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Shifting to more sustainable mobility styles: A latent transition approach

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A R T I C L E I N F O

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A B S T R A C T

Cities around the world make efforts to reduce car use and its negative consequences but even in cycling cities, mobility behaviour is still dominated by car use. This paper examines the effect of life events, changed resources and attitude-behaviour incongruency on changes in people's mobility style. The paper is based on a longitudinal survey including people who participated 2–3 times within a 2.5-year period. Applying latent transition analysis based on participants' mobility attitudes and behaviour, we identified 5 distinct mobility classes: one functional and one enthusiastic car user class; one car-prone and one car-aversive cycling class and a public transport class. Free-floating car sharing subscription had an effect on initial class membership but not on transition probability. However, shifts were significantly related to age and gender, changes in income and place of residence. Yet, most effects disappeared when car ownership was included in the latent transition model. Once people end up in car-centred mobility styles, a voluntary transition back seems difficult to achieve.

1. Introduction

Private car ownership and use does not only contribute to climate change but also leads to local air and noise pollution and congestion. The external costs of car transport are particularly high in cities (Creutzig et al., 2020a), where cars additionally take a disproportional share of public space (Creutzig et al., 2020b). In Europe, car ownership has increased in recent years, particularly in countries that come from a lower car ownership level (EEA, 2021a). In Denmark, the percentage of households with more than one car has grown from 6.7% in 1996 to 16.8% in 2018 (Abegaz et al., 2020). In addition, we observe a European trend towards larger cars leading to higher CO_2 emissions in the overall car fleet (EEA, 2020).

Despite people becoming more and more aware of the urgency and need of climate action (Gössling et al., 2020), the personal value of car ownership remains high and even increased during the Covid-19 pandemic (Moody et al., 2021). The often claimed reduced emotional attachment to the private car by the young generation mainly applies to the urban, cosmopolitan milieu, while car-oriented life styles seem to persist in other sub-groups (Hunecke et al., 2020).

Changes in the life course, such as residential relocation or childbirth, are events where greater changes are more likely to occur as these events require adaption and make people more open to reconsider existing travel habits and the relevance of car ownership (e.g., Müggenburg et al., 2015; Verplanken and Wood, 2006). Available resources, such as income and private parking space are assumed to play a major role in such considerations as well as alternative transport options at the place of residence (e.g., Cao et al., 2007), such as public transport and car sharing. Finally, and in line with the theory of cognitive dissonance (Festinger, 1957), people who show travel behaviour that is in accordance with their mobility attitudes, are assumed to be less likely to change behaviour than people with greater attitude behaviour-incongruence (Kroesen et al., 2017).

In this paper, we examine the effect of life events on changes in people's mobility style (reflected in people's mobility behaviour and attitudes) based on a large longitudinal dataset (Haustein, 2021a) by applying latent transition analysis. In contrast to previous work applying this method to predict changes in travel behaviour that are based on travel behaviour alone (Kroesen, 2014; Kroesen and van Cranenburgh, 2016) or additions by single attitudes (Kroesen et al., 2017; Kalter et al., 2020), our mobility styles are based on behavioural indicators and multiple attitudinal dimensions derived from an extended Theory of Planned Behaviour (Ajzen, 1991), leading to 'rich' mobility styles. We added various explanatory variables (capturing life events) to our model allowing us to assess their role in explaining initial class membership as well as transitions in class membership over time. One of these variables is free-floating car sharing subscription, which makes our study the first study examining the effect of free-floating car sharing on changes in

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mobility style over time.

In the remainder of this paper, we will first present the research background of our paper (Section 2), followed by a description of the applied methods (Section 3), which includes an overview of the sample and data as well as the model conceptualisation and estimation strategy. Section 4 presents the results, which we discuss in Section 5, together with study limitations and conclusions on what we can learn from the results to facilitate a shift to more sustainable mobility styles in urban areas.

2. Research background

This section presents the research background of this study. Section 2.1 explains the role of psychological factors and life events for modal choice and shifts as identified in the literature. Section 2.2 describes different segmentation approaches of road users applied in transportation research and their relevance in the context of behaviour change (Section 2.2). Section 2.3 outlines the study's research focus, while Section 2.4 describes the area the study took place.

2.1. Travel mode choice and modal shifts

Despite various negative effects of cars, in particular in cities, car use and ownership is difficult to change as it has positive functional and symbolic-affective associations on an individual level, such as convenience, time-savings, freedom, and status (e.g., Beirão and Cabral, 2007; Steg, 2005). Indeed, travel mode choice has been identified as one of the most stable travel decisions individuals make (Hess et al., 2007).

The theory of planned behaviour (TPB, Ajzen, 1991) is one of the most frequently applied psychological theories to explain mode choice (Javaid et al., 2020). According to TPB, intention is the main predictor of behaviour. Intention is influenced by attitude (i.e. the evaluation of the positive or negative consequences of the behaviour) and subjective norm (i.e. the perception of social approval or support of the behaviour). In contrast to its predecessor, the Theory of Reasoned Action (Fishbein, 1979), TPB includes another predictor of both intention and behaviour: perceived behavioural control (PBC). It describes the perceived ability to control the performance of the target behaviour. PBC is considered as a direct predictor of both intention and behaviour. In a meta-analysis (Hoffmann et al., 2017), TPB-constructs intention, PBC and attitudes have been identified as the most important psychological factors related to mode choice. As PBC (in a transport context), mostly relates to the perception of the transport infrastructure, Haustein et al. (2007) extended the TPB by the construct of perceived mobility necessities (PMN) to better capture perceived mobility demands from family and work life. Both PMN and actual activity related constraints have been found to encourage car use and discourage the use of public transport. Yet, PMN's effect on cycling seems to depend on socio-cultural and spatial conditions for cycling (Thøgersen, 2006). PMN have also been identified as a relevant determinant of car sharing adoption (Jain et al., 2021) and related to an increase in car ownership over time (Jain et al., 2020; Haustein, 2021a).

While the standard attitude measure in TPB is often limited to the positive versus negative evaluation of the behaviour or to functional and instrumental user motives, such as convenience, saved travel time and money, several transport studies complemented or exchanged the standard attitude measure by symbolic and affective motives (e.g., Hunecke et al., 2007), such as driving fun and passion, status and prestige related to car ownership, or freedom and autonomy perceived while driving or cycling (e.g., Steg, 2005; Zhao and Zhao, 2020). Another addition to TPB in the context of mode choice is ‘cycling weather resistance’ that measures people's willingness to also cycle in bad weather conditions (Hunecke et al., 2007; Haustein, 2012). It has been identified as a significant factor of car use and cycling and is stronger related to mode choice than actual weather conditions (Haustein et al., 2007).

TPB assumes that feedback from one's own behaviour is likely to affect one's own beliefs and thereby also future intentions and actions (Fishbein and Ajzen, 2009). Similar, in the relation between car use and car attitudes multidirectional causality has been found (Moody and Zhao, 2020), meaning that car use is not only influenced by related attitudes but that car use also influences car attitudes; the same multidirectional relation also applies for other travel modes (Dobson et al., 1978; Kroesen et al., 2017; Thøgersen, 2006).

One limitation of TPB, and other theories that explain individual behaviour as determined by various factors, is that they can predict how behaviour may change as consequence of the change in one or more predictors, but it is out of the theory's focus, how such changes are initiated. The mobility biographies approach (MBA; Lanzendorf, 2003; Scheiner, 2007) considers key events in the life course as main drivers of behavioural change in transport. Müggenburg et al. (2015) distinguish between life events (e.g., childbirth), adaptations in long-term mobility decisions (e.g., residential relocation, car purchase/disposal) and exogenous interventions (e.g., provision of new infrastructure, mobility services). Long-term and everyday mobility decisions are assumed to mutually influence each other.

Life events have been found related to modal shifts and/or car ownership changes, most importantly residential relocation, changes in employment and in household composition or family status (e.g., Bonham and Wilson, 2012; Clark et al., 2016; Dargay and Hanly, 2007; Guo et al., 2020; Lanzendorf, 2010; Prillwitz et al., 2006; Yamamoto, 2008). Life events may change the need for a car or lead to a situation, where a (nother) car is not affordable (e.g., Oakil et al., 2018). A change of car ownership may, however, not only be the consequence of a life event but can also be the life event that leads to changes in mode choice. Indeed, there is huge evidence for the effect of car access on travel behaviour and mode choice in particular (e.g., Buehler, 2011). Car access can not only be provided by private car ownership but also by access to car sharing. Car sharing membership is often found to decrease car ownership, yet depending on the service (free floating vs. station-based), and the applied methods (e.g. retrospective data vs. longitudinal data) the identified effects differ greatly (e.g., Becker et al., 2017; Becker et al., 2018; Haustein, 2021). The effect of car sharing on car use differs depending on whether people owned a car beforehand or not.

Residential relocation can both lead to changes in mobility attitudes and behaviour (e.g., De Vos et al., 2018) but at the same time (as considered in literature on residential self-selection), people's mobility preferences play a role in their choice of a new location, which needs to be considered to avoid an overestimation of the physical environment's effect on mode choice (e.g., Cao et al., 2009).

As life events lead to changes in daily routines, they may also encourage mental processes, in which actual travel behaviour and car ownership is reconsidered (Janke and Handy, 2019).

2.2. Road user segmentation

The segmentation of road users into homogenous groups often serves the aim to develop target groups for tailored behaviour change interventions. These are assumed to be more effective than interventions addressed towards the whole population (Haustein and Hunecke, 2013; Haustein, 2021b). Segmentation studies may also be used to explore the relationship between structural (demographic/spatial) and attitudinal variables and their contribution to explaining specific (e.g. multimodal) travel patterns (e.g., Molin et al., 2016; Van Eenoo et al., 2022).

Different groups of variables have been used as a basis for segmentation, in particular behaviour, demographics and attitudes. In terms of behaviour, travellers have for example been segmented based on their trip purpose and mode choice (Prillwitz and Barr, 2011). Frequently, a simple distinction between captive and choice users has been made (Jacques et al., 2013). Based on socio-demographic variables, travellers have been grouped into life styles or life stages (e.g., Ryley, 2006; Salomon and Ben-Akiva, 1983). However, during the past 20 year, it has become more and more common to include more differentiated user motives and constraints into the segmentation of road users. Based on qualitative data, Jensen (1999) distinguished between three types of car drivers (e.g., passionate car drivers), cyclists (e.g., cyclists of heart) and public transport (e.g., public transport users of convenience). Quantitative segmentation approaches have mostly been informed by psychological theories, such as the TPB, and created based on factor and cluster analysis (e.g. Anable, 2005; Hunecke et al., 2010). With regard to such psychographic segmentation approaches, we can distinguish between approaches that only include socio-psychological variables, such as attitudes and norms (also referred to as 'mobility types', Haustein and Hunecke, 2013), and approaches that additionally include socio-economic variables and/or travel behaviour (also referred to as 'mobility styles'). Based on car and bicycle use, vehicle kilometres travelled (VKT) and the perceived need to use a car, Van Eenoo et al. (2022) identified four car-owning mobility styles in a car-independent neighbourhood: two groups of car-dependent motorists mainly differing in VKT and two groups of cyclists differencing in their perceived car-dependence. All groups showed some degree of multimodality, which is explained by the urban neighbourhood characteristics. Yet, the study shows that even multimodal travellers in urban areas may perceived themselves as car-dependent. A similar study was performed by Molin et al. (2016). These authors performed a latent class analysis on travel behaviour indicators, but additionally included attitudinal variables in the class membership function. The revealed behavioural patterns had mostly congruent (mode-related) attitudes, with the exception of one class that relied strongly on public transport but had a relatively negative attitude towards this mode.

While a main focus of earlier segmentation studies has been on developing a basis for tailored interventions and policies, more recent studies based on longitudinal data additionally used the identified segments to examine the effect of specific factors on the probability to switch from one segment to another or to test theoretical assumptions. Several studies in this area have relied solely on behavioural indicators to identify latent segments, thereby revealing various mono- and multimodal travel patterns (Kroesen, 2014; Kroesen and van Cranenburgh, 2016; De Haas et al., 2018). A consistent finding across these studies has been that travel patterns that exclusively use a single mode (e.g., strict car or strict bicycle users) were more likely to stay in their respective pattern over time, whereas multimodal travellers (travellers who use a combination of modes) were found to be less inert. As argued by Kroesen (2020), this finding can be explained by the notion of habit, i.e. a person who (irrespective of the particular context) always chooses a single particular mode is likely to be a (more) habitual traveller. Multimodal travellers, on the other hand, choose the mode that best fit the given circumstances and can thus be identified as 'deliberate-choice' travellers. As such, they will likely change their travel patterns when new circumstances arise.

Other researchers have exclusively used attitudinal indicators to identify the latent segments. This was for example done in a recent study by Kalter et al. (2020). Based on a factor analysis five psychological dimensions were established (car-minded, cost-sensitive, status-sensitive, environmental awareness, and social consciousness), which were then used as indicators of a latent transition model. While the resulting attitudinal segments were found to be quite stable, life events were (generally) found to increase the probabilities of switching from one pattern to another over time. In addition, in line with other studies following a mobility biographies approach, particular events such as childbirth were found to increase the probability of transitioning to the 'car-minded' class.

Finally, in some studies both behavioural and attitudinal indicators were used to identify the segments (Kroesen et al., 2017; McCarthy et al., 2021). These studies were able to test the main premise of cognitive dissonance theory, namely that those with consonant attitude-behaviour patterns are more stable over time, compared to travellers with dissonance attitude-behaviour patterns. Both Kroesen et al. (2017) and McCarthy et al. (2021) were able to provide evidence in favour of this expectation. However, both studies used quite straightforward measures of (travel) attitudes and behaviours, estimating also separate models for different modes. As such, the revealed patterns arguably do not do justice to the complexity of behaviours and various psychological dimensions that play a role.

2.3. Research focus

Following up on the studies described above, our study also uses both attitudinal and behaviour measures to identify latent segments. Yet, in contrast to Kroesen et al. (2017) and McCarthy et al. (2021), we use various psychological dimensions (drawn from the TPB) and multiple behavioural indicators (considered simultaneously in a single model) to identify the latent segments, allowing us to identify 'rich' mobility styles. In addition, we added various explanatory variables (capturing life events) to the model, allowing us to assess their role in explaining initial segment membership as well as transitions in segment membership over time. To capture all these effects we estimate a latent transition model, which is a longitudinal extension of the latent class model (Magidson and Vermunt, 2004). This model is ideally suited to simultaneously reveal latent classes among a set of indicators as well as model transitions in the resulting classes over time (see Section 3.4 for more details on the modelling framework).

The latent (class) transition model does not assume causal dominance of attitudes over behaviour (or vice versa); it simply assumes that there are different groups of travellers with certain travel patterns and related psychological mindsets.

2.4. Study area

Denmark is a country with a below average motorisation rate when compared to other European countries (approx. 450 cars/1000 inhabitants as compared to Luxembourg/Italy with 681/663 cars at the high end and Romania with 357 cars at the low end of the scale). Yet, car ownership in Denmark is increasing (Abegaz et al., 2020). The study took place in the Capital Region of Denmark (Region Hovedstanden), the region around Denmark's capital Copenhagen, an area that covers 2.561 km^2, which is circa 6% of the whole country (Region Hovedstaden, 2021).

Copenhagen with its dedicated cycling infrastructure and high share of cyclists (Goletz et al., 2020; Haustein et al., 2020) describes itself as "City of cyclists" (City of Copenhagen, 2011). Frederiksberg is a municipality within the borders of Copenhagen and a similar infrastructure and share of cyclists. Many of the surrounding municipalities are connected to Copenhagen by so-called cycle superhighways (Office for cycle superhighways, 2019). Copenhagen has four Metro lines that are served by driverless trains. In Copenhagen and its surrounding several car sharing providers are located, for example the free-floating car sharing providers Green Mobility and SHARE NOW.

3. Method

3.1. Data basis

This study is based on a longitudinal survey of two sub-samples: users of a free-floating car sharing provider in the Capital Region of Denmark ('SHARE NOW', at time of data collection 'DriveNow') and licensed drivers aged 18–65 years living in the operation area of the service, recruited from an online panel of the market research company EPINION.

The user sample consists of people who were already members of the car sharing provider (existing users) and people who just signed up for the service (new users). New users were recruited continuously within the study period (March 2017 – September, 2019). In addition, a sample of 500 non-users were recruited via EPINION's online panel every 6 months. All participants (users and non-users) were contacted again 1 and 2 years after the first survey invitation.

This paper only includes people who participated in at least two survey waves (no matter in which). Table 1 provides an overview on the sample characteristics at the three points in time. Men are over-represented in the overall sample, which can be explained by the high percentage of free-floating car sharing members among which men are generally overrepresented (e.g., Becker et al., 2017; Haustein, 2021a). In wave 2, relatively many men drop out, but in wave 3 attrition among women is again higher, suggesting that there is no selective attrition with respect to gender. Regarding age, there seems to be a tendency for older people to drop out, compared to younger people, although the relatively frequencies of the various age groups remain largely the same. For the number of cars in the household and place of residence, the differences reflect actual changes (e.g., due to residential relocation) but also different dropout rates (e.g., among people who were or were not members of car sharing or lived in or outside Copenhagen in the beginning of the survey). Yet, car ownership rates are relative constant during the three waves. Considering the comparably high dropout rate in wave 3, it needs to be taken into account that not every participant had the chance to be included two or three times as survey recruitment was a continuous process over a 2.5-years-period.

3.2. Measures

An online survey was designed that included mostly the same variables in each of the three survey waves, with some differences between car sharing users and non-users (for details see Haustein and Jensen, 2020; Haustein, 2021a). We used the following variables in the analyses of this paper:

3.2.1. Travel behaviour

In each wave, respondents were asked about their mode choice in the previous week, more specifically on how many weekdays they used the following transport modes: car alone, car in company, metro/train, bus, bicycle, foot. For each mode, numbers between 0 and 7 had to be entered. We created a dummy variable on multimodal travel, where "1" indicates that people used travel modes of at least two out of three different transport mode groups (car, public transport, bicycle; e.g. car in company and bus; car alone and bicycle) within the previous week, while a "0" indicates the use of only travel modes within one group (no matter if combined with walking; e.g. bus and metro/train). People who reported car use, were asked for the kilometres travelled by car in the previous week in an open question.

Table 1
Sample description.

		Wave 1 (*n* = 1393)	Wave 2 (*n* = 1085)	Wave 3 (*n* = 506)
Time-constant variables				
Gender	male	62.4%	56.9%	68.9%
	female	37.6%	43.1%	31.1%
Age groups	18–30	12.4%	11.1%	10.2%
	31–50	45.0%	42.1%	51.7%
	51–60	26.2%	27.3%	22.8%
	61+	16.4%	19.5%	15.4%
Car sharing membership	yes	49.7%	35.5%	31.3%
Time-varying variables				
Nr of cars in household	0	35.5%	31.3%	35.5%
	1	46.4%	47.0%	47.4%
	2 or more	18.1%	21.7%	17.1%
Residential location	Copenhagen or Frederiksberg	52.1%	45.2%	59.5%

3.2.2. Travel-related attitudes

Ten psychological items related to symbolic-affective motives of car use (autonomy, excitement adapted from Hunecke et al., 2010), perceived mobility necessities (Haustein et al., 2007) and cycling weather resistance (Haustein, 2012) were used to assess travel-related attitudes and perceived mobility constraints (see Table 2 for a list of items). C*ar autonomy* captures the perceived autonomy and flexibility of car use and ownership, which was complemented by items on *car dependency*. *Car excitement* covers the affective component of driving a car, such as driving fun. *Perceived mobility necessities* are "people's perceptions of mobility-related consequences of their personal living circumstances" (Haustein et al., 2007, p. 1859). *Cycling weather resistance* assesses the willingness to cycle independently of weather conditions. All items were measured on a 5-point agreement scale (1 = totally disagree; 5 = totally agree).

3.2.3. Socio-demographic variables

Apart from age and gender, we included a question on people's highest education level, which we transferred into a dummy variable (having completed a higher education or not). Also, participants' postal code was turned into a dummy variable (living in Copenhagen/Frederiksberg or not). People were further asked about the number of persons living in their household, their parking conditions at home (turned into a dummy variable about having or not having access to a private parking space) and their income level in 11 categories. Due to the longer length of car sharing users' survey, they were only asked again for demographics in survey wave 2 or 3 when they indicated that they had changed their occupation, household composition or place of living in the past 12 month. If this was not the case, the values of the previous survey were included. However, in case people participated only in the first and third survey wave, missing values were included as it was not clear if changes happened in the meantime (unless people reported changes and were then asked about their updated demographic details).

3.3. Identification of psychological factors

The ten psychological items were included in a principal component analysis with Varimax rotation (see Table 2). The loadings of the resulting 5-factor solution are included in Table 2. In total, 84% of the total variance is explained. Following the allocation of items to factors, five variables were created based on the means of the two items loading on the same factor: *Car independency, Perceived mobility necessities, Cycling weather resistance, Car autonomy*, and *Car excitement*. Cronbach's alphas of the five new variables range from 0.72 to 0.87 (see Table 2) and are thus considered as acceptable.

3.4. Model conceptualisation

Essentially, the latent transition model is a longitudinal extension of the latent class model, which is a model-based clustering technique that probabilistically assigns individuals to classes/clusters (Vermunt and Magidson, 2004). Hence, based on a set of indicators the latent class model subdivides the sample in a number of homogenous clusters with similar configurations on the indicators (the measurement model). Membership of each latent class is probabilistic and modelled separately via a so-called class membership model (the structural model). In this function, additional covariates can be included to explain (initial) class membership.

Next, following the first-order Markov assumption, it is assumed that class membership at one point in time predicts latent class membership at a later point in time (reflecting the survey occasions). The measurement model at later points in time is assumed to be equal as the first (i.e. measurement invariance), so that it is assumed that people switch between the same set of classes over time. Here again, additional explanatory variables can be included to explain the transitions in class membership.

Table 2
Results of a principal component analysis on travel-related attitudes.

	Car independency	Perceived mobility necessities	Cycling weather resistance	Car autonomy	Car excitement
I can easily handle my everyday life without a car.	**0.869**	−0.203	0.194	−0.190	−0.054
It's easy for me to conduct my daily trips without a private car.	**0.888**	−0.197	0.199	−0.127	−0.043
The organization of my everyday life requires a high level of mobility.	−0.181	**0.873**	−0.038	0.130	0.065
I have to be mobile all the time to meet my obligations.	−0.162	**0.888**	−0.027	0.043	0.096
Driving a car means fun and passion to me.	−0.163	0.067	−0.114	0.423	**0.745**
I enjoy applying my driving competence.	0.032	0.100	−0.009	0.048	**0.923**
Driving a car means freedom to me.	−0.125	0.094	−0.133	**0.765**	0.412
To me the car is a flexible and independent means of transport.	−0.176	0.100	−0.094	**0.899**	0.047
I ride my bike in all weather conditions.	0.328	−0.042	**0.834**	−0.113	−0.043
The weather or the season does not influence whether I cycle or not.	0.080	−0.027	**0.923**	−0.094	−0.059
Cronbach's alpha	0.87	0.78	0.79	0.75	0.72

In our application, the six travel behaviour variables and the five psychological factors (operationalized in the previous section) are used as indicators of the latent classes (i.e. reflecting the so-called measurement model). The resulting behavioural and/or attitudinal configurations (the latent classes) can thus be interpreted as 'mobility styles', reflecting typical patterns of travelling accompanied by a certain mindset (if attitudes are included) (Haustein and Hunecke, 2013). On beforehand, since the latent class model is a data-driven method, it is not known which mobility styles will be revealed. Yet, once revealed they can be interpreted and endowed with certain meanings that surpass the original indicators. As argued by Kroesen (2020), the resulting meanings of the mobility styles can be used to formulate expectations regarding the transition probabilities, i.e. based on the meaning of each mobility style, the respective members of the mobility style can be expected to be more inert (i.e. tending to stay in the same class), whereas others can be assumed to be more volatile (tending to switch to another class).

The foregoing conceptualization is summarized in Fig. 1, which provides a graphical representation of the 3-wave latent transition model that was specified and estimated in this study. Since the behavioural variables are count variables, the effects of the latent classes on these indicators were captured using Poisson regression functions. The psychological factors (consisting of summated average scores of multiple items) were considered to be continuous and assumed to follow a different normal distribution for each class (with a particular mean and variance). The latent classes variable is a nominal variable and thus the effects of the (time-constant and time-varying) covariates on the latent classes (and the transitions over time) are estimated using multinomial logit models. Hence, the parameters related to this part of the model are logit-coefficients.

3.5. Modelling strategy

To identify the optimal number of latent classes, we first estimated latent transition models without covariates (measurement model only) for varying numbers of latent classes (1−10). Table 3 presents the model fit of these models. Because the BIC criterion (typically used to identify the optimal number of latent classes (Nylund et al., 2007) kept decreasing with the addition of each latent class, it was not useful to identify in the optimal number of latent classes. As such, we relied on informal alternative criterion, namely the relative increase in the Log-Likelihood (LL) value compared to the baseline 1-class model (Magidson and Vermunt, 2004). This criterion showed that, after 5-classes, the percentage increase in the LL value was relatively small. Since the 5-class model could also be clearly interpreted from a substantive point of view, we decided to opt for this solution.

Next, we tested whether the transition probabilities between the two wave-pairs (1–2 and 2–3) could assumed to be equivalent. For this purpose, we re-estimated the 5-class transition model allowing the transition probabilities across the two wave-pairs to be freely estimated. The results show that the increase in model fit of this model (which is by definition the case) is offset by the increase in number of parameters, yielding a higher BIC value than the 5-class model that assumes stable transition probabilities. Hence, the transition probabilities could assumed to be equivalent across wave-pairs.

Finally, following the approach described by Kankaraš et al. (2018) we tested for measurement invariance, again by re-estimating the 5-class model but now allowing the relationships between the latent class variable and the indicators to be different at each point in time (this is achieved by specifying interactions between the latent class variable and a variable indicating the specific wave in the regression equations of the indicators). Essentially, this model allows the latent classes to shift in structure/meaning over time (measurement heterogeneity). Again, this less constraint model yields a better fit in terms of log-likelihood, but here as well, this increase is offset by the increase in number of parameters, as indicated by a BIC value which is (much) higher compared to the 5-class model that assumes measurement invariance. Hence, we opted for the 5-class transition model that assumes stable transition probabilities and measurement invariance.

In the next step, we included covariates to explain initial class membership and the transitions in class membership over time. First, only time-constant variables are included (Model A), which presently consist of the three socio-demographic variables (gender, age and education level) and the car sharing status (see Section 3.1). It is assumed that these variables may affect both initial class membership and the transitions between the classes over time.

In the following step (Model B), four time-varying variables are added to the model, namely income, whether the subject resides in- or outside Copenhagen, whether the subject has an own parking space or not, and the number of persons in the household. These variables (indirectly) capture various life events, such as moving house, changing jobs, and having a child. The time-varying variables are only assumed to explain transitions in class membership over time (and not initial class membership). To keep the model parsimonious, insignificant effects from the first model (A) are removed from this model.

In Model C, car ownership is included as an additional time-varying covariate. This variable was introduced separately, because we assumed it also to be partly endogenous to the mobility styles (i.e. the latent classes). In addition, the effects of covariates, such as income, may actually run via (changes in) car ownership, which would (unduly) render a variable like income insignificant when car ownership is also introduced to the model. Presently, it is not possible to estimate complex structures of covariates (with direct and indirect effects) within the latent transition modelling framework.

Finally, the latent classes were additionally profiled by considering the distance travelled by car in the last week (in kilometres) as well as an indicator capturing whether the travel pattern of the respondent could be defined as multimodal. These two variables were included as inactive covariates in the model, which means they are not actually part of the

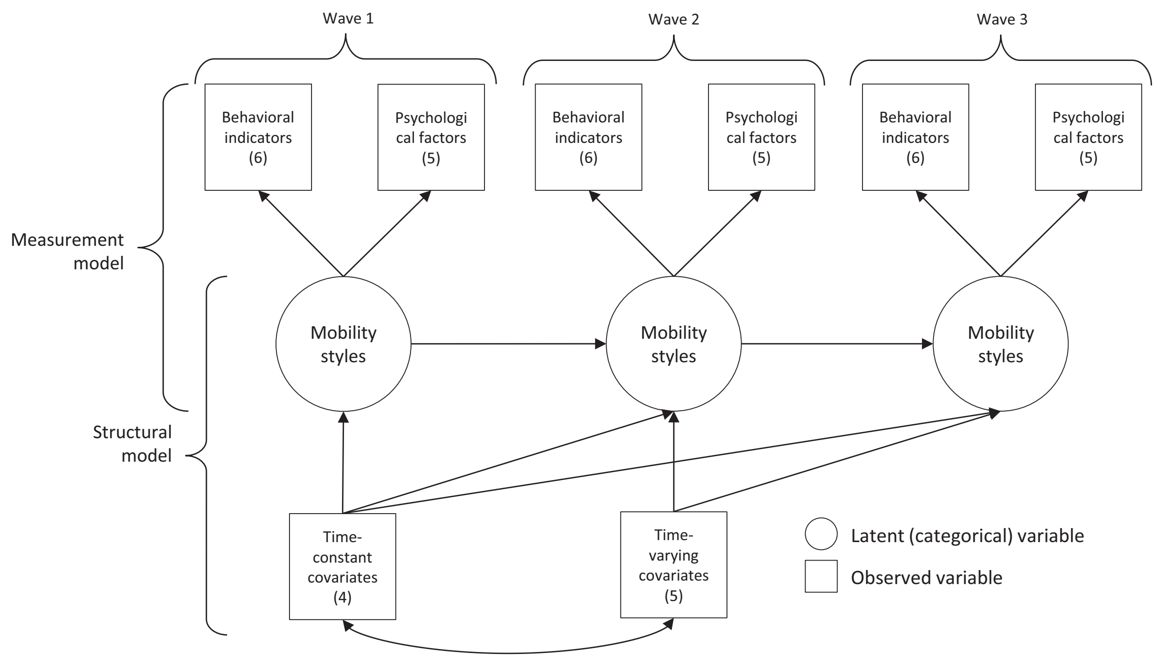

Fig. 1. Model conceptualization.

Table 3
Model fit of latent transition models.

No. of classes	LL	BIC(LL)	Npar	% increase in LL compared to 1-class model
1	−64,755.6	129,627.3	16	
2	−57,554.2	115,362.3	35	11.1
3	−55,434.7	111,275.7	56	14.4
4	−54,349.1	109,271.4	79	16.1
5	−52,445.4	105,645.3	104	19.0
6	−51,857.4	104,665.2	131	19.9
7	−51,367.0	103,894.9	160	20.7
8	−50,950.0	103,285.9	191	21.3
9	−50,399.8	102,424.8	224	22.2
10	−50,110.7	102,100.7	259	22.6
5 - Inequivalent transition probabilities	−52,433.8	105,767.3	124	
5 - Measurement inequivalence	−52,355.8	106,264.2	214	

LL-Log-Likelihood, BIC(LL)-Bayesian Information Criterion (based on LL), Npar-Number of parameters.

model, but – based on the posterior membership probabilities – the conditional means/distribution for these variables are calculated. The reason for not including these variables as indicators is that they overlap with indicators already present in the model. In addition, the travel distance by car is highly skewed and likely quite unreliable.

The transitions models with covariates were estimated simultaneously (so measurement and structural model jointly) using full information maximum likelihood estimation, which can effectively handle missing values on the indicators (i.e. note that such missing values are indeed present due to attribution in wave 2 and 3).[1] To avoid ending up in local optima, all models are estimated with 200 sets of random starting values. The estimations are performed in Latent Gold 6.0.

[1] The full information ML estimation implies that all available data from all waves is used in the estimation, so the sample size remains equal to the sample size in wave 1, meaning that for the covariates (which are not time-constant), many missing values occur.

4. Results

4.1. Identification of mobility styles

We start by presenting the profile output and (overall) transition matrix of the final model (Model C: including all covariates). Afterwards, we will discuss the effects of the covariates, where we also present and discuss the coefficients related to models A and B. Table 4 presents the profile output of the 5-class transition model, including the matrix of transition probabilities (last 5 rows).

We identified two car-reliant groups ('Function drivers' and 'Car-loving busy drivers'), two groups of cyclist ('Car-prone cyclists' and 'Die-hard cyclists') and a group of public transport (PT) commuters. The largest group (23%) are Functional drivers, who are (similar as Car-loving busy drivers) characterised by high driving frequency and car kilometres travelled, low use of alternative transport modes and the lowest share of multimodal travellers. However, both car-reliant groups differ in their car use motives, with Functional drivers being less enthusiastic about driving and also connecting car use to a lesser extent with autonomy than Car-loving busy drivers. The latter are additionally characterised by the highest perceived mobility necessities and lowest car independence and weather resistance, thus perceive the highest barriers to use alternatives modes. In both groups, we find a lower percentage of car sharing members as compared to the overall sample and an overrepresentation of older people.

Similar to the two car-reliant groups differing in car motives, we also find two groups of cyclists who particularly differ in their attitudes. Car-prone cyclists mostly travel by bicycle but are open to the use of other modes, as can be seen in both attitudes and mode choice, and they consist of the highest share of multimodal travellers. Their affective car motives are actually more positive than those of Functional drivers. By contrast, Die-hard cyclists make almost all trips by active modes and hardly use a car, in particular not as a driver. They strike out by the highest independence of both a private car and the weather and are least fond of driving. Die-hard cyclists are the youngest and most highly educated group, balanced in gender, while Car-prone cyclists are mostly men, with the highest percentage of new or existing free-floating car sharing members (70%).

Finally, the smallest group are 'PT commuters' who show high PT use

Table 4
Profiles of the 5-classes and matrix of transition probabilities.

	Functional drivers	Car-prone cyclists	Car-loving busy drivers	Die-hard cyclists	PT commuters
Cluster size (%)	23	21	21	18	17
Travel behaviour					
Car alone	4.0	1.6	4.4	0.2	0.6
Car in company	2.3	1.6	2.2	0.9	0.9
Metro/train	0.4	1.1	0.4	1.1	3.6
Bus	0.2	0.4	0.2	0.7	3.2
Bike	0.4	4.2	0.4	5.5	1.2
Foot	2.3	3.2	2.3	3.7	4.7
Attitudes					
Car independence	2.2	3.5	1.9	4.5	3.9
Car enjoyment (driving fun)	3.1	3.6	3.9	2.7	3.2
Car autonomy	4.0	4.3	5.0	3.3	3.8
Perceived mobility necessities (PMN)	3.5	3.2	4.0	3.1	2.9
Cycling weather resistance	2.1	3.3	1.9	4.4	2.2
Covariates					
Gender					
Male (%)	62	75	55	55	59
Female (%)	37	23	43	43	39
Missing (%)	1	2	2	2	2
Age					
18–30 (%)	6	14	8	18	19
31–40 (%)	12	22	15	25	21
41–50 (%)	22	30	25	27	24
51–60 (%)	33	22	30	19	22
61+ (%)	26	10	20	9	12
Missing (%)	1	2	2	2	2
Level of education					
Low (%)	44	33	45	27	38
High (%)	56	67	55	73	62
Car sharing user group					
Non users (%)	65	30	62	44	41
Existing users (%)	13	24	14	22	19
New users (%)	22	46	25	33	40
Distance travelled by car in the last week					
Mean (km)	243.3	123.3	268.5	51.7	46.2
Multimodality indicator					
Single mode (%)	55	18	55	35	38
Multimodal (%)	19	57	19	40	36
Missing (%)	26	26	26	26	26
State (t + 1)					
Functional drivers (%)	71	7	26	1	6
Car-prone cyclists (%)	5	79	3	6	11
Car-loving busy drivers (%)	21	4	69	0	4
Die-hard cyclists (%)	0	7	0	90	3
PT commuters (%)	3	2	2	4	75

as well as high walking frequencies. On average, they cycle more often than both groups of drivers but less than both groups of cyclists. They do not feel dependent of a car and perceive comparable low perceived mobility necessities, which is also reflected in the lowest number of kilometres travelled by car.

When looking at the probabilities that members of one group switch to another group over time (see Table 4, State (t + 1)), we find the highest stability for Die-hard cyclists – 90% remain in the same group. Together with Car-loving busy drivers they show the highest attitude-behaviour consistency. Yet, Car-loving busy drivers are a less stable group – 26% switch to the group of Functional drivers. Similar, 21% of Functional drivers switch to Car-loving busy drivers. Thus, it is not unlikely, that switches occur among both driving groups who show very similar behaviour but different attitudes. Despite more discrepancies in the attitude-behaviour relationship of Car-prone cyclists, they are a quite stable group: 79% remain in the same group and switches happen both in direction of Die-hard cyclists and Functional drivers, to a lesser degree also to the other two groups. PT commuters take a medium position in terms of stability and also show less clear change tendencies. Yet, most changes go in direction of Car-prone cyclists, followed by Functional drivers.

To obtain a more intuitive grasp of the matrix of transition probabilities, the modality styles can be visualised as nodes in a directed network using the transition probabilities as weights for the edges. This is done in Fig. 2. This presentation of the results clearly shows the centrality of the Car-prone cyclists class, functioning as a ‘gateway’ between the two less sustainable travel patterns (Functional drivers and Car-loving busy drivers) and the two more sustainable travel patterns (Die-hard cyclist and PT commuters). Especially for Die-hard cyclists, the Car-prone cyclist class seems a necessary intermediate step before transitioning to one of the car classes and vice versa, no one seems to directly transition from one of the car-minded classes to the Die-hard cycling class. Hence, a picture arises where at both ends of the sustainability spectrum, the respective modality styles function as strong attractors, which are difficult to ‘escape’. Obviously, this has important implications for policy, which we return to in Section 5.

4.2. Latent transition analysis

Table 5 presents the parameter estimates of the three models separately. Model A includes only time-constant covariates, which are assumed to affect both the initial class membership and class membership at (the two) later points in time. All four covariates have a significant influence on the initial class membership and the effects are intuitively plausible. As we have seen in the cluster profiles, with increasing age, membership of the car-reliant classes increases at the expense of the ‘non-car classes’. In addition, more highly educated people tend to belong to the group of Die-hard cyclists. Women have a lower likelihood to belong to Car-prone cyclists. Being a car sharing member decreases the likelihood of belonging to a driver group and increases the likelihood of being a Car-prone cyclist.

Only two (out of four) covariates also influence the transition probabilities over time, namely gender and age. First of all, this implies that free-floating car sharing does not make it more or less likely that people change to a more or less sustainable mobility styles over time. Also, education showed no effect on the transition probabilities. However, women are less likely to switch to Car-prone cyclists and more likely to switch to Car-loving drivers. A reason might be that women, more than men, increase car ownership over time as they come from a lower level of car ownership. Being older increases the likelihood to turn into a PT commuter, while it decreases the likelihood to become a Die-hard cyclist. The latter may be related to health-related issues and safety perceptions, which vary with age and may keep older people from cycling, particularly in bad weather conditions.

In Model B, we additionally included four time-varying covariates (which are assumed to only affect the class membership at later points in time) and removed insignificant effects from the previous model (note that the effects of the time-constant covariates on initial class membership are retained in the model, but not shown again because they strongly overlap with those of Model A). As expected, increases in income increase the likelihood that people change to car-prone clusters, while moving to Copenhagen increases the probabilities of transitioning

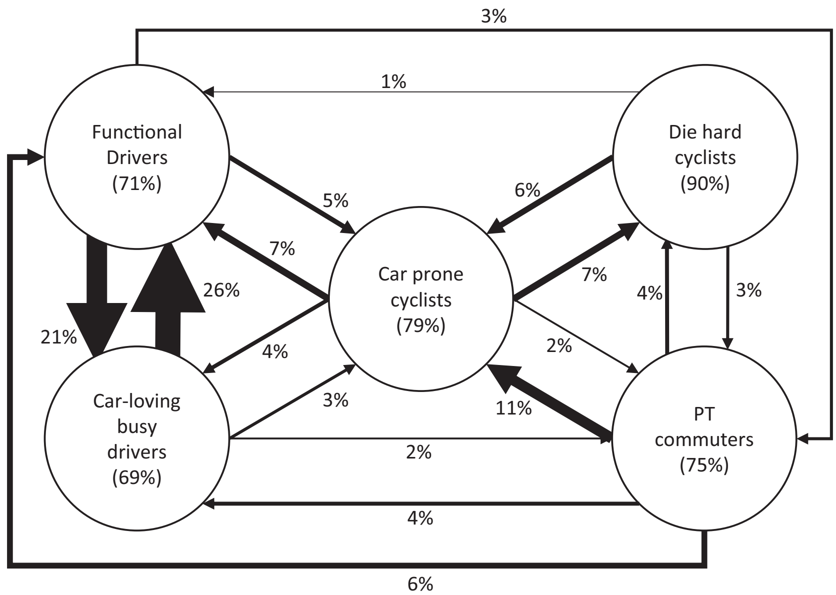

Fig. 2. A directed network of the transitions between the modality styles.
Note: The weights of the arrows are based on the sizes of the associated transition probabilities (when this probability is zero no arrow is drawn).

to more sustainable mobility styles, in particular to becoming a Die-hard cyclist, followed by a PT commuter. However, the effects of income and residential relocation are small and only significant at the 10% level.

In Model C, car ownership is additionally included in the model. It has a strong effect, which forces effects of income and place of residence out, which can be expected when seeing car ownership as a factor that is related to (and rather follows) changes in income and place of residence and is expected to have the more direct effect on mobility styles. The effect of gender on the transition probabilities is quite constant and not strongly affected by the inclusion of car ownership, so the identified gender effects seem quite unrelated to car-ownership. Yet, the age effect is no longer significant in Model C.

5. Discussion and conclusions

We identified five distinct mobility styles based on symbolic-affective car attitudes, perceived mobility related constraints as well as actual travel behaviour. The identified segments turned out to be quite stable over time, probably as both attitudes and behaviour were included as class-defining latent variables. Similar as in previous segmentation studies considering attitudes towards travel modes (e.g., Anable, 2005; Jensen, 1999; Hunecke et al., 2010), we could differentiate between passionate car drivers and more functional, less enthusiastic motorists. Yet, we could identify even more distinct cyclist groups – one very open to car driving and one with a clear preference for active travel and negative car attitudes. These two mobility styles to some extent resemble the groups of car-independent and car-dependent cyclists in the sample of Van Eenoo et al. (2022). Yet in our study the distinction between both cyclist groups is clearer for symbolic-affective car motives than car-dependency, which can probably be explained by the fact that Van Eenoo et al. (2022) sample is restricted to car owners. Finally, we identified a PT commuter segment. Similar as 'Self--determined mobile people' in Hunecke et al. (2010) this group perceived the lowest mobility necessities. Higher mobility necessities have repeatedly been identified as a barrier to PT use (Haustein et al., 2007; Thorhauge et al., 2020), disclosing difficulties of public transport to meet high mobility and flexibility needs. While people perceive that these needs can often only be met with a private car, in cycling cities the bicycle can serve as a competitive alternative to the car as important destinations can be reached in comparable time, facilitated by dedicated cycling infrastructure and supportive social norms (Thorhauge et al., 2020). As in other European studies (e.g., Hudde, 2022; Molin et al., 2016; Van Eenoo et al., 2022), the bicycle is more frequently used by young, highly-educated people.

Yet, the two car-reliant groups make up almost half of the sample (44%), which shows that even in the Capital Region of Denmark – a region characterised by a high cycling share (Haustein et al., 2020) and good public transport access (Goletz et al., 2020) – car-reliant mobility styles predominate. The fact that car sharing members are over-represented in our sample, but underrepresented in the two car-reliant groups, paints an even more bleak picture. However, a positive finding from a sustainability viewpoint are two cycling classes, which turned out to be the most stable groups. Based on their higher attitude-behaviour congruency, we expected Car-loving busy drivers to be more stable than Car-prone cyclist. Yet, the high behavioural similarity of Car-loving busy drivers and Functional drivers led to more switches between these two car reliant groups, despite differences in attitudes, which were, however, smaller than differences between other groups. In addition, we generally found that switches over time were more likely to happen in direction of car-reliant groups than away from car use and ownership.

While Die-hard cyclists are dominated by young people, the age-related shifts to more car-reliant groups give greater support to the hypothesis of delayed than suspended car ownership of Millennials (e.g., Rérat, 2021). As we find young people also well represented among Car-prone cyclist, the view of new generations with a more functional and utilitarian relationship to the car may be true for a specific segment (here best represented by Die-hard cyclists) but does not represent the whole generation – especially beyond the cosmopolitan urban milieu, we can expect a higher representation of car-reliant groups (e.g., Groth et al., 2021; Hunecke et al., 2020; Møller et al., 2018). The clear connection of car ownership and residential location also becomes evident by the effect of moving to Copenhagen, which supports shifts to cycling and public transport dominated mobility styles, while people become less multimodal and car-reliant when moving away from the capital – effects that are clearly connected to changes in car ownership as indicated by the fact that they lose significance when car ownership is controlled for. The question to what extent changes in mode choice after relocation are subject to residential self-selection or direct effects of more or less car-dependent neighbourhoods cannot be conclusively

Table 5
Parameter estimates of the covariates of Model A, B and C.

	Model A						Model B			Model C		
	Class membership at $t = 1$			Class membership at $t > 1$			Class membership at $t > 1$			Class membership at $t > 1$		
	Est.	Wald	p	Est.	Wald	p	Est.	Wald	p	Est.	Wald	p
Time-constant covariates												
Gender (female)→class 1	−0.172	12.7	0.013	−0.053	14.2	0.007	−0.014	15.6	0.004	−0.041	14.5	0.006
Gender (female)→class 2	−0.373			−0.541			−0.583			−0.511		
Gender (female)→class 3	0.009			0.423			0.365			0.313		
Gender (female)→class 4	0.281			0.116			0.284			0.326		
Gender (female)→class 5	0.255			0.055			−0.053			−0.087		
Age→class 1	0.263	57.3	0.000	0.059	11.8	0.019	0.040	14.2	0.007	0.029	12.2	0.016
Age→class 2	−0.078			0.028			0.015			−0.008		
Age→class 3	0.162			−0.064			−0.120			−0.131		
Age→class 4	−0.154			−0.192			−0.129			−0.057		
Age→class 5	−0.193			0.168			0.193			0.166		
Education→class 1	−0.229	19.2	0.001	−0.201	4.9	0.290						
Education→class 2	0.191			0.104								
Education→class 3	−0.325			−0.317								
Education→class 4	0.411			0.454								
Education→class 5	−0.048			−0.039								
Car sharing (non-user)→class 1	0.414	51.7	0.000	0.024	7.5	0.490						
Car sharing (non-user)→class 2	−0.369			−0.182								
Car sharing (non-user)→class 3	0.303			−0.074								
Car sharing (non-user)→class 4	−0.155			0.262								
Car sharing (non-user)→class 5	−0.192			−0.031								
Car sharing (existing user)→class 1	−0.193			0.097								
Car sharing (existing user)→class 2	0.259			0.009								
Car sharing (existing user)→class 3	−0.199			0.083								
Car sharing (existing user)→class 4	0.163			−0.081								
Car sharing (existing user)→class 5	−0.029			−0.108								
Car sharing (new user)→class 1	−0.221			−0.121								
Car sharing (new user)→class 2	0.110			0.172								
Car sharing (new user)→class 3	−0.103			−0.009								
Car sharing (new user)→class 4	−0.007			−0.181								
Car sharing (new user)→class 5	0.221			0.139								
Time-varying covariates												
Income→class 1							0.056	8.0	0.091	−0.022	5.1	0.280
Income→class 2							0.055			0.041		
Income→class 3							0.029			−0.072		
Income→class 4							−0.056			0.059		
Income→class 5							−0.083			−0.006		
Residence (in Copenhagen)→class 1							−0.451	8.4	0.079	−0.256	3.3	0.500
Residence (in Copenhagen)→class 2							0.045			0.255		
Residence (in Copenhagen)→class 3							−0.491			−0.226		
Residence (in Copenhagen)→class 4							0.591			0.120		
Residence (in Copenhagen)→class 5							0.306			0.107		
Own parking place (yes)→class 1							0.398	5.7	0.220			
Own parking place (yes)→class 2							−0.333					
Own parking place (yes)→class 3							0.375					
Own parking place (yes)→class 4							−0.240					
Own parking place (yes)→class 5							−0.200					
No. of persons in the HH→class 1							−0.036	1.3	0.870			
No. of persons in the HH→class 2							0.052					
No. of persons in the HH→class 3							−0.072					
No. of persons in the HH→class 4							−0.017					
No. of persons in the HH→class 5							0.073					
No. of cars available in HH→class 1										1.171	99.5	0.000
No. of cars available in HH→class 2										0.299		
No. of cars available in HH→class 3										1.372		
No. of cars available in HH→class 4										−1.582		
No. of cars available in HH→class 5										−1.260		

answered based on the data. Yet, our results support previous findings of relations between multimodality, car ownership and population density (e.g., Heinen and Mattioli, 2019; Nobis, 2007).

Given the specific characteristics of the sample, with half of it consisting of free-floating car sharing users, we had the chance to examine the effect of car sharing membership on the likelihood of transitions to more sustainable or less sustainable mobility styles. We found car sharing members best represented among multimodal segments (esp. Car-prone cyclists), a result that fits well with previous studies identifying free-floating car sharing users as more multimodal (e.g., Kopp et al., 2015). Yet, we did not find any evidence that car sharing membership (alone) keeps people in multimodal groups or leads to shift from less to more sustainable groups or vice versa. The result is in line with other recent studies according to which free-floating car sharing has limited effects on car ownership (Haustein, 2021a) in particular compared to station-based car sharing (e.g., Becker et al., 2018; Namazu and Dowlatabadi, 2018). However, given that the group of Car-prone cyclist is quite stable and changes in this group go mostly in direction of groups with lower affective car attitudes (Functional drivers and Die-hard cyclist) this may indicate that free-floating car sharing is a service that can play a role in meeting mobility needs without increasing the need for car ownership. Yet, it would be relevant to observe people over a longer period to come to more conclusive results. Recent changes in the examined free-floating service, such as the possibility to rent a car for longer time periods as well as subscriptions similar to station-based car sharing may also lead to more positive results in terms of the possibility to replace car ownership.

Another factor that did not significantly influence transition probabilities was access to private parking space. An effect was expected as access to a parking space had been identified as a relevant factor influencing car ownership (Haustein, 2021a). As having a private parking space is closely connected to living in or outside Copenhagen, we assume that its effect is captured in the effect of moving to Copenhagen offering general better conditions for alternative modes and worse conditions for car owners as compared to the surrounding municipalities that were include in the study. Similar, a change in the number of household members is generally found related to changed car ownership (Clark et al., 2016; Prillwitz et al., 2006; Yamamoto, 2008) but was not identified as a significant factor for changes in mobility style.

In terms of gender, we found that women were more likely to switch to the more congruent mobility styles (Die-hard cyclist and Car-loving busy drivers) which could indicate that women feel a higher need for attitude-behaviour consistency and thus are more likely to adapt attitude or behaviour over time.

In conclusion, we find changes in mobility styles most closely linked to changes in car ownership, which are again related to changes in income and place of residence. As external costs of car transport (congestion, pollution) are higher in cities than in less dense areas (Creutzig et al., 2020a) and cities offer better opportunities for the use of alternative modes, we encourage measures that increase the costs of car ownership in cities, e.g. by increasing parking fees (e.g., Gragera et al., 2021) and/or the reduction of parking space, while at the same time further improving conditions for alternative transport modes. In addition, our analysis highlights the importance of preventing people to end up in unsustainable travel patterns (the two car-reliant classes) and stimulating them to end up in sustainable ones, as the modality styles function at both these ends of the 'sustainability spectrum' seem to act as attractors from which it is difficult to escape. Here, a long-term strategy focused on children and young adults (who typically belong to the sustainable travel patterns) seems crucial to indeed prevent them from ending up in a car-minded travel pattern. Decreasing numbers of in particular young cyclists in Copenhagen in recent years (Christiansen, 2021), make this call even more urgent. With a high share of cyclists, Copenhagen and its surrounding has come a long way. Yet, the city only takes a middle position among European cities in terms of air pollution (EEA, 2021b), and to reach its own climate goals, more effective measures to limit car use are urgently needed.

Finally, some limitations and future research directions may be identified. First, our sample cannot be considered as representative as car sharing members are overrepresented. In particular the two groups of drivers can thus be considered as much larger in reality, as they mainly consist of non-car sharing users. Second, while we included a broad range of psychological factors, one particular factor that would be interesting to include in future research efforts would be the level of (dis)satisfaction with the current travel patterns. Such a measure could validate the notion that attitude/behaviour incongruence indeed leads to dissatisfaction (see also De Vos and Witlox, 2017; De Vos and Singleton, 2020) and aid the model in identifying (in)congruent modality styles. Third, our conceptualization assumes that the included covariates are strictly exogenous. For socio-demographic characteristics this assumption most likely holds, but for other characteristics, like car ownership, this assumption is questionable, since a person's current modality style may also inform his/her future purchase decisions. Ideally, such long-term mobility decisions should be made endogenous to the modality styles in the model. An extension of the latent transition modelling framework is necessary in this regard, but in principle this is possible. As such, this would be an interesting and relevant research direction.

Declaration of interest

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CRediT authorship contribution statement

Sonja Haustein: Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Project administration. **Maarten Kroesen:** Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing.

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