Travel Behaviour and Society 39 (2025) 100978

Contents lists available at ScienceDirect

Travel Behaviour and Society

journal homepage: www.elsevier.com/locate/tbs

# A latent class dynamic discrete choice model for travel behaviour and scheduling

Stephen McCarthy *, Daniel Jonsson, Qian Wang, Anders Karlström

*Transport and Systems Analysis, KTH Royal Institute of Technology, Sweden*

ARTICLE INFO

*Keywords:*
Latent class model
Dynamic discrete choice
Activity-based model
Scheduling model
Behavioural heterogeneity
Modality styles

ABSTRACT

In travel behaviour modelling, latent class models are used to represent underlying discrete groupings of behavioural preferences. The paper presents a latent class extension of a dynamic discrete choice model (DDCM) and applies the model to the problem of activity demand generation and scheduling. The DDCM is a recursive multinomial logit model where agents make sequential decisions in time, maximizing the expected future utility of their decisions in a random utility maximization framework. It generates activities and their associated travel within a full day schedule, endogenously respecting agents' inherent time-space constraints. The latent class DDCM builds on the base model by representing heterogeneous lifestyle preferences. A specification of the model is estimated on a Stockholm travel survey and uses age, income level, gender, car ownership and presence of children in the household as classifying variables. The models result in classes which primarily represent modality styles, finding car-, transit- and bike-primary behavioural groups as well as a multimodal group, each linked with different socio-demographic characteristics. The models improve over non-latent class reference models and provide insight into the structure of heterogeneity in travel behaviour preferences in Stockholm.

## 1. Introduction

Travel behaviour, broadly, is the types and locations of activities that individuals undertake over the course of a day, and the resulting travel they perform to get from place to place. An individual's travel behaviour is performed within certain time-space constraints (Hägerstrand, 1970), but also influenced by underlying preferences such as whether they enjoy driving. Empirical evidence shows that these preferences are correlated with demographic and socioeconomic attributes such as age, gender and income. Further, there are distinct patterns within the heterogeneity of travel behavioural preferences, which Salomon and Ben-Akiva (1983) call lifestyles: discrete groupings of broad behavioural patterns.

Within the discrete choice paradigm, latent class models are used to represent behavioural patterns organized by underlying discrete groups, with classes representing the underlying constructs which drive differences in behaviour between groups. A latent class approach allows the modeller to find and exploit lifestyle-like patterns of heterogeneity in the population. Importantly, latent class models provide an intuitive way to interpret the individual socio-demographic factors which influence class membership probabilities and the impact of classes on behaviour (Hess et al., 2009).

Dynamic discrete choice models (DDCMs), based on the work of Rust (1987), build on the discrete choice framework introduced by McFadden (1974) with agents who make multiple, time-sequential choices in which they choose the alternative which gives the maximum expected future utility. In the travel behaviour field, agents in a DDCM make decisions about their activities and travel over the course of a period of time (e.g. a day), considering at each decision point not just the immediate impact of their choices but also the consequences later on. Karlström (2005) proposed a microeconomically-consistent DDCM for travel behaviour, Scaper, which has been extended by Jonsson et al. (2014) and Blom Västberg et al. (2020) to become a full-scale urban travel behaviour model. With its endogenous representation of time and respect for time-space constraints, Scaper is also inherently a scheduling model.

While latent class models have been explored in many contexts, we are not aware of any latent class DDCMs in the literature; indeed, the literature on dealing with heterogeneity in populations using DDCMs is quite new. This paper aims to fill the gap by developing a latent class dynamic discrete choice model for travel behaviour and scheduling, based on Scaper. We present the structure of the model in a general way that allows for a range of applications within travel behaviour, and potentially in other fields. We then demonstrate the validity and

* Correspondence to: Teknikringen 10A, 11428 Stockholm, Sweden.
*E-mail address:* smcc@kth.se (S. McCarthy).

https://doi.org/10.1016/j.tbs.2024.100978
Received 26 April 2024; Received in revised form 30 September 2024; Accepted 13 December 2024

usefulness of our model through a case study of Stockholm, in which we present a specific travel behaviour and scheduling model using our framework and estimate the model using travel survey data. We design the case study model application with lifestyles — and in particular, patterns of mode choice — in mind, to provide a reasonable and clear illustration of the capabilities of the latent class DDCM.

### 1.1. Latent class choice models

Latent class analysis in statistical research has existed since at least the 1950s as a method for clustering quantitative data; in the 1980s it was combined with discrete choice modelling to create latent class choice models. Formann (1985) describes a binary logistic latent class model, and Kamakura and Russell (1989) introduces a multinomial latent class choice model for market segmentation based on brand loyalty. The core idea is to introduce a discrete latent construct (the *class*) which is used to discriminate between different model specifications in the model's observed utility function in order to capture taste heterogeneity in the population. Class membership is also modelled with a discrete choice model based on known information, usually socio-demographics or choice history. The parameters of the class membership model and main choice model are simultaneously estimated.

Latent classes represent a certain type of population heterogeneity, where there is an underlying construct that is not directly observed and essentially discrete. The latent construct mediates between the observed individual variables (e.g. socio-demographics, attitudes) and the outcome choice variables. Where such heterogeneity exists, they outperform simple multinomial logit models as they capture heterogeneity which would have otherwise been part of the unobserved independent error terms. An example of use to represent an underlying construct is in Owen and Videras (2009), in which latent classes represent levels of social capital; in cases such as this latent class models can be used to provide empirical support for a theoretical model. Latent classes also often represent demographic or socio-economic groupings where these drive differences in behaviour (e.g., Lee et al., 2003, 2019). In this case, latent class models provide the modeller with an intuitive way to interpret the distribution of heterogeneity in the population (Keane and Wasi, 2013). The ability of latent class models to link heterogeneous behaviour, such as differences in willingness to pay with socio-demographic characteristics can aid in policy analysis, especially in modelling distributional effects.

In general, latent class models can be seen as a special case of mixed models with a discrete distribution on the mixed parameters (Greene and Hensher, 2003). Greene and Hensher (2003) and Shen (2014) have directly compared latent class logit models with continuous mixed logit models for long-distance route choice and mode choice respectively; both found better statistical support for the latent class model. Hess et al. (2009) note that the usual use of mixed models in practice is to specify independent normally distributed random parameters; to estimate a more complex continuous-distribution mixed model, the modeller must have prior information on the shape of the joint parameter distribution, which is generally difficult to determine. Conversely, for a latent class model the modeller must only specify the number of latent classes, which is often determined in a search. Mixed models with independent parameter distributions also do not help the analyst understand the source or correlates of heterogeneity, a forte of latent class models (Hess et al., 2009).

### 1.2. Heterogeneity in travel behaviour

The literature on heterogeneity in travel behaviour reveals patterns of behaviour amenable to latent class modelling. An individuals' mobility decisions over time are not independent of each other but have longitudinal consistency (Thøgersen, 2006). Differences in behaviour are not distributed randomly across the population but are clustered in groups that have relatively predictable behaviours (Kitamura, 2009); for instance, a unimodal car-driver group and a multimodal transit- and bike-using group (Kuhnimhof et al., 2006). Many researchers have used latent class models to find and explore group behavioural patterns. Travel mode choice has been studied using latent class models in several contexts: intercity travel (Bhat, 1997), short distance travel (Prato et al., 2017), stated preference in the context of a new transit system (Lee et al., 2003), and travel to high speed rail stations (Wen et al., 2012). Latent classes have been used for market segmentation of airline travellers to identify preference toward carriers (Wen and Lai, 2010; Zhou et al., 2020) and to identify different rail passenger booking behaviours (Hetrakul and Cirillo, 2014). In freight transport, research has been done on shippers' value of time (Massiani et al., 2007) and mode choice (Román et al., 2017) using latent class models.

Salomon and Ben-Akiva (1983) argue for the use of lifestyle groups for travel behaviour analysis, where individuals with similar patterns of behaviour are grouped together. Individuals' decisions depend on a combination of individual preferences and available resources, decided through circumstance and long-term decisions which can collectively be called a lifestyle. We follow research such as Kitamura (2009) in conceiving of lifestyle as a latent construct related to socio-demographic characteristics such as household structure, age, gender and income. In our case study, we are specifically interested in *modality styles*: "behavioral predispositions, characterized by a certain travel mode or set of travel modes that an individual habitually uses" (Vij et al., 2013). Mode share is a core element of most travel behaviour models and a key baseline metric for policy analysis. Behavioural responses to policy or infrastructure changes are likely to be different between individuals with different modality styles, therefore the distribution of these within the population can be important for policymakers (Krueger et al., 2018). Several previous studies have used latent class approaches to categorize and label modality styles at different levels of specificity. Vij et al. (2013) identifies three latent modality styles which capture correlation between work mode choice and non-work trip mode choice; Olafsson et al. (2016) identifies five different multimodal modality styles among Danish cyclists; and Keskisaari et al. (2017) identified seven latent modality style classes in Helsinki with different travel behaviour profiles and greenhouse gas impacts.

Modality styles have been found to relate to several categories of individual characteristics. Socio-demographically, they are consistently found to be related to income, age and gender and presence of children in the household (Vij et al., 2013; Olafsson et al., 2016; Keskisaari et al., 2017; Krueger et al., 2018). Heinen and Chatterjee (2015) find that older people, full-time workers and car owners demonstrate less variability in mode choice decisions, for example. Long-term choices such as car ownership and residential location also relate to modality styles, though different authors place modality styles as either upstream (Krueger et al., 2018) or downstream (Vij et al., 2013; Keskisaari et al., 2017) of long-term mobility choices. This study positions modality styles as a potential proxy for long-term mobility choices when data about these are unavailable, such as in a future scenario where car ownership may be difficult to predict. There is also evidence for the influence on different underlying attitudes, such as level of concern about global warming, on mode choice behaviour (Atasoy et al., 2013; Hurtubia et al., 2014). Krueger et al. (2018) suggests that incorporating normative attitudes in a latent class approach could help forecast shifting travel behaviour patterns over time driven by changes in these attitudes. While the data we use in our case study does not include attitudinal questions, our method could support the inclusion of such data where available.

### 1.3. Dynamic discrete choice models

Rust (1987) developed a model for repeated decision-making taking into account the expected future value of each decision and elements of the decision history: a dynamic discrete choice model. A DDCM can

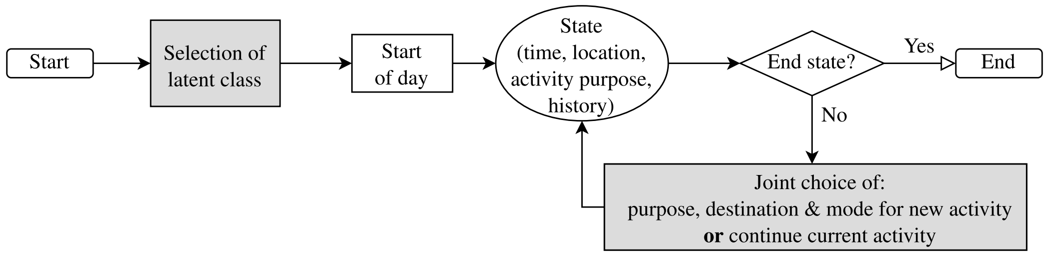


**Fig. 1.** Flowchart showing how the model is used to simulate an agent's complete daypath. Grey boxes indicate stochastic choices made by MNL models. The observed utility for latent class selection is the class membership function ($M_c$). The choice of next state is made on the basis of observed immediate reward plus expected future utility ($u_c + \bar{V}_c$) conditional on latent class.

be framed as a Bellman equation (Bellman, 1957) and solved given certain assumptions about the utilities using dynamic programming. The structure of a DDCM is useful for situations where there are repeated or sequential decision-points which form a decision path, and especially for decisions made over time. Outside of travel behaviour, DDCMs have been developed to model career paths (Keane and Wolpin, 1997), migration (Kennan and Walker, 2011), and retirement (Rust and Phelan, 1997).

Karlström (2005) was the first to outline a dynamic discrete choice approach to daily travel and activity behaviour. This model, Scaper, tied together the random utility maximization approach of McFadden (1974) with the time-geography of Hägerstrand (1970) in a DDCM framework. The concept was further developed by Fosgerau et al. (2013) who demonstrated that the model could be estimated consistently, by Jonsson et al. (2014) in a model prototype, and by Blom Västberg et al. (2020) who presented the first full city-scale version of Scaper. To our knowledge, Scaper is the only model in the travel behaviour field that (a) can interdependently model the complete daily schedule of an individual (including times, mode choices, and activity types, locations and durations), (b) respects time and space constraints without conflict resolution mechanisms, (c) is tractable to microeconomic theory, and (d) has been implemented at the full-city simulation level. Zimmermann et al. (2018) used the Scaper framework to present a mixed recursive logit model with continuous distributions of mode ASC variables. This improved the model fit compared to a non-mixed model but did not provide much insight into the structure of the heterogeneity.

In this paper, we present a latent class DDCM model based on Scaper which retains the advantages of that model as detailed in the previous paragraph, and gains the benefits of the latent class models for representing underlying population groupings. We illustrate our novel approach with a case study which adds to the existing literature on modality styles in a unique modelling context.

## 2. Model

As mentioned above, the paper develops a latent class model which combines the dynamic discrete choice model Scaper with a latent class membership model. Fig. 1 shows how the model functions as a Markov Decision Process (MDP) in simulation, with the agent's class being selected then moving into the DDCM for determining the agent's activity and travel schedule across a full day. Class membership and travel behaviour are properly seen as two parts of the same model rather than two models, as their parameters are jointly estimated.

This section starts by presenting the latent class DDCM model in general, then details the specific full-day scheduling application to which we apply the model. It also discusses estimation and implementation considerations that arise for the latent class DDCM.

### 2.1. General latent class dynamic logit model

We characterize our model as an MDP with an agent moving through the process from a starting state to an attracting end state. For simplicity, we will omit the agent from our notation in the equations below. The agent moves through a state space $S$ by taking actions from the set $A$. The set of possible actions in state $s$ is $A_s$. Transitions are stochastic, meaning that an action $a$ taken in state $s$ does not always end up in the same state, but instead has probability of ending in state $s'$ which we denote $P(s' \mid s, a)$. There is a set of attracting end states $S_{\text{end}} \subset S$ with at least one member. In an end state, the agent does not take an action and the process ends.

The agent receives a reward for transitioning between states which is conditional on their membership in a latent class. Specifically, conditional on membership in latent class $c$, an agent who takes an action $a$ from state $s$ which results in a transition to state $s'$, earns class-specific reward $R_c(s, a, s')$. We could alternatively frame the situation as a single reward function depending on parameters $\beta$ which have a discrete mixing distribution with $C$ possible values. It can be seen from the alternate framing that the latent class model is a discrete special case of the general mixed logit model.

The agent has a probability distribution for class membership; we denote the probability of belonging to class $c$ as $m_c$. As is common in latent class models, we model class membership using a multinomial logit model, assuming we have an observed 'utility' function $M_c$ and unobserved i.i.d. Gumbel-distributed error term. To what extent class membership should be understood as a *choice* of the agent or not depends on the underlying construct that the latent classes represent; for example, lifestyle or modality styles can be understood as a high-level agent choice. We restrict the agent's class membership probabilities to depend on the agent but not the decision process; i.e. $M_c(x)$ is based on a vector $x$ of agent characteristics independent of the MDP. The probability of membership in class $c$ is:

$$m_c(x) = \frac{e^{M_c(x)}}{\sum_{c'=1}^{C} e^{M_{c'}(x)}} \tag{1}$$

The agent takes sequential actions which move it through the states of the MDP. When taking an action, the agent does not know which next state will be reached, but has information on the expected reward, defined as:

$$R_c(s, a) \overset{\text{def}}{=} \mathop{\mathbb{E}}_{s'} \left[ R_c(s, a, s') \right] \tag{2}$$

Conditional on membership in latent class $c$, the agent maximizes the expected reward of their path through the state space by choosing the best policy $\pi_c : S \to A$ which determines which action to make given a state. Note that while an agent in an MDP can only consider the current state and not previous states, the modeller can include state variables which effectively record elements of the agent's history by enlarging the state space. We define the conditional value function $V_c(s_0)$ of a state $s_0$ given latent class $c$ to be the maximum expected utility of the path leading from that state to an end state:

$$V_c(s_0) \stackrel{\text{def}}{=} \max_{\pi_c} \mathbb{E} \left\{ \sum_{i=0}^{n-1} R_c(s_i, a_i, s_{i+1}) \mid \pi(s_i) = a_i,\ s_n \in S_{end} \right\} \tag{3}$$

We define $V_c(s) = 0$ if $s \in S_{\text{end}}$ and $V_c(s) = -\infty$ if there is no path to $S_{\text{end}}$ from $s$. This optimization can be expressed as a Bellman equation (Bellman, 1957):

$$V_c(s) = \max_d \left\{ R_c(s,a) + EV_c(s,a) \right\} \tag{4}$$

where $R_c(s,a)$ is the expected reward defined above, and

$$EV_c(s,a) = \mathbb{E}_{s'} \left[ V_c(s') \mid s, a \right] = \int_S V_c(s')\, dP(s' \mid s, a) \tag{5}$$

The uncertainty in transitions between states may for example be used to capture stochastic travel times, in which case the integral above is over the distribution of travel times. Note that we do not discount future utility.

From the perspective of the modeller, we cannot fully observe the agent's expected reward function. We will thus view the agent's MDP as a dynamic discrete choice model. Following Karlström (2005), we assume that the reward $R_c(s,a,s')$ can be additively separated into observed term $u_c(s,a,s')$ and an unobserved state-independent term $\varepsilon_c(a)$ that is i.i.d. Gumbel distributed with zero mean. We denote our expectation of the value function $V(s)$ with $\varepsilon$ unknown as $\bar{V}(s)$. Under these assumptions, Rust (1987) shows that the expected value function becomes:

$$\bar{V}_c(s) = \log \sum_{a \in A_s} \exp(u_c(s,a) + EV_c(s,a)) \tag{6}$$

The class-conditional probability of making decision $d$ in state $s$ with $\varepsilon$ unobserved is then given by the multinomial logit model on expected utility:

$$P(a \mid c, s) = \frac{\exp(u_c(s,a) + EV_c(s,a))}{\sum_{a \in A_s} \exp(u_c(s,a) + EV_c(s,a))} = \frac{\exp(u_c(s,a) + EV_c(s,a))}{\exp(\bar{V}_c(s))} \tag{7}$$

It is worth noting here that the latent class membership function is applied once — to the agent — rather than to each decision point in the MDP. Conceptually, we want the agent to belong to a certain class for their whole path through the MDP, rather than shifting between classes with each action. An agent with a car-primary lifestyle is unlikely to suddenly change to a transit-primary lifestyle in the middle of a day. Constructing the latent class model in this way allows the agent's preferences to be fixed across the whole path. The conditional probability of a path $\zeta = \{(s_1,a_1),\ldots,(s_{n-1},a_{n-1}),s_n\}$ where $s_n \in S_{end}$ and the agent starts at state $s_1$, given membership in class $c$, is:

$$P(\zeta \mid c, s_1) = \prod_{i=1}^{n-1} P(a_i \mid c, s_i)\, P(s_{i+1} \mid s_i, a_i) \tag{8}$$

and its marginal probability is:

$$P(\zeta \mid s_1, x) = \sum_{c=1}^{C} m_c(x)\, P(\zeta \mid c, s_1) \tag{9}$$

This perspective will become important when we consider estimating the model in Section 2.3.

### 2.2. Full-day travel scheduling application

We now consider the application of the general model above to the problem of full-day activity scheduling. Our goal is to generate an activity and trip sequence, with start times and durations which respects the agent's time-space constraints. We model the agent's activities and travel at a fairly high-level, with a zone system for locations and a delineation of four broad activity types and four modes of travel. The reward function is based on starting and spending time doing activities as well as travelling.

We make two simplifications to the theoretical model presented above in order to produce a computationally tractable and estimable model; these are standard across previous research using the Scaper DDCM. The first is the approximation of the value function at discrete time steps, which makes the model feasible to compute. Time remains continuous, however value functions for states with non-integral time steps are calculated by interpolating the values for the two nearest integral time steps. The second simplification is to use deterministic transitions between states. In the implemented model, an action $a : S \to S$ moves the agent to a known state $a(s)$ deterministically. Therefore, the agent's expected reward of taking an action $R_c(s,a)$ equals its actual reward $R_c(s,a,s')$ where $s' = a(s)$. This means that the conditional EV from (5) becomes $EV_c(s,a) = \bar{V}_c(a(s))$, and our expected value function becomes:

$$\bar{V}_c(s) = \log \sum_{a \in A_s} \exp(u_c(s,a) + \bar{V}_c(a(s))) \tag{10}$$

#### 2.2.1. States and actions

A state is a combination of time, location and activity participation, representing where and when the agent is and what they are doing there. We also include some information about the agent's history at previous states, since this otherwise cannot be used to influence the agent's decisions in an MDP. Table 1 shows the variables in a state and their possible values. We use a zone system with 1375 zones covering the greater Stockholm region and a continuous time variable measured between 5 am and 11 pm in integral increments of 10 min. An 18-hour day is used instead of a 24-hour one for computational efficiency, but this is not an inherent limitation of the model. An agent can act either by continuing to perform the same activity or travelling somewhere (possibly the same location) to start a new activity. The 'continue' action is denoted $a_{\text{cont}}$. A 'travel' action comprises the destination location index, the mode of travel (car, bike, transit or walk), and the purpose of the new activity. Table 1 also shows how each type of action move the agent within the state space.

We require the agent to be at home by 11 pm, having worked if they are supposed to work; this defines the set of attracting end states in the MDP. Recall that end states have zero future utility ($V_c = 0$) and states with $t > 108$, which cannot reach an end state, have $V_c = -\infty$ so that the probability of reaching them is zero. The dynamics of the model also ensures that the value function of any state which can only reach these 'bad' states (and not an end state) is also $-\infty$ and therefore these also have zero probability. This forces agents into a series of actions which reach an end state. Conceptually, our model naturally implements the time-space prism of Hägerstrand (1970), ensuring an agent only takes actions which satisfy their time-space constraints. As an example of such a constraint, we use the 'has worked' state variable to constrain behaviour by linking it to the feasible end states. Other history variables could easily be added to the state to represent new time-space constraints; for example, a variable to record the number of times an agent has shopped. New history variables increase the size of the state space and the resulting computational complexity.

#### 2.2.2. Reward function

We define latent class membership utility $M_c(x)$ for class $c$ and agent $x$, which is only dependent on the agent's socio-demographic and household characteristics. We use six dummy variables, which can be expressed as a vector:

$$\boldsymbol{x} = \begin{pmatrix} 1 \\ \text{agent is female} \\ \text{agent income} > \text{50th percentile} \\ \text{agent age} > 60 \\ \text{agent age} < 35 \\ \text{agent's household includes children under 18} \\ \text{agent has access to car} \end{pmatrix} \tag{11}$$

**Table 1**
State variables and transition rules for continue and travel activities.

| Variable | Notation | Range of values | After $a_{\text{cont}}$ | After $(d, m, p')$[a] |
|---|---|---|---|---|
| Time of day | $t$ | $[0, 108]$ | $t+1$ | $t + TT(l, d, m, t)$[b] |
| Location index | $l$ | $\{1, 2, \dots, 1375\}$ | $l$ | $d$ |
| Purpose | $p$ | $\{p_{\text{home}}, p_{\text{work}}, p_{\text{shop}}, p_{\text{other}}\}$ | $p$ | $p'$ |
| Duration | $\tau$ | $\{0, 1, \dots, 108\}$ | $\tau+1$ | 0 |
| Has Worked? | $w$ | $\{\text{false}, \text{true}\}$ | $w$ | $w \vee p' = p_{\text{work}}$ |

[a] For a travel action, $d$ is the destination index, $m$ is the mode and $p'$ is the new activity purpose.
[b] $TT(l, d, m, t)$ is exogenous travel time for the given O/D pair, mode and time of day.

The constant 1 represents the alternative-specific constant for each class. The 50th-percentile gross monthly income in our sample is 32 000 Swedish kronor (in 2015). Ages 35 and 60 were chosen as reasonable cutoffs to balance our observed data into three age segments with sufficient representation for estimation. With $\boldsymbol{\beta}_c$ as a parameter vector to be estimated and class 0 as the reference class with no estimated parameters, the latent class assignment utility is:

$$M_c(x) \stackrel{\text{def}}{=} \begin{cases} 0, & c = 0 \\ \boldsymbol{\beta}_c \, \boldsymbol{x}, & c > 0 \end{cases} \tag{12}$$

We separate the one-stage action reward $u_c$ into two cases: continuing the current activity and travelling to start a new activity. Further, we separate the new-activity utility into 'travel' and 'start' utilities.[1] With state variables as defined in Table 1, we define:

$$u_c(s, a) \stackrel{\text{def}}{=} \begin{cases} u_{\text{continue}}(t, p, \tau), & a = a_{\text{cont}} \\ u_{\text{travel}}(l, d, m, t) + u_{\text{start}}(t, d, p'), & a = (d, m, p') \end{cases} \tag{13}$$

where:

$$\begin{aligned} u_{\text{continue}}(t, p, \tau) &\stackrel{\text{def}}{=} \begin{cases} u^{\text{timeofday}}_{\text{home}}(t), & p = p_{\text{home}} \\ u^{\text{duration}}_{\text{work}}(\tau), & p = p_{\text{work}} \\ \alpha^{\text{cont}}_{p}, & p \in \{p_{\text{shop}}, p_{\text{other}}\} \end{cases} \\ u_{\text{travel}}(l, d, m, t) &\stackrel{\text{def}}{=} \alpha^{\text{mode}}_{m} + \alpha^{\text{TT}}_{m}\, TT(l, d, m, t) + \alpha^{\text{TC}}\, TC(l, d, m) \\ u_{\text{start}}(t, d, p') &\stackrel{\text{def}}{=} \begin{cases} 0, & p' = p_{\text{home}} \\ \alpha^{\text{act}}_{\text{work}} + u^{\text{start time}}_{\text{work}}(t), & p' = p_{\text{work}} \\ \alpha^{\text{act}}_{\text{shop}} + \alpha^{\text{size}}_{\text{shop}} \log(\text{Emp}(d)), & p' = p_{\text{shop}} \\ \alpha^{\text{act}}_{\text{other}} + \alpha^{\text{size}}_{\text{other}} \log(\text{Pop}(d)), & p' = p_{\text{other}} \end{cases} \end{aligned} \tag{14}$$

In (14), alphas represent estimated parameters. $TT$ represents travel time and $TC$ is travel cost normalized by income. All parameters except cost are class-dependent though for simplicity this is omitted from the notation. Values of estimated parameters are given in the appendix. Functions $u^{\text{start time}}_{\text{work}}(t)$ and $u^{\text{timeofday}}_{\text{home}}(t)$ are dependent on time of day and have estimated parameters every three hours, where the utility is a linear interpolation of the nearest parameters to the activity's start time. These functions were introduced to Scaper by Blom Västberg et al. (2020) and are described in detail in that paper. Similarly, $u^{\text{duration}}_{\text{work}}(\tau)$ is interpolated from estimated parameters dependent on activity duration. $\text{Emp}(d)$ is the total employment and $\text{Pop}(d)$ is the total population in zone $d$; these 'attraction' variables are proxies for the number of opportunities to perform these types of activities in a zone.

[1] The reason for this is practical: the model's computational bottleneck is calculating the total utility for choices which involve all possible origins and destinations, i.e. travel actions. By reducing the dependence of travel utility on variables such as activity purpose, the amount of computation can be reduced.

### 2.2.3. Alternative specifications

For comparison, we also estimate two non-latent class models. The first, the *baseline model*, is equivalent to the model specified above with only one class. This model has no class assignment variables as it reduces to a non-latent class model with no direct dependence on socio-demographics. A latent class model with more than one class will necessarily improve on the baseline model. The second, the *interactions model*, is the baseline model plus interaction variables for mode constants, travel time by mode and travel cost with each of the six socio-demographic dummy variables that are used for latent class assignment. This model uses the same socio-demographic information as the latent class model in a different way to explore which is a better representation of the underlying heterogeneity.

## 2.3. Estimation

Estimation of parameters in the class membership function $M_c$ and behavioural reward $u_c$ is performed jointly using maximum likelihood estimation. There are several considerations to estimating a fairly complex dynamic model with tens or hundreds of parameters. First, the process of computing the full model is computationally expensive: for each agent it takes over a second even with zone sampling (discussed below in Section 2.4). Simulation is feasible with appropriate parallelization, but re-calculating all the value functions for each step of the optimization process would be prohibitive. To solve this, we use the observation of Fosgerau et al. (2013), who show that the underlying DDCM can be viewed as a multinomial logit model over paths through the state space. Specifically, if $\zeta = \{(s_1, a_1), \dots, (s_{n-1}, a_{n-1}), s_n\}$ is a path given class $c$ and starting state $s_1$, then the probability of the agent choosing path $\zeta$ is:

$$P(\zeta \mid c, s_1) = \prod_{i=1}^{n} \frac{\exp(u_c(s_i, a_i) + \bar{V}_c(s_{i+1}))}{\exp(\bar{V}_c(s_i))} = \frac{\exp(\sum_{i=1}^{n-1} u_c(s_i, a_i))}{\exp(V_c(s_1))} \tag{15}$$

Recalling that $V_c(s_n) = 0$ for $s_n \in S_{\text{end}}$, we define $U_c(\zeta) = \sum_{i=1}^{n-1} u_c(s_i, a_i)$ and denote the set of all paths starting from $s$ and ending at a state in $S_{\text{end}}$ as $Z(s)$. Then the marginal probability of our path $\zeta$, with the expanded form of $m_c$ from (1), is:

$$P(\zeta \mid s_1, x) = \sum_{c=1}^{C} \frac{\exp(M_c(x))}{\sum_{c'=1}^{C} \exp(M_{c'}(x))} \cdot \frac{\exp(U_c(\zeta))}{\sum_{\zeta' \in Z(s_1)} \exp(U_c(\zeta'))} \tag{16}$$

We thus reduce the computationally expensive dynamic latent class model into a simpler latent class model composed of multinomial logit models, and we use this probability for estimation.

The second consideration is the size of the choice set. Our state space is large and well-connected enough that even with deterministic travel times, the set of all possible paths is orders of magnitude larger than could be feasibly used for estimation using standard methods. We therefore sample from the choice set of paths using importance sampling with a correction term from McFadden (1978). Where $\pi(\zeta)$ is the prior probability of having selected path alternative $\zeta$ in the choice set from the sampling data generating process, we estimate based on:

$$\hat{P}(\zeta \mid x) = \sum_{c \in C} \left( m_c(x) \cdot \frac{\exp(U_c(\zeta) - \log \pi(\zeta))}{\sum_{\zeta' \in P} \exp(U_c(\zeta') - \log \pi(\zeta'))} \right) \tag{17}$$

As in Blom Västberg et al. (2020), we bootstrap the estimation process by using our own model as the generating process for the importance sampling of paths, using a previous iteration of estimated values. In our experience the estimation process converges to stable parameter values after just a few iterations. The estimates reported in this paper were produced from sampled choice sets generated using a previously-estimated four-class model.

Third, there is a question as to whether the importance sampling process set out by McFadden (1978), which applies to multinomial logit models and not to extensions which violate the assumption of independence of irrelevant alternatives, can also produce consistent estimates in our case. Guevara and Ben-Akiva (2013) claim that the same approach produces consistent estimates for general mixed logit models if the number of alternatives sampled in the choice set rises with the square root of the observation sample size, and that these are distributed around the real values normally with variance given by the well-known robust standard errors (see, e.g., Train, 2009). Nerella and Bhat (2004) and von Haefen and Domanski (2013) present empirical evidence supporting this claim, though in different settings (mixed logit with continuous mixing distributions) and different size choice sets. Our data satisfies the choice set size requirement with $N_{obs} = 11\,474$ and $N_{alts} = 500$.

Finally, as latent class models do not have the desirable convexity properties of multinomial logit, the parameters are not guaranteed to converge to a global maximum. Some authors use the Expectation-Maximization (EM) algorithm, either for the entire estimation (e.g., Vij et al., 2013) or to obtain close estimates which are then used as starting parameters for a quasi-Newton method (Bhat, 1997). As Greene (2001) discusses, while the EM algorithm has desirable stability properties, it does not necessarily solve the convergence problem. For estimation we use the standard BFGS algorithm, starting from several different starting parameter sets to ensure we reach a reasonably global log likelihood maximum. We find that estimated parameters do depend on starting values, especially for higher numbers of classes, and starting from multiple starting points was helpful.

To confirm empirically that the estimation process produces consistent estimates, we validated our estimation process by recovering known parameters from a specified data generating process. We simulated new 'observations' using an estimated version of our model for all agents in the observation set, then treated these fake observations in the same way as our real data, generating choice sets (size 500) using a non-latent class model and estimating using these choice sets to see how well the original parameters are recovered. We performed this process between 2 and 9 times to generate at least 250 parameter estimates for each class. Parameters are compared using the benchmark of robust standard error as computed during estimation: we expect the estimated parameters to be distributed normally around their real values.

An observation of the distribution of parameter errors shown in Fig. 2 shows that the estimated parameters cluster around the real values in a way that matches our expectation of how estimated parameters should be distributed. As each independent estimation took on the order of hours, it was not feasible to produce enough independent observations to perform statistical testing on each parameter. However, visual inspection of the parameter-recovery error distributions suggests that our estimation procedure is producing meaningful parameter and standard error estimates, as claimed by Guevara and Ben-Akiva (2013).

For estimation of parameters from our case study data, following common practice in the field we performed multiple estimation runs starting from different randomly-generated parameters. After correcting for the order of classes the results were largely consistent. As the number of classes (and therefore parameters) increased, the models became much more compute- and memory-intensive to estimate; we only completed estimations for models up to four classes.

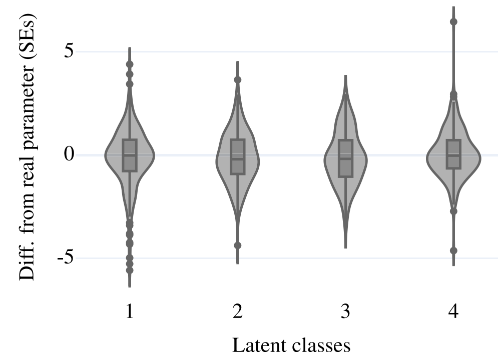


**Fig. 2.** Violin and box plots of the distributions of differences between estimated and real parameters for the parameter-recovery models, measured in standard errors of the estimated parameters.

### 2.4. Implementation

The latent class DDCM is implemented in F#. We implement the value function recursively, taking advantage of tail-call optimization and continuation computation expression features of that language. To avoid unnecessary repeated calculations, once a state's value function has been calculated it is cached for use in future calculations. The computation is feasible due to the approximation of states at non-integral time steps, discussed in Section 2.2. Estimation was performed using the optimization package developed for Blom Västberg et al. (2020), which we updated to calculate appropriate log likelihood gradients for the latent class model.

In our initial model tests, simulating one agent took 152 s on one core, and simulating ~11 500 agents took approximately 16.5 h using 30 parallel processes on a machine with 32 CPUs and 48 GB RAM. We therefore use the approach of importance sampling of zones described in Saleem et al. (2018). With zone sampling using 100 zones, one agent takes about 1.6 s to simulate and we can process all agents in under 15 min without appreciably impacting the quality of the simulation results.

The model uses transport network data from the Swedish national transport model (Trafikverket, 2020) with a base year of 2014, and corresponding 2014 land use data from Statistics Sweden. The network data used comprises travel time and cost origin–destination matrices for the entire 1375-zone region. Travel times for car and transit are differentiated by peak (7–9 am and 4–6 pm) and off-peak times, with an hour-long transition buffer around peak periods. The land use data comprises population and employment totals for each zone.

## 3. Results

We estimated models with up to four latent classes as well as the baseline and interactions models for comparison. Estimation was performed using observed data from the 2015 Stockholm area travel diary survey (Stockholm County, 2016). The survey contained 11 474 individuals with complete daily activity and travel data consistent with our model. The survey weights observations to reflect the regional population; we use these weights in estimation and analysis.

Table 2 shows goodness-of-fit measures for our estimations. We see that as the number of latent classes increases, the goodness of fit also increases, though with diminishing returns. The two latent class model outperforms the interactions model in estimation, even though it has fewer parameters. The full table of estimated parameters along with t-statistics derived from robust standard errors is given in the appendix.

Using each estimated model, we simulate a complete one-day activity schedule for all individuals from the estimation dataset. To validate the estimated models' simulation output, we focus on a few metrics key

**Table 2**
Goodness of fit and validation for estimated models.

| | *Observed* | *Baseline* | *Interactions* | *2-class* | *3-class* | *4-class* |
|---|---|---|---|---|---|---|
| Estimated parameters | | 33 | 93 | 72 | 111 | 150 |
| Log likelihood ($\times 10^4$) | | −9.01 | −8.34 | −7.92 | −7.57 | −7.43 |
| AIC ($\times 10^5$) | | 1.80 | 1.67 | 1.59 | 1.52 | 1.49 |
| BIC ($\times 10^5$) | | 1.81 | 1.68 | 1.59 | 1.52 | 1.50 |
| Activities per capita | 1.64 | 1.47 | 1.54 | 1.60 | 1.65 | 1.64 |
| Mean travel time (min) | 81.2 | 76.6 | 79.0 | 82.2 | 83.4 | 84.2 |
| Mean travek dist. (km) | 30.9 | 29.1 | 29.6 | 30.0 | 30.0 | 30.4 |
| Mode share | | | | | | |
| Car | 0.391 | 0.412 | 0.405 | 0.408 | 0.403 | 0.398 |
| Transit | 0.360 | 0.363 | 0.368 | 0.353 | 0.358 | 0.361 |
| Walk | 0.148 | 0.112 | 0.123 | 0.128 | 0.140 | 0.134 |
| Bike | 0.100 | 0.113 | 0.104 | 0.111 | 0.099 | 0.107 |

for transportation modellers: activity participation rate, travel distance and duration, and mode share. Table 2 also shows how well each of our models performed in simulation compared to the observed data. We note that the latent class models reproduce the behaviour aggregated across the full sample slightly better than the reference models. We compare latent class and interactions models in Section 3.2.

### 3.1. Interpreting the latent classes

As noted in the introduction, one of the primary reasons for choosing a latent class model is the ability to explore and interpret the different groups found by the model. These groups are both socio-demographic and behavioural, in that they are characterized both by their relationship to the socio-economic and demographic class assignment variables and by their influence on travel and activity behaviour. To understand the group composition we will look at both elements.

The largest single behavioural difference between classes in all three latent class models is mode choice. Our results align with our understanding of modality styles from the literature: there is latent heterogeneity in population behaviour in which modal preferences fall roughly into discrete groups. To show this, we take advantage of the fact that our simulation procedure assigns a class to each individual based on their class assignment probability. We track this no-longer-latent assigned class and use it to generate statistics on behaviour by class.

Fig. 3 shows the simulated mode share for each class in the latent class models. We use mode preferences as a convenient label for the classes, though as shown in Table 3 they exhibit differences in other behaviours as well. In the figure, we see that the two-class model finds a difference between individuals who are almost fully reliant on their cars and those who use other modes, mainly transit. Note that this is not a perfect split: there are individuals in the sample data who use both car and transit, for example. Agents in the car-primary class take more non-work out-of-home activities on average than the transit-primary class, but the classes are similar in work behaviour. The transit-primary class is larger with 57% of agents, though since car-primary agents perform more activities the total number of trips performed by each class shown in the figure is more even.

The three-class model adds a smaller class of agents who predominantly cycle; we call this the bike-primary class. The two classes previously identified are both reduced in size and more concentrated in their mode choices, but otherwise have similar behaviours as in the two-class model. The bike-primary class is situated between the other two classes in non-work activity rates. The four-class model retains these three classes and adds a properly multimodal class exhibiting the use of all four modes. Across both three- and four-class models, walking is most common for agents in the transit-primary class.

Fig. 5 illustrates how the different mode behaviours of classes interact with travel duration using the four-class model. Agents in the car-primary and bike-primary classes have the majority of their trip travel times concentrated under 25 min, whereas transit-primary users have a much broader distribution of travel times with walking trips tending to be shorter and transit trips tending to be longer. The distribution of trip durations for the multimodal class sits in between the other classes.

The socio-demographic compositions of our latent classes for the latent-class models also demonstrate how the models relate to each other. Fig. 4 presents radar charts with the six individual characteristics as radial axes and their presence in the class group relative to the overall population. Class compositions were calculated as proportions of all agents weighted by class probability, not from the simulated assigned classes. In the two-class model, apart from the obvious tendency to have access to a car, the car-primary class is more likely than the sample population to be over 60 and less likely to be under 35, and is more likely to have children in the household. The non-car class mirrors this composition, being generally younger and less likely to have children. Income and gender have less impact on the class composition.

As we saw above from the mode choice behaviour, the three-class model adds a bike-primary class, taking agents mostly from the two-class model's transit-primary class. Neither car- or transit-primary classes show much change from the previous model. The bike-primary class in the three-class model is less likely to be over 60 than the average person but is otherwise fairly similar to the overall population. In the four-class model, the new multimodal class is more likely to own cars and be above 60 than the overall population. The bike-primary class in this model is less likely to have access to a car and even less likely to be over 60 than in the three-class model; the socio-demographics of the other classes did not change substantially.

The results overall agree with the authors' intuitions on travel behaviour lifestyles in Stockholm. The models all identify strong differences among groups with different modality styles, which have impacts not just on mode choice but also travel time and activity participation. The model shows large differences across ages. Younger people are more likely to have a transit-oriented lifestyle, whether by choice or circumstance; they also tend to take longer-duration trips and work longer hours and perform fewer non-work activities, likely due in part to having less available time. About 10% of agents choose a bike-centric lifestyle, though this is much less popular with those over 60. Older individuals tend to gravitate toward car-centric lifestyles, though a smaller proportion make an effort to be multimodal, likely using a car when necessary and walking, biking or taking transit when this is a promising alternative.

While car, transit and biking are all represented by latent classes in which they are the primary mode, walking does not appear as a primary class mode in any of the models. Instead, walking seems to be done

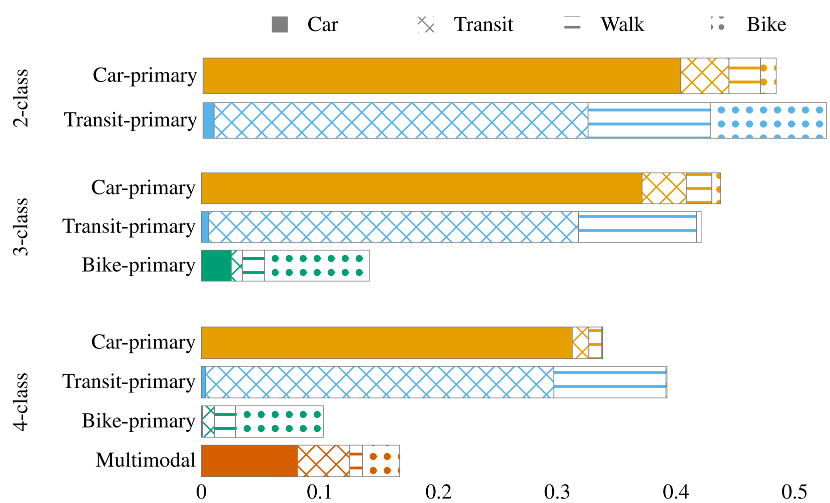


**Fig. 3.** Mode shares by class for different latent-class models. X-axis scale indicates proportion of total simulated trips (not agents).

**Table 3**
Simulation statistics by latent class for different models.

| | *Car-primary* | *Transit-primary* | *Bike-primary* | *Multi-modal* | *Car-primary* | *Transit-primary* | *Bike-primary* | *Multi-modal* |
|---|---|---|---|---|---|---|---|---|
| | Proportion of simulated agents | | | | Average travel time per trip *(min)* | | | |
| *2-class* | 0.43 | 0.57 | – | – | 22.8 | 36.0 | – | – |
| *3-class* | 0.40 | 0.47 | 0.14 | – | 22.3 | 37.3 | 28.5 | – |
| *4-class* | 0.30 | 0.44 | 0.10 | 0.16 | 18.1 | 37.9 | 29.7 | 34.3 |
| | Work activities per agent | | | | Non-work/home activities per agent | | | |
| *2-class* | 0.69 | 0.70 | – | – | 1.28 | 0.85 | – | – |
| *3-class* | 0.69 | 0.67 | 0.71 | – | 1.27 | 0.90 | 1.09 | – |
| *4-class* | 0.69 | 0.68 | 0.78 | 0.65 | 1.38 | 0.88 | 1.01 | 1.05 |
| | Median work start time *(h:mm)* | | | | Median work duration *(h)* | | | |
| *2-class* | 8:02 | 8:15 | – | – | 7.8 | 8.3 | – | – |
| *3-class* | 7:59 | 8:16 | 8:14 | – | 7.8 | 8.2 | 8.3 | – |
| *4-class* | 7:59 | 8:20 | 8:19 | 7:54 | 7.7 | 8.2 | 8.0 | 8.5 |

primarily by transit-primary individuals, suggesting that people see these as complementary modes which can be chosen depending on trip characteristics such as distance and weather. Note that walking to catch a bus or train was not included as a ‘walk’ trip for our estimation; these are distinct trips which did not use transit to reach the destination. Walking and biking do not appear to be complementary modes in the same way.

It is worth noting that income level plays relatively little role in differentiating the classes. We suggest this reflects the reality of mode choice in Stockholm, which in our experience is not well-correlated with income level: unlike in some other cities, well-paid professionals often bike or take the metro into work. This may also reflect our simple division of income into groups at the 50th percentile; it is possible that separating out much higher- or lower-income brackets would introduce some income effects in the models.

### 3.2. Comparison between latent class and interactions models

As we saw above in Table 2, the latent class models compare favourably to both the baseline and interactions models in estimation. The latent class models have a small edge in validation across key travel behaviour metrics, but these evidently do not tell the whole story. The substantial improvements in log likelihood for these models suggest that they are finding dimensions of variation with which to maximize the likelihood of the observed data. Even if these improvements are not reflected in the top-line statistics, better reflecting existing behavioural variation should improve the models’ responsiveness to changes in policy variables.

We illustrate a significant instance where the latent class models improve on the interactions model in Fig. 6. The figure reports how often an agent continues to use the same mode for a subsequent trip (the matrix diagonals) or changes modes. In our observed data, it is most common for individuals to continue using the same mode, however, the baseline and interactions models represent this behaviour very poorly. By separating travel behaviour into largely modality-centric lifestyle classes, the latent class models start to pick up agents’ tendencies for mode stability across the day.

## 4. Discussion

Investigating the makeup and behavioural profile of our latent classes helps us understand how the latent class models are improving on the reference models. The latent classes extract the most important differences in behaviour that can be differentiated by the socio-demographic variables in the assignment function. In our case, this primarily maps to modality styles. The models find three primary modality styles: car-primary, transit-primary, and bike-primary/multimodal. Observed as a progression of increasing numbers of classes, the models

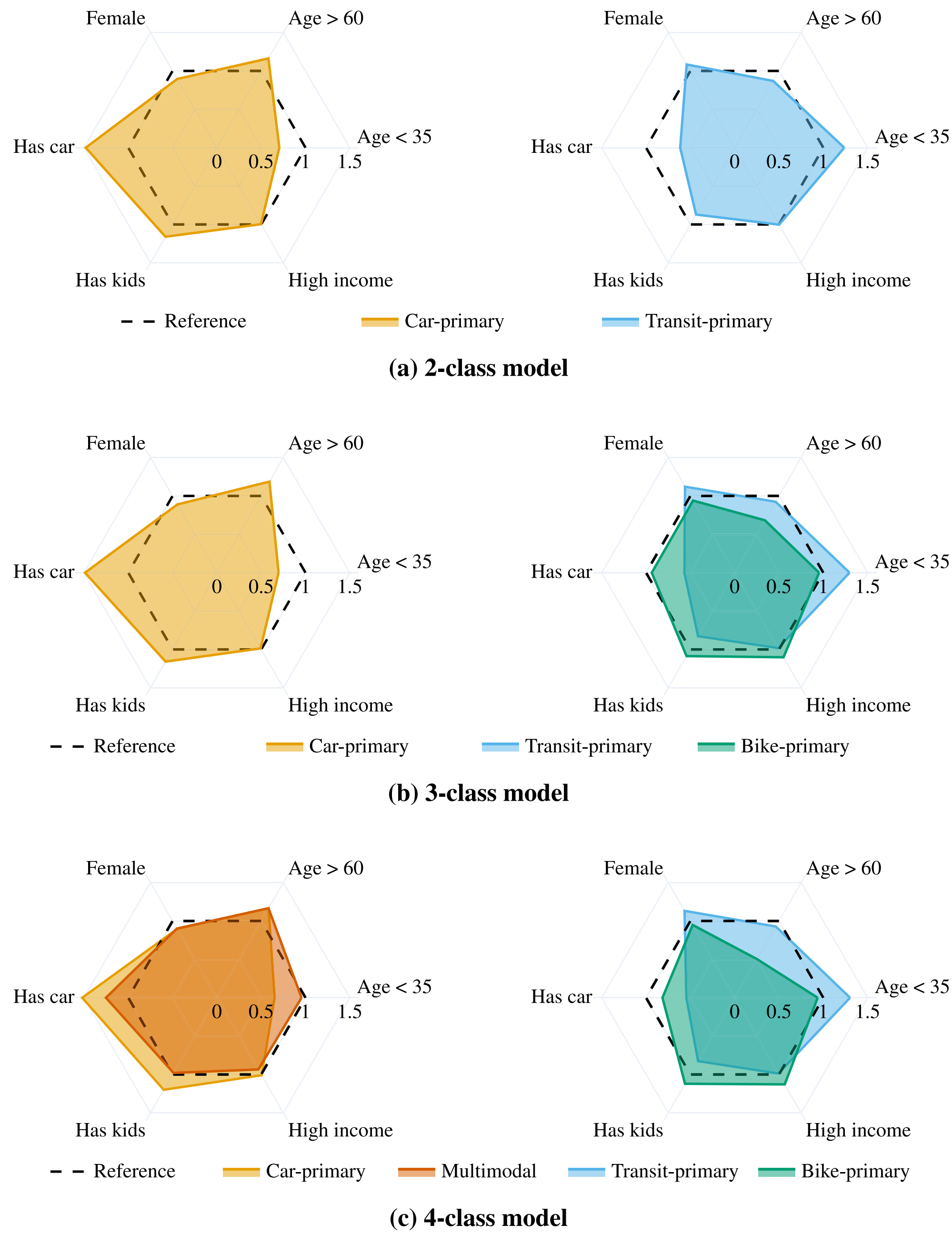


**Fig. 4.** Composition of latent classes relative to population for different models. A value over 1 means the class contains a higher proportion of individuals with the given characteristic than the population does.

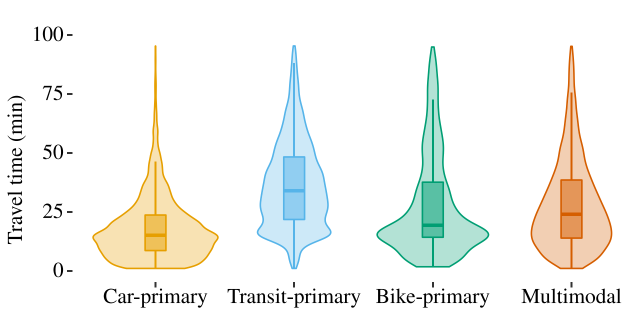


**Fig. 5.** Distribution of simulated travel times by trip, 4-class model. Outlier trips above 100 min not shown.

expose further behavioural and socio-demographic divides in the population with each new class. Each new model largely retains the divisions of the previous model and finds a new behavioural distinction to make.

The results demonstrate the interpretability benefits of latent class models in linking demographics with behaviour. Overall, the socio-demographic characteristics of the class groups align in our intuitive understanding with their observed modality styles. For instance, as expected, younger individuals are more likely to take transit and older individuals are more likely to drive cars and much less likely to cycle. Models which reflect these socio-demographic divides can better predict how future behaviour may change with respect to shifting socio-demographics over time. For behavioural prediction, the latent class models also separate out class membership from the agent's activity/travel decision-making process. An individual does not generally get up in the morning and face a random choice between bike, car and train to get to work; they have made longer-term lifestyle decisions which

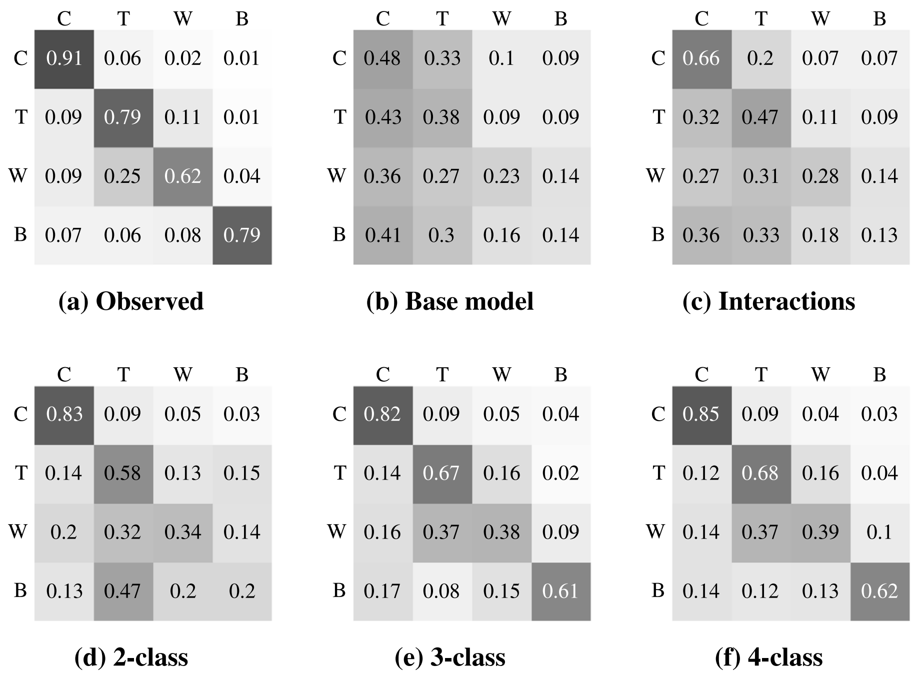


**Fig. 6.** Transition probabilities between modes for subsequent trips made by the same individual. Row indicates the first trip and column the subsequent trip, not necessarily on the same home-based tour. Modes are car, transit, walk and bike.

influence their mode choice. Here we represent these lifestyles through latent classes.

We should carefully consider how to interpret the latent class membership. It is common practice in the latent-class literature to assign labels to classes which present a convenient, if simplified, way of understanding the class's makeup and behaviour. We do so here by labelling our classes after the primary modes they use, since this has emerged from our modelling as the most apparent distinction between classes. We make two related points here. First, we avoid labelling the classes using demographics to avoid giving the impression that the classes represent hard divisions between demographic groups. The socio-economic and demographic distinctions we have found rather represent a shift in the probabilities of belonging to a behavioural class; in the model as in real life there will be many examples of individuals who buck trends, exhibiting non-typical behaviour for an individual with their socio-demographic characteristics.

Second, we do not consider the class to be an unchanging fact about the individual. As noted in the literature review, it is true that for most people lifestyles and particularly modality styles have stability over time; however, they are not necessarily fixed from day to day. In reality, an individual could have a fixed modality style or could shift between more than one as needed. Indeed, the authors have experience with switching modality styles from day to day depending on activity/travel needs and household vehicle-use decisions. We therefore understand our latent classes as some blend of underlying lifestyle preferences and daily situational factors. This is more a philosophical understanding than a modelling choice, as here we only deal with single-day activity patterns. A fuller examination of how modality styles relate to multi-day travel patterns within a latent-class Scaper model would most likely require panel data to estimate and could be an avenue for future research.

Our results also demonstrate the key advantage of Scaper as a combined travel behaviour and scheduling model. Unlike other travel behaviour models which usually consider only one or two aspects of daily activity and travel behaviour, here each behavioural choice is a joint choice over what to do (activity participation and type of activity), where and when to do it (activity location and time) and how to get there (mode choice). The latent class models therefore can draw on differences across all of these axes, and display differences across activity participation rates, travel time distributions and work duration as well as mode choices. The latent-class Scaper models find these differences and exploit them for prediction due to the integrated, joint choice design of Scaper.

### 4.1. Lessons from estimation

In our experience, the difficulty of estimating the latent class version of Scaper tended to scale with the number of classes. This paper struck a balance between model simplicity and behavioural realism that allowed us to demonstrate latent class Scaper models within our existing estimation framework; however, future work using larger state spaces, more utility parameters, or a larger number of latent classes may see challenges.

One issue from a modelling perspective arose in the case where the model represents behaviours that are infrequently observed in the sample. In latent class model estimation, we observed that the models would sometimes split the classes up in such a way that infrequently-observed behaviour was only produced by one class. In this case, the parameters governing the behaviour in the other class(es) would tend toward negative infinity, causing problems with our estimation process. We ultimately found a specification of the model which allowed us to arrive at acceptable estimations with our current estimation approach, though we suggest that it may be necessary to find a solution to the issue of infrequent behaviours in latent class Scaper models in the future. We note that we do not believe that an expectation–maximization approach would solve these issues, as the problems appear to be linked to the underlying model specification, not the optimization technique.

We also note that latent class models may result in estimated parameters that run against the received knowledge of travel demand modellers. As an example, it is conceivable that a latent class could be estimated with travel utility rate higher than the rate for participation in a certain activity—Scaper's equivalent of a positive utility of travel time. This class could represent pleasurable leisure travel or an outlier group of individuals who enjoy time spent travelling more than time spent doing other activities. Simulating with such a model would produce reasonable simulation data, though the model may be less generalizable to other contexts.

One solution to both issues may be found in the direction of the machine learning approach to training predictive models. From a machine learning perspective, we should care less about arriving at estimation results with appropriate signs and standard errors, and more about validating the output of our models. We have kept this paper centred in traditional discrete choice optimization to show that a latent class approach can work with a dynamic ABM/scheduling model in the usual framework. However, we emphasize the validation of our model in simulation as a more important factor in establishing trust in the model. Future research may aim to find alternative methods of estimating or training models, perhaps using machine learning techniques like mini-batch stochastic gradient descent. These methods may also help overcome the resource limitations that prevented us from estimating models with more than four latent classes.

### 4.2. Usefulness of latent class DDCM models

Ultimately, model purpose should guide the decision of what modelling approaches to use. Models built for the purpose of deriving values from their parameters for evaluation will require greater attention to the parameter values than models designed purely for forecasting. It is generally viewed as desirable to have models which are amenable to both evaluation and forecasting; however, there are advantages to separating the two goals. Forecasting models would benefit from considering behaviour, such as travel for the sake of travel, which has traditionally been ignored by travel demand modellers because it contradicts our assumptions. Here we will briefly discuss two ways in which our latent class DDCM approach could be used to investigate and reflect different aspects of heterogeneity in travel behaviour. We assume here that the issues with estimation discussed above can be resolved, and that we are building models more for forecasting than for policy evaluation.

First, future models could explore lifestyle groups in more detail beyond modality styles. Our results hint at the complex relationships between mode choices and other aspects of travel behaviour, such as activity participation rates. However, our behavioural groupings are limited to the socio-economic and demographic variables we had available and chose to include in the class assignment function. We expect that including different individual or household characteristics in class assignment would draw out different behavioural groupings. Estimating a higher number of latent classes would also move in this direction. For example, while the difference between our classes in work start time or duration were modest, it is possible that a different model specification would result in classes reflecting full-time, part-time and perhaps multi-job workers. A latent class model would provide empirical evidence to give insight into the socio-demographic correlates of these groups and could help policymakers understand the differential impacts of policies and such as travel demand management and work-from-home programs.

Second, with the right data, latent class models could move beyond reflecting lifestyles to reflecting groups of normative attitudes. Krueger et al. (2018) show that these attitudes, such as how environmentally-conscious one is, play a role in forming travel behaviour via modality styles. Shifts in normative attitudes due to cultural shifts can therefore lead to changes in the relative sizes of lifestyle/modality style groups and therefore travel behaviour shifts, even without demographic changes or adjustments to the transportation system or land use. Augmented with a travel survey which included attitudinal questions, a latent-class model using our modelling approach would be sensitive to the impacts of shifting attitudes over time and could thus be useful for exploring scenarios around changing societal norms.

## 5. Conclusion

This paper demonstrates a dynamic discrete choice model with latent classes. As a case study, we construct and estimate a travel behaviour and scheduling model for Stockholm. The resulting latent class models differentiate behavioural classes based on modality styles, finding car-primary, transit-primary, bike-primary and multimodal individuals. Since agents in the model make the choice of activity, location, mode and timing jointly, these classes also point towards differences in lifestyles and have differences in scheduling characteristics including travel duration and activity participation rates. The individual characteristics used in the class assignment utility function link these behavioural groups with their socio-demographic makeups, with expected relationships between modality styles and the age of an individual and car availability. While our case study model has limitations due to its relatively simple utility function, it serves well to demonstrate the potential of our approach.

More broadly, through the case study we demonstrate the applicability of our modelling methodology. Our latent class DDCM model interdependently and endogenously models the complete daily schedule of an agent including timing, activity participation, location and mode choices. It respects temporal and spatial constraints without needing conflict resolution mechanisms. It can be used to produce econometric welfare outputs such as logsums. As a latent class model, it finds distinct groups within the population which vary by both behaviour and individual characteristics, and allows the modeller to investigate and explain the relationships found. Not least, it has been estimated and implemented here at the level of a medium-size global city.

We discuss above potential limitations of the methodology with regards to estimation, which we hope will be resolved through further research. The latent class approach is suited for cases where the underlying population-level difference is fundamentally discrete; for continuous heterogeneity in behaviour a mixed model would be more appropriate. However, as the literature and our results suggest, much activity and travel behaviour can indeed be observed in discrete groupings such as lifestyles. Our latent class DDCM approach will thus be applicable to a broad range of future travel behaviour and scheduling modelling needs.

## CRediT authorship contribution statement

**Stephen McCarthy:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Daniel Jonsson:** Writing – review & editing, Supervision, Data curation, Conceptualization. **Qian Wang:** Writing – review & editing, Supervision, Data curation. **Anders Karlström:** Writing – review & editing, Supervision, Resources, Funding acquisition, Data curation.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Acknowledgments

This research was funded in part by the Swedish Transport Administration (Trafikverket) under its research and innovation funding program, grant TRV 2023/32962.

## Appendix

See Tables A.1 and A.2.

**Table A.1**
Estimated parameters for latent class models.

| Class | Parameter | Reference | | 2-class | | 3-class | | 4-class | |
|---|---|---|---|---|---|---|---|---|---|
| | | Est. | T-stat | Est. | T-stat | Est. | T-stat | Est. | T-stat |
| Class assignment parameters | | | | | | | | | |
| Car-primary | Constant | | | −2.442 | −27.4 | −0.940 | −8.0 | −1.473 | −7.1 |
| | High income | | | −0.361 | −7.1 | −0.477 | −6.8 | 0.094 | 1.1 |
| | Age <35 | | | −0.320 | −5.5 | −0.070 | −0.9 | −0.338 | −2.9 |
| | Age >60 | | | 0.155 | 2.0 | 0.494 | 4.2 | 0.005 | 0.0 |
| | Female | | | −0.206 | −4.3 | −0.017 | −0.3 | 0.056 | 0.4 |
| | Kids in HH | | | 0.237 | 4.4 | 0.036 | 0.5 | 0.296 | 1.7 |
| | Car available | | | 3.343 | 44.1 | 2.721 | 25.9 | 2.202 | 7.3 |
| Transit-primary | Constant | | | 0 | – | 1.423 | 16.0 | 1.721 | 12.6 |
| | High income | | | 0 | – | −0.117 | −1.8 | 0.443 | 5.3 |
| | Age <35 | | | 0 | – | 0.356 | 5.1 | 0.135 | 1.2 |
| | Age >60 | | | 0 | – | 0.434 | 3.8 | −0.042 | −0.3 |
| | Female | | | 0 | – | 0.288 | 4.6 | 0.356 | 3.2 |
| | Kids in HH | | | 0 | – | −0.255 | −3.7 | −0.036 | −0.2 |
| | Car available | | | 0 | – | −0.840 | −9.5 | −2.051 | −7.6 |
| Bike-primary | Constant | | | | | 0 | – | 0.252 | 1.4 |
| | High income | | | | | 0 | – | 0.638 | 6.0 |
| | Age <35 | | | | | 0 | – | −0.336 | −2.4 |
| | Age >60 | | | | | 0 | – | −0.801 | −3.8 |
| | Female | | | | | 0 | – | 0.051 | 0.4 |
| | Kids in HH | | | | | 0 | – | 0.259 | 1.6 |
| | Car available | | | | | 0 | – | −1.503 | −5.2 |
| Multi-modal | Constant | | | | | | | 0 | – |
| | High income | | | | | | | 0 | – |
| | Age <35 | | | | | | | 0 | – |
| | Age >60 | | | | | | | 0 | – |
| | Female | | | | | | | 0 | – |
| | Kids in HH | | | | | | | 0 | – |
| | Car available | | | | | | | 0 | – |
| Behavioural parameters | | | | | | | | | |
| All | Income-normalized cost | −0.184 | −15.7 | −0.063 | −5.8 | −0.049 | −4.8 | −0.047 | −4.6 |
| Car-primary | Car trip | −3.824 | −101.6 | −2.742 | −70.5 | −2.701 | −67.3 | −2.860 | −56.0 |
| | Transit trip | −3.761 | −100.5 | −5.313 | −53.1 | −5.403 | −51.1 | −6.044 | −22.5 |
| | Bike trip | −4.293 | −74.8 | −4.819 | −22.9 | −4.879 | −15.3 | −7.507 | −6.6 |
| | Walk trip | −2.907 | −62.3 | −4.512 | −47.5 | −4.827 | −40.1 | −3.905 | −19.0 |
| | Car travel time | −0.096 | −51.5 | −0.118 | −47.6 | −0.123 | −45.9 | −0.138 | −18.7 |
| | Transit travel time | −0.067 | −37.9 | −0.076 | −19.8 | −0.074 | −17.7 | −0.101 | −10.1 |
| | Bike travel time | −0.097 | −41.9 | −0.134 | −14.5 | −0.165 | −7.5 | −0.268 | −3.7 |
| | Walk travel time | −0.078 | −47.1 | −0.060 | −29.0 | −0.057 | −27.1 | −0.097 | −17.9 |
| | Transit wait time | −0.087 | −20.5 | −0.070 | −5.4 | −0.076 | −5.0 | −0.047 | −1.2 |
| | Shop log employment | 0.430 | 24.4 | 0.492 | 24.0 | 0.489 | 23.4 | 0.521 | 21.3 |
| | Shop start | −11.063 | −79.2 | −11.162 | −69.7 | −11.034 | −66.8 | −10.772 | −54.2 |
| | Shop continue | −0.060 | −41.4 | −0.060 | −32.3 | −0.060 | −30.9 | −0.066 | −22.7 |
| | Other log population | 0.055 | 7.9 | 0.112 | 11.0 | 0.111 | 10.4 | 0.122 | 8.8 |
| | Other start | −8.138 | −134.1 | −8.218 | −89.7 | −8.105 | −84.4 | −7.687 | −47.3 |
| | Other continue | −0.046 | −35.5 | −0.049 | −27.9 | −0.049 | −27.0 | −0.057 | −18.3 |
| | Home continue 5:00 | 0 | – | 0 | – | 0 | – | 0 | – |
| | Home continue 8:00 | −0.043 | −27.2 | −0.045 | −21.8 | −0.045 | −20.8 | −0.050 | −15.1 |
| | Home continue 11:00 | −0.049 | −38.9 | −0.048 | −27.8 | −0.048 | −26.7 | −0.056 | −18.2 |
| | Home continue 14:00 | −0.052 | −37.3 | −0.055 | −29.2 | −0.054 | −28.0 | −0.061 | −21.1 |
| | Home continue 17:00 | −0.047 | −35.0 | −0.045 | −25.3 | −0.045 | −24.1 | −0.051 | −17.1 |
| | Home continue 20:00 | −0.033 | −24.0 | −0.037 | −19.6 | −0.036 | −18.8 | −0.038 | −12.9 |
| | Home continue 23:00 | −0.050 | −28.6 | −0.042 | −17.1 | −0.042 | −16.0 | −0.047 | −12.3 |
| | Work continue 0h | −0.014 | −4.7 | −0.023 | −6.6 | −0.023 | −6.4 | −0.028 | −5.0 |
| | Work continue 3h | −0.047 | −32.0 | −0.047 | −23.5 | −0.047 | −22.7 | −0.052 | −17.3 |
| | Work continue 6h | −0.028 | −19.8 | −0.033 | −16.9 | −0.033 | −16.3 | −0.041 | −13.5 |
| | Work continue 9h | −0.042 | −30.6 | −0.043 | −22.6 | −0.043 | −22.0 | −0.048 | −14.7 |
| | Work continue 12h | −0.067 | −28.3 | −0.062 | −17.8 | −0.060 | −19.7 | −0.062 | −17.3 |
| | Work start 5:00 | −2.610 | −13.9 | −1.148 | −5.6 | −1.006 | −4.8 | −0.154 | −0.6 |
| | Work start 8:00 | −2.891 | −17.8 | −2.393 | −13.2 | −2.369 | −12.7 | −1.985 | −7.3 |
| | Work start 11:00 | −6.026 | −35.0 | −5.412 | −25.9 | −5.332 | −24.4 | −4.774 | −13.1 |
| | Work start 14:00 | −4.550 | −25.2 | −4.041 | −18.9 | −4.009 | −18.2 | −3.530 | −10.3 |
| | Work start 17:00 | −5.150 | −22.4 | −4.845 | −16.4 | −4.717 | −15.6 | −4.512 | −8.8 |
| | Work start 20:00 | −7.016 | −18.9 | −5.837 | −15.8 | −5.767 | −14.5 | −5.486 | −8.6 |
| Transit-primary | Car trip | | | −9.601 | −31.4 | −7.451 | −15.1 | −6.617 | −21.6 |
| | Transit trip | | | −3.797 | −80.6 | −3.628 | −67.2 | −3.727 | −60.9 |
| | Bike trip | | | −4.351 | −60.1 | −5.768 | −10.8 | −6.344 | −10.2 |
| | Walk trip | | | −2.185 | −43.3 | −2.374 | −39.3 | −2.398 | −38.9 |
| | Car travel time | | | −0.022 | −2.2 | −0.121 | −4.4 | −0.231 | −7.3 |
| | Transit travel time | | | −0.070 | −28.9 | −0.076 | −30.1 | −0.080 | −24.3 |

(continued on next page)

**Table A.1** (*continued*).

| Class | Parameter | Reference | | 2-class | | 3-class | | 4-class | |
|---|---|---|---|---|---|---|---|---|---|
| | | Est. | T-stat | Est. | T-stat | Est. | T-stat | Est. | T-stat |
| | Bike travel time | | | −0.096 | −32.6 | −0.218 | −3.6 | −0.322 | −4.3 |
| | Walk travel time | | | −0.102 | −44.3 | −0.096 | −39.1 | −0.102 | −35.4 |
| | Transit wait time | | | −0.064 | −11.6 | −0.072 | −11.9 | −0.074 | −8.2 |
| | Shop log employment | | | 0.445 | 16.0 | 0.511 | 16.9 | 0.497 | 16.1 |
| | Shop start | | | −10.772 | −46.9 | −11.205 | −44.0 | −10.917 | −42.4 |
| | Shop continue | | | −0.072 | −29.9 | −0.071 | −28.4 | −0.075 | −24.5 |
| | Other log population | | | 0.047 | 4.9 | 0.026 | 2.7 | 0.020 | 2.0 |
| | Other start | | | −7.760 | −96.9 | −7.554 | −89.7 | −7.366 | −84.0 |
| | Other continue | | | −0.052 | −26.7 | −0.053 | −25.6 | −0.056 | −21.4 |
| | Home continue 5:00 | | | 0 | – | 0 | – | 0 | – |
| | Home continue 8:00 | | | −0.049 | −20.6 | −0.050 | −19.8 | −0.054 | −16.8 |
| | Home continue 11:00 | | | −0.056 | −30.3 | −0.057 | −29.4 | −0.061 | −24.5 |
| | Home continue 14:00 | | | −0.057 | −27.3 | −0.059 | −26.1 | −0.062 | −22.0 |
| | Home continue 17:00 | | | −0.054 | −27.7 | −0.056 | −26.4 | −0.058 | −22.1 |
| | Home continue 20:00 | | | −0.037 | −18.0 | −0.038 | −17.4 | −0.040 | −14.7 |
| | Home continue 23:00 | | | −0.058 | −23.8 | −0.061 | −23.7 | −0.065 | −20.8 |
| | Work continue 0h | | | −0.010 | −2.0 | −0.015 | −2.9 | −0.019 | −3.5 |
| | Work continue 3h | | | −0.053 | −24.9 | −0.055 | −24.6 | −0.058 | −21.2 |
| | Work continue 6h | | | −0.033 | −15.2 | −0.034 | −15.0 | −0.037 | −13.2 |
| | Work continue 9h | | | −0.048 | −22.5 | −0.050 | −22.9 | −0.053 | −19.6 |
| | Work continue 12h | | | −0.079 | −13.4 | −0.076 | −15.9 | −0.076 | −17.4 |
| | Work start 5:00 | | | −4.074 | −12.7 | −3.470 | −10.5 | −3.357 | −10.0 |
| | Work start 8:00 | | | −3.057 | −10.4 | −2.532 | −8.5 | −2.402 | −8.3 |
| | Work start 11:00 | | | −6.208 | −20.6 | −5.629 | −18.5 | −5.404 | −17.8 |
| | Work start 14:00 | | | −4.691 | −15.1 | −4.223 | −13.4 | −3.970 | −12.5 |
| | Work start 17:00 | | | −5.549 | −14.4 | −4.911 | −12.8 | −4.920 | −12.3 |
| | Work start 20:00 | | | −8.267 | −12.7 | −8.565 | −13.7 | −8.318 | −13.2 |
| Bike-primary | Car trip | | | | | −7.633 | −21.7 | −7.885 | −9.1 |
| | Transit trip | | | | | −5.949 | −23.0 | −6.759 | −17.4 |
| | Bike trip | | | | | −3.062 | −27.5 | −3.273 | −27.7 |
| | Walk trip | | | | | −0.585 | −2.9 | −0.770 | −3.4 |
| | Car travel time | | | | | −0.014 | −2.4 | −0.179 | −6.4 |
| | Transit travel time | | | | | −0.063 | −6.4 | −0.057 | −3.3 |
| | Bike travel time | | | | | −0.094 | −20.4 | −0.104 | −14.9 |
| | Walk travel time | | | | | −0.187 | −16.3 | −0.191 | −15.5 |
| | Transit wait time | | | | | 0.014 | 0.8 | −0.050 | −1.7 |
| | Shop log employment | | | | | 0.359 | 7.5 | 0.254 | 4.6 |
| | Shop start | | | | | −9.523 | −22.3 | −7.964 | −17.1 |
| | Shop continue | | | | | −0.090 | −10.8 | −0.102 | −7.8 |
| | Other log population | | | | | 0.161 | 6.5 | 0.250 | 5.1 |
| | Other start | | | | | −8.185 | −41.7 | −7.987 | −26.7 |
| | Other continue | | | | | −0.053 | −13.1 | −0.056 | −10.3 |
| | Home continue 5:00 | | | | | 0 | – | 0 | – |
| | Home continue 8:00 | | | | | −0.050 | −10.2 | −0.048 | −7.0 |
| | Home continue 11:00 | | | | | −0.055 | −14.3 | −0.057 | −11.3 |
| | Home continue 14:00 | | | | | −0.056 | −13.1 | −0.054 | −9.4 |
| | Home continue 17:00 | | | | | −0.053 | −12.9 | −0.056 | −10.5 |
| | Home continue 20:00 | | | | | −0.039 | −9.4 | −0.029 | −4.8 |
| | Home continue 23:00 | | | | | −0.042 | −7.7 | −0.047 | −6.4 |
| | Work continue 0h | | | | | −0.002 | −0.2 | 0.006 | 0.3 |
| | Work continue 3h | | | | | −0.050 | −11.7 | −0.051 | −9.3 |
| | Work continue 6h | | | | | −0.036 | −8.4 | −0.029 | −5.0 |
| | Work continue 9h | | | | | −0.040 | −9.5 | −0.049 | −9.2 |
| | Work continue 12h | | | | | −0.143 | −9.4 | −0.061 | −7.0 |
| | Work start 5:00 | | | | | −5.148 | −7.5 | −4.996 | −4.9 |
| | Work start 8:00 | | | | | −3.626 | −5.3 | −3.238 | −3.1 |
| | Work start 11:00 | | | | | −6.885 | −9.6 | −6.509 | −5.4 |
| | Work start 14:00 | | | | | −5.373 | −7.3 | −4.830 | −3.9 |
| | Work start 17:00 | | | | | −6.888 | −7.0 | −7.642 | −4.4 |
| | Work start 20:00 | | | | | −7.257 | −7.2 | −6.989 | −5.3 |
| Multi-modal | Car trip | | | | | | | −2.918 | −10.8 |
| | Transit trip | | | | | | | −3.162 | −9.3 |
| | Bike trip | | | | | | | −1.971 | −6.9 |
| | Walk trip | | | | | | | −4.002 | −8.8 |
| | Car travel time | | | | | | | −0.062 | −9.1 |
| | Transit travel time | | | | | | | −0.056 | −6.0 |
| | Bike travel time | | | | | | | −0.104 | −12.0 |
| | Walk travel time | | | | | | | −0.041 | −8.2 |
| | Transit wait time | | | | | | | −0.067 | −1.7 |
| | Shop log employment | | | | | | | 0.444 | 5.1 |
| | Shop start | | | | | | | −12.982 | −19.6 |
| | Shop continue | | | | | | | −0.053 | −9.4 |
| | Other log population | | | | | | | 0.050 | 1.7 |
| | Other start | | | | | | | −9.857 | −29.7 |

(*continued on next page*)

**Table A.1** (*continued*).

| Class | Parameter | Reference | | 2-class | | 3-class | | 4-class | |
|---|---|---|---|---|---|---|---|---|---|
| | | Est. | T-stat | Est. | T-stat | Est. | T-stat | Est. | T-stat |
| | Other continue | | | | | | | −0.037 | −8.1 |
| | Home continue 5:00 | | | | | | | 0 | – |
| | Home continue 8:00 | | | | | | | −0.038 | −6.1 |
| | Home continue 11:00 | | | | | | | −0.036 | −7.9 |
| | Home continue 14:00 | | | | | | | −0.044 | −7.8 |
| | Home continue 17:00 | | | | | | | −0.036 | −7.8 |
| | Home continue 20:00 | | | | | | | −0.037 | −7.9 |
| | Home continue 23:00 | | | | | | | −0.027 | −4.8 |
| | Work continue 0h | | | | | | | −0.024 | −1.6 |
| | Work continue 3h | | | | | | | −0.035 | −6.1 |
| | Work continue 6h | | | | | | | −0.029 | −5.1 |
| | Work continue 9h | | | | | | | −0.011 | −1.9 |
| | Work continue 12h | | | | | | | −0.518 | −6.1 |
| | Work start 5:00 | | | | | | | −4.609 | −3.3 |
| | Work start 8:00 | | | | | | | −4.927 | −3.6 |
| | Work start 11:00 | | | | | | | −9.131 | −5.2 |
| | Work start 14:00 | | | | | | | −6.771 | −4.6 |
| | Work start 17:00 | | | | | | | −6.024 | −4.5 |
| | Work start 20:00 | | | | | | | −7.512 | −5.4 |

Travel time, wait time and activity continue parameters are measured in utility per minute.
Cost in SEK is divided by monthly income in thousands of SEK.

**Table A.2**
Estimated parameters for interactions model.

| Parameter | Main parameters | | Interactions | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Est. | T-stat | Est. | T-stat | Est. | T-stat | Est. | T-stat |
| | | | *Female* | | *Age > 60* | | *Age < 35* | |
| Income-normalized cost | −0.049 | −1.6 | 0.031 | 1.6 | −0.103 | −2.7 | −0.018 | −0.8 |
| Car trip | −6.326 | −48.2 | 0.089 | 1.8 | 0.229 | 3.1 | −0.251 | −4.3 |
| Transit trip | −3.727 | −51.4 | 0.141 | 3.0 | 0.028 | 0.4 | 0.136 | 2.5 |
| Bike trip | −4.636 | −33.8 | 0.392 | 3.8 | −0.273 | −1.4 | −0.042 | −0.4 |
| Walk trip | −2.842 | −22.4 | 0.206 | 2.8 | −0.145 | −1.2 | 0.092 | 1.1 |
| Car travel time | −0.094 | −14.2 | −0.012 | −5.0 | 0.000 | 0.0 | 0.010 | 3.7 |
| Transit travel time | −0.076 | −23.5 | 0.005 | 2.5 | −0.004 | −1.1 | 0.006 | 2.4 |
| Bike travel time | −0.082 | −17.1 | −0.027 | −6.9 | −0.006 | −0.8 | −0.006 | −1.4 |
| Walk travel time | −0.083 | −22.0 | −0.002 | −0.8 | 0.005 | 1.6 | 0.000 | −0.1 |
| Transit wait time | −0.066 | −6.4 | −0.015 | −2.1 | 0.036 | 2.9 | −0.001 | −0.1 |
| | | | *High income* | | *Kids in HH* | | *Car available* | |
| Income-normalized cost | | | −0.181 | −7.5 | 0.005 | 0.2 | −0.091 | −3.9 |
| Car trip | | | −0.223 | −4.7 | 0.421 | 7.7 | 2.890 | 24.2 |
| Transit trip | | | 0.056 | 1.1 | −0.142 | −2.7 | −0.723 | −13.8 |
| Bike trip | | | 0.027 | 0.3 | 0.403 | 3.8 | −0.154 | −1.5 |
| Walk trip | | | 0.279 | 3.8 | 0.216 | 2.6 | −0.921 | −11.9 |
| Car travel time | | | 0.003 | 1.0 | −0.012 | −4.5 | −0.003 | −0.5 |
| Transit travel time | | | 0.003 | 1.4 | −0.008 | −3.6 | 0.007 | 3.3 |
| Bike travel time | | | 0.002 | 0.4 | −0.009 | −2.4 | −0.006 | −1.6 |
| Walk travel time | | | −0.007 | −3.5 | 0.000 | −0.1 | 0.011 | 5.4 |
| Transit wait time | | | −0.018 | −2.3 | 0.039 | 4.8 | −0.029 | −3.9 |
| Shop log employment | 0.447 | 27.5 | | | | | | |
| Shop start | −10.987 | −84.7 | | | | | | |
| Shop continue | −0.063 | −44.3 | | | | | | |
| Other log population | 0.066 | 10.1 | | | | | | |
| Other start | −8.052 | −140.4 | | | | | | |
| Other continue | −0.049 | −38.1 | | | | | | |
| Home continue 5:00 | 0 | – | | | | | | |
| Home continue 8:00 | −0.046 | −29.5 | | | | | | |
| Home continue 11:00 | −0.051 | −41.3 | | | | | | |
| Home continue 14:00 | −0.055 | −39.8 | | | | | | |
| Home continue 17:00 | −0.049 | −37.5 | | | | | | |
| Home continue 20:00 | −0.036 | −26.4 | | | | | | |
| Home continue 23:00 | −0.051 | −30.3 | | | | | | |
| Work continue 0h | −0.016 | −5.8 | | | | | | |
| Work continue 3h | −0.049 | −34.6 | | | | | | |
| Work continue 6h | −0.031 | −22.2 | | | | | | |
| Work continue 9h | −0.045 | −33.0 | | | | | | |
| Work continue 12h | −0.069 | −29.2 | | | | | | |
| Work start 5:00 | −2.328 | −13.2 | | | | | | |
| Work start 8:00 | −2.662 | −17.6 | | | | | | |
| Work start 11:00 | −5.795 | −35.7 | | | | | | |

(*continued on next page*)

**Table A.2** (*continued*).

| Parameter | Main parameters | | Interactions | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Est. | T-stat | Est. | T-stat | Est. | T-stat | Est. | T-stat |
| Work start 14:00 | −4.356 | −25.8 | | | | | | |
| Work start 17:00 | −5.074 | −22.9 | | | | | | |
| Work start 20:00 | −6.811 | −20.6 | | | | | | |

Travel time, wait time and activity continue parameters are measured in utility per minute.
Cost in SEK is divided by monthly income in thousands of SEK.

## References


Atasoy, B., Glerum, A., Bierlaire, M., 2013. Attitudes towards mode choice in Switzerland. disP– Plan. Rev. 49 (2), 101–117.

Bellman, R., 1957. A Markovian decision process. J. Math. Mech. 679–684.

Bhat, C.R., 1997. An endogenous segmentation mode choice model with an application to intercity travel. Transp. Sci. 31 (1), 34–48.

Blom Västberg, O., Karlström, A., Jonsson, D., Sundberg, M., 2020. A dynamic discrete choice activity-based travel demand model. Transp. Sci. 54 (1), 21–41.

Formann, A.K., 1985. Constrained latent class models: Theory and applications. Br. J. Math. Stat. Psychol. 38 (1), 87–111.

Fosgerau, M., Frejinger, E., Karlstrom, A., 2013. A link based network route choice model with unrestricted choice set. Transp. Res. B 56, 70–80.

Greene, W.H., 2001. Fixed and random effects in nonlinear models. NYU Working Paper No. EC-01-01.

Greene, W.H., Hensher, D.A., 2003. A latent class model for discrete choice analysis: Contrasts with mixed logit. Transp. Res. B 37 (8), 681–698.

Guevara, C.A., Ben-Akiva, M.E., 2013. Sampling of alternatives in logit mixture models. Transp. Res. B 58, 185–198.

Hägerstrand, T., 1970. What about people in Regional Science? Pap. Reg. Sci. Assoc. 24, 6–21.

Heinen, E., Chatterjee, K., 2015. The same mode again? An exploration of mode choice variability in Great Britain using the National Travel Survey. Transp. Res. A: Policy Pract. 78, 266–282.

Hess, S., Ben-Akiva, M., Gopinath, D., Walker, J.L., 2009. Taste heterogeneity, correlation and elasticities in latent class choice models. In: Transportation Research Board 88th Annual Meeting. pp. 1–24.

Hetrakul, P., Cirillo, C., 2014. A latent class choice based model system for railway optimal pricing and seat allocation. Transp. Res. E: Logist. Transp. Rev. 61, 68–83.

Hurtubia, R., Nguyen, M.H., Glerum, A., Bierlaire, M., 2014. Integrating psychometric indicators in latent class choice models. Transp. Res. A: Policy Pract. 64, 135–146.

Jonsson, D., Karlström, A., Oshyani, M.F., Olsson, P., 2014. Reconciling user benefit and time-geography-based individual accessibility measures. Environ. Plan. B: Plann. Des. 41 (6), 1031–1043.

Kamakura, W.A., Russell, G.J., 1989. A probabilistic choice model for market segmentation and elasticity structure. J. Mar. Res. 26 (4), 379–390.

Karlström, A., 2005. A dynamic programming approach for the activity generation and scheduling problem. In: Timmermans, H. (Ed.), Progress in Activity-Based Analysis. Elsevier, Oxford, pp. 25–42.

Keane, M., Wasi, N., 2013. Comparing alternative models of heterogeneity in consumer choice behavior. J. Appl. Econometrics 28 (6), 1018–1045.

Keane, M.P., Wolpin, K.I., 1997. The career decisions of young men. J. Polit. Econ. 105 (3), 473–522.

Kennan, J., Walker, J.R., 2011. The effect of expected income on individual migration decisions. Econometrica 79 (1), 211–251.

Keskisaari, V., Ottelin, J., Heinonen, J., 2017. Greenhouse gas impacts of different modality style classes using latent class travel behavior model. J. Transp. Geogr. 65, 155–164.

Kitamura, R., 2009. Life-style and travel demand: From Special Report 220: A Look Ahead: Year 2020, Transportation Research Board, National Research Council, Washington, DC, 1988, 149–189. Reproduced with permission of TRB. Transportation 36, 679–710.

Krueger, R., Vij, A., Rashidi, T.H., 2018. Normative beliefs and modality styles: a latent class and latent variable model of travel behaviour. Transportation 45, 789–825.

Kuhnimhof, T., Chlond, B., Von Der Ruhren, S., 2006. Users of transport modes and multimodal travel behavior: Steps toward understanding travelers' options and choices. Transp. Res. Rec. 1985 (1), 40–48.

Lee, Y., Circella, G., Mokhtarian, P.L., Guhathakurta, S., 2019. Heterogeneous residential preferences among millennials and members of generation X in California: A latent-class approach. Transp. Res. D: Transp. Environ. 76, 289–304.

Lee, B.J., Fujiwara, A., Zhang, J., Sugie, Y., 2003. Analysis of mode choice behaviours based on latent class models. In: 10th International Conference on Travel Behaviour Research. Lucerne.

Massiani, J., Danielis, R., Marcucci, E., 2007. The heterogeneity in shipper's value of time: Results from an SP experiment using mixed logit and latent class. Pomorstvo/J. Marit. Stud. 21 (2).

McFadden, D., 1974. Conditional logit analysis of qualitative choice behaviour. In: Zarembka, P. (Ed.), Frontiers in Econometrics. Academic Press, New York, pp. 105–142.

McFadden, D., 1978. Modelling the choice of residential location. In: Karlqvist, A., Lundqvist, L., Snickers, F., Weibull, J.W. (Eds.), Spatial Interaction Theory and Planning Models. North Holland, pp. 75–96.

Nerella, S., Bhat, C.R., 2004. Numerical analysis of effect of sampling of alternatives in discrete choice models. Transp. Res. Rec. 1894 (1), 11–19.

Olafsson, A.S., Nielsen, T.S., Carstensen, T.A., 2016. Cycling in multimodal transport behaviours: Exploring modality styles in the Danish population. J. Transp. Geogr. 52, 123–130.

Owen, A.L., Videras, J., 2009. Reconsidering social capital: A latent class approach. Empir. Econ. 37, 555–582.

Prato, C.G., Halldórsdóttir, K., Nielsen, O.A., 2017. Latent lifestyle and mode choice decisions when travelling short distances. Transportation 44, 1343–1363.

Román, C., Arencibia, A.I., Feo-Valero, M., 2017. A latent class model with attribute cut-offs to analyze modal choice for freight transport. Transp. Res. A: Policy Pract. 102, 212–227.

Rust, J., 1987. Optimal replacement of GMC bus engines: An empirical model of Harold Zurcher. Econometrica 55 (5), 999–1033.

Rust, J., Phelan, C., 1997. How social security and medicare affect retirement behavior in a world of incomplete markets. Econometrica 781–831.

Saleem, M., Blom Västberg, O., Karlström, A., 2018. An activity based demand model for large scale simulations. Procedia Comput. Sci. 130, 920–925.

Salomon, I., Ben-Akiva, M., 1983. The use of the life-style concept in travel demand models. Environ. Plan. A 15 (5), 623–638.

Shen, J., 2014. Latent class model or mixed logit model? A comparison by transport mode choice data. In: The Applied Economics of Transport. Routledge, pp. 127–136.

Stockholm County, 2016. Resvanor i Stockholms län 2015 ['Travel habits in Stockholm County'; in Swedish]. Stockholm.

Thøgersen, J., 2006. Understanding repetitive travel mode choices in a stable context: A panel study approach. Transp. Res. A: Policy Pract. 40 (8), 621–638.

Trafikverket, 2020. Sampers 3.4.4 Användarhandledning ['Sampers 3.4.4 User manual'; in Swedish]. Stockholm.

Train, K.E., 2009. Discrete Choice Methods with Simulation. Cambridge University Press.

Vij, A., Carrel, A., Walker, J.L., 2013. Incorporating the influence of latent modal preferences on travel mode choice behavior. Transp. Res. A: Policy Pract. 54, 164–178.

von Haefen, R.H., Domanski, A., 2013. Estimating mixed logit models with large choice sets. In: Third International Choice Modelling Conference. Sydney.

Wen, C.-H., Lai, S.-C., 2010. Latent class models of international air carrier choice. Transp. Res. E: Logist. Transp. Rev. 46 (2), 211–221.

Wen, C.-H., Wang, W.-C., Fu, C., 2012. Latent class nested logit model for analyzing high-speed rail access mode choice. Transp. Res. E: Logist. Transp. Rev. 48 (2), 545–554.

Zhou, H., Norman, R., Xia, J.C., Hughes, B., Kelobonye, K., Nikolova, G., Falkmer, T., 2020. Analysing travel mode and airline choice using latent class modelling: A case study in Western Australia. Transp. Res. A: Policy Pract. 137, 187–205.

Zimmermann, M., Blom Västberg, O., Frejinger, E., Karlström, A., 2018. Capturing correlation with a mixed recursive logit model for activity-travel scheduling. Transp. Res. C 93, 273–291.