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MaaS potential users' profiles characterization with a K-means clustering algorithm

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Abstract

Mobility as a Service (MaaS) is building its way into cities all across the globe to change how their residents move around today. Given the user-centric nature of this model, it is essential to understand individuals' needs and expectations for its successful deployment. The paper explores different potential users' profiles in the metropolitan area of Madrid (Spain) by applying a machine learning clustering algorithm. Our analysis reveals three clusters in terms of individuals' willingness to adopt MaaS: the "MaaS-enthusiasts", who are significantly open to embrace the new mobility solution; the "innovation doubtful users", who are likely to adopt MaaS but need more persuasive incentives; and the "anti-new technologies", a group averse to innovation. Tailored strategies are defined to foster MaaS within these three groups, with the goal of encouraging more sustainable behaviours. Our results demonstrate how machine learning can be helpful to transport planners and policymakers for getting insightful information from large datasets.

Keywords: MaaS; user profile; cluster; machine learning.

1. Introduction

In the current era of digitalization, Mobility as a Service (MaaS) has gained the attention of transport researchers, policymakers, service operators, and other stakeholders as an opportunity to revolutionize the mobility scenario and encourage sustainability.

Since its emergence in 2014, MaaS is expected to bring a wide variety of benefits, such as addressing the individual

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needs of each traveller by providing them with on-demand and customized services, improving the efficiency of the transport network through the deployment of Information and Communication Technologies (ICTs), facilitating a profitable market for new mobility services, and creating renewed opportunities for the traditional transport alternatives, among others (Hietanan, 2014; Jittrapirom et al., 2017). However, in contrast to the positive views, some experts have pointed out that MaaS may induce unsustainable travel practices (Alyavina et al., 2020). Others sustain that even if MaaS is able to deliver the goals it promises, individuals' acceptance is critical for this new model to succeed and lead to more liveable urban environments (Zijlstra et al., 2020). Therefore, it is crucial to explore individuals' willingness to embrace MaaS.

Following the above premises, we propose to evaluate potential MaaS users' profiles by applying a machine learning algorithm –known as k-means clustering– based on a set of attitudinal latent factors that influence the adoption (or rejection) of MaaS. This paper is structured as follows. After this introduction, Section 2 briefly addresses the concepts of MaaS and machine learning. Section 3 then describes the study case, and the methodology is explained in Section 4. Section 5 comments on and discusses the results, and finally, Section 6 provides the final conclusions.

2. Background: individuals' willingness to adopt MaaS

MaaS is firstly defined by Hietanan (2014, p.2) as a "mobility distribution model in which an individual's major transport needs are met over one (digital) interface and are offered by a service provider". He indicates that transport services are integrated into "bundles" and operate in an interconnected way.

As noted above, MaaS has the promise to be customized for the user, therefore its planning and development requires a deep understanding of the different types of travellers. Previous investigations have already contributed to the identification of who will embrace MaaS. Some of them –such as Alonso-González et al., (2020) and López-Carreiro et al., (2021)– have focused on detecting the relevant factors in people's willingness to adopt MaaS for building clusters of users. While the first study applies a Latent Class Cluster Analysis and obtains five different profiles, the second selects an agglomerative hierarchical clustering technique and recognizes four groups. Their results have in common one cluster: the "MaaS lovers" – who share some characteristics such as a significant environmental sensibility and a strong positive attitude towards new mobility services.

At the moment, machine learning is becoming a more widespread technique in transport studies and, in particular, with clustering purposes (Sumardi et al., 2017; Alkhereibi et al., 2021; Lu et al., 2023). This method applies algorithms to explore the relationships between data, learn patterns, and make predictions on them (Basu & Ferreira, 2020). There are machine learning algorithms for both supervised and unsupervised learning problems. Clustering is usually employed on unsupervised learning problems, where the data are not labelled and therefore the algorithms do not know the outcome in advance. The algorithm tries to find similarities between the data and group them according to the number of clusters k informed as input.

Machine learning has also been applied recently in MaaS-related research. Zijlstra et al. (2020) established five indicators for identifying early adopters of MaaS and performed a regression analysis using Lasso – a popular machine learning algorithm applied for obtaining sparse models with accurate predictions and enhanced interpretability. Duan et al. (2022) developed and tested models to predict MaaS uptake with an Artificial Neural Network (ANN) method. In short, they estimated different models by trip categories, using 33 input variables. Aman and Smith-Colin (2022) recognized a set of factors that influence satisfaction with MaaS as a function of gender, using text mining and then an ordinal logit regression for associating these factors with satisfaction levels. Despite all these studies, to the best of our knowledge, *k-means clustering algorithm* has not yet been applied in this context.

3. Selection of the case study: Madrid Metropolitan Area (Spain)

The study is developed in the metropolitan area of Madrid, Spain, which has a population of 7.3 million inhabitants and covers an area of around 5,335 square kilometres (Comunidad de Madrid, 2021). This region shows a monocentric urban structure that has grown around the City of Madrid, with 3.3 million residents in the 2021 Census.

Madrid Metropolitan Area has a dense and well-structured multimodal public transport system, which is the result of a set of strategic policies that have largely endorsed the extension of the metro and suburban networks, the improvement of the bus networks, the construction of efficient transport interchanges, and the provision of subsidies for public transport services. In recent years, a broad range of shared mobility services (such as car-, moto-, bike-, and scooter-sharing services) have been implemented to complement the ‘traditional’ options. It is worth pointing out that these new alternatives are mostly concentrated in the city centre, which is quite inconvenient for the inhabitants of the periphery and suburban zones.

In addition, several travel-planning applications are currently available in Madrid for moving through its metropolitan area (e.g., Google Maps, EMT App, Mi Transporte). However, none of these applications provides today the same opportunities as MaaS.

4. Methodology

This section describes the methodology applied to evaluate potential users of MaaS, with the aim of outlining customized recommendations for each profile that promote more sustainable behaviours.

4.1. Survey design and Data collection

To achieve our research purposes, we first design an online survey divided into four main blocks of questions:

- **Block 1. Use of technological tools**. Given that MaaS is based on a digital interface, we enquire about respondents’ affinity with these tools in their daily activities.
- **Block 2. Personal attitudes and lifestyle preferences**. To identify attitudinal (latent) factors that may influence individuals’ likelihood of using MaaS, we adapt validated items from the literature aimed at capturing their preferences regarding social connectedness (need to belong to a social network), cost-effectiveness (producing a good service with the least cost possible), self-satisfaction (feeling of personal achievement), social acceptance (fitting in with the social norms), perceived ease of use, openness to new mobility options, openness to new technologies, and environmental values. All these constructs have been associated with MaaS by previous authors (e.g., Mehdizadeh Dastjerdi et al., 2019; Dastjerdi et al., 2019; Lopez-Carreiro et al., 2021). In this block, respondents are also asked about their willingness to adopt MaaS, on a five-point Likert Scale – which represents our dependent variable.
- **Block 3. Mobility patterns and travel-related characteristics**: car ownership, availability of driving licence and public transport pass, etc. We also include questions related to individuals’ daily mobility habits and most frequent trips.
- **Block 4. Socioeconomic and demographic information**: gender, age, level of education, occupation, place of residence, etc.

The data collection campaign was conducted online between March and May 2022. For the sample recruitment we adopted two simultaneous approaches to ensure its representativeness in terms of modal share. On the one hand, we collaborated with the Madrid Public Transportation Authority (Consorcio Regional de Transportes de Madrid – CRTM), which distributed the online questionnaire to subscribers of the monthly public transport pass. On the other hand, we subcontracted a specialized panel provider with extensive experience on the performance of surveys in the case study selected. This company helped us in the distribution with a method that combined the advantages of the face-to-face and the electronic survey (Monzon et al., 2020). Interviewers approached people at strategic points, providing them with a QR code on a card to access the questionnaire. This mixed technique was mainly used to target car users. A pilot survey was carried out before the definitive one to check whether the survey was comprehensible and correct any potential drafting error.

4.2. Data analysis

Cluster analysis is a technique that allows cases to be grouped according to one or more variables (Watters & Andrew, 2008). Elements are aggregated according to similarities between them, calculated using a function of distance. If the number of groups expected to be found in the data is known, it can be fixed as an input parameter for the algorithm and it will generate the cluster accordingly. Otherwise, there are ways to estimate the ideal number of clusters at first and generate them afterwards. This analysis is commonly applied in many areas of transport studies (McCormack et al., 2012; Gomari et al., 2021; Niu et al., 2021; Zhang et al., 2022) for exploring patterns within a set of variables.

In this case, we apply a machine learning clustering algorithm to assess profiles of potential users of MaaS based on a set of attitudinal (latent) factors. This algorithm is referred as the *k-means algorithm* or *Lloyd's algorithm*, and it is part of the Scikit Learn library (Pedregosa et al., 2011) – a well-known Python package for machine learning models. The main algorithm assumption is that the optimal placement of a centre is at the centroid of the associated cluster. For each z centre there is a set V(z) of data points lying in the Voronoi cell of z, being z the nearest neighbour of each k cluster. The algorithm then calculates in each iteration a new centre point z to the centroid V(z) and updates the V(z) set by recomputing the distance from each point to its nearest centre. It stops when certain convergence criterion is met (Kanungo et al., 2002).

In summary, we followed the subsequent steps to achieve our research purposes: (i) first, an Exploratory Factor Analysis (EFA) was developed in SPSS to verify the underlying structure of the attitudinal items measured through the survey (block 2); (ii) second, a Shapiro-Wilk Test was applied to check the normality distribution of the attitudinal (latent) factors; (iii) third, we ran a correlation analysis to identify the attitudinal (latent) factors with a moderate/high association with the willingness to adopt MaaS; (iv) fourth, we performed a cluster analysis with the factors identified in the previous step to uncover profiles of potential users of MaaS; and (v) finally, we outlined a set of customised strategic recommendations to foster MaaS within each cluster, with the ultimate goal of promoting more sustainable behaviours.

5. Results and discussion

In total, we collected 9,095 valid responses. The sample is composed by a higher proportion of women than men (57% versus 43%), with ages mostly distributed between 27 and 64 years old. Regarding the place of residence, 44% of the respondents live in Madrid City and 56% in the metropolitan area.

As previously indicated, we focus on attitudinal (latent) variables for exploring individuals' willingness to adopt MaaS. First, an EFA verified the consistency of the eight factors measured through the survey (block 2): social connectedness, cost-effectiveness, self-satisfaction, social acceptance, perceived ease of use, openness to new transport options, openness to new technologies, and environmental values. The Shapiro-Wilk Test was then performed, showing that none of the variables followed a normal distribution ($p<.05$). As a result, and given the ordinal nature of our variables, the Spearman Correlation Coefficient (rho) was applied.

The matrix in Fig. 1 is used to identify the attitudinal factors associated with the willingness to adopt MaaS. All calculated coefficients are positive, which means that an increase in these variables will also be related to an increase in the dependent variable. The magnitude of the correlations is interpreted accordingly to the guidelines set by Cohen (2013), who refers to a medium correlation between variables when rho > 0.30. As a consequence, five factors (social connectedness, cost-effectiveness, self-satisfaction, social acceptance, and perceived ease of use) were selected for developing the cluster analysis in Python, using the k-means algorithm. With the Elbow Method (Fig. 2), we set the optimal number of clusters k equal to three.

An ANOVA Test allowed us to check the heterogeneity between the groups obtained. The five variables included in the calculation resulted significant ($p<.001$), so the averages are different for each cluster. Finally, we compared the three segments of individuals (Table 1) for assessing their inner particularities in terms of demographic, socioeconomic, and travel-related characteristics.

The first cluster, or "MaaS-enthusiasts", includes those travellers with the highest willingness to adopt MaaS, on average. It also shows the highest average punctuations for all the attitudinal variables. With regard to the socio-demographic characterisation, we detect that the vast majority of these individuals are females. Although it is not a consensus whether female or male are more prone to adopt MaaS, studies that support a higher probability by female are Lopez-Carreiro et al., (2021) and Hasselwander et al., (2022). Finally, it is key to note that environmental values seems very important for this group, which accounts with the highest percentage of daily cyclists (44%). These green concerns are seen as enablers for making people reduce private car usage and shift to more sustainable modes (Fioreze et al., 2019).

Fig. 1. Spearman Correlation matrix.

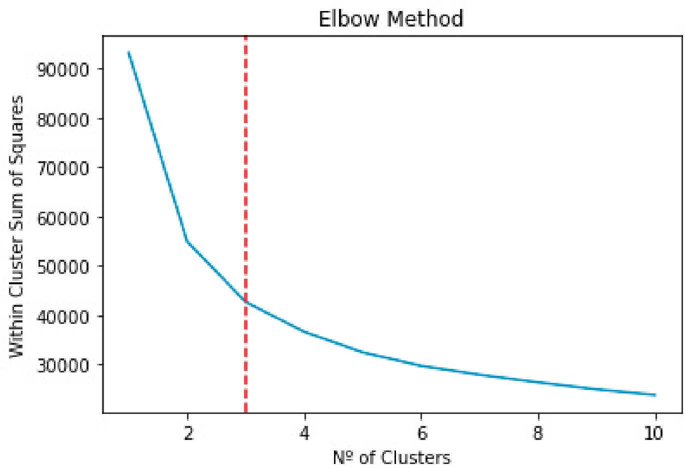

Fig. 2. Elbow Method for finding the optimal number of clusters k.

The second cluster is named "innovation doubtful users". Their average age (41.6 years old) is almost the same as that of the "enthusiasts". However, in terms of yearly income, this group includes a slightly wealthier percentage than the first cluster. They are the ones reporting more car usage in their most frequent trip, and at the same time they stated a high multimodality pattern, a characteristic that has been positively associated with the likelihood of adopting MaaS (Alonso-Gonzalez et al., 2020; Lopez-Carreiro et al., 2021).

Finally, the third cluster, or “anti-new technologies”, shows the lowest intention to embrace MaaS. It is the only group with a slightly higher presence of males than females (50% against 49%), and their average age (50.6) is almost ten years older than that of the individuals in the other two clusters This last result goes along with other researchers who found an inverse relationship between age and the willingness to use MaaS (Ho et al., 2018; Matyas & Kamargianni, 2019; Vij et al., 2020). The “anti-new technologies” commute less than others, and they also bike less. It was found before that people who intend to use shared mobility are more likely to adopt MaaS (Ko et al., 2022), but the bicycle itself is not pleasant for elderly.

Table 1. Three clusters: summary of their demographic, socioeconomic, travel-related, and attitudinal characteristics.

Characteristics	Variable	Indicator	Cluster 1	Cluster 2	Cluster 3
			MaaS-enthusiasts	Innovation doubtful users	Anti-new technologies
			n = 3,665	n = 4,085	n = 1,345
Demographic and socioeconomic	Gender (%)	Male	36	45	50
		Female	63	54	49
		Other	0	1	1
	Age (years old)	M (SD) [1]	40.6 (13.5)	41.6 (14.1)	50.6 (16.3)
	Household income (euros/year) (%)	No information available	2	2	3
		<20,000	22	15	22
		20,001 – 40,000	41	38	40
		40,001 – 80,000	27	33	28
		>80,000	8	12	7
	Place of residence (%)	No information available	1	1	2
		City centre	43	45	42
		Metropolitan area	56	54	56
Travel-related	Main transport mode in the MFT [2] (%)	Public transport	62	58	60
		Car	25	29	23
		Other	13	14	16
	Uses more than one mode in the MFT [2] (%)	No, unimodal	34	29	30
		Yes, multimodal	66	71	70
	Travel frequency (%)	Less than once a week	5	4	10
		Between 1 and 3 times a week	27	29	30
		More than 3 times a week	68	67	59
	Car availability (%)	No	25	24	24
		One car	55	56	57
		More than one car	21	21	18
	Riding a bicycle (%)	No	56	62	68
		Yes	44	38	32
Personal attitudes and lifestyle preferences M(SD) [1]	Willingness to adopt MaaS [3]		4.34 (0.66)	3.92 (0.68)	2.90 (1.08)
	Social connectedness [4]		5.43 (1.04)	4.39 (1.17)	3.35 (1.22)
	Cost-effectiveness [4]		5.26 (0.56)	4.43 (0.80)	4.13 (1.29)
	Self-satisfaction [4]		6.32 (1.02)	5.30 (1.09)	3.59 (1.05)
	Social acceptance [4]		5.55 (0.89)	3.59 (1.20)	2.30 (1.26)
	Perceived ease of use [4]		5.99 (0.75)	4.17 (0.99)	2.65 (1.44)
	Openness to new mobility options [4]		5.18 (1.35)	4.03 (1.41)	2.92 (1.58)
	Openness to new technologies [4]		6.46 (1.70)	5.66 (1.73)	3.31 (1.68)
	Environmental values [4]		5.90 (1.29)	4.95 (1.41)	2.92 (1.60)

[1] M(SD): Mean (Standard Deviation); [2] MFT: Most Frequent Trip. It is the trip a person makes most often, for example, to go to work or school; [3] M(SD): five-point Likert Scale; [4] M(SD): seven-point Likert Scale.

After developing the cluster characterization, we outline a set of strategic recommendations to encourage the adoption of MaaS for each profile, while promoting more sustainable habits:

- Given that MaaS operates through a digital application, “MaaS-enthusiasts” can be attracted by their high openness to new technologies. In addition, and based on their strong appreciation of social connectedness, we propose the definition of awareness-raising campaigns with a gamification approach (i.e., accumulating points for making trips by active modes and sharing burned calories or CO2 emissions saved in social media) to promote MaaS among these individuals (Casquero et al., 2022). Motivated by their significant environmental consciousness, this group seems more likely to embrace a behavioural shift towards public transport services and active modes.
- “Innovation doubtful users” have the highest car usage among the individuals of the three clusters. Hence, we

believe that certain new mobility services such as car-sharing and car-pooling would inevitably appeal to them. In line with the findings of Paundra et al. (2017), we propose to include these new mobility services in the "bundles" of MaaS, offering them as an alternative option for those occasions in which the private car is unavailable. This can help this second cluster to experience the new system and move away from car-dependent habits.

- The "anti-new technologies" are the most challenging individuals, given their low affinity with technological tools and aversity to uptake new mobility services. For this group, we recommend a hybrid system with SMS correspondence and the availability of a traditional call centre able to process trip orders for those individuals with no smartphone or internet connection to use on-demand services. In addition, a smart card ticket for validating trips in the different transport modes can help to address this issue. For this group it is also needed the promotion of new mobility services.

6. Conclusions

The present study identifies three groups of potential users of MaaS, based on an online survey developed in the Madrid Metropolitan Area (Spain). Previous literature has shown that these findings are a key starting point for defining individually tailored recommendations that encourage a shift towards more sustainable travel behaviours.

To achieve our objective, we first assessed relevant attitudinal factors on the willingness to adopt MaaS and identified the ones that most affect individuals' acceptance. Then, a *k-means clustering algorithm* was performed to find similarities within individuals and group them in meaningful clusters.

We recognised one group with a high openness to embrace MaaS ("MaaS-enthusiasts"), another group with a neutral to moderate likelihood of use ("innovation doubtful users), and a third group opposed to this new solution ("anti-new technologies"). The individuals most likely to adopt MaaS are those with higher environmental values and who are significantly open to trying new technologies and new mobility options. They are also the most frequent users of public transport services and cycling in their daily trips.

Given that MaaS technologies are not yet implemented in Madrid, we should note that our findings correspond to a dummy application, described in the survey. While this approach may be appropriate as a first step, we believe that as a future extension of this research, a study of revealed preferences would allow assessing the needs of different user profiles and obtaining relevant information for deploying a MaaS app prototype.

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