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Mobility-as-a-Service (MaaS): A latent class cluster analysis to identify Dutch vehicle owners' use intention

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A R T I C L E I N F O

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A B S T R A C T

A restructuring of the current mobility and transportation system seems to be inescapable, as a result of the increasing urbanization and challenges regarding global sustainability. The concept of Mobility-as-a-Service (MaaS) is regarded by policy-makers as an answer to the needed change. Generally speaking, MaaS is an online platform that enables users to plan, book and pay a trip out of a variety of transport modes, conventional and shared. However, in the literature, the potential impact of MaaS on mobility is still relatively unclear. This study, therefore, aims to provide insights into which factors influence the intention to use MaaS among private vehicle owners, who have until now been identified as relatively MaaS-averse travellers. Policy-makers are highly interested in this group to start using MaaS since their shift from private vehicles to other transport options might positively contribute to easing the congestion and environmental problems. In order to create some insights on possible travel behavioural shift and adoption of new systems, an empirical study has been conducted among (co–)owners of motorized vehicles (passenger car, electric passenger car, van, motorcycle; moped) that live in the Netherlands. The survey was based on a conceptual model that explains why people would use this new system (MaaS) and has asked respondents about their travel behaviour, socio-economic characteristics and attitudes towards MaaS. Using Latent Class Cluster Analysis (LCCA) five clusters in the sample population regarding the intention to use MaaS were identified. The cluster profiles show that private vehicle owners who often use public transport and active modes are most inclined to use MaaS, whereas the 'conservative' passenger car owners who use the car as their main mode of transport for all their trips (e.g. commuting, leisure) show a lower intention to use MaaS. As it can be expected that the societal benefits of MaaS will especially occur when these conservative car owners adopt MaaS, we conclude that, from a policy perspective, implementing MaaS could be less effective in reducing transport externalities (e.g. pollution and wasted time in congestion) as perhaps expected.

1. Introduction

Rapid global urbanization results in higher traffic volumes (Utriainen & Pöllänen, 2018) which negatively affect daily life (Mulley,

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2017). Together with the global need to decrease greenhouse gas emissions, new solutions for daily transport are increasingly needed (Utriainen & Pöllänen, 2018). Transport policymakers and planners are consequently searching for innovative ways that enable people to travel more sustainably (Alyavina et al., 2020), for instance using smart mobility solutions. Among these is Mobility-as-a-Service (MaaS), which is an integrated system that enables travellers to plan, book and pay for trips through a single online interface. Various transport options are provided by a MaaS operator, which makes it easier for the end-users to choose trips utilizing a range of mobility providers (Butler et al., 2021; MaaS Alliance, 2021). As a relatively new concept, the development of MaaS is still in its early stages (Vonk Noordegraaf et al., 2021). Consequently, the exact impact of MaaS on the current transport system is unclear, but it is speculated that MaaS comprehensively restructures the way mobility services are delivered and consumed (Araghi et al., 2020; Caiati, Rasouli & Timmermans, 2020). MaaS is for instance expected to induce a shift from the current dominant transport modes, where individuals primarily move in privately owned vehicles (Utriainen & Pöllänen, 2018) towards a preferred mobility outlook, where individuals have access to several travel services and do not require owning a transport mode (Araghi et al., 2020). Travellers may also choose to mix their journeys, partly using their own mode and partly using MaaS services. Since MaaS provides access to several travel modes with only a single platform for booking and payments, optimal trips in a specific context and travel time can be calculated for travellers, given their specific preferences. The aim is to offer attractive alternative transport modes with MaaS, especially for owners of private motorized vehicles, thereby promoting less resource-intensive transportation modes (active modes, public transport) at the expense of privately owned vehicles (Jittrapirom et al., 2017). This could potentially result in a decrease in per capita vehicle kilometres travelled by private vehicles as well as in the associated externalities of private vehicle ownership, such as urban sprawl, community severance, climate change, air pollution, parking pressure and parking congestion (Butler et al., 2021; Populus Technologies Inc, 2021).

However, preceding studies also suggest that MaaS may potentially be counterproductive by mainly replacing trips currently made by public transport or active modes instead of replacing trips currently made by private vehicles (Casadó et al., 2020). In this case, MaaS could lead to unsustainable travel practices among the users and fail to achieve the expected modal shift and reduction in car ownership (Alyavina et al., 2020). Faber et al. (2020) and Alonso-González et al. (2020) suggest that vehicle owners, i.e. users of non-environmentally modes, are identified as the least likely to adopt MaaS whereas the group likely to adopt MaaS already uses the environmentally friendly transport modes. In order to improve sustainability, MaaS should on the one hand maximize the use of environmentally friendly transport modes among users that previously used non-environmentally friendly modes, and on the other hand, MaaS should minimize the use of non-environmentally friendly modes among consumers that previously used environmentally-friendly modes (Jang et al., 2021). These earlier papers, however, indicate that the introduction of MaaS might do the exact opposite.

The reasons for the lower willingness to use MaaS among private vehicle owners have received little attention. As Keller et al. (2018) point out, the available literature on integrated multimodal mobility platforms, such as MaaS, lacks a systematic and theory-driven investigation of potential user perceptions, requirements and acceptance. It is therefore uncertain whether the anticipated benefits of MaaS will be achieved, what the impact of MaaS on transport and society will be and what the individual adoption intentions are (Caiati et al., 2020; Matyas & Kamargianni, 2019). More insight on what holds private vehicle owners back to use MaaS could be of value for increasing its success once introduced. However, not all private vehicle owners have similar behaviour. Rather there may be a variety of tastes and travel behaviours existing among these people, which requires a more in-depth study in their travel choices and preferences and better analysis of their potential response towards MaaS.

This research, therefore, aims to detect the heterogeneity among private vehicle owners regarding their intentions to use MaaS and to understand which factors explain the (non) adoption of MaaS amongst vehicle owners. This is done by identifying latent groups that may exist among these people that have similar choices and preferences within each group. In this research, "private vehicle (co–) owners" refers to individuals that (collectively) possess a motorized vehicle, either with mechanical or electric power supply, which is primarily used by the person who owns or has the right to use it. In the remainder of this paper, these individuals will be referred to with the term "vehicle owners".

This study builds further on preceding research and their recommendations, for example, that of Alonso-González et al. (2020) and their recommendation to use a theoretical basis for determining the attitudinal indicators for MaaS adoption. The Unified Theory of Acceptance and Use Technology (UTAUT) model (Venkatesh et al., 2003) is used in this research as a theoretical basis, given the model's high suitability for researching individual acceptance and adoption of an innovation (Morrison & Van Belle, 2020). As an empirically validated model based on eight preceding theoretical frameworks (Alshehri, 2012), the UTAUT model was expected to enable obtaining a comprehensive prediction of MaaS' adoption potential. In recent years the UTAUT-model has increasingly been used in transportation research, for example in studies regarding the user acceptance of Automated Road Transport Systems (Madigan et al., 2016; Madigan et al., 2017), driverless busses (Chen et al., 2020), bicycle sharing systems (Jahanshahi et al., 2020) or electric vehicle (Jain et al., 2022). To the authors' knowledge, the only study that applied the UTAUT-model in the context of Mobility-as-a-Service, similarly to our research, is that of Ye, Zheng and Yi (2020). They investigated the use potential and requirements of MaaS among residents of a small, car-reliant town in the suburbs of Shanghai. We build further on their research approach by applying the UTAUT-model to study the intention to use MaaS in a Western country (The Netherlands) with another cultural background and a longer history of car usage. We also apply a different analysis method. This research therefore also adds to the body of literature that uses this theoretical framework to study the adoption potential of MaaS and consequently sheds light on the suitability of this approach for meeting the research objectives.

The remainder of the paper is structured as follows. Section 2 describes the conceptual model created for this research and its theoretical underpinnings. The methodological steps taken in this research are described in section 3. Starting with a description of the survey and followed by the applied statistical analyses. Section 4 presents the estimation results from the analyses and the obtained clusters. Section 5 discusses the implications of our findings in relation to previous research findings. Finally, section 5 discusses the limitations of this research and suggests directions for further research and policy-making.

2. Conceptual model

The UTAUT model is used in this study as a theoretical basis to identify potential influential factors on the intention to use MaaS. This resulted in a conceptual model specified to the context of the intention to use MaaS among vehicle owners living in the Netherlands. This section will discuss the items incorporated in this conceptual model.

2.1. Conceptual model

The UTAUT-model (Venkatesh et al., 2003) is an empirically validated model (Alshehri, 2012) that allows researchers to obtain a more comprehensive prediction of users' behaviour than other models do (Khechine, Raymond & Augier, 2020). The original UTAUT-model consists of four key determining constructs that influence the use behaviour of an individual: Performance Expectancy, Effort Expectancy, Social Influence and Facilitating Conditions. The moderators gender, age, experience and voluntariness of use are modelled in the UTAUT-model to influence the relationships between the constructs and use behaviour (Venkatesh et al., 2012). Despite the wide adoption of the UTAUT-model, its capability to explain individual's technology acceptance has been a point of discussion. Increasing the number of variables has been suggested to enhance the model's predictive ability, resulting in extensions to the model with additional variables (Chao, 2019).

The combination of the UTAUT-model with preceding research findings on the adoption potential of MaaS and similar concepts resulted in a conceptual model specified to the use intention of MaaS among vehicle owners. This conceptual model consists of eight constructs, grouped as extrinsic or intrinsic motivations, and eleven moderators (see Fig. 1), that are intended to explain the behavioural intention to use MaaS. Different from the original UTAUT-model is in our study the intention to use the dependent variable, instead of the actual use. This is done because the availability of MaaS in the Netherlands is limited, which makes assessing the actual use of MaaS hardly possible. Additionally, behavioural intention is viewed as the consideration of the pros and cons involved in decisions leading to the performance of a certain behaviour (Hunecke et al., 2007), making it a good predictor of the use of MaaS when available. The constructs and moderators included in the conceptual model will be explained in detail in the next sub-sections.

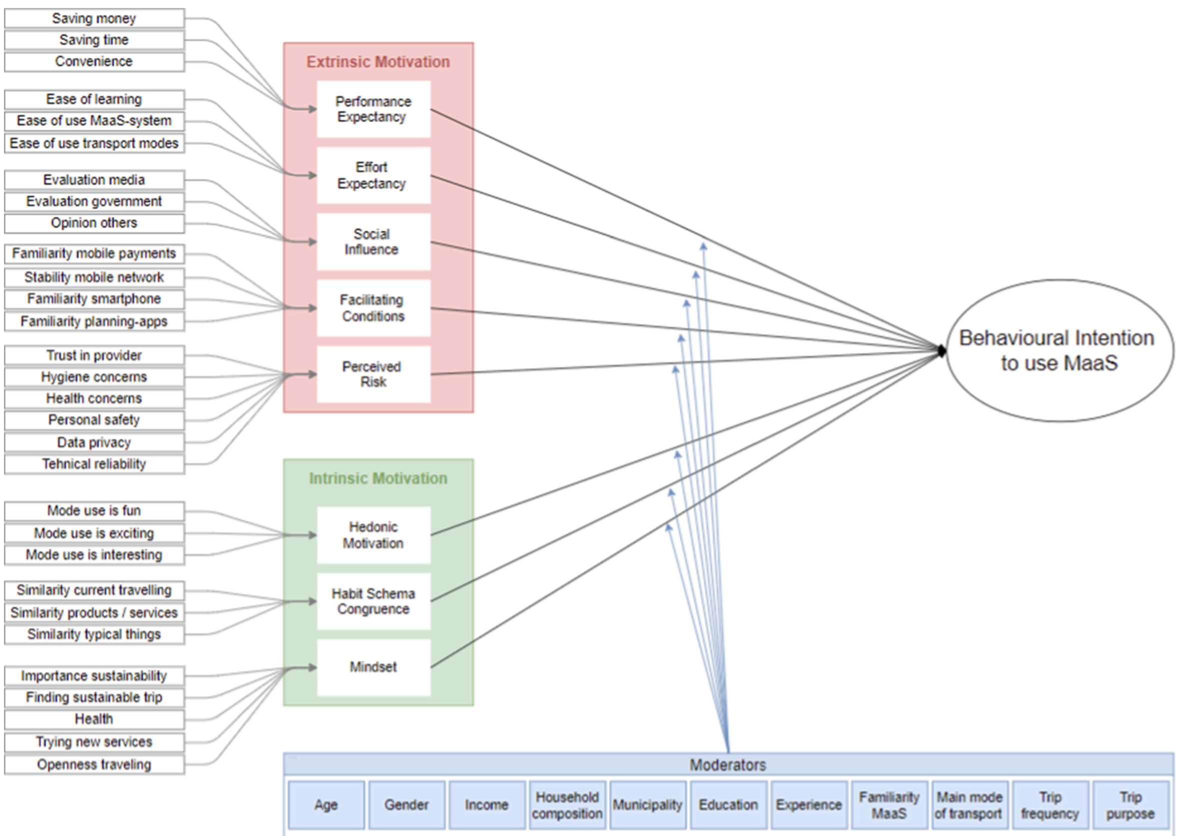

Fig. 1. Conceptual Model.

2.2. Extrinsic motivation

The UTAUT-construct 'Performance Expectancy' is 'the degree to which using a technology will provide benefits to consumers in performing certain activities' (Venkatesh, Thong & Xu, 2012, p. 159) and is, therefore, included in the conceptual model. Expected potential benefits of MaaS compared to other transport modes relate to travel time (Nemþanu et al., 2016), out-of-pocket costs (Liljamo et al., 2020) and convenience (Utriainen & Pöllänen, 2018). The constructs 'Effort Expectancy' and 'Social Influence' are also included in our conceptual model since preceding research identified the perceived ease of using MaaS (Schikofsky, Dannewald & Kowald, 2020) and evaluations by media, government or 'people of importance' (for the potential user) (Caiati et al., 2020; Ye et al., 2020) to influence the intention to use.

MaaS applications require the ownership of and familiarity with a smartphone to successfully make use of the system. Alyavina et al. (2022) for instance suggest the exclusion of transport users with lower digital literacy could be a potential weakness of MaaS' long term use. The resources an individual has available to use MaaS, i.e. the construct 'Facilitating Conditions' from the UTAUT-model is therefore also assumed to influence the intention to use MaaS. Next, the perceived risks of using MaaS could potentially influence an individual's intention to use MaaS, such as concerns over data privacy (Polydoropoulou, Pagoni & Tsirimpa, 2020), concerns about receiving honest, safe and reliable services instead of services that are in the advantage of the provider (Alyavina et al., 2020) and potential physical risks (Casadó et al., 2020).

2.3. Intrinsic motivation

The remaining three constructs refer to motivations to use MaaS coming from an individual's inherent satisfaction or interest in using MaaS, instead of the potential benefits that MaaS offers. Schikofsky et al. (2020), for instance, found that the perceived enjoyment of using MaaS, i.e. Hedonic Motivation, has a considerable influence on the intention to use MaaS. Individuals' travel habits might also influence the intention to use. Alonso-González et al. (2020) found that individuals more open to using MaaS show weaker habitual travel behaviour. The fit between the characteristics of a new object and an associated habit related to a reference schema

Mobility as a Service (MaaS) is a mobility concept which offers access to several transport modes via one single smartphone app. This app helps the user to find transport for a certain trip, depending on the traveller's preferences (costs, travel time, convenience etc.) and based on real-time travel data. Only a single payment for the whole trip is possible, instead of separate payments for each travel mode in the trip. The MaaS-traveller can pay per trip or at the end of the month. Various subscriptions are also possible. The image below gives an example of the app interface and which transport modes are offered. The provided transport modes can differ per area, depending on the existing supply in that region.

To illustrate: a traveller opens the MaaS app to see what the best transport option is for the journey between home and work. The traveller indicates in the app that active modes (walking or cycling) are not preferred since it is raining. The app shows that the traveller should use a shared car to the train station and then the train to work. Directly driving to work with the shared car today is discouraged by the app, because the real-time traffic data show that the highway to the work address is congested. The traveller pays for this way of travelling in the app and begins the journey to work.

Fig. 2. Explanation of MaaS given in the questionnaire.

(Habit Schema Congruence) is therefore included in this research. Lastly, vehicle owners' intention to use MaaS might also be influenced by their innovativeness, their interest in combatting climate change and being healthy. This is because a pro-environmental attitude (Hoerler et al., 2020, Matowicki et al., 2022), innovative mindset (Ye et al., 2020) and individuals' health perception (Zijlstra et al., 2020) have been found to result in a higher intention to use MaaS.

2.4. Moderators

Finally, several socio-economic variables are assumed to influence an individual's behavioural intention. Men seem for instance to be less inclined to use MaaS (Alonso-González et al., 2020) whilst younger generations seem to be more positively inclined to use MaaS (Caiati et al., 2020). Other variables that have been found to be related to MaaS' adoption potential are income (Zijlstra et al., 2020), education (Ye et al., 2020), household composition (Hoerler et al., 2020) and the size of the municipality where people live (Zijlstra et al., 2020). The experience an individual has with shared transport modes is also found to influence the intention to use MaaS (Alonso-González et al., 2020). An individual's familiarity with MaaS is therefore assumed to influence the behavioural intention in the conceptual model. Moreover, an individual's main mode of transport was identified as a determining factor (Ho et al., 2018; Tsouros et al., 2021) as well as the trip purpose (Storme et al., 2020) and trip frequency (Zijlstra et al., 2020). These variables were therefore included as potential important moderators explaining the behavioural intention to use MaaS.

3. Methodology

To study the relationships assumed in the conceptual model, data has been collected among Dutch vehicle owners using a self-administered survey. The data was analysed with two statistical analysis methods: an Exploratory Factor Analysis (EFA) and Latent Class Cluster Analysis (LCCA). The latter method identifies clusters of respondents concerning their attitude towards MaaS, thereby shedding light on the factors influencing vehicle owners' behavioural intention and which type(s) of vehicle owners are likely to use the mobility concept. The following sub-sections desctribe these methodological steps.

3.1. Data and the survey

Related to the conceptual model we performed a questionnaire in which we asked respondents about their travel behaviour, socio-economic characteristics and their attitudes regarding MaaS. To measure the attitudes regarding MaaS, respondents were first given a written explanation of MaaS and an explanatory image that was adopted from Schikofsky et al. (2020) to ensure all respondents had a good and similar understanding of the concept (Fig. 2). After this explanation, the questionnaire consisted of several statements for each construct incorporated in the conceptual model (Appendix A gives an idea of the statements used). For each statement, respondents could indicate on a five-point Likert scale to what extent they agreed or disagreed with the statements. The questionnaire included three additional statements, independent of the constructs, referring to the extent to which respondents intended to use MaaS.

Data was gathered with the digital distribution of a self-administered questionnaire built in the program Qualtrics between July 19th and August 5th, 2021. The questionnaire was meant for individuals (co–)owning a motorized vehicle (passenger car, electric passenger car, van, motorcycle; moped) and living in the Netherlands. Respondents were recruited using the researcher's network and a panel of an established online fieldwork service provider (Respondenten.nl), which respectively resulted in 196 and 287 responses. The recruitment approach and combination of the two samples into one dataset was regarded as valid since the questionnaire was distributed in the same way among both samples and participants were prohibited to fill in the survey multiple times.

3.2. Exploratory factor Analysis

Exploratory Factor Analysis (EFA) was used to achieve two goals: a) test for the existence of relationships other than those initially assumed in the conceptual model and b) to reduce the number of variables in the dataset. The EFA was performed with SPSS (version 25). EFA was chosen over Confirmatory Factor Analysis (CFA) since in an EFA each item is free to load on each factor whereas in a CFA items only load on the factors they were designed to measure. This means that EFA enables to test for the existence of relationships other than the initial theory (Mueller & Hancock, 2001) as desired in this study. An EFA was therefore assumed to potentially provide more insightful results. EFA is also deemed to be more appropriate when conducting research aimed at identifying latent factors than Principal Component Analysis (PCA) (Schreiber, 2021) and is therefore chosen for this research.

The factors were extracted with the Principal Axis Factoring and oblimin oblique rotation. To ensure the suitability of the data, a KMO value higher than 0.6 (Kaiser & Rice, 1974), a Bartlett's Test of Sphericity p-value lower than 0.05 (Field, 2013) and a correlation matrix determinant higher than 0.00001 (Maskey et al., 2018) were required in this research. Factors with an eigenvalue above 1 (Taherdoost, 2016), adhering to the Scree test (Costello & Osborne, 2005) and with a communality higher than 0.2 (Child, 2006) are considered for further analysis if the factor loadings are above 0.4 and cross-loadings below 0.3 (Taherdoost, 2016; Howard, 2016). Factor scores were then calculated using an averaged Sum Score by Factor because it is a suitable method for exploratory research situations. The calculation method also retained the scale metric, which increases interpretability and enables comparisons across the factors in case of differing number of items per factor (DiStefano, Zhu & Mindrila, 2009). When the Cronbach's alpha coefficient lies above 0.6, the factors can be assumed to be reliable and thus adequate for further analysis.

3.3. Latent class cluster analysis

The factor scores and moderating variables, similarly to the research by Alonso-González et al. (2020), were used as input for an LCCA to obtain clusters of vehicle owners (passenger car, electric passenger car, van, motorcycle; moped) that are similar in their characteristics and attitudes towards MaaS. A LCCA-model assigns individuals to different clusters based on a latent nominal variable that explains the individuals' responses on a set of observed indicators (Molin, Mokhtarian & Kroesen, 2016). The goal of LCCA is to maximize the homogeneity within clusters and the heterogeneity between clusters (Sasidharan, Wu & Menendez, 2015). LCCA provides several statistical criteria to identify the optimal number of classes, enables computation of the significance of the model parameters and different types of variables can be used without additional standardization needed (Molin et al., 2016; Sasidharan et al., 2015). The LCCA was performed using Latent GOLD (version 5.1) to identify latent clusters. The obtained clusters in this research provide information about common characteristics within the clusters, thereby indicating which factors influence vehicle owners' intention to use MaaS. This provides more information about potential measures that can be taken to increase the adoption potential of MaaS once it is introduced in the Netherlands.

The mathematical formulation of the entire model with continuous indicators and covariates is the following (Vermunt & Magidson, 2005; Alonso-González et al., 2020; Molin et al., 2016):

$$f(y_i|z_i^{cov}) = \sum\nolimits_{x=1}^{K} P(x|z_i^{cov}) * \prod\nolimits_{m=1}^{M} f(y_{im}|x) \tag{1}$$

Where x *is* the latent variable, which has K categories that are typically called classes or clusters. Each individual i is assumed to have a certain probability of belonging to a certain latent class. This class membership is conditional on the individual's personal characteristics (covariates). The response of individual i to a set of covariates is represented with z_i^{cov}(Alonso-González et al., 2020; Molin et al., 2016). The first part of the model ($\sum_{x=1}^{K} P(x|z_i^{cov})$) estimates the probability of individual i belonging to a certain latent class given their covariate values (Lee et al., 2020). This sub-model is parameterized using the multinomial logit model. The second part of the model ($\prod_{m=1}^{M} f(y_{im}|x)$) is the probability density of individual's i response to indicator m (y_{im}) given latent class membership. M *is* the number of indicators (Molin et al., 2016) and this second submodel assumes a normal distribution for those indicators.

Executing an LCCA means the consecutive estimation of two models (Fig. 3 below shows the results): the measurement model and the structural model. Estimation of the measurement model only includes the indicators, in this research the factor scores resulting from the EFA, and results in the identification of the appropriate number of clusters using the Likelihood ratio chi-square statistic (L^2), Bayesian Information Criterion (BIC), Akaike Information Criterion (AIC) and Bivariate Residual (BVR) values. A Likelihood ratio statistics with a p-value higher than 0.05 indicates that the specified model holds in the population, i.e. a good model fit (Vermunt & Magidson, 2004). The model that minimizes the values of the BIC or AIC is deemed to be the model with the appropriate number of clusters (Sun, Sun & Shan, 2019). A BVR-value smaller than 3.84 indicates no significant covariation remaining between a pair of indicators (Vermunt & Magidson, 2005).

When the number of clusters is determined, the structural model is estimated by adding the covariates (the moderating variables in the conceptual model). An entropy value above 0.8 indicates a good prediction of cluster membership (Clark & Muthén, 2009). Covariates with a Wald statistic greater than 3.84 (p-value < 0.05) were made inactive. Inactive covariates do not influence the cluster probabilities but provide information about the distribution of the variable throughout the cluster (Molin et al., 2016).

The structure of the LCCA presented in Fig. 3 differs from the conceptual model presented in Fig. 1. The models are similar in the relationship between constructs (indicators in the LCCA) and dependent variable (latent variable in the LCCA). The moderating variables (covariates in the LCCA) are presented differently in the models: in the conceptual model the moderator variables are

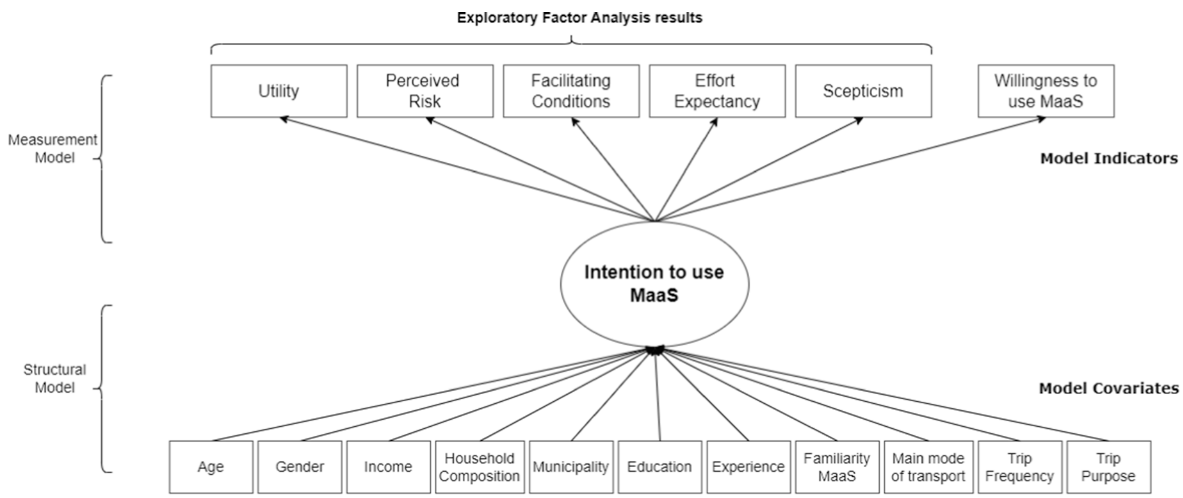

Fig. 3. Graphical representation of the Latent Class Cluster Model.

modelled to influence the relationship between a construct and the behavioural intention. In the LCCA on the other hand, the moderating variables are named covariates and are modelled to influence the latent variable (behavioural intention). Since the execution of a LCCA means that covariates are made active when they influence the cluster composition, which consists of a relationship between the latent variable and an indicator, the LCCA result was assumed to be an adequate representation of the relationships modelled in the conceptual model.

4. Results

In total 339 valid responses were gathered among (co–)owners of motorized vehicles living in the Netherlands. This exceeds the recommended minimum sample size of 300 for both an Exploraty Factor Analysis (Field, 2013) and a Latent Class Cluster Analysis (Nylund-Gibson and Choi, 2018). Similar sample sizes have been used in previous studies executing a factor analysis, such as Mola et al. (2020) who had a sample of 201 indivuals to test the Technology Acceptance Model on mobility behaviour and intention to adopt MaaS, Madigan et al. (2017) using the UTAUT-model to investigate user acceptance of Automated Road Transport Systems among 315 participants or Mattia et al. (2019) on the motives for re-using free-floating car sharing with a sample of 300 individuals. Similar sample sizes have been used in previous studies that performed a latent class analysis: Araghi et al. (2016) performed a discrete-choice latent class model to reveal heterogeneity in preferences to passenger-oriented environmenta policies on a sample of 275 air travellers and Krueger et al. (2018) applied a LCCA to a sample of 516 individuals to study the interrelation of normative beliefs and modality styles.

Compared with the population of vehicle owners in the Netherlands, the sample has a high share of women, motorcycle owners and multi-person households with children. Data on the age, municipality, income and education level is not available about vehicle owners in the Netherlands, but are available for the Dutch population as a whole. When compared with the Dutch population (Table 1), the sample has a high share of individuals between 25 and 44 years old, living in larger municipalities and with a higher income- as well as education level. Representativeness tests using the Pearson chi-square statistics indicated that only car ownership distributed over gender is representative of the population ($p = 0.132$). We will further discuss the issue of representativeness of the sample below in section 5.

4.1. Factor Analysis

The first iteration of the EFA resulted in a KMO-value of 0.891 and a significant Bartlett's test of sphericity result (less than0.001) indicating a meritoriously adequate sample and the existence of sufficient correlations between the variables. The common variance of the variables was adequate with all communality values greater than 0.2. In the following iterations of the EFA, variables with factor loadings less than 0.4, cross-loadings greater than 0.3 or only a few correlations were removed to obtain a simple structure and a determinant greater than 0.00001. This resulted in five factors to be retained that explain 67.6 % of the variance (KMO = 0.840 and Bartlett's test of Sphericity less than 0.001). Table 2 presents the retained factors and their loadings for the rotated pattern matrix. The statements belonging to each item and factor are shown in Appendix A. Only the loaded items presented in this table are considered for the posterior LCCA. The factors cohere to the constructs in the conceptual model, except for the constructs Mindset and Hedonic Motivation since the iterative deletion of variables resulted in the exclusion of all items belonging to these constructs.

Habit Schema Congruence is the only remaining construct representing intrinsic motivation and is combined with Performance Expectancy. This is because the items initially related to Habit Schema Congruence loaded on the same factor as the items related to Performance Expectancy. The common factor loadings of these items might be due to the similarity in their questionnaire statements,

Table 1
Some characteristics of the sample compared to the Dutch population.

	Sample (%)	The Netherlands (%)
Age		2020 (Central Bureau for Statistics CBS, 2021a)
18–24	7.4	8
25–34	28	16.4
35–44	26.8	15.2
45–54	19.2	18.1
55–64	13.6	17.4
65 or older	5	24.9
Municipality		2021 (Central Bureau for Statistics CBS, 2021b)
The big four (Amsterdam, Rotterdam, The Hague and Utrecht)	20.6	13.9
Big municipality (excluding the big four)	27.7	23.8
Middle-sized municipality	23.3	21.6
Small municipality	28.6	40.7
Household income		2019 (Central Bureau for Statistics CBS, 2021c)
less than € 10,000	2.1	4
€ 10,000 until € 20,000	7.4	13.6
€ 20,000 until € 30,000	1.6	21.6
€ 30,000 until € 40,000	15.6	16.6
€ 40,000 until € 50,000	16.2	12.9
€ 50,000 or more	45.1	31.4

Table 2
Results - Exploratory Factor Analysis.

	Factors				
Items	1	2	3	4	5
Utility					
Convenience	0.879				
Saving time	0.841				
Similarity current travelling	0.688				
Similarity typical things	0.623				
Saving money	0.522				
Perceived Risk					
Data Privacy		0.749			
Health concerns		0.695			
Personal safety		0.682			
Technical reliability		0.659			
Hygiene concerns		0.588			
Trust in provider		0.539			
Facilitating Conditions					
Familiarity smartphone			0.894		
Stability mobile network			0.799		
Familiarity mobile payments			0.682		
Familiarity planning-apps			0.605		
Effort Expectancy					
Ease of Learning				0.935	
Ease of Use MaaS-system				0.924	
Ease of Use Transport modes				0.705	
Scepticism					
Evaluation Media					−0.923
Evaluation government					−0.852
Opinion others					−0.566

as these were formulated as a comparison between the respondent's current transport mode and MaaS. Since the items that loaded on this factor represent the value of MaaS when compared with the respondents' current main mode of transport, i.e. the perceived utility, the factor is named 'Utility'. The remaining four factors all reflect the constructs in the conceptual model. 'Social Influence' has been named 'Scepticism', because the negative factor loadings indicate that the item needs to be interpreted in the opposite direction from how it is formulated for the factor. Thus, people that score high on this item are lower in Social Influence (Leech, 2012) meaning that they are less influenced by positive evaluations from the government, media or people that are important to them.

4.2. Latent class model

The Latent Class Cluster Analysis was performed with the indicators and covariates shown in Fig. 3. First, the measurement model was estimated with the five EFA factors and an additional factor: 'Willingness to use MaaS'. This sixth factor has been added since it reflects how willing respondents are to use MaaS. In the same manner as the EFA factor scores, this additional factor has been calculated with an averaged Sum Score by Factor from three additional statements that have been included in the questionnaire referring to how willing respondents are to use MaaS (see Appendix A for the respective statements). The indicators are continuous variables, due to the calculation with the averaged Sum Score. The chi-squared statistics are not available for this type of data. The number of clusters is therefore determined using the BIC-, AIC- and BVR-values as well as the cluster profiles.

The model fit statistics for the LCCA models ranging between 1 and 10 clusters are given in Table 3. According to the Log-Likelihood, BIC and AIC values, a 10-cluster model is the best. Since these statistics often do not reach a minimum value with an increasing number of clusters (Sun et al., 2019), the percentual change in the BIC-value was computed to see where the decrease

Table 3
Model fit statistics.

Number of Clusters	LL	BIC(LL)	AIC(LL)	Npar	Δ% BIC(LL)
1	−2641.30	5352.52	5306.61	12	
2	−2346.63	4838.90	4743.25	25	−9.60 %
3	−2172.27	4565.94	4420.55	38	−5.64 %
4	−2026.20	4349.52	4154.39	51	−4.74 %
5	−1931.36	4235.58	3990.71	64	−2.62 %
6	−1882.25	4213.09	3918.49	77	−0.53 %
7	−1811.28	4146.90	3802.56	90	−1.57 %
8	−1775.47	4151.03	3756.95	103	0.10 %
9	−1731.80	4139.42	3695.60	116	−0.28 %
10	−1692.16	4135.88	3642.33	129	−0.09 %

Table 4
Cluster sizes and profiles.

	MaaS – conservative car users	MaaS – ready & sustainable travellers	MaaS – aware enthusiasts	MaaS – indifferent car users	MaaS – curious urban dwellers	Sample
Cluster size	26 %	26 %	17 %	16 %	15 %	
Indicators (mean)						
Utility	2.19	2.57	3.23	1.42	2.85	
Perceived Risk	2.77	2.74	3.08	2.74	2.90	
Facilitating Conditions	3.82	5.00	4.28	4.10	4.00	
Effort Expectancy	3.44	4.24	4.01	2.67	3.93	
Scepticism	2.70	3.43	3.66	1.80	3.44	
Willingness to use MaaS	2.35	3.20	3.76	1.00	3.21	
Active Covariates						
Gender						
Female	27 %	46 %	44 %	47 %	56 %	58 %
Male	73 %	54 %	56 %	53 %	44 %	42 %
Age						
18–24	3 %	11 %	16 %	0 %	8 %	7 %
25–34	14 %	50 %	25 %	15 %	32 %	28 %
35–44	26 %	27 %	32 %	26 %	22 %	27 %
45–54	27 %	7 %	18 %	29 %	17 %	19 %
55–64	23 %	4 %	9 %	21 %	10 %	14 %
65 or older	7 %	0 %	0 %	9 %	12 %	5 %
Knowledge MaaS						
Yes	25 %	54 %	65 %	28 %	27 %	40 %
No	75 %	46 %	35 %	72 %	73 %	60 %
Experience						
Yes	7 %	43 %	56 %	3 %	42 %	29 %
No	93 %	57 %	44 %	97 %	58 %	71 %
Inactive Covariates						
Main Transport Mode						
Car	73 %	52 %	54 %	65 %	63 %	61 %
Electric/hybrid car	4 %	7 %	9 %	14 %	11 %	7 %
Van	1 %	0 %	0 %	2 %	2 %	1 %
Vehicle with a moped license	4 %	2 %	4 %	2 %	2 %	3 %
Motorcycle	1 %	1 %	2 %	2 %	4 %	2 %
Public Transport, Walking, Cycling	16 %	38 %	30 %	15 %	18 %	24 %
Frequency						
Less than 1 day a week	3 %	7 %	0 %	2 %	2 %	3 %
1 day a week	2 %	3 %	0 %	2 %	4 %	2 %
2 days a week	5 %	7 %	8 %	9 %	8 %	7 %
3 days a week	3 %	16 %	17 %	12 %	13 %	12 %
4 days a week	17 %	14 %	18 %	19 %	11 %	16 %
5 days a week	26 %	18 %	9 %	15 %	23 %	19 %
6 days a week	27 %	16 %	19 %	21 %	17 %	20 %
7 days a week	15 %	21 %	28 %	20 %	23 %	21 %
Purpose						
To and from work	68 %	55 %	64 %	59 %	53 %	60 %
Business, professional purposes	7 %	11 %	4 %	6 %	14 %	8 %
Services, personal care	2 %	0 %	2 %	2 %	5 %	2 %
Shopping, doing groceries	12 %	11 %	18 %	15 %	13 %	14 %
Education, (extra) courses, childcare	1 %	4 %	0 %	4 %	4 %	3 %
Visiting, overnight stay	5 %	10 %	5 %	6 %	4 %	6 %
Going out, sport, hobby	3 %	5 %	2 %	1 %	0 %	3 %
Touring, walking	2 %	2 %	3 %	4 %	5 %	3 %
Other travel purposes	1 %	1 %	3 %	4 %	1 %	2 %
Education						
Primary education*	32 %	10 %	23 %	48 %	23 %	26 %
Senior secondary**	9 %	8 %	4 %	9 %	15 %	9 %
Higher professional education	40 %	36 %	32 %	35 %	31 %	35 %
University education	16 %	34 %	36 %	7 %	25 %	24 %
PhD or higher	4 %	12 %	6 %	2 %	6 %	6 %
Household Composition						
One-person household	10 %	17 %	16 %	19 %	21 %	16 %

(*continued on next page*)

Table 4 (*continued*)

	MaaS – conservative car users	MaaS – ready & sustainable travellers	MaaS – aware enthusiasts	MaaS – indifferent car users	MaaS – curious urban dwellers	Sample
Multi-person household without children	41 %	48 %	40 %	35 %	39 %	41 %
Multi-person household with children	49 %	35 %	44 %	46 %	40 %	43 %
Municipality						
The big four	12 %	31 %	15 %	9 %	37 %	20 %
Big municipality	26 %	29 %	38 %	22 %	24 %	28 %
Middle-sized municipality	28 %	18 %	24 %	30 %	16 %	23 %
Small municipality	34 % %	23 %	23 %	39 %	24 %	29 %
Income						
less than € 10.000	0 %	4 %	2 %	0 %	4 %	2 %
€ 10.000 until € 20.000	8 %	7 %	6 %	4 %	12 %	7 %
€ 20.000 until € 30.000	11 %	8 %	23 %	19 %	11 %	2 %
€ 30.000 until € 40.000	25 %	7 %	7 %	19 %	19 %	16 %
€ 40.000 until € 50.000	16 %	16 %	15 %	16 %	20 %	16 %
€ 50.000 or more	40 %	58 %	47 %	41 %	35 %	45 %

* Preparatory secondary general education / senior secondary vocational education.
** Pre-university education.

becomes marginal. The percentual change becomes less than 2 % from the five-cluster model onwards. The entropy value of this model is 0.91, thereby indicating a good prediction of cluster membership (Clark & Muthén, 2009).

The BVR-values indicated that a significant degree of covariation remained for all models between the indicator pairs 'Willingness to use MaaS – Utility' and 'Facilitating Conditions – Effort Expectancy'. This indicates that correlations still existed between the indicator pairs that cannot be explained by the clusters (Molin et al., 2016). Direct effects were therefore subsequently added to the two pairs of indicators to account for bivariate associations outside of the latent class model, thereby improving the model fit (Vermunt & Magidson, 2005) The resulting BVR-values and cluster profiles supported dividing the data into five clusters.

The structural equations have been added using effect-coding. When estimating the structural model (Fig. 3), four covariates (gender, age, experience and familiarity) proved to be significant and including these covariates improved the model. Appendix B shows the parameters of the estimated 5-cluster model, split up in the measurement model and the structural model. The profiles of the cluster are depicted in Table 4 together with the sample shares for comparative purposes. The cluster interpretations are given below.

4.2.1. Cluster 1: MaaS–conservative car users

Members of one of the two biggest clusters in the sample (26 %) are identified as 'MaaS–conservative car users', given their lower intention to use MaaS and the big share (73 %) of the car with a combustion engine as their main mode of transportation. A large share (75 %) of the cluster members was unfamiliar with MaaS prior to this research and even a bigger share (93 %) did not even have any experience with vehicle sharing services. These shares are higher than in the sample as a whole. Individuals belonging to this first cluster have the lowest score for the factor Facilitating Conditions out of all clusters, showing that they have fewer resources or competencies at their disposal to use MaaS.

Interestingly, this is the only cluster where the distribution of men and women is not approximately equal since the majority of the members is male (73 %). Most cluster members are between 35 and 64 years old (76 %) and use their main transport mode to travel to and from work (68 %). Most of the MaaS–conservative car users have a higher professional education (40 %), followed by primary education (32 %) and more than half lives in a middle-sized (28 %) or a small (34 %) municipality.

4.2.2. Cluster 2: MaaS–ready and sustainable travellers

Similar to the first cluster, the second cluster also comprises 26 % of the sample but the members of this cluster do intend to use MaaS. Out of all clusters, the members of this cluster perceive the ease of using MaaS the highest. Members of this cluster are younger, with 50 % belonging to the age group 25 – 34 and in total 88 % younger than 45. The percentage of members being familiar with MaaS, or that have used vehicle sharing services, is relatively equally divided. Members of this cluster scored the highest possible score for Facilitating Conditions, which indicates that the members perceive to have the resources and competencies available to use MaaS. Regarding the main mode of transportation, this cluster has the lowest share of the passenger car with a combustion engine and the highest share of public transport, walking and cycling among all clusters. On this covariate this cluster also differs from the sample population as a whole.

Based on their main mode of transport and the value for both Willingness to use MaaS and Facilitating Conditions, members of this cluster are identified to be ready to use MaaS and to be sustainable travellers. Hence the name 'MaaS–ready and sustainable travellers'. Members of this cluster are mostly highly educated with 82 % having completed higher professional education or higher. Almost half (48 %) of the members live together without children and this cluster has the highest share (58 %) out of all clusters, and higher than the sample as a whole, of individuals with a yearly net household income of € 50,000 or more.

4.2.3. Cluster 3: MaaS–aware enthusiasts

Respondents assigned to the third cluster (17 % of the sample) are identified as 'MaaS–aware enthusiasts'. Their intention to use MaaS is the highest out of all clusters. Of all clusters, the members of this cluster attach most value to the similarities between MaaS and their current habits as well as MaaS' benefits in terms of travel time, costs and convenience. Interestingly, the values for the factors Perceived Risk and Scepticism are also higher than in the other clusters, showing that they do not solely rely on evaluations by the media, government or people of importance and that the cluster members are aware of the potential risks. This could be due to the high share of familiarity with MaaS (65 %) and experience with vehicle sharing services (56 %). Hence the cluster name 'MaaS aware enthusiasts'. This is in fact the only cluster with more individuals being experienced with vehicle sharing than inexperienced.

73 % of the members are between 18 and 44 years old and 68 % of the cluster members have completed either higher professional education or university education. This is higher than in the sample as a whole. Compared with the other clusters, the third cluster has the second-biggest share (30 %) of public transport, walking and cycling and the second-lowest share (54 %) of passenger cars with a combustion engine as the main mode of transport.

4.2.4. Cluster 4: MaaS–indifferent car users

Those identified as 'MaaS–indifferent car users' belong to the fourth cluster (16 % of the sample) and have the lowest value for Willingness to use MaaS out of all clusters. Most members (65 %) have a car with a combustion engine as their main mode of transport. Compared with the other clusters, the cluster has the largest share (14 %) of an electric or hybrid car and the lowest share (15 %) of public transport, walking or cycling as their main mode of transport. This cluster has the lowest value for Utility, Effort Expectancy and Scepticism out of all clusters. The low value for Utility indicates that cluster members do not expect MaaS to provide benefits over their current transport mode nor see similarities with their current transport mode.

The low Effort Expectancy and Scepticism values show that the MaaS–indifferent car users do not think using MaaS will be easy, but are willing to use MaaS following positive evaluations. Almost all members are inexperienced with vehicle sharing (97 %) and a majority (72 %) were unfamiliar with MaaS prior to this research. The members of this cluster are relatively older than the other clusters and the sample as a whole. The biggest age group in the cluster is 45 to 54 years old (29 %) and in total 85 % of the cluster members is older than 35. The completed level of education among the cluster members is for a large part either senior secondary vocational education or lower (48 %) or higher professional education (35 %). The cluster has the lowest share of members that completed university education or higher (9 %) compared with other clusters. Most members live in a middle-sized (30 %) or a small (39 %) municipality.

4.2.5. Cluster 5: MaaS–curious urban dwellers

The fifth cluster contains 15 % of the respondents. These respondents are identified as 'MaaS–curious urban dwellers', because of their positive attitude towards using MaaS and the highest share (37 %) of members living in the big four (Amsterdam, The Hague, Rotterdam, Utrecht) out of all clusters. Their value for the factor Willingness to use MaaS is the same for the second and fifth clusters, but members of the fifth cluster value the utility and risks of MaaS slightly higher. Their perceived resources and competencies available for using MaaS are the second-lowest out of all clusters.

The curious urban dwellers differ from the other clusters in several aspects, such as having more women than men and the highest share of the motorcycle as the main transport mode. Similar to the first and fourth clusters, the majority (73 %) of the members were unfamiliar with MaaS prior to this research, but the share of members being experienced with vehicle sharing services is similar to the second and third clusters. Compared to the four preceding clusters and the sample as a whole, this cluster has a larger share of people aged 65 or older, one-person households and the four largest cities as the municipality of residence. Lastly, the travel purpose 'to and from work' is the most often chosen travel purpose in each cluster, but its share is the lowest in this fifth cluster. The purposes 'business, professional purposes', 'services, personal care' and 'touring, walking' are highest in this cluster out of all clusters.

5. Discussion

Building on the research results presented in the previous sections, we will continue in this section by providing an interpretation of the five cluster profiles (Table 4) and how this relates to previous studies regarding MaaS. The clusters indicate that the intention to use MaaS is especially influenced by the added benefits of using MaaS over the current transport modes and the expected ease of using MaaS, given the high Utility and Effort Expectancy values in clusters with a high use intention and vice versa in the remaining clusters. This is in line with previous studies where the perceived usefulness (Alyavina et al., 2020) and expected ease of use (Schikofsky et al., 2020) of MaaS were found to be of influence on the use intention. The intention to use can however differ from real world use as the expected utility of options could differ from the experienced utility (De Vos et al., 2016). In addition, experiences may lead to changes in attitudes towards (travel) options (Van Wee et al., 2019). This would mean that a feedback mechanism occurs which is not included in the conceptual framework in this study.

The cluster profiles, in particular the main mode of transport of the cluster members, show that MaaS mostly provides these added benefits to vehicle owners who often use public transport and active modes. As Matowicki et al. (2022) suggest, this finding is understandable since MaaS provides a more robust service with a similar ease of use to the existing mode of transport. This 'added benefits' factor has less influence on the intention to use MaaS among the 'conservative' passenger car owners (cluster 1 'MaaS – conservative car users' and cluster 2 'MaaS – indifferent car users'). The higher intention to use MaaS among vehicle owners who often use public- or active transport aligns with results from Faber et al. (2020) and Alonso-González et al. (2020) identifying individuals that currently travel by public transport or active-travel modes as the potential user group of MaaS.

Those vehicle owners intending to use MaaS are more sceptic of positive evaluations by the media, government or 'people of importance' (for the potential user) and more aware of potential risks. This, together with the higher levels of experience with MaaS or vehicle-sharing services within these clusters, indicates that familiarity with MaaS-like concepts influences the extent to which individuals intend to use MaaS. The finding that vehicle owners who do not intend to use MaaS seem to rely more on external evaluations whilst being less experienced and familiar with the concept, substantiates this relationship. Interestingly, the awareness of potential risks among the vehicle (co–)owners intending to use MaaS negates the findings by Ye et al. (2020) and Casadó et al. (2020) regarding the perceived risks being related to a lower intention to use MaaS.

The clusters also show that respondents' perceived availability of resources and competencies to use MaaS are important in explaining the intention to use MaaS. The higher Facilitating Conditions values among clusters intending to use MaaS and lower values among clusters not intending to use MaaS show that vehicle owners' perception of their mobile network stability and their familiarity with smartphone use, mobile payments and planning-apps is related to their intention to use MaaS. Lastly, the research results indicate that cluster members' age impacts the perceived availability of resources and competencies to MaaS, as being older is related to a lower value for Facilitating Conditions. These findings align with Smith et al. (2022) who identified the difficulty of learning how an app and /or vehicle of a MaaS-service works as a barrier for users.

Personal characteristics are found in this research to be determinants for the intention to use MaaS, which alignes with previous research findings. In line with the findings of Caiati et al. (2019) and Zijlstra et al. (2020), are younger individuals (18 – 44 years old) found to have a higher intention to use MaaS than older individuals (45 years and older). A higher level of education (Ye et al., 2020; Alonso-González et al., 2020) and a denser living environment (Zijlstra et al., 2020; Alonso-González et al., 2020) are also found in this research to be related to a higher intention to use MaaS.

6. Conclusion and recommendations

We identified five clusters on the attitude of vehicle (co–)owners towards MaaS. This is based on an Exploratory Factor Analysis and Latent Class Cluster Analysis of the collected empirical survey data from private motorized vehicle owners in the Netherlands. The cluster profiles show that MaaS mostly provides benefits for those vehicle owners who already often use public transport and active modes, but provides fewer benefits for the 'conservative' passenger car owners. The results suggest that the extent to which vehicle owners are familiar with MaaS or similar services is related to the intention to use MaaS. Our results show that especially the 'conservative' car owners seem to be least inclined to use MaaS. This implies that implementing MaaS from a policy perspective might be less effective (e.g., in reducing car externalities) than perhaps expected. When complemented with policy measures aimed at the reduction of car ownership, MaaS' implementation might be more effective.

Another conclusion that can be drawn from the research results is that the UTAUT-model is suitable as a theoretical basis for investigating the adoption potential of MaaS. Personal characteristics, such as vehicle owners' main mode of transport, age, education level and the municipality of residence were found to be related to the intention to use MaaS. Therefore the research results confirm the importance of personal characteristics, identified in preceding studies as determinants for the intention to use MaaS, in the context of vehicle (co–)owners in the Netherlands.

The profile of the fifth cluster (MaaS – curious urban dwellers) indicates that several vehicle owners, who do not completely comply with the previously identified personal characteristics, are still relatively interested in MaaS. This might imply that extrinsic factors do not exclusively influence the intention to use MaaS and that other factors are at play, such as the inherent interest of individuals in MaaS. These inherent interests were unfortunately not tested in this research.

Identified limitations of this research refer to the earlier mentioned inability to obtain findings on the effect of intrinsic motivational factors on vehicle (co–)owners' intention to use MaaS. As preceding studies did find effects of these factors on an individual's intention to use, a similar effect was expected to exist among vehicle owners living in the Netherlands. It is therefore recommended to conduct further research on the effect of intrinsic motivations on the intention to use MaaS among vehicle owners. Insight about these factors could shed more light on whether measures can be taken to increase the success of introducing MaaS and if this is true, which measures can play an important role.

A second limitation of this research is that the behavioural intention of vehicle owners has been assessed instead of their actual use behaviour. This choice results from the current (late 2021) limited availability of MaaS in the Netherlands. The research findings therefore only give an indication of the potential effect and uptake of MaaS, but these cannot be generalized towards the actual use of the concept. More investigations regarding the actual use of MaaS are therefore recommended, which can partly be done with the MaaS-pilots that are currently carried out in the Netherlands. An additional and related limitation is that the Covid-19 pandemic might have had an impact on the use intention of vehicle owners. This research did not investigate this effect, but further research on this relationship is recommended.

When compared with the Dutch population, our sample has a high share of individuals between 25 and 44 years old, with a higher level of education, income and living in larger municipalities. Despite this skewness, we were still able to find five different and interpretable clusters in our research. Including the 'conservative car users' cluster that represents a relatively high age, somewhat lower education levels when compared to the other clusters and whose members live relatively often in smaller municipalities. If we would have had an exact representative sample of all Dutch vehicle owners, we expect that this cluster (least inclined to use MaaS) would have been the largest.

Another limitation is potentially related to the way we comunicated about MaaS in our survey (section 3.1). MaaS is a new concept and participants to the survey may not have realized all advantages (and disadvantages) of MaaS for them based on the way we communicated about the concept. An example of an advantage of MaaS that people may have missed in our communication is that

MaaS may provide flexibility and convenience for dealing with people's variablilty in trip making and use of different modes for different purposes on different times of day and week. Research on the relationship between different ways of communication about MaaS and intention to use MaaS is recommended.

Lastly, the research findings, in particular the factor scores for Utility and Effort Expectancy, have substantiated preceding discussions on MaaS not being a fruitful alternative to the private passenger car. The findings on individuals' experience with vehicle sharing services and the familiarity with MaaS do show that the intention to use MaaS can probably be increased since experience and familiarity seem to be related to a higher intention to use. Additionally, it should be noted that due to our cross-sectional approach our results are 'only' a snapshot in time. In future, the support for MaaS may change because, for example, an increasing number of people gain experience with sharing concepts, including those outside the transport domain. Also, the 'older' generation of conservative car users may slowly disappear, and policy-makers may continue with implementing measures to make cities more car-free such as introducing high parking fees, improved public transport, and restricting car entrance for certain urban areas. These measures can positively influence the attractiveness of using MaaS for more individuals than our current results show. Policy-makers and service providers are therefore recommended to aim at increasing the familiarity of citizens with MaaS or similar concepts. Informing more people about MaaS is likely to increase its adoption. These measures could for instance be taken in urban environments targeted at the potential early adopters (the 'MaaS–aware enthusiasts', section 4.2**),** but also in less densely populated areas as the research results indicated that a large share of the vehicle owners not intending to use MaaS live in smaller municipalities, are inexperienced with vehicle sharing services and are unfamiliar with MaaS.

CRediT authorship contribution statement

Renske van 't Veer: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization, Project administration, Funding acquisition. **Jan Anne Annema:** Writing – review & editing, Supervision. **Yashar Araghi:** Resources, Funding acquisition, Writing – review & editing, Supervision. **Gonçalo Homem de Almeida Correia:** Writing – review & editing, Supervision. **Bert van Wee:** Writing – review & editing, Supervision.

Declaration of Competing Interest

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

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Appendix A. Factor statements

Statements used in the questionnaire for the factors resulting from the Exploratory Factor Analysis, ordered from high to low loadings per factor (except for the factor 'Willingness to use MaaS' given its exclusion from the EFA).

EFA factor / LCCA indicator	Statement
Utility	I expect that MaaS will be more convenient compared to my current way of travelling
	I expect that MaaS will save time compared to my current way of travelling
	The MaaS-system has similarities with how I currently travel on a daily basis
	The MaaS-system corresponds to products or things that are typical for me
	I expect that MaaS will save money compared to my current way of travelling
Perceived Risk	I am concerned about the data privacy of the MaaS-system
	I am concerned about the potential spread of a virus when using the modes that are offered by MaaS
	I am concerned about my personal safety when using the MaaS-system
	I am concerned about the network stability of the MaaS-system
	I am concerned about how clean the travel modes provided in the MaaS-system will be
	I am afraid that the MaaS-provider will advise a trip or mode which is to the advantage of the provider rather than the trip that is best for me
Facilitating Conditions	I am familiar with the installation and use of different apps on my smartphone
	I always have access to mobile internet
	I am familiar with using my smartphone for payments
	I am familiar with the use of journey planning apps (for example 9292)
Effort Expectancy	Learning how to use the MaaS-system will be easy for me

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(*continued*)

EFA factor / LCCA indicator	Statement
	I expect that using the MaaS-system on my phone will be easy for me
	I expect that using the transport modes offered in the MaaS-system will be easy for me
Scepticism	I am willing to use the MaaS-system if the evaluation on trusted websites is positive
	I am willing to use the MaaS-system if the evaluation by the government is positive
	I am willing to use the MaaS-system if people who are important to me think that I should use it
Willingness to use MaaS	I intend to use the MaaS-system when it becomes available in the Netherlands
	I intend to use the MaaS-system when the walking time to the transport mode is less than 2 min
	I intend to use the MaaS-system when the walking time to the transport mode is less than 5 min

Appendix B. Parameters of the estimated LCCA-model with covariates

	Values	Intercept	Wald	C.1	C.2	C.3	C.4	C.5	Wald
Prediction of indicators (measurement model)									
Utility		2.4523	3684.9905*	−0.2636	0.1218	0.7754	−1.0355	0.4019	278.0840*
Perceived Risk		2.8443	4732.4941*	−0.0722	−0.1063	0.2361	−0.1091	0.0515	8.4540
Facilitating Conditions		4.2407	18902.1362*	−0.4160	0.7593	0.0421	−0.1446	−0.2407	19022.0009*
Scepticism		3.0053	5382.3792*	−0.3084	0.4287	0.6522	−1.2040	0.4316	205.0916*
Effort Expectancy		3.6596	5588.1905*	−0.2161	0.5853	0.3467	−0.9849	0.2690	92.8143*
Willingness to Use Maas		2.7027	4407.2550*	−0.3551	0.4992	10.545	−1.7027	0.5041	1705.5827*
Prediction of latent class membership (structural model)									
Intercept				0.2283	0.0711	0.0324	−0.9383	0.6065	3.4070
Experience	No			0.5885	−0.3097	−0.6146	0.9213	−0.5854	28.8503*
	Yes			−0.5885	0.3097	0.6146	−0.9213	0.5854	
Knowledge MaaS	No			0.3286	−0.2798	−0.4734	0.1423	0.2823	15.9352*
	Yes			−0.3286	0.2798	0.4734	−0.1423	−0.2823	
Gender	Female			−0.4390	0.0433	0.0877	0.0393	0.2687	10.7591*
	Male			0.4390	−0.0433	−0.0877	−0.0393	−0.2687	
Age	18–24			−0.0691	1.8331	1.7512	−3.5638	0.0486	35.2951*
	25–34			−0.8067	1.2393	0.0916	−0.1267	−0.3975	
	35–44			−0.4759	0.6218	0.4083	0.1623	−0.7165	
	45–54			−0.0260	−0.3319	0.2273	0.6327	−0.5022	
	55–64			0.1909	−0.4295	0.1310	0.6732	−0.5655	
	greater than 65			1.1869	−2.9328	−2.6094	2.2223	2.1330	

*significant at the 5 % level.

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