Transportation
https://doi.org/10.1007/s11116-024-10501-9

Complementing or competing with public transit? Evaluating the parameter sensitivity of potential Mobility-as-a-Service (MaaS) urban users in Germany, the Czech Republic, Poland, and the United Kingdom with a mixed choice model

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Accepted: 30 May 2024

Abstract
In this study, we conducted a comprehensive survey involving a substantial sample size (n = 6,405) of urban daily commuters across four European nations (Germany, the United Kingdom, Poland, and the Czech Republic). Our investigation contributes to an enriched comprehension of the user dynamics associated with Mobility-as-a-Service alternatives and their interrelation with public transit modalities in the context of travel preferences. Specifically, we researched the responsiveness of participants to variations in pricing and travel durations. Additionally, we examine the tendencies of various participant categories, stratified into distinct segments based on shared attributes, toward the adoption of public transportation, MaaS solutions, or private vehicular transport. Our findings highlight the essential role fundamental mobility determinants, such as price and travel time, play in influencing the likelihood of opting for a specific transportation modality. This phenomenon was particularly discernible within the "Unspecified Users" group, which gives us options to alter their behavior. The analytical framework used in our study that combined several mathematical modeling tools provided insight into the choices people make when choosing between different travel options, and our findings may be used by decision makers to create better and more informed approaches to promote sustainable alternatives to the use of cars in urban settings.

Keywords Discrete choice modeling · Multilayer mixed model · Mobility-as-a-Service · Survey data

Introduction

The landscape of urban transportation is undergoing rapid transformation, especially with the emergence of diverse on-demand modes like bike sharing, car sharing, and ride sharing. Although these mobility alternatives have existed for some time, their real-time operation within expansive urban environments has recently become feasible. This influx of services expands travel possibilities and broadens the geographical scope, but the

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profusion of choices can lead to confusion. The concept of Mobility-as-a-Service (MaaS), delivered through unified app platforms, is gaining traction due to its capacity to simplify complexity while harnessing the benefits of diverse travel options that can be seamlessly integrated. Although its definition remains evolving (Hensher et al. 2021), MaaS conventionally covers all aspects of travel, including reservations, payments and pre- / post-trip information (Jittrapirom et al. 2017), aiming to seamlessly transport users from one point to another regardless of the chosen mode. In other words, MaaS is a comprehensive and user-centric approach to urban transportation that aims to provide seamless, integrated, and personalized mobility solutions to individuals. It revolves around the concept of offering various transportation options, such as public transit, ridesharing, bike sharing, car sharing, and more, through a single digital platform or application. The goal of MaaS is to simplify the process of planning, booking, and paying for different modes of transportation, allowing users to easily navigate their journeys across various modes and providers. Particularly in densely populated urban regions where congestion, quality of life, and parking scarcity underscore mobility priorities, a robust public transportation system ideally forms the nucleus of MaaS. This system can provide first / last mile solutions or complement public transportation (PT) for specific journeys where MaaS alternatives prove impractical. When integrated with PT options, MaaS exhibits the potential to reduce car use (Alonso-González et al. 2020).

Despite a decade of discourse, the definitive contours of Mobility-as-a-Service (MaaS) remain elusive and unconsolidated. Hensher et al. (2021) underscores the uncertainty surrounding the adoption of MaaS, tracing it to recent deviations from MaaS's foundational principles. Arias Molinares (Mola et al. 2020) ventures into the facets of MaaS encapsulated by the "Ws"-when, where, who, how, and why-highlighting the ongoing evolution of MaaS's conceptual underpinnings. Amidst this fluid landscape, a common thread emerges that intertwines elements such as service integration, user orientation, mobility packaging, and the digitization of services. In summary, MaaS manifests itself as an integrated digital interface that aggregates various shared mobility services, providing users with a seamless, multimodal mobility solution, accessible through travel arrangements or encompassed within subscription packages (Guidon et al. 2020; Caiati et al. 2020; Matowicki et al. 2022).

In the sphere of influencers, Zhang and Kamargianni (2022) provide a panoramic survey of contemporary insights into the factors that underpin the adoption of emerging mobility technologies, including MaaS. This systematic review, which encompasses a collection of studies across the EU, China and Australia from 2018 to 2022, underscores the positive nexus between personal attributes, attitudes, technology acceptance, and the propensity for MaaS adoption. Further exploration of these findings reveals that an affinity for technology, a predilection for multimodal travel, and favorable perceptions of technological attributes augment the proclivity for MaaS adoption. On the contrary, safety-oriented attitudes, unimodal preferences, car ownership, and household composition exert a damping influence. However, the intersection of age, gender, and positive attitudes towards public transport yields a medley of outcomes.

Delving deeper, Durand's (2018) comprehensive literature review illuminates the nebulous nature of potential MaaS users, underlining the likelihood of early adopters hailing from youthful to middle-aged demographics, predominantly residing in urban locales. The pivotal role of user diversity in MaaS adoption is further highlighted by Lopez-Carreiro et al. (2021) behavioral model based on the Technology Acceptance Model (TAM). Their exploration of user-related latent variables reveals four distinct "mobility profiles," delineating the willingness of clusters, such as "technological car-followers," "unimodal travelers," "MaaS-lovers," and "active public transport supporters," to embrace MaaS. A similar thread is woven by Alonso-González et al. (2020), who classify user attitudes through factor and cluster analyses.

Extending the narrative, Fioreze et al. (2019) delve into user categories, revealing clusters like "MaaS curious," "frequent car drivers," "Multimodal travelers," and "Car lovers." In particular, public transport users and those who prioritize sustainable commuting are predisposed to adoption of MaaS. The relevance of demographics emerges as nuanced, unlike previous studies. Reflecting on the lack of user-focused analyzes, Maas (2022) highlight potential MaaS users as progressive, young and well educated, with a propensity to avoid private motorized vehicles. Furthermore, Matyas and Kamargianni (2021) underscores the lacuna in understanding the heterogeneity of preferences in mobility services and the scarcity of studies classifying user groups.

Addressing these gaps, Dadashzadeh et al. (2022) propose a longitudinal study to capture behavioral changes in MaaS usage after the implementation of the app, thus bridging a research void. Moreover, Ho et al. (2020) traverse the landscape of potential demand, analyzing various business models and their alignment with user preferences. Their insights indicate the resilience of car enthusiasts' preference for private transport and highlight potential conflicts between sustainability and convenience.

Although abundant studies address the heterogeneity of MaaS users, they remain dispersed in time, space, and theme. Consequently, the lack of coherent narratives precludes meaningful comparisons. Our study ambitiously endeavors to provide a comprehensive panorama of MaaS users and their pricing sensitivity, encompassing a broader spatial scope and innovative techniques that seamlessly amalgamate discrete choice modeling and group analysis-unique contributions enhancing the landscape of existing MaaS literature.

Moreover, we believe that MaaS can increase user travel satisfaction rates while facilitating modal shifts towards lifestyles centered more around public transportation and less on private vehicles. Having received substantial recent attention, hopes are high that MaaS will fuel a mobility revolution similar to the introduction of the private car in the 20th century. However, it is unclear whether the general public will follow the modal shifts ignited by MaaS pilots and whether public transportation, not just on-demand services, will play a greater role in urban MaaS offerings. In other words: will MaaS complement public transportation or simply compete with it in the long term?

Therefore, with this study, we enrich our understanding of those who choose to use MaaS and investigate the relationship MaaS has with PT in terms of preferences that can impact decisions about which transport mode to choose. To date, there has been very little quantitative research on this topic beyond the evaluation of early MaaS pilot adoption. In our investigation, we examined whether the different traveler groups we identified preferred using public transportation or, more specifically, other on-demand services, as well as how sensitive these groups were to costs and travel times. Our model analyzed the responses of a large sample of more than 6,000 daily commuters from major cities in Germany, the Czech Republic, Poland and the United Kingdom. In our exploration of commuter traits and their decision-making dynamics in relation to MaaS, we placed particular emphasis on the interplay with public transport offerings. Using an intricate multilevel analysis, we harnessed the mixed logit model, commonly referred to as the "latent class" or "hybrid" model (Walker et al. 2004; Shen 2009), to unravel the complexities inherent in this study.

Methods

This study included an extensive data collection efforts throughout Europe (as described in the following sub-section), involving the implementation of intricate surveys. Consequently, the complexity of the collected data and the study as a whole required a rigorous and deliberate selection of data analysis and modeling techniques.

Discrete choice modeling is a commonly used technique to describe the impact of the characteristics of decision makers and the attributes of alternatives on choices (Yu and Sun 2012). These models have been widely used in numerous applications for the last three decades (Bierlaire 2003). Early transport applications of discrete choice models were to examine the binary choice of travel modes, with further advances in transport applications enhanced by improved discrete modeling methods (Ben-Akiva et al. 1985).

The main statistical models used to support travel behavior research are those of the logit family, such as the multinomial logit model (MNL), the nested logit model (NLM), the kernel logit model (KLM), which is particularly useful when panel data are present, and the mixed logit model (MLM) (Zhao et al. 2020). Historically, a number of theoretical and practical studies have shown that the most suitable tool for such dependencies within the sample of repeated responses is KLM (Ben-Akiva et al. 1985; Qin et al. 2017; Bhat 1997). The most sophisticated modeling methods of discrete choice data including panel data are MLM and LCM where the latter was proven to be more accurate and suitable than the alternative (Shen 2009).

Based on the principle of Latent Class Modeling and to address the limitations of state-of-the-art models, this study was structured into six distinct phases, each encompassing specific research activities. The proposed novelty here is the addition of finite mixture modeling as a latent class (segments) identification process. The comprehensive workflow for these sequential phases is shown in Fig. 1. This illustration delineates the procedural progression in constructing an appropriate LCM tailored to examine the data set in this investigation. Subsequently, a comprehensive elucidation of each stage within the LCM framework is provided, with particular emphasis on critical components. These include the utilization of Finite Mixture Modelling (FMM) to segment respondent data and consequently establish latent classes, followed by the application of a KLM to effectively model the discrete choices made by respondents in accordance with the derived classes.

The results of the first stage of our project have already been presented and elaborated in detail in the Introduction. These were achieved with an extensive and thorough literature analysis and identification of state-of-the-art regarding both the understanding of commuter behaviors and the most promising and novelty methods for discrete choice modeling, namely in the transportation field.

This section is divided into two subsections. First, we deal with the data curation process and methods (the creation of the survey, the choice experiment, the definition of the respondent target group, and the description of the collected data). The second subsection introduces and describes the data analysis methodology, including the complex approach to the Latent Class Model.

Survey description and experiment design

The online survey was conducted in four European countries: Germany, the United Kingdom, Poland, and the Czech Republic. The survey was spread using a panel data

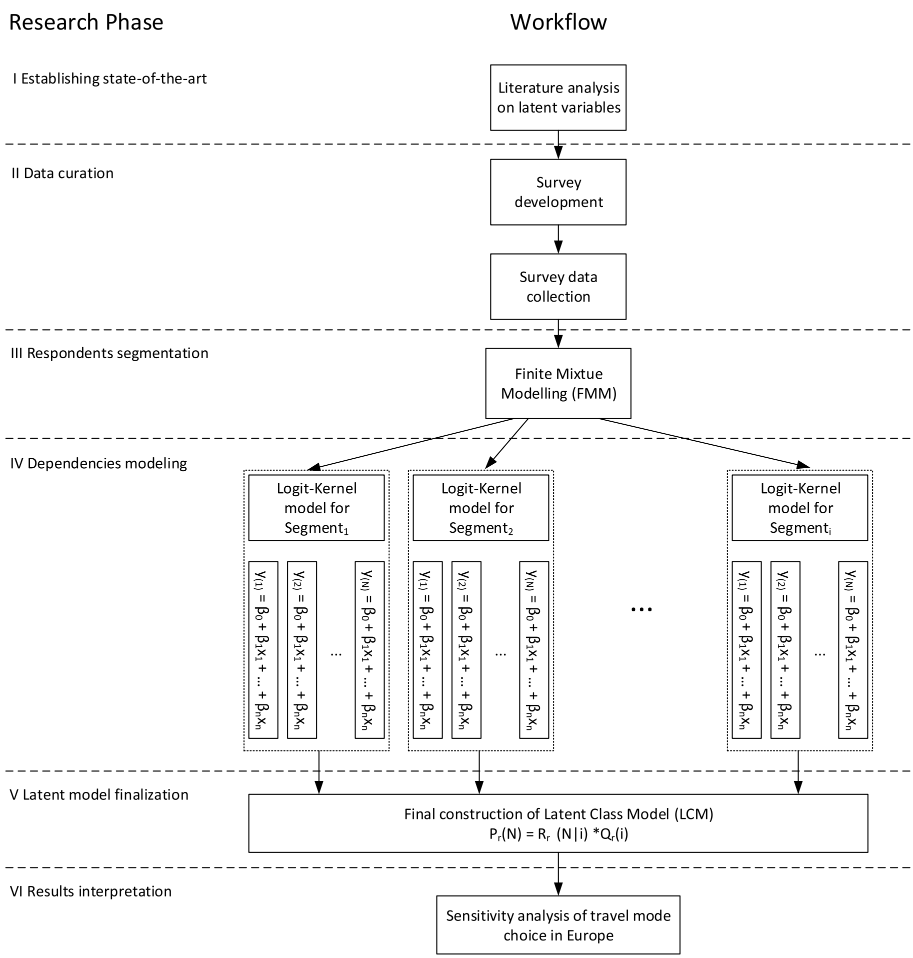

Fig. 1 The workflow of processes during research execution and construction of Latent Class Model

provider which distributes the survey through on-line channels to registered individuals and allows to set representative quota for age, sex, and residence. For each of the four countries, the questionnaire was written in each respective national language and programmed separately. The survey was open to respondents from October 16, 2020, to October 26, 2020 for a total field phase of ten days. The respondents were able to answer the questionnaire online at any time during this ten-day period. It should be emphasized that the COVID-19 pandemic was very much on the media agenda and COVID-related restrictions were also in force. Consequently, a corresponding influence of the pandemic on decision-making behaviors cannot be ruled out.

The questionnaire was divided into five parts including an introduction and a conclusion. Three parts of the survey are of relevance for this work. Part one focused on latent personality variables divided into three blocks and placed at different points in the questionnaire for the sake of variety. Information on the functional components and requirements of a MaaS application was probed within a second part. In the third and core part of the survey that related to this work, respondents were asked to rate the attractiveness of different mobility alternatives for a previously explained commuting scenario using a stated preference design (choice experiment). To create a uniform understanding among the respondents, a definition of MaaS was inserted. This reads (in the English version): "Mobility-as-a-Service describes a shift away from personally owned modes of transportation and towards mobility-provided services. This is achieved by combining public and private transportation providers through a unified gateway. Imagine that there is such a Mobility-as-a-Service offer within your city. This means that you can plan an intermodal trip by combining different modes of transport according to your needs. This service is offered by one single provider so booking, processing, and payment takes place on one and the same platform (app)".

As noted in the summary of the survey components, test participants were invited to participate in a hypothetical thought experiment in which they had to choose between six transport options to cover a commuting trip of around four to five kilometers to the city center. Alternative options included public transport, car sharing, bike sharing, micromobility, mobility-on-demand, and intermodal travel as a proxy for MaaS. For our objectives we want to focus on the seamless, end-to-end and possible intermodal routing of MaaS, and thus we pass to the respondent an option that depicts such features by showing an intermodal trip where there is a unique price, travel time and no walking or distance to reach the first element of the trip. This part of the survey was built according to Hensher et al. (2005) as seen in recent work (Ferreira et al. 2022; Ho et al. 2020). We built our experiment based on workshops conducted with project partners (including partners from Germany, Finland, Czech, Israel) plus workshops with mobility users, to assess relevant attributes and their levels.

The level characteristics were kept identical across the four countries. Only travel costs were adjusted to the respective price structures of the countries to ensure that our probe represented as closely as possible real conditions and product offers, that is, we designed our levels on real cases using cities in each of the countries surveyed where we assume a trip of around 15 min by car using Google Maps and extracted the distance, travel times, and prices for PT, carsharing, bikesharing, micromobility and mobility on demand. When the information was not available on Google Maps, we extracted the information using the respective mobility provider existing in the city. We assumed that PT could run faster for the different levels and that the other modes could run slower due to traffic conditions at the commuting time; therefore, their travel time levels increase. After defining all attributes for each country, an orthogonal design was followed to obtain a representative selection of all possible combinations. The use of an orthogonal design led to a total of 64 cards. Since this high number would have been likely to place an unnecessary burden on the test participants, four blocks of 16 cards were formed while keeping the orthogonal design. The test subjects were then randomly assigned to a block, so in total, approximately 400 participants responded to the set of cards for each block at each Country.

Before being faced with the choice experiment, participants were introduced to the scenario to be considered in the decision-making process. This stimulus served to ensure that all respondents started from the same initial situation and that there would be a common understanding of the framework conditions. The scenario described an ordinary trip through the city center in a car with a given distance and duration. The mobility options presented within the choice experiment represented alternatives to the car, from which respondents could choose the most attractive option. The test subjects were shown a total of 16 different cards as per the result of the orthogonal design and usage of four blocks. An example of the corresponding alternatives and attribute levels, for the case of Germany, is presented in Table 1.

Table 1 Example of attributes and values for the German sample

Mobility alternative	Attribute	Levels
Public transit	Price	For free/1.30€/2.60€
	Trip duration	6min./8min./10min
	Walking time	0min./5min./10min
Carsharing	Price	3.83€/5,10€
	Duration	15min./18min
	Distance to vehicle	400 m/1,000 m
Bikesharing	Price	For free /0.65€/1.30€
	Trip duration	13.2min./16.5min
	Distance to bike	400 m/1,000 m
	Route conditions	Cycling lane/regular street
Micromobility	Price	2.42€/3.64€/4.85€
	Trip duration	13.2min./16.5min
	Distance to Scooter	400 m/1,000 m
	Route conditions	Cycling lane/regular street
Mobility-On-Demand	Price	5.65€/8.47€/11.29€
	Trip duration	15min./18min./22.5min
	Distance to pick-up-point	100 m/500 m
	Number of passengers (you included)	1/3/7
Intermodal routing	Price	1.95€/2.60€/3.90€
	Trip duration	10min./13min./16min
None of the alternatives		

The intended population of the survey included adult commuters who lived in urban regions of the countries mentioned because this is also the potential target group for the use of MaaS. Thus, only people at least 18 years of age with regular mobility behaviors and living in a city of at least 80,000 inhabitants were allowed to participate in the survey. These individuals were identified as 'regular commuters' if they regularly traveled using transport at least three days a week; therefore, they have a mobility need suitable for MaaS use. Since MaaS is primarily a mobility solution for urban areas, it was possible to exclude people living in rural areas by selecting the number of inhabitants of the place of residence. After the survey was completed, the data from the four separate online surveys were combined into one overall data set. After cleaning the data, to the exclusion of participants with very fast completion times and patterns in response behaviors, the sample size was a total of $n = 6,405$ participants ($n_{\mathrm{GER}} = 1,607$, $n_{\mathrm{UK}} = 1,601$, $n_{\mathrm{CZE}} = 1,596$, $n_{\mathrm{PL}} = 1,601$).

For the final estimation of the model, only the most promising variables were incorporated into our model. Based on the extensive review of the literature on existing models that previously investigated the willingness to use MaaS, we selected the 13 variables presented here, briefly explained in Table 2.

Data processing and analysis

This stage of the project spans phases III and IV as depicted in Fig. 1. These phases led to the calculation of the odds ratio for the respondent choosing a particular mode of transportation

Table 2 Explanatory (independent) variables in the sensitivity analysis of choice

Variable	Meaning	Values
Czech Republic, Germany, Poland, United Kingdom	The survey analyzed here was carried out in four countries. This information about the "country of origin" for each completed survey was included as a parameter of the survey language. For the purposes of further analysis, this parameter was transformed into four separate dummy variables. Each of the countries had its own dummy variable	0—No, 1—Yes
Gender	Variable representing the gender each of the respondents identified. Our survey allowed the choice of a 'do not specify' option. These respondents were excluded from this study due to their very small prevalence (less than 0.1%)	0—man, 1—woman
Territory	This variable represents the size of the agglomeration from which the individual survey was collected. The bins of the agglomeration size where <10,000 <80,000 <100,000 <300,000 <1,000,000 and above	coded as discrete values 1 through 6
Household size	The number of inhabitants in a household of the respondent	1-2-3-4-5 (and more)
Age	Age of the respondent	1 through 99, continuous
Income	Income understood as per household of the respondent. Each country had different thresholds according to local conditions	1-2-3-4-5-6
Education	Similar to income level, available responses were adequately adjusted in different countries, this had to be done due to the fundamental differences in the organization of the educational systems (not every level had its equivalent across Europe). Therefore, the scale in each country was adopted as closely as possible to the five-scale pattern presented here, with preservation of the hierarchical character of the variable	1-Secondary school, 2-A-level education, 3-Foundation degree, 4-Higher Education diploma, 5-Bachelor degree or higher
Employment	This variable explained the type of employment rather than an occupation itself. The most common types of employment were provided as choices. Choices and their values were used as categorical variables	1-Student, 2-Employee, 3-Senior executive, 4-Self-employed, 5-Homemaker, 6-Retired, 7-Other (excluded in model)
Time	This variable represented the *travel time* parameter as presented to the participants in the stated preference choice experiment. To compile it in the logistic regression model, it was further coded as the ratio of the 'Travel time of MaaS service' to the PT	Values as specified in Table 1. Transformed into ratio
Price	This variable represented the *travel cost* parameter presented to respondents in the stated preference choice experiment. To compile it in the logistic regression model, it was further coded as the ratio of the *journey cost* of MaaS service to the PT	Values as specified in Table 1. Transformed into ratio

(MaaS or public transport) and the impact of their parameter (see Table 1 changes on the overall odds). It is important to note here that only the options of MaaS and public transport were investigated as direct alernatives in this analysis. Although the following paragraphs will describe an overall approach to the analysis performed, detailed methodological descriptions are available in the Appendix to this paper.

First, the segmentation of the collected respondents was performed using the finite mixture modeling technique on 113 respondent variables and their choices. The final identification of the number of segments existing in the data set analyzed was performed with the Aikake Information Criterion (AIC) and set to 5 using the elbow method. The following analysis used the Kernel-Logit model for panel data analysis within segments. This method was deemed to be the most appropriate to minimize the disturbance effect of addressing panel data when collecting multiple responses from one respondent.

Application of latent class model

Finally, following the segmentation of the data in Sect. 6.1 and model estimation for each segment in Sect. 6.2, the concept of Latent Class Model (LCM) was applied to analyze dependencies in the collected sample. As explained by Qin et al. (2017), LCM formulates latent attitudinal variables from dichotomous survey items. It was first introduced as a modeling framework by Bhat (1997), and in its formulation, although similar to the mixed logit model, it allows for more flexibility, since it does not require any parameter distribution. Nevertheless, this framework did not include details on parameter estimation techniques; rather, it only formulated an overall problem definition and modeling structure. LCM assumes that the preference for the choice and the parameters that influence this choice can differ in society and can be further divided into smaller, more homogeneous and hence easier to model classes (also called segments). Assume that in reality there exist segments of commuters (according to their behaviors) and that the segment each traveler (represented by respondent) belongs to is not known. The probability that the traveler r is in segment i can be expressed in the following way (Qin et al. 2017):

$$Q_r(i) = \frac{exp(Z_i\gamma_i)}{\sum_{i=1}^{I} exp(Z_i\gamma_i)}, \qquad i = 1, 2, \dots I, \tag{1}$$

where γ_i is the estimated parameter of the segmentation function and Z_i is the observed variable.

On the other hand, the probability that the respondent r that belongs to segment i chooses the N option is equal to:

$$R_r(N \mid i) = \frac{exp(\beta_i I_{rN})}{\Sigma_{j\in A_r} exp(\beta_i I_{jN})}, \tag{2}$$

where β_i is the parameter that will be estimated within the segment i and S_{rN} is the variable for the traveler r choosing the mode N in the segment i.

Hence, the resulting probability that the mode N is chosen by the traveler r in the segment i is formulated as follows:

$$P_r(N) = \sum_{i=1}^{I} R_r(N \mid i) \cdot Q_r(i), \tag{3}$$

and the likelihood function follows:

$$\ln L = \sum_{r=1}^{R} \ln P_r = \sum_{r=1}^{R} \ln[\sum_{i=1}^{I} R_r(N \mid i) \cdot Q_r(i)]. \tag{4}$$

Now that the theoretical framework for the Latent Class Model in our study has been introduced, the respondent (traveler) segmentation procedure and within-segment choice modeling is described in more detail, in the following subsections modeling restults are introduced.

With reference to Eq. 3, we now derive:

- $Q_r(i)$ as a probability resulting from segmentation of respondents achieved with the Finite Mixture Model according to Sect. 6.1, and
- $R_r(N \mid i)$ as a probability resulting from the Kernel-Logit model according to Sect. 6.2.

From this we derive the final probability of the predicted response with our model $P_r(N)$. The results of this modeling are presented in the following section.

Results

Before providing in-depth elaboration of the complex modeling results, we consider it interesting and purposeful to briefly identify each of the five segments resulting from finite mixture modeling (FMM). Our model was conceived as a multilevel approach with a separate approach to individual groups of respondents. Morevorer, the segments were not predefined based on experts opinionated decisions on user clusters in the measured sample, but rather were determined by data mining technique known as finite mixture modeling. Therefore, the following section consists of two subsections. First, we describe in more detail results from the FMM, and the second subsection is fully dedicated to the modeling results.

Identification and description of segments

As mentioned in Sect. 6.1, five segments (also called “profiles” here) were identified in the responses to our study. In this section, based on the descriptive statistics analysis of each segment, we provide (if possible) the most prevalent and distinctive characteristics that separate each segment from the rest of the respondents. One of these characteristics is age, but it is not the only one; see Fig. 2.

The histogram showing the number of respondents in each identified commuter profile is presented in Fig. 3 where part (a) of the figure represents the choice of PT and part (b) the choice of MaaS. The number of respondents varies from 264 in segment 5 to 2,673 in segment 4. The right side of the Fig. 3 represents the number of respondents in each segment who chose "public transport", "MaaS", or “none of the alternatives” at least once in the choice experiment.

The number of respondents in each sector was then inspected again, with respect to the number of individual transport mode choices in each segment. It is important to note here that the numerous options available in the choice experiment led to a significant

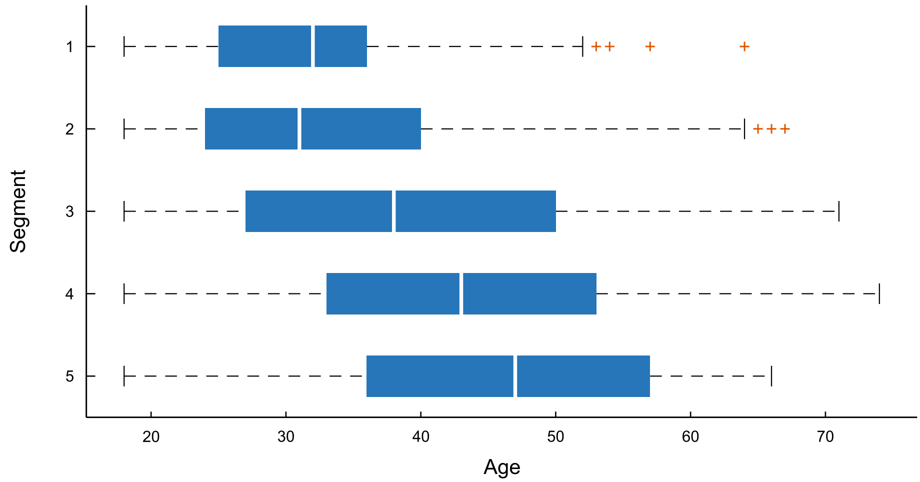

Fig. 2 Box plots of respondents average age in respective segments; 1—Carsharers, 2—Car users by choice and beliefs, 3—Unspecified users, 4—Habitual car users by necessity, 5—Frequent public transport users

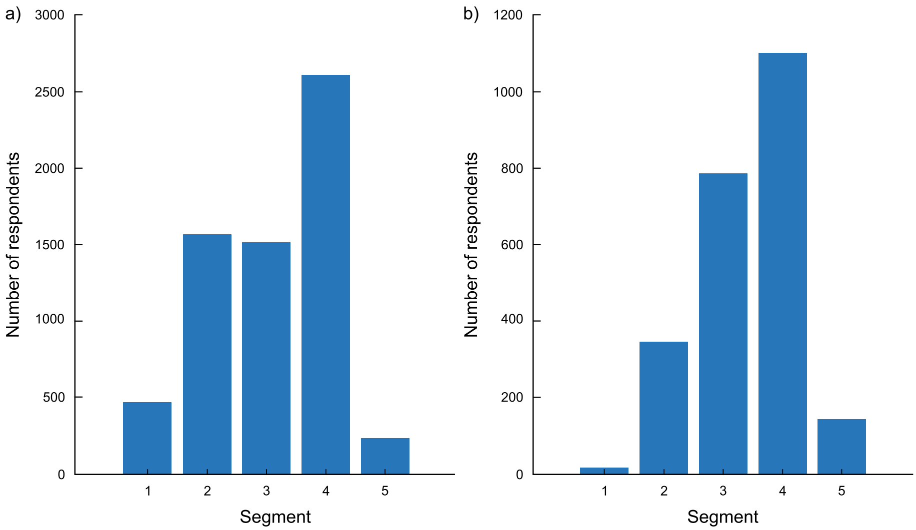

Fig. 3 Histogram of all respondents in segments 1-5 (**a**), and respondents who have chosen "PT", "MaaS" or "none of the above" at least once in choice experiemnt (**b**), where: 1—Carsharers, 2—Car users by choice and beliefs, 3—Unspecified users, 4—Habitual car users by necessity, 5—Frequent public transport users

dispersion of respondent responses to different mobility options. Here, we focus on ’Public transit’, ’intermodal mobility’ (which we describe as MaaS), and the last option in which the respondents did not feel that any option fit them. Since the respondent could not choose a personal vehicle as one of the modes of transport, this option was treated as “I don’t want to change from the current mode’ (mainly personal vehicle).

Segment 1—carsharers

The first identified profile, with almost 500 respondents, can be described as supporters of the shared economy (Fig. 4a). These commuters noted that they often tend to travel using carsharing or carpooling, and they were the youngest respondents in our survey, with the largest families (usually four or more people in the household). According to the results of our survey, they (in general) used carsharing to travel to/from work and believed that it is important to share a ride with colleagues. In addition, they often expressed the belief that social acceptance and image are somewhat important when choosing a mode of travel. Therefore, they could commonly be referred to as 'carsharers'. Notable is that most of the respondents in this category in our survey were men.

Segment 2—car users by choice and beliefs

Segment 2 was described as commuters who are convinced that they must regularly use personal cars for daily travel (Fig. 4b). Here, these were predominantly young people with families (average household size: 3.2) who expressed a belief that cars are important for safety, security, and a high level of comfort. They noted that they are also not very keen to consider a different travel mode in the future based on their stated preference responses. The most valuable advantage of traveling by car for these people was the short travel time and the social image related to the mode of transport used.

Segment 3—unspecified users

Although we were able to specify a user profile for four segments of five, this was not possible for Segment 3 (Fig. 4c). These users had average answers to all the attitudinal and preference questions, consisted of a mixture of both genders, and were an equally distributed cross section in terms of of household sizes, incomes, and so on. The only 'unique' characteristic of this segment was that the dominant age was 40-50 years old and that the majority of these respondents were from the Czech Republic. However, this is not enough to consider a broader characterization of these respondents. We believe that undecided, uncertain respondents who are skeptical of shared mobility options but who could change could be a way to generalize this profile.

Segment 4—habitual car users by necessity

Segment 4 profiling revealed that these are mainly commuters in our survey who reported not living close to their daily travel destinations (Fig. 4d). This was visible from a number of parameters examined, as well as from the responses to the survey. For example, those who responded tended to live in large cities and reported that they usually commute to work every day. They said that they consider the car a valuable travel mode and are less likely to use alternatives such as micromobility, cycling, and walking. However, due to their commuting patterns, public transportation was not very common in their stated choices. Therefore, unlike the respondents in Segment 2, they

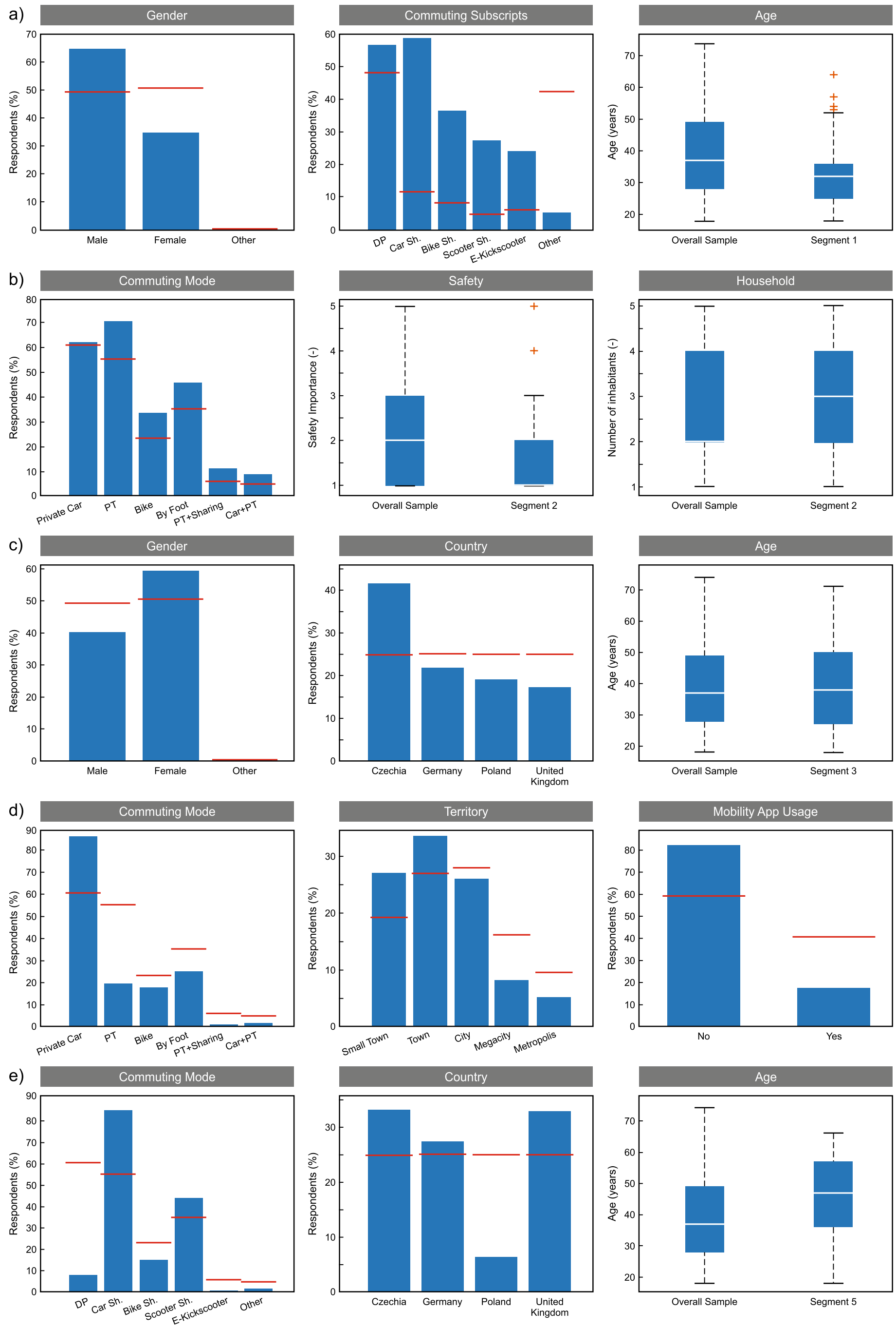

Fig. 4 Most distinctive characteristics of each Segment; a—Carsharers, b—Car users by choice and beliefs, c—Unspecified users, d—Habitual car users by necessity, e—Frequent public transport users. Red line depicts a corresponding level in overall sample

said they do not mind traveling with means other than a private car, but noted that transportation systems do not provide them with viable alternatives to car travel.

Segment 5—frequent public transport users

Segment 5, in general, represented the oldest group of respondents in our study (see Fig. 2).

These travelers, although they noted they use personal vehicles, also report traveling very often by bus or tram (Fig. 4e). Almost 85% of them said they use public transportation at least once a week. This "pro PT" attitude was also visible in the part of the survey in which they answered attitudinal questions about their opinions on public transport and how much they agree with statements such as "Public transport can be problematic with respect to hygiene" or "Safety is a concern when traveling with public transport." For all of these questions, the members of segment 5 tended to assess these statements with very small significance (average 4.7 on the 5-point Likert scale, where significance was in descending order).

This very basic characterization of each segment as the basis for the latter interpretation of user sensitivity modeling regarding a possible choice of travel mode "away from the habitual use of cars." These results will be presented in the following subsection, and discussion regarding their meaning will continue in Sect. 4—Discussion.

Description and elaboration of choice models across segments

In the following subsections, an in-depth elaboration of choice modeling is presented for each particular segment. Our focus was on determining how sensitive participants were to the various parameters of the transport modes when planning everyday trips. Despite the initial framework presented in Fig. 1, the actual sample in this study did not allow the mode choice model to be used with respect to public transport and intermodal mobility for Segment 1. As presented in Table 1, each respondent was presented with the choice of six travel modes and a seventh choice, 'no alternatives'. Only two travel modes (public

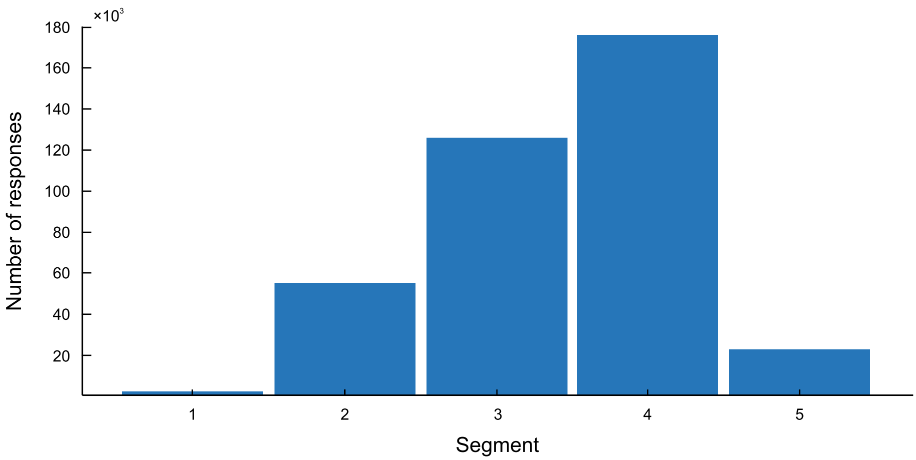

Fig. 5 Histogram of usable response numbers in each Segment; 1—Carsharers, 2—Car users by choice and beliefs, 3—Unspecified users, 4—Habitual car users by necessity, 5—Frequent public transport users

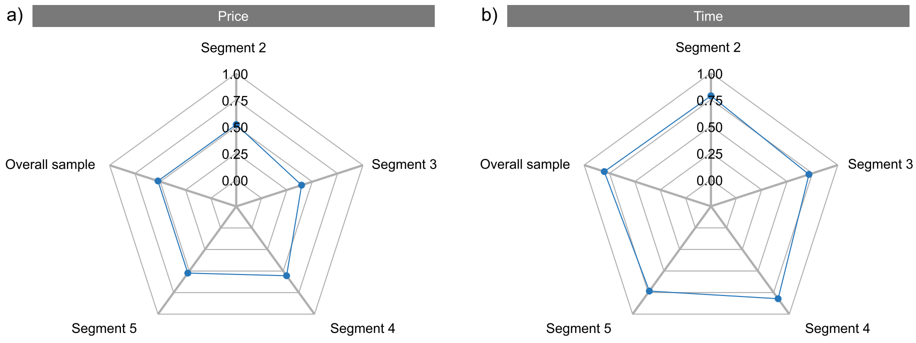

Fig. 6 Radar plot with odds ratios resulting from the influence of price (a) and time (b) factors on public transport choices. Segments; 1—Carsharers, 2—Car users by choice and beliefs, 3—Unspecified users, 4—Habitual car users by necessity, 5—Frequent public transport users

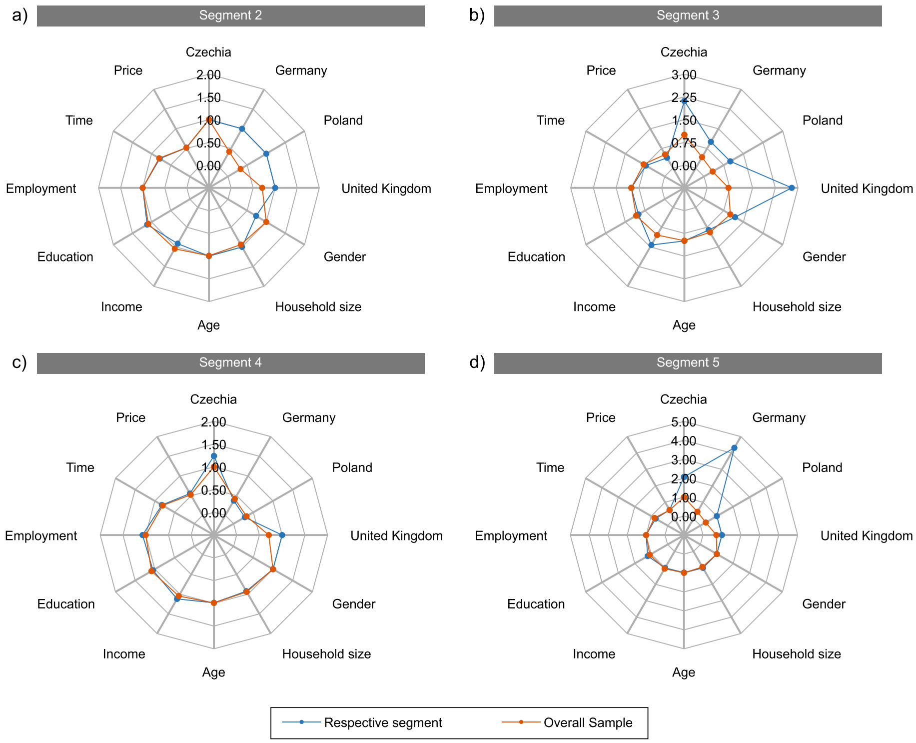

Fig. 7 Radar plot with odds ratios resulting from "willingness to use public transport" modeling in respective Segments (Note, Segment 1 is not elaborated due to unsatisfactory sample size).Segments; 1—Carsharers, 2—Car users by choice and beliefs, 3—Unspecified users, 4—Habitual car users by necessity, 5—Frequent public transport users

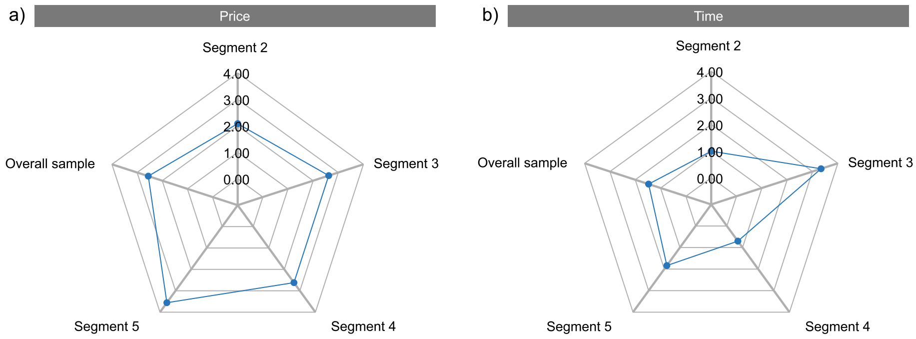

Fig. 8 Radar plot with odds ratios resulting from influence of price (a) and time (b) factors on MaaS choice. Segments; 1—Carsharers, 2—Car users by choice and beliefs, 3—Unspecified users, 4—Habitual car users by necessity, 5—Frequent public transport users

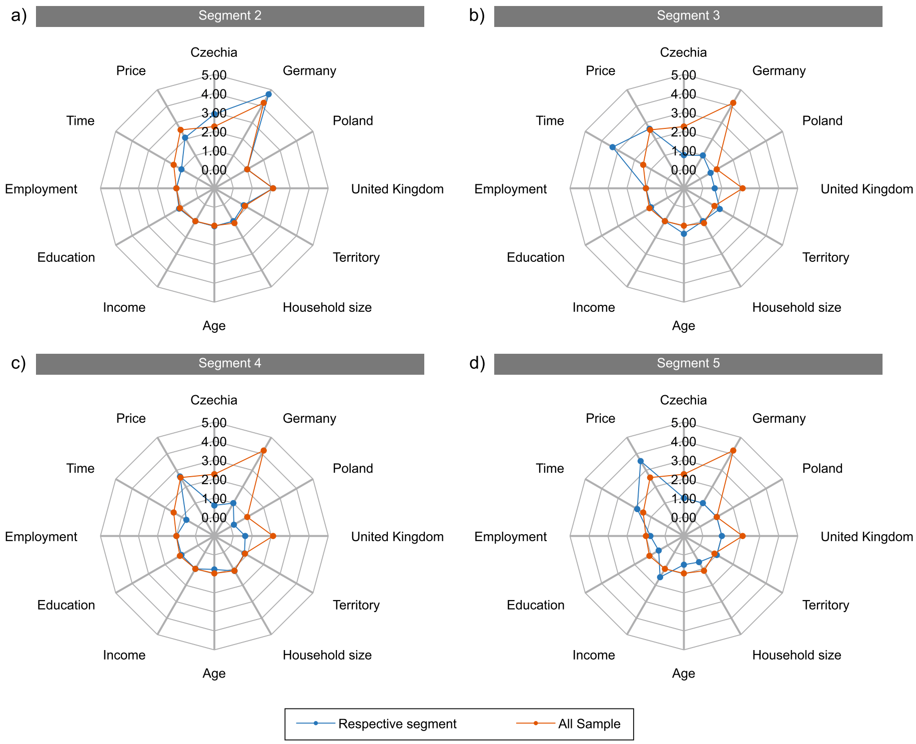

Fig. 9 Radar plot with odds ratios resulting from "willingness to use intermodal transport" modeling in respective Segments; 1—Carsharers, 2—Car users by choice and beliefs, 3—Unspecified users, 4—Habitual car users by necessity, 5—Frequent public transport users (Note, Segment 1 is not elaborated due to unsatisfactory sample size)

Table 3 Odds ratio of public transport preference for each segment for the different commuter or scenario parameters examined

Variables	Log-odds (Logit)				
	Segment 2	Segment 3	Segment 4	Segment 5	Overall sample
Czechia		2.115	1.239	2.067	
Germany			0.374	4.315	0.418
Poland			0.284		0.328
United Kingdom		2.793			0.706
Gender	0.733	1.182			
Household size		0.856	0.925		0.942
Age			0.989	0.979	0.992
Income	0.917	1.426	1.121		1.047
Education	1.116		1.048	1.215	1.086
Employment			1.069		
Time	0.785	0.716	0.821	0.737	0.802
Price	0.518	0.395	0.554	0.524	0.523

transport and intermodal/MaaS) were analyzed here, and the reference category chosen was 'none of the alternatives'. Therefore, from Table 1, we only used Answers 1, 6, and 7. For Segment 1, we encountered a situation where there were not enough choices of categories of our interest. We assign this fact to the identified respondent profile of the respondents of Segment 1. As stated in Sect. 3.1, Segment 1 representing travelers who said that they are very friendly toward shared economy-related transport modes, such as carsharing, carpooling, shared scooters, etc. We believe that the attitudes and characteristics of the respondents in segment 1 are why only 16 respondents in this segment (out of the total of 493—see Fig. 5) chose public transport or the intermodal mode of transport. Due to practical reasons and the nature of regression modeling, the model for these respondents could not be calculated with statistically significant results. Therefore, although a total of five response segments were initially identified, only Segments 2 through 5 will be analyzed below. To better understand the impact of the segmentation of our response base, we present here the regression results for each segment with reference and comparison to the results achieved for the whole sample (see Figs. 6, 7, 8 and 9 or Tables 3 and 4 for the modeling results of the choice PT and MaaS choice, respectively.

The analysis of commuter sensitivity to the price and time values for the alternatives offered is analyzed at the very beginning of each model section and, therefore, although presented in summary table and segment graphs, this is not discussed for each segment separately. This is because these are the parameters of a transport mode itself and, as will be presented below, these tended to be uniform across all sections (they were not influenced by sociodemographic nature of different user segments—their profiles). Note that in the figures depicting the radar plots of the regression results, odds ratios were used to present the influence of personal characteristics or route parameters on a preferred mode of travel. Therefore, this should be read as the influence ratio that a given parameter had on the resulting transport choice (public transport or MaaS). For example, referring to the results of segment 2 in Table 3, an odds ratio value of 0.733 means that the respondent, being male, decreased his chance of choosing public transport for his daily commute by a factor of 0.733 (women were generally more likely to consider a change in our study).

The elaborated results only consider the estimated coefficients that are statistically at the level of $\alpha < 0.01$. Therefore, only the magnitude of the effect of the variable on the dependent variable is presented, and not its statistical significance.

Willingness to use public transport

According to the proposed workflow (see Fig. 1, individual regression models were calculated for each dependent variable modeled Y_n (in our case Y_1—choice of public transport and Y_2—choice of intermodal transport service/MaaS). Thus, the results in this section will be divided into two parts, the first describing the regression results for each segment (and their differences) for the public transport mode, and the second constructed in a similar manner for the MaaS option.

In order to magnify and highlight the effect of different variables for a modeled choice, we analyzed the results for each segment with reference to the overall sample (the unsegmented respondent pool in our survey).

The overall effect of the time and price factors

Separately from the segmentation process and the modeling for each segment, an additional analysis of the sensitivity of participants was performed for the travel mode price and time parameters. To achieve this, price and travel time were variables that changed in each presented scenario (see Table 1. Since, due to the international nature of the study, the exact values of travel cost and time varied between the four countries studied, it was not possible to directly incorporate them into this study. Therefore, these values were converted to discrete ordinal values (1/2/3) and, as such, were used to represent the increase in time or cost value in the scenarios presented. As expected, both price and time were considered important to respondents when choosing their mode of travel. In the case of PT, this effect was relatively constant for each segment analyzed, and for price, the chances of using PT doubled when this mode was cheaper, while the effect of shorter travel times was twice that of the PT. This is an important finding, since it provides data supporting the assumption that possible shorter travel times are valued less than the cheaper cost in the eyes of the respondents to this survey (see Fig. 6).

Segment 2—car users by choice and beliefs

In Segment 2, habitual car users, the most important user characteristics that influenced the odds of using public transport were gender and properties such as price and travel time. It is important to note that this segment, in general, reported not being interested in changing their mode of travel. Although respondents from Germany and Poland were about half as likely to choose public transport, in (constructed) Segment 2, country of origin did not have such a notable effect on their choice of travel mode. However, women were generally less likely to choose public transport, by approximately 25% less than the overall sample. The other factor that slightly negatively influenced the chances of choosing public transport was the income level. The impact of the education level of a respondent was similar in size but opposite in direction from the effect on respondents in Segment 2. All of the effects mentioned above were statistically significant.

Segment 3—unspecified users

The situation for Segment 3 was very different. Here, we observed a very strong impact of the country of origin for the Czech Republic and the United Kingdom. Being from the Czech Republic increased the odds of choosing public transport as a travel mode by a factor of more than two, and being from the United Kingdom, almost 2.8. In the case of Germany and Poland, these effects were significantly smaller or absent. Income again played an even greater role as a factor in terms of choosing public transport, affecting the choice of PT in a positive way. The same can be said for women. The size of the family appears to have led to slightly less use of public transport. We could only hypothesize that there is a source in various family-related constraints and the complex routes that respondents take every day, for example, for transporting children to schools or kindergartens, though this was not examined in this study.

Segment 4—habitual car users by necessity

Similar to unspecified users, we observed for Segment 4 a significant impact of the country of origin on the stated choice of transport mode. This time, the highest impact on public transport use was observed for Germany and Poland, although these odds were negatively affected, unlike in the cases of the Czech Republic and the United Kingdom. For Germany and Poland, being in this category reduced the chances of choosing PT by a factor of three, similar to the levels observed for the overall sample. Although many other variables, such as household size, age, income, and education level, were significant, their importance in terms of public transport choice? was very small.

Segment 5—frequent public transport users

Segment 5, the group of participants who are the most in favor of PT in this study, was again significantly different mainly in terms of country of origin parameters. The biggest impact here was seen for the German and Czech respondents. For both countries, being casual PT users further increased the odds of choosing this transport mode in the future. Again, the Czech respondents (similar to segment 3) showed an increase (by a factor of 2) of the chances of traveling by PT, and the German respondents showed a factor increase of 4.315. Higher levels of education also increased the chances of using PT by more than 20% in this study. This effect was almost three times greater than for the general sample (21.5% vs 8.6%).

Willingness to use intermodal transport services

The second choice modeled was the stated preference for MaaS (the intermodal mode) as transportation for hypothetical situations. For modeling purposes, again, the same choice experiment explained in Sect. 3.2 was used. Table 4 presents an overview of the modeling results for the overall sample and each segment, accordingly.

A brief comparison of Tables 3 and 4 shows a clear tendency towards the opposite effect of particular variables on the results. This is to be expected, as the two transport modes (PT versus MaaS) were presented to participants as direct alternatives to each other. Generally speaking, Czechs, Germans, and citizens of the United Kingdom were significantly

Table 4 Odds ratio of MaaS preference in each segment, for different examined commuter or scenario parameters

	Log-odds (Logit)				
Variables	Segment 2	Segment 3	Segment 4	Segment 5	Overall sample
Czechia	2.909	0.749	0.931		2.252
Germany	4.721				4.199
Poland		0.623	0.802		
United Kingdom	2.092	0.623	0.663		2.094
Territory	0.788	1.182	0.903		0.858
Household size			1.211	0.589	1.117
Age		1.397	0.813	0.513	0.970
Income				1.507	
Education	1.143			0.533	1.095
Employment				0.764	
Time		0.297	1.359	0.641	0.678
Price	0.481	0.382	0,387	0.293	0.391

less likely to choose the MaaS than PT. The same effect is clearly present for high travel times and costs, where travel cost is the more dominant of the two variables. A fascinating result was observed for the territory of residence parameter, where we can see that, overall, the larger the urban area a respondent came from, the lower the odds that they would use MaaS. This goes against the common assumption that multimodal travel and micromobility could be more developed, easier to use, and therefore beneficial in bigger cities. Another interesting result was the positive effect of household size on the odds of using MaaS. Education also had a modest (9.5%) but positive effect on the chances of traveling with MaaS.

The overall effect of the time and price factors

We analyzed the sensitivity of respondents to price and time factors. Unlike public transportation, the effect of travel time on choices was much less uniform for MaaS. Not only did shorter travel time not have a significant effect on habitual car users, it appeared to actually adversely affect people traveling shorter distances. This is an important finding, since it identifies weaknesses of the MaaS travel mode in the eyes of specific potential user groups. Regarding changes in travel costs, the effects were much more unilateral than for travel times, but the effects were not constant in magnitude. In general, how much MaaS costs appears to be a very important parameter to consider when planning a new MaaS service, especially to attract new potential users to a service service (Butler et al. 2021).

Segment 2—car users by choice and beliefs

Segment 2 represented habitual car users. Unlike the PT case, we observed very similar results for this segment compared to the overall sample. Features worth noting are even stronger effects of Czech and German origin (2.909 vs 2.252 for Czech and 4.721 vs. 4.199 for German) resulting in choosing MaaS over PT. Another difference worth noting is the insensitivity to the travel-time factor. In the overall sample, we observe an increase in odds of 1.474 while in the case of segment 2, time was not identified as a statistically significant parameter in our model. Again, as in the case of modeling PT preference, travel time and travel cost sensitivity will be analyzed separately at the end of this section.

Segment 3—unspecified users

In Sect. 3, modeling results appeared to contradict our assumptions about the characterization of these respondents as simply "undecided". During the segment profile achieved by modeling finite mixtures, segment 3 was identified as ’unspecified’. At first glance, this segment might seem as if it were the most similar of all segments to the overall sample. However, because of the extraction of the most characteristic response segments from the overall sample, the unspecified users differed quite a bit from the overall sample. First, Czechs in this segment were actually less likely to choose MaaS than public transport as a travel mode. The odds were 0.749 (roughly 3 to 4), while in the overall sample, the same odds were almost three times as high. A similar decline in the odds of using MaaS can be seen for respondents from the United Kingdom. Here again, the odds dropped from 2.094 to 0.623 compared to the overall sample. Another significant finding was the influence of age, where older respondents said they were more likely to use MaaS. Importantly, the actual travel mode parameters themselves appeared to have the greatest impact on the respondents in this segment, as suggested by our results. This, together with the identification of these users as ’unspecified’ (which can also be understood as not having a specific attitude toward any mode of transportation), could be hypothesized as the result of respondents being the most rational thinking commuters or those with the least prejudices among respondents in this study. Commuters without strong habits or preferences might be the most influenced by MaaS parameters. A quick look at the results of the PT modeling for Segment 3 (Sect. 3.2 or Table 3) seems to confirm these conclusions, although the effect for this segment was not as strong as it was in the PT model.

Segment 4—habitual car users by necessity

Among the respondents who tend to commute to nearby areas on an everyday basis, we observed the greatest dislike for the idea of traveling with MaaS in all segments in this study. This is probably related to their main identifying characteristic, the short travel distance, where there is probably very little or no need/benefit to MaaS. Furthermore, these respondents stated that they occasionally commute to work/school on foot. We observed that not only did most of the parameters have very little effect on MaaS travel decisions, but when they did have an impact, it was mostly negative. Such an effect is surprising, especially for the UK respondents, which might be the result of various factors ranging from insufficient existing MaaS infrastructure, no need to use MaaS, or even such high satisfaction levels with existing PT or other options that MaaS is an attractive alternative, although this study did not examine these factors in greater detail. Our previous work has already suggested that there is a negative effect on MaaS attractiveness if users are satisfied with PT services (Matowicki et al. 2022). Again, travel distance seems to be the most convincing argument to logically interpret the negative influence of shorter travel times on MaaS adoption. Additional application and use of multimodal transpiration might seem excessive and unattractive to these commuters. This is supported by identifying users in this segment who stated they are car travelers by necessity, meaning they are not particularly against public transport but they are unable to use it easily.

Segment 5—casual public transport users

Segment 5, casual public transport users, results support the initial segment profiling. Here, satisfaction with existing PT services could also have played a significant role in the generally negative attitude towards a MaaS travel option. Note that most of the sociodemographic characteristics of the participants in this segment had a negative effect on choosing MaaS. This is especially visible with age, where younger people were more eager to use new travel modes, while the older the respondent, they less willing they said to abandon occasional PT use in favor of MaaS. For people with better incomes who might see MaaS as being more convenient than regular PT, it appeared from our results that they were eager to consider MaaS options without considering price. At the same time, in general, casual public transport users tended to shift towards MaaS if the cost/travel time conditions turned in favor of MaaS. This effect was especially strong for the case of the price variable, where the cheaper MaaS service increased the odds of being used by a factor of over 3.5 (higher prices decreased the odds by 0.293). This is by far the biggest effect observed for this segment of respondents.

Discussion

Our study shows parallels and differences in segmentation approaches and outcomes for MaaS user types compared to the previous studies mentioned in Sect. 2.1. Although categorization is done mainly within four (e.g. Fioreze et al. 2019) to five (e.g., Alonso-González et al. 2020) segments, the characteristics of each segment in this study are different and influenced the distribution of the respondents. With regard to the number of segments, the development of a 'neutral' category is another difference (performed by Alonso-González et al. (2020), for example). Such a category, not used here, would bring with it the advantage of avoiding the dilution of segments, which also influences the distribution as well as the accuracy of the segments. Furthermore, the categorization of sociodemographic values used here is more finely granular compared to previous studies on MaaS adoption (see Alonso-González et al. (2020), Lopez-Carreiro et al. (2021), Fioreze et al. (2019)). Nevertheless, in Lopez-Carreiro et al. (2021). We found parallels to our study in the characteristics for segment descriptions. This applies, for example, to the variables of socioeconomics and demographics (e.g., gender, age, income, or household structure). Taking into account the types and names of the segments, we found that Alonso-González et al. (2020) characterized a segment as 'unspecified users', as we did (Fioreze et al. 2019). Car users were placed in two subsegments, as we did in our study, but an additional segment of "MaaS curious" was not identified in our study.

It is important to note that our results on the choice of mode (public transport or MaaS) per segment refer to a comparison against the odds of choosing a car as a mode of transport.

Overall, taken as a whole, the participants illustrated a tendency toward a higher probability of using MaaS than public transport. This effect is interesting because public transport has been identified as the backbone of MaaS systems (Kamargianni et al. 2015; Matyas 2020; Caiati et al. 2020). We conclude that other modes of transport (or combinations of transport options) lead to a higher probability that people will use MaaS instead of public transport. However, this strongly depends on the experience and satisfaction of travellers with existing transportation options, especially public transport. A comparison between countries shows that the discrepancy (extreme) between nonprobable public transport use and probable MaaS use is most pronounced in Germany. Here, participants were much more open to using MaaS than public transport. This could be because (more) MaaS services might already be established and matured in Germany (e.g., Jelbi is a popular example). Fiorello et al. (2016) showed that people in northern and central Europe have more knowledge about new mobility alternatives (in the case of their study, car sharing) than elsewhere in Europe, which may support our findings for Germany. However, in general, participants in our study shared the same pattern of sensitivity to pricing, both for public transport and MaaS. The higher the price for public transport and MaaS, the less willing one is to use either option. Others have confirmed this finding, such as (see Caiati et al. 2020, p. 138). Since MaaS can be considered a new mobility option, using MaaS as an 'innovation adoption decision' (Caiati et al. 2020), the willingness to pay for MaaS options could illustrate that people are conservative/cautious or sensitive about price points than when considering public transport, which is a long-standing transportation option in the countries observed here. This effect was supported in previous studies (Mola et al. 2020; Brown et al. 2006) that found that perceived costs influence mobility use mainly in the first stage of the life cycle (MaaS can be considered in this phase), while in the maturity phase (where public transport is classified), people are less concerned about prices (Mola et al. 2020).

Female car users by choice and beliefs: using PT and MaaS less often

When looking at car users according to choice and beliefs, the results showed that safety plays the most important role when choosing modes of transport. Doubts about public transport safety, especially for the women in this study, could be the reason behind these concerns (Ait Bihi Ouali et al. 2019) for decisions about public transport and the use of MaaS (Sochor et al. 2017). Furthermore, previous studies have proposed that family responsibilities could be another underlying reason that contributes to perceptions of safety when traveling (Dobbs 2007). Our study confirmed previous findings that families with younger children are less likely to use MaaS than other options (Zhang and Kamargianni 2022). Furthermore, Harumain et al. (2022) found that mothers always depend on cars because they perceive traveling with children in this way to be easier and more convenient. This could also apply to the women in our study, who may have found that cars are more convenient than mobility options, but investigating this question in more detail was beyond the scope of our study. For Female Car Users by Choice and Beliefs, the preference for private cars was so noticeable that even in lower income situations, the women investigated in this study would rather use a car than PT. Furthermore, a fundamental aversion to MaaS has been observed in previous studies showing that car use is an important aspect that influences people's MaaS use decisions (Alonso-González et al. 2020; Fioreze et al. 2019).

Unspecified users: high price sensitivity

The group of "Unspecified Users" in our study was characterized by a high number of people aged 40–50 years. They were more sensitive towards prices-especially in public transport prices-than the whole sample. When prices fell, participants in this group were more likely to use public transport and MaaS options. A reason for this, according to Caiati et al. (2020), is that public transport seems to be the preferred mode for particular age groups, and this may apply to these Generation X participants. When the most frequently used mode of transport in daily life is negatively affected by price, a higher sensitivity is the consequence. In terms of income in our study, higher incomes improved the chance that public transport would be used, but not MaaS. This lower probability of MaaS use for unspecified users could be due to a lower technology affinity, as well as 'attachment to the business-as-usual case' (see Narayanan and Antoniou 2023, p.12), but probing this was also beyond the scope of this study. Another possible reason proposed in previous studies is that older people are often undecided about the potential use of MaaS (Matowicki et al. 2022). For this group, longer travel times led to lower chances of using public transport and MaaS. We conclude that the basic factors that impact the use of mobility options, such as price or travel time (Kamau et al. 2016)—regardless of the respective mobility form (public transport or MaaS)—are basically the drivers of increased usage for the group of unspecified users. However, these findings could also be the result of existing public transport offerings with high frequencies and better service coverage in big cities; as well as the fact that our scenario focuses on a trip of around four to five kilometres and thus travel cost and walking distance are more dominant aspects.

Further research is necessary to test these assumptions and identify additional characteristics of this group. As an example, people living in Czech Republic and United Kingdom both reported a higher chance of using PT but a lower probability of using MaaS. In general, people in the Czech Republic are known to be satisfied with the current quality of PT (Froněk et al. 2020). In general, previous research has shown that people who are satisfied with PT and do not use it often do not feel the need for MaaS, as they are already satisfied (Matowicki et al. 2022), confirmed also by Simma and Axhausen (2001) (a UK study) which shows similar results, however, noting that PT usage increases for interurban travels but that private cars are often chosen for suburban travel.

Habitual car users: MaaS brings greater comfort, by necessity

For the Habitual Car Users by Necessity segment, it is clear from our study that household size matters when considering public transport and MaaS use. The larger the household in our study, the more likely the household member was to use MaaS; the smaller the household, the more likely public transport would be chosen. We assume that Habitual Car Users by Necessity participants perceived MaaS to be more practical and functional than public transport, but this was beyond the scope of our investigation. It might be because MaaS services based on car use (e.g., carsharing, ride pooling, and hailing) are perceived as more advantageous than by public transport. This contradicts a study by Matyas and Kamargianni (2019), which found that in MaaS containing both cars and public transport, only the latter was perceived to have benefits. In our study, longer travel times for this group led to increased MaaS use and lower public transport use. MaaS was perceived as being more comfortable than public transport; traveling longer with MaaS (and probably Habitual Car Users by Necessity participants primarily thought about car use) increased the likelihood of using MaaS. This finding resonates through the literature, where car users show the least likelihood of using MaaS (Ho et al. 2020) "because they usually believe in the necessity of owning a car as a family with children: (Alonso-González et al. 2020). Furthermore, they might be addicted to private vehicle travel (Zhang and Kamargianni 2022). These "car" advantages were observed in our study, with this group being very "car sensitive".

Frequent public transport users: similar as car users by choice and beliefs, however sensible to prices and educational levels

The Frequent Public Transport Users group had the most participants in Germany and the Czech Republic. Our results showed that the higher the income, the more likely participants were to use MaaS but not public transport. This finding suggests that this group uses public transport out of conviction, regardless of financial situation, although a deeper investigation was beyond the scope of this study. We found parallels of this behavior in the results for the Car Users by Choice and Beliefs group (i.e., preference for car use regardless of income). Compared to other groups, Frequent Public Transport Users were more sensitive to higher MaaS prices, confirming previous research (Ho et al. 2018) that revealed a lower willingness to pay for MaaS in the group of frequent public transport users. The main reason, according to previous research, is that public transport users overlap with groups that are sensitive to travel prices and tend to have lower incomes (Zhang and Kamargianni 2022). Furthermore, our study revealed that Frequent Public Transport Users with lower levels of education and a tendency to be unemployed were more likely to use MaaS. Different conclusions were drawn by Vij et al. (2020), who found that full-time employees were more likely than others to use MaaS, while retirees are least likely to consider MaaS. Fioreze et al. (2019) found those with higher education were the core of so-called 'MaaS lovers'.

Conclusion

Although sustainable mobility is currently a widely debated social topic, discussions often narrow down to debates about the phasing out of fossil fuels and adopting electric or hydrogen-powered vehicles. Although such discussions might lead to more efficient engines or spur innovation in renewable energy, we feel that not enough attention is paid to promote changes in our travel behaviors. A trip not made is much better for the environment than a trip in an electric vehicle. The conventional mode choice paradigm necessitates a transformation to encompass emerging alternatives such as micromobility and MaaS, with the latter emphasizing a user-centric rather than a car-centric perspective. This also has the potential to have an impactful improvement on the sustainability of urban transportation systems through comprehensive policy integration.

This paper provides a better understanding of how the more than 6,ooo urban daily commuters in our multilevel study of four European countries (Germany, the United Kingdom, Poland and the Czech Republic), residing in cities over 80 000 population, made choices regarding their likelihood of using public transport and MaaS. It is important to note that the total sample has a slight overrepresentation of males (65%).

However, such a slight overrepresentation is addressed by having gender in our modeling approach. The key underlying objective was to learn more about the circumstances that could convince different types of participants to abandon cars and use alternatives. Using the finite mixture model, we were able to group the respondents, based on their reported travel habits, into five different segments (or user profiles). For each segment, using the Logit-Kernel model, we analyzed which variables could positively or negatively influence the willingness of participants to use alternative transportation modes instead of cars.

Two results of interest from this segment analysis are that females are usually concerned with safety and males are more in favour of car-sharing. Nevertheless, one of the most significant findings is related to the differences between participants who live in the four countries surveyed. Although we confirmed numerous variables that influence the chances of using MaaS among participants, we found that their effect was not the same across national boundaries. This led to the conclusion that, although there are increasing numbers of research studies on MaaS and public transport preferences, conclusions drawn from local studies must be confirmed before they are generalized and applied to a different setting.

Looking at factors that have the potential to increase the attractiveness of public transport and MaaS, our research confirmed previous findings that both time and travel cost are very important factors that influence the choice of transportation. In our study, the effect of travel time and price on public transport was observed fairly uniformly across the different segments, with a higher cost reducing the likelihood of PT travel. Longer travel times did not affect PT choices as much as cost. We however highlight that our results are true for big cities and trips to the city center as our SP experiment scenario represents a trip of around five kilometers to the city center and our sample collected in big cities, thus in general traveling by PT is faster than car based trips, although walking time comes on top. For decision making regarding MaaS, we observed more differences across the segments, apparently influenced by the attitudes of the respondents. For MaaS choices, prices played a greater role than any sociodemographic characteristic. Thus, economic value (as perceived by users) is likely to play a key role in the design of MaaS systems.

We were also able to identify other factors that can make choosing MaaS more attractive, but different user segments in our findings displayed different behaviors. Our results imply that it may be difficult to influence the behavior of those who use cars by choice and beliefs, but there are differences even within this segment that varied between the countries studied. Younger people appear to be more willing to use MaaS than habitual car users (Segment 4 in this study) and casual public transport users (Segment 5), but this was not the case for unspecified users (Segment 3). People with higher incomes who casually use public transport (Segment 5) were more likely to choose MaaS, but other factors such as higher education had the opposite effect.

Finally, we note the fact that the survey was conducted during the pandemic, even though at a point in time when measures were being released, the number of infections was decreasing, and ridership was returning to values pre-pandemic (Ferreira et al. 2022). One of our results showed that segment two had safety concerns about why the car was preferred over PT, which could be linked to hygiene concerns due to COVID-19 and the need to socialize, even though it was asked for the respondent to assume that COVID-19 is no longer a problem. We also remind the reader that our experiment focused on the seamless end-to-end trip that MaaS can provide, thus not focusing on other attributes such as bundles or app characteristics.

Our complex approach, which combines several mathematical modeling tools, has demonstrated its ability to provide insight into mode choice behavior. We were able to identify different segments of participants (user groups) and then study the most significant factors that influence their decision making. This is important not only from the research perspective, but also can be useful to decision makers, who can target their mobility awareness campaigns more effectively to certain types of users or create new and more direct policies (e.g., low pricing) to support alternative travel modes.

Appendix

Segmentation of respondents - finite mixture model

The response patterns among respondents in marketing and various opinion-investigating surveys cannot be assumed to be uniform. People differ in terms of their opinions and attitudes; therefore, it is normal for response behaviors to be heterogeneous. The Multinominal Logit model assumes that each respondent's (r) replies are independent and the model cannot account for the variability in the behavior of the respondents. We applied finite mixture modeling (Nagy et al. 2011) to take into account the data dependency due to unobserved heterogeneity in the sample of the respondents. The general model in our study was expanded to account for two different types of heterogeneity. First, respondents may differ in terms of their answer patterns, resulting in variations in the likelihoods with which they typically check various rating response categories. By applying whole data set segmentation, we could account for these differences in response styles. Second, the heterogeneity aspect was related to the panel character of the collected data (that is, the interdependence of multiple responses collected from the same respondent) and was addressed in the dependency modeling with Logit-Kernel model.

Clustering was used for 113 variables, most of which were represented on a 5-point Likert scale, and some were binary (e.g., gender). The data set had 6,406 records, each representing responses to the questionnaire of individual respondents. The method used for clustering was based on the modeling of the data with a mixture. The components of this mixture described individual clusters in the data set. Furthermore, these clusters (also called segments) were intended to reflect groups of people with specific attitudes toward MaaS-specific answering patterns in our survey.

Due to the large size of the task, two measures were used:

1. The components were described by a binomial distribution. It had only one parameter and the flexibility of its probability function was convenient for the description of clusters.
2. The variables were assumed to be mutually independent. This is acceptable when we want to determine the number of clusters, and not their shapes.

Under these assumptions, we accepted the theory of independent mixtures. The data were treated like realizations of the discrete variable denoted by

$$x = \left[x_1, x_2, \cdots, x_{113}\right], \tag{5}$$

each variable x_i having binomial distribution

$$Binom_{x_i}(p_i) = \binom{N_i}{x_i} p_i^{x_i} (1 - p_i)^{N_i - x_i} \tag{6}$$

For each variable x_i, we also introduced a so-called pointer variable c_i. This was a discrete random process whose values pointed to the active component within variable x_i. These pointers were described by a categorical distribution

$$f(c_i \mid \alpha_i) = \alpha_i. \tag{7}$$

Then, what we needed for estimation was the joint distribution of the unknown objects for each variable x_i

$$f(c_i, p_i, \alpha_i \mid x(t)) \tag{8}$$

, where $x(t) = \{x_1, x_2, \cdots x_t\}$ and the lower index denoted the discrete time.

For this distribution, we applied the Bayes rule and then used factorization.

$$f(c_i, p_i, \alpha_i \mid x_i(t)) \propto f(x_{i;t}, c_i, p_i, \alpha_i \mid x_i(t-1)) \tag{9}$$

$$= f(x_{i;t} \mid p_i) f(c_i \mid \alpha_i) f(p_i \mid x_i(t-1)) f(\alpha_i \mid x_i(t-1)) \tag{10}$$

where we used independence induced by the introduced models and treated each variable x_i separately. This relation presented the Bayes' rule for a mixture but only for known values of the pointer. As they were not known, we needed to estimate them. This estimate was given by the distribution.

$$f(c_{i;t} \mid x_i(t)) = \int_{\alpha_i} \int_{p_i} f(c_i, p_i, \alpha_i \mid x(t)) dp_i d\alpha_i, \ \forall i \tag{11}$$

. This formula determined weights $w_i = [w_1, w_2, \cdots w_{n_c}]_i$ (n_c is the number of components) which were probabilities that the i-th entry of the current data record belonged to an individual component within the i-th variable.

Using this formula in the Bayes' rule above, we could estimate the components in a standard way, with the only difference being that the data coming to the statistics update were multiplied by their respective weights.

However, the above procedure works only for the predetermined and fixed number of components. To discover the real number of components in our dataset, we used the AIC coefficient (Akaike information criterion (Sakamoto et al. 1986)), see Fig. 10. We ran the estimation process for various numbers of components and selected that for which the AIC coefficient had the smallest value.

The search was started with two, four, six and up to 12 components and then refined in the area of minimum. The results are shown in Fig. 10.

From Fig. 10, we can see that the optimal number of components according to the so-called Elbow method (Bholowalia et al. 2014; Syakur et al. 2018) is five. This was further confirmed as a point of the biggest change of the gradient in the AIC figure between the two following segment numbers.

The structure of the resulting segments and their statistical analysis are presented in Sect. 3.

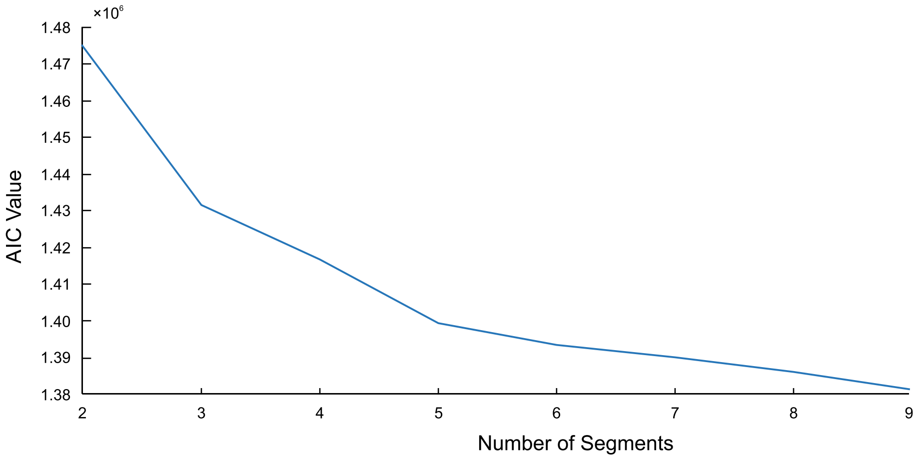

Fig. 10 The results of AIC evaluation for Finite Mixture Modelling for data segmentation

Logit-Kernel - the discrete choice model

The second layer of the proposed model was a parameter estimation to discover the relationship between endogenous and exogenous variables and the explained variable of the model.

The general discrete choice model for a given individual n ($n = 1, \dots, N$) was formulated simply as follows:

$$y_{in} = \begin{cases} 1 \text{ if } U_{in} \geq U_{jn}, \text{ for } j = 1, \dots, J_n \\ 0 \text{ otherwise} \end{cases}, \quad (12)$$

$$U_{in} = X_{in}\beta + \eta_{in} \quad (13)$$

where N was the sample size and an alternative i ($i = 1, \dots, J_n$) was the number of alternatives in the choice set C_n of an individual n. In this case, y_{in} indicated the observed choice and U_{in} was the utility of alternative i as perceived by this user. This model had two natural extensions. The assumption that the disturbances are i.i.d. Gumbel led to the tractable, yet restrictive logit model. The assumption that the disturbances were multivariate normal distributed led to a flexible but computationally demanding probit model.

Since, in the data collection phase, we applied a choice experiment with a survey panel where we collected multiple responses (choices $p = 1, \dots, P_n$) per respondent and the choices were not independent, the probability of a sequence of choices was not equal to the product of individual probabilities. A common method for addressing the panel form of the data is to introduce random variations in preference in the modeling framework. The logit-kernel (LK) model, also known as the Mixed Multinomial Logit (MMNL) model, directly treats the repeated choice nature of the panel data by introducing a variation in sensitivities across respondents, with intrarespondent homogeneity. Typically, to adjust our choice model, the resulting Logit-Kernel for panel data took the following form (Walker et al. 2004):

$$U_n = X_n\beta + F_nT\zeta_n + \nu_n \tag{14}$$

where:

U_n is a $(J_nP_n \times 1)$ vector of utilities

X_n is a $(J_nP_n \times K)$ matrix of explanatory variables

β is a $(K \times 1)$ vector of unknown parameters,

F_n is a $(J_nP_n \times M)$ matrix of factor loadings, including fixed and/or unknown parameters,

T is a $(M \times M)$ lower triangular matrix of unknown parameters

ζ_n is a $(M \times 1)$ vector of i.i.d. random variables with zero mean and unit variance,

ν_n is a $(J_nP_n \times 1)$ vector of i.i.d. Gumbel random variables with zero location parameter and scale equal to $\mu > 0$. The variance is g/μ^2, where g is the variance of a standard Gumbel $(\pi^2/6)$.

In our model (Eq. 14), the unknown parameters were μ, β, and those of F_n and T. X were observed, ζ_n and ν_n were not observed. The key in terms of identification was that the covariance matrix examined for identification was now of dimension $J_nP_n \times J_nP_n$. As noted by Ben-Akiva et al. (2002), this allows potentially many more disturbance parameters to be estimated, which in turn is suggested by the Order Condition alone, stating that the maximum number of (alternative-specific) disturbance parameters may be as high as $JP(JP-1)/2-1$. For our study, the Logit Kernel was used with the inclusion of an additional factor representing latent characteristics of an individual, such as awareness of safety, environmental concerns, or perceived social importance. This approach has already been applied with great success; see Toledo (2003). Such latent characteristics, which are directly unobserved to an analyst, enter all utilities for a person (just as, e.g., income would).

Author Contributions Michal Matowicki: Conceptualization of this study, Methodology, writing—original draft preparation, Project administration. Pavla Pecherkova: Data Analysis, Methodology. Marco Amorim: Conceptualization of the experiment, Validation, Investigation, Writing—Original draft preparation, Project administration, Funding acquisition. Mira Kern: Investigation, data collection. Nicolaj Motzer: Interpretation of results, Writing of original draft preparation. Ondrej Pribyl: Supervision, Validation, Writing, Review, and Editing.

Funding Open Access funding enabled and organized by Projekt DEAL. This study is the result of research carried out in the following projects:

• "Smart City - Smart Region - Smart Community" - project (CZ.02.1.01/0.0/0.0/17 048/0007435) financed by the Czech Operational Program "Research, Development, and Education" for the implementation of the European Social Fund (ESF) and the European Regional Development Fund (ERDF).

• 'MaaS component assessment and system planning for cooperative value creation (MaaS together)' financed by EIT Urban Mobility, as Activity 20006 of the Business Plan 2020.

Declarations

Conflict of interest The authors state that there is no conflict or Conflict of interest in this work.

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