Investigating Heterogeneity in Preferences for Mobility-as-a-Service Packages through a Latent Class Choice Model

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ABSTRACT

The past decade has seen the introduction and widespread availability of a number of new mobility services. These have created a transport environment that is complex to navigate for passengers. The Mobility as a Service (MaaS) concept aims to provide a solution, by offering a single digital interface through which users can plan journeys, pay for and access a variety of transport modes. MaaS can also provide users with various products, including pay-per-use access to transport modes as well as MaaS packages. The latter are bundled mobility services that combine a variety of transport modes and are offered to customers in a one-stop-shop manner. The objective of this paper is to examine individual preferences for MaaS packages, specifically addressing the question of preference heterogeneity. In doing so, a Latent Class Choice Model (LCCM) is developed, allowing us to reveal variations in individuals' preferences. The LCCM is estimated using data from a MaaS-related market research carried out in Greater Manchester. The results imply significant heterogeneity with regards to preferences. Three latent classes emerged through the analysis, all with different MaaS package preferences and individual characteristics. Age, gender, income, education and current travel behaviour all play an important role in determining an individual's propensity to purchase MaaS packages. The results can provide valuable insights into the types of people that should and should not be initially targeted with MaaS packages to maximise uptake.

Keywords: Mobility as a Service (MaaS), MaaS packages, Latent Class Choice Model (LCCM), Heterogeneity, User Groups

1 INTRODUCTION

Urban mobility is going through some significant changes. On the one hand, there are several problems created by the rapid influx of people into cities such as the growth in traffic volumes, and the resulting congestion and pollution. On the other hand, increasingly more solutions are available thanks to technological advancements, widespread data availability and the emergence of the sharing economy. As a result, during the past decade a number of new mobility technologies, services and concepts have been introduced. Many of these have fundamentally changed the way mobility is provided and are promoting the shift away from privately owned transport. Car sharing, bike sharing, on demand transport, and ride hailing are now commonplace in many urban areas. More recently, we have seen the accelerated introduction of shared micromobility in cities, including scooters, electric bikes, electric scooters and electric mopeds. Additionally, the next generation of technological innovations such as automated vehicles and drones are now being tested.

The widespread availability of such a palette of new mobility services together with the more traditional modes, such as public transport, have created a complex mobility environment. Users can find it difficult to navigate through the silos of different information sources, mobile applications, tickets and journey planners that are necessary for them to get around. This complexity can discourage them from choosing alternative options as opposed to their private vehicles (Kamargianni, et al., 2015). The need for a single, integrated, user-friendly system has led to the birth of the Mobility as a Service (MaaS) concept, which aims to decrease the pain points that result from multimodal journeys.

MaaS is still not at full maturity and the definition is continuously evolving as the understanding of MaaS develops. As such, any definition needs to be fluid, and adjusted as necessary. In this paper, we will follow the following definition:

> *"Mobility as a Service is a user-centric, intelligent mobility management and distribution system, in which an integrator brings together offerings of multiple mobility service providers, and provides end-users access to them through a digital interface, allowing them to seamlessly plan and pay for mobility."* (UCL MaaSLab, 2018)

A graphic representation of the concept is also provided in Figure 1. The MaaS operator (MO) is the intermediate between the mobility service providers (MSPs) and the MaaS users. The MO aggregates the MSPs offerings, that can be transport services (fixed and on-demand services), mobility supportive services or even services that advance travellers experience. Users can then have simple access to these directly through the MaaS platform. Integral parts of the MaaS platform are mulimodal journey planning, real time information, booking, payment and ticketing functions and a user account. This means that the MaaS platform provides both information and planning integration and payment and ticketing integration to create a seamless user experience.

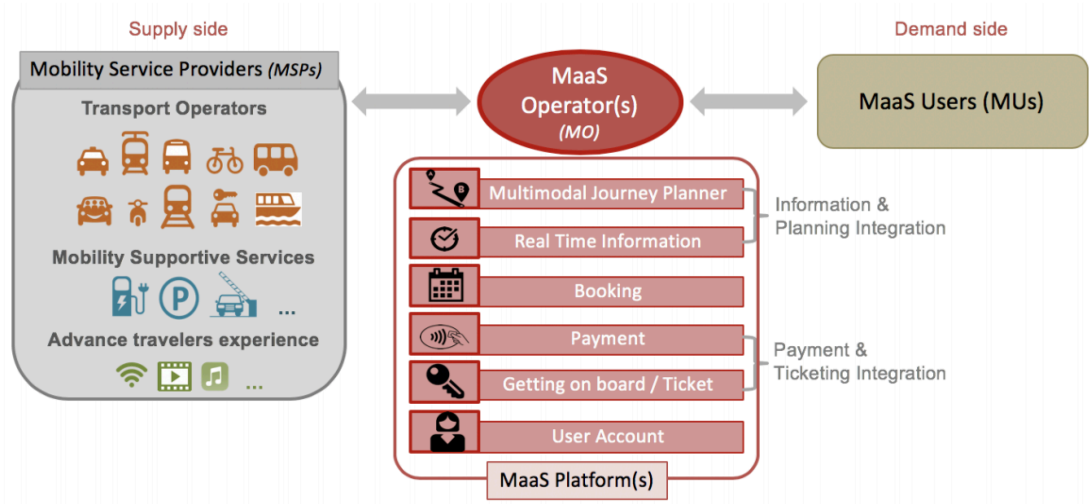

Figure 1: The MaaS concept (source: Kamargianni et al., 2018)

For users, MaaS offers a single digital interface (e.g. an app) through which they can plan journeys, and pay for and access all transport modes. The MO also offers users the option to purchase and use MaaS products, which include, but are not limited to, pay-per-use access to services and MaaS packages. MaaS packages, which are a type of MaaS product, are a bundled mobility services that are offered by the MO to its customers providing one-stop-shop access to a variety of services (Hietanen, 2016; Hensher, 2017; Kamargianni, et al., 2019). These are conceptually very similar to product bundles frequently used in other sectors such as the telecommunication industry.

The number of MaaS services being introduced in the market is growing every year. Initially, these were mainly pilots (e.g. Ubigo in Gothenburg and Smile in Vienna), however now several applications are commercially available (Kamargianni, et al., 2016; Jittrapirom, et al., 2017; Magoutas, et al., 2017; Georgakis, et al., 2018; Kamargianni, et al., 2019). These are mostly centred around European cities, and include services such as the Mobility Shop in Hannover, MyCicero in Italy, Whim in Helsinki, the West Midland and Antwerp, and CityMapper in London. Multimodal journey planning, real time information, booking, payment and ticketing are all at the heart of these services, and these functions are all accessible through a smartphone application. Both pilots and the commercial services integrate a number of different transport modes, such as public transport, taxi, bike sharing, car sharing, car rental and regional rail – although these do vary based on the area. Looking at the products that these services offer users, most of them offer solely pay-per-use access. However, some, such as Ubigo, Whim and CityMapper offer users the option to subscribe to MaaS packages.

The concept of MaaS packages, where users pre-pay for the use of certain services, has been a topic of discussion since early stages of MaaS developments (Hietenan, 2016; Kamargianni, et al., 2016; Sochor, et al., 2015). However, there have not been many attempts to rigorously investigate individuals' preferences for these products (see Section 2 for details), leaving room for further investigations on this subject. As travel behaviour highly depends on individual circumstances, it is not a straightforward task to create packages that fit with a diverse range of users' needs (Matyas and Kamargianni, 2019). One may hypothesise, that there is heterogeneity among preferences for MaaS packages, resulting in potential users falling under distinct customer segments. There will also most likely be certain population groups that are more keen to adopt this new service model than others. Even though the aim of MaaS is to integrate a variety of transport options and simplify the use of these, it would also mean embracing a new way of purchasing and accessing transport modes. This may be attractive to some, while not for others.

Against this background, this paper aims to examine individual preferences for MaaS packages, specifically addressing the question of preference heterogeneity. In doing so, a Latent Class Choice Model (LCCM) is developed, allowing us to reveal variations in individuals' preferences. The analysis of the class sizes and the variables affecting the likelihood of an individual belonging to a certain class also allows us to improve our understanding of how individual characteristics and mobility habits lead to the choice of MaaS packages. The results will help us identify potential user groups that could be targeted during MaaS developments. The LCCM is estimated using data from a MaaS-related market research carried out in Greater Manchester.

The remainder of the paper is organised as follows: after the literature review in Section 2, Section 3 presents the data and methodology used in this study. Next, Section 4 discusses the estimation results of the latent class choice model that investigates MaaS package preferences. Finally, Section 5 provides discussions and conclusions.

2 LITERATURE REVIEW

Recent years have seen the MaaS concept gain wider acceptance and with it, the amount of literature getting published each year is constantly growing. The topics explored include business models (e.g. Kamargianni and Matyas, 2017; Ebrahimi, et al., 2018; Polydoropoulou et al., 2020), impacts on specific transport modes (e.g. Hensher, 2017; Smith, et al., 2017), end user demand (e.g. Sochor, et al., 2015; Ho, et al., 2017; Matyas and Kamargianni, 2017; Lyons et al., 2019; Reck and Axhausen, 2020; Caiati et al., 2020), governance and policy (e.g. Heikkilä, 2014; Smith et al., 2019a; Smith and Hensher, 2020; Pangbourne et al., 2020; Hirschhorn et al., 2019), topology of services (e.g. Kamargianni, et al., 2016; Jittrapirom, et al., 2017; Sochor, et al., 2017) and barriers and opportunities (e.g. Li and Voege, 2017; Matyas and Kamargianni, 2019; Cottrill, 2020; Karlsson et al., 2020; Casado et al., 2020, Matyas, 2020; Smith et al., 2019b).

Focusing on the papers that explore the end user perspective in areas where MaaS is not yet introduced, while some papers use qualitative methods (e.g. Stopka et al., 2018; Matyas, 2020), most studies use quantitative methods. These examine aspects such as individuals' likeliness to adopt MaaS (e.g. Alonso-González et al., 2017), individuals' preferences and willingness to pay (WTP) for MaaS packages (e.g. Ratilainen, 2017; Ho et al., 2017; Matyas and Kamargianni, 2019;

Ho et al., 2020) and individuals' preference towards specific transport modes within MaaS packages (e.g. Guidon et al., 2019; Reck and Axhausen, 2020; Caiati et al., 2020).

All bar one of the examined quantitative studies collect primary data using surveys specifically designed for the purpose of studying MaaS. The exemption is Reck and Axhausen (2020) who repurpose data collected through the Copenhagen Networks Study to examine the viability of different MaaS subscription plan components. Of those studies that collect primary data, the majority use stated preference experiments (SPs) in which respondents are placed in a series of hypothetical situations and are asked to make choices about MaaS products (e.g. Ratilainen, 2017; Matyas and Kamargianni, 2019; Mulley et al., 2020). There are also a handful of studies that use surveys without SPs in which participants respond to questions with single, multiple and/or Likert-scale response frameworks (e.g. Fiorze et al., 2019, Alonso-Gonzalez et al., 2020, Liljamo et al., 2020).

The analysis methods used in the literature vary depending on the type of data that the study collects. Papers that use SPs to collect data on individuals' preferences towards MaaS tend to use discrete choice models for analysis (e.g. Ho et al., 2017; Caiati et al., 2020). Their findings vary but there are some consistencies. Regarding the effect that individuals' characteristics have on their preferences for MaaS, the impact of age on willingness to subscribe is a persistent result; concluding that younger generations are more likely to subscribe to the service (Ratilainen, 2017; Matyas and Kamargianni, 2019; Ho et al., 2020; Caiati et al., 2020). There are no other individual characteristics that are consistently revealed in every examined paper. For example, gender proved significant in a study by Caiati et al. (2020), while other studies pointed to its insignificance in influencing MaaS subscription choice (e.g. Ho et al., 2017).

Similarly, the impact of household characteristics are not consistent throughout the various studies. For example, Ho et al. (2017) find that while the age and number of children in a household are significant in impacting MaaS subscription choice, household structure and size are not. Contradicting this is Caiati et al (2020) who find that household composition is in fact a significant factor. There are some household characteristics that are shown as significant by multiple studies, such as income (Matyas and Kamargianni, 2019; Caiati et al. 2020) and household car ownership and use (Ho et al., 2020; Caiati et al., 2020). In addition to individual and household characteristics, some studies also examine the impact of current mobility habits on preferences towards MaaS (Matyas and Kamargianni, 2019; Ho et al., 2020; Caiati et al., 2020, Mulley et al., 2020). These studies echo one another in that current mobility choices and habits have a significant impact on MaaS preferences and choices of MaaS packages.

Many studies based on SP data explore individuals' preferences towards the specific transport modes included in MaaS packages. There are significant discrepancies in the finding with regards to which modes individuals prefer in the MaaS packages and how much they are willing to pay (WTP) for them. The only consistent result is the respondents' preference for public transport, which is always preferred in packages and has a positive willingness to pay (WTP) (Ho et al., 2020; Matyas and Kamargianni, 2019, Caiati et al., 2020). Additionally, both Railainen (2017) and Guidon et al. (2019) find that public transport is valued higher when offered in a bundle than when it is offered on its own, showcasing the importance of this mode in MaaS packages. Looking at the inclusion of other transport modes the results do not show a universal trend. On the one hand, some studies find that none of the other examined transport modes are preferred in MaaS packages (e.g. Ratilainen, 2017; Matyas and Kamargianni, 2019; Caiati et al., 2020). On the other hand, several studies find preference towards some, but not all other transport modes. For example, Ho et al. (2017) find that individuals on average have a WTP value of zero for car sharing, but have a positive preference and WTP for car sharing, taxi and Uberpool. Guidon et al (2019) conclude that besides public transport, car sharing and park and ride are valued higher when offered in a MaaS bundle but bike sharing, electric bike sharing and taxi are valued lower and have a negative WTP.

Turning to studies based on surveys, these utilize other methods including regression models and cluster analysis (e.g. Alonso-Gonzalez et al., 2020; Liliamo et al., 2020). Two studies are of particular interest as they use cluster analysis to examine heterogeneity within preferences for MaaS (Fioreze et al., 2019; Alonso-Gonzalez et al., 2020). Fioreze et al. (2019) conduct cluster analysis regarding individual's intention to use MaaS. They find four distinct clusters: MaaS curious, Multimodal travellers, Frequent car drivers and Car lovers. They also conclude that MaaS adopters are more likely to be regular public transport users, have a healthy commuting lifestyle and be concerned with the environment. They are also less likely to regard car ownership as important. The other paper using cluster analysis concludes on 5 clusters of MaaS-related attitudes: MaaS-Flexi ready individuals, Mobility neutrals, Technology car-lovers, Multimodal public transport supporters and Anti new-mobility individuals (Alonso-Gonsalez et al., 2020). They find that the two clusters with a most favourable attitude towards MaaS and integration are most multimodal, tend to be young, highly educated people who live in more dense urban areas and have no children

A summary of the discussed quantitative work is presented in Table 1.

Table 1: MaaS user preferences studies using quantitative methods

Reference	Study area and sample size	Data collection and analysis method	Key results
Alonso-González et al. (2017)	Amsterdam, Netherlands N= 797	Stated preference experiment about transport mode choice; basic statistical methods	- Multimodal users are most prone to adopt MaaS.
Ratilainen (2017)	Finland N=252	Stated preference experiment about MaaS package choice; multinomial logit	-Public transport is the only significant transport mode, while bike sharing, car sharing and taxi are insignificant

			- Average WTP for public transport is higher than the cost of the individual mode, while this for the other modes is significantly lower and even negative in the case of car sharing
Ho et al., 2017	Sydney, Australia N = 252	Stated preference experiment about MaaS package choice; non-linear random parameter logit	-Age and number of children have a significant impact on MaaS product choice, while gender, car sharing membership, household structure, household size have no impact. - Positive preference and WTP for all modes (are public transport, car sharing, taxi and Uberpool), although round trip car sharing has a WTP value of zero.
Matyas and Kamargianni (2019)	London, UK N=1068	Stated preference experiment about MaaS package choice; mixed logit model	-Public transport positive and significant, while bike sharing, car sharing and taxi are negative and significant -Current travel habits important influencing factors e.g. people who currently use taxi frequently will want more taxi in their packages and those who currently use bike sharing will want these.
Guidon et al., 2019	Zurich, Switzerland N = 1000	Stated preference experiment about MaaS package choice; mixed logit model	- Public transport, car sharing and park and ride are valued higher when offered in a bundle than when they are offered on their own. - Bike sharing, electric bike sharing and taxi this are valued lower and have negative WTP
Fioreze et al., 2019	's-Hertogenbosh, Netherlands N=568	Survey including Likert-scale questions; ordinal regression, cluster analysis	- 4 clusters regarding intention to use MaaS: MaaS curious, Frequent car drivers, Multimodal travellers, Car lovers. - MaaS adopters are more likely to be regular public transport users, have a healthy commuting lifestyle and are concerned with the environment. They are less likely to regard car ownership as important.
Ho et al., 2020	Tyneside, UK N=290	Stated preference experiment about MaaS package choice; non-linear random parameter logit model	- Household car ownership and use, smartphone ownership and use and age significantly affect choice of MaaS subscription. - Respondents prefer more days of public transport and car sharing; bike sharing as a positive but very small impact indicating this is less important. - WTP lower than average market price.
Caiati et al., 2020	Amsterdam and Eindhoven, Netherlands N=1078	Sequential portfolio choice experiment regarding whether individuals would subscribe and then how much of each transport mode they would want in their bundle; mixed logit model	- Gender, age, household composition, education, work status, income, household cars, driving license, car sharing membership, smartphone ownership and current mobility choices affect choice of subscribing. - Public transport most preferred, all other modes (e-bike sharing, e-car sharing, taxi, car rental, ride sharing, on-demand bus) are not preferred in MaaS subscriptions.
Mulley et al., 2020	New South Wales and Queensland, Australia	Stated choice experiment about MaaS package choice; MML model	- Focusing specifically on older population groups using community transport, they find that respondents with a trip habit are less likely to be interested in subscribing to MaaS or using it as PAYG.

	N=105		- WTP estimates were much smaller than the unit cost of providing the service.
Alonso-Gonzalez et al., 2020	Netherlands, N=1006	Survey including Likert-scale statements; Latent class cluster analysis	- 5 clusters of MaaS-related attitudes are found: MaaS-Flexi-ready individuals, Mobility neutrals, Technology car-lowers, Multimodal public transport supporters, Anti new-mobility individuals. - The two clusters with a most favourable attitude towards MaaS and integration are most multimodal, tend to be young, highly educated people who live in more dense urban areas and have no children.
Liljamo et al., 2020	Finland, N=1176	Survey with questions about current mobility expenses and WTP for MaaS; Linear regression model	- 43% of respondents were willing to adopt a MaaS package - WTP for MaaS package is on average 64% of respondents' monthly costs.
Reck and Axhausen, 2020	Copenhagen, Denmark N=555	Revealed preference data to construct MaaS scenarios where shared modes replace car trips based on generalised costs	- For the sample of students, public transport season tickets are viable for most respondents, but bike sharing, car sharing and taxi are too infrequent to include as reoccurring credits in MaaS plans. - PAYG is the more economically sensible option for most.

While there has been an increasing number of studies on the topic of MaaS packages and end user preferences, their results differ. The results vary, especially regarding individuals' preferences towards transport modes in MaaS packages, their WTP and the socio-demographic characteristics that are all significant factors in determining these preferences. With regards to the inclusion of specific modes, only public transport has recurring results, while the results for the other modes significantly differ. For example, while Ratilainen (2017) found that the inclusion of taxis is not a significant factor affecting an individual's decision between packages, Ho et al. (2017) found that respondents prefer more taxi in their packages, whereas Guidon et al. (2019) and Matyas and Kamargianni (2019) found that they prefer packages without this mode. Results also differ with respect to the personal characteristics that determine MaaS package preferences. However, there seems to be consistency with regards to younger population groups preferring MaaS packages (Ho et al., 2017; Caiati, 2020), but not with regards to other individual and household characteristics. These differences suggest that the specific geographical, societal and MaaS package characteristics lead to potentially contrasting individual preferences for MaaS packages. As such, it is important to further examine these in different locations.

In addition, there seems to be a lack of studies that focus specifically on the heterogeneity of preferences and that identify MaaS package user groups. There are only two studies using cluster analysis techniques that tackle this topic (Fioreze et al., 2019; Alonso-Gonzalez et al., 2020). However, more studies are needed to explore this topic further. As discussed in the sections above, tailoring mobility packages to user needs is important for their success (Hensher, 2017; Ho et al., 2018; Nikitas et al., 2017). To do so, better understanding is needed with regards to the differences in preferences between potential user groups. This will also help identify who could be possible early adopters.

3 DATA

The survey design and data collected in this study was collected as part of a European Commission (EC) H2020 funded research project, MaaS4EU (www.MaaS4EU.eu). The objective of the survey was to collect information about individuals' opinions about the MaaS concept and their preferences for MaaS products. The case study city is Greater Manchester, UK.

3.1 Survey design

The survey consists of both revealed preference (RP) and a stated preference (RP) sections. First, respondents answer an RP questionnaire that focused on collecting information about the respondents' characteristics, their mobility habits and mobility tool ownership.

Next, the MaaS concept is introduced. As the MaaS app is what users would see and interact with in real applications, screen shot mock-ups are provided as illustrations with short descriptions to complement this. Icons are used for transport modes that are included. Using pictorial representations makes users' perceptions of modes more homogenous, and the task more interesting and easily understandable (Morikawa, 1989). Using pictures also increases the chance that respondents will look at this and the text around it, thus leading to overall a greater fraction of respondents understanding the concept. Further, in the industry, currently many products are explained using illustrations, so these are probably more familiar to respondents. The aim of this first MaaS page is to familiarise respondents with the core MaaS service. The core MaaS service consists of a multimodal journey planner and an integrated ticketing and payment function, all which are available through a smartphone application. As such, these core functions of MaaS were presented on smartphone screens, with very short, bullet points describing these functionalities. The descriptions were kept short and clear. After testing various wording options with partners and individuals involved in the project, the text and visual aid presented in Figure 2 was chosen.

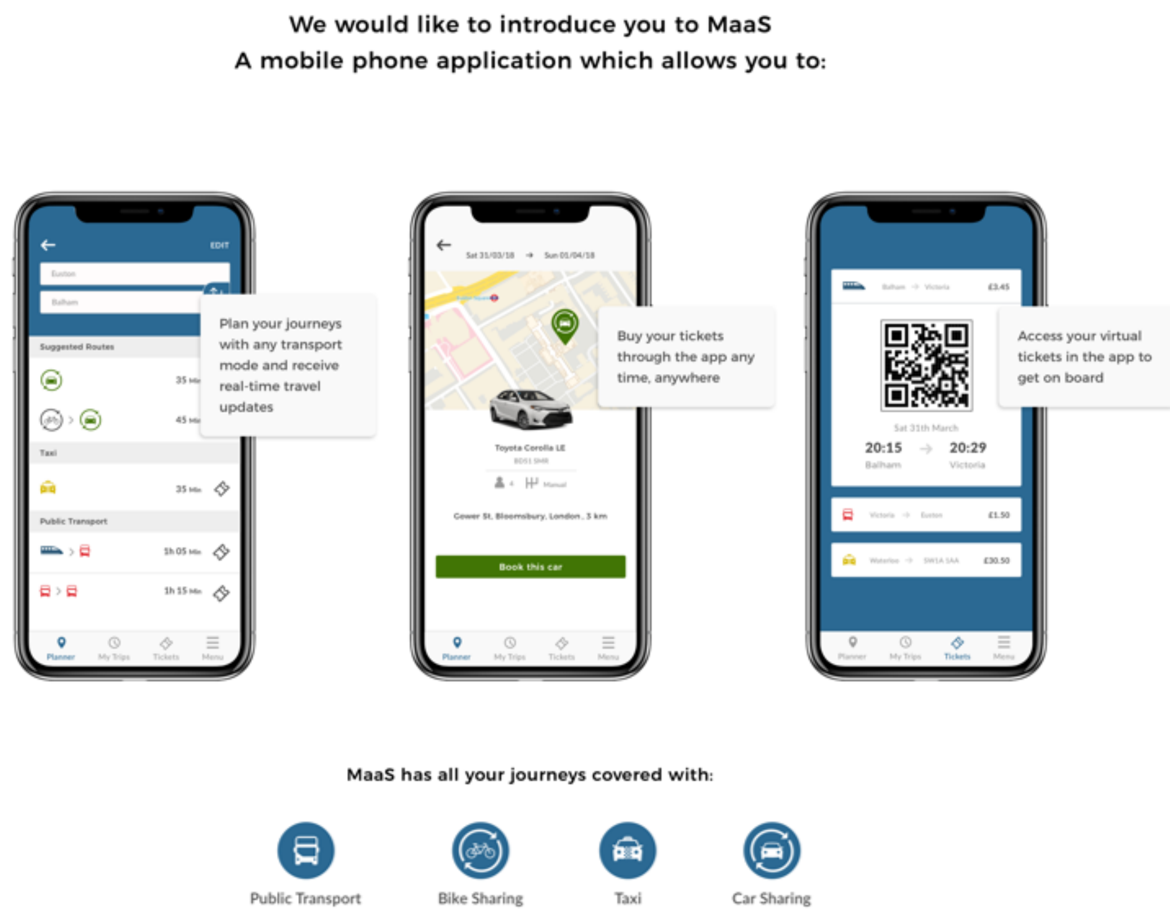

Figure 2: Introduction to MaaS with Smartphone Images

Once the participants were familiar with the concept of MaaS, the SP experiment followed. The first step of the MaaS SP design process is to map out the transport services environment and the services (transport modes) that are included in the MaaS packages. The goal of the survey was to allow for a testing ground of possible MaaS products that will be introduced in later stages of the project. As such, the transport modes to include in the MaaS products were determined by the scope of the project and project partners. Four transport modes were chosen to be part: public transport, bike sharing (Mobike – please note that at the time of the survey design/data collection this service still operated in the Greater Manchester area), taxi and car sharing (Enterprise car club). The MaaS product type examined in this paper is that of ‘fixed MaaS packages’. These include a pre-specified amount of each transport mode, for a fixed price, which can be used up over a certain time horizon (e.g. a week or a month). The fixed amounts can be denominated in number of trips, distance, time or anything else, depending on each mode and their business models.

It is important to note, that the ‘fixed MaaS packages’ approach is just one of the many possible MaaS product types that can be offered. A common approach in MaaS trials has been to offer MaaS packages where there is a fixed monthly subscription fee for which users get discounts on when using each individual transport mode (e.g. iMove in Sydney). For further discussion on MaaS bundles designs please refer to Reck et al., 2020. We chose the 'fixed MaaS package' model as this was deemed possible to adopt during a likely trial in the case study area (determined through workshops with stakeholders in the region). This decision did not take into account the long-term financial viability of this approach, rather how practical it is to implement. There are several questions surrounding business model considerations of different MaaS models. Discussion on this is out of the scope of this paper; for details please refer to Wong and Hensher, 2020 and Polydoropoulou et al. 2020.

Looking at the attributes and levels used in this study, transport mode amounts and prices were included. One important design element was determined early on in the process, and that is to have labelled alternatives. The package types were chosen mimicking industry, where there are usually a small, a medium and a large product which users can choose from. Certain assumptions were created to ensure that the packages are adequately differentiated. These are presented in Table 2.

Table 2: Package types and characteristics

Plan type	**Basic**	**Urban**	**Extra**
Core elements	This package focuses on public transport and/or bike sharing. This is the simplest package with only those two modes in them, and are also the cheapest option.	This package always includes unlimited use of public transport. On top of this, some level of bike sharing and taxi is also included.	This package always has unlimited use of public transport and bike sharing. On top of this taxi and/or car sharing is/are also included.
Price levels	Always the cheapest option	Always the middle option	Always the most expensive option

Each of the three package types -Basic, Urban and Extra- are monthly and have certain characteristics that remain consistent throughout the experiments. The core elements of the Basic package are public transport and bike sharing and is always the cheapest option. The Urban package always includes unlimited use of public transport and on top of this, some level of bike sharing and taxi. The Extra package always has unlimited use of public transport and bike sharing, and on top of this some level of taxi and/or car sharing. The Extra package, as indicated by its name, is always the most expensive.

Public transport, although at different levels, is always included in all three packages. The reason for this is twofold. First, literature has strongly suggested the importance of public transport in MaaS products (see: Matyas, 2020; Caiati et al., 2020) Second, the funding project was only interested in MaaS products that are based around public transport. Further, in this design, for bike sharing and car sharing, the decision was made to use specific, named transport operators: Mobike for bike sharing and Enterprise for car sharing. At the time of the survey, bike sharing did not exist in Manchester. The local transport authority, Transport for Greater Manchester had agreed with Mobike to enter the market. Although this operator eventually did not enter the market, this was not yet known when the survey was designed, which is why this specific operator was chosen. Regarding car sharing, when the survey took place, only Enterprise car sharing was available in Manchester. While having named operators is not the common practice in stated preference experiments, the funding project was interested in how the offerings of these specific operators would be viewed in MaaS products. It should be noted, that all results and interpretations should take into account that the respondents' preferences towards these specific services may bias their choices.

All packages were monthly, the duration of the package was not included as an attribute. Looking at the choice set, besides the three labelled alternatives presented above, the choice was made to include a no-choice ('none') alternative as well. The exact attributes and levels can be seen below in Table 3.

Table 3: SP attributes and levels

	Basic	**Urban**	**Extra**
Public transport	1 month unlimited bus within Greater Manchester	N/A	N/A
	1 month unlimited public transport within Greater Manchester	1 month unlimited public transport within Greater Manchester	1 month unlimited public transport within Greater Manchester
Bike sharing	No (not shown)	No (not shown)	N/A
	Free access to Mobike bike sharing	Free access to Mobike bike sharing	Free access to Mobike bike sharing
Taxi (number of trips within Greater Manchester)	N/A	1,2,3	None (not shown), 3, 4, 8, 10
Car sharing (hours of car sharing access with Enterprise car club)	N/A	N/A	No (not shown) 1,3,5,8,12
Price (sum of base price multiplied by)	0.8, 0.85, 0.88, 0.95, 1, 1.05, 1.12, 1.15, 1.2	0.8, 0.85, 0.88, 0.95, 1, 1.05, 1.12, 1.15, 1.2	0.8, 0.85, 0.88, 0.95, 1, 1.05, 1.12, 1.15, 1.2

There are a number of conditions that were taken into account when creating the packages to ensure that there are no dominating alternatives presented. In addition, the experiments were personalized based on the characteristics of the respondent. For example, if the respondent indicated that they do not have a driving license, car sharing was excluded as an attribute. Also, if a respondent has discounted or free public transport passes, this was taken into account when calculating the cost of the package. To determine the actual prices presented to the respondents, each mode-specific attribute had a 'base price' that was established through the dataset of all non-private modes in the city. The price of the presented package is pivoted around the sum of base prices for each included mode. The base value for each mode was chosen after detailed evaluations of the current market offerings of transport service providers.

A visual example of a MaaS package choice situation (as it was seen by the participants) is presented in Figure 3. Colours and icons (with hover over explanations about what each transport mode is – i.e. in case someone was not aware with car/bike sharing) were used to make it easier for respondents to visually differentiate between the presented packages.

Figure 3: Fixed package visuals

Regarding repetitions, 5 choice situations were presented to respondents. Behind the SP experiment are four D-efficient designs[1] (Rose, et al., 2008). The designs were assigned to respondents based on their ownership of a driving license. The choice experiment was designed using NGene (ChoiceMetrics, 2018). Not all conditions were possible to include within the software, as such, some designs were ruled as ineligible in post-analysis[2]. The designs were

[1] The authors acknowledge that a version of NGene was used that does not yet support latent class models. As such, the efficient design is based on an MNL model. It is unclear how well it performs as such the design may not be optimal.

[2] Ngene has limitations on the number of conditions that can be imposed. In this experiment, there were several inherent conditions including: that the basic plan needs to be the cheapest, the urban the middle priced and the extra the larges; that the extra plan can only have a single 'none' level; and that the amount of modes in the extra plan needs to be the highest. The reason these were conditions, were to ensure that (1) there were no dominating alternatives and (2) the presented plans are in line with their names (meaning that for example an extra plan is not more expensive than

blocked into 100 sets[3]. The priors were determined from the other MaaS studies (Matyas and Kamargianni, 2017; Matyas and Kamargianni, 2019) along with expert judgement.

After each SP experiment, several follow up questions were included. Relevant to this study is that those respondents who chose the 'none' option were asked to provide the reason for choosing this.

The survey itself is a web based self-administered questionnaire. To briefly touch upon the technical implementation of the survey, it was deployed as a web application using the Ruby on Rails (http://rubyonrails.org/) open source framework based on the Ruby programming language. The application was built to be responsive and cross-platform so that users across multiple browsers, devices and systems would be able to access it easily. We opted to use a web application built from scratch using Ruby on Rails, rather than an existing on-line survey development software package, to give us more flexibility and customisation when creating the SP experiment. The data from the completed surveys are automatically verified and stored in secure servers in a MySQL (https://www.mysql.com/) database system.

3.2 Data collection and descriptive statistics

The data collection took place during June to July 2018 and the sample was recruited through a market research company and the community panel of Transport for Greater Manchester (the public authority of the city). MaaS4EU project partners had a very clear sampling strategy based on the target population for the project. The sample is not meant to be representative of the population and this should be taken into account when interpreting the results. Table 4 shows the requirements of the sampling strategy alongside the actual sample characteristics.

Table 4: Sampling strategy and characteristics of the sample

	Sampling strategy	**Sample characteristics**
Eligibility criteria	18 or over Smartphone owner	100% 100%
Sample	400 individuals	475
Eligibility criteria	18 or over Smartphone owner	
Driving license possession	At least 60% have driving license	85.9%
	30% 18-30 years old	28.2%

a basic). It was not possible to include all these conditions in the Ngene, as such some designs produced dominating alternatives, which were later removed.

[3] The authors acknowledge that 100 sets are more than commonly used. Each experiment presented to a respondent was chosen at random.

Age	35% 31-45 years old	37.1%
	30% 46-60	29.9%
	5% more than 61 years old	4.8%
Gender	Representative of population Census 2011: 49.4% men; 50.6% women	Male: 52% Female 48%
Car sharing users	10%	10%

Taking a look at the packages that respondents chose, in 54% of the choice situations, the None option, in 20% the Basic package, in 13% the Urban and in 12% the Extra package was chosen (Figure 4). This means that in 46% of the choice situations one of the MaaS packages was chosen. While these are just descriptive statistics, the fact that over half of the respondents did not choose any of the packages indicates that a significant proportion of respondents are not interested in such subscription based services. There may be many reasons for this, including the attributes of the presented plans or the characteristics and needs of the respondents. This level of interest in MaaS plans supports previous findings in literature. For example, in a study by Liljamo et al. (2020) that looked at the case of Finland, 43% of respondents were interested in adopting a mobility package. Similarly, Ho et al. (2020) found that 45% of respondents in Newcastle, UK were interested in MaaS, with 32% stating that they would subscribe to monthly plans and only 13% opting for the Pay-as-You-Go option. However, in the Dutch study by Caiati et al. (2020), only 17% of respondents were interested in MaaS subscriptions. The level of interest in MaaS packages has also been examined in real life trials, such as the MaaS trial[4] in Sydney, Australia where there was a 36.5% take-up of bundles.

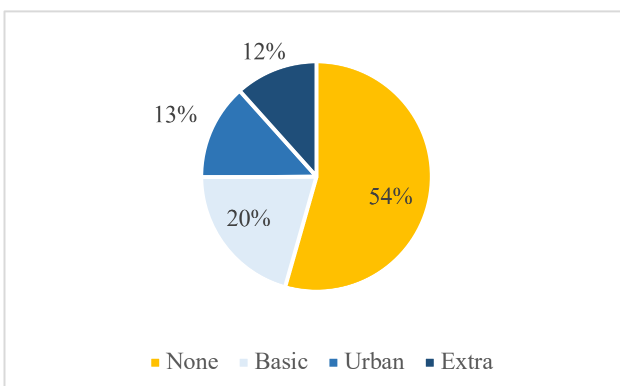

Figure 4: MaaS package types chosen during SP experiments

[4] https://imoveaustralia.com/project/maas-trial-sydney/

4 MODELLING FRAMEWORK

In order to capture individual heterogeneity, Latent Class Choice Models (LCCM) are used. LCCMs assume that the population can be segmented into a finite number of groups, according to some combination of characteristics. Each group is similar in their traits, while dissimilar from those in other groups. The early developments of LCCMs date back to the 1950s with the work of Lazarsfeld (1950), but have since been developed in terms of estimation methods, complexity of models and types of data (Goodman, 1974; Haberman, 1979; Hagenaars, 1990; Vermunt and Magidson, 2000).

Latent class models consist of two components: a class membership model and a class specific model (Green & Hensher, 2003; Vij, et al., 2013; Kamargianni & Polydoropoulou, 2013). The class membership model formulates the probability that a decision-maker belongs to a particular class as a function of the characteristics of the individual. The people within a class share common characteristics, while those in different classes are dissimilar to each other regarding those characteristics (Coogan, et al., 2011). The class specific choice model describes the choice behaviour of each class (Walker and Li, 2007).

Standard statistical tests are used to determine how many segments should be used to classify the population. These latent classes (or segments) capture the heterogeneity within the population. Class membership is assumed to be probabilistic so each individual can, possess characteristics of each class to varying degrees according to their class membership probabilities. The modelling framework used in this paper is presented in Figure 5.

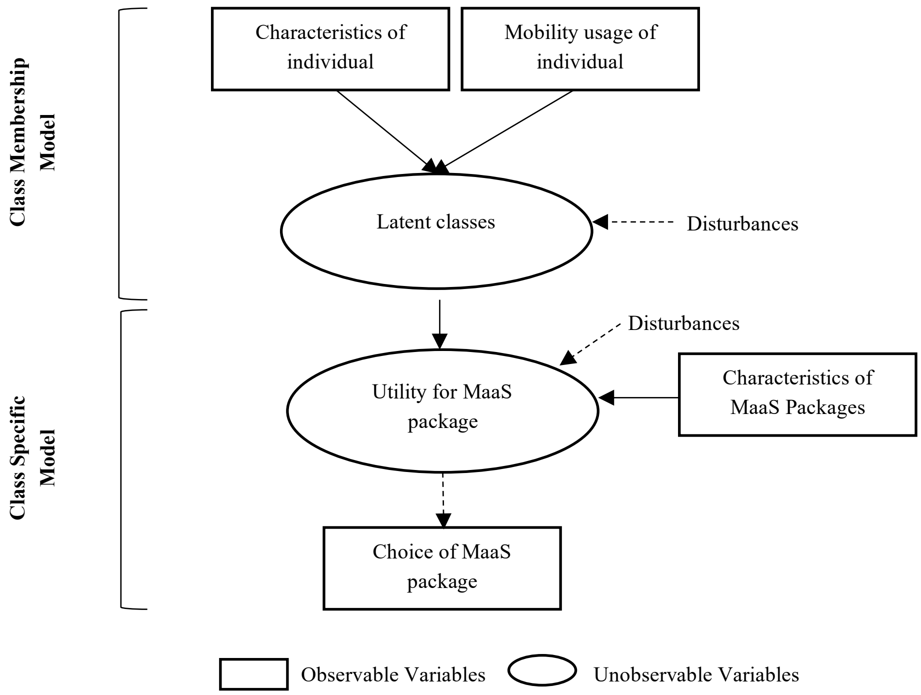

Figure 5: Latent Class Modelling Framework

Based on the framework provided in Greene and Hensher (2003), we begin with a class specific choice model which predicts the probability that individual n over choice situation t choosing MaaS package j, conditional on the individual belonging to latent class s. In the current study, the class specific model is a logit model for discrete choice by individual n belonging to class s from the set of alternatives J_n comprising of j alternatives, in choice situation t_n, is expressed as:

$$P_{jn|s} = \frac{\exp(X_{ntj}\beta_s')}{\sum_{j=1}^{J_i}\exp(X_{ntj}\beta_s')} \tag{1}$$

where β_s' s the parameter vector associated with the vector of explanatory variables X_{ntj}.

Turning to the class membership model, this segments individuals into s_n classes based on their sociodemographic and mobility characteristics (Hess and Daly, 2014). The probability that individual n falls under mobility style s, conditional on the characteristics of that individual X_n, is $P(s|X_n)$.

The class membership and class-specific functions are estimated simultaneously. Given the characteristics of the individual (X_n) and the attributes of the MaaS packages (X_j), the probability of individual n to choose MaaS package j in choice situation t is expressed as:

$$P(j_t|X_n, X_{njt}) = \sum_{s=1}^{S} P(j_t|X_{njt}, s)P(s|X_n) \quad (2)$$

where $P(s|X_n)$ is the probability of individual n with characteristics X_n to have mobility style s, and $P(j_t|X_{njt}, s)$ is the probability of individual n, conditional on having a mobility style s, to choose MaaS package j with attributes X_{njt} as perceived by individual in choice situation t. The associated likelihood function for individual n is given by:

$$L = \prod_{n=i}^{N} P(j_t|X_{j,}s) \sum_{s=1}^{S} P(s|X_n) \quad (3)$$

In determining the final model specification for the sample population, numerous models were estimated, where we varied the utility specification, variables included, and number of classes. The estimation process was exploratory; the behaviour of each class was revealed during the process of testing different model specifications. A number of variables were selected prior to analysis that were identified as potential factors to be tested in the class membership model. The variables that proved significant are summarized in Table 5 below. Additional variables that were tested but did not prove to be significant include: employment status (part time / full time/ retired), flexibility in working hours, license ownership, number of household vehicles, travel time to work, car sharing and bike awareness, car sharing membership, bus, tram, bike sharing, car sharing and private car usage, smartphone usage for travel purposes and multimodal travel behaviour (e.g. using more than 3 modes per week).

Table 5: Significant variables in class membership model

Variable name	Description
Personal and household variables	
Gender	Dummy (male=1; female=0)
Age	Continuous
Education	Dummy (1=has master's degree or above; 0=bachelor's degree or below)
Student status	Dummy (1=student; 0=not student)
Household (HH) income (imputed)	Categorical
Children	Dummy (1=has child(ren) under 6; 0=does not have child(ren) under 6)
Mobility-related variables	
Public transport pass holder	Dummy (1=owns travel pass; 0=does not own travel pass)

Public transport user	Dummy (1=uses public transport; does not use public transport)
Bike user	Dummy (1=uses bicycle; 0=does not use bicycle)
Frequent taxi user	Dummy (1=uses taxi at least once a week; 0=uses taxi less than once a week)
Reason for not using public transport	Too expensive (dummy) Other reasons (dummy)

5 RESULTS

5.1.1 Selection of number of classes

The number of classes, is not a parameter of the model, meaning that the optimal amount cannot be estimated endogenously (Swait and Adamowicz, 2001; Shen, 2009). As such, several model specifications with different numbers of classes and explanatory variables were tested and scrutinized during the process of choosing a final model. Table 6 presents the summary statistics and performance indicators of six estimated models, including a model without segmentation, and five latent class models with segments varying from two to six. The class specific and membership models had the same specification in order to isolate the effect of the varying number of classes.

Table 6: Summary statistics of estimated models

	LL	**BIC(LL)**	**AIC(LL)**	**No. par**	$\bar{\rho}^2$
1-Class Choice	-2507.24	5063.24	5030.47	8	0.0449
2-Class Choice	-1818.59	3826.14	3699.17	31	0.3976
3-Class Choice	-1629.25	**3587.67**	3366.49	54	0.5302
4-Class Choice	-1564.33	3598.04	3282.66	77	0.5896
5-Class Choice	-1511.98	3633.55	3223.96	100	0.6033
6-Class Choice	-1466.07	3681.92	3178.13	123	0.6221

To determine how many classes to use, we first examine the performance estimates in more depth. Following the conventional approach used in the literature, three performance indicators are focused on during this discussion: rho-bar squared, Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) (Kamakura and Russell, 1989; Swait, 1994; Vij, et al., 2013). Higher rho-squared values, while lower BIC and AIC values imply better model fits.

Examining these values Table 6 every statistic suggests that all models with segmentation outperform the no segment model. This supports the existence of heterogenous latent classes within the data. Regarding the models with segmentation, not all performance indicators point to the same model being desirable. On the one hand, increasing the number of parameters implies an increase in the goodness-of-fit when evaluating it based on the rho-bar squared and the AIC. However, the rate of improvement in performances significantly diminishes when estimating four, five and six class models. For example, the increase in rho-bar squared between models 1 and 2 is 0.35 and between 2 and 3 is 0.13, this drops to 0.06 between models 3 and 4 and 0.01 between 4 and 5. On the other hand, when the evaluation is based on the BIC, as this statistic imposes a harsher penalty on the lack of parsimony it points to the 3-class model being superior (Prato et al., 2016). At this point we also introduce the easiness and logic of the behavioural interpretation of the parameter estimates into the process of selecting the number of classes. As discussed by Swait (1994), the statistics of the models, especially AIC and BIC, should only be used as a guide to determine the optimal number of classes; the objective of the study, simplicity and the judgement of the researcher should direct the decision on the final number of classes. Based on these evaluations, the 3-class model was selected. This model gives the best balance between goodness-of-fit, parsimony and the interpretability of the model estimation results

5.1.2 Model estimation results

The selected 3-class model has a rho-bar squared of 0.53. The class membership model includes various individual characteristics and mobility habits as explanatory variables, and the corresponding parameter estimates are presented in Table 7. The class-specific choice models include the MaaS package attributes and alternative specific constants (ASC) and the results are presented in Table 8. The classes have been ordered in terms of increasing interest in MaaS packages.

Table 7: Class membership model

	Class 1		**Class 2**		**Class 3**			
	Est.	**z-value**	**Est.**	**z-value**	**Est.**	**z-value**	**Wald(=)**	**p-value**
Intercept	0.324	0.94	-0.548	-1.33	0.224	0.55	0.32	0.94
Male - dummy	-0.157	-0.92	***-0.443***	***-2.22***	***0.600***	***2.92***	8.68	0.01
Age - continuous	***0.022***	***3.06***	0.007	0.84	***-0.029***	***-3.19***	13.24	0.00
Masters or above - dummy	-0.058	-0.25	***-0.538***	***-1.99***	***0.597***	***2.50***	6.64	0.04
Student - dummy	-0.869	-1.40	***1.602***	***3.25***	-0.733	-1.19	10.58	0.01
Household income								
Under £15,000	0.002	0.01	-0.098	-0.30	0.096	0.30	33.05	0.00
£15,000 - £24,999	-0.155	-0.79	0.002	0.01	0.153	0.67		
£25,000-£34,999	0.127	0.66	***0.492***	***2.30***	***-0.620***	***-2.56***		
£35,000 - £49,999	***0.356***	***1.97***	0.025	0.11	*-0.382*	*-1.84*		
£50,000 - £74,999	*0.344*	*1.69*	0.339	1.34	***-0.683***	***-2.37***		

£75,000 or more	***-0.794***	***-3.40***	0.368	1.54	***0.426***	***2.07***		
Prefer not to answer/Don't Know	0.120	0.30	*-1.129*	*-1.90*	***1.009***	***2.69***		
Kids under 6 - dummy	***-0.606***	***-2.75***	0.248	1.06	0.358	1.52	7.63	0.02
Bike user - dummy	***-0.655***	***-3.62***	***0.475***	***2.29***	0.179	0.85	13.88	0.00
Public transport user	***-0.333***	***-2.33***	0.212	1.34	0.122	0.73	11.47	0.02
Does not use public transport, but not due to the fact that it is too expensive -ordinal	-0.108	-0.91	-0.189	-1.37	***0.297***	***1.97***		
Does not use public transport, due to the fact that it is too expensive - ordinal	***0.441***	***3.02***	-0.022	-0.12	***-0.419***	***-2.02***		
Public transport pass holder - dummy	***-0.347***	***-2.79***	0.045	0.29	*0.302*	*1.90*	8.35	0.02
Frequent taxi user - dummy	***-0.746***	***-2.50***	0.239	0.87	*0.508*	*1.92*	6.71	0.04
Estimates in bold and italic are significant at the 95% level; estimates in italic only are significant at the 90% level. The Wald test for all included variables was significant at the 90% level.								

Table 8: Class specific model

	Class 1		Class 2		Class 3			
Attributes	**Est.**	**z-value**	**Est.**	**z-value**	**Est.**	**z-value**	**Wald(=)**	**p-value**
Constants								
Basic	0.329	0.85	***1.726***	***7.14***	***-0.582***	***-3.77***	142.16	0.00
Urban	-0.320	-0.73	***0.439***	***2.13***	***0.601***	***2.96***		
Extra	***-1.701***	***-1.99***	-0.483	-0.91	***0.925***	***3.29***		
None	***1.692***	***2.27***	***1.726***	***-3.68***	***-0.944***	***-2.05***		
Package characteristics								
Public transport (dummy, where 0 is unlimited bus and 1 is unlimited all public transport)	-0.692	-1.37	0.175	0.67	***0.813***	***2.67***	6.99	0.03
Bike sharing usage* *(dummy)	0.089	0.86	0.089	0.86	0.089	0.86	0.00	.
Taxi (continuous)	***0.371***	***2.81***	***0.260***	***2.84***	0.043	1.35	10.53	0.01
Car sharing hours * (continuous)	***0.045***	***2.07***	***0.045***	***2.07***	***0.045***	***2.07***	0.00	.

Package price	***-0.016***	***-4.08***	***-0.030***	***-6.10***	***-0.011***	***-4.13***	12.94	0.00
Estimates in bold and italic are significant at the 95% level, estimates in italic only are significant at the 90% level. *Car sharing and bike sharing was constrained to be equal across classes as the Wald test did not show significant differences across classes for this attribute. The Wald test for all other attributes was significant indicating that there are differences based on Classes.								

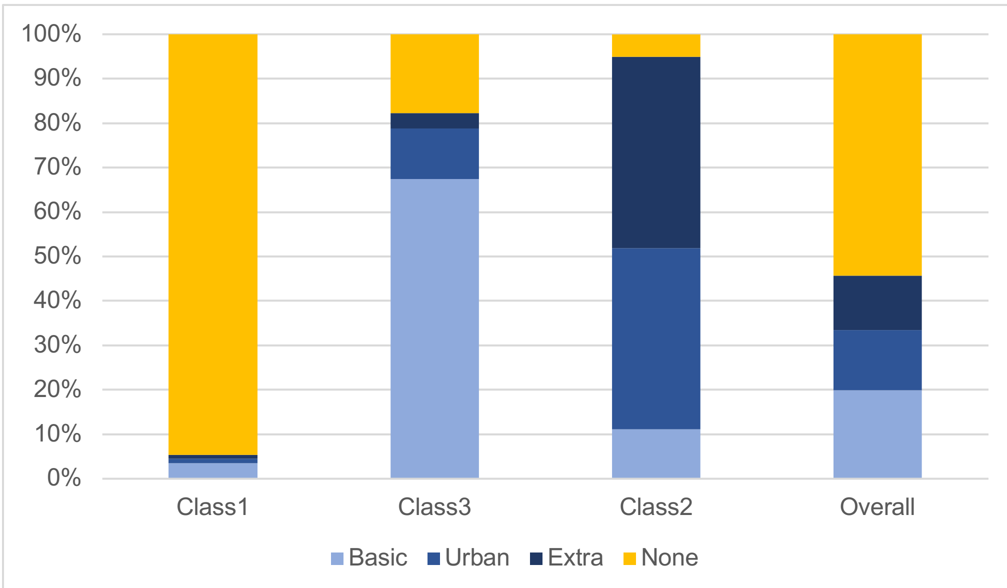

Figure 6: MaaS package choices by class

A high-level summary of the characteristics of each of them are provided in Table 9.

Table 9: High-level summary of classes

	Class 1 **MaaS packages avoiders**	**Class 2** **MaaS package explorers**	**Class 3** **MaaS package enthusiasts**
Class size	52%	23%	25%
Dominant MaaS package purchasing behaviour	95% chose "None"	67% chose Basic package	43% chose Extra package and 41% chose Urban package
Individual characteristics	More likely to be middle aged or older, have middle income, not have young children	More likely to be female, have no master's degree, be a student, have middle income	More likely to be male, be highly educated, have high income and be younger
Current travel behaviour	Less use of bicycle, taxi and public transport, less likely to own a public transport pass, likely to not use public	More likely to be a bike user	More likely to be a public transport pass holder and a frequent taxi user. If not a public transport user, this is less likely to be due to

	transport due to it being too expensive (price sensitive)		financial reasons (less price sensitive)

Class 1 - MaaS package avoiders[5]: Comprising of 52% of the sample, this is the largest class. As indicated by the significant coefficients of the constants, keeping all else equal, these participants prefer the none option and disfavour the Extra plan. With 95% choosing the "none" option it is dominated by those who are the least likely to purchase MaaS packages. Even though this group prefers some of the package attributes, they are unwilling to purchase these. Based on the results of the class membership model, individuals belonging to this Class are more likely to be middle aged or older, are less likely to be in the high income category (over £75,000) and tend to not have young children. 83% of our sample's retired individuals fall into this class, supporting the older age of this group. Turning to their current travel behaviour, they tend to not cycle and are also less likely to be public transport and be frequent taxi users. Looking more closely at their relation to public transport, they are also less inclined to be public transport pass owners. In addition, the model results indicate, that those individuals who do not use public transport stated that they do so because it is too expensive. This gives an indication, that people in this class may be price sensitive, which could be one of the reasons for them not preferring any of the MaaS packages.

Class 2 – MaaS package explorers: This class includes 23% of the sample. The positive coefficient values for the constants indicate that keeping all else equal, individuals prefer the Basic and Urban plans while do not prefer the none option. The majority of individuals favoured the Basic package (67%), while a smaller 17% chose the Urban. This suggests that this Class is interested in exploring the smaller MaaS packages, while completely avoiding the largest Extra package. Compared to the other classes, they are more likely to be female, have no masters' degree and have middle income. They are also significantly more likely to be bike users. An important characteristic of this class is that they are more likely to be students, with 71% of students in the sample fall into it.

Class 3 – MaaS package enthusiasts: This class consists of 25% of the sample and are the most likely to purchase MaaS packages. With 41% opting for the Urban and 43% for the Extra package, they show significant interest in the larger packages that have more modes included and are more expensive. This is also indicated by the positive coefficient values for the constants for the Urban and extra plan, which indicate that keeping all else equal, these plans are preferred. Regarding the MaaS package characteristics, they have a preference towards having unlimited public transport in their packages. In terms of distinguishing characteristics, individuals in this class are likely to be younger, male, have a masters' degree and have higher income. Looking at the descriptive statistics of the class, 81% are full time paid employment (as opposed to 58% and 62% of the other two classes). Turning to their mobility habits, several variables proved statistically significant.

[5] The phrase "MaaS enthusiast" has been used in prior research, such as Smith and Hensher (2020).

Individuals in this class are more likely to be a public transport pass holder and a frequent taxi user. In those cases, where they were not a public transport user, this was less likely to be for a financial reason indicating that this class is less price sensitive. A further insight from descriptive statistics shows that 12% of the class are car sharing users (compared to the 1% and 5% of the other classes).

5.1.3 Reasons behind choosing 'none' option

Since a high fraction of respondents chose the 'none' option (54%), it is interesting to examine the reason behind this. This section is based on descriptive statistics, not model estimation results. The survey included a follow-up question for those who did choose any of the packages, allowing us to shed some light on the reasons that may hinder the uptake of MaaS packages. Respondents who chose the 'none' option were asked to indicate their reason(s) for why they did not choose any of the packages. The responses are presented in Table 11. The most common reason for not wanting any of the proposed packages is the price of the package. 59.4% of those respondents who chose 'none' selected this as one of their reasons for not choosing a package. The second most common response was 'It's not the right fit for me' (39.5%), while the third was 'It's less convenient than driving my car' (30.8%).

Table 10: Reasons for choosing 'None' option

It is too expensive	59.4%
It's not the right fit for me	39.5%
It is less convenient than driving my car	30.8%
I don't want to pre-pay for my monthly travel	18.4%
I would be worried about overpaying	11.7%
I would need more included in my subscription	8.5%
I would be worried about running out of subscribed travel	4.0%

Respondents were also asked what would make them consider buying a package. This was an open-ended question, where respondents could enter any response. Taking a look at the answers, the price aspect of the packages was the most common theme. However, some other concerns also emerged. First, several respondents pointed out that they do not travel frequently, especially not into the city centre of Manchester where several of these modes operate, so such a service would be of no use to them (these individuals are the architype of latent Class 1 discussed above). Second, some respondents pointed out that public transport is just not a viable option for them and that all packages included some level of public transport. Reasons for it not being viable included: living in the suburbs and not having proper access; it would take too long to commute with public transport compared to car; severe dislike of public transport and would only use it as a "last resort"; bus stop being too far away from home; unreliability and low comfort level of public transport;

lack of appropriate bus routes between home and work and not being easily accessible. Third, some respondents pointed out that they would be happier trying the service if it had a pay as you go option (similar to the Oyster card in London). Finally, respondents with a car suggested that they would only consider such a service if they either: did not have their car anymore; could no longer drive; or driving became too expensive. This is a very interesting point, as it seems to indicate that car drivers are quite split regarding MaaS. There are those that are open (as shown in the results of the model) and there are those who are not and are addicted/attached to their cars. This differentiation between different types of attitudes among car drivers seems to indicate that there are underlying latent attitudes and perceptions that can be causing some of these results. Hybrid choice models that are able to capture these can be an important area of future development.

6 CONCLUSIONS

6.1.1 Summary of results

This paper used a Latent Class Choice Model to examine heterogeneity with regards to MaaS package preferences. The data was collected through the MaaS4EU project, and the case study city was Greater Manchester, UK. The results imply significant heterogeneity with regards to preferences towards MaaS packages. Three latent classes emerged through the analysis, all with different MaaS package preferences and individual characteristics. Understanding these groups can provide valuable insights into the types of people that should and should not be initially targeted with MaaS packages to maximise uptake. We use the word 'initially' because the MaaS concept, and the concept of MaaS packages, are very new and attitudes towards them may change as it diffuses and awareness increases.

Some main take away points regarding user segmentation follow. Age inversely related with likeliness to purchase MaaS packages, meaning that younger people are more likely to be interested in purchasing MaaS packages. Students seem interested in purchasing MaaS package, but tend towards the smaller ones including mainly public transport and bike sharing. Those individuals who are most likely to purchase the larger packages have higher income levels and are highly educated. Current travel behaviour seems to play a role in determining an individual's propensity to purchase MaaS packages, especially the larger packages with several transport modes included. Frequent public transport and taxi users seem to be ideal candidates to target with MaaS packages.

An important thing to highlight is the fact that no private vehicle related variables proved to be significant in the model. Several variables, including private vehicle ownership, number of household vehicles, using private vehicle as the main mode to work etc., were tested, however none showed significant differences among classes (insignificant Wald). This is an interesting observation, as it indicates that, contrary to expectations, car users should not necessarily be ruled out as MaaS users. This finding is, of course, specific to the case study city and may differ elsewhere.

One final element to note about these findings is the question of social equality. The groups discussed above, who should be targeted with MaaS packages as they are more likely to purchase these already have good access to transport. As such, will providing MaaS packages to these specific groups increase further transport inequality? The answer to this, is that it will depend on how the wider MaaS ecosystem functions. If MaaS is offered by a company that is only interested in profit and not about social welfare, its products will likely be tailored towards those that are able to pay the most for them. However, if other actors, such as governmental bodies and councils play a role and promote MaaS products that are tailored to those groups who may have less access to transport, MaaS can also become a solution.

6.1.2 Contributions and comparison to literature

The main contribution of this paper is paper is twofold. First, it conducts primary MaaS user research with novel data in Greater Manchester, UK, which is a city that has previously not been examined. While other areas in the UK such as London and Tyneside (Matyas and Kamargianni, 2019; Ho et al., 2020) have been studied, these have significantly different characteristics, thus their results may not hold in other areas. Second, this paper expands on the two existing papers that specifically focus on user groups (Fioreze et al., 2019; Alonso-Gonzalez et al., 2020). While those papers use cluster analysis, this paper uses a latent class choice model to identify user groups, which to the knowledge of the authors is the first use of this model specification to study preferences towards MaaS packages. Additionally, those two studies focus on identifying factors relevant to MaaS adoption in general and use questionnaire responses, while the current study looks more specifically at preferences towards MaaS packages and uses SP data.

Looking at the results of this paper, first we compare them to the two studies also examining potential user groups (Fioreze et al., 2019; Alonso-Gonzalez et al., 2020). Although the two other studies focus on MaaS adoption in general rather than preferences towards MaaS packages, some parallels can be drawn. Despite the fact that the three studies conclude with a different number of user groups (three, four and five) all find significant differences in user groups ranging from those who are likely adopters to those who are not interested in MaaS at all. Regarding the characteristics of individuals in user groups, the most notable symmetry is the high overall mode usage among those who are most inclined to use MaaS in all three studies. The most striking differences in the current study compared to the other two is the importance of car ownership and use. While Fioreze et al. (2019) and Alonso-Gonzalez et al (2020) find that these factors were driving characteristics in those user groups who were least interested in adopting MaaS, the present study does not find that car ownership and use is significant.

Besides the two user groups specific papers, the results of this study can also be compared to literature examining preferences towards MaaS packages. Several of the individual, household and mobility characteristics that were found significant in influencing MaaS package choice support those found in the literature. These include gender (e.g. Ho et al., 2017), age (e.g. Ho et al., 202o); education (e.g. Caiati et al., 2020); household income (e.g. Caiati et al., 2020) and current mode usage (e.g. Matyas and Kamargianni, 2019; Guidon et al., 2019).

6.1.3 Limitations and further work

There are limitations of this paper and areas where further work can be focused. First, the results are specific to this sample and study area, thus they may be very different elsewhere with dissimilar societal and transport characteristics. Next the sample size is limited (475 individuals in a total of 2375 choice situations) and only 5% was over 60 years old. This is not representative of the population of Greater Manchester. While the sample and its characteristics were guided by the funding project, the generalisability of the results could be improved by including weighting adjustments to the data which would have allowed for better representation of the population. As such, all the results should be looked at with the caveat that these are only for the sample and cannot be generalized to the wider population.

Also, since the survey was carried out, the modes available in Manchester have changed (e.g. no bike sharing anymore). As the mobility environment is very volatile (with companies emerging, entering/exiting the market every month), these results may change. More generally, research including additional transport modes in MaaS packages could provide a more comprehensive view into the attractive packages for potential users. Public transport and taxi are present in most current studies, while modes such as on-demand minibuses, electric-bike sharing, car-sharing, car rental, e-hailing and shared electric scooters are only in very few or completely missing. Although the inclusion of each mode is highly dependent on the case study area, including a wider range of transport modes could increase the ability of a MaaS system to serve users' needs. However, it is also possible that the inclusion of more modes discourages users from participating, as it increases the complexity of the system. Studies examining more transport modes could help better understand these uncertainties.

Another limitation of this paper is that some of the survey characteristics were made specific for the needs of this study. For example, the fact that the car sharing and bike sharing attributes were named may introduced some biases towards or against these modes. Additionally, from the model results it was not possible to evaluate the interest of MaaS packages without public transport as this was included in all packages. In addition, the survey design has its limitations. As mentioned above, Ngene is not yet capable of creating an efficient design for LCCMs as such the design was based on an MNL model. It is not clear how well this performs. As such, other designs should be used.

Another area of future work is with regards to the model specification used. In this paper a fixed parameter latent class model was used that assumes homogeneity within each latent class. To include an extra layer of heterogeneity within each class, random parameter latent class models can be used (Hensher et al., 2013; Greene and Hensher, 2013; Vij et al., 2012). This model specification would allow for heterogeneity both within and across classes, which could lead to improvements in model fit (Green and Hensher, 2013). In addition, approaches that identify attribute non-attendance (ANA) and aggregation-of-common-metrics attributes (ACMA) could be explored (Collins et al., 2012; Hensher et al., 2013).

Further regarding the data, the use of stated preference experiments to study a service that is unfamiliar to users may have some limitations (Stathopoulous et al., 2017). As MaaS is a new concept, with no real market application in the case study city, it is likely that respondents only had a limited understanding of the concept. During the experiment, there was only a single page of explanation of what MaaS is and how it works to not overload respondents with too much information. However, this raises the risk of participants not fully understanding the concept before starting to answer the questionnaire. While this is a common problem with all SP experiments about new products or services, the bias it causes could be decreased by having a computer assisted personal interview (CAPI) where the service can be better explained. However, this is only possible with appropriate resources. Another, resource intensive way to get more reliable results and to remove survey-based biases such as hypothetical bias, is to collect choices in a real life MaaS application or a pilot demonstration. By utilizing demonstrations, a wealth of information can be collected about individuals' preferences for MaaS and the impact this service can have.

Finally, future studies could examine preferences for MaaS in different geographic areas. Current research mainly focuses on Europe and Australia, with other areas lagging behind. Conducting studies in Asia and the Americas could provide insights into whether MaaS has potential in other cultures with different transportation systems.

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