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# Latent classes of daily mobility patterns: the relationship with attitudes towards modes

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## Abstract

Active modes (i.e. walking and cycling) have received significant attention by governments worldwide, due to the benefits related to the use of these modes. Consequently, governments are aiming for a modal shift from motorised to active modes. Attitudes are generally considered to play an important role in travel behaviour. Understanding the relationship between the attitude towards modes and the daily mobility pattern, can support policies that aim at increasing the active mode share. This paper investigates the daily mobility patterns of individuals using a latent class cluster analysis. The relationship between these classes and attitudes towards modes is investigated. Data of the Netherlands Mobility Panel (MPN) of the year 2016 is used, in combination with a companion survey focussing on active modes. This study identifies five classes of mobility patterns: (1) car and bicycle users, (2) exclusive car users, (3) car, walk, and bicycle users, (4) public transport + users, and (5) exclusive bicycle users. Eight factors of attitudes towards modes are identified: five mode related attitudes, two public transport related attitudes, and one related to the prestige of using modes. The results show that the majority of the users exhibits a multimodal daily mobility pattern. Generally, individuals are more positive toward used modes, compared to unused modes. Furthermore, a high level of travel mode consonance is found. When this is not the case (dissonance), often active modes or sustainable modes are preferred. Consequently, when the goal is achieving a higher active mode share, some individuals need to be targeted to change their mobility portfolio (exclusive car users and car and bicycle users), whereas others should be encouraged to increase the use of active modes at the cost of car use (public transport + users and car, walk, and bicycle users).

**Keywords** Daily mobility pattern · Travel behaviour · Attitudes towards modes · Latent class cluster analysis

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## Introduction

Walking and cycling (i.e. active modes) have gained significant attention by governments worldwide. They foresee many benefits from high shares of active mode usage. Examples are increased health for individuals, but also reduced emissions and traffic jams if active mode usage replaces car usage. Consequently, many governments have set goals for increasing the active mode share over the next decades (Pan-European Programme 2014). Ideally, this increase in active mode use would be paired with a decrease in car use, so that more sustainable mobility patterns emerge. Kroesen (2014) found that single-mode (habitual) users were less likely to change their mobility pattern over time compared to multi-mode users. Therefore, it is important to evaluate the overall daily mobility pattern of individuals and identify traveller types, as this can provide input for whom to target with policies designed to attain the desired shift towards active modes.

Attitudes are generally considered to play an important role in determining the mode choice and, more general, travel behaviour of individuals (Gärling et al. 1998). An attitude is broadly defined as an affective evaluation, regarding an object or behaviour, which can be positive or negative (Ajzen and Fishbein 1977). The relationship between attitude and behaviour has been translated to theoretical frameworks, the most prominent being the Theory of Planned Behaviour (Ajzen 1991), which has often been applied in the travel behaviour domain (e.g. Bamberg et al. 2003; Heinen et al. 2011; Muñoz et al. 2013). Furthermore, attitudes have been introduced into the discrete choice modelling theory, by developing models that can accommodate subjective latent constructs, like the hybrid choice model (Ben-Akiva, et al. 1999). This model has also been applied in the travel behaviour domain (e.g. Vij et al. 2013; Kamargianni and Polydoropoulou 2013; Habib et al. 2014; Krueger et al. 2018). Two main approaches of investigating the relationship between attitudes and travel behaviour have been identified.

The first approach focusses on quantifying the relationship between attitude towards a mode and the mode choice at a trip-level, while using the abovementioned theoretical frameworks and applying discrete choice modelling theory. Several studies investigate this for a single mode, as a binary choice (e.g. to cycle or not to cycle), while other studies research a broader spectrum of modes. Due to the increased interest in active modes, research has often explored walking and cycling, albeit in a binary fashion. Several studies have investigated the impact of the attitude towards walking on the choice to walk (e.g. Lindelöw et al. 2014; Rodríguez and Vogt 2009). Similarly, past research quantified the impact of the attitude towards cycling on the choice to cycle (e.g. Heinen et al. 2011; Ma and Dill 2015; Fernández-Heredia et al. 2016). Another body of literature has investigated this relationship for multiple modes, i.e. they investigate the one-on-one relationship but accommodate multiple modes (e.g. Akar and Clifton 2009; Maldonado-Hinarejos et al. 2014; Kamargianni et al. 2015). Generally, findings suggest that if a person has a positive attitude towards a mode, the probability of using that mode increases. This approach investigates the mode choice at a trip-level, thus ignoring that individuals have a mobility portfolio and use multiple modes on a daily basis. Therefore, this approach does not show the relationship between mobility patterns and attitudes towards different modes.

The second approach focusses on mobility patterns of individuals. This approach also often applies the aforementioned theoretical frameworks. A common way to deal with the many different mobility patterns that can be present in the population, is to reduce the complexity by identifying segments or classes of individuals. In this, often attitudes are used to help classify individuals into classes or segments. Many different studies set out

to identify classes of individuals based on mobility patterns, attitudes, and other aspects, which is often referred to as modality styles or mobility styles (e.g. Krizek and Waddell 2002; Lanzendorf 2002; Diana and Mokhtarian 2009; Molin et al. 2016; Krueger et al. 2018). These studies integrate attitudes and observed behaviour into one model, consequently assuming a relationship between attitude and behaviour. An issue arises when deriving input for policies from these segments, as it is argued that attitudes are endogenous to travel choices and should not be used as targets for policy design (Chorus and Kroesen 2014). Consequently, it might be better to use only observable variables of the mobility pattern for the segmentation analysis, so that policy design can be tailored to population segments.

To overcome the issues related to trip-level research and endogeneity of attitudes, this study investigates the relationship between daily mobility patterns of individuals and the attitudes towards modes by including only observable variables in the segmentation analysis and by explicitly investigating the relationship between attitudes and mobility patterns. This paper presents the findings of a latent class cluster analysis on individuals' daily mobility patterns, after which the individuals in each class are compared on differences and similarities in their attitudes towards modes. Furthermore, within each class the attitudes towards modes are compared to the observed behaviour to identify whether individuals travel using their most preferred mode. We use census data from the Netherlands. The Netherlands is characterised by a high share of active mode use, consequently we expect a diverse range of mobility pattern clusters. The findings provide insights into how the overall mobility pattern of individuals relates to their attitude towards modes. The results of this study can be used to identify which groups of individuals to target in order to achieve a higher share of active mode usage by means of policy interventions.

The remainder of this paper is organised as follows. The second section describes the data collected for this study and explains the data filtering process. The third section details the research methodology. In the fourth section the results of the analysis are presented and discussed. Finally, the fifth section concludes this study.

## Data collection and filtering

The data that is collected for this research is introduced and the data filtering procedure is described.

### Data collection

This study uses census data from the Netherlands Mobility Panel (MPN). This is a longitudinal household panel, which was commenced in 2013 with the goal of investigating the changes in travel patterns of individuals and households over a longer period of time. The panel is to a large extent representative of the Dutch population, although teenagers and low-income individuals are slightly underrepresented. Every autumn, panel members fill in a personal survey, household survey and three-day travel diary. The personal survey focuses on personal characteristics and asks questions regarding mode preferences for different activity purposes and the attitude of individuals regarding motorized modes and the bicycle. The household survey contains questions regarding household characteristics and ownership or availability of modes. Finally, in the travel diary every individual is asked to write down all the trips made over the course of three days, including the mode of transport, the trip purpose and the distance

covered. We refer the reader to Hoogendoorn-Lanser et al. (2015) for a detailed description of the MPN surveys.

In this study, we investigate the relationship between the daily mobility patterns and attitudes towards modes. The MPN survey contains questions on the attitudes towards motorized modes (i.e. car, train and local public transport) and the bicycle. It does not address walking, even though walking is often used as the main mode of transport in the Netherlands [19% of all trips (CBS 2018)]. In summer 2017, an additional survey on the perceptions, attitudes, and wayfinding styles towards active modes (coined PAW-AM) was distributed among the respondents of the MPN panel, with the goal of enriching the MPN dataset in relation to active modes. We distributed the survey among respondents of the MPN survey, who indicated that they walked or cycled at least once in the last year (consequently excluding 1.3% of the respondents of the MPN panel that did not walk or cycle and are assumed to be largely inactive).

### Data filtering

To perform this research, we need to have data on both the attitude towards modes and mobility patterns. As the attitude towards walking is only measured in 2017, we cannot make use of the longitudinal nature of the MPN dataset. The MPN data of the year 2016 is used, because this dataset contains the most recent travel diaries. Consequently, because we make use of cross-sectional data, we cannot infer causality of the relationship between attitudes and mobility patterns, but only investigate its existence. Next, we merge the MPN surveys (personal, household, and three-day travel diary) and the PAW-AM survey, enabling a complete overview of attitudes towards modes, personal and household characteristics, and daily mobility patterns. Consequently, only individuals that have filled in both the MPN and PAW-AM surveys are included in this study, resulting in a total of 2871 individuals.

The MPN data collection took place in autumn 2016 (September through November), whereas the PAW-AM survey was distributed in summer 2017 (June). During the elapsed time, several major changes or life events could have occurred. The life events that drastically change mobility patterns, such as changing jobs or moving houses, need to be taken into account. We have therefore excluded individuals that have experienced such a life event. Consequently, the final dataset used in this study consists of 2425 individuals.

## Methodology

In this section the methodology for analysing the relationship between daily mobility patterns and attitudes towards modes is presented. The first subsection discusses the definition and classification of the daily mobility patterns. The approach for analysing the attitudes towards modes is described in the second subsection. Finally, in the third subsection the methodology for analysing the relationship between the classified daily mobility patterns and attitudes towards modes is presented. The research methodology is depicted in Fig. 1.

### Daily mobility patterns

The daily mobility pattern can be defined in different ways; therefore, we start by providing the definition used in this study. Afterwards, we describe the approach for classifying the daily mobility patterns.
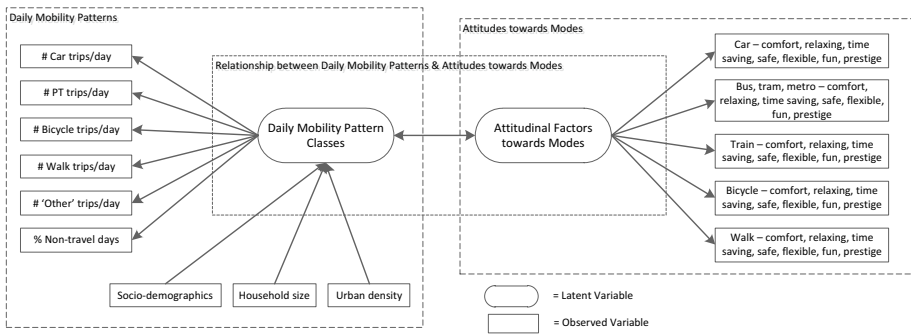
**Fig. 1** Research methodology

## Defining the daily mobility pattern

The definition of the daily mobility pattern, based on the three-day travel diary, should satisfy two conditions. First, it should reflect the mode choices of individuals. Second, it should take into account a preference hierarchy of the individual towards different modes. Three possible indicators for defining the daily mobility pattern have been proposed in the literature (e.g. De Haas et al. 2018): distance per mode, travel time per mode, and number of trips per mode. Table 1 provides the mean and standard deviations of each of the definitions for the modes in our dataset: car, public transport (PT), bicycle, and walk.

The number of trips per mode is found to be the most reliable in self-report studies (De Haas et al. 2018). It also satisfies both conditions. The use of distance would result in the overrepresentation of the car and public transport in the mobility pattern, which might not correctly capture the preferences of individuals. It shows that for longer distances these modes are more attractive, but for shorter trips we cannot conclude anything on the preferences of individuals. The use of travel time would improve the representation of the mode choices and preferences, but here we see very large standard deviations. Especially for public transport this deviation is large, mostly because this mode encompasses both inter-city (train) and intra-city (bus, tram, and metro) trips. Therefore, we define the daily mobility pattern based on the number of trips reported per mode. We average the number of trips per day as reported in the three-day travel diary, to identify the daily mobility pattern.

In addition, we identify two other aspects that need to be addressed as part of the classification of the daily mobility pattern. First, trips that are marked as unreliable (e.g. detours, wrong mode assigned) (9.2%), exceptional modes (0.9%), and trips abroad (0.7%) are present in the dataset. Excluding these trips creates incomplete mobility patterns. Therefore, the category "other" is added to classify these trips. Second, on some days an individual

**Table 1** Characteristics of the average daily mobility pattern of individuals in the data

| Mode | Number of trips Mean (SD) | Distance Mean (SD) | Travel time Mean (SD) |
|---|---|---|---|
| Car | 1.5 (1.6) | 27.9 (66.2) | 34.8 (44.7) |
| Public transport | 0.2 (0.5) | 6.8 (25.9) | 11.1 (38.2) |
| Bicycle | 0.9 (1.3) | 2.8 (5.4) | 13.4 (22.8) |
| Walk | 0.4 (0.9) | 0.4 (1.2) | 5.9 (16.4) |

does not travel. Non-travel is operationalized by the share of non-travel days out of the reported days.

In sum, a total of six indicators define the daily mobility pattern of individuals: the number of trips by car, public transport (PT), bicycle, or walking as the main mode, the number of "other" trips, and the share of non-travel days.

Daily mobility patterns during the week and weekend are very different. Generally, travel during the week is more structured due to work and school. In the weekend individuals travel less, and non-travel occurs more often (Hoogendoorn-Lanser et al. 2015; De Haas et al. 2017). Therefore, we focus on the weekdays for the analysis of daily mobility patterns.

## Classifying the daily mobility patterns

The daily mobility patterns are analysed by applying a latent class cluster analysis (LCCA) using *Latent Gold* (Vermunt and Magidson 2005). This method assigns individuals to classes on a probabilistic basis. It is generally preferred over deterministic clustering techniques, because of the reduction in the misclassification bias (Vermunt and Magidson 2002). Furthermore, LCCA allows for the use of statistical criteria to determine the optimal number of classes and the significance of model parameters can be assessed.

The LCCA assumes that one latent variable can explain the associations between the indicator variables, which is a categorical variable. Each individual has a probability to belong to each class, based on its characteristics. These characteristics are called covariates and are represented by for example socio-demographics. The covariates are used to predict the degree of class membership. The LCCA model therefore consists of two parts: a structural part where the covariates are used to predict the class membership of individuals, and a measurement part where the latent classes explain the associations between the indicators (Vermunt and Magidson 2005).

The active covariates cannot be endogenous to the indicators. An example of a non-suitable active covariate in our case is the possession of a driver's license, which is largely endogenous to the number of car trips. Seven suitable active covariates were identified from literature (e.g. De Haas et al. 2018; Molin et al. 2016), namely urban density, occupation, education level, working hours, number of household members, gender, and age.

Furthermore, inactive covariates are included in the model. These do not help in predicting class membership, but can afterwards help understand the composition of each class. In this study we include ownership (endogenous), distance, and the relevant excluded active covariates as inactive covariates.

In the LCCA, the appropriate number of classes is determined by first estimating only the measurement part of the model, thus by only including indicators. This means that no covariates are used yet for determining class membership. The appropriate number of classes to model daily mobility patterns can be decided by using statistical criteria like the Bayesian Information Criterion (BIC) and the relative increase of log-likelihood per added class, which should exceed a threshold of 4% (Nylund et al. 2007). Furthermore, as we want to statistically test the relationship between the daily mobility pattern classes and attitudes towards modes, we need sample sizes per cluster that allow us to do this. To ensure that differences between cluster sizes remain limited, we set the smallest cluster size to 8% of the data. We test models with 1–10 classes, where the number of classes is determined based only on the six daily mobility pattern indicators. When the number of classes is decided upon, the model is estimated as a combined measurement and structural

model, i.e. with both indicators and active covariates. The initial values of the model were examined; as local optima can be reached in the optimisation process. The best performing setting in the measurement model is used in the combined model, which is tested in terms of stability and performance. The best combination of active covariates, based on improvement in log-likelihood and stability, results in the final model. The combined model is then also estimated for $n+1$ and $n-1$-classes, to check if the n-class model is still the best model.

## Attitudes towards modes

De Vos (2018) mentions that to measure the attitude towards modes, statements need to be presented to individuals, which are framed in a way that enables comparison between attitudes towards different modes. He argues that this is achieved by asking about aspects of different modes (e.g. fun) and asking individuals about their opinion on a Likert-scale (with five or seven answers). This method for asking about individuals' attitudes towards modes has been applied by for example Anable and Gatersleben (2005), Molin et al. (2016), Kroesen et al. (2017) and Kroesen and Chorus (2018).

The questions related to the attitudes towards modes in the MPN and PAW-AM surveys are framed according to the method mentioned by De Vos (2018). The respondents were asked seven attitudinal questions per mode. These questions pertain to *comfort, relaxation, time saving, safety, flexibility, fun and prestige related to using those modes*. Each of these questions was asked in relation to the following five modes: car, bicycle, walking, train (inter-city PT), and bus/tram/metro (BTM—intra-city PT). Because all respondents answer the questions of attitudes towards modes, the public transport modes can be included separately. The questionnaire employed a five point Likert-scale ranging from 'completely agree' to 'completely disagree' (Olde Kalter et al. 2015).

To reduce the size of the analysis and examine whether latent variables underlie the responses to the attitudinal questions, the 35 attitudinal questions are categorized using a factor analysis. We include all questions in the factor analysis, to test if individuals have consistent attitudes towards a mode or consistent attitudinal aspects (e.g. fun) regardless of the mode. This provides insights into how attitudes are formed and also if and for which aspects there is potential for change. A person that has mixed attitudes towards a mode, for example riding a bicycle is fun but unsafe, might change his or her attitude based on changes to the bicycle infrastructure and its related safety (Ma and Dill 2015). However, if a person is completely positive or negative across the board towards a certain mode, this seems to suggest low potential for change.

A principal axis factoring analysis is applied, which ensures capturing the shared variance of attitudinal questions with latent variables (Field 2009). Furthermore, varimax rotation is used, which maximises the possibility of capturing each attitudinal question using one factor (Field 2009). The variables are saved using the regression method. The resulting variables have a mean of zero, however when comparing them to the mobility pattern classes we expect that differences between classes will become visible.

## Daily mobility pattern classes versus attitudinal factors

The latent classes of daily mobility patterns are compared to the latent attitudinal factors to investigate the presence of a relationship between mobility patterns and attitudes. As mentioned before, many studies include the attitudes in the clustering process (e.g. Diana and

Mokhtarian 2009; Molin et al. 2016), which means that a relationship is assumed between attitudes and daily mobility patterns. Previous research has shown that this relationship is indeed present (e.g. Kroesen et al. 2017). Therefore, we investigate statistical differences and similarities in the attitudes of individuals belonging to different mobility pattern classes. Furthermore, within the latent classes of mobility patterns, a comparison with the attitudes towards modes is made. The goal is to identify to what extent individuals in each class travel with their preferred travel mode. De Vos (2018) has previously researched this at the trip level and found a high degree of consonance, i.e. travel using the preferred mode. However, he mentions that it remains unknown whether this also holds for the daily mobility pattern.

As the data does not meet the requirements for performing parametric tests (Field 2009), the Kruskal–Wallis test is used to test whether individuals in different classes have significantly different attitudes (per factor). If this is the case, the Mann–Whitney-U test (with a Bonferroni correction, to control for Type 1 errors) shows which classes are significantly different from one another. Consequently, we can conclude on the presence or absence of a relationship between daily mobility patterns classes and attitudinal factors. Furthermore, we know which classes are significantly similar and different in their attitudes.

The comparison within clusters is based on the latent factors towards different modes that arise from the factor analysis on the attitudinal questions. The most preferred mode is identified using the questions that load on the mode specific attitudes, by evaluating the average preference towards each mode. It is possible that different modes are equally preferred by certain individuals. This is taken into account in the analysis. The goal of this analysis is to identify the extent to which individuals in each class use their preferred mode, but also to identify the extent to which individuals use their least preferred mode.

## Results and discussion

This first subsection describes and discusses the results of the LCCA for mobility patterns and the second subsection presents the factor analysis results with respect to attitudes towards modes. Finally, in the third subsection results of the relationship between mobility patterns and attitudes towards modes are presented.

### Latent classes of daily mobility patterns

A total of 10 models (1–10 classes) were tested for daily mobility patterns, based on the three-day travel diary. The most suitable number of classes is the result of a minimization of the BIC value, relative increase of log-likelihood of more than 4%, and minimum class size of 8%. Table 2 shows the model fit of each of the estimated models. The BIC value decreases with every added class until the 9-class model, the log-likelihood reduction stagnates when exceeding six classes, and the minimum class size is smaller than 8% when more than five classes are introduced. Based on all considerations, we select the 5-class model as the most suitable.

The 5-class model was expanded by identifying different combinations of active covariates. Some of the identified covariates are correlated (e.g. age and occupation), consequently we only included one of the correlated covariates in each model. The best combination of active covariates is occupation, urban density, number of household members, gender and education level (log-likelihood = 2804, improvement log-likelihood = 9.9%).

**Table 2** Evaluation criteria for determining the number of classes of the LCCA

| # Classes | # Parameters | Log-likelihood | BIC(LL) | Smallest class (%) |
|---|---|---|---|---|
| 1 | 14 | − 18,196 | 36,502 | 100.0 |
| 2 | 26 | − 6201 | 12,605 | 35.9 |
| 3 | 38 | − 1297 | 2891 | 12.3 |
| 4 | 50 | 664 | − 939 | 12.2 |
| 5 | 62 | 2553 | − 4622 | 9.9 |
| 6 | 74 | 3654 | − 6732 | 5.4 |
| 7 | 86 | 4693 | − 8715 | 5.2 |
| 8 | 98 | 5742 | − 10,721 | 4.4 |
| 9 | 110 | 6704 | − 12,551 | 4.3 |
| 10 | 122 | 6388 | − 11,826 | 0.4 |

Table 3 shows the parameters of the estimated 5-class model, split up in the measurement model and the structural model.

The measurement model consists of an intercept, which can be interpret as a constant that reflects the baseline preference regarding that indicator, while the effect of the classes is taken into account. Furthermore, class-specific parameters reflect the (un)attractiveness of the indicator variables. The intercepts show that bicycle and car trips are most attractive to all individuals. The non-travel ratio is a discrete indicator, that can take five values, ranging from zero (travel during all days) to one (no travel on any day). For each of the five levels an intercept is estimated, which is used as the baseline to calculate the value for each specific class. Following expectations, travelling during all (week)days is preferred. When looking into the classes, several interesting observations are made. For some classes, the intercept is counteracted with the class-specific parameter, for example class 5 and car trips or class 1 and PT trips. This means that this mode is very unattractive for individuals in these classes. Some very positive parameters are also observed, such as bicycle trips for class 5 and walking trips for class 3. Consequently, individuals in those classes find trips using these modes very attractive. Finally, the non-travel ratio has a very positive parameter for class 2, which suggests that the share of non-travel is high for that class.

The structural model also shows an intercept, which reflects the general fit of the population for a class. The indicators show that class 1 has a better fit compared to class 5. The parameters of the covariates show how well each class fits for individuals with those characteristics. Regarding urban density, individuals living in high urban density are more likely to be associated with classes 4 and 5, whereas individuals in low density areas are more prevalent in classes 2 and 3. In many countries, living in a low density area means that one is forced to use the car. In the Netherlands, however, cycling is a very popular mode of transportation, with a modal share of 27% (CBS 2018). Furthermore, many individuals own bicycles. This means that even in low density areas, bicycles are also available and used, next to the car. The number of household members of an individual influences the daily mobility pattern of individuals. An individual living in a household of 3 + members is more associated with class 1 than class 4, whereas an individual living alone is more associated with class 4. The gender covariate shows that in general more women are present in the population compared to men, however, class 2 and 4 are more associated with men compared to women. Regarding occupation, study/school shows the highest (positive and negative) parameters, meaning that students have the strongest associations. Furthermore,

**Table 3** Parameters of the LCCA model with 5 classes for weekday daily mobility patterns

| | Values | Intercept | *Wald* | C.1 | C.2 | C.3 | C.4 | C.5 | *Wald* |
|---|---|---|---|---|---|---|---|---|---|
| *Prediction of indicators (measurement model)* | | | | | | | | | |
| # Car trips | | 1.19 | 2280.1* | 0.41 | 1.03 | 0.35 | −0.60 | −1.19 | 2470.4* |
| # PT trips | | 0.28 | 1177.2* | −0.28 | −0.28 | −0.28 | 1.11 | −0.28 | 1178.1* |
| # Bicycle trips | | 1.12 | 1922.3* | 0.09 | −1.12 | −0.07 | −0.50 | 1.60 | 2081.5* |
| # Walking trips | | 0.38 | 909.4* | −0.38 | −0.38 | 1.15 | 0.00 | −0.38 | 1221.8* |
| # Other trip | | 0.32 | 824.6* | 0.54 | −0.32 | 0.14 | −0.05 | −0.32 | 902.1* |
| % of non-travel | 0 | 2.61 | 2026.1* | −0.49 | 2.50 | −1.08 | −0.56 | −0.38 | 298.0* |
| Days | 1/3 | 0.15 | | | | | | | |
| | 1/2 | −0.63 | | | | | | | |
| | 2/3 | −1.30 | | | | | | | |
| | 1 | −0.84 | | | | | | | |

| | Values | C.1 | C.2 | C.3 | C.4 | C.5 | *Wald* |
|---|---|---|---|---|---|---|---|
| *Prediction of latent class membership (structural model)* | | | | | | | |
| Intercept | | 0.48 | 0.14 | 0.34 | −0.47 | −0.48 | 127.85* |
| Urban density | High | −0.09 | −0.08 | −0.08 | 0.16 | 0.10 | 32.66* |
| | Medium | 0.08 | −0.22 | −0.01 | −0.01 | 0.15 | |
| | Low | 0.00 | 0.30 | 0.09 | −0.15 | −0.25 | |
| # Household members | 1 | −0.11 | −0.14 | −0.01 | 0.25 | 0.01 | 23.72* |
| | 2 | −0.09 | 0.02 | 0.06 | 0.03 | −0.02 | |
| | 3+ | 0.20 | 0.12 | −0.05 | −0.28 | 0.00 | |
| Gender | Female | 0.03 | −0.13 | 0.09 | −0.03 | 0.05 | 15.43* |
| | Male | −0.03 | 0.13 | −0.09 | 0.03 | −0.05 | |
| Occupation | Study/school | −0.47 | −1.11 | −0.72 | 1.60 | 0.70 | 268.15* |
| | Retired | 0.49 | 0.13 | 0.33 | −0.58 | −0.37 | |
| | Unemployed | 0.03 | 0.51 | 0.45 | −0.93 | −0.06 | |
| | Employed | −0.05 | 0.46 | −0.06 | −0.09 | −0.27 | |
| Education level | Low | 0.09 | 0.08 | 0.02 | −0.36 | 0.17 | 21.04* |
| | Medium | 0.01 | 0.06 | 0.03 | 0.04 | −0.13 | |
| | High | −0.10 | −0.13 | −0.04 | 0.31 | −0.04 | |

*Significant on the 95% confidence interval

the employed individuals only have a positive association with class 2. Finally, individuals with a high (completed) education level show strong associations with class 4, whereas individuals with a low level show a better fit with class 5.

When applying the models on all individuals in the dataset, profiles can be created for each of the classes. Table 4 shows a description of each class and provides the distribution for the population as a whole. The classes are named after the mode use characteristics in the daily mobility pattern. The classes are car and bicycle users (CB), exclusive car users (C), car, walk, and bicycle users (CWB), public transport+users (PT+), and exclusive bicycle users (B). The CB and C segments together consist of more than half of the sample population. Class CWB is the third class and consists of almost a quarter of the sample population. Consequently, the last two classes are much smaller (PT+ and B). Three

**Table 4** Within-class distributions of the indicators and covariates

| | | Class CB | Class C | Class CWB | Class PT+ | Class B | Total |
|---|---|---|---|---|---|---|---|
| Class size | Percentage | 27.5% | 27.0% | 23.7% | 12.3% | 9.5% | 100.0% |
| *Indicators* | | | | | | | |
| Car trips | Mean | 1.6 | 2.2 | 1.5 | 0.6 | 0 | 1.5 |
| PT trips | Mean | 0 | 0 | 0 | 1.4 | 0 | 0.2 |
| Bicycle trips | Mean | 1.2 | 0 | 1.1 | 0.6 | 2.7 | 0.9 |
| Walking trips | Mean | 0 | 0 | 1.5 | 0.4 | 0 | 0.4 |
| Other trips | Mean | 0.9 | 0 | 0.5 | 0.3 | 0 | 0.4 |
| Share of non-travel days | Mean | 6% | 32% | 4% | 6% | 6% | 13% |
| *Active covariates* | | | | | | | |
| Occupation | Study/school | 8% | 3% | 5% | **34**% | **26**% | 11% |
| | Retired | **22**% | 12% | **21**% | 9% | 12% | 16% |
| | Unemployed | 13% | 15% | **20**% | 4% | 13% | 14% |
| | Employed | 57% | **70**% | 54% | 53% | 50% | 59% |
| Urban density | High | 49% | 47% | 50% | **62**% | 57% | 51% |
| | Medium | 23% | 16% | 21% | 17% | 22% | 20% |
| | Low | 28% | **37**% | 29% | 22% | 22% | 29% |
| # Household members | 1 | 18% | 15% | 21% | **26**% | 18% | 19% |
| | 2 | 32% | 32% | **38**% | 26% | 27% | 32% |
| | 3 or more | 50% | **53**% | 42% | 48% | **54**% | 49% |
| Education level | Low | 26% | 22% | 24% | 23% | **35**% | 25% |
| | Medium | 39% | **42**% | 40% | 36% | 33% | 39% |
| | High | 34% | 36% | 36% | **41**% | 32% | 36% |
| Gender | Female | 55% | 49% | **60**% | 54% | 58% | 55% |
| | Male | 45% | **51**% | 40% | 46% | 42% | 45% |
| *Inactive covariates* | | | | | | | |
| Age | 12–19 | 6% | 2% | 3% | 15% | **22**% | 7% |
| | 20–39 | 25% | 34% | 28% | **48**% | 24% | 31% |
| | 40–64 | 46% | **52**% | 46% | 27% | 40% | 45% |
| | 65+ | **23**% | 13% | **23**% | 10% | 13% | 17% |
| Distance (km/day) | Car | 30.6 | 46.3 | 24.4 | 10.2 | 0 | 28.0 |
| | PT | 0 | 0 | 0 | 55.2 | 0 | 6.8 |
| | Bicycle | 4.1 | 0 | 2.7 | 1.7 | 9.0 | 2.8 |
| | Walk | 0 | 0 | 1.5 | 0.4 | 0 | 0.4 |
| Ownership | Car | 78% | **87**% | 75% | 41% | 48% | 72% |
| | Bicycle | 75% | 74% | 78% | **88**% | **88**% | 78% |
| | PT (subscript.) | 25% | 19% | 29% | **83**% | 35% | 32% |

Percentages per variable add up to 100%. Bold = highest shares for category of variable compared to other classes

*CB* car and bicycle users, *C* exclusive car users, *CWB* car, walk, and bicycle users, *PT+* public transport+ users, *B* exclusive bicycle users

classes have a diverse mode use pattern (multimodal users), whereas two classes use on average one mode exclusively (unimodal, habitual users).

### Car and bicycle users

The CB class is characterised by more than average trips by car, bicycle, and 'other' trips. Individuals in this class have a low share of non-travel days. Furthermore, the CB class has a relatively large share of retired individuals, which results in a higher share of individuals that are 65 and older. These individuals travel further than average by car and bicycle and car ownership is slightly higher than average. Furthermore, this class is comparable to the population as a whole in terms of urban density, number of household members, education level, and gender.

### Exclusive car users

Members of class C only use the car. Furthermore individuals in this class have a high share of non-travel days. Given other characteristics of this class, such as the relatively high share of employed individuals, males, ages between 40 and 64, and low urban densities, this most likely represents working at home days. The individuals in this class mostly live in households with three or more individuals. The individuals often own a car. Finally, they travel farthest (on average 46 km), which might be due to the fact that most live in low urban areas.

### Car, walk, and bicycle users

The third class CWB travels by car, on foot, and by bicycle, but does not use public transport. Individuals in this class are relatively often retired or unemployed. Consequently, the population elderly (65 +) is well represented in this cluster. Furthermore, a high share of females is present in this class, which are mostly unemployed (including those who are by choice out of the workforce). In this class there are more than average two-person households. Finally, individuals in this class walk further than average. Individuals in this class are comparable to the entire population in terms of the distribution over urban densities, education levels, and ownership levels.

### Public transport + users

The PT class users travel most often by public transport, however they also travel by car, bicycle, and on foot. The characteristics of the users in this class are very different from the first three classes. The individuals in this class are mostly studying or working, young (< 40 years), highly educated, live quite often alone, and live in high urban areas. The last is not surprising as it is known that the public transport services are more efficient and frequent in densely populated areas in the Netherlands. They travel relatively far by public transport, often involving train travel (inter-city travel). Furthermore, the PT + users often do not own a car, but do own a bicycle and a public transport subscription.

### Exclusive bicycle users

The last class are the exclusive bicycle users (B). This group travels frequently and only by bicycle. The users in this class are relatively often school going teenagers, which live with their parent(s). Consequently, they have a low education level (as they have not yet finished their schooling). They live in highly urban areas, where more facilities are reachable within short distances. Furthermore, they travel relatively long total distances by bicycle (9 km). Car ownership is low (also caused by age restrictions), but bicycle ownership is high. During the data collection period, the weather was relatively stable. Potentially, if data was collected for a longer period of time, with more variability in the weather, other modes would have been observed too (e.g. public transport).

To compare the identified classes of daily mobility patterns to other studies, the differences in the research approaches need to be stressed. In other studies, attitudes have been used in the identification of the mobility patterns (Diana and Mokhtarian 2009; Molin et al. 2016; Krueger et al. 2018) and the objective mobility pattern has been defined differently (Diana and Mokhtarian 2009; Molin et al. 2016; De Haas et al. 2018, Krueger et al. 2018). Furthermore, several studies have investigated different countries, enabling comparison between countries (Diana and Mokhtarian 2009; Krueger et al. 2018). Consequently, a one-on-one comparison between the classes identified in different studies is not possible, notwithstanding we hereby identify the noteworthy differences and similarities.

Diana and Mokhtarian (2009) investigated datasets from two countries: USA and France. The modes included in their research differ for each country (the French dataset contained more modes). They identified four groups of users for the French dataset: unimodal car users, car-dominated but multimodal users, highly multimodal users with moderate travel intensity, and highly multimodal users with heavy travel intensity. Bicycle use is very low in this dataset and they did not include walking as a mode, therefore the multimodality is related to public transport and car use. For the USA dataset, they also identified four groups: unimodal car users, moderate travellers which are multimodal but car-dominated, light travellers which are multimodal but car-dominated, heavy travellers which are multimodal but car-dominated. The first group corresponds to our class C. The other classes mostly show multimodality between car and walking, but the last group also contains a fair share of public transport use. Bicycle use is very low in the USA and was not included in the classification. As a result, both the classifications for France and the USA are very different from our study, because in most of our classes active modes play an important role.

Krueger et al. (2018) investigated mobility patterns in Sydney, Australia. They identified three classes: car-oriented users, public transport-oriented users, and car- and bicycle-oriented users. Class C in our study has large overlap with the car-oriented users, only this class is much larger (50.5%). Furthermore, the car- and bicycle oriented users overlap with our CB class, with the largest difference being that the bicycle is less frequently used. Finally, the public transport-oriented class overlaps with our PT + class, but is again larger (20.9%). Consequently, all the classes reported by Krueger et al. (2018) have also been identified in our study, while we identify two additional classes and find smaller motorised traffic-dominated classes.

Molin et al. (2016) used data from the Netherlands to classify mobility patterns. They identified five clusters: car multimodal, bicycle multimodal, bicycle and car, car mostly, and public transport multimodal. They did not incorporate walking as a separate mode, consequently their classes are mostly build upon bicycle and car use. Their classes to a

large extent correspond to our classes with the exception that they find no bicycle only class.

De Haas et al. (2018) used data from the same panel as our study: the MPN dataset. They identified the daily mobility patterns differently by only including trips per mode, and excluding non-travel and other trips, where they summed the trips over the course of 3 days. They identified six classes: strict car, car and bicycle, bicycle, car and walk, low mobility, and public transport users. Most classes show good correspondence with the classes identified in this study. Their car and walk class is extended to also include bicycle in our study. Because we only include individuals that have used the bicycle or walked in the last half year, we exclude to a large extent the immobile population, consequently we do not identify a low mobility class.

In general, the results from this study are in line with the findings from other studies in the Dutch context (Molin et al. 2016; De Haas et al. 2018). Differences in the classes with other countries are mostly related to the fact that the Netherlands has a high share of active mode use. Most countries are more car-oriented and lack a high share of active modes to this date. Arguably, the Dutch situation may illustrate what the class distribution of daily mobility patterns could be after achieving a shift towards active modes. Next, we examine the relevance and importance of attitudes in this context using the original PAW-AM survey designed and collected for this study.

## Factors of attitudes towards modes

For each of the five modes (car, bicycle, walk, BTM, and train) the respondents answered seven attitudinal questions. Figure 2 shows in a radar chart format the average scores of the population as a whole on each question for each mode, which provides a first insight into which factors might arise from the factor analysis. The two public transport modes are valued the least, with a preference for the train over the urban modes. The Dutch population disagrees on average to the statement that the use of any particular mode relates to one's prestige. Generally, the car is valued highest, followed by the bicycle. However, regarding relaxation during travel, both walking and cycling are valued more positively than the car.

The data is suitable for factor analysis with a score of 0.865 on the KMO test for sampling adequacy ($>0.8$) and total variance explained of 59.8%. Two questions related to walking (*prestige* and *time saving*) were excluded from the factor analysis, because they could not be captured by any of the factors (factor loading $<0.4$). The 33 attitudinal questions were reduced to eight factors; one factor for each mode, one related to the prestige of using modes and two related to PT attitude (combined train and BTM). The eight factors can be characterized as described in Table 5. The results of the factor analysis are in line with the expectations based on Fig. 2. The loading represents how each of the variables load on the factor, where a higher value represents a better fit to the latent factor. Furthermore, the Cronbach's alpha provides a measure of reliability of the resulting latent factors. A value higher than 0.8 is considered good and reflects high internal consistency. A value under 0.7 is questionable, which is observed for the 'public transport safety' factor. This might be attributed to the fact that only two questions are loaded on this factor, where generally at least three are expected. Therefore, the results of this factor need to be interpreted with care.

All questions that are answered in a similar consistent fashion are combined into one latent factor. Interestingly, consistency in answers is exhibited for various attitudes towards a given mode rather than various modes for a given attitude (e.g. comfort). Hence,
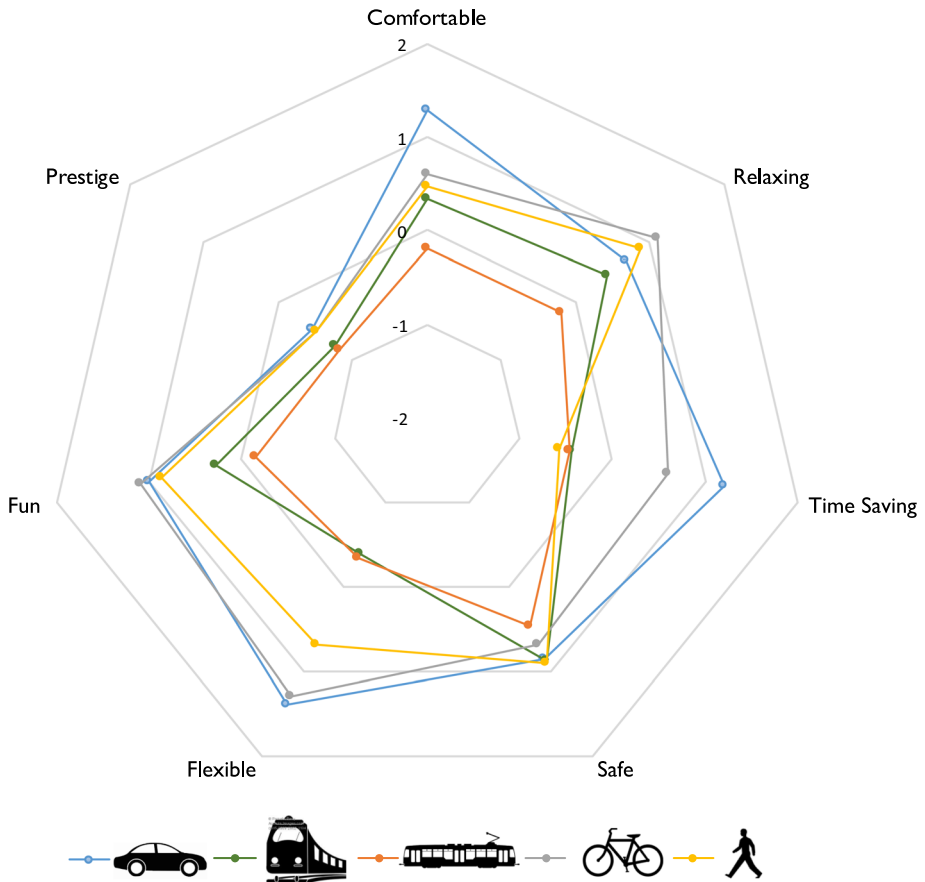
Fig. 2 Average score per attitude question per mode for the entire population

individuals have relatively strong overall opinions towards different modes and therefore it will be harder to change attitudes via, for example, promotional or information campaigns. This especially holds for the car and bicycle, because six out of the seven attitudinal questions are combined into the attitudinal factor. The train attitude includes only four attitudinal questions, meaning that individuals are more varying in their attitude towards the train. Consequently, the attitude towards the train could potentially be changed using promotional campaigns that focus on the flexibility and time saving aspect (PT efficiency). The only latent factor that strongly represents an attitude covering different modes is the prestige of using modes. This latent factor includes statements on the perceived increase in status associated with using car, train, BTM, or bicycle. Individuals have answered these questions in a similar fashion for each of the modes, disagreeing with the statement that it induces prestige (see Fig. 2). Consequently, the general tendency is that modes do not increase status for individuals and status is not part of the attitude towards each of the modes.

**Table 5** Results of the factor analysis on attitudinal questions related to the different modes

| Factor | Variables | | Loading | Cronbach's alpha |
|---|---|---|---|---|
| Car attitude | Travelling by car is… | Comfortable | 0.803 | 0.865 |
| | | Relaxing | 0.747 | |
| | | Time saving | 0.622 | |
| | | Safe | 0.659 | |
| | | Flexible | 0.678 | |
| | | Fun | 0.834 | |
| BTM attitude | Travelling by BTM is… | Comfortable | 0.794 | |
| | | Relaxing | 0.800 | |
| | | Time saving | 0.504 | 0.897 |
| | | Flexible | 0.513 | |
| | | Fun | 0.828 | |
| Bicycle attitude | Cycling is… | Comfortable | 0.740 | 0.827 |
| | | Relaxing | 0.808 | |
| | | Time saving | 0.489 | |
| | | Safe | 0.502 | |
| | | Flexible | 0.621 | |
| | | Fun | 0.833 | |
| Walking attitude | Walking is… | Comfortable | 0.757 | |
| | | Relaxing | 0.794 | |
| | | Safe | 0.437 | 0.816 |
| | | Flexible | 0.562 | |
| | | Fun | 0.822 | |
| Train attitude | Travelling by train is… | Comfortable | 0.736 | 0.849 |
| | | Relaxing | 0.759 | |
| | | Safe | 0.454 | |
| | | Fun | 0.761 | |
| Prestige of using modes | Travelling by… increases status | Car | 0.612 | 0.812 |
| | | Train | 0.831 | |
| | | BTM | 0.734 | |
| | | Bicycle | 0.745 | |
| Public transport efficiency | Travelling by train is… | Time saving | 0.654 | 0.858 |
| | | Flexible | 0.638 | |
| | Travelling by BTM is… | Time saving | 0.609 | |
| | | Flexible | 0.589 | |
| Public transport safety | Travelling by…is safe | Train | 0.583 | 0.697 |
| | | BTM | 0.591 | |

## Attitudinal factors versus latent mobility pattern classes

The comparison between attitudinal factors and the latent mobility pattern classes is done in two parts. First, a comparison between classes is done, which identifies whether individuals in different classes indeed have different attitudes ("Comparison between latent mobility pattern classes" section). Second, a within class comparison is done, which identifies the extent to which individuals use their (least) preferred modes in their daily mobility pattern ("Comparison within latent mobility pattern classes" section).

## Comparison between latent mobility pattern classes

A total of five different latent mobility pattern classes has been identified using a LCCA analysis. The attitudinal questions have been reduced in dimension to eight latent factors. In this section we test whether these five groups of individuals have different attitudes (towards various modes). Figure 3 shows the attitude scores on each factor for each of the classes. The dashed black line represents the average opinion of all respondents.

Several observations can be made in relation to Fig. 3. First, the car attitude is highest for the exclusive car users, which only use the car and lowest for the exclusive bicycle users, which do not use the car. Second, the exclusive bicycle users are most positive towards the bicycle, however the other classes that use the bicycle on a daily basis (CB and CWB) are also more positive than average towards the bicycle. Third, the only class that walks on a daily basis (CWB) is most positive towards walking. Fourth, the PT + users are most positive towards the train. Class C is much less positive towards the train compared to the others. And finally, the PT + users are respectively most positive and least negative towards PT efficiency and PT safety. In summary, these observations indicate that modes that are actively used by individuals are valued more positively compared to modes that are not or less frequently used.
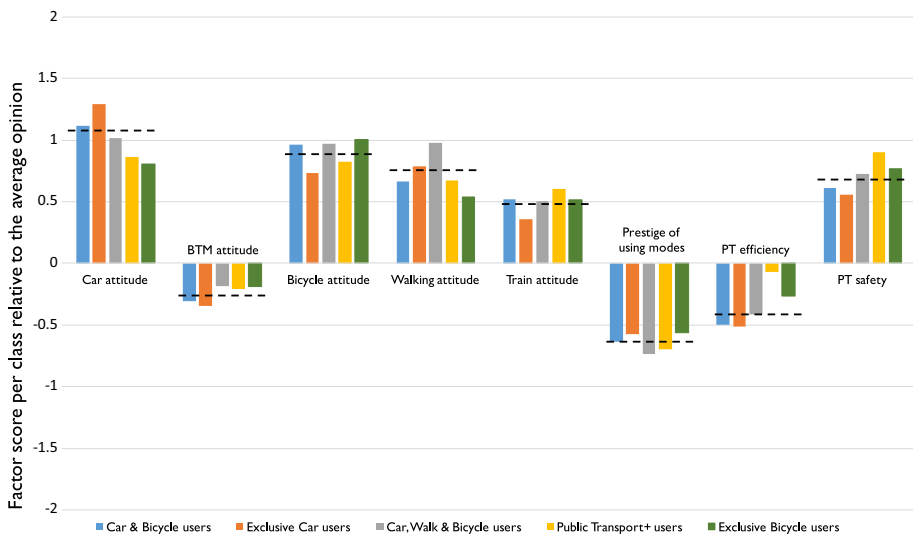


**Fig. 3** Factors representing attitudes of the five classes

**Table 6** Differences between classes on attitudinal factors

| Factor | Class CB Differs from | Class C Differs from | Class CWB Differs from | Class PT+ Differs from | Class B Differs from |
|---|---|---|---|---|---|
| Car attitude | C, PT+, B | All | C, B | CB, C | CB, C, CWB |
| BTM attitude | – | – | – | – | – |
| Bicycle attitude | C | CB, CWB, B | C, PT+ | CWB | C |
| Walking attitude | CWB | CWB, B | all | CWB | C, CWB |
| Train attitude | C | CB, CWB, PT+ | C | C | – |
| Prestige of using modes | – | CWB | C | – | – |
| Public transport efficiency | PT+, B | PT+, B | PT+ | CB, C, CWB | CB, C |
| Public transport safety | PT+, B | CWB, PT+, B | C, PT+ | CB, C, CWB | C |

We test whether the differences observed in Fig. 3 are statistically significant. Table 6 shows which classes are significantly different from other classes on each of the eight identified attitudinal factors. The Kruskal–Wallis test indicated that no significant differences are found in relation to the BTM attitude, which is negative among all user classes. In contrast, statistically significant differences are found for all other attitudes. We then turn to test which classes differ in their attitudes.

Several observations can be made in relation to Table 6. First, the classes PT+ and B are not statistically different in their attitudes. This might be due to the fact that their socio-demographic profiles are rather similar (young people in high urban areas). Second, the classes CB and CWB are only significantly different in their attitude towards walking, where CWB is more positive than CB. The first class also makes much more use of walking as mode of transport, signifying the largest difference between these two classes. Third, classes CWB and B differ in their attitude towards car and walking. Just like the previous case, this echoes the major difference in the mobility patterns of the two groups. Fourth, classes C and CWB are very different in their attitudes. They are only similar in their BTM attitude and PT efficiency. The multimodal mobility pattern of CWB is therefore generally related to a more positive attitude towards the non-used modes, compared to the unimodal C class. Fifth, the unimodal classes C and B are not significantly different in their BTM attitude, train attitude, and the prestige towards modes. Consequently, they have a similar opinion regarding PT modes, but a different opinion towards the other modes where they are more positive towards the mode they use. And finally, the classes C and PT+ have similar attitudes towards the modes they do not actively use in their daily mobility pattern, namely the active modes: cycling and walking.

## Comparison within latent mobility pattern classes

The most positive attitudinal score for a mode is the preferred mode for an individual. Ideally, this mode would be used by the individual in their daily mobility pattern. This would reflect travel mode consonance (De Vos 2018) and would suggest an ideal match between attitudes and behavior. If this is not the case, i.e. travel mode dissonance, other factors also influence both the daily mobility patterns and attitudes towards modes. Table 7 shows the use of the most and least preferred modes for each latent mobility pattern class.

The use of the most preferred mode varies largely between different classes. The PT+ class uses all modes in their daily mobility pattern, consequently their preferred mode

**Table 7** Use of most and least preferred modes in the daily mobility pattern: travel mode consonance and dissonance

| | Most preferred mode | | | | | Least preferred mode | |
|---|---|---|---|---|---|---|---|
| | Use (%) | Not use (%) | Top preferences if not used | | | Use (%) | Not use (%) |
| Class CB | 74 | 26 | Train | Walk | Train-walk | 9 | 91 |
| Class C | 62 | 38 | Walk | Bicycle | Train | 5 | 95 |
| Class CWB | 91 | 9 | Train | | | 21 | 79 |
| Class PT+ | 100 | 0 | – | | | 100 | 0 |
| Class B | 44 | 56 | Car | Walk | Train | 7 | 93 |

is always included in their mobility pattern. The CWB class reaches a 91% travel mode consonance. Only 9% of the individuals in this class do not use their preferred mode, in these cases the train is preferred. BTM is the only other mode that is not used by the CWB users, however no one has BTM as their most preferred mode. Consequently, other influences drive these individuals to not use the train in the daily mobility pattern. The single-mode classes (B and C) have the lowest levels of travel mode consonance. Potentially, the individuals that do not use their preferred mode are captive users. Captive users are bound to one mode, meaning that they cannot or do not have the means to make use of another mode. The most preferred modes for class C are walk, bicycle, and train, whereas in class B these are car, walk, and train. Very few individuals have BTM as their preferred mode.

If an individual uses the least preferred in the daily mobility pattern, this shows a larger discrepancy between attitudes and daily mobility patterns compared to not using the most preferred mode. In this case the single-mode classes show the smallest percentages, 5% for class C and 7% for class B. This means that only few people use a single mode, which they prefer least. As these individuals would most likely have deviated from these single modes, they are indeed likely to be captive users. Again, the PT+class uses all modes in their daily mobility pattern, which means that the least preferred mode is also included in that pattern. The CWB class has a relatively large share of individuals using their least preferred mode, indicating that either car (5%), walk (6%) or bicycle (3%), or a combination of these (7%) is least preferred. However, these individuals are not captive users, as they also deviate from the least preferred mode.

Governments worldwide share the goal for more active mode or sustainable mode use (also including public transport). To identify the potential of these modes, we investigate the active mode and sustainable mode preferences of the individuals in each latent mobility

**Table 8** Active and sustainable mode preferences for each mobility pattern class

| | Preferred mode | | Preferred by dissonant users | | |
|---|---|---|---|---|---|
| | Active (%) | Sustainable (%) | Dissonant users (%) | Active (%) | Sustainable (%) |
| Class CB | 36 | 49 | 26 | 15 | 26 |
| Class C | 30 | 38 | 38 | 30 | 38 |
| Class CWB | 43 | 56 | 9 | 0 | 9 |
| Class PT+ | 39 | 58 | 0 | 0 | 0 |
| Class B | 44 | 59 | 56 | 16 | 27 |

pattern class. Table 8 shows the most preferred modes categorised in active and sustainable for the general population and the dissonant users in each class. The latter reflects users that potentially have a preference for active or sustainable modes, but currently do not use these in their mobility pattern. These individuals are therefore potential future users of active or sustainable modes.

Class CB and C have relatively low preferences for both active and sustainable modes (less than half), suggesting that it might be difficult to persuade the general CB and C users into using active or sustainable modes. However, the shares of dissonant users are relatively large. These dissonant users prefer active modes or public transport. The majority of them prefer active modes over public transport. For Class CB, this is 15% versus 11%, while for class C it is 30% versus 8%. These users can potentially be persuaded to use active modes or public transport, given the right incentives. Class CWB and B have the highest preferences for active modes and show the largest potential in general. However, most of these users already use active modes, resulting in the potential for more use of active modes, not necessarily switching modes. Class B has a large share of dissonant users, of which 27% has a preference for sustainable modes. Therefore, this class also show potential for the use of other sustainable modes, besides the bicycle. Class PT + shows the largest preference for sustainable modes. Besides all the potential shown for active or sustainable mode use, from the attitude perspective, it is striking to see how many individuals, across all classes, have a preference for the car (almost half).

## Conclusions

This paper presents the findings of a latent class cluster analysis, applied on census data from the Netherlands, with the goal of revealing different daily mobility travel patterns. Furthermore, we explicitly investigate the relationship between the resulting daily mobility travel patterns and the attitudes towards (alternative) modes, to identify potential for increasing the active mode share across the population.

A total of five different daily mobility pattern classes was identified: (1) car and bicycle users, (2) exclusive car users, (3) car, walk, and bicycle users, (4) public transport + users, and (5) exclusive bicycle users. These user types differ in their socio-demographics, ownership of modes, distance travelled per mode, household sizes, and urban densities. Active mode use is present in most classes, except for the exclusive car users. Furthermore, three classes exercise multimodality (over the days). Classes of individuals that already use active modes or that are multimodal, might be more inclined to use active modes of transport or to increase their active mode use in the future, as they are already familiar with these. It might be hard to convince the exclusive car users to switch to other, more sustainable, modes.

The attitude towards modes was identified by asking individuals seven questions about the comfort, relaxation, time saving, safety, flexibility, fun and prestige associated with using each of the travel modes. A factor analysis was used to reduce the number of dimensions and to identify likeminded attitudinal questions. A factor made out of statements related to one attitudinal question (e.g. fun) would mean that travel in general is seen as fun or not fun. Whereas, a factor made out of statements related to one mode (e.g. the car) would imply that an individual is generally positive or negative towards that mode regardless of the attitudinal aspect. We identified five mode related factors and three attitude

related factors. Consequently, the population is generally positive or negative on all aspects for a given mode. This especially holds for the car and bicycle, where six attitudinal questions are included. Consequently, it will be difficult to influence the attitude of individuals, as all aspects are seen as positive or negative.

In this study we investigated the relationship between the attitudinal factors and the daily mobility pattern classes. The findings suggest that an individual is more positive towards the modes that are included the daily mobility pattern, compared to the modes that are not part of his or her mobility pattern. This is consistent with previous findings reported in the literature, which state that unimodal car drivers have a biased or more negative attitude towards public transport modes, compared to multimodal car drivers (Diana and Mokhtarian 2009; Molin et al. 2016). In our research this statement is confirmed, but we see a much more negative attitude towards all other modes (it scores lowest on bicycle, local public transport and inter-city public transport). In contrast, the multimodal users are very positive towards the used modes and generally also positive towards the unused modes.

We also investigated the degree of travel mode consonance (use of the most preferred mode) within each mobility pattern class. The single-mode classes (exclusive car and exclusive bicycle users) show the lowest shares of travel mode consonance. The individuals that do not use the preferred mode are dissonant users. We expect that 5% of the exclusive car users and 7% of the exclusive bicycle users are captive users, as they use their least preferred travel mode. A relatively large share of the exclusive car users prefers to travel by active (or sustainable) mode, showing that there is potential for changing behaviour in all classes.

When the goal is to achieve a higher active (or sustainable) mode share, these findings indicate that there is potential in each of the classes, however the approach towards reaching the goal differs. The car dominated classes (car and bicycle users and exclusive car users) show potential for switching modes towards more sustainable or active modes, as they have relatively large shares of dissonant users (26% and 38%). These mobility pattern classes include many employed individuals, therefore the employer could take a role in changing the behaviour by stimulating or enabling the use of sustainable modes to work. However, more than half of the individuals in these classes prefer to use the car, which is consonant with the mobility pattern. Therefore, it is expected to be very challenging to change the behaviour of these individuals. However, they might be stimulated to become more sustainable through the use of car-based shared mobility services (for example by the employer). Ride-sourcing, ride-sharing, and car-sharing are examples of car-based services that offer attributes associated to the car, but steer towards more efficient utilisation of vehicle fleets and thus reducing potentially related externalities. Furthermore, the exclusive car users might be unaware or not fully informed of the attributes, such as level-of-service, of active and sustainable modes. Short-term targeted campaigns can be an effective policy measure to expose these users and potentially enlarge their mobility portfolio. The multimodal classes (car, walk, and bicycle users and public transport + users) already show sustainable behaviour, which is mostly in line with their preferences. These individuals can increase their active mode use and reduce car use, especially for shorter distance travel. Integration of the sustainable modes, via mobility-as-a-service (MaaS), could help in providing more attractive services that increase the use of sustainable or active modes, at the cost of car use. Finally, the majority of the exclusive bicycle users shows dissonant behaviour. Potentially, this results in a change of behaviour in the future. To ensure active or sustainable mode use in the future, these individuals could also benefit from MaaS schemes, especially because the majority of these individuals lives in dense urban areas.

The data used for this research is cross-sectional. Consequently, we cannot identify how potential policies or campaigns have influenced the behaviour of individuals. Future

research entails collecting another wave of data, and identify shifts in behaviour by executing a latent transition analysis (e.g. Kroesen et al. 2017). Also, if another wave of data is available the causality between attitude and behaviour can be investigated. Another interesting aspect that can be investigated when multiple waves of data are available, is the influence of life changing events on individuals' mobility patterns and attitudes towards modes. Next to that, the results found in this study regarding classes of mobility patterns and attitudes towards modes could be used as input for choice models that aim to investigate potential impacts of policies on mode choices. Finally, in this study we regarded the attitudes towards modes in comparison to the latent mobility classes. It would also be interesting to investigate how the covariates of our model, e.g. socio-demographics, explain differences in attitudes towards modes.

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## Compliance with ethical standards

**Conflict of interest** On behalf of all authors, the corresponding author states that there is no conflict of interest.

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