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User attitudes towards a corporate Mobility as a Service

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Abstract

Mobility as a service (MaaS) envisages enabling a co-operative and interconnected single transport market which provides users with hassle free mobility. Among MaaS postulated benefits, MaaS enthusiasts claim that MaaS solutions could persuade people to give up their car. Conversely, there is a fear that MaaS could in fact induce less sustainable travel, by means of inducing extra demand, and even attract current public transport users towards taxi and car-pool alternatives.

In this study we investigate user attitudes and expectations towards a corporate MaaS solution, through a latent class and latent variable model. Results support that there is a trend from car ownership to usership. We also find no evidence that MaaS solutions could produce a shift from public transport users to other less space-efficient shared-mobility solutions such as taxis or car-pool alternatives under our experiment conditions. In connection with user's preference to share a car journey with strangers, we find the existence of two opposite trends. This finding suggests that there might be appetite for both types of solutions, where users could choose between private or shared journeys by car. Moreover, we find that normative beliefs impact user mobility styles, and that the need and feeling for flexibility is found to be one of the key factors for users to embrace a MaaS solution.

Keywords: Mobility as a Service, MaaS, Travel behaviour, Attitudes, Norms, Latent Class and Latent Variable Model (LCLVM).

1 INTRODUCTION

As urbanization trends continue to worsen gridlock plagues in a growing number of cities around the world, transport planners are embracing new ways of tackling the old problem of congestion; and among the solutions, Mobility as a Service (MaaS) has caught international attention in recent years. MaaS envisages enabling a co-operative and interconnected single transport market which provides users with hassle free mobility, whilst accounting for the realities of spatial and temporal efficiency (Wong et al., 2017).

This potential of MaaS to induce significant changes in current transport practices has triggered a lot of on-going discussions about the development of the technical and regulatory elements (backend / frontend systems, route planners, legislation, responsibilities, business models, etc.). Nevertheless, far less attention has been paid to user preferences for MaaS products, as well as the impact that MaaS could have on mode choice behaviour and modal shift, despite of the fact that understanding travellers' choices and behaviour is key to designing solutions that will address user demands and expectations.

MaaS enthusiasts claim that travel behaviour changes derived from the adoption of MaaS solutions could persuade people to give up their car. This is a very ambitious goal and one that does not just rely on the presence of a MaaS platform in a city or region, but more importantly on the availability of alternative transport modes (public transport, taxi, bikes, etc.), their effective combination, and the willingness to adopt such a modality style by the users. Regarding the latter, (Sochor et al., 2016), presented evidence of travel behaviour changes from a 6-month field test of *UbiGo* - a MaaS broker service for everyday urban travel - where all user groups' mode choice shifted in a more sustainable direction. Nevertheless, authors pointed out that field test participants may not represent the "average traveller", as the project target urban households, with a certain level of access to the existing transport solutions, and large enough travel needs for the service to be financially competitive. Hence, these encouraging results might not extrapolate well across the larger group. This finding was also supported at a larger scale by (Maas Global, 2017). This report shows how mode shares shifted among users of *whim* - a MaaS solution implemented in Helsinki -. Here, private car trips were reduced to half, and the share of Public Transport (PT) trips increased by a factor of 1.5, when compared with levels before *whim* was available. Furthermore, a more recent study, (Kamargianni et al., 2018), found evidence of a car-ownership to car-usership among Londoners.

Conversely, there is the fear that MaaS could in fact induce less sustainable travel, by means of inducing extra demand, and even attract current PT users towards taxi and car-pool alternatives. Hence, quantified evidence of the impact of MaaS on travel behaviour is still needed.

Moreover, (Haahtela and Viitamo, 2017), showed that that the most relevant unit of analysis is not an individual commuter but the family and household which determines the prerequisites for travelling of the family members. This finding shows the importance of household dynamics in explaining user decisions, which might seem irrational if these factors are neglected. Hence, the need for flexibility at a household level is postulated as a key element for MaaS systems to succeed.

In this paper we study the interrelation of household dynamics, normative beliefs[1]; modality styles[2]; and, user attitudes towards different transport solutions. We use a latent class latent variables model to quantify the impact that a corporate MaaS solution might have on travel behaviour and modal shift among a company´s employees. To our knowledge, no previous study has explored in this way user demands and expectations about MaaS solutions, although users are the cornerstone of MaaS.

From a methodological point of view, this paper includes a comparison of two different modelling techniques for ordered variables. Where previous studies simplified the modelling of ordered variables by assuming a logistic distribution, which has a closed cumulative form, (Daly et al., 2012; and Krueger et al., 2016), this study estimates the models using both a normal and a logistic cumulative distribution, and compares the results.

The rest of the paper is structured as follows: Section 2 presents the methodology. Section 3 provides an overview of the data. Section 4 presents the user insights towards a corporate MaaS solutions, and Section 5 concludes.

2 METHOD

We estimate a latent class and latent variable model (LCLVM) to classify individuals based on their responses to a variety of survey questions. This model was first used by Krueger et al. (2016), and it combines elements of lifestyle oriented and socio-psychological approaches to travel behaviour analysis to explain the formation of latent modality styles, which are identified through latent class segmentation.

Under this approach, the likelihood of an individual to belong to a particular modality style is a function of the individual socio-demographic characteristics, as well as normative believes towards the use of different transport modes.

The indirect measurement of latent variables, normative beliefs and mobility-related attitudes, is done by collecting various indicators. These indicators consist on a list of statements where each respondent is asked to state their agreement using a Likert scale (Likert, 1932). We start the analysis by

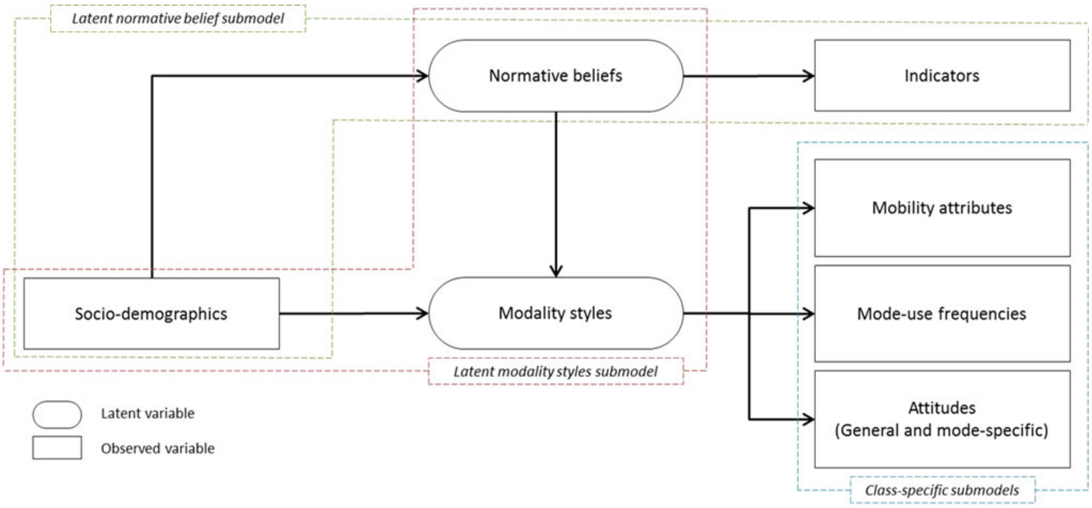
[1] Normative beliefs are defined as an individual’s perception of the beliefs of others regarding a specific behaviour.
[2] Modality styles represent the part of an individual’s lifestyle that is characterised by the use of a certain set of modes

performing a Confirmatory Factor Analysis (CFA) to understand if the formulated latent attributes can be identified. Although these statements have been designed to capture some pre-determined aspects, it is useful to identify what are the indicators that reveal most of the information about the latent variables. Therefore, we combine the CFA with an Exploratory Factor Analysis (EFA) on the indicators.

2.1 Modelling framework

The model in this paper use the framework proposed by Krueger et al. (2016). The framework consists of three different parts: first, a latent normative belief submodel with structural and measurement components; second, a latent modality styles submodel; and third, class-specific submodels for binomial and ordered variables. *Figure 1* below shows the conceptual framework. (See appendix A for details)

Figure 1. Conceptual model framework. Figure adapted from Krueger et al., 2016)



For consistency, we have retained the same formulation and terminology in this study. We also complement the approach taken by Krueger et al. (2016) by implementing an alternative modelling assumption regarding the stochastic component of the ordered response variables; hence, ordered variables are modelled using ordered logit and ordered probit models. . (See appendix A for details).

As explained in Krueger et al. (2016), the larger model includes several class-specific submodels, which are constants-only models, conditional on membership in a latent class k. Depending on the format of the dependent variable these models are either binomial or ordered logit models. *Table 1* provides an overview of the different class-specific submodels.

Table 1. Overview of class-specific ordered and categorical data models

Dependent variable	*Class-specific submodel category*	*Type of model*
Mode frequent user (car, public transport, walk, bicycle, etc.)	Mode-use frequencies	Binomial
Car ownership (Yes, no)	Mobility attributes	Binomial
Bicycle availability (Yes, no)	Mobility attributes	Binomial
Walk time to access PT less than 5 min	Mobility attributes	Binomial
Teleworking frequency (More than once per month , less than once per month)	Mobility attributes	Binomial
Mode-specific attitudes Strongly agree, agree, neutral, disagree, strongly disagree	Attitudes	Ordered

The likelihood function is formed by combining the different components of the model across individuals to obtain the unconditional probability of observing the data. In order to estimate the model, maximum simulated likelihood methods are required, as the objective function loses its closed-form because of the latent variable random error terms. (See Appendix A for details)

3 DATA

The data used for the analysis was collected among employees of a company implementing a corporate MaaS solution. Note that this setup has certain particularities when comparing it to other MaaS studies. For instance; the MaaS system only has one provider, which owns and operates all modes (buses, bicycles, taxis); and there is only one group of users, employees, which have stable travel patters (work commute and intra-campus trips).

Having clarified that, the data was collected by means of an online questionnaire which provided 433 observations. The questionnaire was designed to collect socio-economic variables, transport related information, and answers to 50 attitudinal questions on a Likert scale with 5 levels.

Socio-economic variables include: age; gender; number of children living in the household; home postal code; type of job; car and bicycle accessibility; as well as telework habits. Regarding the transport related information, the survey provides information on: access times to public transport from home; frequent usage of different transport modes to commute, travel inside the work area, and in their free time; average number of work trips inside the work area on a normal day, as well as how much time do they normally spend travelling inside the work area. The final part of the survey was designed to target specific latent normative beliefs that were hypothesised to influence modality styles. These factors included car affective and symbolic attitudes (Steg, 2005); social influence and status; having an environmental mindset; expectations about MaaS; public transport instrumental utility; benefits of active travel; and use of travel information.

Table 2 reports the marginal distributions of selected mobility attributes and socio-economic variables.

After comparing this information with the employer database records for the whole population, we can say that the sample used for the analysis is representative of the larger population within the company.

Moreover, it was hypothesised that residential location plays a critical role on the traveller adopted modality style; hence, three large areas were defined for further analysis.

Table 2. Sample descriptive statistics (N=433)

Variable value	Sample margin (%)
Age	
18-24	4
25-44	56
45-59	36
60-60+	4
Gender (Male)	75
Car Ownership (Yes)	85
Bike accessibility (Yes)	83
Driver license (Yes)	97
Children living in the houseld (yes)	56
Managerial position (Yes)	12
PT access time	
5 min or less	52
5 to 10 min	29
10 to 15 mi	11
More than 15 min	8

These areas are the greater Stockholm area, the Södertälje campus surroundings, and the Stockholm/Södertälje commuter railway line. The reasons to define these areas were:

- Greater Stockholm area (10km buffer around Stockholm city centre). People leaving in this area have more alternatives available to commute, making easier to find a competitive alternative to the use of the private car. This includes the commuter trains, buses, and the employers express bus shuttle.
- Södertälje area. (10 km buffer around Scania campus). These users do not have so many motorized alternatives as people living in the previous area; nevertheless, they have a better situation to use non-motorized modes (walk and bicycle).
- 1 km buffer around the commuter rail line between Stockholm and Sod Södertälje. People leaving along the commuter rail line might be more prone to commute by railway, and even they might have chosen their residential location based on this fact.

Using a geographic information system (QGIS, 2018) a dummy variable was defined for each of the areas described above. These variables take the value one if any part of the user home-post code intersects with the buffers.

Finally, histograms of responses to the 50 attitudinal indicators are reported in Appendix B.

4 RESULTS

In this section we present the parameter estimates, log-likelihood and goodness of fit results for the models estimated with pythonbiogeme (Bierlaire, 2016). To identify the optimum number of latent classes, models with one, two and three classes were estimated. The model specification terminated when none of the specifications with three latent classes converged.

The estimation results for the model specifications with one and two latent classes are meaningful in a statistical and behavioural sense. Yet, both the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) indicate that the model specification with two latent classes outperforms the model specification with a single latent class, as shown in *Table 3*.

Table 3. Summary statistics for different model specifications

Latent classes	Latent variables	Observations	Draws	Estimated parameter	Log-likelihood	BIC	AIC
1	5	433	500	182	-23148.7	47402.3	46661.4
2	5	433	500	225	-22737.8	46841.5	45925.6
3	5	433	500	301	Failure to converge		

Table 4. Comparison of model fit between models with two latent classes, but different assumptions regarding how ordered variables were modelled.

Model	*Logistic*	*Normal*
Assumption difference	$v_{i,m,n} \sim EV_1\left(0, \pi^2/_6\right)$	$v_{i,m,n} \sim N(0,1)$
Iterations	*491*	*361*
Run time (minutes)	*35.32*	*29.43*
Final log likelihood:	*-22740.1*	*-22737.8*

Also, results from comparing the two different modelling assumptions regarding the stochastic component of the ordered response variables show that using a normal distribution provides a better fit in less iterations (see *Table 4*). Hence, in the rest of the paper we present results from the model with two latent classes, and ordered responses modelled by ordered probit models, which goodness of fit statistics are reported in *Table 3.*

Latent Classes description

The class membership function calculates the probability of individual *n* belonging to each class. In this study, these latent classes model latent mobility styles, which are hypothesised to be a function of socio-demographic characteristics; mobility-related attitudes; and normative beliefs towards the use of different modes of transport. Below we summarise the characteristics of each class.

Class 1: Car-oriented class (~75%)

In this class, car ownership, regular commuting by car, and the use of the car for travelling inside the work area is higher than for the other class. Hence, we call this class car-oriented.

Coefficient estimates for observed attributes show that the presence of children in the household, and having a managerial position make users more likely to fall within this car oriented class. These findings make sense from a behavioural point of view, as managers and parents with children in the household are usually time constrained, making them more likely to want to reduce its travel time and have the flexibility to adapt to the household/job needs; hence, opting frequently for the car alternative.

Among the latent factors considered in the class membership function, we find a positive influence of the latent construct “Car Affective” and “High Expectations for MaaS” with the users falling in this class.

Class 2: Shared-mobility oriented class (~25%)

Users within this class are more likely to commute by PT; the employers express shuttle; and use non-motorized transport modes (walk and bicycle).

Within this class we find people leaving in the greater Stockholm area, and with good access to PT. This result indicates the importance of competitive alternatives in the mode choice. Travellers from the greater Stockholm area have the ability to choose between a larger set of PT alternatives, including the employers express shuttle which is restricted to a few routes.

Also young people (18 to 24 years old) are more likely to be shared-mobility oriented. We find two complementary explanations for this. First, young people do not have the purchase power to afford a car; and second, they want to live in the city and they adopted more sustainable travel behaviours, due to the ability to choose between a larger set of alternatives.

Among the latent factors, we find that “Having an environmental mind-set”, and having “High expectations for MaaS inside the work campus” help to explain belonging to this class. This result is interesting, as having high expectations for MaaS also had explanatory power for the car-oriented class. We believe that the difference resides on the fact that users from the shared-mobility class have already a suitable commuting experience, but it is very difficult to travel inside the campus and they are in need of solutions.

Other variables included in the class membership function are: gender; dummy variables for leaving close to the working place, or the commuter railway line; and the latent factor “social influence”. Unfortunately, we cannot find statistical significant (at a 95% confidence level) of these variables in explaining the classes. Detail parameter estimates of the class membership function variables and the mobility attributes are provided on *Tables 5* and *6*. Furthermore, detail parameter estimates of the latent attributes entering the class membership function can be found in *Tables C1* and *C2* in Appendix C.

Table 5. Coefficient estimates of the class membership model

Parameter	Class 1		Class 2	
	Value	t-val	Value	t-val
Constant	-1.80	-1.32*	Reference class	
Gender (reference = female)				
Male	-1.23	-1.92*		
Age (reference = 45 to 59 years old)				
18 to 24	-3.21	-2.32		
25 to 44	-0.19	-0.37*		
60 or more	3.18	1.62*		
Type of employment (reference = employee)				
Manager	1.79	2.07		
Type of worker (reference = blue-collar)				
White-collar	-1.00	-1.48*		
Frequent traveller inside campus (reference = less than 3 trips/day)				
3 or more trips / day	0.77	0.88*		
Children living in the household (reference = none)				
1 or more	3.94	4.04		
Home location				
Sodertalje 10km buffer	1.25	1.88*		
Stockholm 10 km buffer	-0.94	-1.75*		
Commuting line Stockholm-Sodertalje 1km buffer	0.169	0.34*		
Latent attributes				
Car affective	2.48	3.05		
Environmental mindset	-0.40	-2.29		
High expectations about MaaS	0.80	2.10		
High expectations about MaaS (only inside work area)	-0.90	-2.19		
Social influence	-0.60	-1.49*		

* Parameter not statistically different from zero at 95% confidence

Table 6. Estimate of coefficients on mobility attributes

Parameter	Class 1		Class 2	
	Value	t-val	Value	t-val
Bicycle access (reference = no)				
Yes	1.77	11.3	1.19	5.05
Car access (reference = no)				
Yes	4.42	8.56	-0.45	-2.08
Regularly commute by bicycle (reference = no)				
Yes	-2.38	-11.9	-1.62	-6.01
Regularly commute by car (reference = no)				
Yes	4.26	8.12	-2.97	-4.22
Regularly commute by public transport (reference =no)				
Yes	-2.24	-11.1	1.04	4.53
Regularly commute by employer' shuttle (reference =no)				
Yes	-4.41	-8.69	-0.94	-4.23

Table 6.(cont). Estimate of coefficients on mobility attributes

Parameter	Class 1		Class 2	
	Value	t-val	Value	t-val
Regularly commute by walking (reference = no)				
Yes	-2.56	-11.9	-1.67	-6.10
Regularly travel inside campus by bicycle (reference = no)				
Yes	-3.70	-10.3	-2.97	-6.47
Regularly travel inside campus by car (reference = no)				
Yes	1.04	8.07	-3.15	-5.97
Regularly travel inside campus by taxi (reference = no)				
Yes	-2.03	-11.7	-1.16	-4.96
Regularly travel inside campus by walking (reference = no)				
Yes	-0.44	-3.86	0.12	0.59*
Walking time to access public transport (reference = more than 5 min)				
Good access (5 minutes or less)	0.004	0.04*	0.32	1.56*
Telework (reference = less than one per month)				
More than one per month	-1.11	-8.67	-1.07	-4.68

* Parameter not statistically different from zero at 95% confidence

User attitudes towards MaaS trends

Below we discuss user´s attitudes regarding the opportunities that MaaS systems are envisaged to bring, and we point out key differences/similarities between the two classes. *Table 7* shows the estimated distributions of the related attitudinal indicator across latent classes, on which these in-sights are based. Detailed parameter estimates from which the distributions of *Table 7* were calculated can be found in *Table C3* in Appendix C.

Car ownership to usership trend

We observe that individuals in both latent segments express their preference to not own a car, but still they want the benefits of car trips. This finding supports the existence of a car ownership to usership trend, as suggested by (Kamargianni et al., 2018). Furthermore, over 67% of users in any of the two classes agree or strongly agree with the fact that owning a car is a big expenditure for the household, suggesting that the cost of owning a car is the key in their decision to abandon car ownership.

PT to car shift

Our results show that the introduction of a MaaS solution is not likely to produce a shift in transport modes from PT to car under the conditions of this experiment. 64% of users in the shared-mobility class, and 57% of users in the car oriented class, stated that they will not replace PT trips with car if the MaaS app will allow them to book taxis. We believe that this result must be interpreted with caution, as in the setup of this MaaS experiment, taxis can be booked but their cost is billed to the employee’s department; hence booking a taxi must be justified whilst using the other means of travel do not.

Vehicle sharing

Regarding the will to share car journeys with strangers different opinions arise. Around 50% of users in both car-oriented and shared-mobility classes, seem to be in favour of sharing car journeys, whilst around 20% of users, in any of the two classes, reported not to feel comfortable with sharing a car trip with people that they do not know. These results point out that it might be a feasible business case for both types of user needs, where users might choose between "private"[3] or shared journeys by car.

Up to date and real-time information

Results also show the importance of access to information. 97% of users in the shared-mobility class reported that they check real-time information to plan their trips or check for disruptions. But this need for information is not limited to the shared-mobility class, as 60% of the car oriented class reported the same behaviour.

In addition, 39% of the shared-mobility class and 70% of the car-oriented users reported that they always choose the fastest alternative. This result highlights the need for adequate information so users can make informed choices, especially when MaaS will increase the number of alternatives.

Flexibility

From the estimated distributions we can observe that the majority of users, 49% on the shared-mobility class and 71% on the car oriented class, agree of strongly agree with the need for flexibility due to irregular schedules. Also, we observe that 64% on the shared-mobility class and 88% on the car oriented class reported to agree or strongly agree with the fact that non-work related activities condition the commuting mode choice. Furthermore, we observe that 42% on the shared-mobility class and 51% on the car oriented class reported that they travel with their current mode because they do not have other alternative.

[3] Private in this sense mean that the car journey is not shared with strangers, but does not imply that the car needs to be privately owned.

Table 7. Estimated distributions of attitudinal indicators across latent classes

Statement / Response Value	*Class 1 (%)*	*Class 2 (%)*
I would love to have access to a car without the hassle of owning one.		
Strongly disagree	*3*	*3*
Disagree	*11*	*10*
Neutral	*23*	*22*
Agree	*28*	*27*
Strongly agree	*35*	*38*
Owning a car is a big expenditure for my household		
Strongly disagree	*1*	*1*
Disagree	*6*	*6*
Neutral	*24*	*26*
Agree	*41*	*42*
Strongly agree	*28*	*25*
If the new system allowed to book cabs, I will use that feature instead of the PT		
Strongly disagree	*5*	*7*
Disagree	*17*	*21*
Neutral	*35*	*36*
Agree	*28*	*25*
Strongly agree	*15*	*11*
I always choose the fastest travel alternative		
Strongly disagree	*0*	*2*
Disagree	*4*	*15*
Neutral	*26*	*44*
Agree	*43*	*31*
Strongly agree	*27*	*8*
I use information on the internet to check timetables and delays		
Strongly disagree	*6*	*0*
Disagree	*13*	*1*
Neutral	*21*	*2*
Agree	*32*	*11*
Strongly agree	*28*	*86*
I do not feel comfortable when sharing a car trip with people that I do not know		
Strongly disagree	*15*	*13*
Disagree	*34*	*32*
Neutral	*33*	*34*
Agree	*14*	*16*
Strongly agree	*4*	*5*
I need flexibility because normally I have an irregular schedule		
Strongly disagree	*2*	*6*
Disagree	*11*	*23*
Neutral	*16*	*22*
Agree	*39*	*34*
Strongly agree	*32*	*15*
I travel the way I do because I do not have any other alternatives		
Strongly disagree	*4*	*6*
Disagree	*16*	*21*
Neutral	*29*	*31*
Agree	*35*	*31*
Strongly agree	*16*	*11*
I normally travel in the same way and do not plan my trips		
Strongly disagree	*1*	*3*
Disagree	*7*	*12*
Neutral	*18*	*25*
Agree	*35*	*35*
Strongly agree	*39*	*25*
I plan my commute trip based on other (non-work) trips as well		
Strongly disagree	*0*	*3*
Disagree	*2*	*9*
Neutral	*10*	*24*
Agree	*26*	*33*
Strongly agree	*62*	*31*
I often think about moving closer to work in order to reduce my travel time		
Strongly disagree	*85*	*66*
Disagree	*10*	*18*
Neutral	*4*	*10*
Agree	*1*	*4*
Strongly agree	*0*	*2*
A car provides status and prestige		
Strongly disagree	*25*	*24*
Disagree	*35*	*35*
Neutral	*30*	*31*
Agree	*10*	*10*
Strongly agree	*0*	*0*
I like to drive		
Strongly disagree	*0*	*1*
Disagree	*2*	*10*
Neutral	*17*	*38*
Agree	*38*	*36*
Strongly agree	*43*	*15*

5 CONCLUSIONS

MaaS envisages enabling a co-operative and interconnected single transport market which provides users with hassle free mobility. This situation has made MaaS a hot topic in the last five-year period; and even though plenty of research is being carried out on MaaS, and pilot MaaS systems are being deployed all over the world, very little is known about the consequences that MaaS systems will have on travel behaviour, especially when MaaS systems become the norm rather than the exception.

This study provides answers to open questions that previous studies on MaaS systems rose about travel behaviour and user attitudes using a Latent Class Latent Variables Model. This analysis is expected to be of interest not only to this particular employer, but would also be instrumental in supporting relevant stakeholders all over the world which discuss the introduction of similar MaaS solutions. By doing so, we hope to contribute to a more evidence and knowledge-based decision making.

The latent segmentation analysis identifies two classes, which according to their manifested behaviour can be characterised as: (1) car-oriented and (2) shared-mobility oriented. We find statistically significant influence on class membership from socio-demographic and normative beliefs for age; children living in the household; having a managerial position; being environmentally conscious; having car affective attitudes; having high expectations about MaaS solutions; and choice of residential location. Others variables for which we could not find statistically significant influence on class membership, e.g. gender or social influence should not be discarded immediately in other analysis, as values and norms differ widely among societies; hence, it is important to re-evaluate the importance of these factors in each new environment. Furthermore, the outcome of this type of analysis will inform policy makers on how to design high impact policies.

Regarding the existence of a car ownership to car usership trend, we find evidence to support this hypothesis as the majority of respondents in both classes expressed their interest in getting access to a car without owning one, and pointing out that owning a car is rather costly for their households. This trend can lead to a reduction of congestion and driven kilometres due to a smaller number of privately own cars.

We also find evidence to support that MaaS is not likely to produce a shift in transport modes from PT to car under the conditions of this experiment. Nevertheless, we believe that this result must be interpreted with caution, as in the setup of this MaaS experiment, taxis can be booked but their cost is billed to the department of the employee; hence booking a taxi must be justified whilst using the other means of transport do not. We believe that this situation might influence the responses of the survey participants and not be representative of the actual behaviour if the users did not need to justify the trip cost.

Regarding user's preference to share a car journey with strangers, we observe two opposite trends suggesting that there might be appetite for both types of solutions, where users could choose between private or shared journeys by car.

Results also show that users want access to adequate information to plan their trips and check for disruptions. It is foreseen that this need for information will be even more avid, as MaaS systems increase the number of available mode alternatives for each trip, and users try to maximize the utility of their choices. In the bright side, MaaS platforms will be in an excellent position to satisfy this avid demand for information from a single location, reducing the burden associated with the choice.

We also find evidence that users value very highly the possibility to accommodate irregular schedules, where the relevant unit of analysis is not an individual but the family and household. Hence, successful MaaS systems should demonstrate how they can fulfil these demands, especially if they want to attract users with a more car-oriented mind-set.

Finally, these are empirical findings for trips within a particular company in Sweden, and whether they can be generalised to other employers/cities should be further explored. Observable long-term effects of MaaS solutions still remain to be assessed and will allow determining whether the results attained in the analysis are sustained. In the meantime, we hope these user insights help design the MaaS solutions that users want; that enthusiasts claim will make better off their users; but also that benefit society as a whole.

6 ACKNOWLEDGEMENTS

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7 COMPLIANCE WITH ETHICAL STANDARDS

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

8 REFERENCES

Bierlaire, M. 2016. PythonBiogeme: a short introduction. Report TRANSP-OR 160706, Series on Biogeme. Transport and Mobility Laboratory, School of Architecture, Civil and Environmental Engineering, Ecole Polytechnique Fédérale de Lausanne, Switzerland.

Daly, A., Hess, S., Patruni, B., Potoglou, D., Rohr, C., 2012. Using ordered attitudinal indicators in a latent variable choice model: A study of the impact of security on rail travel behaviour. Transportation, 39 (2) (2012), pp. 267-297. https://link.springer.com/article/10.1007%2Fs11116-011-9351-z

Greene, D.L., Hensher, D, 2010.: Modelling Ordered Choices: A Primer. Cambridge University Press, Cambridge

Haahtela, T., and Viitamo, E., 2017. Searching for the potential of maas in commuting-comparison of survey and focus group methods and results. Conference Proceedings 1st International Conference of Mobility as a Service. ICoMaaS. http://www.tut.fi/verne/aineisto/ICoMaaS_Proceedings_FULL_webres.pdf

Kamargianni, M., Matyas, M., Li, W., and Muscat, J., 2018. Londoners' attitudes towards car-ownership and Mobility-as-a-Service: Impact assessment and opportunities that lie ahead. MaaSLab - UCL Energy Institute Report, Prepared for Transport for London. https://www.maaslab.org/reports

Krueger, R., Akshay V., Rashidi H. T., 2016. Normative beliefs and modality styles: a latent class and latent variable model of travel behaviour. Transportation. 10.1007/s11116-016-9751-1.

Likert, R. (1932). A technique for the measurement of attitudes. Arch. Psychol 22(140), 55.

MaaS Global, 2017. SERA Conference. https://www.era.europa.eu/Document-Register/Documents/Impulse%20speech%20Jonna%20P%C3%B6ll%C3%A4nen.pdf

QGIS, 2018. "QGIS Development Team. QGIS Geographic Information System. Open Source Geospatial Foundation Project.". http://qgis.osgeo.org

Sanko, N., Hess, S., Dumont, J., Daly, A., 2014. Contrasting imputation with a latent variable approach to dealing with missing income in choice models. J. Choice Model. 12, 47–57.

Sochor, J., Karlsson, I. M., & Strömberg, H., 2016. Trying Out Mobility as a Service: Experiences from a Field Trial and Implications for Understanding Demand. Transportation Research Record: Journal of the Transportation Research Board, (2542), 57–64

Steg, L., 2005. Car use: lust and must. Instrumental, symbolic and affective motives for car use. Transportation Research A, 39 (2005), pp. 147-162

Wong Y.Z., Hensher D.A., Mulley C.M., 2017, Emerging Transport Technologies and the Modal Efficiency Framework: a case for mobility as a service (MaaS). Presented at the 15th International Conference on Competition and Ownership of Land Passenger Transport (Thredbo 15), Sweden, Stockholm (2017), pp. 13-17.

9 APPENDIX A

The content in this appendix presents the framework of the model that was introduced by Krueger et al. (2016) – Normative beliefs and modality styles: a latent class and latent variable model of travel behaviour. -. For consistency, we have kept equation 1-15, and their explanation identical as described in Krueger et al. (2016), the only difference in the methodology is the addition of a comparison of two different modelling techniques for ordered variables. The reason why we copied this section from Krueger et al. (2016) is to help our readers to understand the framework and the source of the estimation, even if they do not have access to Krueger et al. (2016).

The framework consists of three different parts: first, a latent normative belief submodel with structural and measurement components; second, a latent modality styles submodel; and third, class-specific submodels for binomial and ordered variables.

Latent normative belief submodel

As explained in Krueger et al. (2016), the latent variable model estimates the values of the latent normative beliefs which enter the class membership function as predictors. The structural component of the latent variable model relates the value $l_{m,n}$ of latent variable $\mathrm{m} \in \{1, \ldots, \mathrm{M}\}$ to the vector of observed characteristics $\mathrm{X_n}$ of individual $\mathrm{n} \in \{1, \ldots, \mathrm{N}\}$:

$$l_{m,n}(X_n; \gamma_m, c_m = G(X_n; \gamma_m, c_m) + \varepsilon_{m,n}, \tag{1}$$

$\varepsilon_{m,n}$ is a random disturbance $\sim N(0, \sigma_m^2)$ i.i.d Normal across individuals with variance σ_m^2, where σ_m is a parameter to be estimated. $G(X_n; \gamma_m, c_m)$ is the deterministic part specified to be linear in parameters including a constant (c_m), and a vector of parameters (γ_m). Consequently, the structural model of $l_{m,n}$ is,

$$l_{m,n}(X_n; \gamma_m, c_m) = c_m + X_n' \cdot \gamma_m + \varepsilon_{m,n}, \tag{2}$$

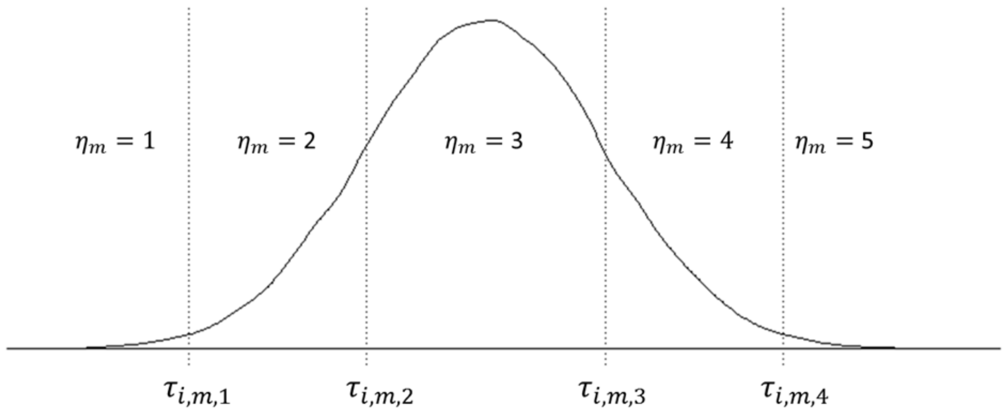
where X_n' is the transpose of X_n . This formulation leads to the probability distribution function of observing a vector l_n of $m \in \{1, \ldots, M\}$ latent variables for individual n:

$$f(l_n | X_n; \gamma_m, c_m, \sigma_m) = \prod_{m=1}^{M} \frac{1}{\sigma_m} \phi\left(\frac{l_{m,n} - c_m - X_n' \cdot \gamma_m}{\sigma_m}\right), \tag{3}$$

where $\phi(.)$ denotes the probability density function of the standard normal distribution.

Since the modeller cannot directly observe the latent variables, a set of $i \in \{1, \ldots, I\}$ Likert-type indicators provides a psychometric measurement of the latent variable in question. For convenience, an index value $\eta_m \in \{1, \ldots, H(m)\}$ is assigned to the ordered response options $\mu_{i,m}$, whereby a greater index value indicates greater agreement with the provided statement. See *Figure A1* below.

Figure A1. Example of Likert-type indicator (i), for latent variable m, with 5 response categories (η)



Multiple indicators are related to the same latent variable by establishing a linear factor model. Consequently, the item response function for indicator i, pertaining to latent variable m, for individual n is

$$\mu_{i,m,n}(l_{m,n}, \lambda_{i,m}) = \lambda_{i,m} \cdot l_{m,n} + \nu_{i,m,n}\,, \tag{4}$$

where $\lambda_{i,m}$ denotes the factor loading, and $\nu_{i,m,n}$ is a stochastic component. Because the dependent variable of the item response function is ordinal, we model the responses to the psychometric indicators with an ordered model (Daly et al. 2012).

At this point we complement the approach taken by Krueger et al. (2016), and implement two different modelling assumptions for these ordered variables. First, we reproduce the modelling assumptions of Krueger et al. (2016) and assume that $\nu_{i,m,n} \sim EV_1\left(0, \frac{\pi^2}{6}\right)$ i.i.d. By setting up the model in this way, the probability of observing response, $\mu_{i,m,n}$, is modelled by a logistic distribution, which has closed form solution. The scale parameter of the logistic cdf is denoted by Λ, and for convenience is set to one. Consequently, the response probability can be expressed as follows:

$$P(\mu_{i,m,n} | \lambda_{i,m}; \tau_{i,m}; l_{m,n}) = \begin{cases} \Lambda(\tau_{i,m,1} - \lambda_{i,m} \cdot l_{m,n}) & for\ \eta_m = 1, \\ \Lambda(\tau_{i,m,\eta_m} - \lambda_{i,m} \cdot l_{m,n}) - \Lambda(\tau_{i,m,\eta_m - 1} - \lambda_{i,m} \cdot l_{m,n}) & for\ 1 < \eta_m < H(m) - 1, \\ 1 - \Lambda(\tau_{i,m,H(m)-1} - \lambda_{i,m} \cdot l_{m,n}) & for\ \eta_m = H(m) \end{cases} \tag{5}$$

where $\tau_{i,m}$ is a set of $H(m) - 1$ threshold parameters for indicator i of latent variable m. For identification, we set $\tau_{i,m,1} = 0$ and $\lambda_{1,m} = 1$ (see Daly et al. 2012).

Second, we assume that $\nu_{i,m,n} \sim N(0, \sigma_\nu)$. Under this second approach, the probability that the given response, $\mu_{i,m,n}$, lies within a particular range of a distribution is no longer modelled by a logistic distribution, but rather by a normal distribution, which has no closed form. We decided to model the residuals, $\nu_{i,m,n}$, with a normal distribution, despite of the increased difficulty in estimation, as it is deemed theoretically more appropriate. For identification, in this case we set $\sigma_\nu = 1$, $\tau_{i,m,1} = 0$ and $\lambda_{1,m} = 1$. This approach was used by Greene and Hensher (2010).

Now, independently of the assumed distribution for $\nu_{i,m,n}$, the probability distribution function of observing the vector $\mu_{m,n}$ of responses to the i indicators pertaining to latent variable m, is defined as:

$$f_m(\mu_{m,n}|\lambda_m, \tau_m, l_{m,n}) = \prod_{i=1}^{I} P(\mu_{i,m,n}|\lambda_{i,m}, \tau_{i,m}, l_{m,n}), \quad (6)$$

As also described in Krueger et al, (2016), not all indicators were obtained for all of the latent variables. Hence, it is more precise to introduce the notation M(n) to label the maximum number of latent variables as a function of the observations. In addition, we introduce the dummy variable $d_{m,n}$ to indicate whether indicators of the m^{th} latent variable were obtained for an observation. Moreover, we modify the probability distribution function to reflect that some indicators are missing for some observations:

$$f_m(\mu_{m,n}|\lambda_m, \tau_m, l_{m,n}, d_{m,n}) = d_{m,n} \cdot f_m(\mu_{m,n}|\lambda_m, \tau_m, l_{m,n}) + (1 - d_{m,n}), \quad (7)$$

where $d_{m,n} = 0$ if the indicators were not obtained. Then the value of the probability distribution function is set to one and the contribution of this observation to the log-likelihood is zero (Sanko et al. 2014).

To summarise, the probability distribution function of observing the $m \times i$ matrix μ_n of indicator responses for $M(n)$ latent variables is:

$$f(\mu_n|\lambda, \tau, l_n) = \prod_{m=1}^{M(n)} f_m(\mu_{m,n}|\lambda_m, \tau_m, d_{m,n}).,\quad (8)$$

Latent modality styles submodels

As explained in Krueger et al. (2016), individuals are assumed to be distributed across K latent classes representing modality styles. Latent class membership probabilities are predicted from the individual´s observed characteristics X_n and a vector l_n of latent variables. This, the class membership function for class $k \in \{1, \dots, K\}$, is expressed as follows:

$$U_{k,n} = V_{k,n}(X_n, l_n; \beta_k, \alpha_k) + \epsilon_{k,n}, \quad (9)$$

where $V_{k,n}$ is the deterministic part of the class membership function, which we specify to be linear in parameters. Hence, we have:

$$U_{k,n} = \beta_k \cdot X_n' + \alpha_k \cdot l_n' + \epsilon_{k,n}, \quad (10)$$

where β_k and α_k are vectors of parameters to be estimated, and $\epsilon_{k,n}$ is a random disturbance assumed to be $\epsilon_{k,n} \sim EV_1(0, \frac{\pi^2}{6})$ i.i.d. For observations, for which indicators pertaining to a latent normative belief were not obtained, the value of the latent normative belief in question is imputed through the structural equation of the latent variable submodel so that the coefficient on the latent can be estimated on the basis of all observations (Sanko et al., 2014).

The class membership model is a multinomial logit model with the scale parameter fixed to one, as shown by equation (11).

$$P_n(k = \mathrm{K}|\beta_k, \alpha_k) = \frac{\exp(V_{l,n}(X_n, l_n; \beta_l, \alpha_l))}{\sum_{k=1}^{\mathrm{K}} \exp(V_{k,n}(X_n, l_n; \beta_k, \alpha_k))}, \tag{11}$$

Class-specific submodels

The model includes several class-specific submodels, conditional on membership in a latent class k. As explained in Krueger et al. (2016), depending on the format of the dependent variable these models are either binomial or ordered logit models. *Table 1* (in Section 2) provides an overview of the different class-specific submodels. In our case study the class-specific models are constants-only models.

First, we specify the probability of the class-specific binomial logit models:

$$P_n(z_n|\mathrm{K_k}; k) = \frac{(1-z_n)+z_n \cdot \exp(\mathrm{K_k})}{1+\exp(\mathrm{K_k})}, \tag{12}$$

where $\mathrm{z_n}$ is a dummy variable indicating, which observation was made. $\mathrm{K_k}$ is a constant, which is to be estimated. Since multiple binomial logit models are estimated for each class, we use the same simplifying notation as Krueger et al. (2016), where $a \in \{1, \dots, A\}$ is an index denoting the binomial choice being modelled,

$$P_{a,k,n}(z_n|\mathrm{K_k}; k) = \prod_{a=1}^{A} P_{a,k,n}(z_{a,n}|\mathrm{K_{a,k}}; k), \tag{13}$$

Similarly, there are multiple ordered models for each class. In these models, the probability of observing response, $\rho_{\mathrm{b,n}}$, is modelled in an identical way as previously seen for the observed latent variable indicators, $\mu_{i,m,n}$. Then, the probability distribution function of the class-specific ordered models is defined as:

$$P_{b,k,n}(\rho_n|\mathrm{\tau_k}; k) = \prod_{b=1}^{B} P_{b,k,n}(\rho_{b,n}|\mathrm{\tau_{b,k}}; k), \tag{14}$$

where $b \in \{1, \dots, B\}$ is an index that denotes the ordered choice being modelled, and $\rho_{b,n}$ denotes the coded ordinal outcome variable for individual n.

Also as explained by Krueger et al. (2016), $\tau_{b,k}$ is a vector of threshold parameters common to all latent classes. This simplification is justified because if the threshold parameters are estimated based on the entire sample, then the difference between the ordered categorical dependent variables is the same across all classes. The additive scale of the outcome variables is adjusted for each class by subtracting the class-specific constant from the sample threshold.

The class-specific submodels for mode-specific attitudes are specified as ordered logit models. The responses reported in *Table B1 (appendix B)* are used as indicators and the corresponding threshold parameters are estimated as being specific to the entire sample. Moreover, it is assumed that the influence of individual characteristics is sufficiently reflected in the latent segmentation. Hence, the structural model for each class only comprises a constant that is specific to the class.

Likelihood function

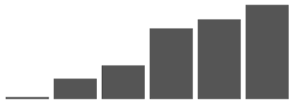
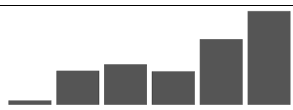
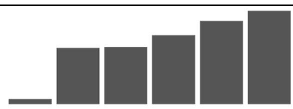
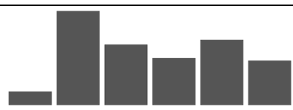
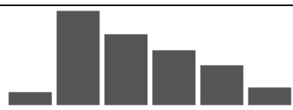
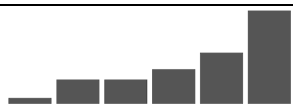
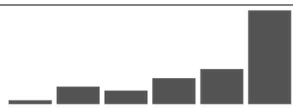
As explained in Krueger et al. (2016), equations 3, 8, 11, 13, and 14 are iteratively combined across individuals to obtain the unconditional probability of observing the combination of observed choices. Where μ_i, ρ_b, z_a are vectors of observed choices; being z_a binomial choices; ρ_b the coded ordinal outcome variables; and μ_i observed indicators of the latent variables.

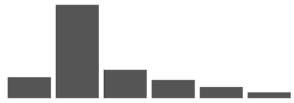
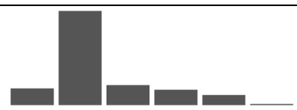
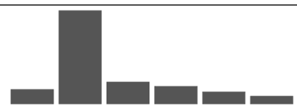
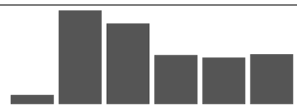
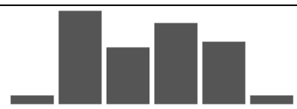
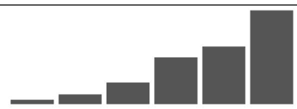
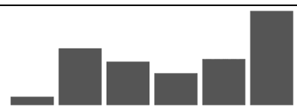
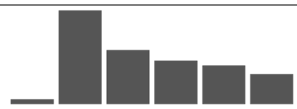
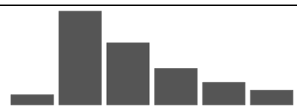
$$\begin{aligned} L\big(\mu_i, \rho_b, z_a \big| X_n; \alpha, \beta, \gamma, \lambda, a, b, c, \mathrm{K}\big) \\ = \prod_{n=1}^{N} \int_m \left(\sum_{k=1}^{K} P_n(k|\beta_k, \alpha_k) \cdot P_{a,k,n}(z_n|K_k; k) \cdot P_{b,k,n}(\rho_n|\tau_k; k) \right) \\ \cdot f(\mu_n|l_n, \lambda, \tau) \cdot f\big(l_{n,m}\big|X_n; \gamma_m, c_m\big) dl_m. \end{aligned} \tag{15}$$

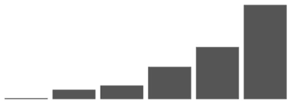
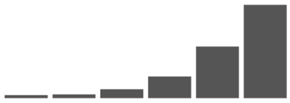
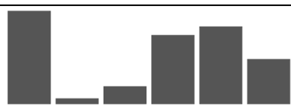
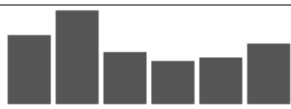
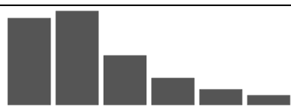
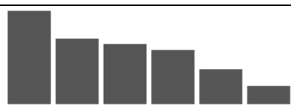
Because of the random error term that enters the structural equation of the latent variable model, the likelihood is integrated over the densities of the latent variables l, hence the dimension of the integral becomes the same as the number of latent variables (m). As a consequence, the objective function does not possess a closed-form solution under any of the two modelling assumptions used to model the ordered variables; hence, models must be estimated through maximum simulated likelihood methods.

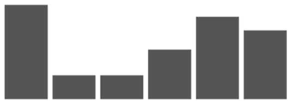
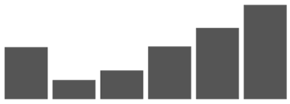
10 APPENDIX B

This appendix presents the survey responses to the 50 attitudinal questions presented to the users. Histograms have levels from 0 to 5 (left to right), where zero shows the number of not respondents, and levels 1 to 5 show the level of agreement with the statement from 1-Strongly disagree; 2-Disagree; 3-Neutral; 4-Agree; and 5- Strongly agree.

Statement (reference code)	*Histogram of responses*
I am regularly stressed in my everyday life. (AQ1)	
Cycling prevents me from having a professional look. (AQ2)	
I always choose the fastest travel alternative. (AQ3)	
I use information on the internet to check timetables and delays. (AQ4)	
I do not feel comfortable when sharing a car trip with people that I do not know. (AQ5)	
I need flexibility because normally I have an irregular schedule. (AQ6)	
I travel the way I do because I do not have any other alternatives. (AQ7)	
I plan my trips the day before. (AQ8)	
I plan my trips early on the same day. (AQ9)	
I normally travel in the same way and do not plan my trips. (AQ10)	
I plan my commute trip based on other (non-work) trip as well. (AQ11)	
I often think about moving closer to Scania in order to reduce my travel time. (AQ12)	
I consider the environment when I plan my trips. (AQ13)	
Social and environmental	

Statement (reference code)	*Histogram of responses*
I can make an impact on the environment by travelling sustainably. (AQ14)	
I make active choices on a daily basis to reduce my carbon footprint. (AQ15)	
Fuel prices should be increased to reduce congestion and air pollution. (AQ16)	
It is important for Scania that we travel sustainable. (AQ17)	
People who are important to me have opinions about my way of commuting. (AQ18)	
People who are important to me say I should use (or buy) a car. (AQ19)	
People who are important to me say I should use the public transport. (AQ20)	
People who are important to me say I should use the bicycle. (AQ21)	
People who are important to me say I should walk more. (AQ22)	
Transport modes	
It does not matter to me which type of car I drive. (AQ23)	
A car provides status and prestige. (AQ24)	
You can tell who a person is by looking at his or her car. (AQ25)	
I like to drive. (AQ26)	
I know of a dream car that I would love to possess. (AQ27)	
I feel free and independent if I have access to a car. (AQ28)	
I like to use public transit because I can make better use of my time. (AQ29)	
When I use public transport, other people come close to me in an unpleasant way. (AQ30)	

Statement (reference code)	*Histogram of responses*
It is difficult to use public transport when I travel with my children. (AQ31)	
It is dangerous to use the bicycle. (AQ32)	
I can reach many of my normal destinations by bike. (AQ33)	
I enjoy walking. (AQ34)	
To walk and cycle helps to keep me healthy. (AQ35)	
MaaS Expectations	
I was familiar with SCANIA GO before this survey (AQ36 – binary question yes/no)	
I have high expectations for SCANIA GO. (AQ37)	
I think the new SCANIA GO system will affect how I commute to work. (AQ38)	
I think the new SCANIA GO system will affect how I travel inside Scania. (AQ39)	
If the new system allowed to book cabs, I will use that feature instead of the PT (AQ40)	
SCANIA GO is going to be easy to use. (AQ41)	
SCANIA GO is going to be a reliable service. (AQ42)	
SCANIA GO app is going to be user friendly. (AQ43)	
Questions only for car owners	
If I did not need a car, I would dispose of it immediately. (AQ44)	
I think that the new SCANIA GO system will help me reduce my car usage ~~in the short term.~~ (AQ45)	
New systems like SCANIA GO would help me depend less on my car. (AQ46)	

Statement (reference code)	*Histogram of responses*
New systems like SCANIA GO would help me substitute car trips with other modes inside scania's area. (AQ47)	
It takes a lot of time to find a parking space when I use my car. (AQ48)	
Owning a car is a big expenditure for my household. (AQ49)	
I would love to have access to a car without the hassle of owning one. (AQ50)	

11 APPENDIX C

Table C1. Estimates of the structural coefficients of the latent normative belief models

Variable	Car affective		Environmental mindset		High expectations for MaaS (everywhere)		High expectations for MaaS (on-campus)		Social influence	
	Est	t-val	Est	t-val	Est	t-val	Est	t-val	Est	t-val
Constant	2.23	9.90	2.73	8.27	1.57	6.76	1.47	9.49	0.21	0.23*
Gender (reference= female)										
Male	0.271	1.96	-0.33	-1.23*	-0.46	-2.86	-0.40	-3.59	0.23	1.50*
Age (reference = 45-59)										
18-24	0.78	2.39	0.21	1.68*	0.36	1.01*	-0.11	-0.76*	1.06	2.95
25-44	-0.29	-2.32	0.11	0.54*	0.19	1.32*	0.32	3.42	0.22	1.57*
60 or more	-0.27	-0.87*	-0.82	-1.56*	-0.31	-0.94*	-0.67	-3.64	-0.24	-0.74*
Children in the hh (reference = no)										
Yes	-0.05	-0.43*	0.54	2.37	-0.12	-0.85*	0.15	1.80*	0.12	0.93
Manager (reference = no)										
Yes	0.13	0.71*	0.43	1.25*	-0.14	-0.54*	0.09	0.68*	0.53	2.47
Standard deviation	1.28	10.0	2.91	10.1	1.52	8.80	1.18	12.47	1.29	6.69

* Parameter not statistically different from zero at 95% confidence

Table C2. Estimates of measurement coefficients of the latent normative belief models

Variable	Loading		Threshold*							
			Disagree		Neutral		Agree		Strongly Agree	
	Est	t-val	Est	t-val	Est	t-val	Est	t-val	Est	t-val
Car affective										
AQ26	1#	-	0#	-	0.81	6.42	1.73	9.48	2.61	10.6
AQ27	0.43	9.46	0#	-	0.56	8.78	0.90	7.35	1.39	9.03
AQ28	0.99	8.27	0#	-	0.47	4.38	1.06	6.42	2.15	11.1
Environmental. mindset										
AQ13	1#	-	0#	-	2.51	11.3	4.02	9.83	5.67	9.21
AQ14	0.40	8.55	0#	-	0.26	5.42	0.79	8.63	1.47	11.1
AQ15	0.41	11.0	0#	-	0.76	9.91	1.77	12.3	3.34	10.2
AQ17	0.24	7.76	0#	-	0.20	5.24	0.79	9.81	2.06	12.5
High expectations for MaaS (everywhere)										
AQ37	1#	-	0#	-	0.59	6.88	1.56	9.49	2.46	9.01
AQ38	0.32	5.62	0#	-	0.95	10.4	1.40	6.26	1.99	5.82
AQ45	0.47	5.62	0#	-	1.07	9.19	1.76	6.78	2.46	5.17
AQ46	0.90	6.53	0#	-	1.12	8.86	2.10	8.53	3.15	6.88
AQ47	0.95	6.51	0#	-	0.37	5.21	1.01	7.54	2.06	10.1
AQ48	0.57	7.18	0#	-	0.51	8.55	1.00	8.54	1.55	8.54
High expectations for MaaS (on-campus)										
AQ37	1#	-	0#	-	0.68	7.87	1.65	11.2	2.50	10.0
AQ39	1.02	10.8	0#	-	0.61	7.41	1.39	9.87	2.54	12.0
AQ41	2.89	9.36	0#	-	1.04	4.71	3.63	9.98	6.55	10.4
AQ42	2.91	8.79	0#	-	1.50	5.99	3.72	10.1	6.48	10.1
AQ43	3.68	6.88	0#	-	1.47	4.25	4.59	8.16	7.75	7.67
Social influence										
AQ24	1#	-	0#	-	0.85	8.55	1.74	8.69	2.80	7.75
AQ25	0.81	4.97	0#	-	0.58	8.57	1.48	10.2	2.97	9.13

 # Constrained for identification
** Categorical value to the right of the threshold value; value to the left of the threshold value is omitted in the interest of brevity*

Table C3. Estimates of coefficients on attitudinal indicators

Attitudinal Question	AQ3		AQ4		AQ5		AQ6		AQ7	
*Threshold**	Est	t-val	Est	t-val	Est	t-val	Est	t-val	Est	t-val
1	0#	-	0#	-	0#	-	0#	-	0#	-
2	1.12	7.02	0.68	6.67	1.02	10.66	0.98	8.36	0.91	8.69
3	2.34	10.90	1.31	7.56	1.95	10.29	1.56	7.67	1.72	9.81
4	3.48	11.88	2.15	9.53	2.81	8.05	2.59	11.30	2.73	10.88
Class-specific modifiers										
Class 1	2.88	13.91	1.57	10.81	1.04	8.45	2.10	13.10	1.73	12.13
Class2	2.07	8.72	3.24	12.16	1.15	5.77	1.53	7.48	1.52	7.44

Table C3 (Cont). Estimates of coefficients on attitudinal indicators

Attitudinal Question	AQ10		AQ11		AQ12		AQ24		AQ26	
*Threshold**	Est	t-val	Est	t-val	Est	t-val	Est	t-val	Est	t-val
1	0#	-	0#	-	0#	-	0#	-	0#	-
2	*0.82*	*6.91*	*0.68*	*5.70*	*0.58*	*6.92*	*0.92*	*10.62*	*1.29*	*6.25*
3	*1.58*	*8.49*	*1.49*	*8.08*	*1.11*	*5.53*	*1.95*	*10.45*	*2.50*	*9.88*
4	*2.51*	*10.68*	*2.34*	*9.63*	*1.67*	*4.64*	*3.41*	*8.18*	*3.56*	*11.41*
Class-specific modifiers										
Class 1	*2.23*	*13.20*	*2.63*	*14.13*	*-1.03*	*-8.16*	*0.68*	*5.95*	*3.37*	*13.37*
Class2	*1.84*	*8.48*	*1.53*	*7.17*	*-0.40*	*-2.04*	*0.69*	*3.47*	*2.52*	*8.97*

Table C3 (Cont). Estimates of coefficients on attitudinal indicators

Attitudinal Question	AQ40		AQ49		AQ50	
*Threshold**	Est	t-val	Est	t-val	Est	t-val
1	0#	-	0#	-	0#	-
2	*0.90*	*7.76*	*1.04*	*6.32*	*0.79*	*6.81*
3	*1.85*	*9.63*	*2.06*	*9.08*	*1.54*	*8.21*
4	*2.73*	*8.70*	*3.16*	*10.95*	*2.24*	*8.49*
Class-specific modifiers						
Class 1	*1.67*	*10.52*	*2.57*	*12.40*	*1.85*	*11.68*
Class2	*1.49*	*6.46*	*2.50*	*7.51*	*1.94*	*6.21*

 # Constrained for identification
** Categorical value to the left of the threshold value*