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Role of traffic stress and family influence in cycling mode choice

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1 Introduction

Cycling is widely recognised as one of the most sustainable and health-enhancing urban transport modes, contributing to reduced greenhouse gas emissions, lower congestion, and improved public health outcomes (Logan et al., 2023; Pucher & Buehler, 2017). As a zero-emission mode, it also plays a vital role in climate change mitigation and in creating more liveable cities (Pucher et al., 2010). Despite these benefits, cycling adoption remains low in many urban areas, highlighting the need for interventions that address barriers to uptake (Goel et al., 2022).

Infrastructure quality and safety are critical determinants of cycling behaviour, with the Level of Traffic Stress (LTS) framework widely used to evaluate road conditions (Mekuria et al., 2012). Low-stress environments (LTS 1–2), such as quiet residential streets or separated bike lanes, are strongly associated with higher cycling participation, whereas high-stress roads (LTS 3–4) discourage riders (Pucher & Buehler, 2016; Yannis & Michelaraki, 2024). In Melbourne, much of the network falls under high-stress categories, limiting accessibility, especially in outer suburbs (Jafari et al., 2025). Speed management is therefore vital: lowering limits to 30 km/h has been shown to convert high-stress routes into safer, low-stress ones while reducing crash risk, fatalities, and injuries (Yannis & Michelaraki, 2024; Mertens et al., 2017). Infrastructure Victoria has recommended such measures, aligning with global best practices to support active travel and protect vulnerable users (Infrastructure Victoria, 2025; Pearson et al., 2025).

Alongside infrastructure, family influence also plays a significant role in shaping cycling uptake. Parental support, household norms, and safety perceptions strongly affect children's and adults' travel decisions (Willis et al., 2015; Kim et al., 2018). Studies show that family members who cycle encourage others to adopt the mode, with social reinforcement linked to higher cycling frequency and purpose (Tiwari et al., 2025a; Tiwari et al., 2025b; Kaplan et al., 2015; Sherwin et al., 2014). However, while the effects of infrastructure are well established, the interaction between traffic stress and family dynamics remains underexplored.

This study contributes by explicitly incorporating a household-level indicator of cycling behaviour into a mode choice model for Greater Melbourne. It mainly addresses three research questions:

1. *How does high LTS impact cyclists' mode choice and behaviour?*
2. *How does family influence impact cyclists' mode choice and behaviour?*
3. *What is the potential increase in cycling ridership when LTS is reduced and family influence is strengthened?*

2 Methodology

2.1 Study area

Melbourne, the capital of Victoria, Australia, has a population of about 5 million, projected to nearly double to 9 million by 2050 (ABS, 2021; DELWP, 2017). Covering roughly 10,000 km², the city faces growing transport demand, making active modes increasingly important. Melbourne's road network was classified into four LTS levels using cycleway type, road hierarchy, speed limits, and traffic volumes (Jafari et al., 2025). Two scenarios were analysed: (1) Baseline, reflecting current OSM speeds, and (2) RSS-30, where residential street limits were reduced to 30 km/h to evaluate the effect of safer, low-stress cycling conditions.

2.2 Data source

This study draws on the Victorian Integrated Survey of Travel and Activity (VISTA)[1] 2012-2020, a household travel survey that records daily trips and activity data, including origins, destinations, modes, purposes, and timings. Two Multinomial Logit (MNL) mode choice models were developed with walking, cycling, driving, and public transport as alternatives. Travel times were estimated using the R5 routing engine (r5r in R) with OSM and GTFS data for PT, and speed/path data for driving and walking. Cycling routes were generated using a custom impedance-based model that prioritised low-stress (LTS 1–2) roads, applied penalties at intersections and unsignalised crossings, and allowed deviations of up to 15% from the shortest path to reflect real-world behaviour (Jafari et al., 2025). Route attributes, including length, LTS composition, and deviation, were recorded for each trip. As the Australian Institute of Petroleum reported, driving costs were estimated using fuel consumption rates from the Australian Transport Assessment and Planning (ATAP)[2] guidelines and average fuel prices in Victoria, as the Australian Institute of Petroleum[3] reported over the same period.

2.3 Mode choice models

We developed two MNL models using VISTA 2012–2020 data to analyse travel behaviour across four modes: walking, cycling, driving, and public transport. A total of 66,223 trips with valid routes for all modes were included. Explanatory variables comprised travel time, travel cost (driving and PT), household vehicle ownership, work purpose, cycling infrastructure quality (share of high-stress LTS segments), and family influence (whether another household member cycles). The base model (Model 1) includes standard mode choice factors with LTS, while the extended model (Model 2) adds family influence to capture household-level effects on cycling. The utility function for this model is formulated as follows:

$$U_{ij}^{(m)} = ASC_j * x_6 + \beta_{TT,j} * T_{ij} + \beta_{money} * C_{ij} * x_3 + \beta_{LTS} * P_{LTS,ij} * x_2 + \beta_{BA} * NB_i * x_2 + \beta_{CA} * NC_i * x_1 + \beta_w * W_i * x_4 + \beta_{family} * F_{cyc,i} * x_2 * \delta_m \quad (1)$$

where,

$U_{ij}^{(m)}$= Utility of the individual i choosing mode j under Model m

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

$P_{LTS,ij}$= Fraction of the total length of the lowest-impedance route for cycling that consists of high-stress road segments for the individual i

[1] https://discover.data.vic.gov.au/dataset/victorian-integrated-survey-of-travel-and-activity-vista

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

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

$F_{cyc,i}$=Binary variable = 1 if any household member of i has a cycling trip, zero otherwise,

NB_i=Number of bikes in the household of an individual i

NC_i=Number of bikes in the household of an individual i

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 driving or cycling, 0 otherwise,

x_6=Binary variable = 1 if j is cycling, PT, or walking, 0 otherwise

δ_m=Binary variable = 1 if m is Model 2, 0 otherwise

$\beta_{TT,j}, \beta_{money}, \beta_{LTS}, \beta_{BA}, \beta_{CA}, \beta_w$ and β_{family} are the coefficients to be estimated.

Mode-shift analysis was performed iteratively: Model 1 estimated shifts under the RSS-30 scenario, and Model 2 updated the probabilities by incorporating family influence. Recalculated utilities guided mode assignments, which were then compared against baseline conditions to determine overall shifts.

3 Main findings

The estimated parameters for the mode choice models are presented in Table 1. Across both models, key variables, including travel time, cost, and ASC, exhibit similar behaviour and are statistically significant. Travel time negatively impacts mode choice across the modes, with coefficients $\beta_{\text{TT_driving}}$, $\beta_{\text{TT_PT}}$, $\beta_{\text{TT_walking}}$ and $\beta_{\text{TT_cycling}}$ all being negative and highly significant across both models. These results indicate that longer travel times decrease the likelihood of choosing a particular mode, highlighting travellers' sensitivity to time-related constraints. Similarly, the coefficient for travel cost (β_{money}) remains negative and statistically significant across both models, reflecting the general aversion to higher transportation costs. The coefficient for β_{w} remains weakly significant, while the coefficients for β_{BA} and β_{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}) is introduced as an independent variable, and its coefficient ($\beta_{\text{LTS}} = -0.754$, $p < 0.001$) 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 inclusion of P_{LTS} results in a reasonable model fit, with an R^2 of 0.5898. The magnitude of β_{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 (β_{family}), which has a substantial positive effect ($\beta_{\text{family}} = 2.321$, $p < 0.001$), indicating that individuals are more likely to choose cycling if other household members do the same. The introduction of family influence reduces the absolute magnitude of β_{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 suggests that individuals from households where cycling is common are more likely to choose cycling, even in areas with high traffic stress. Additionally, the effect of employment status (β_{w}) becomes slightly more negative (-0.123). However, it is now only significant at the $p < 0.05$ level, indicating that work trip purpose may play a reduced role in mode choice when family influence is considered. The

model fit improves slightly, with R^2 increasing to 0.5949, suggesting that including family influence improves the model.

Table 1: Estimated mode choice model parameters for Model 1 and Model 2

Coefficient	Model 1			Model 2		
	Estimate	S.E.	95% CI	Estimate	S.E.	95% CI
ASC_{PT}	0.499***	0.102	[0.299, 0.698]	0.489***	0.110	[0.274, 0.704]
$ASC_{cycling}$	-2.829***	0.096	[-3.017, -2.64]	-3.045***	0.101	[-3.242, -2.848]
$ASC_{walking}$	2.133***	0.042	[2.051, 2.216]	2.117***	0.042	[2.034, 2.199]
$\beta_{TT_driving}$	-0.037***	0.003	[-0.042, -0.032]	-0.037***	0.003	[-0.042, -0.031]
β_{TT_PT}	-0.027***	0.001	[-0.029, -0.024]	-0.027***	0.001	[-0.029, -0.024]
$\beta_{TT_cycling}$	-0.057***	0.002	[-0.061, -0.052]	-0.055***	0.002	[-0.059, -0.051]
$\beta_{TT_walking}$	-0.085***	0.001	[-0.088, -0.083]	-0.086***	0.001	[-0.088, -0.083]
β_{LTS}	-0.754***	0.148	[-1.044, -0.464]	-0.678***	0.148	[-0.969, -0.388]
β_{money}	-0.381***	0.022	[-0.424, -0.338]	-0.382***	0.024	[-0.428, -0.336]
β_{w}	-0.121*	0.047	[-0.214, -0.029]	-0.123*	0.07	[-0.261, 0.015]
β_{BA}	0.323***	0.014	[0.296, 0.351]	0.215***	0.016	[0.183, 0.247]
β_{CA}	0.574***	0.014	[0.546, 0.602]	0.562***	0.014	[0.534, 0.590]
β_{family}	-	-	-	2.321***	0.083	[2.159, 2.484]
	R^2 = 0.5898				R^2 = 0.5949	
*** p < 0.001, ** p < 0.01, * p < 0.05, ' p < 0.10						

Table 2 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 by 49.60% in RSS-30. This suggests that reductions in traffic stress have a pronounced impact on cycling adoption, highlighting the importance of infrastructure improvements. However, walking declines, with a -57.80% reduction in RSS-30, suggesting that individuals who previously walked may shift to cycling when road conditions become more favourable. Model 2, which introduces family influence, exhibits an even more substantial increase in cycling adoption, with a 73.84% increase in the RSS-30 scenario. The rise in cycling share suggests that when family members cycle, individuals are 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 8.38% in the RSS-30 scenario. This suggests that family encouragement for cycling may reduce reliance on PT. Unlike Model 1, walking remains relatively stable, with minor increases of 1.40%, indicating that family influence does not encourage the same level of walking-to-cycling substitution observed in the first model.

Table 2: Comparison of mode choices across models

Mode	Scenario	Model 1		Model 2	
		N	% Change	N	% Change
Cycling	Baseline	998	-	998	-
	RSS-30	1493	49.60	1735	73.84
Driving	Baseline	51246	-	51246	-
	RSS-30	54493	6.33	49920	-2.59
PT	Baseline	5633	-	5633	-
	RSS-30	6715	19.20	6105	8.38

Walking	Baseline	8346	-	8346	-
	RSS-30	3522	-57.80	8467	1.40

4 Discussion

This study underscores the importance of reducing traffic stress and leveraging family influence to promote cycling adoption in Greater Melbourne. The findings support Infrastructure Victoria's proposal to lower residential speed limits and encourage active transport (Infrastructure Victoria, 2025). Reducing limits to 30 km/h significantly increases low-stress cycling routes (LTS 1 and 2), creating safer, more attractive conditions. This aligns with prior research showing reduced crash severity and greater active travel uptake (Pucher & Buehler, 2016; Yannis & Michelaraki, 2024), as well as with international initiatives in Brussels, Paris, and Amsterdam, where 30 km/h zones combined with education and awareness campaigns foster long-term behavioural change.

Family influence also plays a key role. Households with cycling members were more likely to cycle even in high-stress environments, reinforcing evidence that peer and familial habits shape travel behaviour (Kim et al., 2018; Willis et al., 2015). These results highlight that expanding cycling networks alone may not be sufficient; household encouragement can substantially boost adoption. Integrating infrastructure improvements with family-oriented strategies offers a stronger pathway toward sustainable urban mobility.

Empirical results show that reduced traffic stress increased cycling by 49.6%, while adding family influence raised adoption to 73.8%. This demonstrates that while speed reductions can drive initial uptake, long-term change relies on social reinforcement. Overall, an integrated approach that combines safer infrastructure with behavioural support is essential to building cycling-friendly urban environments.

This study has some limitations. It focused only on trips originating from home and did not differentiate between drivers and passengers, which could affect mode-choice estimates. The low share of cycling trips in the dataset may limit the statistical strength of cycling-related variables, including family influence. Additionally, the model does not segment individuals by age, limiting insights into the cycling behaviour of younger people, particularly the 1–17 age group, which is known for higher cycling rates.

Future research should examine long-term changes in cycling behaviour following speed limit reductions and explore how family influence sustains cycling adoption over time. Additionally, investigating the role of broader social norms could provide further insights and aid in developing more comprehensive strategies to promote cycling as a mainstream mode of transportation. Future research could explore age-specific models or interaction effects to better understand how intra-household dynamics influence cycling uptake among younger individuals.

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