

Establishing the Level of Support for Transport Initiatives which make a Positive Impact on Travel Behaviour

Hensher, D A^a, Wei, E^a, Nelson, J D^a, Kandanaarachchi, T^a, Mulley, C^a, Balbontinn, C^{a,b}, Liu, W^a and Ho, C^a

^a Institute of Transport and Logistics Studies (ITLS), The University of Sydney Business School, Sydney, 2006, Australia

^b Pontificia Universidad Católica de Chile, Chile

20 October 2025

Abstract

The concept of “windows of change” (WoC) highlights periods when established behaviours are unsettled and individuals are more open to alternatives. This paper advances the understanding of sustainable transport policy by highlighting WoC and segmentation as complementary tools for designing and implementing effective interventions. Data is collected from over 4,000 respondents spread across Australia, Finland, New Zealand, the United States, the United Kingdom, Singapore, and Sweden, investigating respondents’ WoC over the period 2023–2025. We also explore the influence of 50 transport-influencing initiatives on how people travel.

From a three class Latent Class Analysis model we labelled the classes as “Urban strivers” (characterised noticeably by a majority of members in full-time employment); “Settled simplifiers” (in addition to retirees, including homemakers and other “not working”); and “Dynamic jugglers” (including part-time and flexible workers). Dynamic jugglers are found to be the most receptive of the range of transport-influencing initiatives explored. The comparative analysis of these three classes demonstrates how segmentation, when combined with WoC, can guide policymakers in tailoring transport interventions more effectively.

Key words: Windows of change, transport-influencing initiatives, survey of seven countries, latent class model, sustainable transport policy

1 Introduction

Transport is widely recognised as a critical sector in climate change mitigation, contributing substantially to greenhouse gas emissions while shaping daily mobility practices. Although there is increasing attention globally to develop pathways towards decarbonisation, time has taught that technological advances and infrastructure investment alone are insufficient. Effective policy must also account for the temporal and social dynamics that influence mobility choices (Wiltshire, 2023). It is necessary to understand the circumstances under which individuals are more receptive to reconsidering established travel patterns.

The concept of “windows of change” (WoC) highlights periods when established behaviours are unsettled and individuals are more open to alternatives. These windows may occur at critical life stages, such as entering employment, relocating, or household restructuring, but can also arise through wider policy or institutional shifts (Klößner, 2004; Li and Kamargianni, 2019). Designing interventions that align with such transition points offers significant potential to accelerate sustainable mobility (Hensher et al., 2025; Jin et al., 2020). However, this perspective has received limited systematic attention in transport research and policy.

Conventional approaches often adopt population-wide measures, assuming homogeneity in travellers’ capacity and willingness to adapt. These risk reducing effectiveness and reinforcing inequities. Evidence suggests that treating populations as uniform has frequently produced only

marginal change in travel outcomes (Piras et al., 2022; Roaf et al., 2024). Segmentation offers a corrective by classifying travellers according to socio-economic characteristics, life stage, and responsiveness to change. When combined with windows of change, segmentation enables interventions to be more precisely timed and tailored, improving both equity and policy impact.

This paper advances the understanding of sustainable transport policy by highlighting WoC and segmentation as complementary tools for designing and implementing effective interventions. After a brief review of both concepts, the paper outlines the methodology and presents findings from a Latent Class Analysis (LCA) of user preferences toward sustainable transport initiatives. Data is collected from over 4,000 respondents spread across Australia, Finland, New Zealand, the United States, the United Kingdom, Singapore, and Sweden, investigating respondents' WoC over the period 2023–2025. We explore the influence of 50 transport-influencing initiatives on how people travel. The results demonstrate how segmentation, when combined with WoC, can guide policymakers in tailoring interventions to specific person-types more effectively. The paper is organised as follows: Section 2 introduces the literature context for the study with a focus on segmentation. This is followed by a discussion of the methodological approach of LCA adopted in this study. Results are presented in Section 4. Finally, the paper concludes with recommendations for leveraging these approaches to enhance the design and impact of sustainable transport policies.

2 Literature context

Research has consistently shown that pivotal life events can trigger shifts in travel behaviour. Van der Waerden et al. (2003) and Klöckner (2004) demonstrated that milestones such as obtaining a driving licence, starting university, moving residence, or changes in employment can alter mode preferences, with distinct behavioural clusters emerging around car use. Longitudinal analyses, such as a study by Scheiner (2014) using German Mobility Panel data, confirmed that events like childbirth, entering the labour market, or relocation influence trip rates, though impacts were generally moderate and varied across genders. Comparable findings in the U.S. (Gehrke et al., 2019) and China (Li and Kamargianni., 2019) highlighted that marriage, parenthood, and commuting changes often encourage shifts toward car use, reinforcing calls for policy intervention during these transition periods. Life stage has also been examined as a mediating factor. Janke et al. (2020) found that while stages such as young adulthood, parenthood, or later life did not strongly moderate event impacts, they shaped dominant mobility patterns, with relocations in particular pushing families and young couples toward greater car dependence.

Residential moves represent one of the most studied transitions. Reviews (Ding et al., 2018; Zarabi and Lord, 2018) show that relocation often influences walking, cycling, and driving, with neighbourhood design, public transport, and parking availability proving decisive. Other work suggests relocation can increase car ownership and type of public transport ticket purchases while reducing active travel (Beige and Axhausen, 2017), with lifestyle aspirations and housing preferences shaping neighbourhood choices (Gehrke et al., 2019). However, such moves frequently place families, especially millennials, in poorly connected areas, limiting sustainable travel options (Delbosc and Nakanishi, 2017). Collectively, this body of work underscores relocation and other life events as critical intervention points for policies promoting sustainable mobility.

Recent work has advanced this line of inquiry by broadening the scope of events considered as potential triggers of behavioural change. A large-scale cross-national study of over 4,000 respondents across Australia, Finland, New Zealand, the United States, the United Kingdom, Singapore, and Sweden conceptualised these windows of change (WoC) as lifestyle, work-related, mobility-related, and social or environmental shifts (Hensher et al., 2025). Using negative binomial count models to link these influences with weekly modal trip frequencies, the study identified both facilitators and barriers to transitions away from car use. The WoC framework thus

provides a more comprehensive lens for understanding when and how interventions might support sustainable travel behaviour, extending earlier research that focused primarily on discrete life events such as relocation, childbirth, or employment changes.

While life events and transitions create important opportunities for behavioural change, the effectiveness of transport interventions ultimately depends on how well they account for traveller heterogeneity. Much of the literature highlights that transport initiatives are too often evaluated without sufficient attention to the fact that different groups of travellers respond in distinct ways (Anable, 2005; Fan et al., 2023; Hunecke et al., 2010; Hunecke et al., 2007). These differences are not only shaped by socio-demographic variables such as income, gender, or household structure, but also by more subtle factors including tastes, habits, and attitudes toward mobility (Hunecke et al., 2010). For example, car enthusiasts are typically more sensitive to waiting times at bus stops compared to travellers who already favour public transport. This illustrates how the same intervention may elicit very different reactions depending on an individual's predispositions and circumstances (Anable, 2005).

Traditional travel choice models have attempted to address these differences by incorporating observable characteristics, a practice commonly described as system heterogeneity. However, such models struggle when behavioural shifts are driven by unobservable factors or random variations, resulting in biased parameter estimates and limited explanatory power (Fan et al., 2023). This has led scholars to argue that attitudes and context-specific beliefs are often better predictors of behaviour than broad values or generic environmental concerns (Hunecke et al., 2007). In this regard, segmentation provides a more nuanced lens, moving beyond demographic categories to reflect the diverse psychological, social, and situational factors that shape mobility decisions.

Anable's (2005) influential typology demonstrates the value of such approaches by categorising travellers into six distinct groups ranging from "malcontented motorists", who are dissatisfied with car dependence and open to change, to "die-hard drivers", for whom car use is central to identity and lifestyle. Other groups, such as "aspiring environmentalists" or "reluctant drivers", capture the spectrum of motivations and constraints that influence travel mode choices. More recent frameworks continue this effort to map heterogeneity. For example, Pearson et al. (2022) introduced a four-part cyclist classification, "strong and fearless", "enthused and confident", "interested but concerned", and "no way no how", which has since become a widely applied tool in cycling policy. Similarly, De-Toledo et al. (2022) applied the Sunio et al. (2018) self-regulated behaviour change model, identifying temporal stages of pre-decision, pre-action, action, and post-action to explain how individuals progress through mobility transitions. These approaches emphasise that mobility preferences are both diverse and dynamic, and that individuals may shift categories depending on context. For instance, a confident commuter cyclist may adopt an "interested but concerned" orientation when travelling with children.

The practical implications of segmentation are significant for policy design. By identifying the types and compositions of users within a given jurisdiction, interventions can be better tailored to match both motivations and barriers (De-Toledo et al., 2022). Evidence from personalised travel planning (PTP) illustrates this clearly: programmes targeted at specific groups, such as employees for work trips, parents for school travel, or residents in new housing developments, have successfully reduced car use by offering tailored incentives (e.g., free bus passes), personalised information, or direct engagement through home visits, group meetings, and digital platforms (Redman et al., 2013). Earlier evaluations suggest that these approaches can lead to substantial increases in walking and active travel, particularly when positive messaging is employed to resonate with older adults and more sedentary groups (Notthoff and Carstensen, 2014; Ogilvie et al., 2007).

Overall, the literature on segmentation makes clear that a blanket “one size fits all” policy risks overlooking the diverse ways in which people perceive and experience mobility. By contrast, segmentation enables policymakers to design more precise, equitable, and impactful interventions. When aligned with the concept of windows of change, segmentation offers a powerful framework for identifying when and how to intervene most effectively. This combined perspective highlights that policy design should not only target the moments when individuals are most receptive to change, but also tailor strategies to the specific needs, motivations, and contexts of different traveller groups. In doing so, it provides a more systematic foundation for advancing sustainable transport policies, one that this paper develops through the integration of windows of change and segmentation in the analysis of user preferences and policy implications.

3 Method and Model Specification of Latent Class Analysis (LCA)

3.1 Overview of LCA

The purpose of the LCA model for this research is to identify clear patterns from the respondents about their attitudes as reflected in their responses towards transport initiatives questions on a 5-point Likert scale from “strongly negative impact” to “strongly positive impact” (described further in Section 4.1). This analysis additionally includes many exogenous variables, including respondents’ socio-demographic characteristics, changes that occurred in their lives, and other aspects from 2023 to the present. By including both response and exogenous variables in the LCA, the resulting latent classes can be profiled, allowing for actionable insights into potential future transport initiatives.

LCA has its roots in behavioural and decision theories. These theories suggest that people’s behaviour and decisions in life and choice situations are based on their beliefs and intentions (e.g., Ajzen 1991; Ajzen & Fishbein 1969; Slovic, Fischhoff & Lichtenstein 1977). A recent literature review on behavioural change in transport can be found in Hensher et al. (2025). This literature identifies that individual behavioural differences can be determined from the pattern of their selections and choices in answering questions covering their lifestyle and other changes, their opinions on transport initiatives, and their differences in socio-economic and demographic characteristics. LCA aims to identify several unique and distinctive “*Latent Classes*” to represent these patterns best (sometimes referred to as personas). Within each latent class, class members are generally homogeneous in their opinions, background, behaviour and experience. Between different classes, these characteristics are heterogeneous and dissimilar. Therefore, the LCA parameters for related variables, such as transport initiatives, differ in either their effects or preference orders in each of the classes.

The methodological foundation for LCA and the literature on LCA are well-established. Some have been discussed in a more specific context, such as market segmentation (e.g., Kamakura & Russell, 1989; Wedel & Kamakura, 2000) or discrete choice models (e.g., Hensher, Rose, & Greene, 2015). Other literature is more specific in discussing the development of the method itself and specifications, following benchmark development in areas such as Structural Equation Model (SEM) and mixture models in latent variable-oriented or latent person-oriented approaches (e.g., Jöreskog 1971; Jöreskog, 1973; Rabe-Hesketh, Skrondal & Pickles 2004; Masyn, 2013). Goodman (2002) and Collins and Lanza (2010) provide a detailed introduction and review of these benchmark developments in LCA.

In practice, LCA can be estimated using various packages and routines, such as using the Generalized Structural Equation Model (GSEM) routine in Stata, covering a wide array of models (Stata, 2025). LCA and related analyses, such as Latent Profile Analysis, which refers to cases when both response and latent variables are continuous instead of categorical, are often estimated using GSEM because these models with latent variables and latent classes are connected over the course of their development (e.g., Goodman 2002; Collins & Lanza, 2010;

Masyn, 2013). The models are estimated using maximum likelihood estimation (MLE) and the expectation-maximisation (EM) algorithm, which is particularly advantageous for estimating models when latent variables, missing data, and many parameters are all present. This is precisely the situation for the LCA in this research, where responses to transport initiatives and lifestyle changes (termed “Windows of Change” or WoCs) have incomplete but legitimate data because respondents only selected the initiatives and changes relevant to them. There is a latent variable (i.e., latent class), where many parameters are involved, including several sets of parameters across the 50 initiatives: there are over 20 WoC variables, and other socio-demographics. As each latent class has its own set of parameters, all of which are included in the LCA analysis, the total number of parameters are in the hundreds.

Masyn (2013) gave a simple description of the LCA measurement model conceptually. Assuming there are M indicator response variables (e.g., response to a binary variable) and K latent classes a respondent j belonging to a latent class k can be expressed as $c_j = k$. The proportion or probability of individuals in class k is denoted as π_k , and every person has membership in exactly one class (i.e., classes are exhaustive and mutually exclusive), so $\sum_{k=1}^K \pi_k = 1$. The responses to M response variables ($u_{1j}, u_{2j}, \dots, u_{Mj}$) can be expressed as Equation (1) with the probability of responses from each of the K latent classes contributing to the overall pattern.

$$Pr(u_{1j}, u_{2j}, \dots, u_{Mj}) = \sum_{k=1}^K [\pi_k \cdot Pr(u_{1j}, u_{2j}, \dots, u_{Mj} | c_j = k)] \quad (1)$$

3.2 LCA Estimation and EM Algorithm

The GSEM fits the LCA model via MLE. Let Y be the vector of observed response variables and X be the vector of observed exogenous variables. We assume a single categorical latent variable C with k levels. There are N number of respondents. The likelihood function for the parameter vector θ is denoted in Equation (2).

$$\mathcal{L}(\theta) = \sum_{i=1}^k \pi_i \cdot \prod_{j=1}^n f_{ij}(Y_{ij}, X_{ij}, \theta) \quad (2)$$

The log-likelihood is denoted in Equation (3).

$$\log \mathcal{L}(\theta) = \sum_{i=1}^k \pi_i \cdot \sum_{j=1}^N f_{ij}(Y_{ij}, X_{ij}, \theta) \quad (3)$$

LCA uses a multinomial distribution to predict latent class probabilities. For the i^{th} latent class, the probability is denoted in Equation (4), where \hat{z}_i is the linear prediction using the variable vector and parameter vector for the i^{th} class, given a total of k classes.

$$\hat{\pi}_i = \frac{\exp(\hat{z}_i)}{\sum_{a=1}^k \exp(\hat{z}_a)} \quad (4)$$

The main breakthrough for estimation is the development of the EM algorithm (Dempster, Laird, & Rubin 1977) for MLE for using incomplete data with missing data and latent variables to estimate. The EM algorithm is the algorithm of choice for estimating LCA. When models involve latent variables/classes and incomplete or missing values in the data, EM is effective in estimation (Masyn 2013). The EM algorithm seeks to find the maximum likelihood estimate of the marginal likelihood by iteratively applying the Expectation and the Maximisation steps. For LCA, the Expectation step (E-step) derives the functional form of the expected complete-data log likelihood, which is a linear function of the latent class indicator variables (Stata 2025), as shown

in Equation (5). This is an iterative process, with the g^{th} guess of the model parameters denoted as $\theta_{(g)}$.

$$E\left(c_i \mid y, x, \theta_{(g)}\right) = \frac{\pi_i f_i\left(y, z_i, \theta_{(g)}\right)}{\sum_{j=1}^k \pi_j f_j\left(y, z_j, \theta_{(g)}\right)} \quad (5)$$

The posterior probability is denoted as p_i so the expected complete-data log likelihood for a given observation can be expressed as Equation (6), solely through the posterior probability p_i :

$$Q\left(\theta \mid \theta_{(g)}\right) = \sum_{i=1}^k p_i \left\{ \log \pi_i + \log f_i\left(y, z_i, \theta\right) \right\} \quad (6)$$

The Maximisation step (M-step) is to maximise the function $Q\left(\theta \mid \theta_{(g)}\right)$ to compute the next guess $\theta_{(g+1)}$ (Stata 2025).

3.3 The Families and Links of Variables Allowed in LCA Estimation

The GSEM estimation can accommodate both categorical and continuous variables, and depending on the variables, different families and links can be used in the estimation. Stata's GSEM (2025) shows a table of family/link combinations allowed; some of the common combinations include Bernoulli/logit, beta/logit, Poisson/log, and Gaussian/identity.

For example, the Bernoulli family can be applied to all the response variables for the 50 transport initiatives in the survey, which are binary responses taking on the values 0 or 1, and the default link for the Bernoulli family is the logit link. The logit link function is $g(\mu) = \log \mu - \log(1 - \mu)$ and its inverse is $\mu = g^{-1}(z) = \frac{1}{1 + e^{-z}}$.

For some continuous variables, such as working hours, we used the Gaussian family with the identity link function $g(\mu) = \mu$. For count variables, such as the number of cars in households, we used the Poisson family with the default log link function $g(\mu) = \log \mu$, and its inverse function $\mu = g^{-1}(z) = e^z$.

3.4 Model Fit Statistics of LCA

The main model fits for LCA can be summarised below, given the number of latent classes as k and the sample size as N . Several information criteria can be derived, as summarised below in Equations (7) to (10), with AIC and BIC often reported.

Akaika's (1974) information criterion:

$$AIC = -2\ln L + 2k \quad (7)$$

Schwarz's (1978) information criterion:

$$BIC = -2\ln L + k \ln N \quad (8)$$

One unique model fit statistic for LCA is the entropy computed from the predicted posterior latent class probabilities, developed by Ramaswamy et al. (1993). Let \hat{p}_{kj} be the predicted posterior probability for class k in observation j , where $k = 1, \dots, C$ and $j = 1, \dots, N$, then

$$entropy = 1 + \frac{1}{N \ln(C)} \sum_{j=1}^N \sum_{k=1}^C \hat{p}_{kj} \ln(\hat{p}_{kj}) \quad (9)$$

This specific entropy ranges from 0 to 1, and values closer to 1 indicate a better separation of latent classes. Entropy is effective in model selection, and a higher entropy shows a more distinctive latent class approach. This can be illustrated by a simple example: considering two

sets of class probability predictions for three classes: {0.3333, 0.3333, 0.3334} and {0.001, 0.001, 0.999}. The first set of class predictions would yield an entropy close to 0, and the second set of class predictions would yield an entropy close to 1. The second set of class predictions appears to provide a better separation of latent classes.

4 Results

A survey was undertaken in May 2025 with participants from Australia, Finland, New Zealand, the United States, the United Kingdom, Singapore, and Sweden. These countries were selected based on their advanced transport systems, progressive policy initiatives, diverse approaches to sustainable mobility, and the ability of respondents to complete the survey in English. The survey explores how key lifestyle changes between 2023 and 2025, described by WoCs, have influenced travel behaviour¹. A key section of the survey assessed the impact of 50 government and business initiatives, including public transport pricing and frequency, active travel modes, road user charging, car sharing, and employer-led benefits such as on-site facilities to encourage active travel (see Table 1). Results of the analysis using a three-class LCA model are discussed in this section.

4.1 A Summary of the Three-Class LCA Model

In the trial and testing of the LCA analysis, we used both the original 5-point Likert scale for the 50 transport-influencing initiatives² as response variables and the recoded binary responses, with positive impact codes of 4 and 5 coded as 1, and codes of 1 to 3 coded as 0 in the test. We found that using binary response variables yields a more precise and better separation of latent classes, informed by both information criteria and entropy. This indicates that the binary-coded response gives a sharper comparison of whether respondents support an initiative or not. In the original 5-point scale, differences are embedded in the smaller gaps between each code, and the large number of respondents rated neutral (i.e., selected code 3) also contributes to the less optimal class separation.

Next, including the 50 response variables on initiatives and a set of standard demographic questions such as age, gender, education, work status, and income of the respondents in the LCA yields clear latent classes with statistically satisfactory model fit statistics (e.g., entropy is over 0.90). However, the resulting latent classes do not have a sharp enough difference in their demographic profiles, for example, with closer age gaps or income levels. A lack of sharp profile comparison would limit the usefulness of these latent classes in transport policymaking. We then include the WoCs binary variables representing changes in people's lives from 2023 to the present day. The testing results show that including the 36 variables covering people's changes in their lifestyle and work from 2023 in the LCA gives unique patterns in both responses to transport initiatives and class profiles in terms of socio-demographics. This is because WoCs provide a much richer set of socio-demographic questions to cover a wide variety of socio-demographic changes such as job changes, moving residence, shifting to flexible work, partner retirement, improved or worsening health conditions and many more. In fact, these WoC questions provide such a rich and unique profile of individual respondents, explaining what happened in their lives far more effectively than standard demographic questions can.

¹ From the full list of potential WoC influences, we categorise them into four classes: (i) Lifestyle and household changes, (ii) Work and commuting changes, (iii) Transport and mobility changes, and (iv) Social and environmental considerations.

² The wording was: *Governments, businesses and other organisations often promote initiatives to influence how people travel. Below are a range of such initiatives. Please rate each initiative on a scale from "Big negative Influence" to "Big Positive Influence".*

Finally, we compared different class solutions by running 3, 4 and 5 latent classes using the same variables included in the LCA (i.e., 50 initiative variables, 36 WoC variables and 41 standard demographic variables). The 5-class LCA failed to converge. Out of the 3-class and 4-class solutions, the 3-class solution yields a better class separation with a higher entropy. In comparing the demographic profiles, the 3-class solution also gives more clearly defined class profiles. The final resulting LCA is a 3-class solution. Table 1 presents the class parameters along with t-statistics for the three latent classes: C1, C2, and C3 (with statistically insignificant parameters highlighted in orange). This shows that all the demographic and WoC variables are statistically significant, and the majority of the initiative parameters are highly statistically significant. Out of the total 4,088 respondents from the seven countries, there are 33% in Class 1, 29% in Class 2, and 37% in Class 3, based on predicted posterior class probabilities.

To represent the characteristics of the three classes and for the brevity of discussion, we labelled the three classes as follows:

- Class 1 (“US”): *Urban strivers* (characterised noticeably by a majority of members in full-time employment);
- Class 2 (“SS”): *Settled simplifiers* (in addition to retirees, this includes homemakers and other "not working"); and
- Class 3 (“DJ”): *Dynamic jugglers* (including part-time and flexible workers).

Table 1: Model parameters and model fit statistics of the latent class model (LCM)

Note: t-values in brackets

		“US”	“SS”	“DJ”
Variables		Parameters	Parameters	Parameters
Transport-influencing Initiatives				
IFrPT	Free local public transport	0.1465 (2.42)	0.6514 (8.53)	2.4542 (24.08)
I25cPT	Fixed public transport fares at US\$0.25 per trip	-0.067 (-1.11)	0.3699 (4.92)	2.2586 (24.13)
IFreqPT	Double public transport services frequency	-0.283 (-4.66)	0.1099 (1.50)	1.7611 (22.62)
IFrPnR	Free Park and Ride facility close to transport hubs	-0.324 (-5.26)	0.2221 (2.92)	1.9914 (23.52)
ILockBk	Free secure lockers for bikes/scooters at transport hubs	-0.8268 (-12.16)	-0.5169 (-6.04)	1.8155 (22.52)
IBkPk50	Bike/scooter parking at transport hubs for US\$0.50/day	-1.2205 (-16.30)	-0.8948 (-9.77)	1.3049 (18.98)
IToll25	Tolled roads ensuring 25% faster travel time than free roads	-1.1849 (-16.08)	-1.1688 (-12.74)	1.3352 (18.86)
IToll50	Tolled roads ensuring 50% faster travel time than free roads	-1.0351 (-14.66)	-0.9931 (-11.23)	1.407 (19.44)
IRUC05	Peak-period road user charge US\$0.05/mile	-2.0305 (-20.84)	-2.4933 (-16.69)	0.7932 (12.63)
IRUC10	Peak-period road user charge US\$0.10/mile	-2.0965 (-20.84)	-2.5438 (-16.39)	0.6934 (11.24)
IRUC15	Peak-period road user charge US\$0.15/mile	-2.0308 (-20.63)	-2.8517 (-15.59)	0.5968 (9.84)
IRUC20	Peak-period road user charge US\$0.20/mile	-1.9319 (-20.35)	-2.7533 (-16.00)	0.5565 (9.22)
ICFL05	Congestion-free lanes what you pay US\$0.05/mile	-2.0593 (-20.86)	-2.5267 (-16.39)	0.883 (13.80)
ICFL10	Congestion-free lanes what you pay US\$0.10/mile	-1.9612 (-20.52)	-2.4598 (-16.25)	0.7522 (12.11)
ICH15Cr	A supplementary charge of US\$15 per car in a defined area around the city which is designed to reduce congestion	-1.9994 (-20.71)	-2.5026 (-16.92)	0.5827 (9.63)

ICh10Cr	A supplementary charge of US\$10 per car in a defined area around the city which is designed to improve air quality	-1.9464 (-20.63)	-2.5088 (-16.87)	0.6997 (11.35)
IFrReg	Free annual vehicle registration with US\$0.10/mile peak-hour charge	-1.4846 (-18.93)	-1.1137 (-12.59)	1.3115 (18.79)
I50Reg	50% reduction in annual vehicle registration with US\$0.05/mile charge	-1.426 (-18.31)	-0.9866 (-11.5)	1.362 (19.4)
I75Reg	75% reduction in annual vehicle registration with US\$0.03/mile charge	-1.2378 (-16.91)	-0.7881 (-9.68)	1.4837 (20.34)
ITaxPEV	Tax deduction for acquiring hybrid/plug-in hybrid vehicle	-0.9447 (-13.78)	-0.6957 (-8.23)	1.7628 (21.84)
ITaxFEV	Tax deduction for acquiring a full electric vehicle	-0.9861 (-14.24)	-0.7784 (-9.02)	1.6977 (21.46)
IFrBus	Bookable door-to-door bus services at transport hubs, free	-0.6967 (-10.72)	-0.0228 (-0.29)	2.2666 (23.02)
IPTBus	Bookable door-to-door bus services at transport hubs, same fare as regular public transport	-0.99 (-14.36)	-0.3983 (-4.94)	1.7525 (22.01)
I10Bus	Bookable door-to-door bus services at transport hubs, +10% fare of regular public transport	-1.5532 (-19.27)	-1.2219 (-12.81)	1.2025 (18.00)
IFrCShP	Free, bookable voluntary car-sharing: you are a passenger	-1.1071 (-15.60)	-0.8962 (-10.24)	1.6217 (21.00)
IFrCShD	Free, bookable voluntary car-sharing: you are a driver	-1.5037 (-18.63)	-1.5621 (-14.48)	1.2506 (18.01)
ICSh05	Bookable car-share subscription at US\$10/month + US\$0.05/mile	-1.9155 (-20.82)	-1.9579 (-16.09)	1.1767 (17.09)
ICSh10	Bookable car-share subscription at US\$10/month + US\$0.10/mile	-1.9881 (-20.94)	-2.1115 (-16.29)	1.0366 (15.69)
ICSh15	Bookable car-share subscription at US\$10/month + US\$0.15/mile	-1.9572 (-20.74)	-2.2067 (-16.24)	1.0143 (15.51)
IEvFrPT	Event ticket includes free public transport	-0.1776 (-2.94)	0.4121 (5.34)	2.5373 (23.47)
ICrPo25	25% off parking cost for car-pooling (T3+)	-1.051 (-15.15)	-0.42 (-5.25)	1.8048 (22.02)
IVaPk20	Valet parking at event at +20% extra cost	-1.858 (-20.98)	-1.8013 (-16.43)	0.6606 (11)
IEv15PT	15% off event tickets for public transport users	-0.6565 (-10.28)	-0.0841 (-1.11)	1.9855 (23.06)
IEvSePT	Special seats at a 25% discount when you use public transport	-0.5882 (-9.20)	-0.0719 (-0.92)	2.1289 (23.42)
I10RbEB	10% government rebate for e-bike/e-scooter purchases	-1.3079 (-16.77)	-1.3012 (-12.38)	1.4224 (19.33)
I20RbEB	20% government rebate for e-bike/e-scooter purchases	-1.2241 (-16.09)	-1.0756 (-10.92)	1.5535 (20.29)
I200EB	\$200 voucher for e-bike/e-scooter purchases	-1.0621 (-14.67)	-0.8426 (-9.07)	1.7216 (21.15)
ITaxEB	Tax deduction for e-bike/e-scooter purchases	-1.1375 (-15.32)	-1.0131 (-10.38)	1.611 (20.62)
IFrChEv	Free charging at your workplace for EV and other electric mobility devices such as E-bikes or E-scooters	-0.8909 (-12.69)	-0.218 (-0.56)	2.1042 (20.33)
IShwBk	Showers and storage available for bikes, scooters, and personal items to support active travel	-0.9709 (-13.75)	-0.2828 (-0.75)	1.7178 (19.31)
IPTSub	Public transport on travel card will be subsidised	-0.5899 (-9.06)	0.4346 (1.12)	1.9375 (20.72)
IFuelLC	1% fuel discount for every 1% reduction in car use	-1.1496 (-15.59)	-0.0614 (-0.16)	1.6091 (18.92)
IBenfAc	Highlighting the health benefits of walking, cycling, scootering	-1.0643 (-15.12)	0.4944 (1.39)	1.6558 (19.65)
ICstAc	Promoting cost savings of active modes and public transport	-1.1164 (-15.50)	0.1333 (0.34)	1.6917 (19.86)

IEnvLC	Highlighting environmental benefits of driving less	-1.3114 (-17.38)	0.3837 (1.06)	1.4207 (18.10)
ILdBac	Monthly leaderboard of employees using active transport	-1.6528 (-19.60)	-0.6353 (-1.58)	1.0797 (15.17)
ILdBLC	Monthly leaderboard of employees reducing car use	-1.6804 (-19.73)	-0.3885 (-1.04)	1.0714 (14.95)
IEVInf	A government-enabled platform providing consumers with real-time EV charging information	-1.3449 (-17.23)	-0.633 (-7.17)	1.5853 (20.83)
IEVPol	A consistent and transparent pricing policy for EV charging services	-1.1367 (-15.45)	-0.4941 (-5.67)	1.6357 (21.26)
IEvChTR	Innovative charging solutions that reduce charging time by 50%	-0.8737 (-12.57)	-0.3169 (-3.69)	1.9178 (22.54)
Lifestyle and work changes (WoCs)				
LMvAr	Moved to a new area	-1.5428 (-21.11)	-1.9954 (-21.73)	-1.2599 (-20.18)
LUpsiz	Upsized to a larger home	-2.1462 (-23.32)	-3.447 (-18.30)	-1.9532 (-24.91)
LDowns	Downsized to a smaller home	-2.7817 (-23.35)	-2.6926 (-22.11)	-2.7186 (-25.18)
LHHInc	Household size increased	-2.0795 (-23.00)	-3.3019 (-18.34)	-1.9192 (-24.81)
LHHDec	Household size decreased	-2.4123 (-23.91)	-2.8263 (-22.04)	-2.2428 (-25.57)
LMarSt	I changed marital status	-2.5515 (-23.81)	-3.1616 (-20.87)	-2.4844 (-25.67)
LCareg	I started or increased caregiving responsibilities	-3.1314 (-22.57)	-2.835 (-21.97)	-2.6996 (-25.39)
LImpHl	My health improved	-1.5922 (-21.39)	-2.3362 (-21.99)	-1.2333 (-19.88)
LHIConc	I had health concerns that affected my travel	-2.4057 (-23.87)	-1.7506 (-21.11)	-2.1887 (-25.29)
IWKHlt	I started walking/exercising more for health reasons	-1.5031 (-20.61)	-1.1064 (-16.17)	-1.1319 (-18.69)
LImpFn	My financial situation improved	-1.9354 (-23.07)	-2.6698 (-21.96)	-1.6571 (-23.45)
LFinTg	My financial situation became tighter	-1.3391 (-19.48)	-1.1693 (-16.86)	-1.4441 (-21.79)
LSvMon	I have adjusted my lifestyle to prioritise saving money	-1.7512 (-22.22)	-1.6917 (-20.86)	-1.6896 (-23.51)
LIncOSh	I increased online shopping to reduce personal travel	-2.0398 (-23.36)	-1.8688 (-21.66)	-1.6781 (-23.60)
LRedOSh	I have reduced online shopping spending	-2.2613 (-23.82)	-2.1864 (-22.41)	-2.4032 (-25.58)
LCICol	I started using click-and-collect more often	-2.9063 (-23.25)	-2.9524 (-21.90)	-2.7971 (-25.30)
LHmDel	I now rely more on home delivery	-2.9867 (-23.27)	-2.9298 (-21.91)	-3.1306 (-24.32)
LDog	I acquired a dog	-2.6915 (-23.72)	-2.7952 (-22.16)	-2.7875 (-25.22)
LNoDog	I no longer have a dog	-3.3266 (-21.84)	-2.6801 (-22.37)	-3.6632 (-21.70)
Lret	I retired from the workforce	-4.2742 (-17.94)	-2.3365 (-22.68)	-3.6741 (-21.89)
LTmpNW	I was temporarily not working	-3.7004 (-20.30)	-3.0717 (-21.30)	-3.4066 (-22.76)
LPrtRet	My partner retired	-4.239 (-17.84)	-3.841 (-18.64)	-4.4007 (-17.86)
LPrtChJ	My partner changed jobs	-4.0681 (-18.83)	-4.0919 (-17.72)	-4.2519 (-19.03)
LPrtWkF	My partner started or re-entered the workforce	-5.4054 (-12.77)	-5.9254 (-10.08)	-4.4532 (-18.53)
LPrtFlex	My partner moved to more flexible working hours	-5.1234 (-14.37)	-4.4513 (-16.26)	-4.9153 (-16.26)
WkNotWf	I was not in the workforce during this period	-2.7664 (-23.28)	0.4271 (6.91)	-1.5768 (-22.21)
WkLookWk	I was looking for a job during this period	-1.8936 (-22.62)	-2.2304 (-21.68)	-1.6045 (-23.16)
WkChJSm	I changed jobs but stayed in the same residential area	-1.6403 (-21.79)	-3.2406 (-20.03)	-1.6791 (-23.59)
WkChJR	I changed jobs and moved to a new residential area	-2.5486 (-23.93)	-3.9721 (-17.59)	-2.8298 (-25.25)
WkFlex	I moved to flexible working hours and days	-1.2814 (-18.76)	-2.6246 (-20.28)	-0.8797 (-15.43)
WkOff	I recently had to work in the main office/work location more	-1.7862 (-22.50)	-3.6868 (-18.04)	-1.7376 (-23.91)
WkFrPark	Free parking	-1.8441 (-22.77)	-3.3582 (-19.32)	-1.9024 (-24.66)
WkChEV	Charging facilities for electric cars	-3.0682 (-22.78)	-4.3678 (-15.71)	-2.6177 (-25.67)
WkShow	Showers for walking/cycling commuters	-2.7951 (-23.08)	-3.9122 (-16.78)	-2.5894 (-25.67)

WkHeal	Free on-site health & wellness facilities	-2.9663 (-23.05)	-4.2666 (-16.13)	-2.6043 (-25.65)
WkPerkPT	Perks for using public transport, carpooling, cycling, or e-scooters	-3.3682 (-21.87)	-3.7685 (-18.90)	-3.0462 (-24.66)
Socio-demographics, work and travel behaviour				
Aust	Australia	-1.046 (-16.55)	-1.0904 (-15.96)	-1.1101 (-18.42)
Finl	Finland	-2.0207 (-23.27)	-2.3203 (-22.34)	-2.368 (-25.36)
nz	New Zealand	-2.0879 (-23.52)	-2.3118 (-22.35)	-2.1131 (-25.29)
sing	Singapore	-2.0761 (-23.48)	-3.427 (-19.88)	-1.7795 (-24.17)
swed	Sweden	-2.0156 (-23.30)	-2.6736 (-21.99)	-2.1082 (-25.15)
uk	UK	-2.3109 (-23.74)	-1.8148 (-21.40)	-2.4558 (-25.26)
females	Females	-0.275 (-4.88)	0.1782 (3.02)	-0.119 (-2.28)
paidjob	Paid job	3.5502 (13.59)	-3.904 (-13.21)	1.2395 (18.54)
manage	Manager	-1.3241 (-19.31)	-7.0346 (-6.98)	-1.2338 (-19.77)
prof	Professional	-1.1901 (-18.11)	-4.4401 (-14.51)	-1.4931 (-22.28)
tech	Technical	-2.4456 (-23.95)	-5.5539 (-11.05)	-2.6103 (-25.54)
commtty	community worker	-2.5751 (-23.88)	-6.4171 (-7.89)	-2.967 (-24.73)
cleri	Clerical	-1.709 (-22.16)	-5.0323 (-12.13)	-2.1138 (-25.24)
sales	Sales	-2.4094 (-23.77)	-5.0015 (-12.46)	-2.9642 (-24.55)
uniplus	University degrees	0.5594 (9.64)	-0.4875 (-8.02)	0.4961 (9.17)
famhld	Family household	-1.3427 (-19.50)	-2.0135 (-21.62)	-1.3034 (-20.57)
cpnochd	Couple no children	-1.1322 (-17.43)	-0.6 (-9.68)	-1.3457 (-20.70)
cpchd	Couple children	-1.2 (-18.23)	-2.2865 (-22.31)	-0.977 (-16.75)
onepat	One parent family	-2.7478 (-23.56)	-3.1326 (-21.20)	-2.8701 (-25.00)
singprn	Single person	-1.5041 (-20.71)	-0.7416 (-11.76)	-1.5455 (-22.31)
wwhrsm	work hours office weekdays	22.1252 (55.52)	0.2186 (0.56)	16.6482 (45.17)
wndhrsm	work hours office weekend	1.2236 (15.44)	0.0331 (0.41)	1.1352 (15.44)
wwhrsh	work hours home weekdays	8.1094 (30.98)	0.145 (0.54)	5.5775 (22.95)
wndhrsh	work hours home weekend	0.7846 (13.61)	0.0258 (0.43)	0.6779 (12.62)
wwhrso	work hours other place weekdays	1.968 (11.91)	0.1663 (0.98)	1.8543 (12.11)
wndhrso	work hours other places weekend	0.3509 (8.29)	0.0283 (0.64)	0.4649 (11.67)
TotHrs	Total working hours	34.5618 (81.00)	0.6171 (1.54)	26.3581 (67.27)
TotRemWk	Total remote work hours	11.2129 (33.74)	0.3654 (1.08)	8.5747 (27.82)
TotTrips	Total trips	19.3803 (61.90)	12.9106 (39.26)	21.3083 (72.90)
TotCrTr	Total car trips	12.9351 (47.08)	8.201 (28.48)	12.8627 (50.29)
AvKmCrTr	Average km per car trip	5.9277 (12.61)	5.1695 (10.20)	6.8471 (15.46)
ageno	Age	43.8296 (105.24)	58.2063 (124.38)	42.9644 (107.82)
icecars	No of ICE car (avg)	0.2054 (8.02)	0.0637 (2.10)	0.0573 (2.19)
evcars	No of EV car (avg)	-2.0996 (-26.60)	-3.6223 (-19.91)	-1.8969 (-28.50)
hybrid	No of hybrid car (avg)	-1.9448 (-26.62)	-2.4627 (-24.37)	-1.7177 (-28.26)
pushbks	No of push bikes (avg)	-0.2771 (-8.50)	-0.8813 (-18.53)	-0.3647 (-11.43)
ebikes	No of E-bikes (avg)	-1.8784 (-25.83)	-2.7969 (-18.12)	-1.6459 (-26.85)
escoots	No of E-scooters (avg)	-2.1538 (-26.38)	-3.0615 (-22.06)	-1.9514 (-28.46)
Model fit statistics				
			Sample size	4088
			Log-likelihood	-335632
			Rank	386
			Entropy	0.9457
			AIC	672036.76
			BIC	674474.66

4.2 Profiling the Three Latent Classes

A Summary of the Socio-demographics, Work and Travel Characteristics

Table 2 shows the socio-demographic profiles of the three classes. A summary of the characteristics for each latent class is as follows.

Class 1 (“Urban strivers”)

There are 56.4% males in Class 1, with an average age of 44 years old. The households have an average of 2.7 members, with 48% from a couple family with/without children. Additionally, 20% of them are from family households. They have the highest level of education among the three classes, with 63% having a bachelor's degree or higher. Among the seven countries, except Finland and Sweden, Class 1 members have the highest personal income. In Finland and Sweden, Class 1 have the second-highest personal income behind Class 3. A similar case applies to annual household income. Class 1 has the highest level of household income in Australia, Singapore, the UK, and the USA. In the other three countries, Finland, New Zealand, and Sweden, Class 1 members have the second-highest household income. Nearly 98% of Class 1 members are doing paid work, with an average of 34.8 hours per week. They also work an average of 11.3 hours per week, either remotely at home or other locations. Of all working people in Class 1, the top three occupations are professionals (24%), managers (21%) and clerical/administration workers (16%). They make an average of 19.4 trips per week, with 66% of them car trips. Their households have an average of 1.48 cars per household. We label this class *Urban strivers*.

Class 3 (“Dynamic jugglers”)

Class 3 is quite close to Class 1 in many aspects. There are 53% males in Class 3, with an average age of 43 years old. The households have an average of 2.8 members, with 48% from a couple family with/without children. Compared to Class 1, Class 3 has a lower proportion of couple families with children. They have 1% fewer members with a university education (62% vs. 63% in Class 1), but a higher proportion of members hold postgraduate degrees (29% vs. 26% in Class 1). In Finland and Sweden, Class 3 has the highest level of average personal income. In the other five countries, Class 3 has the second-highest personal income behind Class 1. A similar case applies to annual household income. Class 3 has the highest level of household income in Finland, New Zealand and Sweden. In the other four countries, Class 3 has the second-highest household income. Approximately 78% of Class 3 members are employed in paid work, with an average of 26.4 working hours per week. They also work an average of 8.6 hours per week remotely. Of all working people in Class 3, the top three occupations are managers (28%), professionals (23%) and clerical/administration workers (13%). They make an average of 21.4 trips per week, with 60% of them car trips. Their households have an average of 1.39 cars per household. There are also more postgraduates and managers among the Class 3 members, which is consistent with their higher levels of unit earnings compared to *Urban strivers*. We label this class *Dynamic jugglers*.

Overall, the main differences between *Urban strivers* and *Dynamic jugglers* are their working status. While *Urban strivers* are predominantly full-time workers (nearly 98%), *Dynamic jugglers* have 22% with another work status, including 4.9% who are seeking employment, 3.9% who are students, 4.1% who are homemakers, and 8.3% who are retired, not working or retired but doing some casual work.

Table 2: Summary of socio-demographics, work and travel characteristics

	Urban Strivers	Settled Simplifiers	Dynamic Jugglers
Gender			
Females	43.4%	54.7%	46.6%
Males	56.4%	44.7%	53.0%
Nonbinary/Prefer not to say	0.2%	0.6%	0.4%
Age			
Average age	44	58	43
Household size			
Average number of members	2.7	2.2	2.8
Household type			
Family household	20%	12%	22%

Couple family with no children	25%	35%	20%
Couple family with children	23%	9%	28%
One parent family	6%	4%	5%
Other family	1%	2%	1%
Single person household	18%	32%	18%
Group household (i.e., shared)	5%	3%	4%
Prefer not to answer	1%	2%	2%
Highest education			
Postgraduate degrees and graduate diploma/certificate	26%	18%	29%
Bachelor's degree	37%	20%	33%
Total university degrees	63%	38%	62%
Below bachelor's degree	35%	58%	36%
Prefer not to answer	2%	4%	2%
Average annual personal income (local currency)			
Australia	AUD 93,100	AUD 40,100	AUD 83,100
Finland	43,600 €	28,600 €	46,600 €
New Zealand	NZD 82,900	NZD 40,500	NZD 80,100
Singapore	SGD 78,500	SGD 34,100	SGD 75,000
Sweden	SEK 548,400	SEK 333,600	SEK 580,500
UK	£42,900	£24,000	£40,400
USA	USD 67,100	USD 37,900	USD 66,700
Average annual household income (local currency)			
Australia	AUD 143,200	AUD 68,800	AUD 132,200
Finland	86,400 €	57,400 €	90,800 €
New Zealand	NZD 123,900	NZD 68,900	NZD 127,100
Singapore	SGD 121,700	SGD 64,700	SGD 116,600
Sweden	SEK 859,400	SEK 393,800	SEK 992,500
UK	£62,500	£36,200	£60,500
USA	USD 97,400	USD 59,600	USD 94,100
Work status			
Paid job	97.6%	1.8%	77.8%
No paid job and looking for work	0.4%	17.3%	4.9%
Student	0.5%	5.0%	3.9%
Homemaker	0.2%	15.4%	4.1%
Retired and not working	0.0%	56.3%	6.3%
Unpaid job / Volunteer	0.5%	1.3%	0.9%
Retired and doing casual work	0.7%	2.8%	2.0%
Occupation of workers			
Manager	21%	1%	28%
Professional	24%	19%	23%
Technicians and trades	8%	6%	8%
Community and personal services	7%	3%	6%
Clerical and administration	16%	11%	13%
Sales	8%	11%	6%
Machine operators / drivers	3%	6%	4%
Labourer	7%	17%	7%
Other	5%	26%	5%
Average working hours per week			
Weekly working hours in main office/location	22.2	0.2	16.7
Weekend working hours in main office/location	1.2	0.0	1.1
Weekly working hours at home	8.1	0.1	5.6
Weekend working hours at home	0.8	0.0	0.7
Weekly working hours at other locations	2.0	0.1	1.9
Weekend working hours at other locations	0.4	0.0	0.5

Total number of weekly working hours	34.8	0.6	26.4
Total number of weekly remote working hours	11.3	0.4	8.6
Weekly trips			
Total number of weekly trips	19.4	12.9	21.4
Total number of weekly trips by car	12.9	8.2	12.9
Percentage of car trips (as drivers or passengers)	66%	64%	60%
Total weekly car kilometres as a driver or passenger (km)	77.3	41.9	76.3
Average distance of car trips (km)	5.9	5.1	6.9
Numbers of trips for each purpose			
To / from work	6.0	0.2	5.0
To / from the shops	3.5	4.0	4.1
Visiting friends and relatives	2.1	2.1	2.6
Care trips	2.1	1.5	2.5
Personal business	2.2	2.0	2.5
Recreational activities	2.6	2.5	3.2
Education/Training for students	0.9	0.7	1.4
Mode shares (%)			
Car as Driver	59%	50%	50%
Car as Passenger, incl taxi, Uber	7%	14%	10%
Train, Tram, Bus, Ferry	14%	11%	16%
Walk	15%	21%	18%
Regular Bicycle	3%	3%	4%
E-Scooter, e-Bike	1%	1%	2%
Average number of vehicles			
ICE cars	1.22	1.07	1.06
EV cars	0.12	0.03	0.15
Hybrid cars	0.14	0.08	0.18
Total number of cars	1.48	1.18	1.39
Push bikes	0.76	0.41	0.70
E-bikes	0.15	0.06	0.19
E-scooters	0.12	0.05	0.14
Total number of active travel devices	1.02	0.53	1.03

Class 2 (“*Settled simplifiers*”) are distinctly different to the other two classes. There are about 55% females, with an average age of 58 (compared to 44 and 43 of *Urban strivers* and *Dynamic jugglers*). By examining their work status, only 1.8% are doing paid jobs. The predominant class members (59.1%) are retired or non-working people, or those who are retired but still engage in some casual work. However, many are at younger ages, including 17.3% who are seeking employment, 5% who are students, and 15.4% who are homemakers. However, because nearly 60% of the class members are of retirement age, the average household size is only 2.2, compared to 2.7 and 2.8 for *Urban strivers* and *Dynamic jugglers*, respectively. For household type, there is a significantly higher proportion of couple families without children (i.e., children might have grown up and are living separately). There is also a significantly higher proportion of single-person households, at 32%, which is far higher than the 18% for both *Urban strivers* and *Dynamic jugglers*. The personal and household income levels of Class 2 are significantly lower than those of *Urban strivers* and *Dynamic jugglers* in all seven countries. In many instances, the income level is even below the 50% levels of the other two classes (e.g., in the case of Australia), indicating that Class 2 members are either living on a retirement income or have very low incomes. Class 2 members only have an average of 0.6 working hours per week, with 0.4 hours working remotely. This means that, on average, Class 2 members almost do not work in the main office. With respect to transport, Class 2 members travel less with an average of 12.9 weekly trips (compared to 19.4 and 21.4 trips per week by *Urban strivers* and *Dynamic jugglers*, respectively). Among all trips, 64% are car trips. They have an average of 1.18 cars. They also noticeably own

fewer devices for active travel such as push bikes, E-bikes and E-scooters. Given their age and income levels, the above is not unexpected. We label Class 2 as *Settled simplifiers*.

When looking at income by age it does seem that *Dynamic jugglers* reach their peak income before they are 30 and *Urban strivers* at around 50 years old (Figure 1). Looking at the number of trips by purpose it appears that *Dynamic jugglers* do more trips across all non-commuting purposes, in particular recreational activities (Figure 2) while *Urban strivers* are very clearly focussed on commuting.

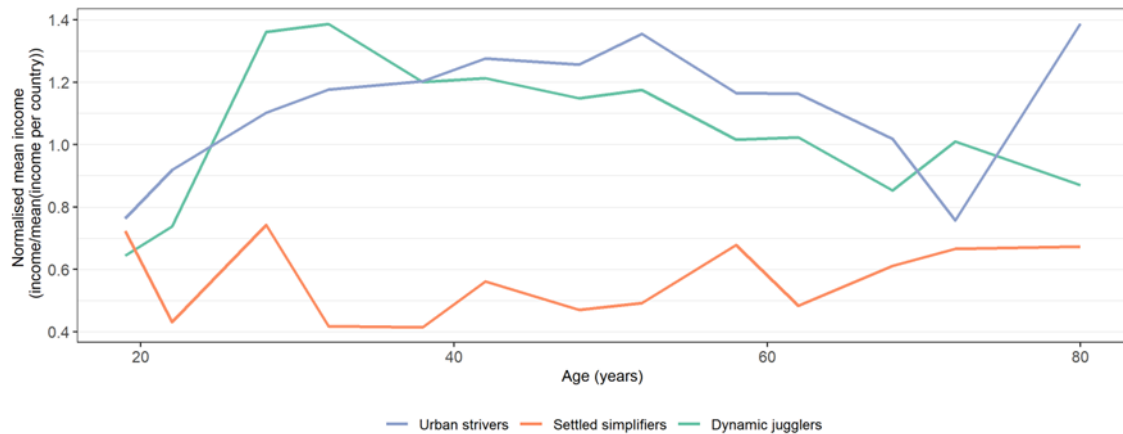
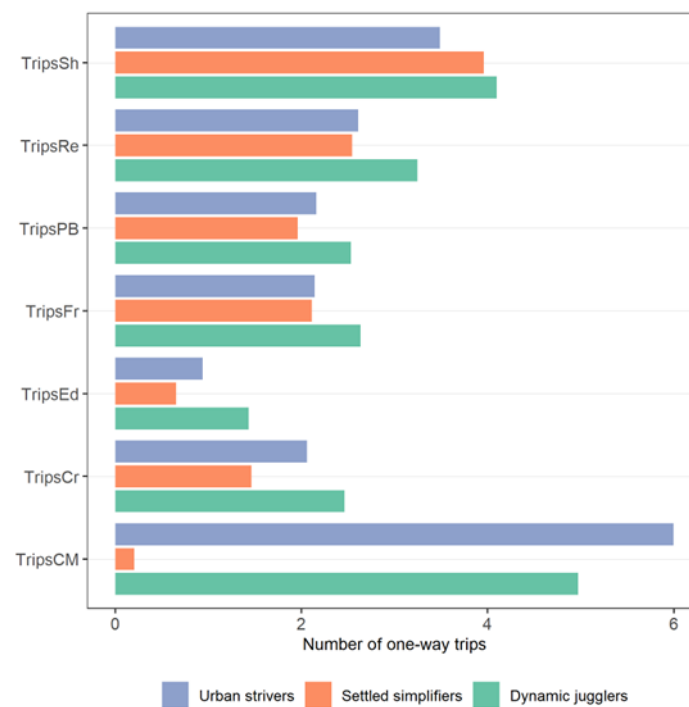


Figure 1: Income by age for the three latent classes



Key:

- CM: To/from work
- Cr: Care trips
- Ed: Education/training for students
- Fr: Visiting friends and relatives
- PB: Personal business
- Re: Recreational activities

- Sh: To/from the shops

Figure 2: Number of trips by purpose

Table 3 shows the proportions of the three latent classes in each country. Given that the sample was collected randomly, there may be some influence due to the specific online panel characteristics in a country on the distributions of the three classes. Australia's class distribution is the closest to the total sample distributions with 34% *Urban strivers*, 29% *Settled simplifiers* and 37% *Dynamic jugglers*, almost identical to the total sample. New Zealand, Finland and Sweden follow this level of similarity to the total sample, but with bigger differences compared to Australia. In the UK and USA samples, there is a higher proportion of *Settled simplifiers*, both at the 40% level. In contrast, Singapore samples only have 9% of *Settled simplifiers*, with significantly higher levels of *Dynamic jugglers* and *Urban strivers* (e.g., 54% for *Dynamic jugglers*, compared to 37% in the total sample).

Table 3: The three latent classes by country

	Urban Strivers	Settled Simplifiers	Dynamic Jugglers	Total
Country				
Australia	34%	29%	37%	1,034
Finland	40%	27%	33%	397
New Zealand	36%	26%	38%	423
Singapore	37%	9%	54%	411
Sweden	39%	20%	41%	403
UK	30%	40%	30%	411
USA	26%	40%	34%	1009
Total	33%	29%	37%	4,088

Using Australia as an example for more detailed investigation, among the 1,034 Australian samples (see Table 4), 69% of the *Urban strivers* live in state capital cities such as Sydney and Melbourne, 17% live in sizeable regional cities/centres such as Newcastle, Wollongong, Geelong and the Gold Coast, with only 14% living in regional towns or rural areas. In contrast, only 56% of *Settled simplifiers* stay in the state capital cities, with 21% living in regional centres and 24% living in regional towns or rural areas (10% higher than *Urban strivers*); this is a pattern more consistent with retirees. Compared to *urban strivers*, a slightly smaller proportion of *Dynamic jugglers* live in capital cities (65%) and a higher proportion live in regional centres (22% vs. 17%), which could be due to more flexible work arrangements and quality of life aspirations. The proportion of *Dynamic jugglers* who live in regional towns or rural areas is similar to that of *Urban strivers*, at 13%.

Table 4: The three latent classes by residential area: Australia

Australia	Urban Strivers	Settled Simplifiers	Dynamic Jugglers
State capital city	69%	56%	65%
Regional city	17%	21%	22%
Regional town	11%	18%	11%
Country, rural or remote area	3%	6%	2%

4.3 A Summary of the Main “Windows of Changes” (WoCs) from 2023 to present

Table 5 summarises the top 15 changes in lifestyle and work conditions for the three classes.

To validate, for *Urban strivers*, the top 5 changes they experienced since 2023 include 1) moved to flexible working hours and days; 2) tighter financial situation; 3) started walking/exercising more for health reasons; 4) moved to a new area; and 5) improved health. These top changes are all consistent with the changes in the working environment during and post-pandemic. Employees have flexible work hours and work from various locations, blending office hours with working hours at home and other non-office locations (about one third of paid working hours are completed at home or other locations). They also experienced the cost-of-living pressure in the recent two years, and many have moved residential location due to housing affordability or change of working patterns. With saved travel time and WFH popularity, people have more time to spend on walking/exercising to gain better health and work-life balance.

Dynamic jugglers have the same top 5 changes as *Urban strivers*, with only order differences. However, the top change or the central theme of their lifestyle change is also “moved to flexible working hours and days” and about one third of paid working hours are completed at home or other locations. *Dynamic jugglers* appear to experience less financial stress compared to *Urban strivers*, with a lower ranking of cost-of-living-related changes among them. This seems reasonable, given the almost equivalent personal and household income levels of the two classes, but much fewer working hours for *Dynamic jugglers*, implying relatively higher unit earnings.

On the other hand, the top 5 changes for *Settled simplifiers* have a different central theme. The top 5 changes in their lives are: 1) was not in the workforce during the period; 2) started walking/exercising more for health reasons; 3) a tighter financial situation; 4) I have adjusted my lifestyle to prioritise saving money; and 5) I had health concerns that affected my travel. These top changes have fully characterised what is typically faced by retired/or non-working individuals. They are not working but have more time to walk and exercise. The main negative aspects they face are tighter finances and more health concerns due to age. These concerns also cause them to spend and travel less.

Table 5: Top 15 changes to lifestyle and work status from 2023 to present

Rank	Acronyms	WoCs	Urban Strivers
1	WkFlex	I moved to flexible working hours and days	22%
2	LFinTg	My financial situation became tighter	21%
3	IWkHlt	I started walking/exercising more for health reasons	18%
4	LMvAr	Moved to a new area	18%
5	LImpHl	My health improved	17%
6	WkChJSm	I changed jobs but stayed in the same residential area	16%
7	LSvMon	I have adjusted my lifestyle to prioritise saving money	15%
8	WkOff	I recently had to work in the main office/work location more	14%
9	WkFrPark	Free parking	14%
10	WkLookWk	I was looking for a job during this period	13%
11	LImpFn	My financial situation improved	13%
12	LIncOSh	I increased online shopping to reduce personal travel	12%
13	LHHInc	Household size increased	11%
14	LUpsiz	Upsized to a larger home	11%
15	LRedOSh	I have reduced online shopping spending	9%
Rank	Acronyms	WoCs	Settled Simplifiers
1	WkNotWf	I was not in the workforce during this period	60%
2	IWkHlt	I started walking/exercising more for health reasons	25%
3	LFinTg	My financial situation became tighter	24%
4	LSvMon	I have adjusted my lifestyle to prioritise saving money	15%
5	LHlConc	I had health concerns that affected my travel	15%

6	LIncOSh	I increased online shopping to reduce personal travel	13%
7	LMvAr	Moved to a new area	12%
8	LRedOSh	I have reduced online shopping spending	10%
9	WkLookWk	I was looking for a job during this period	10%
10	LImpHl	My health improved	9%
11	Lret	I retired from the workforce	9%
12	WkFlex	I moved to flexible working hours and days	7%
13	LDowns	Downsized to a smaller home	6%
14	LImpFn	My financial situation improved	6%
15	LNoDog	I no longer have a dog	6%
Rank	Acronyms	WoCs	Dynamic Jugglers
1	WkFlex	I moved to flexible working hours and days	30%
2	IWkHlt	I started walking/exercising more for health reasons	25%
3	LImpHl	My health improved	23%
4	LMvAr	Moved to a new area	22%
5	LFinTg	My financial situation became tighter	19%
6	WkNotWf	I was not in the workforce during this period	17%
7	WkLookWk	I was looking for a job during this period	17%
8	LImpFn	My financial situation improved	16%
9	LSvMon	I have adjusted my lifestyle to prioritise saving money	16%
10	WkChJSm	I changed jobs but stayed in the same residential area	16%
11	LIncOSh	I increased online shopping to reduce personal travel	16%
12	WkOff	I recently had to work in the main office/work location more	15%
13	WkFrPark	Free parking	13%
14	LHHInc	Household size increased	13%
15	LUpsiz	Upsized to a larger home	12%

The sharp differences among all three classes, especially between *Urban strivers* and *Dynamic jugglers*, despite their similarities in other aspects, are reflected in their views about the environmental impact of their travel choices. Over half (51%) of *Dynamic jugglers* are more conscious of the environmental impact of their travel choices, compared to only 31% among *Urban strivers* and 29% among *Settled simplifiers*. On the other hand, only 10% of *Dynamic jugglers* are less conscious about the impact, which is lower than that of *Urban strivers* (13%). This could have implications for marketing campaigns to promote sustainable travel choices.

Table 6: Consciousness of the environmental impact of travel choices by latent class

	Urban Strivers	Settled Simplifiers	Dynamic Jugglers	Total
I am now more conscious of the environmental impact of my travel choices	31%	29%	51%	38%
I am now less concerned about the environmental impact of my travel choices	13%	9%	10%	11%

4.3 The Level of Support of Transport Initiatives for Making a Positive Impact on Travel Behaviour

Over the 50 transport-influencing initiatives, the percentages of class members nominating the negative impact (points 1 and 2), no/neutral impact (3) and positive impact (points 4 and 5) demonstrate very different patterns. Among *Urban strivers*, the dominant choices of impact are neutral (57%), followed by positive (24%), and negative (19%). This means that, even though the level of support for initiatives is low among them (at 24%), the level of non-support is also low (19%). Most members may either feel indifferent to the initiatives or lack adequate information to assign either positive or negative impact ratings. As mentioned in Section 4.1, the only significant

difference in socio-demographics between *Urban strivers* and *Dynamic jugglers* is related to their work status (where the lower number of paid hours/week is an important difference) and occupation. Even though *Dynamic jugglers* are quite similar to *Urban strivers* in many ways, they have shown unambiguous support for transport initiatives, at a rate as high as 80%. Moreover, the average level of non-support is as low as 6%. More distinct from *Dynamic jugglers* than *Urban strivers*. *Settled simplifiers* have demonstrated a higher level of average support for transport initiatives at 30%. They also show a lower-level selection of no / neutral impact at 49%. As will be further discussed next, this implies that they may be more certain about the transport initiatives that they would like to support. These results are presented in Figure 3, and further details of each initiative are provided in Table A1 of the Appendix.

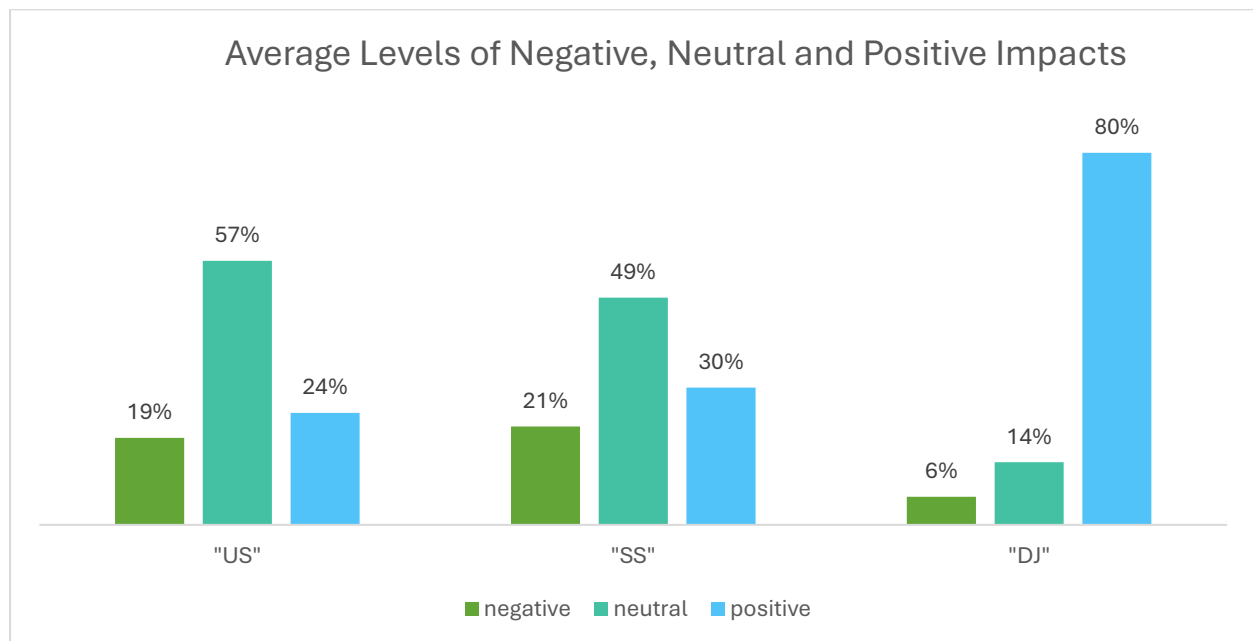


Figure 3: The average levels of negative (1/2), neutral (3) and positive impacts (4/5) to transport-influencing initiatives by latent classes

Table 7 highlights the significant differences among the three classes and the initiatives they support. As a cell highlighted in red, the only initiative that has gained over 50% level of support by *Urban strivers* is “Free local public transport” (54%) which may appeal to people whose journey to work is by public transport. The few other initiatives that gained between 40% to 49% levels of support are either public transport-related or parking-related. Overall, *Urban strivers* support low- or free public transport and free parking near transport hubs (which of course are opposites in terms of contribution to sustainability). It is noticeable that levels of support for roading pricing-related initiatives are the lowest among all initiatives, ranging from 10% to 15%. Considering the relevance to *Urban strivers* and the approximately 24 hours per week spent in the main offices, it is expected that their higher support will be for more affordable and efficient public transport services for commuting purposes, which could also be to other locations.

In contrast to *Urban strivers*, *Dynamic jugglers* have demonstrated a strong level of support to almost all initiatives (i.e., all above 60%). Their support levels for initiatives relating to improving public transport and active transport are very high, at 80% to 90% levels. Their support for road pricing and car-related initiatives is relatively lower but still above the 60% level.

Settled simplifiers have selective support for transport initiatives related to their background (e.g., retired, students, or looking for work), such as supporting public transport more, the health benefits of active travel, cost savings, free services, and environmental benefits. They have given over 50% of support. However, their negative attitudes towards transport initiatives that are likely

to increase the costs of travel are undeniable. For example, they have the lowest levels of support among the three classes on all road pricing initiatives, at levels all below 10%, perhaps reflective of their lower levels of household income compared to the other two classes.

Table 7: Percentages of Support for Transport-influencing Initiatives

Initiatives	“US”	“SS”	“DJ”
Free local public transport	54%	66%	92%
Fixed public transport fares at US\$0.25 per trip	48%	59%	91%
Double public transport services frequency	43%	53%	86%
Free park and ride facility close to transport hubs	42%	56%	88%
Free secure lockers for bikes/scooters at transport hubs	31%	38%	86%
Bike/scooter parking at transport hubs for US\$0.50/day	23%	29%	79%
Tolled roads ensuring 25% faster travel time than free roads	24%	24%	79%
Tolled roads ensuring 50% faster travel time than free roads	26%	27%	80%
Peak-period road user charge US\$0.05/mile	12%	8%	69%
Peak-period road user charge US\$0.10/mile	11%	7%	67%
Peak-period road user charge US\$0.15/mile	12%	6%	64%
Peak-period road user charge US\$0.20/mile	13%	6%	63%
Congestion-free lanes what you pay US\$0.05/mile	11%	7%	71%
Congestion-free lanes what you pay US\$0.10/mile	12%	8%	68%
A supplementary charge of US\$15 per car in a defined area around the city which is designed to reduce congestion	12%	8%	64%
A supplementary charge of US\$10 per car in a defined area around the city which is designed to improve air quality	12%	8%	67%
Free annual vehicle registration with US\$0.10/mile peak-hour charge	18%	25%	79%
50% reduction in annual vehicle registration with US\$0.05/mile charge	19%	27%	80%
75% reduction in annual vehicle registration with US\$0.03/mile charge	23%	31%	82%
Tax deduction for acquiring hybrid/plug-in hybrid vehicle	28%	33%	85%
Tax deduction for acquiring a full electric vehicle	27%	32%	85%
Bookable door-to-door bus services at transport hubs, free	33%	49%	91%
Bookable door-to-door bus services at transport hubs, same fare as regular public transport	27%	40%	85%
Bookable door-to-door bus services at transport hubs, +10% fare of regular public transport	18%	23%	77%
Free, bookable voluntary car-sharing: you are a passenger	25%	29%	84%
Free, bookable voluntary car-sharing: you are a driver	18%	17%	78%
Bookable car-share subscription at US\$10/month + US\$0.05/mile	13%	12%	77%
Bookable car-share subscription at US\$10/month + US\$0.10/mile	12%	11%	74%
Bookable car-share subscription at US\$10/month + US\$0.15/mile	13%	10%	73%
Event ticket includes free public transport	46%	60%	93%
25% off parking cost for car-pooling (T3+)	26%	40%	86%
Valet parking at event at +20% extra cost	14%	14%	66%
15% off event tickets for public transport users	34%	48%	88%
Special seats at a 25% discount when you use public transport	36%	48%	89%
10% government rebate for e-bike/e-scooter purchases	21%	21%	81%
20% government rebate for e-bike/e-scooter purchases	23%	25%	83%
\$200 voucher for e-bike/e-scooter purchases	26%	30%	85%
Tax deduction for e-bike/e-scooter purchases	24%	27%	83%
Free charging at your workplace for EV and other electric mobility devices such as E-bikes or E-scooters	29%	45%	89%
Showers and storage available for bikes, scooters, and personal items to support active travel	28%	44%	85%
Public transport on travel card will be subsidised	36%	62%	87%
1% fuel discount for every 1% reduction in car use	24%	50%	84%

Highlighting the health benefits of walking, cycling, scootering	26%	62%	84%
Promoting cost savings of active modes and public transport	25%	55%	85%
Highlighting environmental benefits of driving less	21%	61%	81%
Monthly leaderboard of employees using active transport	16%	36%	75%
Monthly leaderboard of employees reducing car use	16%	42%	75%
A government-enabled platform providing consumers with real-time EV charging information	21%	35%	83%
A consistent and transparent pricing policy for EV charging services	24%	38%	84%
Innovative charging solutions that reduce charging time by 50%	30%	42%	87%

The common initiatives that have gained the highest levels of support across all three classes are those related to public transport fares and services.

Summary Profiles of the Three Latent Classes

In seeking to appreciate the profiles of the three classes, and the way in which travel initiatives might be directed, several points stand out:

- Of the three latent classes *Dynamic jugglers* are likely to be most responsive to policy initiatives designed to influence travel choices while demonstrating unambiguous support (Figure 3). They have lifestyles which are characterised by more flexible working patterns (an average of 26.4 hours / week of which approximate one third are completed remotely or at another location). They report the move to more flexible work arrangements as their top WoC in the last three years (Table 4) and they make larger numbers of recreational and shopping trips. Their positive attitudes towards transport-influencing initiatives imply that they are open to trying options that will give them flexibility and fit with their lifestyles, They are particularly open to public transport initiatives (see Table 3) and show an interest in micromobility initiatives (free lockers and modest parking charges at transport hubs) and tolled roads which offer a higher travel time. They exhibit a better wellbeing status than their counterparts in *Urban strivers* which is also consistent with a more relaxed lifestyle. They also have higher unit earnings which can be reflected by an equivalent level of personal income with less working hours. They would be responsive to event ticketing including public transport and to receiving discounts on events when using public transport. Of all three classes, they express the greatest interest in the environmental benefits of driving less.
- By contrast, the *Urban strivers* are noticeably dominated by people in full-time employment (working an average of 34.8 hours week, with one third completed remotely or at another location). This class are likely to be experiencing a higher tax burden and tighter financial situation (see Table 4) which makes them less responsive to transport influencing initiatives (other than free local public transport which could be attractive for journeys to work). They report less experience of walking and cycling for health reasons as a WoC than either of the other classes (see Table 4). This class show little interest in most of the transport-influencing initiatives (they either feel indifferent to the initiatives or lack adequate information or interest to assign either positive or negative impact ratings). Overall, it is arguable that they would benefit from greater information, via targeted communication strategies, about the transport-influencing initiatives that could be available to them and what benefits these initiatives could bring to their lives.
- The *Settled simplifiers* who mostly comprise retirees, homemakers and other "not working" population, are more focussed on retirement and leisure, and might have been expected to show more interest in the transport-influencing initiatives. They cite walking/exercising more for health reasons as a key WoC. They show a lower-level selection of no / neutral impact at 49% (see Figure 3), which implies that they may be more certain about the transport initiatives they would like to support. They have

demonstrated support for free public transport, and would likely appreciate the cost savings associated with active modes and public transport. Since the majority of this class are retirees, many might have been receiving welfare benefits such as senior cards, lower fares, and pensions. The implications for transport initiatives may be a need to integrate these initiatives into their existing programs. They are unlikely to be the primary population segment to support the implementation of challenging transport initiatives, such as road pricing schemes.

5 Conclusions and Implications

Experience shows that effective transport policy must account for the temporal and social dynamics that influence mobility choices. This means that it is necessary to understand the circumstances under which individuals are more receptive to reconsidering established travel patterns. Our study has shown the value of considering the concept of “windows of change” (WoC) or periods when established behaviours are unsettled and individuals are more open to alternatives. Designing interventions that align with such transition points offers significant potential to accelerate sustainable mobility.

In this study data is collected from over 4,000 respondents spread across Australia, Finland, New Zealand, the United States, the United Kingdom, Singapore, and Sweden, investigating their WoCs over the period 2023–2025 and the influence of 50 transport-influencing initiatives on how people travel.

In the latent class analysis, we identified three classes:

- Class 1 (“*Urban strivers*”) are comprised of 56.4% males, with an average age of 44 years old. Households have an average of 2.7 members, with 48% from a couple family with/without children; 20% are family households. They have the highest level of education among the three classes. and the highest level of household income in Australia, Singapore, the UK, and the USA. *Urban strivers* work an average of 11.3 hours per week, either remotely at home or other locations. They make an average of 19.4 trips per week, with 66% of them car trips and their households have an average of 1.48 cars.
- Class 3 (“*Dynamic jugglers*”) are quite close to Class 1 in many aspects; the main difference being working status. There are 53% males, with an average age of 43. Households have an average of 2.8 members, with 48% from a couple family with/without children. Compared to Class 1, this class has a lower proportion of couple families with children and just 1% fewer members with a university education (62% vs. 63% in Class 1). Approximately 78% of *Dynamic jugglers* are employed in paid work, with an average of 26.4 working hours per week. They also work an average of 8.6 hours per week remotely. They make an average of 21.4 trips per week, 60% of them by car. Households have an average of 1.39 cars per household.
- Class 2 (“*Settled simplifiers*”) are distinctly different to the other two classes. There are about 55% females, with an average age of 58 (compared to 44 and 43 of class 1 and 3). The predominant work status (59.1%) is retired or non-working people, or those who are retired but still engage in some casual work. However, many are younger. The average household size is only 2.2, compared to 2.7 and 2.8 for *Urban strivers* and *Dynamic jugglers*, respectively. The personal and household income levels of *Settled simplifiers* are significantly lower than those of *Urban strivers* and *Dynamic jugglers* in all seven countries. Class 2 members only work an average of 0.6 hours per week, with 0.4 hours working remotely. With respect to transport, *Settled simplifiers* travel less with an average of 12.9 weekly trips (compared to 19.4 and 21.4 trips per week by *Urban strivers* and

Dynamic jugglers, respectively). Among all trips, 64% are by car. They have an average of 1.18 cars per household.

We considered the top 15 changes in lifestyle and work conditions for the three classes. For *Urban strivers*, the top 5 changes they experienced since 2023 include 1) moved to flexible working hours and days; 2) tighter financial situation; 3) started walking/exercising more for health reasons; 4) moved to a new area; and 5) improved health. These top changes are all consistent with the changes in the working environment during and post-pandemic. With saved travel time and the popularity of WFH (Hensher et al., 2024), people have more time to spend on walking/exercising to gain better health and work-life balance. *Dynamic jugglers* have the same top 5 changes as *Urban strivers*, with only order differences. However, the top change (or the central theme of their lifestyle change) is also “moved to flexible working hours and days”. *Dynamic jugglers* appear to experience less financial stress compared to *Urban strivers*, with a lower ranking of cost-of-living-related changes among them. On the other hand, the top 5 changes for *Settled simplifiers* have a different central theme. The top 5 changes in their lives are: 1) was not in the workforce during the period; 2) started walking/exercising more for health reasons; 3) a tighter financial situation; 4) I have adjusted my lifestyle to prioritise saving money; and 5) I had health concerns that affected my travel. These top changes fully characterise what is typically faced by retired/or non-working individuals.

An important aspect of this study has been to establish the level of support for transport initiatives which make a positive impact on travel behaviour and to appreciate where travel initiatives might be directed. In summary, of the three latent classes *Dynamic jugglers* have lifestyles which are characterised by more flexible working patterns. They report the move to more flexible work arrangements as their top WoC in the last three years and they make larger numbers of recreational and shopping trips. Their positive attitudes towards transport-influencing initiatives (see Table 7) imply that they are open to trying options that will give them flexibility and fit with their lifestyles. *Dynamic jugglers* are particularly open to public transport initiatives and show an interest in micromobility initiatives (free lockers and modest parking charges at transport hubs) and tolled roads which offer a higher travel time. They exhibit a better wellbeing status than their counterparts in *Urban strivers*, which is also consistent with a more relaxed lifestyle. They would be responsive to event ticketing including public transport and to receiving discounts on events when using public transport. Of the three classes, they express the greatest interest in the environmental benefits of driving less.

By contrast the *Urban strivers*, since they are noticeably dominated by people in full-time employment, are likely to be experiencing a higher tax burden and tighter financial situation which makes them less responsive to transport influencing initiatives (other than free local public transport which could be attractive for journeys to and from work). They report less experience of walking and cycling for health reasons as a WoC than either of the other classes. This class show little interest in most of the transport-influencing initiatives (they either feel indifferent to the initiatives or lack adequate information or interest to assign either positive or negative impact ratings). It is arguable that they would benefit from greater information about the transport-influencing initiatives and associated benefits that could be available to them.

The *Settled simplifiers* who mostly comprise retirees, homemakers and other "not working" are more focussed on retirement and leisure, arguably might have been expected to show more interest in the transport-influencing initiatives. They cite walking/exercising more for health reasons as a key WoC. They have demonstrated support for free public transport and would likely appreciate the cost savings associated with active modes and public transport. The implications for transport initiatives may be a need to integrate these initiatives into their existing programs. They are unlikely to be the primary population segment to support the implementation of challenging transport initiatives, such as road pricing schemes.

Overall, our findings demonstrate that when aligned with the concept of windows of change, segmentation offers a powerful framework for identifying when and how to intervene most effectively. Indeed, the WoC analysis explains what happened in the lives of respondents far more effectively than a focus on standard demographics. This implies that policy design should not only target the moments (or “windows”) when individuals are most receptive to change, but also tailor strategies to the specific needs, motivations, and contexts of different traveller groups.

The next step is to design a marketing campaign that is directed to specific classes of individuals, tailored to offer ideas that can work to change travel behaviours in ways aligned with broad sustainable goals. The segments identified in this paper provide an appealing start to contribute to delivering on actionable change outcomes.

References

- Ajzen, I. (1991). The Theory of Planned Behavior. *Organizational Behavior and Human Decision Processes*, 50, 179-211.
- Ajzen, I., & Fishbein, M. (1969). The Prediction of Behavioral Intentions in a Choice Situation. *Journal of Experimental Social Psychology*, 5, 400-416.
- Akaike, H. (1974). A new look at the statistical model identification. *IEEE Transactions on Automatic Control*, 19, 716–723.
- Anable, J. (2005). ‘Complacent Car Addicts’ or ‘Aspiring Environmentalists’? Identifying travel behaviour segments using attitude theory. *Transport Policy*, 12(1), 65-78. doi:10.1016/j.tranpol.2004.11.004.
- Beige, S., & Axhausen, K. W. (2017). The dynamics of commuting over the life course: Swiss experiences. *Transportation Research Part A: Policy and Practice*, 104, 179-194. doi:10.1016/j.tra.2017.01.015.
- Collins, L.M. & Lanza, S.T. (2010). *Latent Class and Latent Transition Analysis – With Application in the Social, Behavioral, and Health Sciences*. Hoboken, New Jersey: John Wiley & Sons, Inc.
- Dempster, A. P., Laird, N. M., & Rubin, D. B. (1977). Maximum likelihood from incomplete data via the EM algorithm (with discussion). *Journal of the Royal Statistical Society*, 39, 1–38.
- De-Toledo, K. P., O’Hern, S., & Koppel, S. (2022). Travel behaviour change research: A scientometric review and content analysis. *Travel Behaviour and Society*, 28, 141-154. doi:https://doi.org/10.1016/j.tbs.2022.03.004.
- Delbosc, A., & Nakanishi, H. (2017). A life course perspective on the travel of Australian millennials. *Transportation Research Part A: Policy and Practice*, 104, 319-336. doi:10.1016/j.tra.2017.03.014.
- Ding, D., Nguyen, B., Learnihan, V., Bauman, A. E., Davey, R., Jalaludin, B., & Gebel, K. (2018). Moving to an active lifestyle? A systematic review of the effects of residential relocation on walking, physical activity and travel behaviour. *British journal of sports medicine*, 52(12), 789–799. doi:https://doi.org/10.1136/bjsports-2017-098833.
- Fan, A., Chen, X., Yu, L., & Li, M. (2023). Investigating heterogeneity in travel behaviour change when implementing soft transport interventions: A latent class choice model. *IET Intelligent Transport Systems*, 17, 1072-1086. doi:10.1049/itr2.12355.
- Gehrke, S. R., Singleton, P. A., & Clifton, K. J. (2019). Understanding stated neighborhood preferences: The roles of lifecycle stage, mobility style, and lifestyle aspirations. *Travel Behaviour and Society*, 17, 62-71. doi:10.1016/j.tbs.2019.07.001.
- Goodman, L.A. (2002). *Latent Class Analysis: The Empirical Study of Latent Types, Latent Variables, and Latent Structures*. In Hagenaars, J.A. & McCutcheon, A.L. (Eds), *Applied Latent Class Analysis* (pp. 3-55). Cambridge, UK: Cambridge University Press.

- Hensher, D.A., Rose, J.M. & Greene, W.H. (2015). *Applied Choice Analysis* (2nd edition). Cambridge, UK: Cambridge University Press.
- Hensher, D.A., Beck, M. J. & Nelson, J.D. (2024). What have we learned about long term structural change brought about by COVID-19 and working from home? *Transportation Letters*, 16(7), 738–750. doi.org/10.1080/19427867.2023.2237269
- Hensher, D. A., Nelson, J. D., Wei, E., Kandanaarachchi, T., Balbontin, C., Ho, C., . . . Liu, W. (2025). Windows of change as precursors to changing travel behaviour aligned with sustainable mobility. ITLS Working Paper ITLS-WP-25-19. <https://hdl.handle.net/2123/34154>.
- Hunecke, M., Haustein, S., Böhler, S., & Grischkat, S. (2010). Attitude-Based Target Groups to Reduce the Ecological Impact of Daily Mobility Behavior. *Environment and Behavior*, 42(1), 1-42. doi:10.1177/0013916508319587.
- Hunecke, M., Haustein, S., Grischkat, S., & Böhler, S. (2007). Psychological, sociodemographic, and infrastructural factors as determinants of ecological impact caused by mobility behavior. *Journal of Environmental Psychology*, 27(4), 277-292. doi:10.1016/j.jenvp.2007.08.001.
- Janke, J., Thigpen, C. G., & Handy, S. (2020). Examining the effect of life course events on modality type and the moderating influence of life stage. *Transportation*, 48(2), 1089-1124. doi:10.1007/s11116-019-10077-9.
- Jin, L., Lazar, A., Sears, J., Todd-Blick, A., Sim, A., Wu, K., . . . Spurlock, C. A. (2020). Clustering Life Course to Understand the Heterogeneous Effects of Life Events, Gender, and Generation on Habitual Travel Modes. *IEEE Access*, 8, 190964-190980. doi:10.1109/access.2020.3032328.
- Jöreskog, K.G. (1971). Simultaneous factor analysis in several populations. *Psychometrika*, 36, 409-426.
- Jöreskog, K.G. (1973). A general method for estimating a linear structural equation system. In A.S. Goldberger & O.D. Duncan (Eds.), *Structural Equation Models in the Social Sciences* (pp. 85-112). New York: Seminar.
- Kamakura, W. A. & Russell, G. J. (1989). A Probabilistic Choice Model for Market Segmentation and Elasticity Structure. *Journal of Marketing Research*, 26, 379-390.
- Klößner, C. (2004). How single events change travel mode choice - a life span perspective. Paper presented at the 3rd international conference on traffic and transportation psychology, Nottingham, United Kingdom.
- Li, W., & Kamargianni, M. (2019). Investigating the Mode Switching Behavior from Different Non-Car Modes to Car: The Role of Life Course Events and Policy Opportunities. *Transportation Research Record: Journal of the Transportation Research Board*, 2673(3), 676-685. doi:10.1177/0361198119835526.

- Masyn, K.E. (2013). Latent class analysis and finite mixture modeling. In T.D. Little (Ed.) *The Oxford Handbook of Quantitative Methods: Vol. 2. Statistical Analysis* (pp. 551-611). New York, NY: Oxford University Press.
- Notthoff, N., & Carstensen, L. L. (2014). Positive messaging promotes walking in older adults. *Psychology and Aging*, 29. doi:<https://doi.org/10.1177/1359105315616470>.
- Ogilvie, D., Foster, C. E., Rothnie, H., Cavill, N., Hamilton, V., Fitzsimons, C. F., . . . Scottish Physical Activity Research, C. (2007). Interventions to promote walking: systematic review. *BMJ*, 334(7605), 1204. doi:10.1136/bmj.39198.722720.BE.
- Pearson, L., Dipnall, J., Gabbe, B., Braaf, S., White, S., Backhouse, M., & Beck, B. (2022). The potential for bike riding across entire cities: Quantifying spatial variation in interest in bike riding. *Journal of Transport & Health*, 24. doi:10.1016/j.jth.2021.101290.
- Piras, F., Sottile, E., Tuveri, G., & Meloni, I. (2022). Does the joint implementation of hard and soft transportation policies lead to travel behavior change? An experimental analysis. *Research in Transportation Economics*, 95(101233), 1-15.
- Rabe-Hesketh, S., Skrondal, A., & Pickles, A. (2004). Generalized Multilevel Structural Equation Modeling. *Psychometrika*, 69 (2), 167-190.
- Ramaswamy, V., Desarbo, W. S., Reibstein, D. J., & Robinson, W. T. (1993). An empirical pooling approach for estimating marketing mix elasticities with PIMS data. *Marketing Science*, 12(1), 103-124.
- Redman, L., Friman, M., Gärling, T., & Hartig, T. (2013). Quality attributes of public transport that attract car users: A research review. *Transport Policy*, 25, 119-127. doi:10.1016/j.tranpol.2012.11.005.
- Roaf, E., Lawlor, E. R., & Larrington-Spencer, H. (2024). What interventions increase active travel? *Advances in Transport Policy and Planning*, 13, 89-142.
- Scheiner, J. (2014). Gendered key events in the life course: effects on changes in travel mode choice over time. *Journal of Transport Geography*, 37, 47-60. doi:10.1016/j.jtrangeo.2014.04.007.
- Schwarz, G. (1978). Estimating the dimension of a model. *Annals of Statistics*, 6, 461-464.
- Slovic, P., Fishhoff, B., & Lichtenstein, S. (1977). Behavioral Decision Theory. *Annual Review of Psychology*, 28, 1-39.
- Stata (2025). *Stata Structural Equation Modeling Reference Manual Release 19*. College Station, Texas: Stata Press Publication, StataCorp LLC.
- Sunio, V., Schmöcker, J.-D., & Kim, J. (2018). Understanding the stages and pathways of travel behavior change induced by technology-based intervention among university students. *Transportation Research Part F: Psychology and Behaviour*, 59, 98-114. doi:10.1016/j.trf.2018.08.017.
- Train, K.E. (2009). *Discrete Choice Methods with Simulation* (2nd Edition). New York: Cambridge University Press.

- Van der Waerden, P., Timmermanns, H., & Borgers, A. (2003). The influence of key events and critical incidents on transport mode choice switching behaviour: A descriptive analyses. Paper presented at the 10th International Conference on Travel Behaviour Research, Lucerne, CH.
- Wedel, M., & Kamakura, W. A. (2000). *Market Segmentation - Conceptual and Methodological Foundations*. Boston Dordrecht London: Kluwer Academic Publishers.
- Wiltshire, P. (2023). Behaviour change in travel and transport for sustainable visitor development: the example of Buxton, UK. In H. Ramkissoon (Ed.), *Handbook on Tourism and Behaviour Change* (pp. 122-137). Cheltenham, UK: Edward Elgar Publishing Limited.
- Zarabi, Z., & Lord, S. (2018). Toward More Sustainable Behavior: A Systematic Review of the Impacts of Involuntary Workplace Relocation on Travel Mode Choice. *Journal of Planning Literature*, 34(1), 38-58. doi:10.1177/0885412218802467.

Appendix A

Table A1. A Summary of the Negative, Neutral and Positive Impact of the 50 Initiatives

Initiatives	Acronyms	Class 1			Class 2			Class 3		
		negative	neutral	positive	negative	neutral	positive	negative	neutral	positive
Total	Total	19%	57%	24%	21%	49%	30%	6%	14%	80%
Free local public transport	IFrPT	11%	35%	54%	6%	28%	66%	2%	5%	92%
Fixed public transport fares at US\$0.25 per trip	I25cPT	12%	40%	48%	7%	34%	59%	2%	7%	91%
Double public transport services frequency	IFreqPT	9%	48%	43%	7%	41%	53%	3%	12%	86%
Free park and ride facility close to transport hubs	IFrPnR	10%	48%	42%	4%	40%	56%	1%	11%	88%
Free secure lockers for bikes/scooters at transport hubs	ILockBk	10%	60%	31%	6%	56%	38%	1%	13%	86%
Bike/scooter parking at transport hubs for US\$0.50/day	IBkPk50	13%	64%	23%	10%	61%	29%	4%	17%	79%
Tolled roads ensuring 25% faster travel time than free roads	IToll25	23%	54%	24%	27%	49%	24%	7%	14%	79%
Tolled roads ensuring 50% faster travel time than free roads	IToll50	25%	49%	26%	26%	47%	27%	7%	12%	80%
Peak-period road user charge US\$0.05/mile	IRUC05	36%	53%	12%	42%	51%	8%	14%	17%	69%
Peak-period road user charge US\$0.10/mile	IRUC10	37%	52%	11%	44%	48%	7%	16%	17%	67%
Peak-period road user charge US\$0.15/mile	IRUC15	38%	51%	12%	47%	47%	6%	20%	16%	64%
Peak-period road user charge US\$0.20/mile	IRUC20	39%	48%	13%	47%	47%	6%	21%	15%	63%
Congestion-free lanes what you pay US\$0.05/mile	ICFL05	36%	53%	11%	41%	52%	7%	14%	15%	71%
Congestion-free lanes what you pay US\$0.10/mile	ICFL10	35%	53%	12%	42%	50%	8%	15%	17%	68%
A supplementary charge of US\$15 per car in a defined area around the city which is designed to reduce congestion	ICh15Cr	40%	48%	12%	50%	42%	8%	23%	13%	64%
A supplementary charge of US\$10 per car in a defined area around the city which is designed to improve air quality	ICh10Cr	39%	48%	12%	49%	43%	8%	20%	13%	67%
Free annual vehicle registration with US\$0.10/mile peak-hour charge	IFrReg	30%	52%	18%	29%	46%	25%	9%	13%	79%
50% reduction in annual vehicle registration with US\$0.05/mile charge	I50Reg	27%	54%	19%	29%	43%	27%	8%	12%	80%
75% reduction in annual vehicle registration with US\$0.03/mile charge	I75Reg	24%	53%	23%	25%	44%	31%	7%	11%	82%
Tax deduction for acquiring hybrid/plug-in hybrid vehicle	ITaxPEV	18%	54%	28%	18%	48%	33%	4%	11%	85%
Tax deduction for acquiring a full electric vehicle	ITaxFEV	20%	53%	27%	19%	50%	32%	4%	12%	85%

Bookable door-to-door bus services at transport hubs, free	IFrBus	11%	56%	33%	8%	43%	49%	2%	8%	91%
Bookable door-to-door bus services at transport hubs, same fare as regular public transport	IPTBus	11%	62%	27%	9%	51%	40%	2%	13%	85%
Bookable door-to-door bus services at transport hubs, +10% fare of regular public transport	I10Bus	17%	65%	18%	20%	57%	23%	7%	16%	77%
Free, bookable voluntary car-sharing: you are a passenger	IFrCShP	14%	61%	25%	14%	58%	29%	3%	13%	84%
Free, bookable voluntary car-sharing: you are a driver	IFrCShD	16%	66%	18%	22%	61%	17%	5%	17%	78%
Bookable car-share subscription at US\$10/month + US\$0.05/mile	ICSh05	24%	63%	13%	26%	61%	12%	7%	17%	77%
Bookable car-share subscription at US\$10/month + US\$0.10/mile	ICSh10	24%	64%	12%	28%	61%	11%	8%	18%	74%
Bookable car-share subscription at US\$10/month + US\$0.15/mile	ICSh15	23%	64%	13%	28%	62%	10%	9%	17%	73%
Event ticket includes free public transport	IEvFrPT	10%	44%	46%	6%	34%	60%	1%	6%	93%
25% off parking cost for car-pooling (T3+)	ICrPo25	12%	62%	26%	9%	52%	40%	2%	12%	86%
Valet parking at event at +20% extra cost	IVaPk20	23%	64%	14%	26%	60%	14%	13%	21%	66%
15% off event tickets for public transport users	IEv15PT	11%	54%	34%	10%	43%	48%	2%	10%	88%
Special seats at a 25% discount when you use public transport	IEvSePT	11%	54%	36%	8%	44%	48%	2%	9%	89%
10% government rebate for e-bike/e-scooter purchases	I10RbEB	17%	62%	21%	19%	60%	21%	4%	15%	81%
20% government rebate for e-bike/e-scooter purchases	I20RbEB	17%	60%	23%	18%	57%	25%	4%	13%	83%
\$200 voucher for e-bike/e-scooter purchases	I200EB	16%	58%	26%	17%	53%	30%	4%	11%	85%
Tax deduction for e-bike/e-scooter purchases	ITaxEB	15%	61%	24%	17%	56%	27%	4%	13%	83%
Free charging at your workplace for EV and other electric mobility devices such as E-bikes or E-scooters	IFrChEv	13%	58%	29%	8%	48%	45%	1%	10%	89%
Showers and storage available for bikes, scooters, and personal items to support active travel	IShwBk	11%	62%	28%	8%	49%	44%	2%	13%	85%
Public transport on travel card will be subsidised	IPTSub	10%	54%	36%	5%	33%	62%	1%	11%	87%
1% fuel discount for every 1% reduction in car use	IFueLLC	12%	64%	24%	5%	45%	50%	2%	15%	84%
Highlighting the health benefits of walking, cycling, scootering	IBenfAc	10%	65%	26%	4%	34%	62%	1%	15%	84%
Promoting cost savings of active modes and public transport	ICstAc	10%	65%	25%	5%	40%	55%	1%	15%	85%
Highlighting environmental benefits of driving less	IEnvLC	10%	69%	21%	7%	33%	61%	1%	18%	81%
Monthly leaderboard of employees using active transport	ILdBAC	15%	69%	16%	10%	55%	36%	5%	20%	75%
Monthly leaderboard of employees reducing car use	ILdBLC	16%	68%	16%	7%	51%	42%	4%	21%	75%

A government-enabled platform providing consumers with real-time EV charging information	IEVInf	12%	67%	21%	11%	55%	35%	2%	15%	83%
A consistent and transparent pricing policy for EV charging services	IEVPol	11%	64%	24%	10%	52%	38%	2%	14%	84%
Innovative charging solutions that reduce charging time by 50%	IEvChTR	10%	60%	30%	8%	50%	42%	1%	11%	87%

