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Do changes in travellers' attitudes towards car use and ownership over time affect travel mode choice? A latent transition approach in the Netherlands

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ABSTRACT

This paper examines how changes in travellers' attitudes towards car use and ownership change over time and how these changes influence car use, based on the 2014 and 2016 waves of the Netherlands Mobility Panel (N = 1640). A latent transition model was estimated to investigate transitions between different segments based on travellers' attitudes towards car use and ownership, and the latent transition probabilities were used to predict changes in mode use. Four latent classes were found to reflect the participants' attitudes: cost-sensitive, car-minded, environmentally aware and social-conscious travellers. Most of the participants remained in the same class between 2014 and 2016, which suggests that attitudes towards car use and ownership are stable over time. Also, the results indicate that car use and car ownership may be less widespread among younger adults. Only when younger adults face life events, such as moving, starting a job or become parents, transitioning to more car-oriented profiles appears more likely. Changes in attitudes towards car use and car ownership do not significantly affect car use (number of trips per day), except for the social-conscious travellers who switched to the car-minded class. This suggests that, in most cases, a more positive or negative attitude towards car use and ownership does not directly affect the frequency of car use.

1. Introduction

In the Netherlands, like in other industrialised countries, car use is dominant. In 2016, almost half of all trips were by car (47%), and at 73%, the share of distance travelled by car was even higher (CBS, 2016). Between 1995 and 2005, the number of car trips increased by 5% and the number of car kilometres by 12%. Since 2005, car use has approximately remained the same. Considerable differences in the development of car use exist by age group (KIM, 2017). For older adults (i.e., 65 years or older), both the number of trips and the distance travelled by car strongly increased, while people aged 40 and younger did not drive as much as before. This decrease in car use among young adults and the increase in car use among older adults do not merely reflect a change in population size, but also changes in behaviour and the household situation.

Explanations for a change in car use are related to various factors, such as social characteristics or residential location (KIM, 2017). For example, nowadays, young people in the Netherlands tend to live in urban areas and remain enrolled at university longer. As a result, young people more frequently use public transport and the bicycle, rather than the car. Differences in the development of

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car use by age are not unique to the Netherlands. For example, Kuhnimhof et al. (2012) found a reduction in car use among young travellers in six industrialised countries (i.e., Germany, France, Great Britain, Japan, Norway and the USA). Also, a recent study of the travel patterns of older adults in England, Germany, USA and Japan showed a significant increase in car use (Zmud et al., 2017). To understand these increases and decreases in car use, and changes in other modes of transport, more insight is required into the processes and determinants affecting mode choice behaviour.

According to existing research findings, travel mode choice is determined and influenced by attitudes people have towards the car, public transport and inactive modes (Steg et al., 2001; Anable, 2005; Donald et al., 2014; Paulssen et al., 2014; Molin et al., 2016). The Theory of Planned Behaviour (Ajzen, 1991) and Swartz's Norm Activation Model (Schwartz, 1977) are two of the most widely used models to study the effects of attitudes on behaviour, and have been applied in different studies to improve our understanding of travel behaviour (Donald et al., 2014; Bamberg et al., 2015; Kaewkluengklom et al., 2017). These models provide insight into the relationship between attitudes, social norms, intention and behaviour. Although it is recognized that behaviour may influence attitudes (Ajzen, 2015), in most research, it is assumed that attitudes affect behaviour. This follows from the basic principle that people's behaviour can be derived from their intentions, and attitudes determine intentions (Ajzen, 1991). However, the impact of temporal dynamics in attitudes on transport mode choice has been much less studied, in particular the extent to which changes in attitudes are caused by changes in time-dependent variables such as life events (e.g. childbirth, new job, moving home).

The main aim of this paper is to examine the effects of changes in attitudes towards car use and ownership over time on mode use. We identify different profiles or population segments based on attitudes towards specific modes and investigate how these profiles tend to change over time as well as how these changes relate to car use. The paper addresses the following research questions:

- Which travellers' profiles can be defined based on their attitudes towards car use and ownership?
- Do these travellers' profiles change over time, and if so, are these changes related to life events?
- Are changes in attitudes towards car use and ownership related to changes in mode use?

To answer these research questions, we used panel data from the Netherlands Mobility Panel (in Dutch: Mobiliteitspanel Nederland, MPN), the largest ongoing mobility panel in the world. This panel is specifically designed to examine annual changes in travel behaviour and contains individual and household characteristics, questions on mode attitudes and preferences as well as life events, and the actual travel behaviour recorded in a three-day trip diary. To allow a detailed analysis of the dynamics in attitudes towards car use and ownership, and the relationship with individual mobility, an additional dedicated survey was designed and conducted for this study in the 2014 and 2016 waves of the MPN.

This research is novel for three reasons. First, to our knowledge, this is the first study analysing changes in attitudes towards car use and ownership over time for a large panel of individuals, as well as the effects of these changes on car use. Although segmentation of travellers based on attitudes has been the subject of many studies, most of those studies were based on cross-sectional data of only one year. The dynamics of attitude change have hardly been investigated due to the lack of longitudinal data. The 2014 and 2016 waves of the MPN provided us with data about attitudes and travel behaviour of the same people at different time points, enabling us to study the dynamics in attitude-based segments over time. Second, because also data was collected about several life events, the MPN allowed testing the impact of life events on changes between attitude-based segments. Although the effects of life events on changes in travel behaviour have been the subject of many studies, still little is known about the relationship between life events and changes in attitudes. Third, the MPN comprises a three-day trip diary which enabled us to link changes in attitudes with actual travel behaviour, and therefore to examine to what extent these changes affected mode use.

We organised the remainder of this paper as follows. Section 2 reviews the existing research on attitudes and travel mode choice. Next, Section 3 describes the data and measures we used for the analysis and some descriptive statistics for the selected sample. Section 4 defines model specification and model selection, followed by the results in Section 5. Section 6 discusses the results and ends with directions for further research. Finally, Sections 7 wraps up the paper with the main conclusions.

2. Attitudes and travel mode choice

Various factors influence travel mode choice, such as sociodemographic characteristics at the individual and household level, characteristics of the built environment, and trip characteristics. Gaining knowledge about factors that determine mode choice is a major topic in transportation research (Paulssen et al., 2014; Feng et al., 2014; Vij et al., 2013). In recent years, the effects of the attitudes of the individual traveller on his or her travel mode choice have received increasing attention. Most of these studies refer to the Theory of Planned Behaviour (Ajzen, 1991) to show that individual travel behaviour is a result of attitude, subjective norm, perceived behaviour control and intention (Donald et al., 2014; Abrahamse et al., 2009). To facilitate shifts from car use towards more sustainable means of transportation, a better understanding of travellers' motivations is needed. Steg and Kalfs (2000) argued that individual mode choices are primarily determined by personal values, feelings, preferences and social norms, much more than, for example, by the availability of alternatives. However, little is known about the cause of changes in travel behaviour from the dynamics of attitudes. For example, concerning car use, there are widespread indications of a declining popularity of the car among young adults (Davis and Dutzik, 2012; Delbosc and Currie, 2013; Dutzik and Baxandall, 2013). However, these indications mostly rely on declining trends in car use based on cross-sectional surveys. There is no empirical evidence that changes in attitudes towards car use and ownership causes this decrease in car use.

To examine the differences between individual travellers, the concept of market segmentation is widely used to divide the population into meaningful subgroups of individuals. Traditionally, sociodemographic characteristics, such as gender, age and car ownership, were used as a basis for segmentation (e.g., De Jong et al., 2004). Recently, to capture behavioural components, segments have been based on frequency of mode use (Kroesen, 2014; Molin et al., 2016; Prillwitz and Barr, 2011), characterised as ‘strictly car users’ or ‘multimodal users’, for example. However, segmentation based on either sociodemographic characteristics or mode use does not explain attitudes towards transport modes and, therefore, does not provide insight into potential changes (Semanjski and Gautama, 2016). Segmentation based on attitudes helps gain more insight into mode choice behaviour (Anable, 2005). However, those attitudes might also change over time, so mode choice decisions might change as well, and vice versa. Analysing attitudes based on longitudinal data is therefore crucial.

Most research findings on the relationship between attitudes and mobility choices have certain limitations. First, the results are usually based on a stated preference survey, which means that respondents are presented with a limited number of choices and settings. The theoretical choices respondents make, based on the provided information, can be entirely different from the decisions they make in daily life. Monitoring of attitudes and travel behaviour is needed to examine the relationship between changes in attitudes and travel behaviour. Second, most research on mode attitudes is based on cross-sectional survey data, which does not provide insights into changes at the individual level. For example, Molin et al. (2016) found that travel mode use and attitudes are strongly correlated for four of the five identified travel groups. However, because this analysis was based on a dataset from one year, it is not clear if and to what extent a change in attitude affects travel mode use. Just a few studies have examined the relationship between attitudes and mode choice behaviour over time. For example, Thøgersen (2006) showed that past behaviour is the main predictor of current behaviour, and when accounting for past behaviour, the influence of attitudes on public transport use decreases. Recently, Kroesen et al. (2017) investigated the bidirectional relationship between attitude and behaviour over time and found that attitudes and mode use influence each other in both directions. However, we still know little about changes in attitudes and the effect of these changes on travel behaviour.

3. Data

3.1. Survey and sample selection

The analyses in this paper are based on data from the 2014 and 2016 waves of the Netherlands Mobility Panel (MPN). The MPN was set up to study short-run and long-run dynamics in travel behaviour of Dutch individuals and households, and to study how changes in personal and household characteristics and other travel-related factors correlate with (changes in) travel behaviour (Hoogendoorn-Lanser et al., 2015). Socio-economic attributes for households and their members were collected for each household through individual questionnaires. Participants who completed questionnaires were invited to keep a three-day online trip diary for three successive days. In 2014 and 2016, additional questions were added about attitudes towards car use and ownership.

A total of 3622 individuals aged 18 years and older completed the additional survey in the fall of 2014 and 2016. From this sample, missing values were deleted list-wise and respondents without completed household questionnaire were removed. The final sample contained 2484 individuals, of who 1640 completed the three-day trip diary. To examine changes in attitudes towards car use and ownership with actual mode use, as highlighted in previous sections, we used the sample with individuals who completed both the questionnaire and the trip diary.

Panel data may contain possible attrition biases. Regarding our main variables of interest, we found insignificant differences in respondents’ attitudes between participants who completed the additional survey and the trip diary in 2014 and 2016, and those who dropped out. For mode use, we detected no significant differences for bicycle and bus, tram and metro (BTM) use. However, those who dropped out used the car more often and the train less frequently relative to those who participated in both waves. Although the differences are small, this indicates a small attrition bias. More information on the impact of non-random attrition (between and within waves) in the MPN data on travel behaviour can be found in La Paix Puello et al. (2017).

3.2. Measures

To analyse travellers’ attitudes towards car use and ownership and the relationship with travel behaviour, we developed a construct to measure car attitudes and derived mode use from the MPN trip diary.

Car attitudes. To examine the travellers’ car attitudes towards car use and car ownership, sixteen statements were formulated in an additional dedicated survey, conducted at the same time as the individual questionnaires were collected in 2014 and 2016. We used five-point Likert scales ranging from (1) completely disagree to (5) completely agree as response scales for all statements. We conducted a common factor analysis (principal components analysis with oblimin rotation[1]) to explore if there were unobserved (latent) variables that describe the variation in sixteen statements. In 2014 we identified five underlying factors (based on eigenvalues > 1) reflecting travellers’ attitudes towards car use and ownership: *car-minded (F1), cost-sensitive (F2), status-sensitive (F3), environmental awareness (F4)* and *social consciousness (F5)*. These factors explain 47% of the total variance in the statements. Table 1 presents a list of all statements and the corresponding factor loadings in 2014. To determine the internal consistency reliability, we calculated Cronbach’s alpha and found all factors within an acceptable range, i.e. between 0.65 and 0.80 (Nunnally, 1978).

Furthermore, in longitudinal research, measurement invariance is an important issue, and testing for measurement invariance

[1] This rotation technique can be used when some correlation among the factors is assumed or expected. For example, we observed that the factors ‘*environmental awareness* ‘and ‘*social consciousness*’ can be correlated.

Table 1
Factor loadings from factor analysis in 2014 and reliability scores (N = 1640).

Factors	Statements	Factor loadings				
Car-minded	Owning a car allows me to do whatever I want	0.684				
	Travelling by car offers a lot of advantages compared with other modes	0.630				
	I can't live without a car	0.599				
	Nearly every time I travel, I use the car	0.529				
	Driving a car is fun	0.436				
Cost-sensitive	Because of the costs, I'm using the car less frequently		0.831			
	My financial situation is a reason to postpone buying a (new) car		0.722			
	Owning a car is difficult because of the expenses		0.541			
Status-sensitive	A car represents someone's taste			0.769		
	A car represents someone's position in society			0.682		
Environmental awareness	It makes no sense to care about the environment; you can't change it by yourself				−0.845	
	It makes no sense to use the car less frequently because others keep driving				−0.743	
	The environment would benefit from less car use				0.588	
Social consciousness	My friends think you should only use the car when there is no other option					0.647
	I only use the car when it is necessary					0.611
	Because of the environment, I tried to use the car less frequently					0.584
	Reliability scores					
	Cronbach's alpha	0.734	0.748	0.694	0.740	0.709
	Tucker's coefficient of congruence	0.994	0.994	0.991	0.997	0.989

across the two waves is a necessary stage (Chung et al., 2011). Regarding factor analysis, this means that there should be no differences in the number of underlying factors and the sizes of the factor loadings between both waves (Collins and Lanza, 2010). We calculated Tucker's coefficient of congruence to examine the two-factor structures for 2014 and 2016 (Lorenzo-Seva and Ten Berge, 2006). As can be seen in Table 1, all coefficients are higher than 0.95, and, therefore we concluded that the factor loadings were invariant and the factor model applied across both waves (Lorenzo-Seva and Ten Berge, 2006). We saved each respondents' latent factor scores on each of the five factors reflecting their attitudes towards car use and ownership in the database.

Mode use. Mode use was derived from the three-day trip diary and was operationalised as the number of trips and distance travelled per person per day by mode (Table 2). The number of trips per person per day in our sample is comparable with the average number of trips of the total sample of the MPN. Compared with the Dutch National Travel Survey (NTS), a yearly cross-sectional survey, the number of trips per person per day was substantially higher, mostly because short walking and cycling trips and locations not regularly visited are underreported in the NTS (Hoogendoorn-Lanser et al., 2015). Between 2014 and 2016, we observed a slight decrease in the total number of trips, and a small increase in the distance travelled for the same respondents. This suggests that the distance per trip increased, in particular, the distance of car trips.

3.3. Sample characteristics

Table 3 shows individual, household and spatial characteristics of the sample used in the analyses for both years. Relative to the overall Dutch population, older adults and individuals without a driving licence were somewhat underrepresented and single households and people living in rural areas overrepresented. Of all selected participants, 75% were between 25 and 64 years old. More than half were female and had a personal income of between €1000 and €3000. More than 9 out of 10 people had a driving licence, whereas a third had a public transport season ticket. Most people in the selected sample were living in urban regions, and almost two-third thought that the accessibility of their neighbourhood by public transport was good.

As the analysis presented in this paper concerns the 2014 and 2016 waves of the MPN, which covers a relatively short period, there were no major changes in individual, household and spatial characteristics at the aggregated level, as expected. For example, only 1% of the participants obtained their driving licence in 2016, and about 2% reported a higher income class for 2016. The most considerable changes occurred in the urbanisation level of the residential location. There was a significant shift from suburban

Table 2
Mode use based on the three-day trip diary in 2014 and 2016 (N = 1640).

	2014		2016	
	Per person per day		Per person per day	
	Trips	Km's	Trips	Km's
Total	3.2	36.7	3.0	37.6
Car	1.5	26.2	1.5	27.7
Train	0.1	5.3	0.1	4.8
Bus, tram, metro	0.1	1.0	0.1	0.8
Bicycle	1.0	2.8	0.8	2.5

Table 3
Individual, household and spatial characteristics of the sample (N = 1640).

Individual level	Categories	MPN	
		2014	2016
		%	%
Age group	18–29 yrs	21	17
	30–39 yrs	17	18
	40–49 yrs	22	19
	50–64 yrs	28	31
	> 64 yrs	13	15
Gender	Male	45	45
	Female	55	55
Educational level	No or low	10	10
	Medium	48	47
	High	42	43
PT season ticket holder	Yes	35	35
	No	65	65
Driving licence holder	Yes	91	92
	No	9	8
Employment status	> 12 hrs paid work per week	60	61
	Self-employed	4	5
	Student	8	6
	No paid work	28	29
Personal income	No personal income	7	6
	Less than €1000 per month	19	19
	Between €1000 and €2000	36	35
	Between €2000 and €3000	21	22
	€3000 or more	6	7
	Missing	11	11
Household level			
Household composition	Single	24	22
	Couple without children	28	29
	Couple with children	42	43
	Other	6	6
Spatial level			
Residential location	Urban (≥1500 inhabitants/m^2)	49	55
	Suburban (1000–1500 inhabitants/m^2)	25	20
	Rural (≤1000–1500 inhabitants/m^2)	26	26
Attitude PT accessibility	Negative	19	20
	Not negative, not positive	17	17
	Positive	64	63

towards urban; however, this does not mean that participants moved towards more urban regions. For example, because of a change in the number of inhabitants per km^2, the level of urbanisation changed for several municipalities in the Netherlands between 2014 and 2016.

As our research questions primary focus on changes in attitudes and travel behaviour over time, we compared the individual scores for the five factors reflecting travellers' attitudes towards car use and ownership and mode use between 2014 and 2016. *Car-minded* was the most stable factor between 2014 and 2016, followed by *social consciousness* and *environmental awareness*. About one-third of the participants stated to have become less cost-sensitive in 2016, which might be related to greater optimism about the country's economy (smaller chance of losing one's job). Although we did not find any significant changes in mode use (measured in trips per person per day) for the total sample, at the individual level, we did. The percentage of individuals in our sample that showed changes in trip rate by mode ranged from 47% (train) to 69% (car). This means that a substantial number of people changed their chosen mode of transport between 2014 and 2016.

The MPN uses questionnaires to collect a large amount of mobility-related and background information on households and their members, including information about different life events. There is evidence from several studies that life events form a trigger for changes in travel behaviour (Clark et al., 2014; Oakil et al., 2016; Rau and Manton, 2016). In our analysis, we were also interested in the impact of life events on changes in travellers' attitudes towards car use and ownership. For our sample, we asked retrospective questions about 14 different life events in the past 12 months and the influence of these life events on people's travel behaviour. The most frequently reported life events in the selected sample between 2014 and 2016 were a change in working hours (19%), a new job (18%), and a change in work location (14%). Some life events were rare, such as 'household member passed away' (1%) and 'divorced/broke up' (2%). Included life events in our analysis were moving home, a change in the number of children in a household

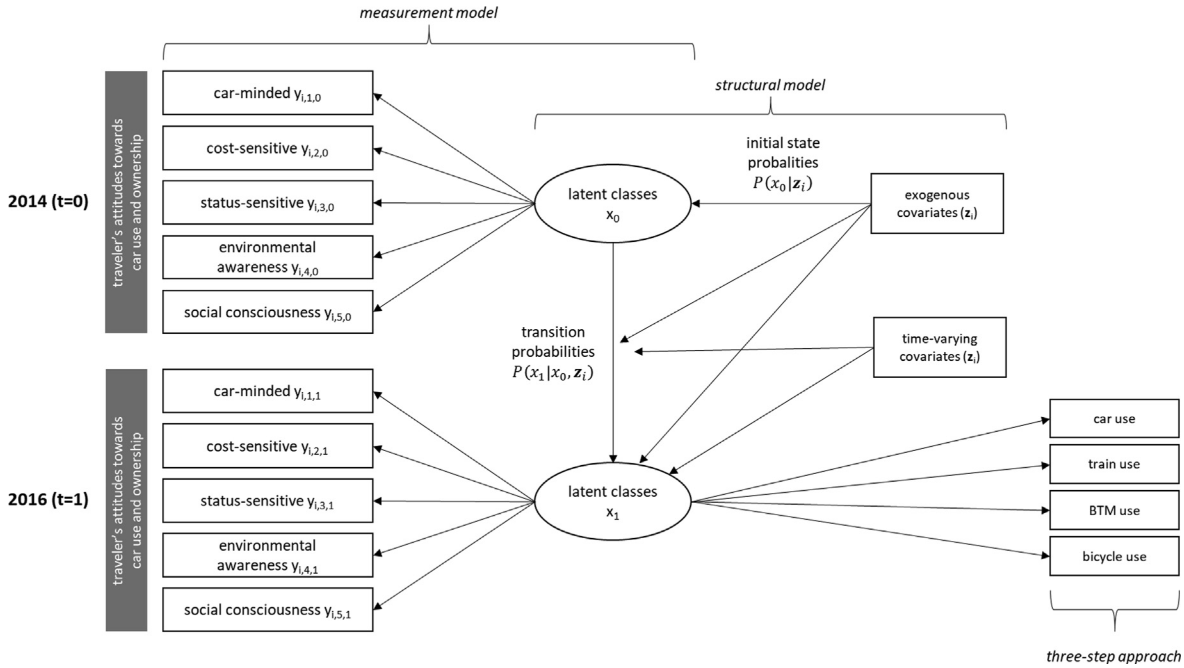

Fig. 1. Path diagram for the latent transition model to study changes in latent classes between 2014 and 2016. Ovals represent latent (i.e., unobserved) variables, rectangles represent observed variables, and arrows represent causal relationships.

and starting or changing jobs. These three life events are identified in the literature as influential travel behaviour factors (Rau and Manton, 2016; Clark et al., 2014). In the selected sample, 28% of the respondents reported one or more of these three life events.

4. Method

4.1. Model specification

We estimated a latent transition model to explore changes in attitude-based segments over time. Latent transitions models are cluster models for longitudinal data in which persons can switch between clusters (Vermunt et al., 2008). The 'repeated' nature of the MPN data allows distinguishing persons whose attitudes changed over time from those whose attitudes stayed the same. Because we were also interested in the relationship with travel behaviour, we related the latent classification scores to the observed number of trips from the travel diary. In our approach, we assumed changes in travellers' attitudes towards car use and ownership precede mode choice behaviour and not vice versa.

Fig. 1 shows the path diagram we used to study changes in patterns between 2014 and 2016. Examples of the application of latent transition models in travel behaviour research can be found in Kroesen (2014) and Haas et al. (2018).

In the present paper, the latent transition model is formulated in two parts that are estimated simultaneously. The first part is known as the measurement model and explains how the five factors reflecting travellers' attitudes towards car use and ownership (car-minded, cost-sensitive, status-sensitive, environmental awareness and social consciousness) are associated. The second part, known as the structural model, explains how the latent classes are related over time. Thus, the latent transition analysis aims to estimate parameters corresponding to the proportion of individuals in each latent class at both time points, and the probability of moving from one class to another, conditional on prior membership status (Collins et al., 2000; Collins and Lanza, 2010). We used the Latent Gold software with maximum likelihood estimation with robust standard errors for model estimation. See Vermunt et al. (2008) for a detailed discussion of latent transition analysis with Latent Gold.

We let y_{itj} denote the response of each participant i at time t to response variable j. In our study, the total number of response variables is 5 (i.e., car-minded, cost-sensitive, status-sensitive, environmental awareness, social consciousness). The vector of responses for a person, i at time t, is denoted as $\boldsymbol{y}_{it}$ and the vector of responses at all occasions as $\boldsymbol{y}_i$. The vector of the exogenous covariates and time-varying covariates is denoted by $\mathbf{z}_i$. We can then make x_0 a latent class variable for 2014 and x_1 for 2016. Hence, individual scores on the five response variables are each classified into 1 of the k latent classes in 2014 and 2016. Latent class membership is explained by exogenous covariates (e.g., age, education and household composition). The initial state probabilities and latent transition probabilities also depend on these covariates. The latent transition probabilities represent movement from a latent class in 2014 to a latent class in 2016. Transition probabilities also depend on time-varying covariates that do not explain class membership in 2014, such as major life events (for example childbirth, moving or changing job) between 2014 and 2016. These are represented in the path diagram (Fig. 1) by an arrow from the box with time-varying covariates to the transition probabilities. Latent classes in 2016 can be explained both by exogenous covariates and time-varying covariates.

Additionally, we used the new three-step approach in Latent Gold in which the latent classification scores are related to mode use, correcting for the classification error to prevent bias (Vermunt, 2010; Bakk et al., 2013). If we performed this analysis separate from the latent transition model, any conclusions about the relationship between latent class membership and variables of interest might be incorrect because the uncertainty related to class membership is not considered and parameter estimates are underestimated (Lanza et al., 2013).

The general model describes the probability density associated with **y** responses of individual i with covariates **z**, and is expressed as follows (Magidson, 2013):

$$P(\boldsymbol{y}_i|\boldsymbol{z}_i) = \sum_{x_0=1}^{K}\sum_{x_1=1}^{K} P((x_0, x_1|\boldsymbol{z}_i)P(\boldsymbol{y}_i|x_0, x_1, \boldsymbol{z}_i) \tag{1}$$

Eq. (2) defines the first part of Eq. (1), the class membership probabilities:

$$P(x_{0,}x_1|\boldsymbol{z}_i) = P(x_0|\boldsymbol{z}_{i0})P(x_1|x_0, \boldsymbol{z}_i) \tag{2}$$

In the second part of Eq. (1), the measurement sub-model, the conditional response probabilities are estimated as follows:

$$P(y_i|x_0, x_1, \boldsymbol{z}_i) = \prod_{t=0}^{1} P(\boldsymbol{y}_{it}|x_t, \boldsymbol{z}_i) = \prod_{t=0}^{1}\prod_{j=1}^{5} P(y_{itj}|x_t, \boldsymbol{z}_i) \tag{3}$$

In summary, we estimated three sets of parameters:

- $P(\mathbf{x}_0|\mathbf{z}_{\mathrm{io}})$ is an initial-state probability, namely the probability of having a particular latent initial state conditional on covariate values at $t = 0$.
- $P(\mathbf{x}_1|\mathbf{x}_0,\mathbf{z}_\mathrm{i})$ is a latent transition probability, namely the probability of being in a particular state at time point $t = 1$ conditional on the latent state occupied at time point $t = 0$ and covariate values.
- $P(\mathbf{y}_{\mathrm{itj}}|\mathbf{x}_\mathrm{t},\mathbf{z}_{\mathrm{it}})$ is a response probability, which is the probability of having a particular observed value on response variable j at time point t conditional on the latent state occupied at time point t and covariate values.

4.2. Model selection

In this study, we performed the following three steps:

1. Assessing the optimal number of latent classes
2. Specification of the latent transition model
3. Relating latent classification scores to mode attitude and mode use.

The results of each step are described in the following sections.

4.2.1. Step 1: Assessing the optimal number of classes

The first step was to find the optimal number of latent classes (LC) in the data, a process commonly known as latent class enumeration (Masyn, 2013). The five latent factor scores reflecting travellers' attitudes towards car use and ownership are used to examine the number of underlying latent classes. Each latent class consists of respondents who share similar patterns of latent factor scores. Both for 2014 and 2016, we estimated alternative models separately. Table 4 presents the fit indices of eight subsequent models with a different number of classes. Various approaches exist to evaluate which number of latent classes is appropriate (Magidson and Vermunt, 2004). A common approach is the chi-square goodness-of-fit test. However, in situations involving sparse data, as is the case in our study, the chi-square distribution should not be used (Magidson and Vermunt, 2004). An alternative approach to assessing model fit in the case of sparse data utilises an information criterion weighting both model fit and parsimony. Most widely used in LC analysis is the Bayesian information criterion (BIC) statistic, which definition is based on the log-likelihood (LL) and the number of parameters (Npar). Log-likelihood values alone cannot be used as an index of fit because they are a function of sample size. The BIC(LL) statistic determines whether a change in the log-likelihood fails to decrease by a significant amount, for which lower values indicate a better fit (Raftery, 1995). According to the BIC values in Table 4, a four-class model is preferred for both the 2014 and 2016 data.

Testing for measurement invariance across the LC model parameters is a necessary stage in latent transitions analysis to aid the interpretation of trend data over time (Chung et al., 2011). Measurement invariance means the number and definitions of classes remain the same over time (Lanza et al., 2010). Two models were estimated to test measurement invariance across time. The first model constrained the item-response probabilities (used to assign each participant to the most likely latent class) to be equal across time (measurement invariance model), and the second model had no restrictions (measurement variance model). We used the BIC value to compare the two models (Nylund, 2007). Our results show that relying on this criterion, the fit of the constrained model is better, which indicates that the structure of the latent class patterns did not change between 2014 and 2016, i.e., the latent classes for both years show the same patterns. Section 5.1 details the sample characteristics of the four latent classes.

Table 4
Model fit of the latent class models in 2014 and 2016 (N = 1640).

	N classes	LL	BIC(LL)	Npar	df	p-value
2014	1	−10784	21,716	20	1620	0.00
	2	−10377	21,118	49	1591	0.00
	3	−10206	20,989	78	1562	0.00
	4	**−10092**	**20,976**	**107**	**1533**	**0.00**
	5	−10016	21,038	136	1504	0.00
	6	−9962	21,145	165	1475	0.00
	7	−9919	21,275	194	1446	0.00
	8	−9877	21,405	223	1417	0.00
2016	1	−10640	21,427	20	1620	0.00
	2	−10288	20,940	49	1591	0.00
	3	−10110	20,798	78	1562	0.00
	4	**−10002**	**20,795**	**107**	**1533**	**0.00**
	5	−9932	20,871	136	1504	0.00
	6	−9866	20,953	165	1475	0.00
	7	−9808	21,051	194	1446	0.00
	8	−9781	21,212	223	1417	0.00

Note. LL = Log Likelihood; BIC(LL) = Bayesian Information Criterion (based on log-likelihood); df = degrees of freedom.

4.2.2. Step 2: Specification of the latent transition model

The second step involved the specification of the latent transition model. This model resulted in a matrix of transition probabilities between the four identified latent classes over the period 2014 to 2016. We used different covariates as predictors for both initial state membership and transitions between 2014 and 2016. From previous research, we knew which variables were most likely to differ between segments based on attitudes; see, for example, the work by Anable (2005, 2013). Based on the literature, we used socio-demographic characteristics (gender, age, employment status, educational level, household composition, personal income), variables related to the built environment (urbanisation of the residential location) and mobility-related factors (driving license, PT season ticket holder). Also, time-varying covariates, such as life events, were incorporated in the model to interact with the transitions between the latent classes. Section 5.2 contains the model results.

4.2.3. Step 3. Relating latent classification scores to mode use

In the final step, mode use for different transport modes (i.e., car, train, BTM and bicycle) were regressed on the latent transition probabilities. This final step is necessary to answer our research question to what extent changes between attitude-based segments affect travel behaviour. Section 5.3 presents the results for this step.

5. Results

5.1. Latent class characteristics (results of step 1)

In step 1, the optimal number of latent classes was assessed, which resulted in four latent classes. After that, the highest mean score of the five latent factor scores served as the primary basis for labelling the four identified latent classes: cost-sensitive, car-minded, environmentally aware and social-conscious. For ease of interpretation, in our analysis, the scores of the first two statements that belonged to the 'environmental awareness' factor (see Table 1) were reversed, so a higher score implied a higher sense of environmental awareness. The mean score for each factor for each latent class remained stable over time. A brief description of the latent classes is set out below, based on the mean factor scores, as expressed in Fig. 2., the latent class characteristics (Table 5) and mode use (Table 6).

Latent Class 1 – Cost-sensitive. Cost-sensitive travellers, 33% of the sample in 2014, had a negative attitude towards the car. Their mode choice depended largely on travel costs and owning a car was not common among them. For members of this class, their financial situation was an important consideration in using or owning a car. Contrary to class 3, this class was more cost-sensitive and less aware of the environmental consequences of car use. Although class 1 and class 3 are different latent classes based on their attitudes towards car use and ownership, mode use hardly differed between these two classes. This class had a high share of participants under 29 years of age and females. Almost half of the cost-sensitive travellers had no paid job, partly because of a relatively high percentage of students.

Latent Class 2 – Car-minded. Car-minded travellers, 26% of the sample in 2014, scored very high on the car-minded factor. This means they liked travelling by car, appreciated the flexibility of driving and preferred the car in favour of other transport modes. Conversely, they tended to have lower scores on the other factors. As expected, car-minded travellers had the highest number of car trips per person per day. They rarely used public transport or cycled. The low number of trips by bicycle is very different from the behaviour of the average population in the Netherlands. Car-minded travellers were remarkably different from the other three classes in many characteristics. Car-minded travellers tended to be more often male, between 30 and 49 years old, were mostly employed, were not often PT season ticket holders and more often lived in rural areas.

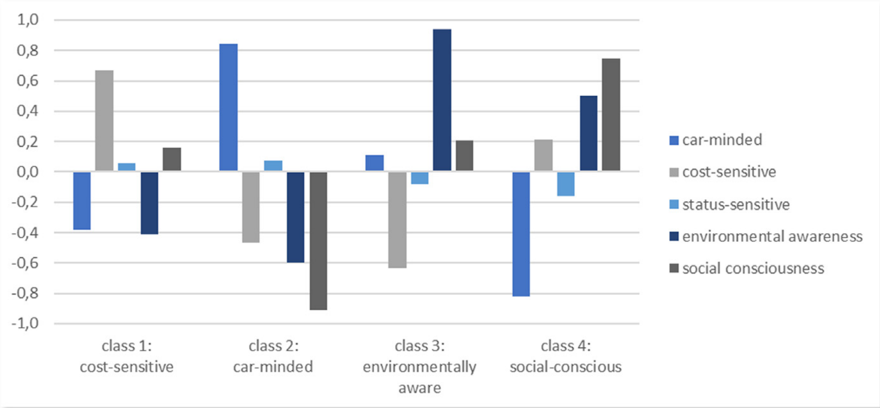

Fig. 2. Mean score of the latent factors reflecting traveller's attitudes towards car use and ownership for each latent class in 2014 (N = 1640).

Table 5
Characteristics latent classes in 2014 (N = 1640).

		class 1: cost-sensitive	class 2: car-minded	class 3: environ-mentally aware	class 4: social-conscious	Total sample
	Class size	33%	26%	23%	18%	*100%*
Indicators (factor scores)						
Car-minded	*Mean*	−0.24	0.84	0.13	−0.91	0.00
Cost-sensitive	*Mean*	0.64	−0.49	−0.63	0.35	0.00
Status-sensitive	*Mean*	0.13	0.09	−0.07	−0.28	0.00
Environmental awareness	*Mean*	−0.41	−0.60	0.94	0.50	0.00
Social consciousness	*Mean*	0.16	−0.91	0.21	0.75	0.00
Exogenous covariates (%)						
Gender	Male	42	**51**	49	37	45
	Female	58	49	51	**63**	55
Age group	18–29 yrs	**31**	17	11	22	21
	30–39 yrs	13	**24**	18	12	17
	40–49 yrs	19	**27**	22	19	22
	50–64 yrs	24	25	**34**	30	28
	> 64 yrs	13	7	16	**17**	13
Education	No or low	**16**	11	5	7	10
	Medium	**55**	50	39	43	48
	High	29	39	**56**	50	42
Employment	> 12 hr paid work	48	**75**	68	50	60
	Self-employed	4	4	**5**	**5**	4
	Student	**16**	3	2	10	8
	No paid work	32	18	25	**36**	28
Household composition	Single	24	17	18	**38**	24
	Couple without children	23	30	**35**	28	29
	Couple with children	44	**48**	44	30	42
	Other	**9**	5	3	4	6
Residential location	Urban	46	45	46	**64**	49
	Suburban	**27**	25	26	18	25
	Rural	27	**30**	28	18	26
PT season ticket holder	Yes	43	17	28	**56**	35
	No	57	**83**	72	44	65
Driving licence	Yes	83	**99**	97	85	91
	No	**17**	1	3	15	9
Personal income	No personal income	**11**	4	5	8	7
	< €1000	**27**	11	12	25	19
	€1000-€2000	36	**40**	32	35	36
	€2000-€3000	12	25	**31**	20	21
	≥ €3000	3	6	**9**	5	6
	missing	12	**14**	11	7	11
Attitude PT accessibility	Negative	19	**27**	18	12	19
	Neutral	16	**19**	**19**	13	17
	Positive	66	54	64	**75**	64

*__Bold__ numbers indicate the highest share (%) of each category across the latent profiles.

Table 6
Mode use (number of trips per person per day) of the four latent classes in 2014 (N = 1640).

		class 1: cost-sensitive	class 2: car-minded	class 3: environmentally aware	class 4: social-conscious	Total sample
Mode use (# trips per person per day)	Car	1.1	2.3	1.7	0.9	1.5
	Train	0.1	0.0	0.1	0.2	0.1
	BTM	0.1	0.1	0.0	0.1	0.1
	Bicycle	1.2	0.2	1.0	1.7	1.0

Latent Class 3 – Environmentally aware. This class, 23% of the sample in 2014, scored high on the environmental awareness factor, relative to class 4. However, this class reported relatively low scores on the cost statements. They were most aware of the harmful impact car use has on the environment. Travels costs seemed to play a minor role in their willingness and opportunities to drive. This class was not car-dependent or addicted to the car, liked to cycle and had a positive attitude toward PT accessibility (64%). Although this class rarely used PT on a weekly base, data from the MPN household questionnaire showed that more than 65% used PT at least a few times a year. This suggests they were not frequently PT users, however, they used PT for non-daily and weekly trips. This class had a high share of participants aged over 50 years. Only a small percentage of this class (11%) consisted of younger participants. Travellers who were most environmentally aware were more often higher educated and part of couples without children. Also, this class had the highest share of higher incomes.

Latent Class 4 – Social-conscious. This class, 18% of the sample in 2014, was characterised by the lowest score on the car-minded factor and the highest score on the social-consciousness factor. Also, members of this class tended to have higher scores on the cost-sensitive and environmental awareness factors. Social-conscious travellers tended to make well-considered choices in determining the best transport mode, being aware of the negative consequences of car use for society and partly affected by financial constraints. Social-conscious travellers used public transport more frequently and cycled most often of all classes. This class had a relatively high share of young adults and elderly, women, singles and participants without a driving licence. Also, social-conscious travellers more often lived in urban areas than people in the other classes, which means that other opportunities of (public or non-motorized) transport might be available.

5.2. Examining transition behaviour between latent classes (results of step 2)

Table 7 shows the estimated transition probabilities between the latent classes. The higher values on the diagonal indicate that most of the participants were in the same class in 2014 and 2016. The share of participants that stayed in the same class was higher than what other studies found in which latent classes were based on the frequency of mode use instead of attitudes (Haas et al., 2018; Kroesen, 2014; Kroesen and Cranenburgh, 2016; Molin et al., 2016). This might suggest that travellers‘ attitudes towards car use and ownership are more stable over time than the frequency of mode use, prompting us to take a closer look at the relationship with mode use (see Section 5.3).

The first class, the cost-sensitive travellers, had a high share of participants who remained in the same class between 2014 and 2016 (85%) and was also the most stable class over time. Participants who changed their attitudes towards car use and ownership switched to either the environmentally aware class (4%), the car-minded class (8%) or the social-conscious class (3%). Most participants who moved from the car-minded class transitioned to the cost-sensitive class (10%). Among the travellers who were most environmentally aware, 76% maintained the same attitudes towards car use and ownership between the two waves. Most of the participants who belonged to this class in 2014 and changed their attitudes, changed into the car-minded class (9%) or cost-sensitive class (11%). A small group (4%) switched to the social-conscious class. Table 8 indicates approximately 72% stability in the social-conscious class, which means that 28% transitioned to a different class. This mostly concerned a transfer to the environmentally aware class (16%) or the cost-sensitive class (9%). Only a small percentage transitioned to the car-minded class (3%). Conversely, all classes showed a low probability of transitioning to the social-conscious class.

Regarding the factors that made people switch to a different class, Table 8 presents the parameter estimates of the four-class transition model. All covariates that were significant in estimating initial latent class membership were retained in the analysis, and time-varying covariates were added. Also, Table 8 includes standardised coefficients and corresponding p-values for all variables. For

Table 7
Estimated latent transition probabilities between 2014 and 2016 (N = 1640).

2014	2016			
	Class 1: cost-sensitive	Class 2: car-minded	Class 3: environmentally aware	Class 4: social-conscious
Class 1: cost-sensitive	**85%**	8%	4%	3%
Class 2: car-minded	10%	**79%**	5%	6%
Class 3: environmentally aware	11%	9%	**76%**	4%
Class 4: social-conscious	9%	3%	16%	**72%**

*In **bold** the probability of staying in the same class.

Table 8
Parameter estimates of latent class membership in 2016.

2014	Parameter	2016			
		Class 1: cost-sensitive	Class 2: car-minded	Class 3: environmentally aware	Class 4: social-conscious
Class 1: cost-sensitive	Constant	0.00	−13.30 (0.24)	−49.85 (0.06)	−24.01 (0.07)
	Gender (male = ref)	0.00	−1.62 (0.12)	**−9.69 (0.05)****	**−14.61 (0.01)****
	Age 30–39 yrs (18–29 yrs = ref)	0.00	−1.68 (0.23)	1.21 (0.66)	**−45.31 (0.02)****
	Age 40–49 yrs (18–29 yrs = ref)	0.00	1.16 (0.22)	**−14.12 (0.05)****	−11.63 (0.12)
	Age 50–64 yrs (18–29 yrs = ref)	0.00	−6.22 (0.44)	−2.86 (0.78)	10.12 (0.12)
	Age > 64 yrs (18–29 yrs = ref)	0.00	−6.24 (0.57)	10.92 (0.08)	−28.99 (0.06)
	Moderately educated (low = ref)	0.00	0.70 (0.70)	−13.82 (0.39)	−6.35 (0.25)
	Highly educated (low = ref)	0.00	−0.10 (0.95)	9.84 (0.48)	**17.09 (0.02)****
	Employment (no = ref)	0.00	1.24 (0.19)	**10.12 (0.05)****	9.88 (0.09)
	Driver license (np = ref)	0.00	5.74 (0.60)	−2.08 (0.76)	**−30.40 (0.01)*****
	PT season ticket (no = ref)	0.00	−0.91 (0.29)	**15.17 (0.03)****	**19.70 (0.01)****
	Urban environment (no = ref)	0.00	0.89 (0.21)	3.29 (0.27)	11.44 (0.07)
	Attitude accessibility PT (negative = ref)	0.00	1.38 (0.22)	**−25.13 (0.02)****	−5.78 (0.17)
	Increase # children < 17 yrs (no change = ref)	0.00	0.79 (0.54)	9.66 (0.10)	16.31 (0.35)
	Decrease # children < 17 yrs (no change = ref)	0.00	−1.25 (0.27)	−2.48 (0.80)	**25.59 (0.02)****
	New job/started working (no = ref)	0.00	**1.99 (0.01)*****	**24.24 (0.02)****	−7.01 (0.21)
	Moved home (no = ref)	0.00	**0.96 (0.03)****	−5.35 (0.27)	14.86 (0.07)
Class 2: car-minded	Constant	−3.62 (0.69)	0.00	1.07 (0.96)	−14.56 (0.63)
	Gender (male = ref)	−0.43 (0.56)	0.00	−3.81 (0.23)	2.03 (0.78)
	Age 30–39 yrs (18–29 yrs = ref)	−2.56 (0.06)	0.00	**−44.78 (0.04)****	0.06 (0.99)
	Age 40–49 yrs (18–29 yrs = ref)	**−2.51 (0.04)****	0.00	−10.62 (0.29)	−2.77 (0.86)
	Age 50–64 yrs (18–29 yrs = ref)	−2.02 (0.08)	0.00	**20.14 (0.05)****	7.99 (0.61)
	Age > 64 yrs (18–29 yrs = ref)	−9.40 (0.40)	0.00	**29.36 (0.05)****	−0.29 (0.99)
	Moderately educated (low = ref)	−0.74 (0.44)	0.00	−12.76 (0.08)	1.71 (0.93)
	Highly educated (low = ref)	**−2.49 (0.05)****	0.00	−10.55 (0.07)	6.44 (0.75)
	Employment (no = ref)	−0.58 (0.51)	0.00	5.50 (0.21)	1.17 (0.93)
	Driver license (np = ref)	−0.65 (0.74)	0.00	−20.56 (0.15)	−10.97 (0.44)
	PT season ticket (no = ref)	1.45 (0.08)	0.00	**–23.13 (0.04)****	−1.02 (0.90)
	Urban environment (no = ref)	**−1.64 (0.03)****	0.00	**16.52 (0.05)****	7.72 (0.44)
	Attitude accessibility PT (negative = ref)	7.95 (0.35)	0.00	−6.38 (0.09)	5.97 (0.50)
	Increase # children < 17 yrs (no change = ref)	−8.13 (0.55)	0.00	**34.19 (0.04)****	9.87 (0.32)
	Decrease # children < 17 yrs (no change = ref)	−2.10 (0.22)	0.00	−14.85 (0.27)	1.82 (0.91)
	New job/started working (no = ref)	−2.31 (0.09)	0.00	**27.94 (0.05)****	9.76 (0.39)
	Moved home (no = ref)	−0.18 (0.88)	0.00	**−38.27 (0.05)****	−5.21 (0.67)

(*continued on next page*)

Table 8 (*continued*)

2014	Parameter	2016			
		Class 1: cost-sensitive	Class 2: car-minded	Class 3: environmentally aware	Class 4: social-conscious
Class 3: environ-mentally aware	Constant	−17.36 (0.22)	−10.13 (0.76)	0.00	−15.96 (0.48)
	Gender (male = ref)	−4.47 (0.09)	6.94 (0.07)	0.00	−9.46 (0.15)
	Age 30–39 yrs (18–29 yrs = ref)	8.36 (0.33)	−12.72 (0.06)	0.00	6.17 (0.52)
	Age 40–49 yrs (18–29 yrs = ref)	**−45.21 (0.00)*****	**−24.66 (0.02)****	0.00	2.92 (0.77)
	Age 50–64 yrs (18–29 yrs = ref)	−15.68 (0.07)	**−13.76 (0.05)****	0.00	2.05 (0.85)
	Age > 64 yrs (18–29 yrs = ref)	**23.53 (0.03)****	−28.77 (0.29)	0.00	2.11 (0.82)
	Moderately educated (low = ref)	−3.92 (0.20)	15.52 (0.45)	0.00	3.86 (0.65)
	Highly educated (low = ref)	**−29.71 (0.00)*****	−15.22 (0.47)	0.00	−11.96 (0.28)
	Employment (no = ref)	**9.78 (0.05)****	**15.56 (0.05)****	0.00	−11.77 (0.13)
	Driver license (np = ref)	−15.95 (0.16)	3.06 (0.80)	0.00	−13.49 (0.09)
	PT season ticket (no = ref)	−4.31 (0.30)	**−30.38 (0.02)****	0.00	12.81 (0.14)
	Urban environment (no = ref)	**9.76 (0.02)****	2.07 (0.46)	0.00	−11.84 (0.09)
	Attitude accessibility PT (negative = ref)	3.43 (0.65)	−7.32 (0.09)	0.00	−3.10 (0.36)
	Increase # children < 17 yrs (no change = ref)	**23.58 (0.00)*****	**19.37 (0.01)*****	0.00	−3.26 (0.76)
	Decrease # children < 17 yrs (no change = ref)	**26.18 (0.00)*****	−1.48 (0.94)	0.00	−0.66 (0.98)
	New job/started working (no = ref)	−7.60 (0.16)	**20.90 (0.00)*****	0.00	**20.46 (0.04)****
	Moved home (no = ref)	**−19.90 (0.03)****	−18.30 (0.11)	0.00	22.07 (0.09)
Class 4: social-conscious	Constant	3.30 (0.72)	−8.02 (0.68)	−8.03 (0.56)	0.00
	Gender (male = ref)	−2.72 (0.45)	4.19 (0.50)	**−12.32 (0.03)****	0.00
	Age 30–39 yrs (18–29 yrs = ref)	−19.33 (0.36)	−6.65 (0.68)	−6.55 (0.17)	0.00
	Age 40–49 yrs (18–29 yrs = ref)	**−39.89 (0.05)****	−1.20 (0.93)	**−45.52 (0.02)****	0.00
	Age 50–64 yrs (18–29 yrs = ref)	**−25.84 (0.07)****	−13.02 (0.41)	**−15.76 (0.05)****	0.00
	Age > 64 yrs (18–29 yrs = ref)	10.12 (0.12)	−2.90 (0.84)	16.06 (0.09)	0.00
	Moderately educated (low = ref)	**−19.07 (0.05)****	−7.26 (0.32)	**−51.07 (0.01)****	0.00
	Highly educated (low = ref)	**−39.28 (0.04)****	−13.73 (0.21)	−10.97 (0.07)	0.00
	Employment (no = ref)	9.98 (0.11)	−10.60 (0.30)	4.02 (0.23)	0.00
	Driver license (np = ref)	−8.68 (0.18)	6.69 (0.72)	5.19 (0.67)	0.00
	PT season ticket (no = ref)	1.56 (0.58)	−3.49 (0.67)	**−20.72 (0.01)****	0.00
	Urban environment (no = ref)	**−15.36 (0.03)****	4.79 (0.33)	**−8.25 (0.03)****	0.00
	Attitude accessibility PT (negative = ref)	−4.19 (0.34)	**−17.89 (0.09)***	−3.90 (0.32)	0.00
	Increase # children < 17 yrs (no change = ref)	8,73 (0.72)	2.24 (0.88)	**59.45 (0.01)****	0.00
	Decrease # children < 17 yrs (no change = ref)	**35.86 (0.04)****	−8.38 (0.58)	**15.29 (0.05)****	0.00
	New job/started working (no = ref)	−30.19 (0.09)	7.31 (0.60)	**35.54 (0.01)****	0.00
	Moved home (no = ref)	9.14 (0.56)	−11.58 (0.46)	**9.33 (0.05)****	0.00

Note: P-values are presented in parentheses; significant p-values are in **bold.**

** $p < 0.05$.

*** $p < 0.01$).

every variable in Table 8, we found significant results for transitioning from one class to another.

Among the cost-sensitive travellers, employed and higher educated people had a higher chance of switching to a different class, especially to the environmentally aware and social-conscious class, possibly related to having a higher income and a lower travel cost-sensitivity. Cost-sensitive travellers with a PT season ticket did not switch to the car-minded class; however, they were more likely to transfer to the environmentally aware or social-conscious class. Conversely, females and people with a drivers' license are less likely to switch to another class. Finally, a new job or moving home significantly influenced the attitudes of cost-sensitive travellers.

As we have seen, car-minded travellers had a probability of 79% of staying in the same class in our study. After an increase in the number of children in the household or a new job, car-minded travellers were more likely to switch to the environmentally aware class. Also, car-minded travellers aged over 50 years had a higher chance of changing to the environmentally aware class. Apparently, for car-minded travellers, these life-changing moments and ageing form a trigger for reconsideration their attitudes towards car use and ownership. None of the variables showed a significant effect on transitioning from the car-minded to the social-conscious class.

Of the travellers who were most environmentally aware, higher-educated people had a higher probability of remaining in this class. This corresponds to the results of other studies. For example, Anable (2005) found that within the travel segment ‘aspiring environmentalists’ (i.e., people who feel the highest responsibility concerning environmental problems), the share of higher-educated people is very high. Class members living in urban areas were less likely to become car-minded. In general, the level of public transport services and the availability of bicycle facilities in Dutch cities are excellent, so there is no need to change car attitude, especially if people care about the environment.

As expected, an increase in the number of children younger than 17 had a higher probability of switching to class 1 (parents become more cost-sensitive) and class 2 (parents experience travelling by car as more convenient). Moving to class 1 and 2 also implies less environmentally awareness. This contrasts with the so-called ‘legacy hypothesis’, which states that parents become more concerned about the environment. However, Thomas et al. (2018) did not found evidence in support of this theory. In line with Thomas et al., we found mixed results, suggesting changes in environmental concern after having a child depends on other factors such as individual attitudes in relation to practical considerations such as comfort. When children reach adulthood, members from this class were more likely to transition to the cost-sensitive class. This seems counter-intuitive; however, when children leave home, parents become less car-oriented as they don’t have to bring and collect their children anymore. Job changes make them more likely to switch to the car-minded or social-conscious class. Turning to the social-conscious profile might be the result of a new work location with excellent PT facilities, while the opposite might be right for changing to the car-minded profile.

Finally, for social-conscious travellers, increasing age had a negative association with transitioning to other classes. This might suggest that car use and ownership are indeed less widespread among young adults (Kuhnimhof, 2012, 2011), reflected by the higher share of young people in this class. Increasing age does not seem to affect this; however, members of this class showed the highest transition probabilities. From this point of view, it is arguable that other factors are responsible for developing a more positive attitude towards the car, such as being employed, starting or changing jobs, moving and changes in household composition. These characteristics all show significant effects for switching to the environmentally aware profile. Furthermore, PT season ticket holders and higher educated people are less likely to switch to other classes.

Although attitude-based segments appear very stable over time, we draw some interesting conclusions from the observed switching behaviour. We found the highest transition probabilities for less frequent car users (i.e. social-conscious travellers). This suggests that once people use the car more frequently, changes in attitudes become less likely. Furthermore, we found that car use and ownership were less prevalent among younger adults, as both the cost-sensitive and the social-conscious profile have a higher share of younger people. Less car dependency among younger adults is in line with what was found in previous studies (Klein and Smart, 2017; Delbosc, 2016; Kuhnimhof et al., 2013). Even so, for cost-sensitive and social-conscious travellers, increasing age is not positively associated with transitioning to more car-oriented profiles. One explanation might be that in the Netherlands, younger people stay longer at home, extend their study, and postpone buying a car (CBS, 2018). Because of this changing social position of young adults, their attitudes remain the same for a longer period. Only when younger adults face life events, such as moving, starting a job or become parents, transitioning to more car-oriented profiles appears more likely. This suggests that there is no fundamental difference in the popularity of the car among young adults. However, people become more car-dependent at a later stage.

The results set out above show that life events were significantly associated with transitioning between the four latent classes. To explore the impact of life events on changes in the membership of the latent classes further, we compared the share of participants who switched to a different class and had a life event with the share of participants who stayed in the same class and experienced a life event (Table 9). In general, transitioning to a different class was associated with a higher share of participants who had a life event. In particular, the non-car minded’ profiles showed significantly more movers after the occurrence of a life event. Also, an increase in the number of children resulted in a substantially higher share of travellers who were environmentally aware and social-conscious transitioning to another class. Because life events often coincide, we also compared the percentage of stayers and movers for people facing more than one life event. As can be seen from Table 9, all profiles showed significantly more movers when different life events occur in the same year. These results are in line with other studies, which found a positive relationship between life events and, for example, car preferences (Olde Kalter et al., 2018).

5.3. Impact of changing between latent classes on mode use (results step 3)

Besides the dynamics of change in attitudes towards car use and ownership, we were also interested in the effects of this switching behaviour on changes in mode use. In our descriptive analysis, we found a meaningful and significant difference in mode use between

Table 9
Share of respondents with a life event between 2014 and 2016.

Classes	New job		Moving		Increase children		New job, moving or increase children	
	Stayers	Movers	Stayers	Movers	Stayers	Movers	Stayers	Movers
Cost-sensitive	17%	**59%**	7%	**20%**	5%	5%	26%	**67%**
Car-minded	17%	**30%**	7%	6%	9%	5%	29%	**36%**
Enviromentally aware	11%	**24%**	8%	10%	6%	**16%**	20%	**35%**
Social-conscious	19%	23%	9%	**13%**	2%	**11%**	25%	**40%**

Note: Significant differences between stayers and movers are in bold.

Table 10
Parameter estimates 3-step model approach: Predicting the number of trips by car, train, BTM and bicycle with latent transition probabilities.

From	To	Change in the number of trips by:		
		Car	PT	Bicycle
		β	β	β
Cost-sensitive	Cost-sensitive	−0.35	−0.12	−0.23
	Car-minded	0.08	**−0.23**	−0.02
	Environmentally aware	0.36	026	0.01
	Social-conscious	−0.09	0.09	0.23
Car-minded	Cost-sensitive	−0.30	0.09	−0.14
	Car-minded	0.24	0.04	−0.00
	Environmentally aware	−0.10	**−0.26**	0.55
	Social-conscious	**−0.65**	0.13	−0.40
Environmentally aware	Cost-sensitive	−0.41	0.07	0.38
	Car-minded	**0.94**	**−0.18**	−0.14
	Environmentally aware	−0.04	0.05	−0.05
	Social-conscious	−0.49	0.06	−0.19
Social-conscious	Cost-sensitive	−0.00	−0.02	0.16
	Car-minded	**0.68**	**−0.24**	−0.09
	Environmentally aware	0.40	−0.01	−0.09
	Social-conscious	−0.19	**0.12**	0.03

* In bold: significant estimates (p-value < 0.05).

the four estimated latent classes (see Section 5.1). The results of the latent transition model made us interested in whether stability or change in attitudes towards car use and ownership might explain stability or change in mode use. Following the three-step approach developed by Vermunt (2010) and extended by Bakk et al. (2013), we used the posterior latent transition probabilities to predict changes in the number of trips by car, public transport and bicycle (Table 10).

A change in the number of trips by car was significantly ($p < 0.05$) and positively affected by changing from both the environmentally aware profile and social-conscious profile to the car-minded profile. Other transitions to the car-minded profile did not increase car use. Also, changing from the car-minded profile to a less car-oriented profile had only a significant and negative effect on the number of trips by car of changers to the social-conscious profile. This suggests that in most cases, different attitudes towards car use and ownership did not directly affect the frequency of car use.

6. Discussion

In the past decade, several studies explored the attitude-behaviour relationship in transportation research. In the current paper, we developed a latent transition model to examine the impact of temporal dynamics in attitudes on transport mode choice. Latent classes were based on traveller's attitudes towards car use and ownership. This study shows that traveller's profiles based on attitudes are very stable over time. Kroesen and Cranenburgh (2016) and Haas et al. (2018) found lower probabilities for staying in the same class. However, these classes were based on the frequency of mode use and not, as in this study, attitudes. This suggests that attitudes are more stable over time than the frequency of mode use. One possible explanation for fewer observed changes in attitudes is that we used only two waves of data and these changes are difficult to measure in a relatively short period. When conditions change, there might be a possible delayed response of changes in travellers' attitudes.

Based on the literature, we expected transitioning to more car-oriented profiles to be positively associated with car use and transitioning to less car-oriented profiles negatively related to car use. For example, Kroesen (2014) found that switching from a 'multimodal' profile to a 'strictly car users' profile is significantly and positively related to the frequency of car use. However, in that study, latent classes were based on the frequency of mode use, which means that transitioning from one class to another has a direct relationship with the frequency of mode use. The results of the present study show that in most cases, there is no significant relationship between changes in attitudes and the frequency of car use. Although the outcome of several studies in other countries found indications of the opposite effect (Delbosc and Currie, 2013; Dutzik and Baxandall, 2013), the empirical results of our study are in line with earlier findings by Jorritsma and Berveling (2014) in the Netherlands, based on a one time survey among young adults. The fact that different attitudes towards car use and ownership did not directly affect the frequency of car use might reflect that people do not directly change their mode choice behaviour when they become more or less car-oriented, and travellers might postpone changes in the frequency of car use. A more logical explanation is that individuals who switch to a different class already show behaviours that fit in the class that they are moving to. This is confirmed by Kroesen et al. (2017), who found people are more likely to adjust their attitudes in such a way that it matches their behaviour. Also, Thøgersen (2006) found that travel mode choices are strongly influenced by habits, despite changes in personal beliefs and attitudes.

We identified different attitude-based segments, each segment existing of individuals with unique characteristics and behaviours. The identification of differences in attitudes towards car use and ownership between sub-groups, and stability in these attitudes, can help policymakers to develop specific policy strategies for these sub-groups. For example, to stimulate more sustainable modes of transport, policymakers could develop policy measures targeting “car minded” or “non-car minded” people after a life event (e.g. moving house, childbirth) when they are more likely to switch to less or more car-oriented profiles. However, this study also confirms that changing attitudes of car-minded travellers is very hard, considering their low chance of transitioning to less car-oriented profiles. Although we focus in the present paper on the impact of changes in personal conditions, we know changing the attitude of die-hard drivers is also found to be difficult in practice with ‘soft’ measures or improvements of the quality of alternative modes. For example, stated preference and early adopter studies on mobility innovations, such as bike and car-sharing and mobility-as-a-service, typically find infrequent car users and multi-modal travellers as the most likely adopters (Burghard and Dütschke, 2019; Ho et al., 2018) and car-sharing to mainly replace a second or third car (Nijland and Van Meerkerk, 2017). This means policy makers should make a well-informed decision about the target group and suitable measures. However, as we found attitudes are very stable over time, it is still the question if policy makers should target on attitudes, behaviour or both? Testing interventions that focus on attitudes or behaviour can help to improve our understanding of temporal dynamics in attitudes and behaviour.

7. Limitations and future research

One of the limitations of this study is that we examined the attitude-behaviour relationship in one direction. Examining the reciprocal relationship between attitudes and behaviour requires the use of panel data. With panel data, attitudes and behaviour at time point 1, can be explained by attitudes and behaviour at time point 0 and vice versa. There are a few examples of studies that examined this reciprocal relationship. Thøgersen (2006) developed a cross-lagged panel model to explore the causal relationship between attitudes and public transport use and found several significant effects in both directions. Kroesen et al. (2017) investigated the mutual relationship between attitudes and travel behaviour, and concluded that travellers with a difference between their behaviour and attitude are more inclined to change their attitudes. Because our primary goal of interest was to identify travellers’ profiles based on their attitudes towards car use and ownership, to examine switching behaviour between these latent profiles and the relationship with mode use, we focussed on the attitude-behaviour relationship. However, including the reciprocal relationship between attitudes and behaviour in this approach will enhance our understanding of the direction of causation, and therefore is an interesting topic for further research.

Another limitation is that only two waves of data exist with the measurement of attitudes towards car use and ownership. An important direction for future research is to repeat the measurement of attitudes using the dedicated surveys analysis in future waves of the panel survey, for example, every two years. A longer period could provide more variation in changes in attitudes and mode use for different population segments over time, and both first-order and second-order effects could be included. Similarly, a latent transition model can be implemented to analyse the impact of transport measures in the attitudes before and after the implementation. Bamberg et al. (2003) showed that interventions affect travel behaviour through changes in attitudes.

One of our research questions was to examine the impact of life events on changes between attitude-based segments. We did find that life events were significantly associated with transitioning between the four identified latent classes and that all profiles showed significantly more movers when life events coincide in the same year. However, we did not examine the impact of two specific related life events. For example, increased car ownership is more likely after a new job, except when household income reduces, and someone moves to an urban area at the same time. In future research, it will be interesting to examine such relationships and the impact of these interactions on attitudes and travel behaviour.

Furthermore, in our analysis, we used one type of attitudes (i.e. attitudes towards car use and ownership). Changes in other mode attitudes might also affect changes in travel behaviour, which can be explored as well. Also, a relative analysis of observable versus unobserved (latent) elements could be conducted. Finally, additional models can be developed that not only look at the impacts of changes in attitudes on mode choice but also on trip distance and kilometres driven. Overall, it can be said that there are some exciting topics for further research.

8. Conclusions

In this study, we examined the impact of changes in traveller’s attitudes over time, and the effect of these changes on mode use, using panel data of 1640 Dutch respondents from 2014 and 2016. Firstly, based on 16 different statements, we identified five factors reflecting travellers’ attitudes towards car use and ownership. Secondly, we developed a latent transition model to investigate transitions between different population segments and used the five factors reflecting attitudes towards car use and ownership to identify these segments. Shifts to more and less car-oriented profiles were investigated, including the influence of life events on these changes. Thirdly, we examined the relationship between transitioning behaviour between the latent classes and changes in mode use.

One of the main conclusions of this paper is that latent classes can be distinguished based on attitudes towards car use and ownership. And, these classes, which are related to socio-economic profiles, influence the stability over time of both attitudes and behaviour. Furthermore, three specific conclusions can be derived from the results of this paper.

Firstly, in our sample, we have identified four latent profiles: cost-sensitive, car-minded, environmentally aware and social-conscious. The four latent profiles represent clusters of travellers with different personal values about car use and ownership, while at the same time travel behaviour can be the same. Particularly, cost-sensitive and social-conscious travellers score differently on the five car attitude factors; however, they show a similar frequency of car use.

Secondly, we examined changes in the latent profiles reflecting travellers’ attitudes towards car use and ownership over time, which is not often done in the literature. The latent transition analysis revealed that most of the participants remained in the same class between 2014 and 2016. The probability of staying in the same class lies between 72% (social-conscious travellers) and 85% (cost-sensitive travellers).

Thirdly, we predicted observed changes in mode use by the estimated latent transition probabilities. The frequency of car use was not significantly affected by changes in travellers' attitudes towards car use and ownership, except for social-conscious travellers who transitioned to the car-minded class.

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