | −0.027 ** | 0.238 * | −0.016 * | 0.306 ** | 1.00 |

** p < 0.01, * p < 0.05.

**Table 3**
Variance Inflation Factor (VIF) results for three models.

| Variable | VIF values as independent variables | | |
|---|---|---|---|
| | $P_{LTS}$ | $S_{cyc}$ | $F_{cyc}$ |
| $S_{cyc}$ | 1.131 | – | 1.041 |
| $F_{cyc}$ | 1.163 | 1.067 | – |
| $P_{LTS}$ | – | 1.014 | 1.017 |

acceptance. Nonetheless, this relationship should be interpreted as associative rather than causal, as both factors may evolve together over time rather than one directly determining the other.

These results indicate that, although some variables are correlated across the dataset, they are not included within the same utility function for any single mode, thereby avoiding multicollinearity issues in the model specification. To further assess the interdependencies between $P_{LTS}$, $S_{cyc}$ and $F_{cyc}$, VIF were computed, as shown in Table 3, where each variable is treated as independent variable while the remaining two serve as predictors.

As indicated in Table 3 When $P_{LTS}$ is the independent variable, the VIF values for $S_{cyc}$ and $F_{cyc}$ were 1.131 and 1.163, respectively, suggesting that while infrastructure conditions and household cycling participation influence cycling stress levels, they do so independently. Similarly, when $S_{cyc}$ was modelled as the independent variable, $P_{LTS}$ and $F_{cyc}$ exhibit VIF values of 1.014 and 1.067, respectively, confirming that both infrastructure and household cycling habits shape cycling mode share, but without strong collinearity. Lastly, when $F_{cyc}$ was the dependent variable, the VIF values for $S_{cyc}$ and $P_{LTS}$ remain low at 1.041 and 1.017, respectively, reinforcing that household-level cycling decisions are not entirely dependent on broader social trends or infrastructure quality.

The results indicate minimal multicollinearity concerns, with all VIF values remaining close to 1. These findings confirm that family influence, social influence and infrastructure function as distinct yet complementary determinants of cycling behaviour.

### 4.2. Mode choice models

#### 4.2.1. MNL models

The estimated parameters for the mode choice models are presented in Table 4. A total of 66,223 trips were used to evaluate the models, and the numbers were similar across all three models. Across all models, key variables, including travel time, cost, and ASC, exhibit similar behaviour and statistical significance. Travel time negatively impacts mode choice across all modes, with coefficients $\beta_{TT,cycling}$, $\beta_{TT,walking}$, $\beta_{TT,PT}$, and $\beta_{TT,driving}$ all being negative and highly significant ($p < 0.001$) across all models. These results indicate that longer travel times decrease the likelihood of choosing a particular mode, highlighting the sensitivity of travellers to time-related constraints. The magnitude of these coefficients suggests that walking was the most affected by travel time ($\beta_{TT,walking} = -0.085$ in Model 1), followed by cycling ($\beta_{TT,cycling} = -0.057$), and driving ($\beta_{TT,driving} = -0.037$), while PT was the least impacted ($\beta_{TT,PT} = -0.027$). Similarly, the coefficient for travel cost ($\beta_{money}$) remains negative and statistically significant across all models, reflecting the general aversion to higher transportation costs. The coefficient for work trip indicator ($\beta_W$) remains weakly significant, while the coefficients for bike ownership ($\beta_{BA}$) and car ownership ($\beta_{CA}$) remain positive and significant across all models, indicating the continued influence of bike and car ownership on mode choice.

In Model 1, high LTS ($P_{LTS}$) was introduced as an independent variable, and its coefficient ($\beta_{LTS} = -0.754$, $p < 0.001$) suggests a strong negative association with cycling mode choice. This indicates that an increase in the proportion of high-stress road segments significantly reduces the probability of choosing cycling. The negative coefficient aligns with findings from previous studies that emphasise the negative effect of high LTS environments on active travel adoption (Jafari et al., 2025b; Lilasathapornkit et al., 2025). Including high LTS ($P_{LTS}$) contributes to a reasonable model fit, with an $R^2$ value of 0.5898. The magnitude of the coefficient of high-stress environment ($\beta_{LTS}$) underscores the crucial role of cycling infrastructure quality in promoting cycling, as reducing exposure to high-stress roads could significantly enhance cycling mode share.

Model 2 expands upon Model 1 by incorporating family influence ($\beta_{family}$), which has a substantial positive effect ($\beta_{family} = 2.321$, $p < 0.001$), indicating that individuals were more likely to choose cycling if other household members do the same. The introduction of family influence reduces the absolute magnitude of stressful cycling environments $\beta_{LTS}$ from −0.754 to −0.678, suggesting that while high-stress cycling infrastructure remains a significant negative factor, family influence can partially counteract its adverse effects. This implies that individuals from households where cycling was a common practice were more likely to choose cycling, even in areas with high-traffic stress conditions. Additionally, the effect of employment status ($\beta_{worker}$) becomes slightly more negative (−0.123) and significant at the $p < 0.05$ level. The model fit improves slightly, with an increase in $R^2$ to 0.5949, suggesting that including family influence enhances the model.

Model 3 further extends the previous models by introducing social influence ($\beta_{social}$), which has a positive and highly significant effect ($\beta_{social} = 0.184$, $p < 0.001$), indicating that regions with a high cycling mode share encourage people to choose cycling. The introduction of social influence leads to a further reduction in the absolute magnitude of stressful cycling environments $\beta_{LTS}$, which now decreases to −0.344, and its statistical significance weakens to $p < 0.05$. This suggests that strong social and community engagement in cycling can substantially mitigate the negative impacts of high-stress infrastructure. The weakening of $\beta_{LTS}$ implies that in socially supportive environments, individuals were more likely to cycle despite fewer road conditions. This highlights a critical trade-off-while poor infrastructure remains a barrier, a strong cycling culture can counteract some of these negative impacts. Model 3 achieves the highest model fit, with $R^2 = 0.6003$,

**Table 4**
Comparison of estimated mode choice model parameters across three models.

| Coefficient | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| $ASC_{PT}$ | 0.499*** [0.299, 0.698] | 0.489*** [0.274, 0.704] | 0.465*** [0.256, 0.673] |
| $ASC_{cycling}$ | −2.829*** [−3.017, −2.64] | −3.045*** [−3.242, −2.848] | −3.942*** [−4.166, −3.717] |
| $ASC_{walking}$ | 2.133*** [2.051, 2.216] | 2.117*** [2.034, 2.199] | 2.097*** [2.014, 2.179] |
| $\beta_{TT\_driving}$ | −0.037*** [−0.042, −0.032] | −0.037*** [−0.042, −0.031] | −0.037*** [−0.043, −0.032] |
| $\beta_{TT\_PT}$ | −0.027*** [−0.029, −0.024] | −0.027*** [−0.029, −0.024] | −0.027*** [−0.029, −0.025] |
| $\beta_{TT\_cycling}$ | −0.057*** [−0.061, −0.052] | −0.055*** [−0.059, −0.051] | −0.055*** [−0.059, −0.050] |
| $\beta_{TT\_walking}$ | −0.085*** [−0.088, −0.083] | −0.086*** [−0.088, −0.083] | −0.086*** [−0.088, −0.083] |
| $\beta_{LTS}$ | −0.754*** [−1.044, −0.464] | −0.678*** [−0.969, −0.388] | −0.344* [−0.656, −0.033] |
| $\beta_{money}$ | −0.381*** [−0.424, −0.338] | −0.382*** [−0.428, −0.336] | −0.379*** [−0.424, −0.335] |
| $\beta_{W}$ | −0.121* [−0.214, −0.029] | −0.123* [−0.261, 0.015] | −0.127' [−0.268, 0.014] |
| $\beta_{BA}$ | 0.323*** [0.296, 0.351] | 0.215*** [0.183, 0.247] | 0.250*** [0.216, 0.284] |
| $\beta_{CA}$ | 0.574*** [0.546, 0.602] | 0.562*** [0.534, 0.590] | 0.549*** [0.520, 0.577] |
| $\beta_{family}$ | – | 2.321*** [2.159, 2.484] | 1.4*** [1.221, 1.579] |
| $\beta_{social}$ | – | – | 0.184*** [0.171, 0.196] |
| $R^2$ | 0.5898 | 0.5949 | 0.6003 |
| $LL$ | −26904.7 | −26573.6 | −26218.2 |
| $AIC$ | 53 833.4 | 53 173.2 | 52 464.5 |

*Note:* Coefficients are reported with 95% confidence intervals in brackets.
Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, ' $p < 0.10$.
"–" indicates the variable was not included in the respective model.

reflecting the improved modelling resulting from including family and social influence. The incremental improvement in $R^2$ across the three models suggests that adding behavioural and social influence factors provides a more comprehensive understanding of travel behaviour.

#### 4.2.2. ML models

The estimated parameters for the ML models are presented in Table 5. In Model 1 (ML), only $\beta_{LTS}$ variable was specified as random. The mean LTS coefficient is negative and statistically significant, indicating that higher LTS reduce the likelihood of cycling, as also seen in Model 1. However, its SD is not significant, suggesting that the effect of LTS on cycling is largely homogeneous across individuals. This means that stressful traffic conditions have a negative influence on most individuals, and there is limited variation in the intensity of this effect.

Model 2 (ML) extends the specification by including both $\beta_{LTS}$ and $\beta_{family}$ as random parameters. In this model, the family variable exhibits a significant mean and SD, providing clear evidence of heterogeneity. This suggests that individuals with family members who cycle differ considerably in their sensitivity to cycling mode choices; some may prefer cycling, while others may not be very attracted to it. The LTS variable remains significant with a negative mean, reaffirming its constant effect on cycling, and still exhibits limited heterogeneity.

In Model 3 (ML), $\beta_{LTS}$, $\beta_{family}$ and $\beta_{social}$ variables were added to capture the influence of social influence. The mean of the social variable is positive and highly significant, indicating that a stronger cycling culture increases the likelihood of choosing cycling. However, the SD is not significant, suggesting that social influence is uniform across the population. Interestingly, the LTS parameter becomes statistically insignificant in Model 3, despite being significant in the MNL and previous ML models. This likely occurs because the social influence variable now absorbs part of the previously attributed variation in perceived traffic stress. In areas with a stronger cycling culture, the negative perception of traffic stress is reduced, thereby diminishing its independent explanatory power.

Overall, the results reveal that among the three variables tested for heterogeneity, the $\beta_{family}$ variable demonstrates the strongest and most consistent evidence of preference heterogeneity, while the effects of LTS and social influence appear relatively homogeneous across individuals.

#### 4.2.3. LR test results

Table 6 summarises the LR test results comparing the MNL and ML specifications across the three models. For Model 1, the LR statistic is not statistically significant ($LR = 0.00$, $df = 1$, $p = 1.00$), indicating that allowing for random taste heterogeneity does not improve model performance relative to the MNL specification.

In contrast, Models 2 and 3 exhibit statistically significant LR statistics. For Model 2, the LR test yields $LR = 7.40$ ($df = 2$, $p = 0.025$), while Model 3 shows a substantially stronger result with $LR = 29.90$ ($df = 3$, $p < 0.001$). These results indicate that incorporating taste heterogeneity leads to a markedly better representation of observed mode choices in both models.

Based on these findings, the ML specification is adopted for Models 2 and 3 in all subsequent analyses, whereas the MNL specification is retained for Model 1.

### 4.3. Elasticities results

The elasticity results presented in Table 7 highlight notable differences in sensitivity across different modes and how these sensitivities evolve with varying models as family and social influences were introduced. Across all three models, travel time elasticities indicate that walking is the most sensitive to changes in travel duration, with the highest elasticity (−1.573 in Model 1), followed by cycling (−1.075). PT also shows a high negative elasticity (−1.394), whereas driving remains the least affected by travel time variations (−0.151). These results suggest that interventions targeting travel time reductions for active and PT modes could significantly influence mode choice. Monetary cost elasticities show that PT users (−1.358) were far more responsive to price changes than car users (−0.136), indicating that affordability is a stronger determinant of PT use than driving.

The impact of high LTS on cycling was evident in all models, with a negative elasticity of −0.307 in Model 1, confirming that higher proportions of high-stress cycling infrastructure significantly reduce cycling adoption. However, as family and social influence variables were introduced, the magnitude of this elasticity decreases, dropping to −0.296 in Model 2 and further to −0.180 in Model 3, consistent with the fact that the associated coefficient is not statistically significant in the ML specification for Model 3. This suggests that while infrastructure remains a critical determinant of cycling behaviour, its negative impact was partially mitigated when cycling was normalised within families and social groups.

Including family influence in Model 2 introduces a strong positive elasticity (0.637), highlighting that households, where cycling is practiced, were significantly more likely to choose cycling. Although family influence is binary at the individual level, elasticities are computed with respect to its mean, reflecting 1% changes in population-level

**Table 5**
Parameter estimates from the three Mixed Logit models.

| Coefficient | Model 1 (ML) | Model 2 (ML) | Model 3 (ML) |
|---|---|---|---|
| $ASC_{PT}$ | 0.499*** [0.280, 0.717] | 0.487*** [0.268, 0.706] | 0.467*** [0.248, 0.686] |
| $ASC_{cycling}$ | −2.829*** [−3.014, −2.643] | −3.097*** [−3.308, −2.885] | −4.108*** [−4.362, −3.854] |
| $ASC_{walking}$ | 2.133*** [2.050, 2.216] | 2.123*** [2.039, 2.206] | 2.103*** [2.020, 2.186] |
| $\beta_{TT,\ driving}$ | −0.037*** [−0.042, −0.031] | −0.037*** [−0.043, −0.032] | −0.038*** [−0.043, −0.032] |
| $\beta_{TT,\ PT}$ | −0.027*** [−0.029, −0.024] | −0.027*** [−0.029, −0.025] | −0.027*** [−0.029, −0.025] |
| $\beta_{TT,\ cycling}$ | −0.057*** [−0.061, −0.052] | −0.055*** [−0.060, −0.051] | −0.055*** [−0.059, −0.050] |
| $\beta_{TT,\ walking}$ | −0.085*** [−0.088, −0.083] | −0.086*** [−0.088, −0.083] | −0.086*** [−0.088, −0.083] |
| $\bar{\beta}_{LTS}$ | −0.756*** [−1.055, −0.458] | −0.728*** [−1.055, −0.401] | −0.442 [−1.278, 0.393] |
| $\sigma_{LTS}$ | 0.071 [−1.442, 1.583] | 0.036 [−1.120, 1.193] | 0.415 [−2.140, 2.969] |
| $\beta_{money}$ | −0.381*** [−0.428, −0.334] | −0.380*** [−0.427, −0.333] | −0.379*** [−0.426, −0.332] |
| $\beta_{W}$ | −0.121’ [−0.249, 0.006] | −0.125’ [−0.253, 0.003] | −0.130* [−0.257, −0.002] |
| $\beta_{BA}$ | 0.323*** [0.296, 0.351] | 0.244*** [0.206, 0.282] | 0.282*** [0.243, 0.321] |
| $\beta_{CA}$ | 0.574*** [0.546, 0.603] | 0.564*** [0.536, 0.593] | 0.551*** [0.523, 0.580] |
| $\bar{\beta}_{family}$ | – | 1.536*** [0.850, 2.221] | 0.536* [0.069, 1.003] |
| $\sigma_{family}$ | – | 1.736*** [0.858, 2.614] | 1.913*** [1.372, 2.455] |
| $\bar{\beta}_{social}$ | – | – | 0.201*** [0.185, 0.217] |
| $\sigma_{social}$ | – | – | 0.002 [−0.233, 0.238] |
| $R^2$ | 0.5898 | 0.5949 | 0.6005 |
| **LL** | −26904.7 | −26569.9 | −26203.25 |
| **AIC** | 53 835.4 | 53 169.9 | 52 440.5 |

*Note:* Coefficients are reported with 95% confidence intervals in brackets. Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, ’ $p < 0.10$.
"–" indicates the variable was not included in the respective model.

**Table 6**
LR tests comparing MNL and ML specifications.

| Model | LR | $df$ | $p$-value |
|---|---|---|---|
| Model 1 | 0.00 | 1 | 1.000 |
| Model 2 | 7.40* | 2 | 0.025 |
| Model 3 | 29.90*** | 3 | < 0.001 |

Significance levels: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

**Table 7**
Elasticities for mode choice models 1, 2, and 3.

| Model | Variable | Mode | | | |
|---|---|---|---|---|---|
| | | Driving | PT | Cycling | Walking |
| Model 1 | Travel Time | −0.151 | −1.394 | −1.075 | −1.573 |
| | Monetary Cost | −0.136 | −1.358 | – | – |
| | LTS | – | – | −0.307 | – |
| Model 2 | Travel Time | −0.151 | −1.394 | −1.037 | −1.591 |
| | Monetary Cost | −0.136 | −1.354 | – | – |
| | LTS | – | – | −0.296 | – |
| | Family Influence | – | – | 0.647 | – |
| Model 3 | Travel Time | −0.154 | −1.394 | −1.037 | −1.591 |
| | Monetary Cost | −0.135 | −1.350 | – | – |
| | LTS | – | – | −0.180 | – |
| | Family Influence | – | – | 0.240 | – |
| | Social Influence | – | – | 1.532 | – |

exposure. In Model 3, introducing social influence further strengthens this effect, with social influence exhibiting the highest elasticity (1.532), reinforcing that in areas where cycling is a common and socially accepted practice, individuals were far more inclined to cycle regardless of infrastructural constraints. Notably, as social influence gains prominence, the impact of family influence declines, with its elasticity reducing from 0.647 in Model 2 to 0.240 in Model 3. The declining effect of LTS across models also highlights the trade-off between infrastructure investments and behavioural interventions-although reducing LTS through improved cycling infrastructure remains crucial, fostering a supportive social and familial environment for cycling can significantly enhance its adoption even in areas where infrastructure is suboptimal.

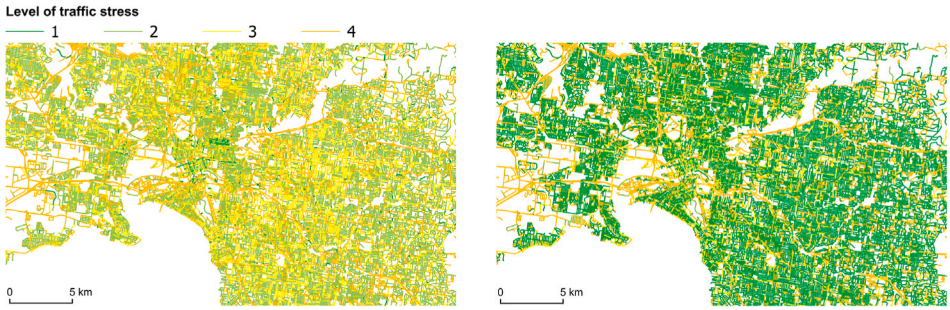
### 4.4. Modal shift results

Fig. 6 shows the LTS levels across different roads under each scenario. As shown in the figure, in RSS-30, the network was primarily covered by LTS 1 and LTS 2, providing a safer environment for cyclists.

Table 8 presents the distribution of trip lengths and LTS across the lowest-impedance cycling routes, presented by demographic characteristics, age, sex, and trip purpose, under both the baseline and RSS-30 scenarios. For each group, the table contains the mean and SD of trip lengths, along with the percentage of trip distance falling within each LTS category (LTS 1 to 4). Across all groups, the RSS-30 scenario resulted in a clear shift towards lower-stress routes, while average trip lengths remained largely unchanged compared to the baseline. On average, LTS 1 coverage increased from 26.8% to 63.8%, and the share of high-stress segments (LTS 3 and 4) declined from 45.2% to 26.0%, highlighting the positive impact of residential speed reduction policies on route quality.

Trip lengths varied substantially across demographic groups, reflecting differences in travel behaviour and accessibility needs. Children (aged 1–17) and older adults (61+) had the shortest average trips, 5.5 km and 6.9 km, respectively, suggesting more localised travel patterns. In contrast, young adults (18–30) recorded the longest average trips at 10.1 km, likely due to work or education-related travel. Males had longer trips on average (8.9 km) compared to females (7.4 km), and work trips (9.6 km) were significantly longer than non-work trips (5.9 km). Despite these differences in trip length, high-stress roads (LTS 3 and 4) were relatively consistent across groups in baseline, ranging between 39% and 46%, indicating that cyclists of all backgrounds face substantial stress levels in the existing network. However, under the RSS-30 scenario, all groups experienced marked reductions in high-stress exposure and increases in LTS 1 coverage. For example, children's LTS 1 coverage rose from 23.7% to 65.6%, and older adults' from 23.6% to 62.7%. Similarly, females saw LTS 1 coverage increase from 25.9% to 64.1%, and males from 27.8% to 63.6%. Both work and non-work trips benefited, with LTS 1 shares rising to 63.3% and 64.5%, respectively. These findings suggest that while trip distances differ by demographic group, speed reduction measures consistently improve the quality of cycling routes, making them more accessible and attractive across diverse populations.

Table 9 displays chosen modes across different models for both scenarios. In Model 1, which incorporates only LTS as an explanatory factor, cycling experiences a substantial increase in mode share, rising




(a) (b)

**Fig. 6.** A snapshot of the street network in Greater Melbourne categorised by LTS for (a) baseline and (b) RSS-30 scenarios.

**Table 8**
Distribution of LTS levels and trip lengths in lowest impedance routes, by demographic group and trip purpose.

| Scenario | Group type | Group value | Trip length (km) | | LTS 1 | | LTS 2 | | LTS 3 | | LTS 4 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Mean | SD | Mean | SD | Mean | SD | Mean | SD | Mean | SD |
| Baseline | *Age* | 1–17 | 5.51 | 6.63 | 23.70 | 25.06 | 30.19 | 23.82 | 23.34 | 20.96 | 22.75 | 22.34 |
| | | 18–30 | 10.14 | 9.62 | 30.73 | 24.45 | 24.32 | 20.47 | 20.71 | 17.41 | 24.23 | 20.50 |
| | | 31–45 | 8.80 | 9.30 | 28.38 | 24.95 | 26.50 | 22.28 | 21.74 | 18.85 | 23.36 | 20.90 |
| | | 46–60 | 8.96 | 9.25 | 27.70 | 24.54 | 25.83 | 21.53 | 21.43 | 18.66 | 25.03 | 21.30 |
| | | 61+ | 6.89 | 8.07 | 23.61 | 24.32 | 28.53 | 23.42 | 22.29 | 19.93 | 25.54 | 22.73 |
| | *Sex* | Male | 8.83 | 9.36 | 27.80 | 24.74 | 26.31 | 22.03 | 21.52 | 18.80 | 24.36 | 21.34 |
| | | Female | 7.34 | 8.21 | 25.87 | 24.87 | 27.84 | 22.82 | 22.30 | 19.65 | 23.97 | 21.80 |
| | *Purpose* | Work | 9.59 | 9.54 | 29.08 | 24.64 | 25.23 | 21.30 | 21.29 | 18.29 | 24.38 | 20.83 |
| | | Non-Work | 5.88 | 7.11 | 23.58 | 24.73 | 29.74 | 23.73 | 22.83 | 20.50 | 23.83 | 22.60 |
| | *Average* | All | 8.05 | 8.81 | 26.79 | 24.83 | 27.11 | 22.46 | 21.93 | 19.26 | 24.15 | 21.59 |
| RSS-30 | *Age* | 1–17 | 5.52 | 6.64 | 65.59 | 24.38 | 9.56 | 14.04 | 6.20 | 11.27 | 18.63 | 21.12 |
| | | 18–30 | 10.16 | 9.64 | 62.82 | 21.89 | 10.42 | 12.63 | 6.92 | 10.49 | 19.82 | 19.34 |
| | | 31–45 | 8.82 | 9.32 | 63.93 | 22.84 | 10.28 | 13.24 | 6.73 | 10.94 | 19.03 | 19.66 |
| | | 46–60 | 8.98 | 9.27 | 63.66 | 22.67 | 9.82 | 12.84 | 6.06 | 9.71 | 20.44 | 20.14 |
| | | 61+ | 6.90 | 8.10 | 62.68 | 24.53 | 10.17 | 14.41 | 6.09 | 10.92 | 21.04 | 21.56 |
| | *Sex* | Male | 8.85 | 9.38 | 63.55 | 23.03 | 10.07 | 13.25 | 6.37 | 10.45 | 19.99 | 20.18 |
| | | Female | 7.36 | 8.23 | 64.05 | 23.56 | 9.99 | 13.61 | 6.39 | 10.85 | 19.55 | 20.57 |
| | *Purpose* | Work | 9.62 | 9.57 | 63.31 | 22.44 | 10.23 | 12.94 | 6.55 | 10.31 | 19.88 | 19.63 |
| | | Non-Work | 5.90 | 7.13 | 64.50 | 24.46 | 9.75 | 14.11 | 6.14 | 11.13 | 19.59 | 21.40 |
| | *Average* | All | 8.07 | 8.83 | 63.81 | 23.31 | 10.03 | 13.44 | 6.38 | 10.66 | 19.76 | 20.39 |

by 30.36% in RSS-30. This suggests that reductions in traffic stress have a pronounced impact on cycling adoption, highlighting the importance of infrastructure improvements. This increase is accompanied by a substantial reduction in driving, indicating a strong substitution effect from driving to cycling.

Model 2, which introduces family influence, exhibits an even more substantial increase in cycling adoption, with a 88.37% increase in the RSS-30 scenario. The increase in cycling mode share suggests that when family members use cycling, individuals become even more inclined to shift towards cycling, reinforcing the role of household dynamics in shaping travel behaviour. Interestingly, PT sees a much smaller mode shift than Model 1, with increases of only 4.05% in the RSS-30 scenario. This suggests that family encouragement for cycling may reduce reliance on PT. Similar to Model 1, walking remains relatively stable, with minor increases of 0.88%, indicating that family influence does not encourage the same level of walking-to-cycling substitution observed in the first model.

Model 3, which incorporates family and social influence, shows a more moderate increase in cycling mode share compared to Model 2, with increases of 27.85% in the RSS-30 Scenario. While cycling adoption remains positive, the magnitude of the shift was lower than in the previous models, suggesting that when social influence was considered, individuals may distribute their mode choices more evenly rather than overwhelmingly shifting towards cycling.

The results highlight the interplay between infrastructure, family, and social influence in shaping modal shifts. While reductions in traffic stress in Model 1 significantly promote cycling, the addition of family influence in Model 2 further amplifies this effect, emphasising the role of household-level support in active travel adoption. However, in Model 3, where social influence was also considered, the increase in cycling was more moderate, likely due to a broader set of factors influencing mode choice decisions. These findings underscore the need for integrated policies that enhance infrastructure and develop supportive social environments and household incentives to encourage active and sustainable mobility. Ultimately, while policies promoting cycling can drive significant behavioural shifts, their effectiveness depends on including social and family influence factors.

## 5. Discussion and implications

This study highlights the critical role of social and family influence in shaping cycling adoption, particularly when combined with interventions aimed at improving cycling infrastructure and lowering traffic stress. Cycling adoption increased by 27.85% to 88.37% under different models, demonstrating that behavioural factors reinforce cycling uptake alongside infrastructure and environmental improvements. This supports findings from previous studies, which show that regions with high cycling prevalence normalise the mode, making it more socially acceptable and reducing perceived barriers to adoption (Willis

**Table 9**
Comparison of mode choices across models.

| Mode | Scenario | Model 1 | | | Model 2 | | | Model 3 | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | N | % Change | Abs. % Change | N | % Change | Abs. % Change | N | % Change | Abs. % Change |
| Cycling | Baseline | 998 | – | – | 998 | – | – | 998 | – | – |
| | RSS–30 | 1301 | +30.36% | +0.75% | 1880 | +88.37% | +1.33% | 1276 | +27.85% | +0.42% |
| Driving | Baseline | 51,246 | – | – | 51,246 | – | – | 51,246 | – | – |
| | RSS–30 | 50,302 | −1.84% | −1.42% | 50,062 | −2.31% | −1.78% | 50,380 | −1.69% | −1.30% |
| PT | Baseline | 5633 | – | – | 5633 | – | – | 5633 | – | – |
| | RSS–30 | 6069 | +7.74% | +0.65% | 5861 | +4.05% | +0.34% | 6207 | +10.18% | +0.86% |
| Walking | Baseline | 8346 | – | – | 8346 | – | – | 8346 | – | – |
| | RSS–30 | 8551 | -+2.45% | +0.31% | 8420 | +0.88% | +0.11% | 8512 | +1.99% | +0.25% |

et al., 2015; Heeremans et al., 2022; Berghoefer and Vollrath, 2023). The presence of family members or peers who cycle appears to provide additional motivation, reinforcing habitual cycling behaviour and increasing the likelihood of sustained adoption (Kim et al., 2018; Goetzke, 2008). The results also align with observational learning theories, which suggest that frequent exposure to cycling leads to higher bicycle ownership rates and increased engagement with active transport over time (Maness and Cirillo, 2016). The influence of social norms has been particularly evident in cities with established cycling cultures, where mode choice is shaped not only by infrastructure but also by community-wide acceptance of cycling as a viable transport option. The elasticity analysis findings are consistent with prior studies, which show that social and family influences can lower barriers to cycling (Willis et al., 2015; Pike, 2014).

To demonstrate how such behavioural factors interact with planning strategies, we evaluated a specific infrastructure-based intervention: lowering residential speed limits to 30 km/h. The speed limit intervention builds on prior research showing that reducing vehicle speeds enhances road safety and lowers cyclist stress, particularly on residential streets (Wegman et al., 2012; Pucher and Buehler, 2016). Slower speeds also contribute to a safer cycling environment by reducing crash severity, improving driver–cyclist interactions, and lowering cyclist-involved fatalities (Yannis and Michelaraki, 2024; Wegman et al., 2012; Pucher and Buehler, 2016). Cities such as Brussels, Paris, Helsinki, Amsterdam, and Bilbao have adopted 30 km/h citywide speed zones, improving safety outcomes and increasing active transport participation (Brussels Government, 2023; Ville de Paris, 2021; City of Bilbao, 2020; City of Helsinki, 2019; City of Amsterdam, 2023). In Greater Melbourne, Jafari et al. (2025b) demonstrated that reducing residential speeds to 30 km/h had only a marginal effect on driving times but significantly lowered the prevalence of high-stress roads for cyclists. Building on this, our study highlights that infrastructure interventions are most effective when complemented by behavioural factors, particularly social and household-level support. The findings provide strong evidence that speed limit reductions alone are not sufficient; a supportive social environment can significantly enhance the effectiveness of such measures.

The recent speed limit reductions in Wales, United Kingdom, have also highlighted the importance of public awareness initiatives, introducing a 20 mph (approximately 30 km/h) default speed limit in urban areas and educational campaigns to support the transition (Welsh Government, 2023). Evidence from Victoria, Australia, and British Columbia, Canada, suggests that regulatory barriers, policy misalignment, and limited local government capacity often make the widespread adoption of lower speed limits difficult despite their demonstrated safety and mobility benefits (Pearson et al., 2025). Moreover, strong political leadership is essential, particularly in the face of public resistance to change. For instance, Paris has undertaken extensive reforms under Mayor Anne Hidalgo, including reduced speed limits and low-traffic zones, as part of a broader push to promote active transport and reclaim urban space (Tramuta, 2020). Despite criticism, the mayor has remained firm in advancing these policies, leading to measurable improvements in noise levels and air quality across the city (POLIS Network, 2021).

### 5.1. Policy implications

The results of this study have clear implications for cities like Greater Melbourne aiming to increase active transport participation. Infrastructure Victoria's 30-year strategy has already identified reducing speed as a priority to enhance safety and support the uptake of active transport (Infrastructure Victoria, 2025). While the results of this study provide empirical support for this, they also show that speed reduction alone is insufficient. Social influence, through peer encouragement, family cycling habits, and community support, can enhance the effectiveness of infrastructure improvements.

Global evidence shows that speed reduction policies are most effective when combined with infrastructure improvements, regulatory support, and behavioural interventions. Cities such as Helsinki and Amsterdam have successfully integrated extensive cycling infrastructure upgrades and public awareness campaigns alongside speed limit reductions, leading to long-term increases in cycling uptake and improvements in road safety (City of Helsinki, 2019; City of Amsterdam, 2023). In the Netherlands, legal frameworks, such as Article 185 of the Road Traffic Act, establish a form of strict liability, whereby in collisions between motor vehicles and cyclists, the motorist is presumed liable. This presumption enhances protection for vulnerable cyclists and reinforces the effectiveness of infrastructure and behavioural interventions (SWOV Institute for Road Safety Research, 2023). In contrast, cities that implemented speed limit reductions without complementary measures often experienced lower compliance rates and minimal changes in travel behaviour (Davis, 2024).

For Greater Melbourne, a comprehensive strategy should prioritise the creation of low-stress cycling networks, including protected bike lanes and safer intersections, while also investing in community-based programs. Peer-led initiatives, local cycling clubs, and social ride events help normalise cycling and foster long-term behavioural shifts. Family-centred interventions, including safe routes to school, cycling education, and incentives for family bike ownership, further reinforce cycling as a practical transport option. Behavioural change campaigns, such as advertising, employer-supported cycling schemes, and bike-sharing incentives, create social reinforcement and sustain participation in active travel. Aligning infrastructure with behavioural strategies ensures that cycling becomes widely adopted and integrated into urban transport, making it a feasible and attractive alternative to motorised travel.

To be effective, however, these efforts must be equitably implemented. Without inclusive planning, there is a risk of reinforcing or widening transport inequalities, particularly in car-dependent or underserved communities. Local leadership, flexible governance, and urban design that promotes lower speeds are essential for delivering broad-based outcomes (Pearson et al., 2025). Plan Melbourne's vision for 20-minute neighbourhoods provides a timely framework for operationalising these goals (Victoria State Government, 2024).

Simply expanding cycling networks may not be sufficient to achieve these policy goals in the short to long term. Targeted social reinforcement strategies, such as community-led cycling initiatives, financial incentives for active travel, and educational programs, could further enhance cycling adoption by shifting social norms and perceptions around cycling.

## 6. Conclusion

This study examined the impact of traffic stress, family influence, and social norms on cycling adoption, exploring how these factors shape mode choice behaviour. The results show that social and family factors have a positive and significant impact on cycling likelihood, whereas higher LTS have a negative effect.

To demonstrate these effects, we applied the model to a residential speed reduction scenario (RSS-30), where reducing speed limits to 30 km/h lowered the share of high-LTS roads from 45% to 30%. This shift in network stress was associated with significant gains in predicted cycling mode share. Under the model considering only LTS, cycling increased by 49.6%. When social and family influence variables were included, predicted cycling shares increased further, with gains ranging from 27.85% to 88.37% compared to the baseline. These findings highlight that while safer infrastructure is crucial for enabling cycling, social and household environments are also contributing factors for cycling uptake.

## 7. Future research

This study has several limitations. It only considered trips originating from home, assuming that all transport modes were equally accessible to household members. This does not account for potential mode availability restrictions, such as car access during travel, which could influence mode choice. Additionally, the study does not distinguish between drivers and passengers in car trips, which may affect mode shift estimations. Nonetheless, given that the primary focus was on LTS and its impact on cycling behaviour rather than a comprehensive mode choice model, these limitations are unlikely to alter the core findings significantly.

In addition, using routinely collected data from travel surveys limits the extent to which social and family factors can be captured. In this study, it was necessary to use creative approaches to construct social environmental variables based on the available information. Future research may benefit from incorporating more specific and theoretically grounded measures of the social environment, as suggested in the literature, which may be even more predictive of cycling behaviour. Although the inclusion of family and social influence variables offers valuable contextual insights, they are interpreted as associative rather than causal. Future studies could address potential feedback and spatial aggregation effects through longitudinal analysis or instrumental variable methods to better isolate causal relationships.

Future research should examine long-term behavioural shifts following speed limit reductions to determine whether initial increases in cycling uptake are sustained or even increased. This could provide deeper insights into how cycling adoption evolves beyond short-term responses to infrastructure changes (Sugiyama et al., 2013). Future studies could provide deeper insights into how cycling adoption evolves beyond short-term responses to infrastructure changes. Further investigation is needed about social, family and environmental factors to understand how different demographic groups respond to social influences and infrastructure modifications, particularly in suburban and regional contexts where car dependency remains high. Expanding this research to other metropolitan areas with different urban structures could offer valuable insights into how the built environment and social dynamics interact to shape cycling behaviour.

Future research should also focus on integrating social behavioural dimensions into an agent-based modelling framework. Our existing model, AToM (Jafari et al., 2024), has been previously used to investigate cycling uptake under various infrastructure scenarios (Jafari et al., 2025a). While ATOM currently captures travel behaviour responses to physical network changes, there is a substantial opportunity to enhance its capabilities by incorporating social influence mechanisms, such as family and neighbourhood cycling norms. Addressing these research gaps will contribute to developing more effective, evidence-based policies that promote cycling as a viable and widely accepted mode of transportation.

## CRediT authorship contribution statement

**Sapan Tiwari:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Afshin Jafari:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Funding acquisition, Conceptualization. **Nikhil Chand:** Writing – review & editing, Writing – original draft, Software, Formal analysis. **Billie Giles-Corti:** Writing – review & editing, Supervision, Conceptualization.

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## Declaration of competing interest

None.

## Appendix. Derivation of travel time and cost variables

This appendix outlines the procedure used to derive the travel time and cost variables from VISTA, ensuring replicability of the modelling framework.

*Travel time estimation*

Reported travel times in VISTA were cross-validated using network-based estimates obtained from the Google Maps Distance Matrix API. For each origin–destination pair, travel times were estimated for all available modes (driving, PT, walking, and cycling) during representative time periods. The validated travel times replaced inconsistent or missing survey values and were used to construct mode-specific impedance attributes in the choice models. For active modes, cycling speeds were standardised at 15 km/h and walking at 4.5 km/h to ensure comparability across trip distances.

*Travel time estimation using r5r*

In this study, all non-cycling travel times reported were generated using the R5 routing engine, accessed through the `r5r` package in R. R5 combines OSM street data with General Transit Feed Specification (GTFS) timetables and implements schedule-based PT routing. We prepared an R5 bundle for Greater Melbourne and initialised it with `setup_r5()`. We then read the MB coordinates for the origin and destination of each observation in the VISTA trip data. Travel time computations were performed for a single morning peak period, 07:00 AM, to reflect typical network conditions. PT and walking travel time durations were estimated using the `travel_time_matrix()` function in `r5r`. For PT, we set the 'mode' parameter to 'TRANSIT' and 'mode_egress' to 'WALK'. The median travel times were obtained with the default time window set to 1, resulting in one estimate per minute, which accounts for five departure times (Saraiva et al., 2025). The 'max_walk_time' and 'max_trip_duration' parameters were set to 60 and 700 min, respectively, utilising the default walking speed of 3.6 km/h. This function returns the travel time in minutes, recorded as the trip's PT travel time. If no feasible itinerary was available under these constraints, we assigned a travel time of 'NA' for that trip. Walking durations were estimated using the same function and parameters, except the 'mode' parameter, which was set to 'WALK'. Car times were calculated using the r5r's `detailed_itineraries()` function with the 'mode' parameter set to 'CAR'. This function returns the shortest path route itinerary between the origin and destination pair. We retained the 'total_duration' returned by the function as the car travel time for the trip.

*Cycling travel time estimation using LTS-based routing*

Cycling travel times were computed separately from other modes. Following our previous work on LTS based routing (Jafari et al., 2025b), we constructed a directed, routable network for Greater Melbourne using OSM data and classified each link according to its LTS level (1–4). The routing procedure was implemented in R using the `igraph` package, and all calculations were performed on the same VISTA trip dataset used in the R5 computations. Each VISTA trip record includes the exact origin and destination MB coordinates, as well as a pair of SA1 codes for the origin and destination of the trip. For trips where only SA1 zones were available, we employed a node selection procedure to identify network access and egress points. For each SA1, we first identified all candidate network nodes located within or bordering a 10 m buffer of the zone boundary. If LTS 1–2 nodes were available, these were selected. If none existed, nodes on LTS 1–2 links intersecting the zone within a 10 m buffer were used; otherwise, the search expanded to any link or node within the zone. One node was then drawn at random from the candidate set for the origin and another for the destination. The randomisation step ensures that multiple trips from the same SA1 pair are not artificially constrained to a single centroid while maintaining replicable results when the same random seed and network snapshot are used. Routing between selected node pairs was performed on the LTS network using the `igraph` package. For each OD pair, a shortest-time path was calculated by weighting each link by its length divided by a constant cycling speed of 4.167 m/s (15 km/h). Hence, the total travel time in minutes for a path P containing links e is given by:

$$T_P = \frac{1}{60} \sum_{e \in P} \frac{L_e}{v_{\text{bike}}} \tag{9}$$

where $T_P$ is the total cycling travel time for the path $P$ between two network nodes corresponding to a survey trip (in minutes), $L_e$ is the length of the link $e$ (metres), and $v_{\text{bike}}$ is the cycling speed ($v_{\text{bike}} = 4.167\,\text{m/s}$).

*Travel cost estimation*

Travel costs were calculated by applying a fixed fare for PT trips and a distance-based cost for private car trips derived from fuel price and consumption rates. According to VISTA (2012–2020), individuals who reported using PT, on average, two PT trips per day. Based on the Myki fare structure in Greater Melbourne during the survey period, a standard daily fare of approximately AUD 8 was assumed. Consequently, trips with a total duration of up to two hours were assigned a cost of AUD 4, while longer trips exceeding two hours were assigned the full daily fare of AUD 8. This rule reflects the time-based validity of Myki fares, which allow unlimited travel within a two-hour window before automatically upgrading to the daily cap.

Driving costs were determined using a distance-based fuel consumption cost function expressed as:

$$\Delta m_{\text{driving}} = \gamma_{d,\text{car}} \times d_{\text{trav,driving}}, \tag{10}$$

where $\Delta m_{\text{driving}}$ represents the total fuel expenditure for a trip (AUD), $d_{\text{trav,driving}}$ is the travel distance (km), and $\gamma_{d,\text{car}}$ denotes the average fuel cost per kilometre (AUD/km).

The fuel consumption rate (11.8 litres/100 km) for a medium car travelling at an average journey speed of 60 km/h was adopted from the Australian Transport Assessment and Planning (ATAP) guidelines. The average retail fuel price for unleaded petrol in Victoria between 2012 and 2020 was AUD 1.35 per litre, as reported by the Australian Institute of Petroleum. Using these parameters, the unit fuel cost was derived as:

$$\gamma_{d,\text{car}} = \frac{11.8\,(\text{lit}/100\,\text{km}) \times 1.35\,(\text{AUD/lit})}{100} = 0.1593\,(\text{AUD/km}).$$

Accordingly, the total driving cost per trip was estimated as the product of travel distance and $\gamma_{d,\text{car}}$. Additional trip-related costs such as parking and tolls were excluded due to the limited spatial coverage of such data within the VISTA sample. For active modes such as walking and cycling, direct monetary costs were assumed to be zero, consistent with previous travel behaviour modelling practice.

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