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Drivers and barriers in adopting Mobility as a Service (MaaS) – A latent class cluster analysis of attitudes

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ABSTRACT

Mobility as a Service (MaaS) is expected to significantly change mobility patterns, yet it is still not clear who will embrace this new mobility paradigm and how MaaS will impact passengers' transportation. In the paper, we identify factors relevant for MaaS adoption based on a survey comprised of over thousand respondents in the Netherlands. We find five clusters in relation to individuals' inclinations to adopt MaaS in the context of urban mobility. We characterize each of the clusters, allowing for the examining of different customer segments regarding MaaS. The cluster with the highest inclination for future MaaS adoption is also the largest cluster (representing one third of respondents). Individuals in this cluster have multimodal weekly mobility patterns. On the contrary, current unimodal car users are the least likely to adopt MaaS. We identify high (mobility) ownership need and low technology adoption (present in three of the five clusters) as the main barriers that can hinder MaaS adoption. Policies that directly address these two barriers can stimulate MaaS adoption.

1. Introduction

Urban transportation is changing rapidly, with the emergence of a broad spectrum of on-demand modes such as bike-sharing, car-sharing or ride-sharing appearing in urban areas. Even if these mobility services have been around since the 20th century, only recently their real-time operation in large settings has become a reality. They increase the modal choice set of travellers and their accessibility to different locations, but the wide range of options available also implies some degree of extra complexity for the user. In order to avoid this extra complexity and to maximise the benefits that all these options can bring when integrated, Mobility as a Service (MaaS) is emerging.

MaaS is a service offered to the user in a single mobile app platform, which integrates all aspects of the travel experience, including booking, payment, and information both before and during the trip (Jittrapirom et al., (2017) and Kamargianni et al. (2016) provide an overview of early MaaS schemes). In essence, MaaS brings an individual from A to B regardless of the mode. In dense urban settings in which congestion, liveability and parking space are high on the urban mobility agenda, a robust public transport system would ideally constitute the core of MaaS, with the new on-demand modes acting as first/last mile solutions or to complement public transport for trips for which it does not provide a convenient service (Li and Voege, 2017). The transport integration that has for long been considered a precondition to reduce car use in favour of public transport (Chowdhury and Ceder,

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2016; Givoni and Banister, 2010; Janic, 2001) is therefore provided in MaaS.

Previous research indicates that MaaS has the potential to induce modal shifts towards a more public transport and less car oriented lifestyle (Karlsson et al., 2017; smile mobility, 2015) while it increases users' travel satisfaction (Sochor et al., 2016). As a result, MaaS has recently attracted much attention, to the extent that it is expected to become the drive of a mobility revolution comparable with the introduction of the private car in the 20th century (Goodall et al., 2017; Shaheen et al., 2018). However, there has been a self-selection effect among individuals participating in the researched early stage MaaS pilots (Strömberg et al., 2016). It is unknown if the general population will replicate the modal shifts of individuals in these MaaS pilots and whether public transport or rather on-demand services will play the mayor role in urban MaaS schemes (car users partly explain their current mode choice decisions by referring to the inflexibility of transit (Clauss and Döppe, 2016)).

In this study, we contribute to the understanding of who will embrace MaaS and which shifts in mobility patterns MaaS is likely to occasion. Limited quantitative research has been done so far on this topic other than the resulting from pilot evaluations, even if MaaS is expected to significantly change our travel patterns. Our study goes beyond the consideration of early adopters and identifies not only the characteristics of potential users of MaaS, but also the barriers that may be holding other individuals from adopting this new mobility paradigm. We also investigate if public transport, or rather other on-demand services are more attractive to the different traveller groups, which indicate which changes in mobility patterns can take place as a result of MaaS. In our study, we focus on urban areas of the Netherlands, and we discuss what the results indicate for other urban settings.

Within the study of the on-demand modes present in MaaS, we pay special attention to pooled on-demand services. They can add flexibility without compromising on sustainability and efficient use of mobility resources. By pooled on-demand modes, we refer to the new generation of taxi-like services (usually booked via an app) that match different travel requests in the same vehicle (usually) in real-time, without these matched trips needing to start or end at the same location. Examples of these services are pooled ride-sourcing services such as UberPool or UberExpressPOOL, or microtransit services such as the services offered by Via or Chariot. Tachet et al. (2017) demonstrated that pooled on-demand services have a high potential in urban settings, given that individual mobility patterns are highly shareable for very diverse urban networks. Moreover, simulation studies show that combinations of pooled on-demand services with traditional public transport (Martinez and Viegas, 2017) or with individual on-demand services (such as bike-sharing (Luo et al., 2017)), lead to drastic reductions in the number of vehicles needed, carbon emissions and congestion, and they improve passenger trip times and accessibility simultaneously. As a result, their contribution can indeed be key in future MaaS schemes.

The main contributions of the present study are the following. First of all, we identify user clusters with respect to their attitudes towards MaaS, identifying which segments of the population are more likely to engage in MaaS (and whether pooled on-demand services also deem apt in them from an attitudinal perspective). Second of all, we investigate if there is a relation between current mobility patterns and the inclination towards MaaS, and interpret what this can mean to future urban mobility. Third of all, we identify barriers that can hold back users from adopting MaaS. Finally, based on the presented new insights, we propose a series of recommendations and policy implications tailored to the different clusters present in the study to support future MaaS adoption.

The remainder of the paper is organised as follows: Section 2 explains the methodology employed in this research; Section 3 presents the study results; Section 4 gives detailed insights on the individuals belonging to the clusters presented in Section 3; Section 5 discusses the key results, focusing on policy implications, and Section 6 provides the final conclusions.

2. Research methodology

In this section, we discuss the overall research approach, including the design of the survey and the data analysis approach.

2.1. Survey design

We performed a survey in order to identify potential future users of sustainable MaaS schemes in the Netherlands. Given that the higher densities of urban areas better allow for the economically viable coexistence of a robust transit system and different on-demand services, we exclusively targeted individuals living in (sub)urban areas in The Netherlands in our study. The survey included several attitudinal Likert-scale statements regarding attitudes towards MaaS, with an emphasis on pooled on-demand services. The included attitudinal indicators are explained in detail in the following subsection.

Survey respondents were recruited from the Netherlands Mobility Panel (MobiliteitsPanel Nederland, MPN), which is an annual household panel designed for the longitudinal study of travel behaviour in the Netherlands (Hoogendoorn-Lanser et al., 2015). In addition to the annual panel waves, MPN respondents occasionally take part in specific questionnaires, as is the one designed for the current piece of research.

2.1.1. Attitudinal indicators

MaaS is still in its first stages. Therefore, the study of transport behaviour in real MaaS settings is still limited to the small number of MaaS pilots currently available. We add to this knowledge by carefully designing a series of attitudinal indicators to better understand the mobility changes MaaS will spark. This methodology is underpinned by previous research which has found a relation between attitudes and behaviour in mode choice (Molin et al., 2016). Moreover, previous research has shown that attitudinal approaches that are used as a base for mobility segmentation are advantageous as a starting point for related policy interventions (Haustein, 2012; Haustein and Hunecke, 2013).

Durand et al. (2018) identified three main aspects relevant when investigating changes in travel preferences that can take place as

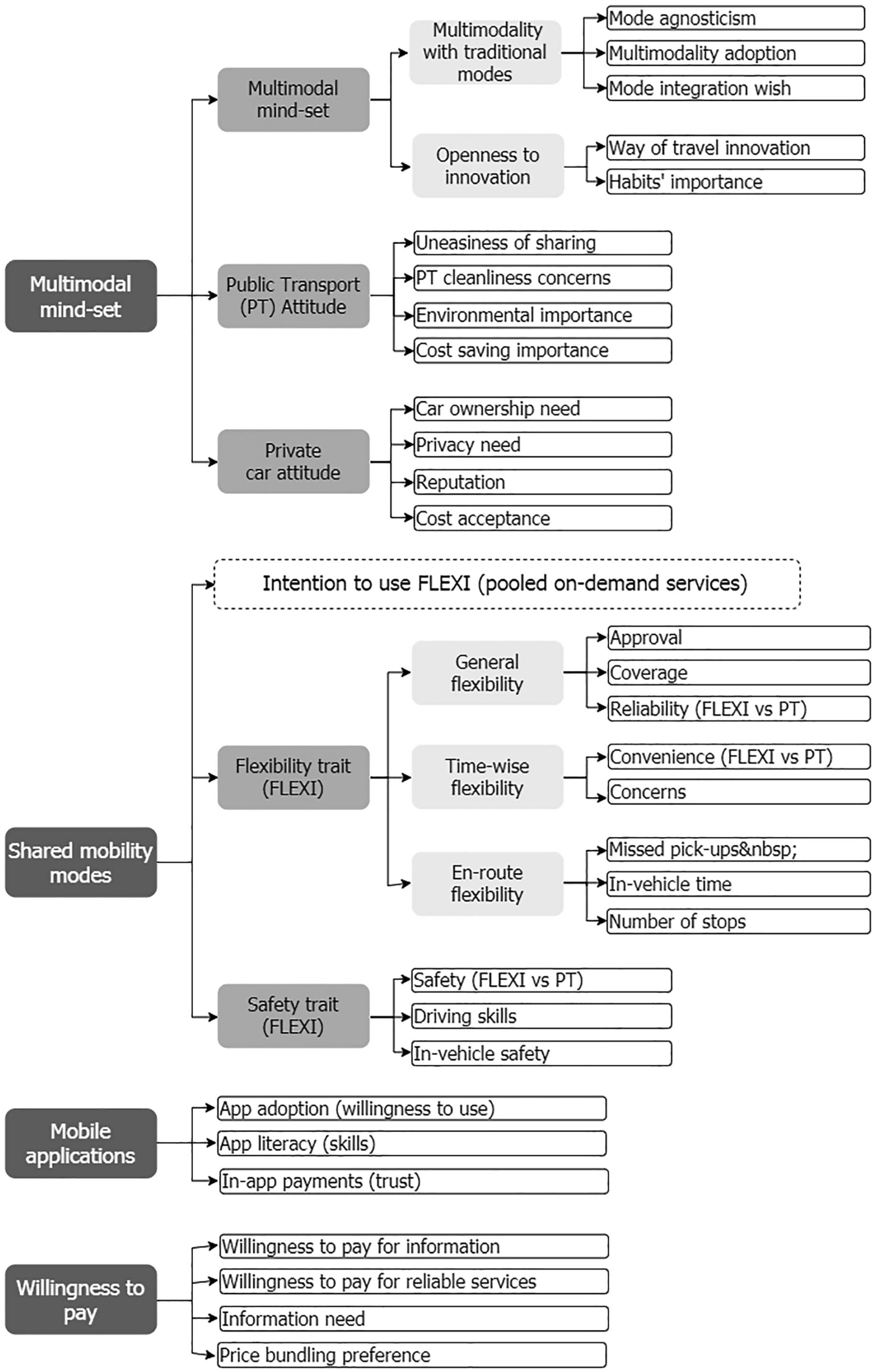

Fig. 1. Key aspects of the attitudinal Likert-scale indicators.

a result of MaaS: (i) mobility integration, (ii) shared mobility modes, and (iii) mobile applications. In our analysis, we add a category focusing on willingness to pay, to have a notion of the business case for MaaS. Fig. 1 shows the key aspects of the attitudinal indicators included in the survey, which will be described in detail below. The complete formulation of the attitudinal indicators as well as their source (where applicable) are detailed in Appendix A.

Mobility integration. Individuals need to be willing to integrate different modes of transport as part of their travel patterns in order to exploit the benefits provided by MaaS. This willingness to use different modes can, in turn, be influenced by individuals' attitudes towards public transport and private car. Therefore, we include three subcategories:

(i) **Multimodal mind-set.** We understand the multimodal mind-set as the willingness to integrate different modes of transport into one's travel patterns. Similarly, we refer to multimodal individuals as those who include different transport modes in their weekly mobility. With regard to the multimodal mind-set, we differentiate two aspects, namely the attitude towards multimodality with the traditional modes, and the openness to innovate in mobility.

(ii) **Public transport attitude**. Attitudes towards public transport in the Netherlands are more negative than those towards bike or car (Kennisinstituut voor Mobiliteitsbeleid (KiM), 2018), yet a positive attitude towards public transport is helpful in order to accept a MaaS scheme with public transport as its core. We do not include operational aspects in our statements due to large differences in frequency and reliability between different available services. Rather, we focus on sharing (common characteristic for all public transport modes) and common goals of public transport and MaaS: cost and environmental impact reduction.

(iii) **Private car attitude**. From a utilitarian perspective, MaaS can offer a good alternative to using a privately-owned car. However, symbolic and affective motives related to car usage have been found more important than utilitarian ones (Steg, 2005). This would make it more difficult to shift from the current mobility paradigm towards MaaS. Therefore, we address these motives in our indicators.

Shared mobility modes. Given the still limited experience of most individuals with these services, we consider novel shared mobility modes independently, and not merged in the attitudes towards the more general mobility integration, as suggested by Durand et al. (2018). In this study, we focus on pooled on-demand services as an example of shared mobility modes. These services do not only provide the flexibility of on-demand services, but they also offer a collective service, fitting the needs of congested urban areas.

Pooled on-demand services (referred to as FLEXI when presented to respondents) were described in detail in the questionnaire. It was introduced as a mobility service which could have a maximum of six people in a vehicle and was bookable in real time via an app (or via a mobile phone for those not owning a smartphone). The pick-up point was assumed to be 1-minute walking distance from their location, and detours could take place to pick up or drop off other passengers. Before being presented with the related attitudinal indicators, respondents also completed two stated preference experiments focusing on reliability of these pooled on-demand services. This way, respondents had a better understanding of both the flexibility (+) and the variability (−) associated with flexible route and schedule services and could form an opinion towards these services prior to indicating their attitude towards the envisaged service. In turn, this allowed us to ask respondents about their intention to use pooled on-demand services.

Within pooled on-demand services, our main interest is to analyse their flexibility trait. Flexibility is the common characteristic of all on-demand services, and is arguably the fundamental difference between these services and traditional public transport. Therefore, even if only pooled on-demand services are explicitly addressed, the outcomes of some of the indicators included can (at least partially) be transferred to other on-demand services. We cover aspects that address both temporal and spatial flexibility.

Additionally, we analyse the safety construct. Adequate safety is the (non-performance related) most basic transportation need (Peek and van Hagen, 2002) and a point of concern of some individuals for pooled on-demand services specifically (Morales Sarriera et al., 2017). Traffic safety and social safety are covered in the indicators.

Mobile applications. Given that individuals interact with MaaS services via an app interface, it is necessary to investigate their willingness to adopt the app. Even in countries where mobile phone adoption is almost ubiquitous, attitudes and skills can widely differ among individuals. Potential users need to not only have a smartphone and internet connection to operate the app, they also need to be willing to install the app, have enough skills to operate it, and have trust in the app. These three aspects are covered in our study.

Willingness to pay. The added value of MaaS lies in its integration of all modes of transport and travel stages, and in its real-time information functions, which enable both better services and better information. Under this category, we want to better understand respondents' willingness to pay for improved mobility, as well as their perceived need for improvements. Some studies consider bundling packages (i.e., having monthly subscriptions instead of paying per individual trip) a key aspect in MaaS. MaaS, as is considered in this study, does not require bundles. However, we also include a statement regarding bundling preferences to obtain a first impression on this aspect. We refer the reader to Ho et al. (2018) and Matyas and Kamargianni (2018) for those looking for studies regarding MaaS willingness to pay in bundling options.

All attitudinal indicators are presented to respondents as 5-point Likert-scale statements (strongly disagree/disagree/neutral/agree/strongly agree). Moreover, respondents are also given the 'Not applicable' answer option. Indicators are presented to respondents in blocks of either 4 or 5 statements. The order of the statements is randomised within each block.

2.1.2. Habits and current behaviour

Since habits and current behaviour are important predictors of future transportation behaviour (Lanzini and Khan, 2017), we complemented the previous attitudinal indicators with questions related to respondents' experience with aspects relevant to MaaS.

We inquire respondents' adoption of mobile technology (needed to operate any MaaS app) and their usage experience with the predecessor of the MaaS app: the journey planners (multimodal journey planners are considered Level 1 MaaS apps (Sochor et al., 2017)). Also, we look into individuals' current mobility patterns. We already had information regarding individuals' travel patterns from the 2017 wave of the MPN general annual survey. We add to this information by inquiring about respondents' familiarity with on-demand services. Additionally, to better understand what drives respondents while shaping their transport mode choices in their trips, we ask them for their motives in this decision process.

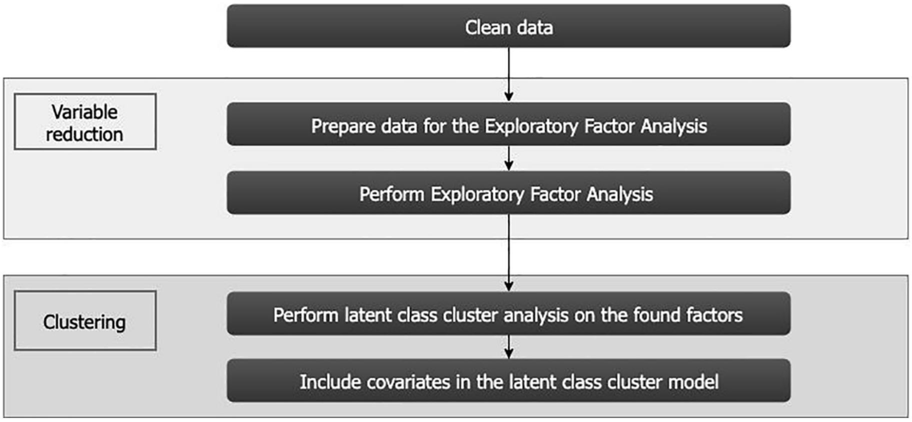

Fig. 2. Step-wise scheme of the analysis framework.

2.2. Analysis framework

Fig. 2 provides a step-wise overview of the main steps of the analysis. First, the data is cleaned. Respondents who require an unrealistically low time to complete the questionnaire, recurrently straight line (i.e., do not differentiate in ratings) and repeatedly select the 'not-applicable' option are considered invalid. Following, exploratory factor analysis and latent class cluster analysis are performed for variable reduction and clustering purposes.

Even if segmentation in transport literature often stems from differences in socioeconomic characteristics or current travel behaviour, previous research has identified attitudes as important predictors of travel behaviour (Pronello and Camusso, 2011). For example, Hunecke et al. (2010) found mobility-related attitude-based segmentation to yield greater differences in mobility behaviour than those based on socioeconomics, and Redmond (2000) found it to result in the highest predictive power for travel mode choice. Research into attitude-based segmentation has significantly increased in recent years. The common methodology, as the one followed in the paper at hand, is composed of a variable reduction technique and a subsequent cluster analysis. We refer the reader to Anable (2005), Haustein and Hunecke (2013) or Pronello and Camusso (2011) for further literature on previous research regarding mobility attitude-based segmentation. The following Sections 2.2.1 and 2.2.2 explain the methodology used in our research in more detail.

2.2.1. Exploratory factor analysis

In this study, we look for relationships among the variables that may be different from the prior expectations of the categories presented in Fig. 1. Therefore, Exploratory Factor Analysis (EFA; (Williams et al., 2010)) is the variable reduction technique used in this study. EFA accounts for the common variance among the variables (and is not to be confused with principal component analysis) (Suhr, 2005).

EFA can be performed exclusively on interval or ratio level variables (Suhr, 2005). Equidistance is often assumed between the different levels of Likert-scales, which allows us to perform EFA on our data. To identify if a considerable number of respondents does not feel addressed by some of the statements, we included the 'non-applicable' option. However, this option introduces data that falls out of the Likert-scale. We remove from the analysis any variable with a considerable number of non-applicable responses from the posterior analysis (not-applicable responses are not distributed at random). Low recurrence of non-applicability in a variable ($< 5.5\%$) is accepted and this data is treated as missing at random. This data is imputed using expectation maximisation, which produces the maximum likelihood estimation of parameters using all observed information (Acock, 2005). We impute the correlation matrix (using the SPSS add-on module presented in Weaver and Maxwell (2014)) instead of imputing the variables themselves, to overcome SPSS shortfall in including standard errors in the expectation maximisation imputation (von Hippel, 2004).

Factor scores are then calculated using a non-refined method. These methods are more stable across different samples than refined methods (Distefano et al., 2009). If factor loading differences among the indicators of the different factors are small, the 'non-weighted sum score method' will be used. Otherwise, the 'weighted sum score method' will be preferred. Both methods allow for a direct interpretation of the factor value in relation to the 5-point Likert scale presented to respondents.

2.2.2. Latent class cluster analysis

We aim at identifying respondents that share similar attitudes on the researched indicators. We hypothesise that attitudes on these indicators are to some extent related to each other, encompassed in their attitude towards MaaS. To this end, we perform latent class cluster analysis (LCCA). LCCA models, also referred to as finite mixture models, group individuals in different classes according to an unobserved (latent) class variable that explains their responses on a set of observed indicators (Molin et al., 2016).

Fig. 3 shows the conceptual latent class model used in the analysis. The EFA factors are the indicators of the model that help delve into the latent variable that is behind the differentiation of the latent classes. The covariates, represented in the lower part of Fig. 3, help characterise the different classes. Covariates on socioeconomic, mobility and technology-related characteristics are added to the model after a model without covariates with adequate model fit has been identified. Whenever the covariates do not improve the

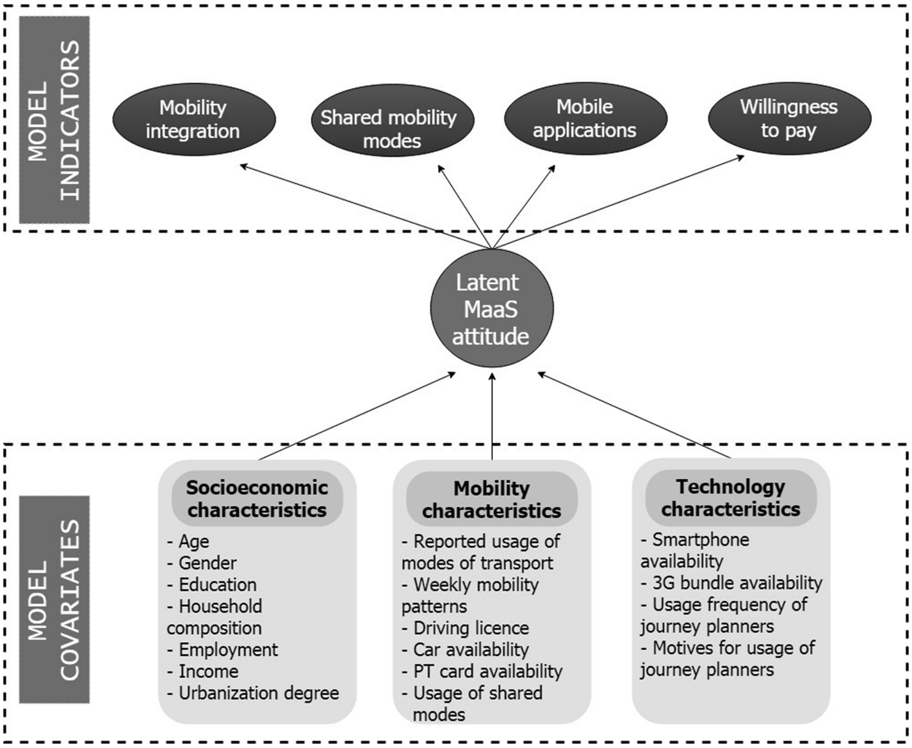

Fig. 3. Scheme of the latent class cluster model with the investigated covariates.

model, they are only included as passive covariates, to aid cluster identification.

The mathematical formulation of the model with the covariates takes the following form (Vermunt and Magidson, 2016):

$$f(y_i|z_i^{cov}) = \sum_{x=1}^{K} P(x|z_i^{cov}) \cdot \prod_{m=1}^{M} f(y_{im}|x), \tag{1}$$

where x is the latent variable with its K categories, z_i^{cov} individual's i set of covariates and y_{im} individual's i response to indicator m (M being the number of indicators). The first factor of the equation refers to the probability of belonging to a certain latent class given the individual's covariates, and the second factor is the probability density of y_i given x. This mathematical formulation holds assuming that the indicator variables are independent of each other conditional on the latent variable x (Vermunt and Magidson, 2016). A violation of this assumption in our model, which can be measured by means of the bivariate residuals, would indicate that the model lacks local fit and that it cannot be trusted (Oberski, 2016). We therefore examine this assumption by studying the bivariate residuals (BVR). Applied research often considers BVR to be chi-squared distributed, yet this approach does not always work satisfactorily (Oberski et al., 2013). Instead, Oberski et al. (2013) suggest to analyse the BVR p-values of the parametric bootstrapping. We follow this procedure in combination with the study of the bootstrapped L^2 of the overall model, as done in Oberski (2013).

Some of the variance present in the initial data of the attitudinal indicators is lost by using the obtained factors as only model indicators in the LCCA. Additionally, this approach treats the EFA factors as observed variables in the LCCA, ignoring the uncertainty that arises from the measurement of the factors through its attitudinal indicators. Still, the large number of statements included makes this double approach (variable reduction and subsequent cluster analysis) the rule in attitude-based segmentation studies, as previously mentioned in Section 2.2.

3. Results

The analysis and modelling approach detailed in the previous section has been applied to a dataset representative of the urban Dutch population. Fig. 4 indicates the research questions that are answered in the different sections of the analysis and interpretation of the results. Data collection and descriptive statistics are first presented (Section 3.1) followed by the Exploratory Factor Analysis (Section 3.2) and the Latent Class Cluster identification (Section 3.3). These clusters are further characterised in Section 4.

3.1. Data collection and sample description

To test our questionnaire, an on-line pilot was performed on April 2018. No modifications of the attitudinal indicators used in this

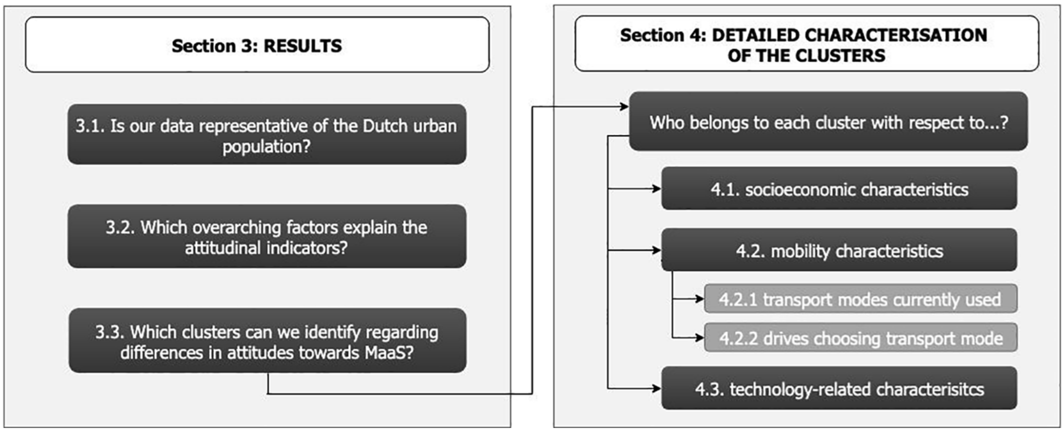

Fig. 4. Research questions answered in the analysis and interpretation of the results.

study were needed after the pilot. Our final questionnaire (conducted on-line and in Dutch) was distributed on May 2018. A total of 1077 respondents finished the questionnaire, of which 1006 (93%) were considered valid respondents after data cleaning. Only individuals aged 18 and older in possession of a mobile telephone took part in the questionnaire. We targeted respondents living in areas with more than 1500 inhabitants/km^2 (highly urbanised areas according the 'urbanity degree' indicator used in the Netherlands (Centraal Bureau voor de Statistiek (CBS), 1992)), and all respondents belonged to different households. The socio-economic characteristics of the sample, as well as the Dutch values (both for (very) high urbanised areas and for the whole of The Netherlands) are included in Table 1.

Our sample satisfactorily represents the shares between the two levels of urbanisation levels (high urbanised areas and very high urbanised areas) and gender. Regarding age, middle aged adults are a bit underrepresented and the elderly population slightly overrepresented. We can observe some differences between the age shares of the urban areas exclusively and the average of the Netherlands. As expected, younger adults are more prominent in urban environments. This is well represented in our sample.

We do not have values regarding education level, working status and household composition for the urbanised areas, only for the average of the Dutch population. Differences between our sample and the national average are as expected: a higher proportion of highly educated respondents and working individuals as well as a higher share of single person households than the national average. In general, we consider the representativeness of our sample to the shares of the target population to be adequate.

3.2. Exploratory factor analysis of MaaS indicators

2.6% of the total data from the attitudinal indicators was marked as 'not applicable', a high share of which is present in three out of the 31 indicators. These three indicators are not considered for the EFA analysis. The remaining missing values (1.4% of the total

Table 1

Comparison between the sample and Dutch population for different socio-economic variables. Sources for the population data: Centraal Bureau voor de Statistiek (CBS) (2018a), Centraal Bureau voor de Statistiek (CBS) (2018b), Centraal Bureau voor de Statistiek (CBS) (2018c) and Centraal Bureau voor de Statistiek (CBS) (2018d).

Socio-economic variable	Category	Share sample	Dutch (very) high urbanised areas	Dutch 2018 shares
Gender	Male	48.2%	48.9%	49.6%
	Female	51.8%	51.1%	50.4%
Age	18*–39	38.1%	38.1%	31.8%
	40–64	35.6%	42.0%	44.0%
	65 and above	26.3%	19.8%	24.2%
Education	Low	25.2%		31.5%
	Average	32.5%		37.8%
	High	42.0%		29.2%
	Unknown	0.2%		1.4%
Work status	Working	59.9%		50.9%
	No working	40.1%		49.1%
Household	1 person household	49.0%		38.2%
	> 1 person household	51.0%		61.8%
Urbanisation level	Very high urbanised (> 2500 inhab./km^2)	46.9%	48.2%	23.3%
	High urbanised (1500–2500 inhab./km^2)	53.1%	51.8%	25.1%

* 18–39 for the share sample, but 20–39 for the Dutch 2018 values.

Table 2
Results of the pattern matrix of the exploratory factor analysis.

Factors and their indicators	Factor loading
Mobility integration factor	
It is important to use public transport to preserve the environment	0.586
I choose to travel with public transport or to share rides to reduce my trip costs	0.580
I do not mind which transport mode I use, as long as it suits my trip needs	0.491
I am willing to try new ways to travel	0.474
People like me only use their own bike and/or car (reversed)	0.473
I often compare different travel options and transport modes before choosing how to travel	0.467
I like the privacy in the car or bike (reversed)	0.423
It makes me uncomfortable to ride with strangers on public transport	
I would not mind if other travellers get in or off the FLEXI vehicle during my ride	
I think the public transport is not so clean or decent	
I like travelling always in the same way	
It is essential to be able to easily combine different transport modes (such as bus, car, bike or car-sharing) in order to improve transportation in the Netherlands	
FLEXI over Public Transport (PT) factor (shared mobility modes)	
FLEXI seems to me more reliable than current public transport	0.595
I would feel safer in FLEXI than in a regular bus	0.587
I find FLEXI's flexibility in the departure time more convenient than traditional transit.	0.565
The proximity of a driver would make me feel safe in FLEXI	0.558
FLEXI would give me the freedom to travel where I need to be when needed	0.548
I like that FLEXI does not have a fixed schedule or route	0.543
FLEXI concerns factor (shared mobility modes)	
FLEXI does not have fix schedules. That would worry me.	0.624
I would be worried that FLEXI departs without me	0.587
I think that FLEXI drivers do not drive carefully	0.414
I would find it annoying that FLEXI does not drive the fastest route (e.g., FLEXI's route is 18 min instead of 15 min)	
Mobile application factor	
I would use a (smartphone) app if it gave me access to all available travel alternatives	0.727
I like to pay for my rides via a (smartphone) app	0.562
It is easy for me to find FLEXI's pick-up point if it is displayed on a map in the (smartphone) app	0.535
Willingness to pay factor	
I would be ready to pay for precise and reliable travel information	0.605
I am willing to pay more to have a more predictable travel time for my journey	0.420
I find it difficult to find information of all available travel alternatives	

data) were imputed using expectation maximisation. We performed the EFA employing the Principal Axis Factoring extraction method (unlike other methods it does not require the multivariate normality assumption (Fabrigar et al., 1999)) with oblimin oblique rotation (which allows for correlation among factors and thus better replicates human behaviours (Williams et al., 2010)). We investigate the suitability of the data for EFA with the Kaiser-Meyer-Olkin's (KMO) measure of sampling adequacy and Bartlett's test of sphericity (Field, 2009). We obtain a KMO of 0.835, which shows good sample adequacy (Hutcheson and Sofroniou, 1999), and the Bartlett's test of sphericity is < 0.001, which indicates sufficient relations between indicators for the EFA. Since the average communality (i.e., the proportion of the common variance present in the variables (Field, 2009)) is lower than 0.6, and the sample size is well over 200, we follow the scree plot criterion (Cattell, 1966) to decide on the number of factors (Field, 2009). This leads us to retain 5 factors in the factor analysis, which explains 44.6% of the variance.

Table 2 shows the factors founds and the factor loadings for the rotated pattern matrix. For interpretation, we only consider loadings bigger than 0.4, as advised in (Field, 2009). The rest of the indicators belonging to a factor are depicted in Table 2 in grey without the loading. A subsequent EFA on the variables that loaded significantly (> 0.4) on the previous factors, leads to the exact same factors and very similar indicators (KMO $= 0.802$, Bartlett's test of sphericity < 0.001, 51.1% variance explained). Only these loaded statements are considered for the posterior LCCA. The comparable loadings of the indicators belonging to the different factors indicate that they all contribute to a similar degree to the factor to which they belong. Therefore, factor scores are calculated using the "non-weighted sum scores" method. (For the interested reader, the scree plots of both EFA are included in Appendix B).

The factors found are well in line with those from the survey design phase (Fig. 1). The mobility integration factor shows how a positive multimodal mind-set aligns with a positive attitude towards public transport and a low car drive. In line with expectations, those three subcategories belong to an overarching factor. Interestingly, we found two factors regarding indicators pertaining (pooled) shared mobility modes, and they do not pertain to the flexibility and safety traits of these services. Instead, they refer to (i) the comprehensive preference of FLEXI (i.e., pooled on-demand services) over traditional transit (or vice versa), and (ii) concerns towards the new mobility service. The two factors being distinct suggests that even if there may be people that prefer public transport over pooled on-demand services, they may not necessarily have concerns related to using pooled on-demand services; similarly, individuals that prefer pooled on-demand services over public transport are still not necessarily very positive towards these services and may have concerns related to their usage.

3.3. Latent class cluster identification

We perform the Latent Class Cluster Analysis (LCCA) using the Latent GOLD software (version 5.1) (Vermunt and Magidson, 2016). We include the five EFA factors as well as the intention to use pooled on-demand services (binary variable, yes/no) as model indicators. To decide on the number of classes, we analyse both the BIC and the AIC global goodness-of-fit statistics in models ranging from one to seven classes. While the lowest BIC is shown for the 3-class model, the AIC keeps decreasing with the increase in the number of classes. We also examine the classification errors for all models. Taking all these three things into account, we consider the 5-class model as the most adequate. In this model, the BVR of the pair 'FLEXI over PT' & 'FLEXI concerns' is very low. Thus, we add a direct effect between these two factors, freeing the local dependence between them. All the attitudinal statements involved in these two factors share attitudes towards (the fictitious) FLEXI. Similar wording and varying interpretation of this new service from different respondents (as a result of the service description in the survey) may have led to the association between the two factors in the LCCA. As a result, we consider adding the direct effect useful (Magidson and Vermunt, 2004). Given that the overall bootstrapped L^2 *p*-value of the model is adequate, we do not add additional direct effects.

As the next step, we explore the effect of covariates presented in Fig. 3 on the latent class membership. Inclusion of covariates leads to changes in the clusters, but it helps differentiate individuals in the different clusters further, which, in turn, helps target policy recommendations. The covariate analysis is first done per type (using the types mentioned in Fig. 3). Covariates that prove significant per type are then put together incrementally one by one, and deleted if they become insignificant when combining different covariates. We find seven covariates to improve the model: 3G bundle availability, working status, education level, urbanisation level, bike use frequency, acquaintance with bike-sharing systems and presence of children in the household. The overall bootstrapped L^2 *p*-value of the final model is 0.30 (values > 0.05 provide an adequate fit (Vermunt and Magidson, 2005)), and the entropy of the model amounts to 0.66.

The profile of the indicators and active covariates of our final model are depicted in Table 3 (for the interested reader, parameters are included in Appendix C). We name the five clusters, ordered by their share from the largest to the smallest, as follows:

– Cluster 1 (32% of the sample): "*MaaS-FLEXI-ready individuals*". This cluster, which includes roughly one third of the respondents, has the highest average on all six indicators in comparison to all other 4 clusters, indicating the highest inclination for MaaS adoption and a remarkable 99% usage intention towards pooled on-demand services (FLEXI). It has the highest willingness to pay of all clusters, albeit still lower than the neutral value (2.9) – suggesting that the urban Dutch society is not willing to pay for improvements in mobility.
– Cluster 2 (25%): "*Mobility neutrals*". With a quarter of the sample, this cluster has an average of neutral in relation to almost all factors. They can be regarded as conservative, undecided or neutral-minded. Intention to adopt pooled on-demand services is the second highest among the five clusters, which can indicate that even if they have an overall neutral approach regarding the analysed attitudes, they are still open towards adopting new mobility services.
– Cluster 3 (22%): "*Technological car-lovers*". This cluster differs from the two previous clusters in the low value of the 'mobility integration' factor, showing a stronger inclination towards privately owned modes over public transport or other shared modes. Further, adoption intention towards pooled on-demand services is lower than the average of our sample despite this group having a neutral attitude towards these services. The further analysis of the covariates shows that within the owned modes, it is the car which is most dominant in this cluster. This preference may stem from enthusiasm towards the car or due to perceived need. Despite the low value of the factor related to mobility integration, this cluster is associated with a high value in the 'mobile application' factor. This underscores the importance of differentiating mobile-application from mobility-related aspects in the study of MaaS adoption.
– Cluster 4 (15%): "*Multimodal public transport supporters*". With roughly one sixth of the sample, this is the only cluster that next to Cluster 1 has a higher than neutral average value for both 'mobility integration' and 'mobile application' factor. Notwithstanding, this cluster strongly differs from Cluster 1 in the FLEXI over PT factor: while individuals of Cluster 1 prefer pooled on-demand services over traditional public transport, this is the other way around for individuals in this cluster. This difference highlights that having a positive attitude towards mobility integration does not imply future adherence to the new shared modes. Intention to use pooled on-demand services is at a level between the one observed among respondents in Cluster 3 and Cluster 1. Also, respondents in this cluster have a lower average score in the willingness to pay factor than the previous three clusters for improvements in mobility, showing higher cost sensitivity.
– Cluster 5 (6%): "*Anti new-mobility individuals*". The smallest cluster can be described as the contra of Cluster 1: showing negative attitude towards all presented factors and an extremely low intention to use pooled on-demand services (12%). This cluster shares with Cluster 3 the low value for the 'mobility integration' factor. However, unlike Cluster 3, respondents in this cluster also show limited technology affinity and a very negative attitude towards pooled on-demand services. Respondents in this cluster are therefore very unlikely to adopt any new mobility solution that is presented to them.

We graphically present the scores of the five EFA factors for the different clusters in Fig. 5. We further investigate the average values of the individual attitudinal indicators for the different clusters in Fig. 6. Indicators excluded from the LCCA (share of 'non-applicable' values $> 5\%$ or EFA factor loadings < 0.4) are also included in the radar graphs for a more comprehensive overview of all studied aspects. To ease the interpretation, indicators negative to MaaS and/or to their pooled on-demand services have been reversed. The radar graphs confirm that the general trends represented by the factors are also present for the individual attitudinal indicators, with 'MaaS-FLEXI-ready individuals' scoring, in general, highest and 'anti new-mobility individuals' scoring lowest. The

Table 3
Profile of the final LCCA model for both indicators and active covariates. For the active covariates, we highlight in bold the class with the highest share for each characteristic.

			LC1 MaaS-FLEXI-ready individuals	LC2 Mobility neutrals	LC3 Technological car-lovers	LC4 Multimodal public transport supporters	LC5 Anti new-mobility individuals
	Cluster Size		32%	25%	22%	15%	6%
Indicators	Mobility integration factor						
		Mean	3.4	3.1	2.5	3.3	2.1
	FLEXI over PT factor						
		Mean	3.3	3.1	3.1	2.5	2.2
	FLEXI concerns factor						
		Mean	2.8	3.0	2.9	2.8	3.4
	Mobile application factor						
		Mean	3.9	3.0	3.5	3.3	2.2
	Willingness to pay factor						
		Mean	2.9	2.7	2.6	2.4	2.2
	Intention to use FLEXI for free-time purposes						
		No	1%	25%	40%	28%	88%
		Yes	99%	75%	61%	72%	12%
Active covariates	Working (voluntary work excluded)						
		No	30%	**79%**	22%	27%	31%
		Yes	70%	22%	**78%**	73%	69%
	Highest education						
		Low	15%	**48%**	23%	13%	31%
		Medium	25%	36%	**43%**	26%	38%
		High	60%	17%	34%	**61%**	31%
	Child under 12 years old in household						
		No	88%	**98%**	77%	88%	90%
		Yes	12%	2%	**23%**	12%	10%
	Urbanisation level						
		Highly urbanised	44%	63%	**66%**	35%	58%
		Very highly urbanised	56%	37%	34%	**65%**	42%
	Reported bike use frequency						
		(almost) never	5%	**24%**	16%	2%	20%
		less than 1 day/month	5%	6%	9%	5%	**11%**
		1–3 days a month	10%	6%	**19%**	9%	15%
		1–3 days a week	**27%**	22%	26%	24%	20%
		4 or more days a week	52%	42%	29%	**60%**	34%
	Heard about bike sharing systems (no Dutch OV-bicycle)						
		No	46%	54%	60%	53%	**75%**
		Yes	**54%**	46%	40%	47%	25%
	3G bundle available on smartphone or tablet						
		No	4%	**72%**	0%	11%	43%
		Yes	96%	28%	**100%**	89%	57%

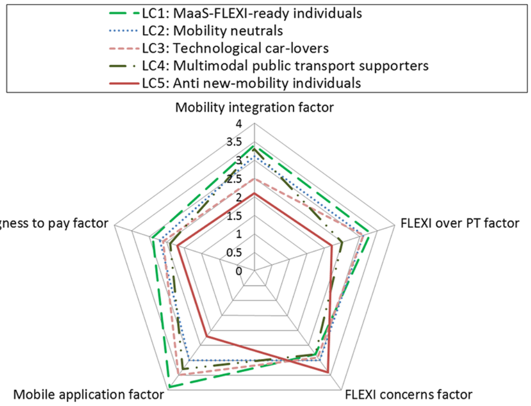

Fig. 5. Average score of the five EFA factors for the different clusters.

strong positive attitude of the 'multimodal public transport supporters' towards public transport is also clear from the public transport related statements in the graphs. The graphs also provide deeper insights into the extent to which MaaS related indicators differ. Privacy stands out for its importance while willingness to pay for travel information is distinct for its low scores. Regarding the mobile application factor, the app payment acceptance indicator scores significantly lower than the other related indicators.

4. Detailed characterisation of the clusters

The five clusters of our final model are further profiled with the information of covariates (active and passive). We differentiate three aspects (as indicated in Fig. 3): (a) socioeconomic characteristics, (b) mobility characteristics, and (c) technology related characteristics. They are discussed in the following Sections 4.1, 4.2 and 4.3, respectively.

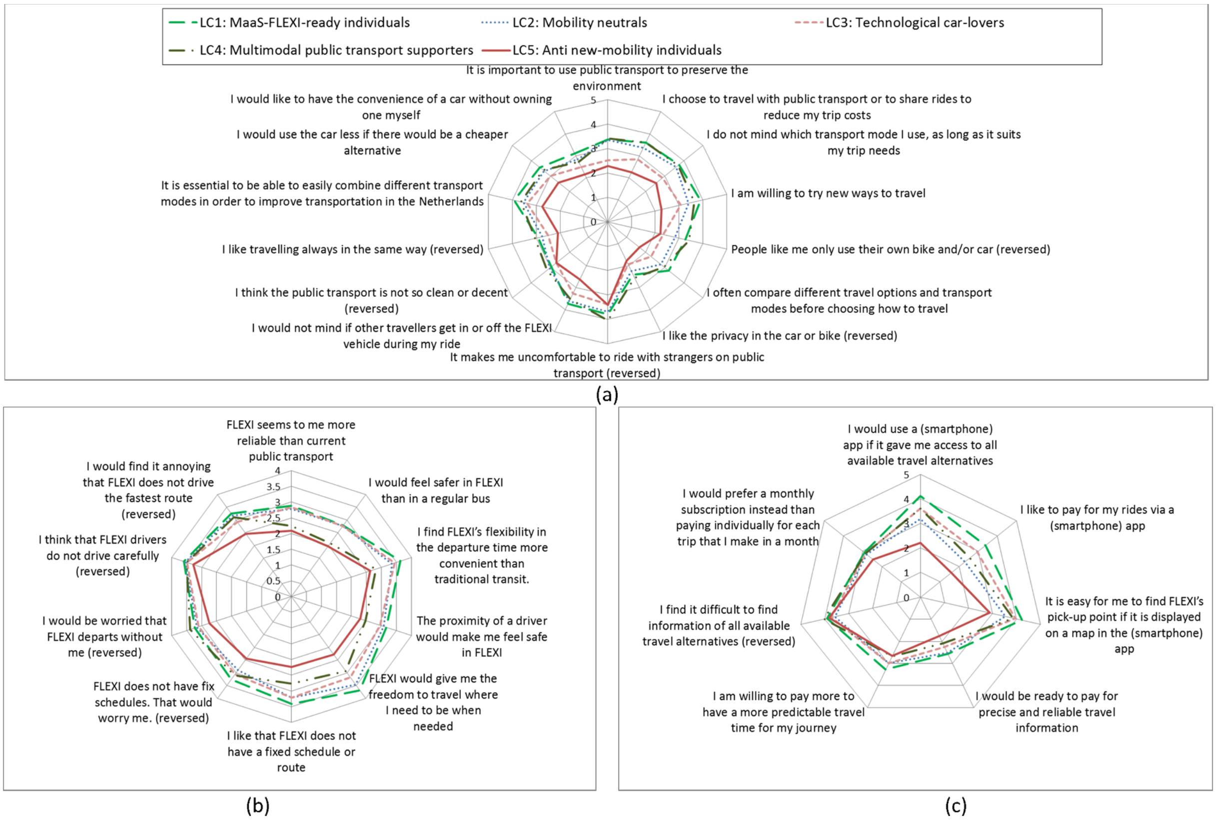

Fig. 6. Average score for the attitudinal indicators related to: (a) mobility integration; (b) (pooled) shared mobility modes, and; (c) mobile applications and willingness to pay.

Table 4
Socioeconomic inactive covariates for individuals of the five clusters. For each characteristic, we highlight in bold the class with the highest share.

	LC1 MaaS-FLEXI-ready individuals	LC2 Mobility neutrals	LC3 Technological car-lovers	LC4 Multimodal public transport supporters	LC5 Anti new-mobility individuals
Gender					
Male	48%	44%	54%	45%	**55%**
Female	52%	**56%**	46%	55%	45%
Age					
18–34 years old	**39%**	10%	33%	38%	27%
35–49 years old	24%	7%	**29%**	27%	24%
50–64 years old	20%	25%	25%	20%	**28%**
65+ years old	17%	**57%**	13%	15%	21%
Household composition					
Single	52%	50%	38%	**60%**	42%
Couple	25%	**38%**	25%	18%	35%
Couple (or single parent) + children	23%	12%	**37%**	22%	23%
Personal net monthly income					
No personal income	8%	10%	8%	9%	**12%**
< 2000 Eur	34%	**48%**	35%	35%	42%
2000–3000 Eur	36%	35%	**41%**	38%	38%
> 3000 Eur	**21%**	7%	15%	17%	8%
Missing value	1%	0%	1%	1%	0%

4.1. Socioeconomic characteristics' analysis of the latent clusters

Different socioeconomic covariates are included in the model to better understand the five clusters. Working status, education level, urbanisation level of the residence location, and the existence of children under 12 years old improve the membership function of the model (active covariates, depicted in Table 3). We also add age, gender, household composition and income as passive covariates in the model (see Table 4).

'MaaS-FLEXI-ready individuals' tend to be highly educated, young, have slightly higher average incomes and reside in the highest urbanised areas. These characteristics go in line with the characteristics that have been attributed to adopters of shared-mobility services (Alemi, 2018; Clewlow, 2016; Shaheen et al., 2012). 'Multimodal PT supporters' have a similar socioeconomic profile, only differing from the first cluster in their slightly lower average income.

'Mobility neutrals' are associated with a high percentage of 65+ age old respondents (57%). Most of the individuals in this cluster (79%) do not work, arguably due to the large number of retired people in this cluster, and have a lower average income.

The 'technological car-lovers' and the 'anti new-mobility individuals', the classes less inclined towards mobility integration, share the (slight) over-representativeness of males. This may be explained by the higher modal share of car among men than women in the Netherlands (Molin et al., 2016). These two classes strongly differ in relation to other socioeconomic characteristics, though. 'Technological car-lovers' are distinct from all others for the higher percentage of households with children (37%), many of them including children aged 12 or younger (23%). In line with this result, Md Oakil et al. (2016) found a higher car dependency among those becoming parents. 'Anti new-mobility individuals' have the most balanced age composition, representing roughly even shares of all age segments, and this cluster is associated with relatively lower income individuals, higher only those of the 'mobility neutrals'.

4.2. Mobility characteristics' analysis of the latent clusters

This subsection presents a detailed analysis of the mobility characteristics of the five clusters. We first examine respondents' travel patterns and then their main drives when choosing a transport mode.

4.2.1. Travel patterns

Reported bike frequency use and bike sharing awareness are active covariates of the model. Other variables related to mobility are also added to the model as inactive covariates (presented in Table 5), namely: car ownership, public transport card possession, car use (stated frequency), public transport use (stated frequency), weekly mobility patterns (stated), usage of new modes and main reasons to choose a transport mode.

'MaaS-FLEXI-ready individuals' and 'multimodal PT supporters' are the classes with the highest share of individuals in possession of a public transport smartcard (over 90%) while the 'technological car-lovers' and the 'anti new-mobility individuals' have the highest household car ownership shares (roughly 90%). The shares of the 'mobility neutrals' in these two aspects are in the middle of the five groups, in line with their intermediate position towards mobility. Usage of car and public transport resemble the trends in car ownership and smartcard possession. Interestingly, bike usage follows the same pattern as public transport, with 'MaaS-FLEXI-ready individuals' and 'multimodal PT supporters' biking the most often and 'technological car-lovers' and 'anti new-mobility individuals'

Table 5
Mobility inactive covariates for individuals of the five clusters. For each characteristic, we highlight in bold the class with the highest share.

	LC1 MaaS-FLEXI-ready individuals	LC2 Mobility neutrals	LC3 Technological car-lovers	LC4 Multimodal public transport supporters	LC5 Anti new-mobility individuals
Car in household					
No	30%	27%	8%	**37%**	12%
Yes	70%	74%	**92%**	63%	88%
Public transport card					
No	8%	17%	29%	5%	**31%**
Yes	92%	83%	71%	**95%**	69%
Reported car frequency					
(almost) never	8%	**11%**	2%	**11%**	4%
Less than 1 per month	8%	7%	2%	**14%**	5%
1–3 days per month	**19%**	14%	8%	**19%**	7%
1–3 days per week	33%	**38%**	28%	32%	36%
4 or more days per week	32%	30%	**60%**	24%	48%
Reported train frequency					
(almost) never	18%	39%	45%	11%	**52%**
Less than 1 per month	41%	42%	**44%**	33%	38%
1–3 days per month	18%	11%	7%	**23%**	4%
1–3 days per week	12%	5%	2%	**17%**	4%
4 or more days per week	12%	3%	3%	**15%**	4%
Reported BTM (Bus/Tram/Metro) frequency					
(almost) never	13%	23%	47%	16%	**48%**
Less than 1 per month	34%	36%	**38%**	34%	36%
1–3 days per month	**31%**	22%	7%	23%	9%
1–3 days per week	15%	15%	3%	**20%**	4%
4 or more days per week	**8%**	4%	5%	**8%**	4%
OV-bicycle ever used (specific bike sharing scheme)					
No	75%	93%	94%	68%	**96%**
Yes	25%	7%	6%	**32%**	4%
Bike sharing ever used (different from OV-bicycle)					
No	97%	**100%**	**100%**	98%	98%
Yes	**3%**	0%	0%	2%	2%
Uber ever used					
No	81%	**98%**	94%	88%	97%
Yes	**19%**	2%	6%	12%	3%
Car sharing used (in the past 12 months, question from annual 2017 MPN wave)					
No	96%	99%	99%	94%	**100%**
Yes	4%	1%	1%	**6%**	0%

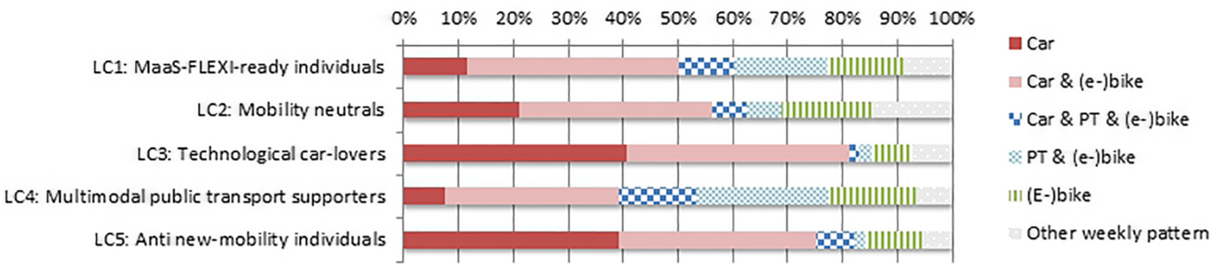

Fig. 7. Current weekly mobility patterns of respondents of het different latent classes (train and BTM have been merged in the PT category).

the least often.

We visualise the weekly mobility patterns of the individuals in Fig. 7 (considering car, public transport and (e-)bike). 40% of 'technological car-lovers' and 'anti new-mobility individuals' have an unimodal car behaviour, while this percentage drops to around 10% for 'MaaS-FLEXI-ready individuals' and 'multimodal PT supporters' (the two most multimodal clusters). Nonetheless, car usage is still more recurrent than public transport usage in all five clusters. Around 40% of 'multimodal PT supporters' and around 30% of 'MaaS-FLEXI-ready individuals' use some sort of public transport on a weekly basis. This percentage drops to less than 10% for 'technological car-lovers' and 'anti new-mobility individuals'. Moreover, a large share of individuals in these last two clusters report that they never use public transport. These results further show the alignment between attitudes and behaviour regarding mobility. Current unimodal car users are the least likely to be attracted by MaaS and the shared flexible transport modes offered by it.

We also analyse both individuals' awareness and usage of new shared mobility modes. Uber and OV-bikes (station-based bike-sharing of the Dutch train operator NS) are familiar to the large majority of respondents. Respondents are less familiar with bike-sharing schemes other than the OV-bikes (now proliferating in the Netherlands) (Table 3), with the two clusters with higher multimodal mind-sets ('MaaS-FLEXI-ready individuals' and 'multimodal PT supporters') being more aware of their existence than the non-multimodal-minded clusters ('technological car-lovers' and 'anti new-mobility individuals'). When examining usage of new modes of transport, we observe that the share of people who have used these modes varies depending on the mode, but is always highest for 'MaaS-FLEXI-ready individuals' and 'multimodal PT supporters' (OV-bike 25–32%; other bike-sharing systems 4–6%; Uber 12–19%; car-sharing 4–6%) than for the other groups (for which values under 5% are the rule). 'Mobility neutrals' resemble more 'technological car-lovers' and 'anti new-mobility individuals' with respect to new mobility modes. Presumably, the higher age range of these respondents (and somewhat lower technology capabilities) may be a hindrance in the usage of new modes of transport, even if they might be more willing to be multimodal.

4.2.2. Drives in mode choice

Next, we analyse the main drives for choosing a mode of transport for the individuals in each of the clusters. Among 15 different possibilities (comfort, relax, time, safety, flexibility, joy, status, reliability, price, environment, directness, ownership, health, carrying space, and other) respondents were asked to choose the three that are most relevant for them in deciding which mode of transport to use. These drives are depicted in Fig. 8, ordered from most to least chosen. Three characteristics set the two more car-driven clusters ('technological car lovers' and 'anti new-mobility individuals') apart from the other three.

The first one is ownership. Despite it not being a strict reason to choose a mode of transport but rather a precondition state, it is the most often mentioned reason among respondents from these two clusters (50–60% chose this factor in contrast to around 30% of respondents in the other three clusters). Therefore, mode ownership may indeed be one of the reasons behind their lesser interest in MaaS. The second is price relevance. There seems to be a link between multimodal-minded individuals and price consciousness, the more unimodal car individuals being less driven by economic reasons in their mobility decisions. And the third is environmental friendliness. The two more car-driven clusters are less environmentally friendly than the other three (even if this is not a major drive for any of the clusters). When asked directly whether respondents took into account the environment in their travel behaviour, less than 25% from the two more car-driven clusters did so, in contrast to around 40% of respondents in the other three clusters.

It is also worth noticing the low number of respondents that chose safety as driving force in their mode decisions. This is likely not due to them granting safety a low importance. Rather, they presumably consider safety a precondition present in all modes from which they make their mode decisions.

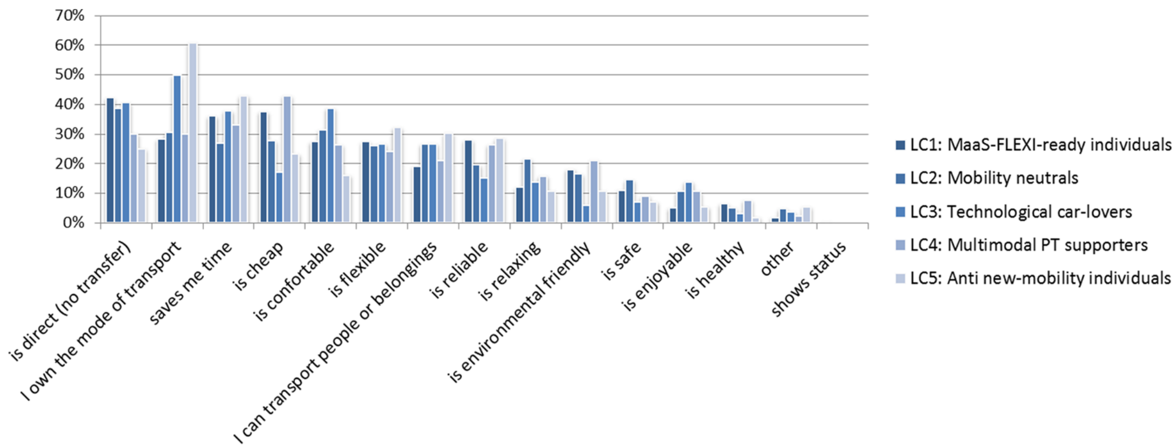

Fig. 8. Share of respondents of the different latent clusters for whom each of the presented statements were among the three most important reasons to choose a mode of transport.

Table 6
Journey planners' usage for individuals of the five clusters. For each characteristic, we highlight in bold the class with the highest share.

	LC 1 MaaS-FLEXI-ready individuals	LC 2 Mobility neutrals	LC 3 Technological car-lovers	LC 4 Multimodal public transport supporters	LC 5 Anti new-mobility individuals
How often do you look for travel information via your smartphone and/or tablet?					
Never	3%	34%	7%	7%	**35%**
Less than once a month	19%	30%	**32%**	16%	27%
1–3 days a month	**25%**	19%	21%	**25%**	16%
1–3 days a week	**36%**	15%	23%	**36%**	15%
4 or more days a week	**17%**	1%	16%	16%	7%
I use travel or route information …					
…to decide which mode of transport I use	**34%**	14%	11%	33%	7%
[car or motorcycle]…to find information about my travel time, congestion or accidents	64%	45%	**68%**	57%	54%
[car or motorcycle]…to decide which route to take	50%	45%	**60%**	49%	58%
[public transport] … to get information about schedules, travel time and delays	80%	54%	46%	**81%**	39%
[public transport] … to decide which route to take	53%	37%	23%	**58%**	17%
[bicycle, moped or on foot] … to decide which route to take	43%	24%	25%	**44%**	14%
I do not use any online travel and route information	1%	**9%**	6%	2%	7%

4.3. Technology related characteristics' analysis of the latent clusters

For a user to make use of MaaS and their on-demand services, he needs to have a smartphone and internet connection. However, 29% of the 'mobility neutrals' and 22% of the 'anti new-mobility individuals' do not currently own a smartphone, and a much higher percentage (79% and 43% respectively), are not subscribed to a 3G bundle, necessary for ubiquitous internet connection. As a result, these two groups are in a disadvantageous situation to use new mobility solutions. 'Multimodal public transport supporters' also lie a bit behind the top tier technology classes ('MaaS-FLEXI-ready individuals' and 'technological car lovers'), with 11% of respondents lacking 3G bundles (see Table 3).

Additionally to the MaaS-related attitudinal statements included in our analysis, respondents were faced with five Likert-scale statements regarding their innovativeness attitude (see Appendix A for the statements' description). A 'general innovativeness factor' is calculated from these using the "non-weighted sum scores" method (after checking that all five statements load together satisfactorily). "MaaS-FLEXI ready individuals" are the most positive towards innovativeness (3.4), followed by "Mobility neutrals" (3.2) and "Technological car-lovers" (3.1). The somewhat lower score of "Multimodal public transport supporters" (2.8) highlights that their lower openness to innovation encompasses other aspects beyond new on-demand mobility services. Finally, as could be expected, "Anti new-mobility individuals" have the lowest average value (2.4).

We also analyse journey planner usage (see Table 6). Technology adoption and attitude towards integrated mobility seem to explain the encountered differences among the clusters. The vast majority of individuals in the two pro-integrated-mobility clusters ('MaaS-FLEXI-ready individuals' and 'multimodal public transport supporters') use travel information via their smartphone or tablet (over 50% of them on a weekly basis), whereas over one third of respondents in the less technological clusters ('mobility neutrals' and 'anti new-mobility individuals') never do so. Motives to look for travel information also vary widely among classes. While one third of respondents from the pro-integrated-mobility clusters use travel information to help them decide the most adequate mode for a given trip, only 7–14% of respondents in the other three clusters do so. 'Technological car-lovers' have the highest percentage of individuals using car-related travel information, but their rates using travel information for public transport or active mode trips are half than those for the pro-integrated-mobility clusters.

5. Discussion

In this section, we discuss the key findings and provide some policy recommendations specific for each of the clusters.

5.1. Key findings

From the mobility point of view, MaaS integrates the available mobility alternatives. Results of this study show that there is an underlying mobility integration factor, in which a positive multimodal mind-set is aligned with a favourable attitude towards public transport and a low car drive. Results also show that these attitudes are aligned with current mobility patterns. As a result, individuals with more unimodal car behaviours seem less inclined to adopt MaaS. This is in line with earlier research; e.g. Ho et al. (2018) also identified very frequent car users as less likely to adopt MaaS.

Our two clusters with a most favourable attitude towards mobility integration are also the two most multimodal clusters. Individuals in these two clusters tend to be young, highly educated people who live in more dense urban areas and have no children. These socioeconomic characteristics have also been found among early adopters of shared modes (Alemi, 2018; Clewlow, 2016; Dias et al., 2017; Shaheen et al., 2012), as well as among the more general multimodal individuals (both in Europe (Molin et al., 2016) and in the USA (Buehler and Hamre, 2015)). We also found that it is more common among individuals belonging to these two clusters to rely on travel information for their transport mode choices instead of solely considering their preferred or habitual mode of transport. Indeed, multimodal individuals are known to have more complex strategies to choose transport mode and exercise weaker travel habits (Verplanken et al., 1997). This, in turn, facilitates the introduction of new mobility solutions such as MaaS.

We found, however, a strong difference between these two more multimodal clusters. While 'MaaS-FLEXI-ready individuals' (32% of the sample) have a very positive attitude towards pooled on-demand services, 'multimodal public transport supporters' (15% of the sample) strongly prefer traditional transit over other new modes. Previous research has highlighted that public transport users are less likely to shift from fixed public transport usage to pooled on-demand services (Al-Ayyash et al., 2016) or to adopt MaaS (Ho et al., 2018), in line with our observations for the 'multimodal public transport supporters'. This can be due to the (in general) higher usage of public transport by lower income individuals (Hensher, 1998; Ryley et al., 2014), for which the on-demand modes of transport included in MaaS may be perceived as a premium and potentially expensive service. In fact, while 'MaaS-FLEXI-ready individuals' show the highest average score regarding willingness to pay, 'multimodal public transport supporters' have the second lowest willingness to pay among the five found clusters.

In the Dutch setting, having less income inequalities (Gini coefficient of 0.28 (World Bank, n.d.)) than in the two countries of the abovementioned studies (Lebanon 0.32 and Australia 0.35 (World Bank, n.d.)), and relatively high fares of public transport (eurostat, 2018), some current public transport adepts (the 'MaaS-FLEXI-ready individuals') are arguably more open towards accepting alternative on-demand services. This reasoning seems consistent with Hall et al. (2018), who suggest that it is current public transport users with the higher incomes that are more open to complementing their public transport usage with on-demand services, which is what makes adopting MaaS an attractive alternative. In addition, the share of public transport users in the Dutch population is currently quite low, with most individuals not using public transport on a weekly basis, even in the more public transport minded clusters. As a result, there is potential for these users to incur a modal shift from their car trips to MaaS. In contexts different than the Netherlands, we expect clusters that resemble the same characteristics as the ones found in this study. The higher the percentage of public transport users, the higher their technological capabilities and interest, and the lower their cost sensitivity; the higher the adoption potential for MaaS will be in that setting.

This research has also shown that pooled on-demand services are more appealing than transit for 'mobility neutrals' and 'technological car-lovers'. Pooled on-demand services can thus attract individuals from these clusters to more sustainable mobility patterns. Similarly, pooled on-demand services can facilitate a switch from the private car and into MaaS for areas characterised by poor public transport, as suggested by Lavieri and Bhat (2018) for the American context.

We identify two main barriers for potential MaaS adoption: (a) high (car) ownership need as a determinant of mode choice (for 'technological car-lovers' and 'anti new-mobility individuals'), and (b) low technology adoption (for 'mobility neutrals' and 'anti new-mobility individuals'). Additionally, clusters more inclined to keep their unimodal car behaviour showed lower environmental and financial sensitivity. Strong sense of ownership, as well as low environmental and financial sensitivity have also been found in literature as important variables that deter individuals from moving away from a car-centric behaviour and into adopting new mobility solutions (Burkhardt and Millard-Ball, 2006; Efthymiou et al., 2013; Lane, 2005; Paundra et al., 2017; Zheng et al., 2009). Additionally, Lavieri and Bhat, (2018) also found technology adoption as a relevant barrier for MaaS adoption in the USA context. To this end, some policy recommendations tailored to each of the five latent classes found in our analysis are described in the following subsection.

5.2. User cluster specific recommendations

Based on the results of this study, we highlight some relevant policy recommendations that can increase the adoption of (sustainable) MaaS schemes in relation to the five clusters:

1. The "*MaaS-FLEXI-ready individuals*" (32% of the sample) are most inclined to adopt MaaS schemes and use pooled on-demand services thereby. These individuals are therefore more likely to reduce their car usage in favour of other modes. Simultaneously, they can also be expected to (slightly) lower their public transport usage by switching to on-demand services such as pooled on-demand services, given their attitudinal preference towards the new mode against traditional transit. Travel awareness campaigns can support the modal shift of this cluster away from private car usage by focusing on concrete functional benefits that MaaS can bring them (time and price benefits) while avoid a major shift from traditional transit usage by appealing to their environmental sensibility.
2. The *"Mobility neutrals"* (25%) are mainly composed of individuals aged 65 and older. The analysis of technology related covariates showed how their lower technological adequacy can prevent them from profiting from new mobility trends. Providing hybrid systems that do not only rely on a mobile app but also include a smartcard ticket version can address this barrier. Allowing for SMS correspondence or having a call centre for ordering purposes (even if implemented at a small fee for the customer) can also allow that individuals with no smartphones or internet connection can profit from on-demand services or real time information.
3. The *"Technological car-lovers*" (22%) have a car-centred attitude and behaviour, as well as a below average environmental friendliness or cost sensitivity, making it difficult to trigger a behavioural shift. Previous research suggests promoting new mobility modes to these individuals solely as an alternative for the occasions in which their car is unavailable instead of suggesting to replace it altogether (Paundra et al., 2017). This can help them experience the new system and its novelty, which may appeal to their high technological affinity. Attention should also be given to providing mobility alternatives that suit the needs of families with children, more prevalent in this cluster. Additionally, measures to avoid that young families shift towards unimodal car usage with the birth of their first child as well as measures to facilitate a mode shift away from car-based patterns once these children grow older can help reduce the size of this cluster.
4. The *"Multimodal public transport supporters"* (15%) have positive attitudes and behaviour towards public transport usage. These individuals do not exclude new shared modes yet (strongly) prefer scheduled public transport. Still, only around 40% of their individuals use public transport weekly, less than the percentage that use car on a weekly basis. The introduction of new modes can help these individuals reach destinations for which arguably they currently need the car. As a result, their multimodal mindset with positive attitudes towards public transport and lower car drive can become more aligned with their future travel patterns. Given their above average positive attitude towards transit, they can become the most sustainable MaaS users, considering public transport as main mode and other on-demand services as mere complements to transit when necessary. Compared to 'MaaS-FLEXI-ready individuals' and 'technological car lovers', this cluster has a somewhat lower technology affinity. Easy to use MaaS apps offered by trusted public transport operators can provide a familiar and reliable environment for these individuals in their MaaS

adoption process. Their public transport card/subscription could be extended to give them access to additional shared mobility services and enable them to try these for free. This measure could help them overcome their resistance to innovation and does not require them to pay via an app (which they would rather not do).

5. The cluster "*Anti new-mobility individuals*" (6%) represents the individuals least inclined to adopt MaaS, since they show both high psychological car ownership and low technology adoption. Strategies applied to 'mobility neutrals' and 'technological car lovers' can also be of relevance to individuals in this cluster. Still, these individuals are unlikely to adopt MaaS or on-demand services such as pooled on-demand services in the short term. This cluster likely represents the laggards of mobility innovations (Rogers, 1983).

6. Conclusions

The present study has identified five different clusters in relation to individuals' inclination to adopt MaaS based on attitudinal indicators. Special focus was given in this research to pooled on-demand services, which exemplify the flexibility characteristics of on-demand services while accounting for the collective mobility services, needed to meet the objectives of urban mobility (reduce congestion, reduce parking space, increase liveability, etc.).

To this end, we first identified relevant factors regarding MaaS and designed a series of attitudinal indicators addressing them. We presented these aspects to a representative sample of urban Dutch population, having a valid sample size of over thousand respondents. We then performed an exploratory factor analysis and latent class cluster analysis on the data as data reduction and clustering techniques so as to identify homogeneous clusters. To provide a comprehensive picture of the individuals belonging to the different clusters, we enriched our model with a series of covariates that covered socioeconomic, mobility and technology-related characteristics.

Two of the identified clusters ('MaaS-FLEXI-ready individuals' and 'multimodal public transport supporters', which represent 47% of the respondents) have positive inclinations towards two main aspects of MaaS (mobility-integration aspects and mobile-application aspects). However, the somewhat lower (despite positive) app inclination of individuals in the latter cluster, their below average willingness to pay and their strong preference of traditional public transport over (pooled) on-demand services by individuals belonging to this cluster, may prevent individuals of this cluster to adopt MaaS at a first instance. Even if these two clusters are the ones with the highest shares of public transport usage, their average car usage is still higher, indicating potential for shifts from private car. The MaaS adoption potential on settings different from the one in this study will likely also depend on the share of public transport users, with urban areas with higher shares of public transport users having more individuals that are ready to adopt MaaS.

Nonetheless, before any modal shifts are materialised, enough availability of on-demand services needs to be granted, so that these individuals can find the anticipated mobility benefits that MaaS promises them. Also, their willingness to pay showed to be average to low. This should be taken into account when designing the offered services. Individuals belonging to the other three clusters presented high (car) ownership needs and/or low technology adoption, which have been identified in this study as main barriers towards MaaS adoption and as a starting point for policy recommendations to increase MaaS adoption by these individuals. Policy makers, public transport operators, MaaS providers and companies entering the shared mobility landscape can use findings in this research to evaluate the possible changes that urban settings can undergo as a result of MaaS and provide targeted strategies to different customer segments of the population.

Even if behaviour and attitudes are closely linked, our research (pertaining to attitudes) does not allow us to conclude to what extent those attitudes will culminate in a behavioural change or if habitual behaviour will emerge. This is best tested in real life pilots or full launch MaaS schemes. Also, the obtained results are dependent on the attitudinal statements presented to respondents in the study. While we tried to cover a wide range of attitudes, some aspects such as autonomy/perceived behavioural control, which have been previously found to be predictors of PT usage (Anable, 2005; Hunecke et al., 2010), have not been included in the present study. In our study, we adopted the main MaaS aspects identified in Durand et al. (2018) in defining the indicators. Further research could consider a theoretical basis such as the Theory of Planned Behaviour (Ajzen, 1991) or the Technology Acceptance Model (Davis, 1989) as basis for deriving the single indicators.

Future MaaS pilots could consider involving a representative sample of the population among their participants, so as to assess mobility shifts and characteristics beyond those for early adopters. This would enable the comparison between the expectations derived from attitudes and behavioural intentions to actual behaviour, and could additionally help analyse the impact of MaaS for different trip types. Given the novelty of the research topic, and to avoid overloading respondents, this research only considered pooled on-demand services explicitly. Further research could also consider other on-demand services different from pooled on-demand services.

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Appendix A. Attitudinal indicators

See Table A1.

Table A1
Attitudinal indicators used, including their sources (where applicable) and their relation to the keywords used in Fig. 1.

CATEGORY	Keywords Fig. 1	Full statement in English	Source (where applicable)
MOBILITY INTEGRATION			
Multimodal mind-set			
	Mode agnosticism	I do not mind which transport mode I use, as long as it suits my trip needs	
	Multimodal considerations	I often compare different travel options and transport modes before choosing how to travel	Modified from (Atasoy et al., 2010)
	Mode integration wish	It is essential to be able to easily combine different transport modes (such as bus, car, bike or car-sharing) in order to improve transportation in the Netherlands	
	Way of travel innovation	I am willing to try new ways to travel	
	Habits' importance	I like travelling always in the same way	
Public transport attitude			
	Uneasiness of sharing	It makes me uncomfortable to ride with strangers on public transport	Modified from (Rubin, 2011)
	PT cleanliness concerns	I think the public transport is not so clean or decent	
	Environmental importance	It is important to use public transport to preserve the environment	
	Cost saving importance	I choose to travel with public transport or to share rides to reduce my trip costs	
Private car attitude			
	Ownership need	I would like to have the convenience of a car without owning one myself	Modified from (Kamargianni et al., 2017)
	Privacy need	I like the privacy in the car or bike	Modified from (Spears et al., 2013)
	Reputation aspects	People like me only use their own bike and/or car	
	Car usage vs cost	I would use the car less if there would be a cheaper alternative	
SHARED MOBILITY MODES			
Flexibility trait FLEXI			
	Approval	I like that FLEXI does not have a fixed schedule or route	
	Freedom	FLEXI would give me the freedom to travel where I need to be when needed	
	Reliability (FLEXI vs PT)	FLEXI seems to me more reliable than current public transport	
	Convenience (FLEXI vs PT)	I find FLEXI's flexibility in the departure time more convenient than traditional transit.	
	Concerns	FLEXI does not have fix schedules. That would worry me.	
	Missed pick-up	I would be worried that FLEXI departs without me	Modified from (Khattak and Yim, 2004)
	In-vehicle time	I would find it annoying that FLEXI does not drive the fastest route (e.g., FLEXI's route is 18 min instead of 15 min)	Modified from (Al-Ayyash et al., 2016)

(continued on next page)

Table A1 (*continued*)

CATEGORY	Keywords Fig. 1	Full statement in English	Source (where applicable)
	Number of stops	I would not mind if other travellers get in or off the FLEXI vehicle during my ride	Modified from (Al-Ayyash et al., 2016)
Safety trait FLEXI			
	Safety (FLEXI vs PT)	I would feel safer in FLEXI than in a regular bus	
	Driving skills	I think that FLEXI drivers do not drive carefully	
	In-vehicle safety	The proximity of a driver would make me feel safe in FLEXI	
MOBILE APPLICATIONS			
	App adoption	I would use a (smartphone) app if it gave me access to all available travel alternatives	
	App literacy	It is easy for me to find FLEXI's pick-up point if it is displayed on a map in the (smartphone) app	
	In-app payments	I like to pay for my rides via a (smartphone) app	
WILLINGNESS TO PAY			
	Willingness to pay for information	I would be ready to pay for precise and reliable travel information	
	Willingness to pay for reliable services	I am willing to pay more to have a more predictable travel time for my journey	Modified from (Shiftan et al., 2008)
	Information need	I find it difficult to find information of all available travel alternatives	
	Price bundling preference	I would prefer a monthly subscription instead than paying individually for each trip that I make in a month	
INNOVATIVENESS (exclusively used for the technology related characteristics in Section 4.3)			
		I try new services, such as Netflix or Uber, before my friends and family	Modified from (Roehrich, 2004)
		I try new products, such as a fitbit or the newest smartphone, before my friends and family	Modified from (Roehrich, 2004)
		I often purchase new products, even though they are expensive	Modified from (Jensen et al., 2014)
		My family and friends usually come to me for advice about new products and services	Modified from (Caiati, 2018)
		I am enthusiastic about the possibilities offered by new technologies	Modified from (Ewing and Sarigöllü, 2000)

Appendix B. Scree plot of the exploratory factor analyses

See Fig. A1.

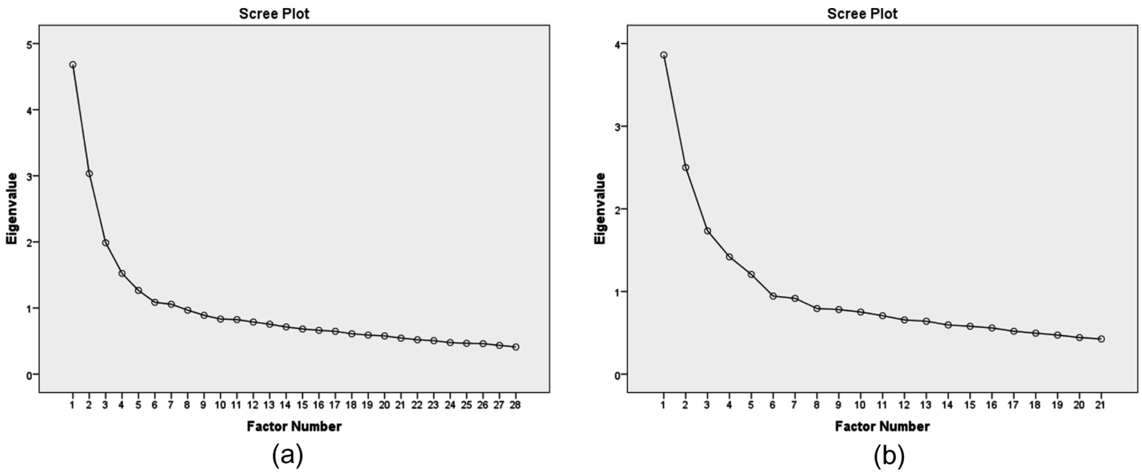

Fig. A1. Scree plot of the EFA with (a) all mentioned indicators, and (b) only indicators loading significantly (> 0.4) in the first EFA.

Appendix C. Parameters of the final LCCA model

See Tables A2–A4.

Table A2
Parameters of the model indicators.

	Cluster1	Cluster2	Cluster3	Cluster4	Cluster5	Wald	p-value	R^2
Mobility integration factor	2.115	0.8158	−1.7815	1.9748	−3.1241	73.3311	4.5e−15	0.415
Mobile application factor	2.0171	−0.683	0.7071	0.1711	−2.2123	106.5489	4.0e−22	0.377
FLEXI over PT factor	1.6592	1.052	0.8745	−1.4864	−2.0993	46.6031	1.8e−9	0.2803
FLEXI intention to use	3.4818	0.0861	−0.5709	−0.0431	−2.9538	47.3265	1.3e−9	0.2556
Willingness to pay factor	0.748	0.3775	0.1191	−0.427	−0.8177	41.2514	2.4e−8	0.0929
FLEXI concerns factor	−0.0816	0.1854	0.071	−0.5231	0.3483	15.2871	0.0041	0.0402

Table A3
Parameters of direct effects.

FLEXI over PT & FLEXI concerns		Wald	p-value
	−0.6323	32.6183	1.1e−8

Table A4
Parameters of the active covariates.

Intercept	Cluster1	Cluster2	Cluster3	Cluster4	Cluster5	Wald	p-value
	−0.1999	1.0566	−0.6576	−1.0304	0.8313	5.0817	0.28
Covariates	Cluster1	Cluster2	Cluster3	Cluster4	Cluster5	Wald	p-value
Working (voluntary work excluded)							
No	−0.1265	0.943	−0.4215	−0.1867	−0.2084	24.3239	6.9e−5
Yes	0.1265	−0.943	0.4215	0.1867	0.2084		
Highest education							
Low	−0.3906	0.4872	0.0442	−0.4359	0.2952	25.5977	0.0012
Medium	−0.3644	0.6375	−0.0171	−0.2721	0.0161		
High	0.755	−1.1247	−0.027	0.7079	−0.3113		
Exists child under 12 years							
No	−0.2798	1.1592	−0.7493	−0.2971	0.167	13.2564	0.010
Yes	0.2798	−1.1592	0.7493	0.2971	−0.167		
Urbanisation level							
Highly urbanised	−0.305	0.5747	0.1248	−0.5047	0.1102	20.9191	0.00033
Very highly urbanised	0.305	−0.5747	−0.1248	0.5047	−0.1102		
Bike usage frequency							
	0.2473	−0.2608	−0.1026	0.3586	−0.2425	26.1517	2.9e−5
Bike sharing systems heard about							
No	−0.2668	−0.1167	0.1157	−0.1056	0.3735	13.3494	0.0097
Yes	0.2668	0.1167	−0.1157	0.1056	−0.3735		
3G bundle available							
No	−0.7581	2.1628	−2.3895	−0.2051	1.1898	31.8151	2.1e−6
Yes	0.7581	−2.1628	2.3895	0.2051	−1.1898		

References

Acock, A.C., 2005. Working with missing values. J. Marriage Fam. 67, 1012–1028. https://doi.org/10.1111/j.1741-3737.2005.00191.x.
Ajzen, I., 1991. The theory of planned behavior. Organ. Behav. Hum. Decis. Process. 50, 179.
Al-Ayyash, Z., Abou-Zeid, M., Kaysi, I., 2016. Modeling the demand for a shared-ride taxi service: an application to an organization-based context. Transp. Policy 48, 169–182. https://doi.org/10.1016/j.tranpol.2016.02.013.
Alemi, F., 2018. What Makes Travelers Use Ridehailing? Exploring the Latent Constructs behind the Adoption and Frequency of Use of Ridehailing Services, and Their Impacts on the Use of Other Travel Modes. University of California Davis.
Anable, J., 2005. "Complacent Car Addicts"; or "Aspiring Environmentalists"? Identifying travel behaviour segments using attitude theory. Transp. Policy 12, 65–78. https://doi.org/10.1016/j.tranpol.2004.11.004.
Atasoy, B., Glerum, A., Hurtubia, R., Bierlaire, M., 2010. Demand for public transport services: integrating qualitative and quantitative methods. 10th Swiss Transport Research Conference.
Buehler, R., Hamre, A., 2015. The multimodal majority? Driving, walking, cycling, and public transportation use among American adults. Transportation (Amst) 42, 1081–1101. https://doi.org/10.1007/s11116-014-9556-z.
Burkhardt, J.E., Millard-Ball, A., 2006. Who is attracted to carsharing? Transp. Res. Rec. J. Transp. Res. Board 1986, 98–105. https://doi.org/10.1177/0361198106198600113.
Caiati, V., 2018. Innovation adoption and diffusion in transportation: modelling the long-term demand for new mobility services based on platform technology. 97th Annual Meeting of the Transportation Research Board. Washington D.C.
Cattell, R.B., 1966. The Scree Test For The Number Of Factors. Multivariate Behav. Res. 1, 245–276. https://doi.org/10.1207/s15327906mbr0102_10.
Centraal Bureau voor de Statistiek (CBS), 2018a. Bevolking; kerncijfers (in Dutch) [WWW Document]. https://opendata.cbs.nl/statline/#/CBS/nl/dataset/37296ned/table?ts=1541413888808 (accessed 11.5.18).
Centraal Bureau voor de Statistiek (CBS), 2018b. Bevolking; hoogstbehaald onderwijsniveau en onderwijsrichting (in Dutch) [WWW Document]. https://opendata.cbs.nl/statline/#/CBS/nl/dataset/82816NED/table?ts=1541415076597 (accessed 11.5.18).
Centraal Bureau voor de Statistiek (CBS), 2018c. Arbeidsdeelname; kerncijfers (in Dutch) [WWW Document]. https://opendata.cbs.nl/statline/#/CBS/nl/dataset/82309NED/table?ts=1541426506205 (accessed 11.5.18).
Centraal Bureau voor de Statistiek (CBS), 2018d. Regionale kerncijfers Nederland; Bevolking; Stedelijkheidsklasse (in Dutch) [WWW Document]. https://opendata.cbs.nl/statline/#/CBS/nl/dataset/70072ned/table?ts=1541423939562 (accessed 11.5.18).
Centraal Bureau voor de Statistiek (CBS), 1992. Sociale kerncijfers - Nieuwe maatstaf van stedelijkheid. Mens en Maatsch (in Dutch).
Chowdhury, S., Ceder, A., (Avi), 2016. Users' willingness to ride an integrated public-transport service: a literature review. Transp. Policy 48, 183–195. https://doi.org/10.1016/j.tranpol.2016.03.007.
Clauss, T., Döppe, S., 2016. Why do urban travelers select multimodal travel options: A repertory grid analysis. Transp. Res. Part A Policy Pract. 93, 93–116. https://doi.org/10.1016/j.tra.2016.08.021.
Clewlow, R.R., 2016. Shared-use mobility in the united states: current adoption and potential impacts on travel behaviour. Present. 95th Annial Meet. Transp. Res. Board.
Davis, F.D., 1989. Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Q. 13, 319–340.
Dias, F.F., Lavieri, P.S., Garikapati, V.M., Astroza, S., Pendyala, R.M., Bhat, C.R., 2017. A behavioral choice model of the use of car-sharing and ride-sourcing services. Transportation (Amst) 44, 1–17. https://doi.org/10.1007/s11116-017-9797-8.
Distefano, C., Zhu, M., Mîndrilă, D., 2009. Understanding and using factor scores: considerations for the applied researcher. Pract. Assessm. Res. Eval. 14, 1–11 https://doi.org/10.1.1.460.8553.
Durand, A., Harms, L., Hoogendoorn-Lanser, S., Zijlstra, T., 2018. Mobility-as-a-Service and changes in travel preferences and travel behaviour: a literature review.

Efthymiou, D., Antoniou, C., Waddell, P., 2013. Factors affecting the adoption of vehicle sharing systems by young drivers. Transp. Policy 29, 64–73. https://doi.org/10.1016/j.tranpol.2013.04.009.
Eurostat, 2018. Price levels for personal transport equipment, transport services, communication, restaurants and hotels [WWW Document]. Comp. price levels Consum. goods Serv. https://ec.europa.eu/eurostat/statistics-explained/index.php/Comparative_price_levels_of_consumer_goods_and_services#Price_levels_for_personal_transport_equipment.2C_transport_services.2C_communication.2C_restaurants_and_hotels (accessed 1.8.19).
Ewing, G., Sarigöllü, E., 2000. Assessing Consumer preferences for clean-fuel vehicles: a discrete choice experiment. J. Public Policy Mark. 19, 106–118.
Fabrigar, L.R., Wegener, D.T., MacCallum, R.C., Strahan, E.J., 1999. Evaluating the use of exploratory factor analysis in psychological research. Psychol. Methods 4, 272–299.
Field, A., 2009. Discovering Statistics Using IBM SPSS Statistics, third ed. SAGE Publications Ltd, London.
Givoni, M., Banister, D., 2010. Integrated Transport: From Policy to Practice. Routledge.
Goodall, B.W., Dovey, T., Bornstein, J., Bonthron, B., 2017. The rise of mobility as a service. Deloitte Rev.
Hall, J.D., Palsson, C., Price, J., 2018. Is Uber a substitute or complement for public transit? J. Urban Econ. 108, 36–50. https://doi.org/10.1016/j.jue.2018.09.003.
Haustein, S., 2012. Mobility behavior of the elderly: An attitude-based segmentation approach for a heterogeneous target group. Transportation (Amst) 39, 1079–1103. https://doi.org/10.1007/s11116-011-9380-7.
Haustein, S., Hunecke, M., 2013. Identifying target groups for environmentally sustainable transport: assessment of different segmentation approaches. Curr. Opin. Environ. Sustain. https://doi.org/10.1016/j.cosust.2013.04.009.
Hensher, D.A., 1998. The imbalance between car and public transport use in urban Australia: why does it exist? Transp. Policy 5, 193–204. https://doi.org/10.1016/S0967-070X(98)00022-5.
Ho, C.Q., Hensher, D.A., Mulley, C., Wong, Y.Z., 2018. Potential uptake and willingness-to-pay for Mobility as a Service (MaaS): a stated choice study. Transp. Res. Part A Policy Pract. 117, 302–318. https://doi.org/10.1016/j.tra.2018.08.025.
Hoogendoorn-Lanser, S., Schaap, N.T.W., Olde Kalter, M.J., 2015. The netherlands mobility panel: an innovative design approach for web-based longitudinal travel data collection. Transp. Res. Procedia 11, 311–329. https://doi.org/10.1016/j.trpro.2015.12.027.
Hunecke, M., Haustein, S., Böhler, S., Grischkat, S., 2010. Attitude-based target groups to reduce the ecological impact of daily mobility behavior. Environ. Behav. 42, 3–43. https://doi.org/10.1177/0013916508319587.
Hutcheson, G.D., Sofroniou, N., 1999. The Multivariate Social Scientist: Introductory Statistics using Generalized Linear models. Sage.
Janic, M., 2001. Integrated transport systems in the European Union: an overview of some recent developments. Transp. Rev. 21, 469–497. https://doi.org/10.1080/01441640110042147.
Jensen, A.F., Cherchi, E., de Dios Ortúzar, J., 2014. A long panel survey to elicit variation in preferences and attitudes in the choice of electric vehicles. Transportation (Amst) 41, 973–993. https://doi.org/10.1007/s11116-014-9517-6.
Jittrapirom, P., Caiati, V., Feneri, A.-M., Ebrahimigharehbaghi, S., Alonso-González, M.J., Narayan, J., 2017. Mobility as a service: a critical review of definitions, assessments of schemes, and key challenges. Urban Plan. 2, 13. https://doi.org/10.17645/up.v2i2.931.
Kamargianni, M., Li, W., Matyas, M., Schäfer, A., 2016. A critical review of new mobility services for urban transport. Transp. Res. Procedia 14, 3294–3303. https://doi.org/10.1016/j.trpro.2016.05.277.
Kamargianni, M., Matyas, M., Li, W., 2017. Londoners' Attitudes Towards Car-ownership and Mobility-as-a-Service: Impact Assessment and Opportunities that Lie Ahead. UCL Energy Institute's MaaSLab Rep. Prep. Transp, London, pp. 52.
Karlsson, M., Sochor, J., Aapaoja, A., Eckhardt, J., König, D., 2017. Deliverable 4: Impact Assessment. MAASiFiE project funded by CEDR.
Kennisinstituut voor Mobiliteitsbeleid (KiM), 2018. Stabiele beelden: Trends in beleving en beeldvorming van mobiliteit (Trends in perception and mobility imaging).
Khattak, A.J., Yim, Y., 2004. Traveler response to innovative personalized demand-responsive transit in the San Francisco Bay Area. J. Urban Plan. Dev. 130, 42–55. https://doi.org/10.1061/ASCE0733-94882004130:142.
Lane, C., 2005. PhillyCarShare: first-year social and mobility impacts of carsharing in Philadelphia, Pennsylvania. Transp. Res. Rec. J. Transp. Res. Board 1927, 158–166. https://doi.org/10.3141/1927-18.
Lanzini, P., Khan, S.A., 2017. Shedding light on the psychological and behavioral determinants of travel mode choice: a meta-analysis. Transp. Res. Part F Traffic Psychol. Behav. 48, 13–27. https://doi.org/10.1016/j.trf.2017.04.020.
Lavieri, P.S., Bhat, C.R., 2018. MaaS in Car-Dominated Cities: Modeling the adoption, frequency, and characteristics of ride-hailing trips in Dallas, TX. Tech. Pap.. Dep. Civil, Archit. Environ. Eng. Univ., Texas, Austin.
Li, Y., Voege, T., 2017. Mobility as a Service (MaaS): challenges of implementation and policy required. J. Transp. Technol. 7, 95–106. https://doi.org/10.4236/jtts.2017.72007.
Luo, Q., Dou, X., Di, X., Cornelius Hampshire, R., 2017. Multimodal Connections between Bikesharing and Ride-Hailing: An Empirical Study in New York City.
Magidson, J., Vermunt, J., 2004. Latent class models. pp. 175–198.
Martinez, L.M., Viegas, J.M., 2017. Assessing the impacts of deploying a shared self-driving urban mobility system: an agent-based model applied to the city of Lisbon, Portugal. Int. J. Transp. Sci. Technol. 6, 13–27. https://doi.org/10.1016/j.ijtst.2017.05.005.
Matyas, M., Kamargianni, M., 2018. Survey design for exploring demand for Mobility as a Service plans. Transportation (Amst). https://doi.org/10.1007/s11116-018-9938-8.
Md Oakil, A.T., Manting, D., Nijland, H., 2016. Dynamics in car ownership: The role of entry into parenthood. Eur. J. Transp. Infrastruct. Res. 16, 661–673.
Molin, E., Mokhtarian, P., Kroesen, M., 2016. Multimodal travel groups and attitudes: a latent class cluster analysis of Dutch travelers. Transp. Res. Part A Policy Pract. 83, 14–29. https://doi.org/10.1016/j.tra.2015.11.001.
Morales Sarriera, J., Escovar Álvarez, G., Blynn, K., Alesbury, A., Scully, T., Zhao, J., 2017. To share or not to share: investigating the social aspects of dynamic ridesharing. In: Transportation Research Board 96th Annual Meeting, pp. 109–117. https://doi.org/10.3141/2605-11.
Oberski, D.L., 2016. Beyond the number of classes: separating substantive from non-substantive dependence in latent class analysis. Adv. Data Anal. Classif. 10, 171–182. https://doi.org/10.1007/s11634-015-0211-0.
Oberski, D.L., 2013. Local dependence in latent class models : application to voting in elections. In: Advances in Latent Variables [Sis 2013 Conference Proceedings]. Vita e Pensiero, Milan, Italy, pp. 1–10.
Oberski, D.L., van Kollenburg, G.H., Vermunt, J.K., 2013. A Monte Carlo evaluation of three methods to detect local dependence in binary data latent class models. Adv. Data Anal. Classif. 7, 267–279. https://doi.org/10.1007/s11634-013-0146-2.
Paundra, J., Rook, L., van Dalen, J., Ketter, W., 2017. Preferences for car sharing services: Effects of instrumental attributes and psychological ownership. J. Environ. Psychol. 53, 121–130. https://doi.org/10.1016/j.jenvp.2017.07.003.
Peek, G.-J., van Hagen, M., 2002. Creating synergy in and around stations: three strategies for adding value. Transp. Res. Rec. J. Transp. Res. Board 1793. https://doi.org/10.3141/1793-01.
Pronello, C., Camusso, C., 2011. Travellers' profiles definition using statistical multivariate analysis of attitudinal variables. J. Transp. Geogr. 19, 1294–1308. https://doi.org/10.1016/j.jtrangeo.2011.06.009.
Redmond, L., 2000. Identifying and Analyzing Travel-Related Attitudinal, Personality, and Lifestyle Clusters in the San Francisco Bay Area. University of California Davis.
Roehrich, G., 2004. Consumer innovativeness – concepts and measurements. J. Bus. Res. https://doi.org/10.1016/S0148-2963(02)00311-9.
Rogers, E.M., 1983. Diffusion of Innovations, third ed. The Free Press.
Rubin, J., 2011. Choosing Transit: The Influence of Past Travel Behavior, Attitudes and Habits on Present Choices. University of California, Berkerley.
Ryley, T.J., Stanley, P.A., Enoch, M.P., Zanni, A.M., Quddus, M.A., 2014. Investigating the contribution of Demand Responsive Transport to a sustainable local public transport system. Res. Transp. Econ. 48, 364–372. https://doi.org/10.1016/j.retrec.2014.09.064.
Shaheen, S.A., Martin, E.W., Cohen, A.P., Finson, R.S., Shaheen, S.A., 2012. Public bikesharing in North America: early operator and user understanding. Mineta Transp. Inst. https://doi.org/10.1006/jssc.1996.7207.

Shaheen, S., Totte, H., Stocker, A., 2018. Future of Mobility White Paper. UC Berkeley. https://doi.org/10.7922/G2WH2N5D.

Shiftan, Y., Outwater, M.L., Zhou, Y., 2008. Transit market research using structural equation modeling and attitudinal market segmentation. Transp. Policy 15, 186–195. https://doi.org/10.1016/j.tranpol.2008.03.002.

Smile Mobility, 2015. SMILE einfach mobil – Pilot operation and survey [WWW Document]. http://smile-einfachmobil.at/pilotbetrieb_mobile_en.html (accessed 1.11.19).

Sochor, J., Arby, H., Arlsson, M.K., Sarasini, S., 2017. A topological approach to Mobility as a Service: a proposed tool for understanding requirements and effects, and for aiding the integration of societal goals. In: ICoMaaS 2017 Proceedings, pp. 187–208. https://doi.org/10.1109/ICPP.1993.23.

Sochor, J., Karlsson, M., Strömberg, H., 2016. Trying out mobility as a service. Experiences from a field trial and implications for understanding demand. Transp. Res. Rec. J. Transp. Res. Board 57–64. https://doi.org/10.3141/2542-07.

Spears, S., Houston, D., Boarnet, M.G., 2013. Illuminating the unseen in transit use: a framework for examining the effect of attitudes and perceptions on travel behavior. Transp. Res. Part A Policy Pract. 58, 40–53. https://doi.org/10.1016/j.tra.2013.10.011.

Steg, L., 2005. Car use: Lust and must. Instrumental, symbolic and affective motives for car use. Transp. Res. Part A Policy Pract. 39, 147–162. https://doi.org/10.1016/j.tra.2004.07.001.

Strömberg, H., Rexfelt, O., Karlsson, I.C.M.A., Sochor, J., 2016. Trying on change – trialability as a change moderator for sustainable travel behaviour. Travel Behav. Soc. 4, 60–68. https://doi.org/10.1016/j.tbs.2016.01.002.

Suhr, D.D., 2005. Principal component analysis vs. exploratory factor analysis. SUGI 30 Proceedings.

Tachet, R., Sagarra, O., Santi, P., Resta, G., Szell, M., Strogatz, S.H., Ratti, C., 2017. Scaling law of urban ride sharing. Sci. Rep. 7, 42868. https://doi.org/10.1038/srep42868.

Vermunt, J.K., Magidson, J., 2016. Technical Guide for Latent GOLD 5. 1: Basic, Advanced, and Syntax. Statistical Innovations Inc.

Vermunt, J.K., Magidson, J., 2005. LatentGOLD 4.0 User's Guide. Statistical Innovations.

Verplanken, B., Aarts, H., Van Knippenberg, A., 1997. Habit, information acquisition, and the process of making travel mode choices. Eur. J. Soc. Psychol. 27, 539–560. https://doi.org/10.1002/(SICI)1099-0992(199709/10)27:5 < 539::AID-EJSP831 > 3.0.CO;2-A.

von Hippel, P.T., 2004. Biases in SPSS 12.0 Missing Value Analysis. Am. Stat. 58, 160–164. https://doi.org/10.1198/0003130043204.

Weaver, B., Maxwell, H., 2014. Exploratory factor analysis and reliability analysis with missing data: A simple method for SPSS users. Quant. Methods Psychol. 10, 143–152. https://doi.org/10.20982/tqmp.10.2.p143.

Williams, B., Onsman, A., Brown, T., 2010. Exploratory factor analysis: a five-step guide for novices. Austr. J. Paramed. 8, 1–13. https://doi.org/10.33151/ajp.8.3.93.

World Bank, n.d. GINI index (World Bank estimate) | Data [WWW Document]. https://data.worldbank.org/indicator/SI.POV.GINI?locations = AU-LB-NL (accessed 1.8.19).

Zheng, J., Scott, M., Rodriguez, M., Sierzchula, W., Platz, D., Guo, J., Adams, T., 2009. Carsharing in a university community. Transp. Res. Rec. J. Transp. Res. Board 2110, 18–26. https://doi.org/10.3141/2110-03.