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ABSTRACT

The concept of Mobility-as-a-Service (MaaS) is rapidly gaining momentum. Parties involved are eager to learn more about its potential uptake, effects on travel behaviour, and users. We focus on the latter, as we attempt to reveal the profile of groups within the Dutch population that have a relatively high likelihood of adopting MaaS in the near future, apart from the actual supply side.

MaaS is a transport concept integrating existing and new mobility services on a digital platform, providing customised door-to-door transportation options. Based on common denominators of MaaS as found in the literature, we have established five indicators to identify early adopters: innovativeness, being tech-savvy, needing travel information, having a multimodal mindset, and wanting freedom of choice. These five indicators are the building blocks of our Latent Demand for MaaS Index (LDMI), and were constructed using 26 statements and questions from a special survey conducted in 2018 among participants of the Netherlands Mobility Panel (MPN). The features derived from the MPN serve as independent variables in a regression analysis of the indicators used to ascertain the profile of early adopters.

The results of our model indicate that early adopters are likely to be highly mobile, have a high socio-economic status, high levels of education and high personal incomes. Young people are more eager to adopt MaaS than older adults. Early adopters are healthy, active and frequent users of trains and planes. The characteristics of MaaS's early adopters overlap in numerous ways with those of innovative mobility services users and with the general characteristics of early adopters as found in innovation studies.

1. Introduction

The idea of Mobility-as-a-Service (MaaS) is gaining momentum internationally. Transport researchers, policy makers, transport service providers, developers and others are all eager to get involved. The word 'hype' is appropriate, as already noted by Giesecke et al. (2016), Matyas and Kamargianni (2017a), and Lyons et al. (2019).

In this paper, MaaS is defined as a transport concept integrating existing and new mobility services into one single digital online platform, providing customised door-to-door transport options. Instead of owning individual modes of transport, or to complement them, customers would purchase mobility service packages tailored to their individual needs, or simply pay per trip. Although public transport (PT) is frequently dubbed 'the backbone of MaaS' (Karlsson et al., 2017; Matyas and Kamargianni, 2018; UITP, 2016), shared mobility modes are seen as having an important role as well (Utriainen and Pöllänen, 2018), with nearly all existing MaaS schemes integrating them (Jittrapirom et al., 2017). Following the terminology of Shaheen et al. (2015), shared mobility services include, but are not restricted to, car sharing, bike sharing and ride sourcing.[2] Ultimately, the strength of MaaS would lie in the combination of these various modes (Karlsson et al., 2017) and in their integration (Kamargianni et al., 2016).

Commentators describe how MaaS could support a decrease in the negative externalities caused by transport, and, more generally, could be an efficient travel demand management tool with environmentally and socially desirable outcomes (Arbib and Seba, 2017; CIVITAS, 2016;

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[1] At the time of submitting, these authors are no longer working at 1.
[2] See Soares Machado et al. (2018) and Shaheen and Cohen (2018) for recent overviews of shared mobility modes.

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Matyas and Kamargianni, 2017b). However, these outcomes will be highly dependent on the people willing and able to use MaaS. Acquiring a better picture of the most promising groups within the population is a necessary part of MaaS research, as this allows for the impacts of this new concept to be further quantified.

Such a picture is relevant for multiple parties involved. From a commercial and marketing perspective, interest is to be expected. Mobility brokers can optimise their MaaS offers - and particularly the monthly packages (referred to as bundles) - to fit the right profiles. Researchers on MaaS could benefit from our results, allowing them to pinpoint interesting subjects for their studies. A better picture of early adopters is also important for policymakers and governments seeking to anticipate and better grasp what MaaS means for the future of transportation. The latter is precisely the starting point of this study, conducted on behalf of the Dutch Ministry of Infrastructure and Water Management in 2018 and 2019. Our task was to identify early adopters of MaaS among the Dutch population, apart from the actual supply side. The main research question in this study is: Who has the highest likelihood of adopting Mobility-as-a-Service in the Netherlands in the near future?

For our research goal we developed a *Latent Demand for MaaS Index* (LDMI), built on key elements of MaaS as derived from the literature, and subsequently transformed these elements into indicators. The indicators are informed by statements and questions that were included in a questionnaire distributed to a sample of the Dutch population in 2018. Although this study was conducted in the Netherlands, it can provide valuable insights to researchers worldwide in terms of approach. Furthermore, this paper presents one of the few attempts to estimate the potential for MaaS among users at a country level, along with the study of ITS Australia (2018). As such, it can also deliver relevant insights in terms of results for scholars, professionals and policymakers.

In this study, the early adopters are people within a certain population who are most likely to adopt MaaS. Their potential is relative, however; they are more likely to adopt MaaS compared to other groups within the population. Our approach does not elucidate the absolute market potential of MaaS. The amount of people that will adopt MaaS is beyond our scope. We also do not incorporate the supply side, in terms of MaaS apps and transport modes accessible through these apps, into our study. This supply side will depend on civic society with local actions, commercial initiatives with suitable business cases and governmental initiatives and interventions. Furthermore, urban density is generally regarded as an important factor, with relatively more supply, competition and diversity in denser areas. At the moment, it is impossible to tell what kind and level of MaaS services will be available in which parts of the country in the near future.

In line with Rogers (2003), we define the adoption of MaaS as a decision to make full use of MaaS as the best cause of action available when planning or making trips. Via a MaaS platform (e.g. application), multiple modes of transport are compared, used and paid for within a given period.

This paper is structured as follows. In Section 2, we introduce the concept of the LDMI, as based on the core characteristics of MaaS. In Section 3, our data and method are discussed. The findings pertaining to the LDMI and the profile of early adopters are presented in Section 4. At the end of Section 4 we also compare our findings to those found by other researchers. We conclude in Section 5.

2. Latent demand for MaaS index

In this section, we discuss the key characteristics of MaaS from a user's perspective and the way these characteristics are used and transformed into indicators within the LDMI.

2.1. General characteristics of the MaaS concept

Although MaaS is not always defined uniformly (Smith et al., 2018), some common denominators prevail in literature. We present here those that concern users, leaning on MaaS′ core characteristics as defined in the literature review of Jittrapirom et al. (2017): integration of transport modes, tariff option, one platform, multiple actors, use of technologies, demand orientation, registration requirement, personalisation and customisation. We leave aside considerations on the characteristics of the MaaS ecosystem such as the 'multiple actors' characteristic (see Goulding and Kamargianni (2018), Mayas and Kamargianni (2017) and Jittrapirom et al. (2018) on that point).

Commentators refer to MaaS as an innovation: "a hybrid innovation" in the "smart mobility arena" (Pangbourne et al., 2018, p.34), a "niche innovation" (Lyons et al., 2019, p.26), an "innovative service" (Jittrapirom et al., 2017, p. 13), to cite but a few examples. Caiati et al. (2020)explicitly refer to MaaS as "an innovation" (p. 125). The first users of Ubigo, the MaaS Swedish pilot, can be considered as innovators and early adopters, drawn by curiosity and the prospect of convenience (Sochor et al., 2014). The participants of Vienna's MaaS pilot, Smile, matched the gender and age distribution for early adopters (Durand et al., 2018). In Rogers' diffusion of innovations theory, innovators and early adopters lead the way in the adoption of innovations (Rogers, 2003). The majority is not yet accustomed to MaaS, as illustrated by the numerous questions the concept raises during focus group meetings: people have trouble understanding the added value of the concept (Fioreze et al., 2019; Harms et al., 2018). It is acknowledged that a diffusion of innovation will need to take place (Jittrapirom et al., 2017; Smith et al., 2018). MaaS is therefore an innovation, enabled through technology. Indeed, in every presentation, definition, study and media article on the topic, Mobility-as-a-Service is presented as a service accessed through a digital platform (e.g. The Economist (2016), Hietanen (2014); Hensher (2017); MaaSLab (2018)). The term 'app' (smartphone, mobile or tablet application) is usually mentioned at some point. Literature reviews clearly highlight this point: Internet and technologies have key functions in MaaS (Jittrapirom et al., 2017; Sochor et al., 2017). MaaS's use of technologies is considered to be a core characteristic of the concept, as is its reliance on a single platform (Jittrapirom et al., 2017). Access to a smartphone or tablet is therefore likely to be necessary to use MaaS. However, this is an insufficient condition to using MaaS: one also must know how to operate such a device successfully and to effectively navigate the digital world, as cautioned by Groth (2019) and Pangbourne et al. (2019).

Through MaaS′ platform, end users can plan, book, pay, retrieve their tickets and get real-time information for their trip (Jittrapirom et al., 2017; Kamargianni et al., 2016). All of this is made possible through the integration of information about these modes, which is the first, basic level in the MaaS topology proposed by Sochor et al. (2017). As a matter of fact, Kamargianni et al. (2016), Lyons et al. (2019) and Pangbourne et al. (2019) suggest that MaaS is an innovation that extends what preceded it, namely integrated multimodal travel information. 'Multimodal' means that the travel information provided and the options available within MaaS transcend the level of single modes of transport, thereby justifying the integration of transport modes as a core characteristic of the concept (Jittrapirom et al., 2017). The demand-oriented nature of the service and its users' registration requirement allowing for tailor-made solutions mean that MaaS considers each user uniquely. Furthermore, the possibility to customise the offered service according to one's preference can increase MaaS′ attractiveness and loyalty (Jittrapirom et al., 2017). For instance, MaaS can offer the possibility to choose from a variety of options, brands or services for a single mode. Both Whim and UbiGo offer(ed) a virtual garage containing different types of available vehicles (Sochor et al., 2016; Whim, 2019). Consequently, MaaS provides users with a freedom of choice regarding the individual modes of transport they can make use of. For instance, one may want to use a convertible car on a sunny day while still having access to a regular city car on the following day. According to Spickermann et al. (2014), having a flexibly applicable "virtual fleet" (p. 211) that combines various vehicles and modes will be key for groups in which private cars will be less important in the future. As stated by Kamargianni et al. (2016), MaaS "stands for buying mobility services based on consumer needs instead of buying the means of mobility" (p. 3295). A number of studies argues that the strategic goal of such intense user orientation is to achieve more sustainable transport patterns by providing people with personalised alternatives to private cars (Chowdhury and Ceder, 2016; Giesecke et al., 2016; König et al., 2016; Matyas and Kamargianni, 2018).

Last but not least, the pricing of the service is important from a user perspective. MaaS platforms offer a choice between pay-as-you-go and mobility bundles. The latter are a more advanced form of integration (Sochor et al., 2017), as they are pre-purchased sets of credits on a fixed basis for a combination of modes. These credits could be in time, distance or money units, with pre-determined service level agreements (Jittrapirom et al., 2017).

2.2. From characteristics to indicators

Inspired by the innovation diffusion theory of Rogers (2003) and variants of the Theory of Acceptance Model (TAM) of Davis (1989) focusing on mobile apps adoption (see Hsiao et al. (2016) and Xu et al. (2015)), we posit that the people who are likely to adopt MaaS need to perceive its utility, to acknowledge its compatibility with them and their needs, and to recognise its potential for offering a relative advantage compared to their current situation. A recent study on ride-sourcing apps[3] continued intention of use confirms this. Joia and Altieri (2018) demonstrated that relative advantage, compatibility and perceived utility (and trust) are all antecedents of user satisfaction with such app, and that user satisfaction positively influences the ride-sourcing app continued intention of use, i.e. its adoption.

Based on this, we translated MaaS's characteristics as described above into indicators that we then used in our model, with the end goal to uncover who the early adopters of MaaS in the Netherlands would most likely be. These indicators should be broad enough so that they do not discriminate for any form of Mobility-as-a-Service with the characteristics presented in section 2.1.

Firstly, while some people tend to be very conservative in the adoption of new ideas and concepts, others are much faster (Planing, 2014). As MaaS is an innovative service (at least for the public), we define *innovativeness* as our first indicator. Innovativeness manifests in individuals who are earlier in adopting new ideas and is an indication of overt behavioural change (Rogers, 2003, p. 295). Secondly, people who are willing and able to easily navigate new technologies are more likely to recognise the potential of MaaS, and by extension more likely to be amongst the early adopters of MaaS: *tech-savviness* is therefore our second indicator. Although innovativeness and being tech-savvy might appear overlapping, this is only true to a certain extent. Innovativeness includes the adoption of new ideas and concepts, not necessarily driven by new technologies, while tech-savviness is about the adoption, usage and skills with respect to digital technologies. This is why these indicators are complementary. Thirdly, people who will be most interested in this service in the first place are more likely to be mobile, and in particular to lead lifestyles where travel information offers them an added value. The *need for travel information* is therefore used as a third indicator. Fourthly, the overview offered within the MaaS online platform would be of little added value to someone who does not want to use a variety of transport modes. Early adopters of MaaS are expected to be more open to the possibility of using various modes within one trip and/or of not using the same mode for every single trip. Therefore, we can expect that people who have a *multimodal mindset* are more inclined to use MaaS. Furthermore, when employers offered a virtual bundle to their employees who used company cars, the option of choosing from a variety of cars was deemed more important than the option of choosing from a variety of transport modes (Zijlstra, 2016). This is why we can expect that people who are more interested in MaaS are more likely to *want diversity within a transport mode*, our fifth indicator.

No indicator related to price is present in our model, as the development of consumer prices within MaaS is uncharted territory. We do not expect significant changes in terms of prices in the near future. Higher prices will hinder the popularisation of MaaS, and are therefore unlikely. Significantly lower prices are not realistic as many services are not yet commercially feasible and the MaaS platform itself also needs to generate income. Furthermore, prices of multiple services, such as taxi services and public transport are regulated in the Netherlands.

The key characteristics of MaaS from a user perspective as presented in section 2.1 therefore result in five indicators, namely: *travel information*, *multimodal mindset*, *choice within modes*, *tech-savvy* and *innovativeness*. From a theoretical perspective, we do not assume that someone who is tech-savvy is also multimodal or interested in travel information. Therefore, the indicators are not aggregated to a single index. The LDMI refers to a set of five indicators, as depicted in Fig. 1. In turn, each indicator relies on multiple statements and questions as presented to participants (Appendix 1).

We validated the concept of the LDMI via a second study, not included in this paper, where we consulted Dutch transport experts or experts in the field of MaaS (n = 100) (Zijlstra and Durand, 2019). We requested these experts to provide a definition of MaaS in an open text field in the beginning of an online survey. Many experts referred to the multimodal nature of MaaS, which sometimes also included having the choice within modes. A majority of the experts referred to the important contribution of technology to the service, often referring to smartphones, ICT, digital tools and connectivity. Integration was often cited, in the sense of the integration of multiple modes and/or the integration of searching, booking and paying onto one platform. In both cases, a defining characteristic of the service is that travel information is available on one platform.

Our approach to identify early adopters of MaaS offers multiple advantages over other approaches. Unlike many stated preference experiments, it does not depend on a specific type of MaaS offer or service levels. Indeed, MaaS is still in a nascent state, and the actual offer might differ from the offer presented to respondents. Moreover, there are or there have been start-ups, pilots and experiments here and there, but not yet at a country scale. Hence, country-wide revealed preference data is

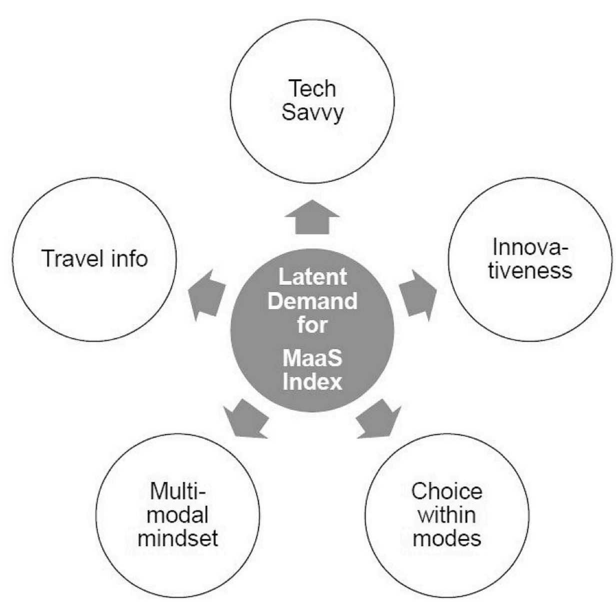

Fig. 1. Latent demand for MaaS index.

[3] These are essentially ride sourcing applications, i.e. mobile applications including geo-location where users can request and pay for a ride, typically Uber and Lyft applications.

Table 1
List of respondents' features included in the model with basic descriptive statistics of the sample.

Features	Mean (range)	Features (cont'd)	Mean (range)
Gender: female	0.509 (0–1)	Dist. highway: linear (km)	4.08 (0.2–26.2)
Gender: male	*ref.*	Dist. highway: squared (km)	32.885 (0–684)
Age group: 18-24	*ref.*	Dist. train station: linear (km)	12.52 (0.3–75.6)
Age group: 25-39	0.231 (0–1)	Dist. train station: squared (km)	265.691 (0.1–5715.4)
Age group: 40-54	0.274 (0–1)	Dist. bus stop: linear (km)	0.394 (0–6.7)
Age group: 55-64	0.166 (0–1)	Dist. bus stop: squared (km)	0.440 (0–45.1)
Age group: 65-74	0.162 (0–1)	Park at home: private space	0.512 (0–1)
Age group: 75+	0.062 (0–1)	Park at home: public space	0.730 (0–1)
Education: low	*ref.*	Park at home: permit needed	0.066 (0–1)
Education: medium	0.452 (0–1)	Park at home: paid parking	0.040 (0–1)
Education: high	0.365 (0–1)	Activity: groceries	0.463 (0–1)
Income: linear (in K€)	1.835 (0–5.3)	Activity: shopping	0.125 (0–1)
Income: squared (in K€)	4.459 (0–28.1)	Activity: go to pick-up point	0.030 (0–0.4)
Occ.: self-employed	*ref.*	Activity: go to private sellers	0.041 (0–1)
Occ.: work (non-gov.)	0.419 (0–1)	Activity: visit café, restaurant	0.076 (0–1)
Occ.: work at government	0.087 (0–1)	Activity: leisure	0.183 (0–1)
Occ.: student	0.07 (0–1)	Activity: on a day trip	0.059 (0–1)
Occ.: homemaker	0.066 (0–1)	Activity: sports	0.239 (0–1)
Occ.: incapacitated	0.068 (0–1)	Activity: volunteer	0.133 (0–1)
Occ.: on welfare/jobseeker	0.028 (0–1)	Activity: visit someone	0.196 (0–1)
Occ.: volunteer	0.017 (0–1)	N vehicles: linear	1.835 (0–6)
Occ.: retired	0.199 (0–1)	N vehicles: squared	3.973 (0–36)
Occ.: other	0.008 (0–1)	Ownership: bicycle	0.702 (0–1)
Health status: good	*ref.*	Ownership: folding bicycle	0.034 (0–1)
Health status: moderate	0.138 (0–1)	Ownership: pedelec	0.191 (0–1)
Health status: poor	0.026 (0–1)	Ownership: speed pedelec	0.002 (0–1)
Env. concern: low	*ref.*	Ownership: moped (25 km/h)	0.032 (0–1)
Env. concern: neutral	0.374 (0–1)	Ownership: moped (40 km/h)	0.020 (0–1)
Env. concern: high	0.465 (0–1)	Ownership: motorcycle	0.031 (0–1)
Env. concern: very high	0.063 (0–1)	Ownership: car	0.766 (0–1)
HH size: linear	2.587 (1–9)	Ownership: hybrid car	0.028 (0–1)
HH size: squared	8.495 (1–81)	Ownership: van	0.016 (0–1)
HH: single	*ref.*	Ownership: mobility scooter	0.022 (0–1)
HH: couple	0.337 (0–1)	Mode use: bicycle	0.436 (0–1)
HH: couple + children	0.377 (0–1)	Mode use: pedelec	0.124 (0–1)
HH: single parent + children	0.060 (0–1)	Mode use: speed pedelec	0.001 (0–1)
HH: couple + children + others	0.006 (0–1)	Mode use: moped (25 km/h)	0.012 (0–1)
HH: couple + others	0.003 (0–1)	Mode use: moped (40 km/h)	0.005 (0–1)
HH: other comp.	0.003 (0–1)	Mode use: motorbike	0.011 (0–1)
N children: linear	0.311 (0–7)	Mode use: car	0.627 (0–1)
N children: squared	0.700 (0–49)	Mode use: bus. tram or metro	0.099 (0–1)
Density: linear (10^3 houses/km^2)	1.459 (0–11)	Mode use: train	0.082 (0–1)
Density: squared (10^3 houses/km^2)	3.685 (0–121.2)	Mode use: mobility scooter	0.016 (0–1)
Dist. city centre: linear (km)	17.146 (0.3–96.6)	N flights: private	0.711 (0–6)
Dist. city centre: squared (km)	488.006 (0.1–9324.3)	N flights: business	0.125 (0–8)

Notes: occ. = primary occupation, gov. = government, env. concern = environmental concern, HH = household, dist. = distance (as the crow flies). Income is net monthly personal income.

not available. In addition, our experience from focus groups meetings on MaaS is that the way the concept is explained strongly biases people's reactions (Harms et al., 2018). Our method spares us from such (lengthy) explanations, which are often problematic in survey research (Lenzner et al., 2010, 2011). At the same time, because this approach is grounded in the core characteristics of MaaS, it still applies uniquely to that concept.

3. Method and data

Our multistage analysis is based on survey data. In this section, we first discuss the data, and then the method used.

3.1. Data

Our sample is drawn from participants of the Netherlands Mobility Panel (MPN). The MPN is a household-based longitudinal study on travel behaviour (Hoogendoorn-Lanser et al., 2015). Each year, participants complete a household survey, personal survey and a three-day travel diary. As such, much is known about the MPN participants, especially in relation to current travel patterns. In order to be a candidate in our survey, a full and complete record of the latest MPN wave (wave five) was required. Only people aged 18 years or older were eligible to participate.

In June 2018, a group of 2150 participants of the MPN received an invitation for our questionnaire. This gross sample was based on five representation criteria, namely age group, gender, education level, household size and region. In total, 1621 people completed the questionnaire, yielding a response rate of 75.4%. The sample was thoroughly analysed in order to detect unsatisfactory respondents. In total, we deleted 74 cases. The criteria used for data cleaning were inconsistency in the answers provided (e.g. being 20 years old and already retired), non-differentiation in matrix questions (drawing a straight line in grids) and speeding (respondents with fewer than 6 s per screen were removed from the sample; median time per screen was 21 s). Respondents accumulating multiple deficiencies or very fast completion times were excluded from further analysis.

The final sample contains 1547 cases. Due to non-random participation and data cleaning, our final sample differs slightly from the initial selection criteria. Hence, weights were calculated based on the same criteria as previously mentioned and applied to the cases in the dataset. Due to this manipulation, we improved the representativeness of our sample. The features of the respondents are obtained from the fifth wave of the MPN. This data was collected in September and October 2017. The used features include, among other things, socio-demographics, socio-economics, vehicle ownership, frequency of activities (such as volunteering), frequency of transport mode use, and information about the built environment around a respondent's residential location. Most features are dummy-coded (0/1). For the ease of interpretation, both activities and mode use are transformed into a ratio ranging from zero to one, where zero indicates no mode use or activity, and one indicates a daily mode use or a daily activity. Here, the maximum is arbitrarily set to 4.5 days a week or 234 days per year for the category 'four days or more per week'. A full list of the features with descriptive statistics is provided in Table 1.

3.2. Confirmatory factor analysis

The LDMI is built using a confirmatory factor analysis (CFA) (Brown, 2014; Harrington, 2009). Per indicator, multiple informative variables – statements and questions – are used (Fig. 2). Their relevance within the LDMI is tested by assessing the model fit and goodness-of-fit of the variable itself. The relative importance of these variables is based on the estimates of the model. In the estimation procedure, the indicators or latent variables are standardised and normalised ($\mu = 0$, $\delta = 1$). The CFA is conducted using the *lavaan* package (Rosseel et al., 2018) in the platform for statistical modelling "R". The model's goodness-of-fit statistics will be compared with strict thresholds, as found in the rules of thumb summarised by Brown (2014), Harrington (2009) and Kline (2005).

The statements and questions (here referred to as *items*) used in our questionnaire were all directly inspired by the concept they aim to cover. In some cases, we were able to use readily existing and tested items. This is especially true for the statements on 'Innovativeness', inspired by Rogers (2003), and the statements on technological innovativeness and technological opinion leadership of Bruner and Kumar (2007). Nevertheless, multiple items had not been previously tested in surveys. A full list of the items included in the survey can be found in Appendix 1.

In our approach, the results of the CFA are subject to a machine learning technique in order to reveal the profile of the early adopters (Section 3.3). It is somewhat uncommon to first conduct a CFA and then move to a separate regression analysis. Usually, these two steps are combined within one model, namely a structural equations model (SEM). This traditional approach is unsuited for our research goal though, as SEM is most powerful when strong assumptions or prior knowledge is present. In our case, while we do have a clear picture of what MaaS entails, we do not have a hypothesis to test with respect to the features of early adopters. Instead, we want to be able to freely associate these features with the LDMI and to explore possibilities. The result should be a concise list of the most important features. SEM is not an attractive option for variable selection.

3.3. Lasso regression

In order to link personal characteristics with the LDMI's five indicators, we used a multivariate multiple linear regression model with a least absolute shrinkage and selection operator (Lasso). The regression model is *multivariate* because we have not one but five indicators (Section 2; Fig. 2). Indeed, our model needs to cope with 'multi-task learning'. The model is *multiple* because we want to test a great deal of potentially interesting features (Table 1). The model is *linear* because we expect the residuals to be normally distributed. Finally, we used a *Lasso* for regularisation and variable selection (Hastie et al., 2015; Tibshirani, 1996). Lasso is a popular machine learning technique used for obtaining sparse models with accurate predictions and enhanced interpretability. Commonly, a limited number of features are capable of capturing a large part of the deviance. Lasso relies on this Pareto-principle (see also 'bet-on sparsity principle' in Hastie et al. (2015)). To date, Lasso has been rarely used in transport studies.

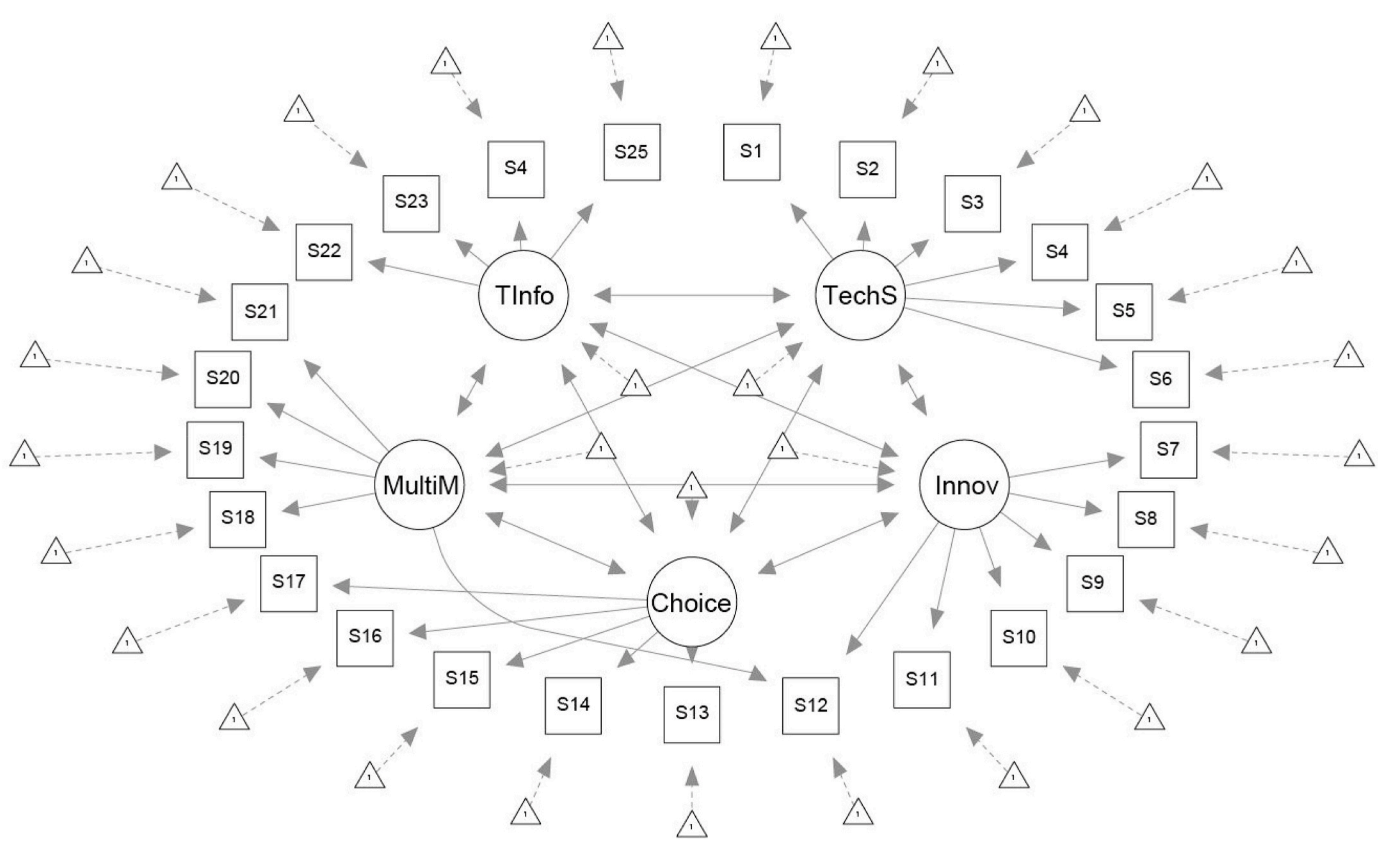

Fig. 2. Path diagram to be tested with CFA (for statements and questions see also Table 3). Triangles are standard errors.

The multivariate multiple linear regression with Lasso is performed in "R" using the *glmnet* package (Friedman et al., 2018; Hastie and Qian, 2016). We called it the *glmnet* function, which automatically standardises all features in the model. This is a necessary step for Lasso, as all features then have equal chances to be selected (Tibshirani, 1997). The coefficients in the final model are rescaled to correspond to the original input. Cross-validation with ten subgroups (folds) is used to determine the optimal cut-off point (λ).

In order to obtain a sparse model, two values for cut-off points are generally suggested, namely the point at which deviance is minimised and the point within one standard error (s.e.) distance of the minimum (Hastie and Qian, 2016). In our model, the minimum mean squared error is found at $\lambda = 0.019$, according to the results of the cross-validation (Fig. 3). The total deviance captured by the model is good ($\rho^2 = 0.350$). However, at this point, 76 out of 83 parameters remain present in the model. This does not provide a sparse model. We therefore use the *'within one s.e.'*-rule, readily provided by the *glmnet* function output and shown in Fig. 3. At this point ($\lambda = 0.099$), 31 of the 83 variables are present. The remaining 52 are not included. Even though only 37% of the variables remain in this final model, the captured deviance remains good ($\rho^2 = 0.255$).

Due to the use of a Lasso regression, levels of significance are to some extent redundant information. Only features with relevant effects on one or more dependent variable are included in the sparse model. The relative size of the effect is the most important piece of information. By 'effect' we mean the predicted and standardised ('ceteris paribus') differences of the means of two groups, as derived from the regression model. All dependent variables are readily scaled and easily comparable (Section 3.2). Most independent variables are dummy-coded. Hence, coefficients and additional effects are often one and the same thing. By default, Lasso regression only provides point estimates, which also means that standard errors are unknown. In line with this, we should restate that statistical significance is different from societal significance or scientific relevance (Ziliak and McCloskey, 2008).

4. Results and discussion

In this section, we first discuss the performance of the Latent Demand for MaaS Index, before presenting regression results. The latter part of this section compares our results regarding the profile of MaaS early adopters to results from other studies on innovation and innovative mobility services.

4.1. Performance of the latent demand for MaaS index

The results of the confirmatory factor analysis (CFA) are satisfying. Table 2 presents the frequently used indicators for assessing the fit of a CFA model and the rules of thumb regarding the strictest thresholds. The performance on the relative fit indices (TLI and CFI) is certainly on the correct side of the threshold. The Standardized Root Mean Square Residual (SRMR) is within the 0.10 threshold, and even within the 0.08 threshold. The Root Mean Square Error of Approximation (RMSEA) is a bit trickier however, as our model is not under the strict 0.06 threshold, although it is within one standard error distance of this point and under thresholds suggested by others (Harrington, 2009). These results indicate that our model is plausible and can be accepted.

The signs of all 26 coefficients are in the expected directions. Further, all coefficients are highly significant ($p < 0.001$), which is also a result of

Table 2
Model fit statistics of CFA model.

Model statistics	Threshold	Model results
Number of observations	*> 300*	1547
Degrees of Freedom	*Positive*	263
Model fit test statistic		1834.5
p-value (Chi-square test)	*< 0.001*	0.000
Comparative fit index (CFI)	*> 0.950*	0.975
Tucker-Lewis Index (TLI)	*> 0.950*	0.972
Root Mean Square Error of Approximation (95% CI) (RMSEA)	*< 0.060*	0.062 (.059–.065)
Standardized Root Mean Square Residual (SRMR)	*< 0.080*	0.060

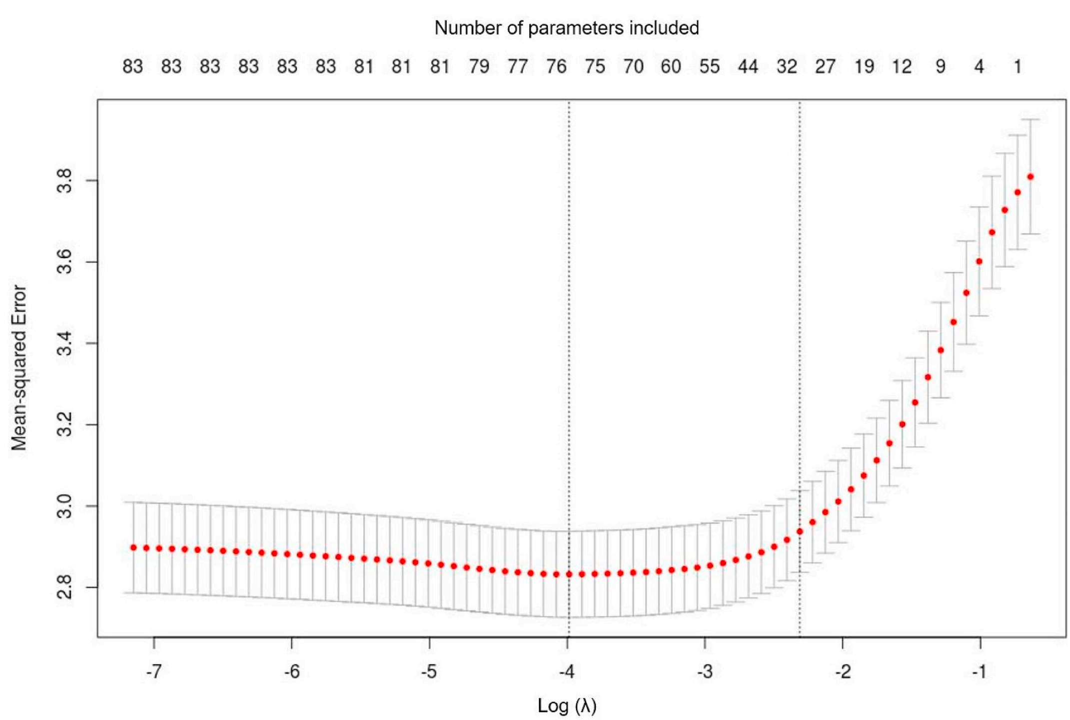

Fig. 3. Results of the cross validation with two suggested cut-off points (left-most dotted line: minimum mean squared error, right-most dotted line: one standard error from the minimum).

Table 3
Coefficients from the CFA.

Indicator	Abbreviation	Item short name	Estimate (s.e.)
Tech-Savvy	S1	Search of information on mobile device	0.774 (0.014)
	S2	Social media use on mobile device	0.624 (0.018)
	S3	Other use of mobile device	0.675 (0.017)
	S4	Reservations or bookings with mobile device	0.885 (0.008)
	S5	Purchase of products or services with mobile device	0.895 (0.008)
	S6	Mobile device as proof of payment	0.760 (0.014)
Innovativeness	S7	Trying new services first	0.848 (0.011)
	S8	Purchase of latest products even if expensive	0.811 (0.013)
	S9	Opinion leadership	0.747 (0.014)
	S10	Techno-optimism	0.669 (0.019)
	S11	Purchase of new product before others	0.784 (0.013)
	S12	Being open to new ways of travelling	0.464 (0.022)
Choice private modes	S13	Choice in type of car	0.548 (0.031)
	S14	Interest in using e-bike now and then	0.229 (0.033)
	S15	Interest in convenience of a car without owning one	0.413 (0.028)
	S16	Car sharing use	0.674 (0.029)
	S17	Bike sharing use	0.719 (0.027)
Multimodal mindset	S18	Letting transport mode depend on activity	0.590 (0.024)
	S19	Comparing travel options	0.739 (0.021)
	S20	Combining transport modes	0.675 (0.022)
	S21	Using travel information to determine mode choice	0.557 (0.047)
	S12	Being open to new ways of travelling	0.400 (0.023)
Travel information	S22	Using travel app with overview	0.671 (0.021)
	S23	Willingness to pay for information	0.221 (0.027)
	S24	Willingness to pay for personalised advice	0.163 (0.029)
	S25	Travel information use	0.606 (0.024)
Covariance	C1	S23 ~ S24	0.719 (0.013)

the relatively large sample. A comparison or further interpretation of the estimates of the CFA model is beyond the main scope and purpose of this paper; moreover, it is also somewhat complicated, as not all items used the same scale. The 'Innovativeness' items are an exception to this rule, as all of these are statements using a five-point Likert scale.

The individual level estimates for the LDMI indicators are positively correlated (Fig. 4 in Appendix 2; covariance of indicators not shown in Table 3). Seemingly, being tech-savvy and an early adopter is somewhat related (R = 0.68). There is also an overlap between choice of private modes, a multimodal mindset and the need for travel information, with correlation coefficients between 0.71 and 0.82. The correlation between tech-savviness and early adopter on the one hand, and the remaining three indicators on the other, is weak.

A modest correlation between multiple indicators suggests that working with one indicator to capture the latent demand for MaaS would be insufficient. Multiple indicators are needed to capture the full essence of the potential to adopt MaaS. Indeed, tests we performed indicate that with one indicator only, about 40% of the variance is lost. Hence, our theoretical assumptions (Section 3) are supported by the empirical material: being tech-savvy is different from being multimodal, to give just one example.

4.2. Regression results

A profile of the early adopters can be sketched as based on the results of the Lasso regression (Table 4). Age seems to be highly relevant. Especially older people, aged 75 and older, have strong negative coefficients in all five dimensions of the LDMI. People aged 55 and older already seem to have a lower probability of adoption, although this is not true with respect to the multimodal mindset. The high-potential adopters are between 25 and 39 years of age. Individuals in the reference group (18–24 years old) also have a high probability of adoption.

The results are somewhat ambivalent regarding household composition. Couples and couples living with others (not children) have a lower potential. Nevertheless, the number of people in a household is positively associated with the LDMI in 4 out of 5 dimensions. This could mean that couples with children living at home have a somewhat higher potential. One-person households (*ref.*) outperform all other combinations with respect to a multimodal mindset. Nonetheless, the effects found with respect to household composition are (very) small.

Regarding the respondents' main occupations, we find that students have strong positive estimates in all dimensions, which could also explain the non-linear trend for age groups and why the 25–39 age group outperforms the 18–24 age group. The group of 'people working for the government' also has positive estimates on all dimensions of the LDMI, although the size of the coefficients is negligible compared to those of students. Homemakers have strong negative coefficients for most dimensions of the LDMI. Retirees are also represented in the sparse model; their coefficients are mostly negative. This leads to the finding that older adults have a lower adoption potential.

A high socio-economic status is positively associated with a higher potential to adopt MaaS. The linear effect of income is not included in the model, although a squared effect is present, suggesting that higher income groups strongly differ from the rest. For someone with a personal net income of €2160 per month,[4] effects range from 0.005 to 0.015. For someone with three times that income, effects range from 0.05 to 0.134. Effects for a high education level are also relatively strong, with coefficients ranging from 0.101 to 0.231. As income and education level are highly correlated, the effects tend to accumulate in practice: a significant importance of socio-economic status is to be expected.

Most of the characteristics of the built environment are not represented in the sparse model. The distance to train stations, bus stops or city centres are not present. Urban density does however have a positive effect on all dimensions, suggesting that people living in denser environments have a higher potential to adopt MaaS.

Self-declared health condition is positively associated with the potential to adopt MaaS: the healthier people say they are, the more likely they are to adopt MaaS. The coefficients for people with moderate health conditions are slightly negative. The coefficients for people in poor health are strongly negative. In line with this finding, we also find negative coefficients in all five dimensions for people using mobility scooters, which are commonly used by people with mobility impairments.

The ownership of specific vehicles is largely irrelevant. The results from the sparse model suggest that ownership of a motorcycle, car, van or bicycle is not a real benefit to the model. However, people who have

[4] Approximate net mode income in 2018 in the Netherlands, based on the gross mode income determined by the Netherlands Bureau for Economic Policy Analysis (2018).

Table 4
Results of the sparse model.

Feature	Type[a]	Tech-savvy	Innovative	Choice	Multimodal	Travel info
Gender: female	D	0.008	−0.046	−0.008	0.003	−0.006
Age group: 25-39	D	0.133	0.102	0.041	−0.024	0.066
Age group: 55-64	D	−0.033	−0.022	0.000	0.010	−0.013
Age group: 65-74	D	−0.106	−0.085	−0.034	0.040	−0.039
Age group: 75+	D	−0.591	−0.383	−0.317	−0.209	−0.467
Education: high	D	0.115	0.101	0.204	0.206	0.231
Income: squared	I	0.001	0.002	0.002	0.003	0.003
Occ.: work at government	D	0.009	0.009	0.005	0.003	0.007
Occ.: student	D	0.178	0.177	0.067	0.041	0.154
Occ.: homemaker	D	−0.230	−0.262	−0.106	−0.067	−0.200
Occ.: retired	D	−0.098	−0.069	−0.040	0.009	−0.051
Health status: moderate	D	−0.032	−0.033	−0.021	−0.047	−0.045
Health status: poor	D	−0.078	−0.082	−0.148	−0.162	−0.151
HH size: linear	I	0.017	0.009	0.004	−0.006	0.006
HH: couple	D	−0.024	−0.018	−0.003	0.000	−0.013
HH: couple + others	D	−0.034	−0.023	−0.023	−0.015	−0.034
Density: linear	I	0.012	0.006	0.017	0.025	0.021
Dist. highway: squared	I	0.000	0.000	0.000	0.000	0.000
Activity: groceries	R	−0.001	−0.002	0.005	0.008	0.004
Activity: go to pick-up point	R	1.525	1.200	0.789	0.556	1.259
Activity: visit café, restaurant	R	0.459	0.383	0.210	0.211	0.420
Activity: on a day trip	R	0.376	0.338	0.334	0.312	0.443
Activity: sports	R	0.155	0.091	0.061	0.110	0.144
N vehicles: linear	I	0.017	0.003	0.015	0.011	0.014
Ownership: folding bicycle	D	0.010	0.004	0.055	0.040	0.037
Ownership: mobility scooter	D	−0.002	−0.001	−0.003	−0.005	−0.004
Mode use: bicycle	R	−0.001	−0.038	0.103	0.182	0.094
Mode use: car	R	0.107	0.077	−0.075	−0.126	−0.007
Mode use: bus, tram or metro	R	0.061	0.049	0.148	0.178	0.179
Mode use: train	R	0.090	0.096	0.304	0.396	0.356
N flights: private	I	0.125	0.113	0.111	0.118	0.152
Intercept	C	−0.329	−0.198	−0.250	−0.277	−0.375

[a] Type D = dummy variable [0,1], type I = interval, type R = ratio [0,1] and type C = constant, see also Table 1.

folding bicycles (n = 52) do have small positive estimates in all dimensions of the LDMI. Ownership of a mobility scooter has small negative estimates. Further, the total number of vehicles owned seems to be relevant here; the more vehicles people own, the more potential they have to be among early adopters, although the effects are modest. Such a relationship is contradictory to conceptions of MaaS and the end of ownership, but is likely due to the number of vehicles also being an indicator of personal wealth, net worth and highly active and mobile lifestyles.

With respect to transport mode use, we find multiple relevant variables, namely the use of cars, trains, buses, trams and metros, bicycles and airplanes. Of these, the use of public transport and air travel have clear positive estimates in all dimensions of the LDMI. Hence, frequent PT users and frequent flyers are likely to be among the early adopters of MaaS. The direction of the effect is less clear for cycling and driving, as both positive and negative effects are present.

Finally, we discuss the findings regarding the frequency of activities at various locations. Five out of ten variables made it to the final model (50%), which is above average (31/83 = 37%). 23 of the 25 coefficients in Table 4 are positive. This, in combination with the findings summarised in the previous paragraph, suggests that more active and mobile people have a higher potential to use MaaS, which makes sense for a platform that supports trips. Strong positive coefficients are found for the frequency of retrieving online purchased goods at a pick up point, although the overall frequency is modest (Table 1), which means the effects are also small for most of the respondents. People who take many leisure trips are seemingly especially likely to adopt MaaS, as strong positive coefficients are found for the ratios 'on a day trip' and 'visit café or restaurant'. The importance of leisure trips aligns with the conclusion that the number of flights a person takes for personal reasons is positively associated with a high LDMI score.

4.3. Comparison with other studies

Our study's results can be validated with the results from other studies. As noted below, some discrepancy remains in relation to some of the variables found. Further, not all of the features included in our model are used in other studies.

The notion that early adopters have a higher socio-economic status is supported by multiple studies on the diffusion of innovations (Rogers, 2003). Innovators and early adopters often must have sufficient means in order to try new ideas, products or services. A high income certainly helps. A higher level of education implies that people generally have better abilities to adopt new (abstract) ideas, also from other cultures and languages. Assessing the added value of new concepts is also easier. The dominance of users with high socio-economic status is also revealed in relation to bike sharing (Fishman, 2016; Ricci, 2015), ride sourcing (Alemi et al., 2018; Rayle et al., 2016), and car sharing (Becker et al., 2017; Burkhardt and Millard-Ball, 2006; Clewlow and Mishra, 2017; Martin and Shaheen, 2011; Namazu et al., 2018; Shaheen and Rodier, 2005). More importantly, based on the user profiles in MaaS pilots with self-selection, we can conclude that participants have incomes that are distinctively above average (Durand et al., 2018).

Our research reveals that young adults and students are more eager to adopt MaaS. Conversely, older adults and retirees have strong negative estimates. Fishman (2016) and Ricci (2015) report similar findings in relation to bike sharing. According to the stated preferences surveys done by Caiati et al. (2020), ITS Australia (2018), Ho et al. (2018) and Ho et al. (2019), young people are more likely to be interested in MaaS than older people. These results bolster the conclusion that young people do have a higher potential to be among MaaS's early adopters. However, the general literature on the diffusion of innovations is inconclusive with respect to age (Rogers, 2003). Some studies suggest that older people are more likely to adopt new ideas, other studies suggest young people are more eager (Planing, 2014), and other studies find no effect of age.

In line with other studies, we find a positive effect of housing density. Additionally, we know that higher educated and higher income groups, public transport users, younger people and students are well represented in Dutch cities (Government of the Netherlands, 2018; Netherlands Institute for Transport Policy Analysis, 2015; Statistics Netherlands, 2009; van Dam and de Groot, 2017). Hence, merely by looking at the demand side, we can already expect more interest in MaaS in urban regions. Moreover, multiple studies and commentators (Glaeser, 2011; Hall, 1998; Jiang, 2019) have revealed the importance of cities and urban densities in the adoption of innovative services. In numerous cases, researchers have already limited their scope to urban environments when assessing MaaS's potential, as they expect cities to lead in the adoption of MaaS (Alonso-González et al., 2017; Caiati et al., 2020; Fioreze et al., 2019; Ho et al., 2018; Matyas and Kamargianni, 2018). This does not mean that less dense areas do not have potential, but they present their own challenges, notably in terms of supply and profitability (Geurs et al., 2018).

In our study, the typical profile of the early adopter is clearly that of a highly active person: someone who flies frequently, uses public transport frequently, and frequently takes day trips, to visit restaurants and participate in sports. In contrast, people who are more likely to stay at home are less likely to adopt MaaS in the short term. In line with these conclusions, Alemi et al. (2018) found positive correlations between ride-sourcing adoption and the frequent use of transportation-related apps on smartphones, previous taxi and car sharing experience, the frequent undertaking of long-distance business trips and flying frequently. Sochor et al. (2015) suggest that people who frequently travel or enjoy travelling are more eager to participate in a MaaS pilot study. According to ITS Australia (2018), MaaS's innovators and early adopters are people with high travel needs. Rogers (2003) also suggests that being mobile and visiting other cities or countries has a positive effect on the adoption of new ideas generally. A cosmopolitan lifestyle means that innovators are less bound to the local social system.

5. Conclusion and discussion

The goal of this study was to identify the groups within the Dutch population that are most likely to adopt MaaS in the near future. In order to identify these early adopters, we created the Latent Demand for MaaS Index (LDMI), fed by data from a questionnaire distributed among participants in the Netherlands Mobility Panel ($n = 1547$). The various features of the individuals are linked to the LDMI using a multivariate multiple linear regression with Lasso. Our approach allows us to gain a clear picture of the early adopters, without being strongly dependent on the actual product, which is especially useful since MaaS is still in an early stage of development. We also avoid the use of stated choice experiments or costly pilot projects, where the outcomes strongly depend on the set up and design of the experiment, and assumption regarding prices.

5.1. Conclusions

Our results indicate that the people with the highest potential for adopting MaaS have a high socio-economic status, with high personal incomes and high levels of education. Further, high-potential adopters are more likely to be below the age of 55, to reside in densely populated neighbourhoods and to be in good health. More generally, we find that an active, highly mobile lifestyle is strongly and positively associated with the LDMI. People who frequently undertake leisure trips stand out. Frequent public transport use and frequent flying are both positively associated with a high potential to adopt MaaS.

The innovators – the people preceding the early adopters – are likely to have most, if not all, of the following characteristics: they will be young, highly educated, healthy and relatively wealthy, users of public transport, pursuers of active lifestyles and residents of urban environments. Conversely, people who may never adopt MaaS (or the 'laggards') are more likely to be older people who never fly, reside in rural areas, undertake a limited number of trips per week, and are in poor health.

In a number of cases, the regression model provides less distinct results. The direction of the effects for the five indicators is not always the same, with the effects for the *gender* or *car use* features an example of this. A positive association with one indicator and a negative association with another indicator renders it difficult to draw pronounced conclusions, although it does stress the added value of assessing the LDMI indicators separately.

5.2. Discussion and outlook

Our study's findings are an interesting extension to the state-of-the-art knowledge available about the adopters of MaaS. Multiple surprising results pop up in the explorative regression analysis, such as the frequency of flights or frequency of using pick-up points for products purchased online. Other findings stress the importance of earlier findings, such as the central role of cities and the importance of income.

Based on our findings, we can conclude that the profile of MaaS's early adopters deviates from the general population. This has implications both for the outcomes of pilots that allow self-selection and for the early stages of MaaS in practice. The travel behaviour insights, such as observed modal shifts, gained in these pilots or at these early stages will most likely be largely unrepresentative of the general population. People from the early or late majority are probably not as highly mobile as the early adopters, hence the amount of trips per person is also likely to drop as adoption rates rise.

Note that this observation only holds if MaaS is widely adopted by the population. Whether or not MaaS will be widely adopted remains unknown. MaaS adoption rates are also beyond the scope of the research presented in this paper, and this has consequences for labels such as 'early adopter', 'late majority' or 'laggard'. In fact, such labels can only be applied successfully with hindsight.

Our study assumes a balanced exposition and non-targeted marketing. Indeed, our study's results are not deterministic: the profile we revealed may differ from the profile of the early adopter in practice. Consequently, our findings are highly relevant for the stakeholders involved in trying to reach certain groups within society. By altering the services offered in MaaS or through targeted marketing, it could be possible to reach other social groups at an early stage. In innovation studies, this is known as audience segmentation (Rogers, 2003). Still, in order to reach diverse groups, inclusive design is needed. It is not simply about asking what people want or not, but about "organising technology around the way users process information and make decisions, keeping them in control and aware" (Harvey et al., 2019, p. 176), based on Endsley and Jones (2016)). As Pangbourne et al. (2019) caution, there may be a strong public sector input required in order to avoid (further) disadvantaging less mobile groups.

Our study provides multiple methodological insights and advancements. The use of Lasso regression offers clear benefits when testing a wide range of potentially relevant features and yields interesting and sometimes surprising results. A sparse model is easier to interpret, understand and explain. Nearly two out of three features are not included in the final model, yet this hardly hampers the captured deviance. Lasso regression is relatively new in transport studies. A minor issue is the fact that we are dealing with a machine learning technique, which yields inconsistent or non-stylized results. Decomposing MaaS into key indicators was done through a mixed inductive-deductive process; this approach can be generalised to other innovations. Another road could be to examine Rogers' five perceived characteristics of the innovation (relative advantage, compatibility, complexity, trialability, observability), which influence persuasion in the innovation-decision process, and subsequently adoption or rejection (Rogers, 2003). However, this requires a more explicit presentation of the innovation to respondents. Our flexible approach to the subject – with a decomposition of a new concept in key indicators, a survey, confirmatory factor analysis and a machine learning technique to uncover profiles of early adopters – can easily be applied to other regions or countries. Moreover, it is suited for additional studies on the diffusion of other innovations in and beyond the field of transport.

A minor issue with our study is the fact that we did not sufficiently take into account the current travel options of the individuals in the sample. Current vehicle ownership could be a barrier to the adoption of MaaS due to sunk costs. Similarly, one might expect to see discount cards for frequent PT users or subscriptions to shared mobility services. However, this issue is mitigated by the fact that people need not adopt MaaS instantly; rather, there will likely be windows of opportunity when current arrangements have expired.

Further research on this topic could focus on the type of trips that have the highest potential for MaaS. In this study, we assumed the need for travel information as a preliminary, which to some extent likely rules out short-distance and routine trips. As previously mentioned, we have no knowledge of MaaS's potential in terms of market share, with the exception of one study conducted in Australia (ITS Australia, 2018). Further research on the probability of adopting MaaS is a necessary next step, to complement and reinforce the findings of the small pool of insightful studies on MaaS, as cited in this paper. Finally, we strongly encourage researchers from elsewhere to apply and improve the LDMI. The LDMI could be improved with the addition of items pertaining to customisation, the all-inclusiveness of the service, the convenience it may provide, costs, and other aspects.

CRediT authorship contribution statement

Toon Zijlstra: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Writing - original draft, Writing - review & editing, Visualization, Project administration. **Anne Durand:** Conceptualization, Methodology, Validation, Investigation, Writing - original draft, Writing - review & editing. **Sascha Hoogendoorn-Lanser:** Methodology, Writing - review & editing. **Lucas Harms:** Conceptualization, Methodology, Investigation, Writing - review & editing.

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Appendix 1. Items and corresponding short names

In this appendix we present the translated questions and statements used in the original (Dutch language) survey.

Table 5
Items used in the survey.

Indicator	Abb.	Type	Item	Item short name
Tech-Savvy	S1	Q	How often do you use your smartphone and/or tablet … to look for information?	Search for information on mobile device
	S2	Q	How often do you use your smartphone and/or tablet … for social media?	Social media use on mobile device
	S3	Q	How often do you use your smartphone and/or tablet … for other purposes?	Other use of mobile device
	S4	Q	Do you use your smartphone and/or tablet to reserve or book products or services (like tickets)?	Reservations or bookings with mobile device
	S5	Q	Do you use your smartphone and/or tablet to pay for products or services (like tickets)?	Purchase of products or services with mobile device
	S6	Q	Do you use your smartphone and/or tablet to reserve as a proof of payment (like QR-code)?	Mobile device as proof of payment
Innovativeness	S7	S	I try new services, like Netflix or Uber, before my friends or my family.	Trying new services first
	S8	S	I often buy the latest products, like a smartphone, even if they are expensive.	Purchase of latest products even if expensive
	S9	S	Friends and family look to me for help when they are making decisions involving new services or products.	Opinion leadership
	S10	S	I am enthusiastic about the possibilities that new technologies offer.	Techno-optimism
	S11	S	I buy new products, like the latest 3D TV, before my friends or family do.	Purchase of new product before others
	S12	S	I am open to try new ways of travelling.	Being open to new ways of travelling
Choice private modes	S13	S	I would like more opportunities to choose between different types of cars, such as a small city car or a fancy SUV.	Choice in type of car
	S14	S	I would like to be able to make use of an e-bike from time to time.	Interest in using e-bike now and then
	S15	S	I would like to have the convenience of a car without owning one.	Interest in convenience of a car without owning one
	S16	B	I have used a shared car in the past 12 months via a company and against payment, like Greenwheels or Snappcar.	Car sharing use
	S17	B	I have used a shared bike in the past 12 months via a company and against payment, like OV-fiets, FlickBike or MoBike.	Bike sharing use
Multimodal mindset	S18	S	How I travel depends on the activity at the destination of my trip.	Letting transport mode depend on activity
	S19	S	I often compare different travel options before I make a choice for my trip.	Comparing travel options
	S20	S	I do not mind combining various transport modes within one trip, like bicycle and train.	Combining transport modes
	S21	S	I use online travel information, a route planner or a navigation system to determine which transport mode I will use.	Using travel information to determine mode choice
	S12	S	I am open to new ways of travelling.	Being open to new ways of travelling
Travel information	S22	S	I would use a (smartphone) travel app if it were to give me an overview of all the possible travel options.	Using travel app with overview
	S23	S	I would be willing to pay for more precise and reliable travel information.	Willingness to pay for information
	S24	S	I would pay more for personalised travel information.	Willingness to pay for personalised advice
	S25	Q	How often do you look for travel information?	Travel information use

Q = closed question with one answer, S = 5-point Likert-scale statement, preceded by: "To what extent do you agree with the following statement?", B = statement with binary answer only (yes/no).

Appendix 2. Correlation plot

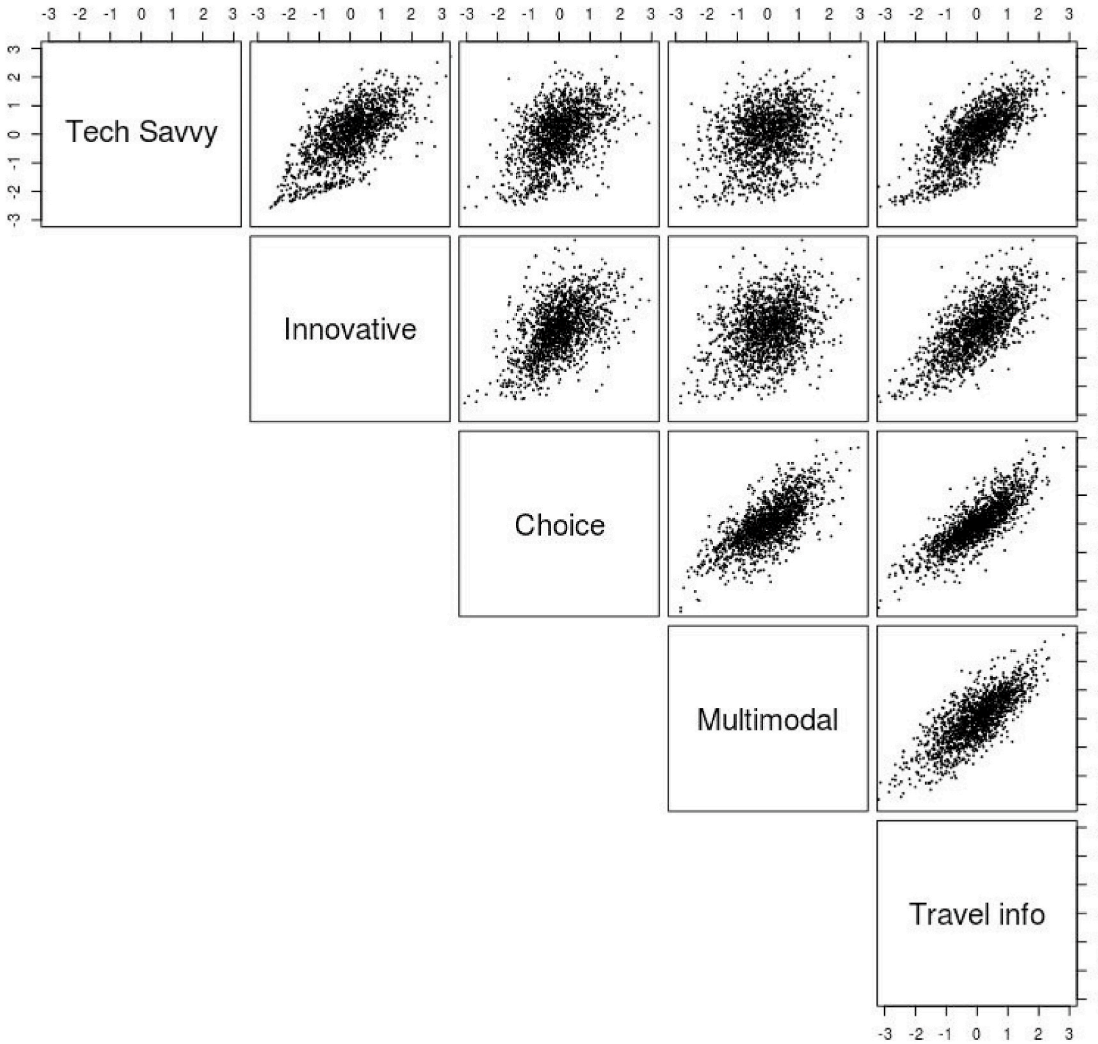

Fig. 4. Correlation plots based on individual level estimates for the five indicators of the LDMI

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