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How does transport supply and mobility behaviour impact preferences for MaaS bundles? A multi-city approach

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ABSTRACT

Mobility-as-a-Service (MaaS) bundle design has recently gained increasing attention. Previous work has identified socio-demographics and current travel behaviour as drivers towards adopting MaaS bundles. Yet, the focus has been on (scientific) trials in one specific area or on one specific service. We extend this work by analysing the influence of transport supply and mobility behaviour on preferences for MaaS bundles in multiple cities. To this end, we conduct a stated preference experiment in 83 cities in Germany. Respondents choose between two MaaS bundle options and one pay-as-you-go option. Besides public transport, we include shared e-scooters and bikes or carsharing and ridepooling in the bundles. To integrate city characteristics we merge this data with supply data from the shared services and data about public transport quality in the respective cities. We find previous shared mobility usage to positively and car usage to negatively influence bundle uptake. While included units are crucial for bundles integrating car-based shared modes, additional prices beyond these units are more important for shared micro-mobility services. The quality of the local transport system and shared mobility supply is an important precondition for MaaS bundle uptake.

1. Introduction

Mobility-as-a-Service (MaaS) is a popular term currently taken up by academia and practitioners. Using travellers' everyday companion, the smartphone, MaaS providers offer the service by drawing on digitised infrastructure (Guidon et al., 2020). This enables the integration of several modes, particularly emerging ones such as shared cars and bikes or ridesourcing (Tsouros et al., 2021; Reck et al., 2020). Precisely, "MaaS is a framework for delivering a portfolio of multi-modal mobility services that places the user at the centre of the offer" (Hensher et al., 2021b). Further, "[...] MaaS is an integrated transport service brokered by an integrator through a digital platform" (Hensher et al., 2021b). Many expect a mobility revolution from this concept that can be traced back to 1965 (Reck et al., 2020). This expectation focuses on challenges especially urban areas face, such as emissions, noise or competition for space (Mouratidis et al., 2021; Mulley, 2017). To realise this expectation, the supply- and demand-side have to be combined across different cities to support actors in offering appropriate services in viable cities and enable transport planners to mitigate the challenges. Doing so can help increase transport efficiency, facilitate first- and last-mile trips, and reduce car dependence.

The idea of integration can be found in MaaS bundles. Bundles as a business practice are rooted in marketing (Stremersch and Tellis, 2002). A bundle is a package combining several different products or services into one. Transferred to transportation, MaaS

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bundles are mobility plans that integrate several modes into packages with a certain amount of useable units per mode (Reck et al., 2020; Caiati et al., 2020; Ho et al., 2021b).

Previous work finds bundles to be significantly more attractive to potential users than separate services (Guidon et al., 2020). However, subscription rates are low (Caiati et al., 2020). Resulting choice behaviour is investigated using stated (SP) and revealed preference data although the latter is still scarce (Mulley et al., 2020; Ho et al., 2020, 2021a; Hensher et al., 2021a). The impact of multimodal mobility behaviour has been in the focus of some work, too (Matyas and Kamargianni, 2021; Ho et al., 2021a). Bundles integrating public transport (PT) are more attractive to users (Tsouros et al., 2021; Caiati et al., 2020; Song et al., 2021) but travellers prefer both the traditional as well as more innovative services (Tsouros et al., 2021). While PT is integrated in most experiments, previous work differs in integrating further shared modes (Reck et al., 2020). Ridehailing or on-demand buses are less often and shared e-scooters are not at all part of experimental designs so far (Reck et al., 2020). The surveys conducted are usually part of trials with a specific service or location focus. This makes drawing more general implications from these surveys difficult and limits transferability. Further, there is a demand-side focus, which implies that differences of city characteristics such as PT quality or supply of integrated modes has not been considered in quantitative analyses. However, considering these characteristics is crucial to understand choice behaviour of respondents in different contexts and shed light on where MaaS bundles could be attractive and how they should be designed.

Current work leaves two gaps: first, what is the effect of integrating more and different shared modes, particularly shared e-scooters and ridepooling, into MaaS bundles across different cities? Second, which influence do different prevailing transport supply and city characteristics have on MaaS bundle choice? Answering these questions has important implications for policy and practice regarding infrastructure development meeting both the standards of modern transport planning and user needs. Using SP data and integrating further data for German cities, we contribute to the growing body of knowledge in two ways: first, we present findings about MaaS bundles including shared e-scooters and bikes or shared cars and ridepooling. These two designs allow comparisons across the bundles. Second, by following a multi-city approach and using data about transportation characteristics of cities, we draw conclusions about the effect of different preconditions of cities towards MaaS bundle choice.

Following this introduction, we provide an overview about the status quo in the literature and derive our contributions (Section 2). We introduce the data used in Section 3 and describe the survey design and method used in Section 4. We present our findings in Section 5, and discuss these in Section 6. The conclusion and potential future research completes this paper (Section 7).

2. Literature review

MaaS has particularly been enabled by information and communication technology, i.e. mobile internet and smartphones, making it one of the latest emerging technological solutions for current challenges in transportation (Mouratidis et al., 2021; Feneri et al., 2020; Mulley, 2017). These are especially salient in urban areas where emissions, noise or competition for space are very noticeable (Keskisaari et al., 2017; Nocera et al., 2015; Zawieska and Pieriegud, 2018; Zhu et al., 2020; Hagen and Tennøy, 2021; González-Guzmán and Robusté, 2011; Liu et al., 2014; Pavón and Rizzi, 2019). MaaS has the potential to mitigate several negative consequences (Mouratidis et al., 2021), especially in cities (Mulley, 2017). Yet, technology alone cannot solve longstanding transportation challenges (Mulley, 2017). To encounter these, the supply-side has to be understood in more detail for two reasons: first, to enable commercial actors to supply appropriate MaaS bundles and select viable cities. Second, to enable transport planners to respond to the challenges by increasing capacity and efficiency, facilitate first- and last-mile trips, increase space efficiency, and reduce car dependence.

We first define MaaS bundling and give a general overview before distinguishing three directions of previous work: the demand-perspective, i.e. individual characteristics of transport users; the supply-perspective on bundle design; and the supply-perspective focusing on city-specific preconditions.

2.1. MaaS bundles

MaaS offers can be understood using the level-approach classifying MaaS platforms in a range from level 0 ('no integration') to 4 ('integration of societal goals') (Sochor et al., 2018). MaaS bundles are mobility plans integrating various modes offered as subscriptions for a certain 'amount of mobility' (Reck et al., 2020). Applying bundles coincides with level 3 MaaS ('integration of the service offer') (Sochor et al., 2018). How to design bundles has been approached conceptually (Reck et al., 2020; Hensher and Mulley, 2021) and empirically (Matyas and Kamargianni, 2019a). Modes, free units, geographical region, market segment, and subscription cycle are crucial design factors. Most services are limited to one city and monthly subscriptions. While providers are interested in how to bundle for maximising profit (Reck et al., 2020; Surakka et al., 2018) and how to configure their business model (Krauss et al., 2022; Polydoropoulou et al., 2020b; Karlsson et al., 2020; Pandey et al., 2019), bundle characteristics and their consequences for uptake are analysed (Caiati et al., 2020; Ho et al., 2021a; Matyas and Kamargianni, 2019b). Previous work about the latter has focused on using SP data with few approaches using revealed preferences (Ho et al., 2021a,b).

2.2. Demand-side for MaaS bundles

Previous work about the demand-side and (potential) users can be distinguished in three approaches: adoption and usage (e.g. Alonso-González et al., 2020; Ho et al., 2020; Karlsson et al., 2020; Lyons et al., 2019; Schikofsky et al., 2020; Tsouros et al., 2021; Vij et al., 2020), design-related choices (e.g. Caiati et al., 2020; Guidon et al., 2020; Ho et al., 2021a,b; Mulley et al., 2020; Reck et al., 2020; Matyas and Kamargianni, 2019b), and consequences of usage (e.g. Hensher et al., 2021a; Hörcher and Graham, 2020; Pangbourne et al., 2020; Becker et al., 2020; Storme et al., 2020; Jang et al., 2021). We focus on the former two, particularly on bundle choices regarding offered modes and units. We use this information for our bundle design.

Socio-demographic and mobility-specific variables of subjects influence their bundle decision (Caiati et al., 2020; Ho et al., 2018). Young people subscribe to MaaS more (Caiati et al., 2020; Ho et al., 2018; Matyas and Kamargianni, 2019b, 2021; Alonso-González et al., 2020; Ho et al., 2020; Jang et al., 2021). Caiati et al. (2020) and Ho et al. (2018) find females to choose MaaS bundles more often. Matyas and Kamargianni (2021) find the opposite. Findings regarding the effect of children are inconclusive, too: Caiati et al. (2020) find people with children to be more likely to choose MaaS bundles, whilst Alonso-González et al. (2020) find the contrary. Ho et al. (2018) find a negative effect for those with two or more children compared to one. People with higher income and education choose MaaS more often (Caiati et al., 2020; Matyas and Kamargianni, 2021; Alonso-González et al., 2020). Concerning current mode choice or mobility tools, car drivers are less and multimodal travellers more likely to choose MaaS bundles (Caiati et al., 2020; Alonso-González et al., 2020; Ho et al., 2018). However, Caiati et al. (2020) find a positive effect for people with one car and a negative effect for those with more than one. Ho et al. (2020) also point towards a substitution effect of MaaS for the second car. Individuals tend to try new modes when they are integrated in MaaS bundles (Matyas and Kamargianni, 2019b). Car passengers, PT, carsharing members, and taxi users show higher probabilities to choose MaaS bundles than car drivers, cyclists or pedestrians (Caiati et al., 2020; Fioreze et al., 2019; Matyas and Kamargianni, 2021). People with access to just one car select carsharing for their MaaS bundle more frequently Caiati et al. (2020). Sochor et al. (2016) find travellers to overestimate the amount of mobility they need when buying bundles. From the demand-side literature it follows that persons using shared modes (PT, carsharing, car passengers etc.) show a higher probability to buy MaaS bundles and to try new modes in bundles. Thus, it is crucial to also understand the behaviour towards the two so-far not or sparsely investigated modes: shared e-scooters and ridepooling. Particularly as these are crucial to solve the first-/ last-mile problem (EEA, 2020). Further, demand-side work is dominated by single city analyses, neglecting different transportation systems across cities.

2.3. Supply-side: bundle characteristics

Regarding the first supply-dimension, bundle design and consequences for uptake, price and integrated modes have been in focus of previous work. Increasing bundle prices decreases people's utility (Caiati et al., 2020; Matyas and Kamargianni, 2019b; Jang et al., 2021). Offering PT, shared (e-)bikes, and ridesharing at flat prices increases utility (Caiati et al., 2020). Ho et al. (2018) find travellers are more sensitive to bundle prices than to long-term costs of private vehicles. Ho et al. (2021a) find a 7.3%–10% increase in choice probability for bundles in case of these saving 10% of the respondents' current mobility cost. Multimodal travellers show a higher willingness to pay (WTP) for integrating conventional and new modes (Polydoropoulou et al., 2020c). However, Liljamo et al. (2020) find people to exhibit a WTP that accounts for 64% of their current mobility costs only. People living in densely populated urban areas showed the lowest absolute but the highest relative WTP (Liljamo et al., 2020). Regarding integrated modes, PT has been found to be the most preferred mode (Caiati et al., 2020; Guidon et al., 2020; Matyas and Kamargianni, 2021, 2019b; Polydoropoulou et al., 2020c; Jang et al., 2021). Besides PT, car-based shared services such as carsharing (Caiati et al., 2020; Guidon et al., 2020; Ho et al., 2021a,b, 2020; Matyas and Kamargianni, 2019b; Polydoropoulou et al., 2020c) and taxi, or less frequently ridehailing (Caiati et al., 2020; Ho et al., 2018; Polydoropoulou et al., 2020c) were applied to choice experiments. Bikesharing was integrated, too (Caiati et al., 2020; Guidon et al., 2020; Ho et al., 2021a,b, 2020; Matyas and Kamargianni, 2019b; Polydoropoulou et al., 2020c). However, although shared e-scooters are widely discussed in other contexts (Abduljabbar et al., 2021; Reck et al., 2021), there is no piece of work so far integrating this expanding mode in MaaS bundle studies (Reck et al., 2020). Further, while ridehailing was integrated, its pooled counterpart ridepooling was only applied as on-demand bus (Reck et al., 2020). Thus, shared e-scooters and ridepooling have gained little to no attention so far. However, due to their efficiency in space and energy-consumption and their important role for first- and last-mile trips (EEA, 2020), these are crucial to face the cities' challenges raised above. Further, as the demand-side literature points out, shared mode users show the highest probability to use MaaS bundles, which makes it necessary to include all shared modes in respective MaaS bundle analyses.

2.4. Supply side: city characteristics

Previous work about the second supply-dimension, city-specific preconditions, has focused on land-use and qualitative views on transport supply (Wright et al., 2020; Lee et al., 2022; Wong et al., 2020; Smith et al., 2018a; Hensher, 2017; Mulley and Kronsell, 2018; Nalmpantis et al., 2019; Arias-Molinares and Carlos García-Palomares, 2020). Vij et al. (2020) distinguish inner city, inner regional, and outer regional to analyse MaaS consumer preferences. However, respective characteristics of these are not included in the estimation. Mulley (2017) concludes that MaaS can alter how people live in cities and tailored solutions can better match respective travel demand. Smith et al. (2018b) compare MaaS between Sweden and Finland qualitatively to find practice-based and structural changes are required. Polydoropoulou et al. (2020a) follow a similar approach focusing on two cities. Esztergár-Kiss and Kerényi (2020) design MaaS bundles integrating city characteristics such as PT satisfaction and modal-split, however no uptake is estimated. Feneri et al. (2020) conduct a study across three cities but do not control for city-specific characteristics. Liljamo et al. (2020) analyse WTP for bundles in differently populated areas but do not include the areas' characteristics. In their literature review, Butler et al. (2021) identify transport service coverage as one major supply-side barrier for MaaS adoption. The basis for this is infrastructure and vehicles as well as mobility services using these (Lyons et al., 2019). Conceptually, the role of PT as backbone has been discussed (Smith et al., 2018a, 2019; Matyas, 2020; Mulley et al., 2018; Enoch et al., 2020), the extent of how to integrate modes (Mulley and Yen, 2020; Ambrosino et al., 2016), and how policy can support MaaS (Jittrapirom et al., 2020; Smith and Hensher, 2020). Hirschhorn et al. (2019) qualitatively investigate possible governance approaches for PT drawing on three use cases. Using semi-structured interviews in three cities, Alyavina et al. (2020) find car dependence, value, and cost as crucial factors affecting MaaS usage. Empirically, more integrated modes, thus increased flexibility, are found to be more attractive for customers (Guidon et al., 2020; Kamargianni et al., 2016; Strömberg et al., 2018; Sochor et al., 2015; Karlsson et al., 2016), especially when taking account of mode-chains (Song et al., 2021) and seamlessness for PT (Lee et al., 2022; Hensher and Xi, 2022; Matyas and Kamargianni, 2019b). This requires a sufficiently high supply density for PT and shared services, which is easier found in urban settings (Hensher et al., 2020; Göddeke et al., 2022). However, which supply density can be understood as sufficient is unexplained and decisive city-characteristics such as PT quality or shared mobility density have not found its way into quantitative analyses. For PT, qualitative approaches about its importance exist but studies integrating PT quality and modelling bundle choices, are missing. This is even more so for shared modes and their supply densities whose impact has not been investigated. This is also due to the focus of previous work on single cities, which leaves the question about differences in supply and demand of MaaS bundles across multiple cities open.

2.5. Contributions of this work

As the literature review reveals, previous empirical work about uptake of MaaS bundles has focused on the demand-side (vs. supply-side) and on single cities (vs. multiple cities). Thus, the impact of supply-side attributes (e.g., quality of the PT system, existence and supply of shared e-scooters) as well as city structure remain underexplored. Further, demand-side work showed higher probabilities for bundle uptake for shared mode users but has paid little to no attention to shared e-scooters and ridepooling. Specific characteristics such as type of city or supply densities of shared services across cities have not been investigated. With our work, we aim to combine these to ends. We conduct the same SP study in 83 German cities and include supply-side attributes such as PT quality and shared service supply densities. Thus, we provide two contributions to the current debate: first, combining all relevant shared mobility services including shared e-scooters and ridepooling in one MaaS bundle study and one joint model, which reflects the status quo mobility supply in cities. This is also connected to the question of the impacts of current usage of these modes towards bundles including these. Second, by using demand- and supply-side data from multiple cities, we evaluate differences between them regarding their transportation systems, i.e. PT quality and supply density of shared modes, concerning their impact on bundle choice. Doing so also contributes to solve the problems MaaS providers and transport planners currently face regarding which MaaS offer to provide in which type of city. This understanding helps to mitigate challenges cities currently face: increase transport efficiency, facilitate first-/last-mile trips, reduce emissions, increase space efficiency, and reduce car dependence.

3. Data

We merge three data sets using primary survey data (Section 3.1) and supply and city characteristic data (Section 3.2). The sample is described in Section 3.3.

3.1. Survey data

All persons holding a driver's licence and living in one of Germany's larger cities or metropolises were eligible to take part in the survey. Since shared mobility services are still predominantly an urban phenomenon, we focus on larger cities. For the cities of interest, we use the RegioStaR7 classification (BMVI, 2020) and select all cities classified as metropolis (category 71, e.g. Berlin), regiopolis or large city (category 72, e.g. Stuttgart), making 83 cities relevant. As not every city offers the relevant mobility services, we focus on 62 cities with valid complete cases (see the map in Fig. 1). For sampling, we used an online-panel (Norstat Germany) that sent out invitations to participate in this survey by e-mail. Most respondents live in cities with more than one million inhabitants (32.7%), closely followed by those in cities with 0.5–1 million inhabitants (29.7%). 14.6% live in cities with 100–200,000, 12.4% in those with 200–300,000, and 10.6% in cities with 300–500,000 inhabitants. Besides the spatial focus, fixed quotas for age, gender (in combination), and education were used to select the sample in order to match the urban population in Germany (Eurostat, 2020). The SP-survey encompasses $N = 1779$ respondents who were contacted between 27th of August and 25th of September 2020. If and how the COVID-19 pandemic might influence our results is discussed in Section 6 (Fig. A.1 shows the COVID-19 cases). As MaaS bundles are a very recent development that is not widespread in Germany, we select those respondents for the analyses who already use at least one of the two shared services integrated in the presented bundle or have any interest to do so in the future. This and selecting cities with respective shared mobility supply results in a data set of 444 respondents.

We asked respondents to fill out an SP experiment concerning MaaS bundles. Respondents were randomly selected for one of two bundles — one integrating shared micro-mobility ('micro'), i.e. shared e-scooters and bikes, and one integrating shared motorised (car-based) services, i.e. carsharing and ridepooling ('moto'). We differentiate bundles by services integrated for two reasons: first, as micro-mobility and car-based modes have different preconditions for infrastructure and hence city characteristics. Second, since MaaS as well as the modes included are still rather new to respondents such that these have to be thoroughly explained, which increases response burden. Personal data of the respondents, i.e. socio-demographics and their zip code is integrated, too. Further, we use data of the respondents' current mobility behaviour, i.e. their mobility tools and current usage of (shared) modes.

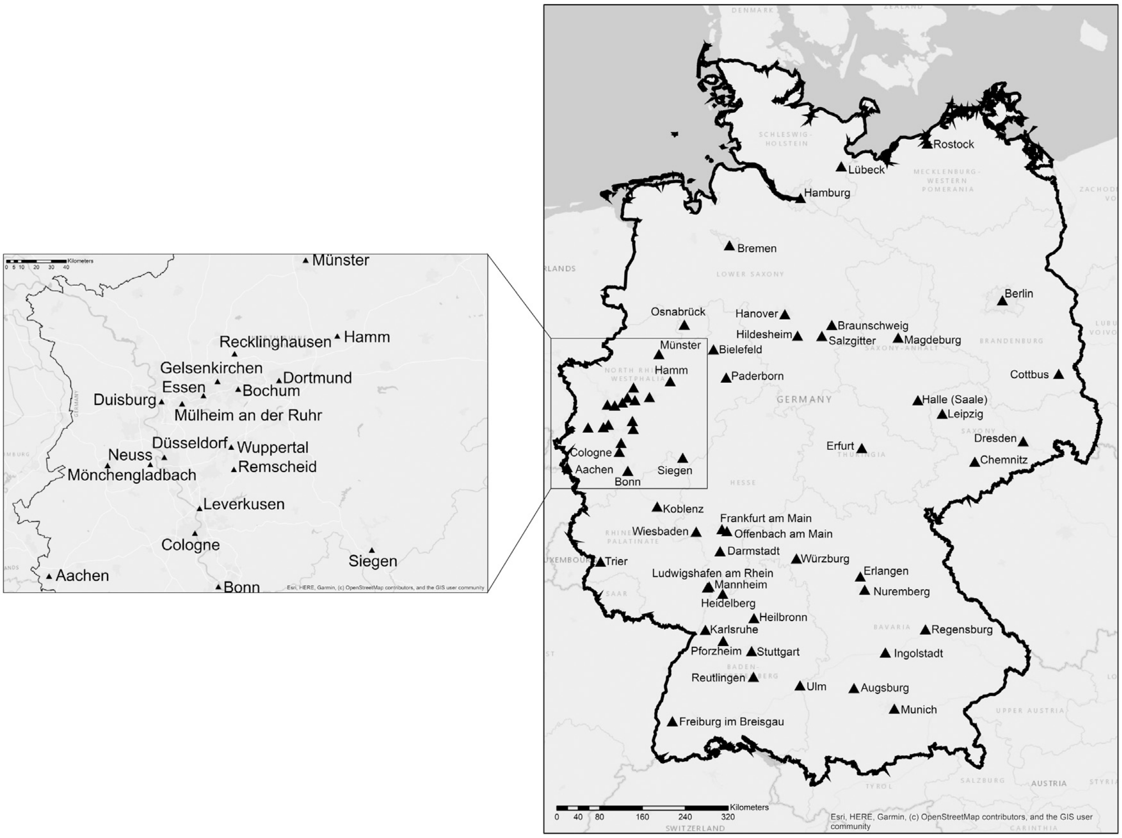


Fig. 1. Map of Germany showing the residential cities of the survey respondents.

3.2. Supply and city characteristics data

For the city characteristics data, we draw on both primary and secondary data by BCS (2019), BMVI (2019), and use data by Destatis (2020) to merge these.

The primary data contains information about fleets and supply density of shared e-scooters and bikes as well as ridepooling. This data is surveyed at the same time as the SP survey was conducted. To gather this data, providers' information and newspaper articles are combined. We searched the providers' information and validated and enriched this by using (local) newspapers, city announcements or PT authorities collaborating with the providers. For carsharing, we use data by the 'Bundesverband Carsharing' (BCS), the German lobby organisation of carsharing providers (BCS, 2019).

The information about the city characteristics of the respondents' residence is taken from the latest and largest transport survey in Germany, 'Mobilität in Deutschland' 2017 ('Mobility in Germany' (MiD) BMVI, 2019). It provides representative information from households and persons regarding their mobility behaviour. Amongst others, these are mobility tools and their evaluation of infrastructure. We use information about the PT quality as evaluated by the respondents for their city. To calculate these numbers we use the weights provided to extrapolate the values of the variables from the respondents to the overall city population in Germany relevant for our work. Hence, we use values being representative for this population.

We combine the data as shown in Fig. 2 to generate our analysis data set. To integrate the additional information, we first add the city respondents indicate by their zip code. We add supply data concerning the shared mobility services for the respondents' cities. To combine our survey data with the MiD 2017 data, we draw on municipality data (Destatis, 2020) by using the municipalities' names and their regional key (ARS, 'Amtlicher Regionalschlüssel'). The latter is required to merge the MiD 2017 data regarding the city characteristics. As the data from BMVI (2019) is provided on district-level, we aggregate it at city-level, which enables us using these values as city characteristics. Thus, we integrate MaaS bundle choice, respondents' socio-demographic, and mobility behaviour data with the supply of shared modes and PT quality in their cities.

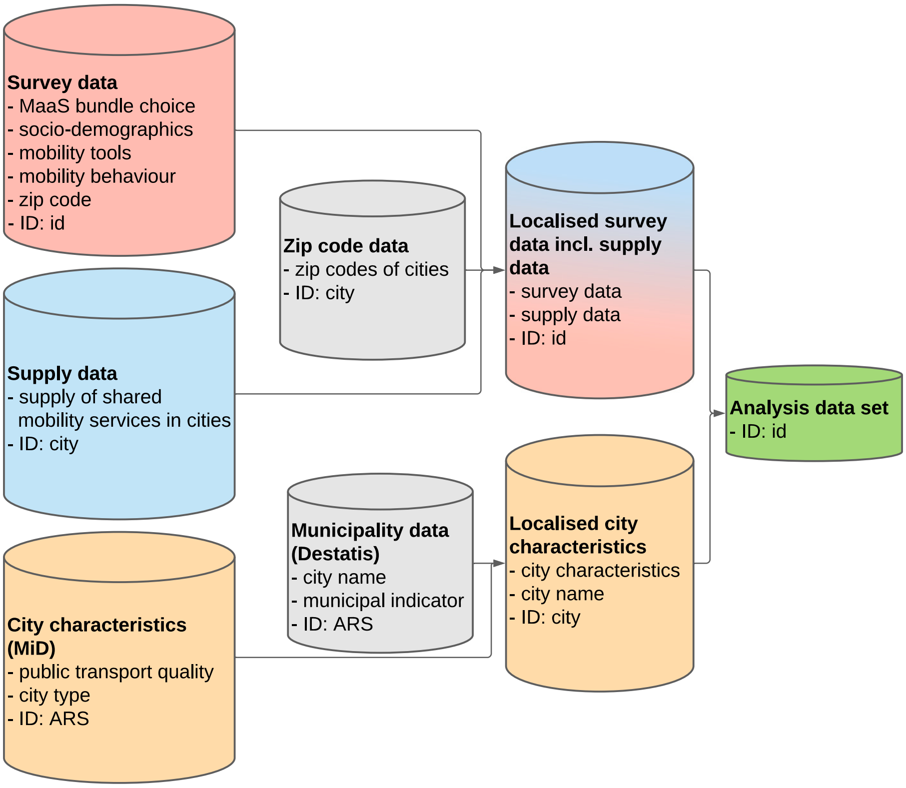


Fig. 2. Data flow chart showing the data generation process.

3.3. Sample description

Table 1 gives an overview about the socio-demographics of the sample in comparison to these of the MiD 2017 as described above. The χ^2 goodness of fit and Mann–Whitney-U test are used to test for differences. Females account for 42.3% of the sample and for 51.2% in MiD 2017. The age distribution shows the largest proportion between 40 and 59 years (46.8%) in our sample. People between 18 and 39 years account for 38.1% and people above 60 years for 15.1%. This makes our sample younger (mean: 45 years) than represented in MiD 2017 (mean: 49 years). The subjects' households in our sample and in MiD 2017 mostly have a net income of up to 2499 Euro. On average, both the households in our sample and in MiD 2017 own one private car and have access to a bicycle. 56.8% of the sample hold a PT pass whereas this share is lower in MiD 2017 (34.2%). To control for the differences of our sample compared to MiD 2017, we integrate these socio-demographic variables into our analyses.

Table 1
Socio-demographic characteristics of sample.

Characteristic	Level	Sample	MiD 2017	Test of difference
Gender	Female	42.3%	51.2%	$p < 0.01$
Age	18–39	38.1%	37.7%	$p < 0.01$
	40–59	46.8%	32.5%	
	≥ 60	15.1%	29.8%	
Monthly household net income [EUR]	0-2,499	44.4%	30.6%	$p < 0.01$
	2,500-3,499	23.2%	22.0%	
	3,500-4,499	19.6%	17.3%	
	≥ 4,500	12.8%	30.1%	
Cars in household	Median	1	1	$p > 0.1$
Bicycle accessibility in household		always	2	
PT pass		56.8%	34.2%	$p < 0.01$

Table 2
Stated preference design for MaaS bundles: Attributes and attribute levels used in survey.

Attribute	Unit	Bundle A	Bundle B	Pay-as-you-go
Micro bundle design incl. PT, shared e-scooters, and shared bikes				
Bundle price	[EUR]	50, 80, 120	50, 80, 120	–
PT pass included		incl., not incl.	incl., not incl.	–
PT trip price	[EUR]	0, 1.00, 1.70, 2.70	0, 1.00, 1.70, 2.70	1.70, 2.70
Shared e-scooters included	[min]	15, 100, 200	15, 100, 200	–
Shared e-scooters price	[EUR/min]	0.15, 0.25, 0.35	0.15, 0.25, 0.35	0.20, 0.30, 0.40
Shared bikes included	[h]	1, 7, 15	1, 7, 15	–
Shared bikes price	[EUR/h]	1.50, 2.00, 3.00	1.50, 2.00, 3.00	2.00, 2.50, 4.00
Moto bundle design incl. PT, carsharing, and ridepooling				
Bundle price	[EUR]	70, 150, 250	70, 150, 250	–
PT pass included		incl., not incl.	incl., not incl.	–
PT trip price	[EUR]	0, 1.00, 1.70, 2.70	0, 1.00, 1.70, 2.70	1.70, 2.70
Carsharing included	[km]	25, 100, 150	25, 100, 150	–
Carsharing price	[EUR/km]	0.50, 0.70, 1.00	0.50, 0.70, 1.00	0.75, 0.95, 1.25
Ridepooling included	[km]	15, 20, 40	15, 20, 40	–
Ridepooling price	[EUR/km]	1.50, 2.00, 2.25	1.50, 2.00, 2.25	1.75, 2.25, 2.50

4. Methods

This section presents the SP-design, the modelling, and post-estimation approach to analyse the data.

4.1. Stated preference design

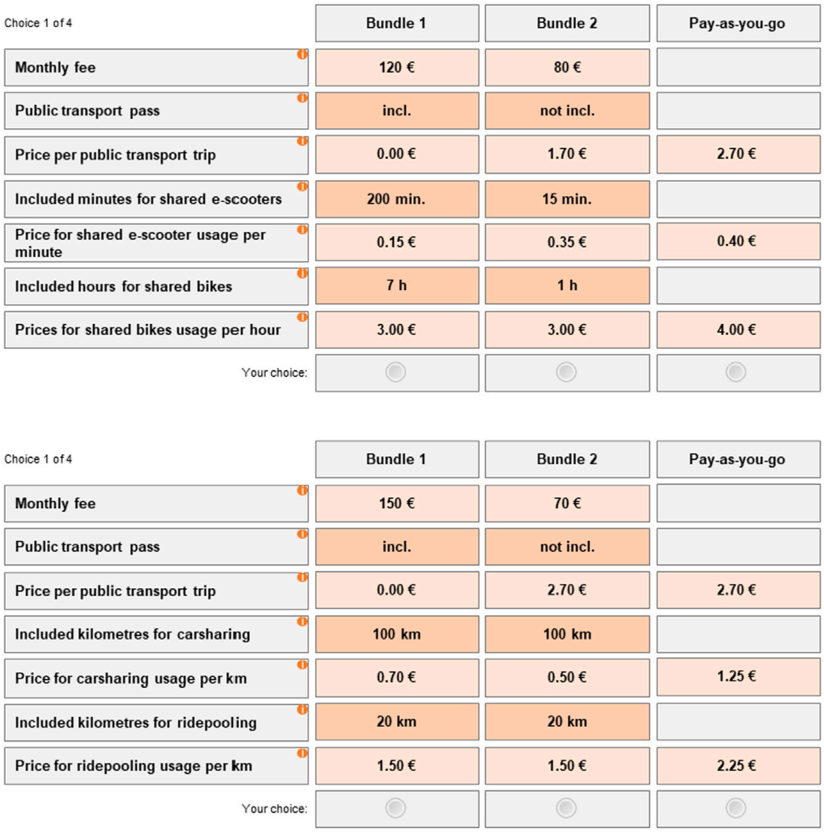
The SP-design is informed by empirical observations regarding current MaaS packages and single mobility service prices, which is in combination used to calculate reasonable packages and bundle prices. We conducted a survey to gather household and mobility behaviour data and to inform the SP-survey incorporating the choice experiments, which we also discussed with experts to optimise it (autumn 2019).

As outlined above, we distinguish two MaaS bundles: shared micro-mobility ('micro'), i.e. shared e-scooters and bikes, and shared motorised (car-based), i.e. shared cars and ridepooling ('moto'), bundles. Table 2 shows the attributes and levels for the MaaS bundles. For the alternatives, we differentiate two bundles that draw on the same attributes and attribute levels and one pay-as-you-go (PAYG) option. The latter does not offer any subscription but consists of prices per trip. The bundles micro and moto share the logic of attributes used: they consist of a monthly bundle price, have a PT pass included or not and include a certain amount of free units (minutes, hours or kilometres) for shared mobility usage. We applied conditions on the design to not create unrealistic, strictly dominant or redundant choice sets. If a PT pass is included, the PT trip price is zero. For additional units of the integrated shared modes a price per minute, hour or kilometre applies. The prices for the PAYG-option are slightly higher than those for the bundles in order to offer subscribed customers a price advantage that can be observed on the market.

For the micro bundle price, we use 50, 80, and 120 Euro as monthly fee. This results from calculations using real prices per unit for shared e-scooters and bikes as well as the respective amounts of units included. The trip price for PT, if not included in the bundle and thus zero, is taken from the average of a comparison of real rates (1.00, 1.70, 2.70 Euro) (ADAC, 2019). For shared e-scooters, we use 15, 100, and 200 min and for shared bikes 1, 7, and 15 hour(s) as levels for the included units. The difference in units from minutes to hours is based on observable service characteristics in Germany. The price for shared e-scooters is 0.15, 0.25 or 0.35 Euro/minute. For shared bikes, this is 1.50, 2.00, and 3.00 Euro/hour. Only if the respondent decides to use the service beyond the free units in the bundle, these prices become relevant. For the PAYG-option, the price for PT is either 1.70 or 2.70 Euro/trip. For shared e-scooters, the PAYG prices are 0.20, 0.30 or 0.40 Euro/minute. For shared bikes, this is 2.00, 2.50, and 4.00 Euro/hour.

Regarding the moto MaaS bundles, the same logic applies. For bundle price, attribute levels are 70, 150, and 250 Euro per month. The trip price for PT is the same as in micro (1.00, 1.70, 2.70 Euro). For shared cars attribute levels are 25, 100, and 150 kilometres, for ridepooling 15, 20, and 40 kilometres. Shared cars cost either 0.50, 0.70 or 1.00 Euro per additional kilometre. Ridepooling costs 1.50, 2.00 or 2.25 Euro per additional kilometre. The PAYG-option uses the same prices for PT trips as micro. Shared cars prices are 0.75, 0.95 or 1.25 Euro/kilometre and ridepooling costs 1.75, 2.25 or 2.50 Euro/kilometre.

We calculate the experimental design using Ngene (ChoiceMetrics, 2018) to create a block design with 40 rows and ten blocks for each micro and moto. Hence, to account for cognitive burden (Bech et al., 2011), each respondent saw four choice tasks. We use a D-efficient multinomial logit design to increase the amount of preference information by forcing the respondents to make trade-offs (Rose and Bliemer, 2009). To generate the design, we used priors derived from previous choice-experiments about MaaS bundle choice as they were, amongst others, presented in Tsouros et al. (2021), Caiati et al. (2020), Ho et al. (2020), Mulley et al. (2020), Polydoropoulou et al. (2020c), Vij et al. (2020) or Ho et al. (2018). Based on these previous findings, we used priors slightly



Choice 1 of 4	Bundle 1	Bundle 2	Pay-as-you-go
Monthly fee	120 €	80 €	
Public transport pass	incl.	not incl.	
Price per public transport trip	0.00 €	1.70 €	2.70 €
Included minutes for shared e-scooters	200 min.	15 min.	
Price for shared e-scooter usage per minute	0.15 €	0.35 €	0.40 €
Included hours for shared bikes	7 h	1 h	
Prices for shared bikes usage per hour	3.00 €	3.00 €	4.00 €
Your choice:			

Choice 1 of 4	Bundle 1	Bundle 2	Pay-as-you-go
Monthly fee	150 €	70 €	
Public transport pass	incl.	not incl.	
Price per public transport trip	0.00 €	2.70 €	2.70 €
Included kilometres for carsharing	100 km	100 km	
Price for carsharing usage per km	0.70 €	0.50 €	1.25 €
Included kilometres for ridepooling	20 km	20 km	
Price for ridepooling usage per km	1.50 €	1.50 €	2.25 €
Your choice:			

Fig. 3. Example of SP-design for MaaS bundles including PT, shared e-scooters and bikes (micro) or PT, carsharing and ridepooling (moto).

negative for price variables and slightly positive for those representing the units integrated per mode. Fig. 3 shows an exemplary micro and moto design of one choice-set. Note that respondents either saw the micro or the moto design. One block was randomly assigned to the respondents. To keep potential bias from the blocks or order of choice set within the block at a minimum, the order of the choice sets was randomised.

4.2. Model estimation

Following pre-analyses (see Section 5.1), we estimate one joint normal error component logit-mixture model (Walker et al., 2007) including the city-level respondents reside in and three nests for bundle choice. We distinguish the type of city respondents live in by including an indicator for the city type, i.e. metropolitan vs. non-metropolitan and the type of bundle, i.e. micro, moto or the PAYG alternative. We use one random error component for each micro (σ_{micro}) and moto (σ_{moto}) bundle. This way we also control for panel effects (Ortúzar and Willumsen, 2011). Following Walker et al. (2007), the observed choice y_{in} of individual n regarding the alternative i is

$$y_{in} = \begin{cases} 1 \text{ if } U_{in} \geq U_{jn}, \text{ for } J = 1, \dots, J_n \\ 0 \text{ otherwise} \end{cases}$$

and U_{in} is the respective utility $U_{in} = X_{in}\beta + \epsilon_{in}$ with X_{in} as $(1 \times K)$ vector of explanatory variables, β as $(K \times 1)$ vector of coefficients, and ϵ_{in} as random error. With $\mathbb{D}$ reflecting the number of draws, C_n the choice set, μ the Extreme Value scale term, F the $(J_n \times M)$ matrix of fixed loadings, T the $(M \times M)$ lower triangular matrix of unknown parameters and ζ_{nd} indicating draw d for individual n from distribution ζ, the response probabilities of the individuals can be computed as

$$\hat{P}_n(i) = \frac{1}{\mathbb{D}} \sum_{d=1}^{\mathbb{D}} \frac{e^{\mu(X_{in}\beta + F_i T \zeta_{nd})}}{\sum_{j \in C_n} e^{\mu(X_{jn}\beta + F_j T \zeta_{nd})}} \tag{1}$$

We use 5000 Sobol draws (ζ_{nd}) for simulation to approximate the probabilities (Ortúzar and Willumsen, 2011; Czajkowski and Budziński, 2019) as estimates show stable values for this number of draws.[1] We use normal distributions for ζ_{nd} and include a scale ξ_{pooled} due to pooling the designs in one model. For estimation, we use `mixl` (Molloy et al., 2021).

To identify the specification of the modelling approach, we have analysed the bivariate relationships between the choice probabilities and the SP-design attributes, respondents' mobility behaviour and tools, their socio-demographics, and city characteristics (see Section 5.1). Due to the focus of this work, the respondents' mobility behaviour (Table 3), particularly regarding the shared modes, and the mobility supply in cities serve as point of departure (Figs. 4, 5, 6). Those variables showing significant and substantial impact on bundle choice are introduced in the model. The same logic is applied for socio-demographic information (Table 3). Respondents' mobility behaviour is reflected by including binary variables that identify the respondent as frequent (at least on a monthly basis) user of private cars and the shared mobility services. A dummy variable for holding a PT pass is added. We include age, income (two of three categories), gender (is 1 if female), and number of children (0–18 years) distinguished in whether there is one or more than one in the household. We add the PT quality specified whether the local PT system is evaluated to be very good. The shared mobility densities are included by identifying those showing high densities based on their distributions (shared e-scooters: > 4.97, shared bikes: > 3.70, shared cars: > 1.60 vehicles/1000 inhabitants). Since ridepooling is not as widespread, for this service we identify those cities having supply at all. We use the city type respondents live in by including a variable indicating whether they live in a regiopolis or large city (RegioStaR 72), which also serves as first level of our multi-level analysis. The specifications of the utility functions can be found in Appendix B.

To provide a more detailed understanding of the model results, we use the statistically significant estimates to conduct post-estimation analyses: we do partworth analysis and calculate elasticities and marginal probability effects (MPE). The partworth analysis allows to derive each parameters' contribution to the overall utility, thus, their importance for the respondents. For this, we multiply the attribute levels' means per respondent with the respective coefficient and average these numbers. While we calculate the elasticities based on a +10% increase in the respective explanatory variable, we use 10%pts. steps for the MPE in the range of −50% to + 50%, which enables us to derive corresponding behavioural implications.

5. Results

We first show differences in respondents' choices for the MaaS bundle or PAYG-option regarding their mobility behaviour and socio-demographics. Second, we show these differences with respect to city characteristics, i.e. PT quality and shared mobility supply. Third, we integrate these results into our modelling approach and conduct post-estimation analyses.

5.1. *Mobility behaviour and socio-demographics*

Table 3 summarises the mobility behaviour and socio-demographics affecting bundle choice by contrasting choices for the bundle against choices for the PAYG-option. The percentages indicate the row percentages per variable, i.e. the share of respondents having chosen the bundle or PAYG given the category of explanatory variable. Further, χ^2 tests indicate that all variables show statistically significant differences in the bundle and PAYG distributions.

Regarding mobility behaviour, respondents having access to a private e-scooter (68.8%) or bike (51.7%) choose the micro bundle more often. For the moto bundle, this only holds for private e-scooters (59.5%) but not for private bikes (46.8%). Respondents having a PT pass choose bundles more often, which is similar for micro (58.1%) and moto (58.3%). Frequent car users predominantly do not choose the bundles (micro: 44.3%, moto: 47.4%). For respondents never using the car, the micro bundle is more attractive (58.7%) than the moto bundle (31.8%). All respondents having used shared mobility services before more often choose the bundles. Especially so if the services are used frequently (micro: 80.0%, moto: 92.9%) or regularly (micro: 91.7%, moto: 68.8%). For PT usage in the moto case, the pattern is similar but on an overall lower level: the share of respondents choosing the bundle increases with each category of using PT more often, peaking at 56.3% for those frequently using PT. For micro, the picture is divided: those frequently (56.7%) and those never (68.8%) using PT choose the bundle more often. The mobility tool and behaviour of the respondents reveals that bundle choice is highly dependent on both previous investment decisions regarding mobility tools and previous mode choice decisions, particularly regarding shared mobility usage.

Concerning socio-demographics, younger respondents choose the bundles more often. The share of respondents selecting the bundle is highest and greater for the lowest age category only (micro: 58.0%, moto: 60.5%) and decreases towards the highest age category (micro: 40.2%, moto: 36.4%). Highest take-up for the bundles is observed for more than three household members (micro: 64.7%, moto: 72.8%). In the moto case, the share of respondents choosing the bundle increases with each additional household member. For micro, only households with one child choose the bundle more often (64.4%), which is true for both one (60.3%) and two (80.8%) children for the moto bundle. The income does not show a clear pattern: while for micro, in the lowest (50.3%) and medium (51.7%) category more respondents select the bundle, this holds for the medium category in the moto case only (50.8%). We summarise that bundles are more often selected by respondents who are younger, do not live in single-households, and have one (micro) or at least one (moto) child(ren).

[1] The estimates given different number of draws can be obtained from Figs. C.1–C.5.

Table 3
Influences of socio-demographics and mobility behaviour on MaaS bundle choice.

Variable			Shared e-scooters & bikes (micro)				Carsharing & ridepooling (moto)			
			Bundle [%]	PAYG [%]	Σ	χ^2	Bundle [%]	PAYG [%]	Σ	χ^2
Mobility behaviour										
E-scooter in household	yes		68.8	31.2	100.0	28.9***	59.5	40.5	100.0	18.0***
	no		44.7	55.3	100.0		42.4	57.6	100.0	
Bike in household	yes		51.7	48.3	100.0	6.2**	46.8	53.2	100.0	0.7
	no		40.7	59.3	100.0		43.2	56.8	100.0	
PT pass	yes		58.1	41.9	100.0	32.8***	58.3	41.7	100.0	75.8***
	no		37.5	62.5	100.0		29.8	70.2	100.0	
Car usage[a]	frequently		44.3	55.7	100.0	26.6***	47.4	52.6	100.0	14.4**
	regularly		70.0	30.0	100.0		53.7	46.3	100.0	
	seldom		45.8	54.2	100.0		45.0	55.0	100.0	
	never		58.7	41.3	100.0		31.8	68.2	100.0	
Shared mobility usage[a,b]	frequently		80.0	20.0	100.0	37.3***	92.9	7.1	100.0	53.1***
	regularly		91.7	8.3	100.0		68.8	31.2	100.0	
	seldom		64.1	35.9	100.0		55.6	44.4	100.0	
	never		44.8	55.2	100.0		39.7	60.3	100.0	
PT usage[a]	frequently		56.7	43.3	100.0	49.8***	56.3	43.7	100.0	63.4***
	regularly		29.2	70.8	100.0		36.1	63.9	100.0	
	seldom		40.8	59.2	100.0		30.0	70.0	100.0	
	never		68.8	31.2	100.0		26.9	73.1	100.0	
Socio-demographics										
Age	18–39		58.0	42.0	100.0	26.4***	60.5	39.5	100.0	61.7***
	40–59	years	43.5	56.5	100.0		39.3	60.7	100.0	
	≥60		40.2	59.8	100.0		36.4	63.6	100.0	
Household size	1		46.9	53.1	100.0	31.9***	33.9	66.1	100.0	80.2***
	2	persons	49.3	50.7	100.0		40.8	59.2	100.0	
	3		36.0	64.0	100.0		52.0	48.0	100.0	
	> 3		64.7	35.3	100.0		72.8	27.2	100.0	
Children in household	0		47.4	52.6	100.0	10.9***	41.1	58.9	100.0	44.1***
	1	persons	64.4	35.6	100.0		60.3	39.7	100.0	
	2		45.6	54.4	100.0		80.8	19.2	100.0	
Income[c]	0 - 2,499		50.3	49.7	100.0	28.1***	42.9	57.1	100.0	27.1***
	2,500 - 3,499	EUR	51.7	48.3	100.0		50.8	49.2	100.0	
	≥ 3,500		47.2	52.8	100.0		46.9	53.1	100.0	

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.
[a]'Frequently' means on a weekly basis at least; 'regularly' means on a monthly basis at least; 'seldom' means less than monthly; 'never' means (almost) never.
[b]Regarding modes in respective bundles.
[c]Net income of household.

5.2. City characteristics

Fig. 4 illustrates the choice distribution between MaaS bundles and the PAYG-option depending on the PT quality of the city respondents live in. The abscissa shows the quintile ranks of the PT quality distribution that is taken from the MiD 2017 data set (BMVI, 2019) with respect to the best evaluated city in Germany. Whilst the share of respondents choosing the bundle increases with the PT quality in the micro case, this trend is not so clear in the moto case. However, both show the highest take-up for bundles in the highest two quintile ranks. In the best PT quintile, more than half of respondents choose the bundle, which is true for the second highest quintile in the micro case, too.

In Figs. 5 (micro) and 6 (moto) the choice shares depending on the supply density of shared services are shown in the same logic as the PT quality in Fig. 4 but in quartile ranks: the supply densities on the abscissa are relative to the maximum of all cities in our sample. For all services but ridepooling (Fig. 6B) the share of choices in favour of the MaaS bundles is maximal for highest service densities. Ridepooling shows a significant dip towards the fourth quartile. The supply density for ridepooling might not be as informative as for the other three services. Due to its pooling characteristic and respective algorithms for covering as much trips as possible, ridepooling might not be as dependent on the number of vehicles. For shared e-scooters, there are two peaks regarding bundle choice, one in the lowest and one in the highest supply density quartile. In the case of shared bikes, a higher density leads to more bundle uptake with the second and third quartile being rather equal. The supply density for shared cars influences bundle choice only if it is very high, which makes respondents choose the bundle more often than the PAYG-option. For ridepooling, the trend is increasing up until the third quartile before bundle choices drop. Thus, in general, only a very high supply density with shared services increases respective MaaS bundle choice.

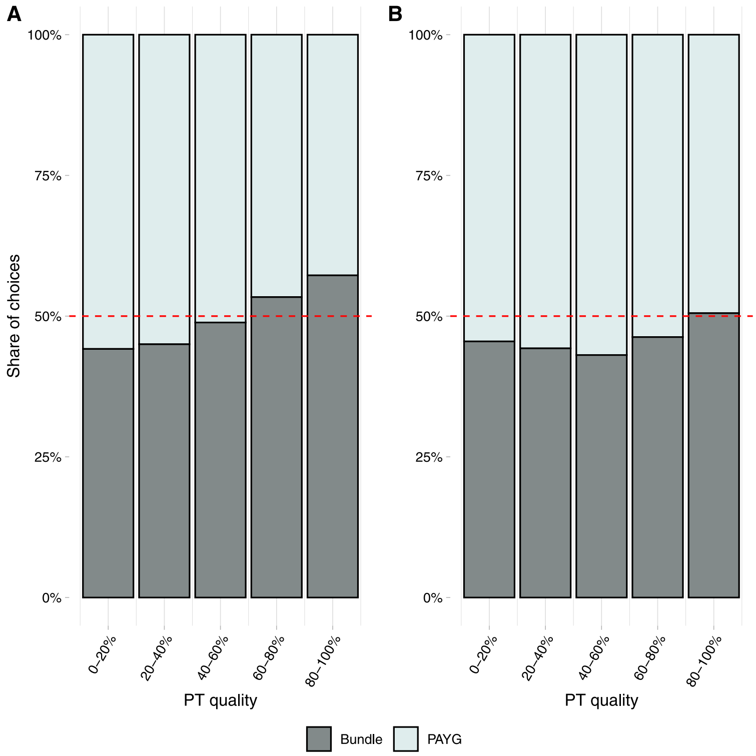


Fig. 4. Shares of choices for MaaS bundles and PAYG-option with respect to the PT quality in the city of residence (A: bundle including shared e-scooters/bikes, B: bundle including carsharing/ridepooling).

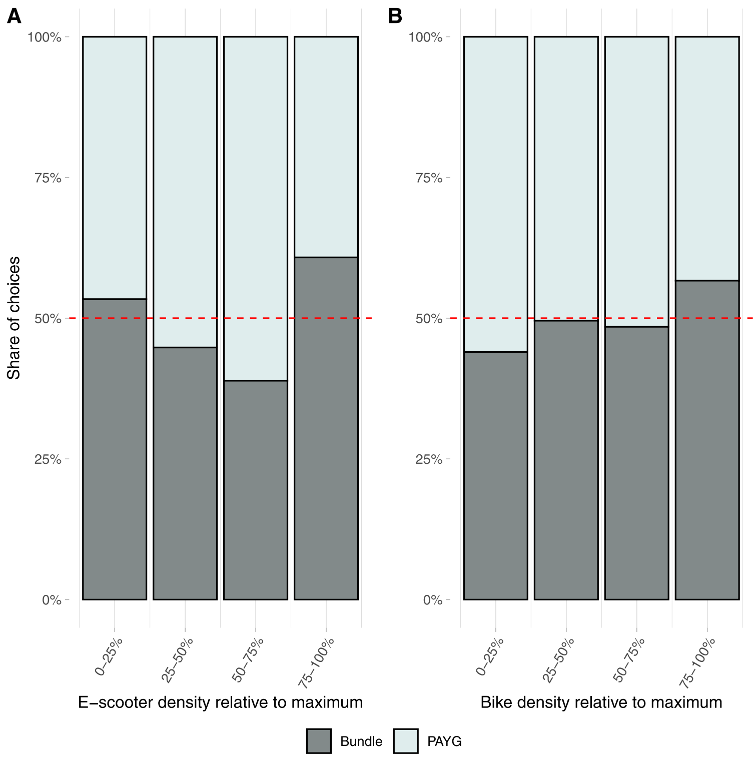


Fig. 5. Shares of choices for MaaS bundles and PAYG-option with respect to shared e-scooter (A) and bike (B) density in city.

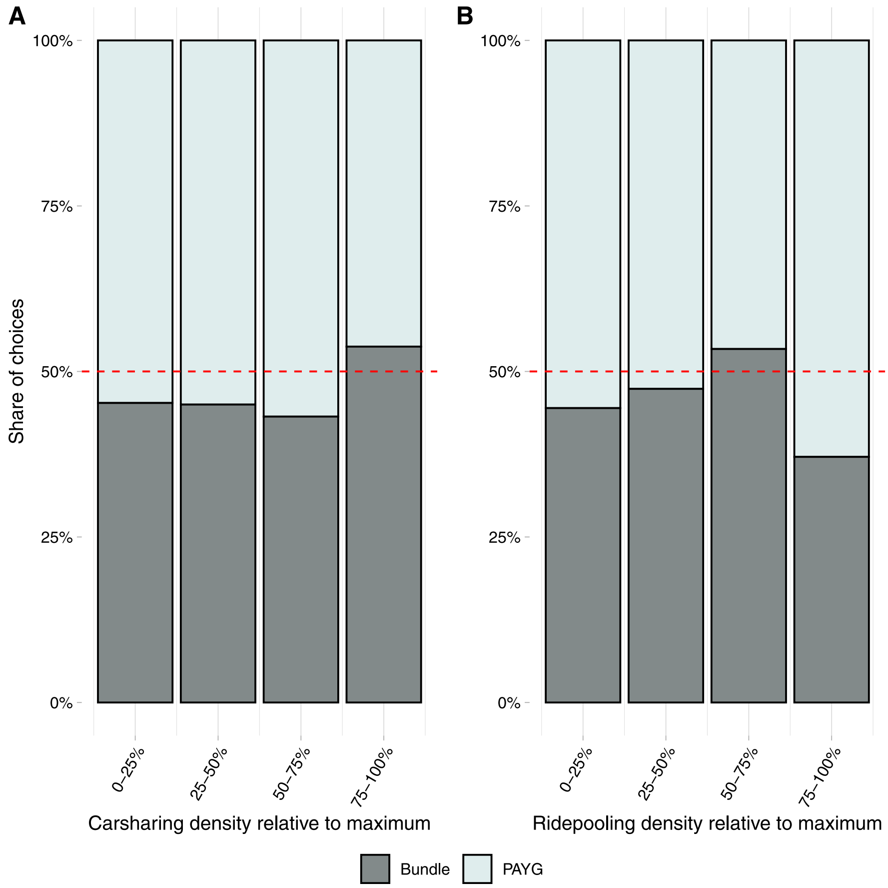


Fig. 6. Shares of choices for MaaS bundles and PAYG-option with respect to shared car (A) and ridepooling (B) density in city.

5.3. Modelling results

We estimate one joint model for both bundle options micro (shared e-scooters and bikes) and moto (shared cars and ridepooling) to model the choice behaviour of the respondents. Results are shown in Table 4 distinguishing bundle attributes, mobility behaviour, city characteristics, and socio-demographics. With a Rho-squared of 0.30 the model shows a very good overall fit.

The estimates for bundle attributes show the expected direction: increasing prices reduces utility and increasing included units increases utility. The overall bundle price is highly statistically significant on a high level (−0.02). So is the inclusion of a PT pass (0.47). While the included units for the car-based shared services are statistically significant with ridepooling showing the higher magnitude (shared cars: 0.01, ridepooling: 0.03), those for the shared micro-mobility services are not (shared e-scooters: 0.01, shared bikes: 0.02). All prices are statistically significant (shared e-scooters: −0.03, shared bikes: −0.32, ridepooling: −0.41) with the exception of shared cars (−0.06).

Regarding mobility behaviour, car usage shows a negative sign while usage of any shared mobility service shows a positive sign. Private (−0.73) and shared car (1.65) as well as shared bike (1.75) usage show statistically significant impacts.

All city characteristic variables positively influence the utility of the respondents with the supply density of shared e-scooters being the largest and only statistically significant factor (1.16). While the PT quality (0.57) shows a similar magnitude as shared car (0.56) and ridepooling (0.51) supply, shared bike supply is slightly larger (0.67). Respondents living in a large city or regiopolis generate a higher utility from the bundles although this effect is not statistically significant (0.53). This effect shows the tendency that especially people in non-metropolitan areas can generate higher utility from MaaS bundles. Yet, this first level of analysis also shows that the type of city itself is not significantly impacting bundle utility but particularly shared e-scooter supply is.

Turning to socio-demographics, age is statistically significant and negative (−0.04) while gender is not (0.06). Interestingly, having children in the household positively influences the utility from the MaaS bundles. Especially so if there are two or more children, which shows a statistically significant impact on bundle utility (1.95) that one child does not (0.30). Having a high income negatively influences utility (−0.21) with the opposite holding for a medium income (0.04) but both variables being not statistically significant.

The error components σ_{micro} (3.15) and σ_{moto} (3.56) are statistically significant, indicating that the expected hierarchy in the decision-making process of the respondents seems to be present.

Table 4
Combined model results for MaaS bundles integrating shared e-scooters and bikes or shared cars and ridepooling.

Variable	Unit	Estimate
Bundle attributes		
Bundle price	[EUR]	−0.02*** (0.00)
PT pass incl.		0.47* (0.28)
Own PT pass		0.72*** (0.22)
Shared e-scooters incl.	[h]	0.01 (0.08)
Shared bikes incl.	[h]	0.02 (0.02)
Shared cars incl.	[km]	0.01*** (0.00)
Ridepooling incl.	[km]	0.03** (0.01)
Price PT trip	[EUR]	−0.15* (0.09)
Price shared e-scooters	[EUR]	−0.03** (0.01)
Price shared bikes	[EUR]	−0.32** (0.13)
Price shared cars	[EUR]	−0.06 (0.33)
Price ridepooling	[EUR]	−0.41** (0.18)
Mobility behaviour		
Car usage		−0.73* (0.43)
Shared mobility usage		
Shared e-scooters		1.20 (1.10)
Shared bikes		1.75** (0.73)
Shared cars		1.65* (0.92)
Ridepooling		0.60 (0.76)
City characteristics		
PT quality		0.57 (0.52)
Supply density		
Shared e-scooters		1.16* (0.61)
Shared bikes		0.67 (0.63)
Shared cars		0.56 (0.82)
Ridepooling		0.51 (0.70)
Residence is large city		0.53 (0.54)
Socio-demographics		
Age	years	−0.04** (0.02)
Female		0.06 (0.42)
Child(ren) in household		
One child		0.30 (0.56)
Two or more children		1.95*** (0.62)
Medium income[a]		0.04 (0.52)

(*continued on next page*)

Table 4 (*continued*).

Variable	Unit	Estimate
High income[a]		−0.21 (0.50)
σ_{micro}		3.15*** (0.40)
σ_{moto}		3.56*** (0.40)
ξ_{pooled}		0.00 (0.00)
Respondents	444	
Choice observations	1,776	
Draws	5,000	
LL(null)	−1,951.14	
LL(choicemodel)	−1,365.29	
Rho2	0.30	
AICc	2,799.71	

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

[a]Medium income refers to the net income of households from 2500 to 3499 EUR and high income is 3,500 EUR and above.

5.4. Post-estimation analyses

To make the modelling results tangible and comparable to previous work, we conduct post-estimation analyses by calculating the partworth of parameters, their elasticities, and MPE.

The partworth, i.e. the importance of each attribute for the respondents' utility, is shown in Fig. 7. Besides the importance, the graph also shows very similar shares within the two micro and moto alternative respectively, underlining the well-balanced

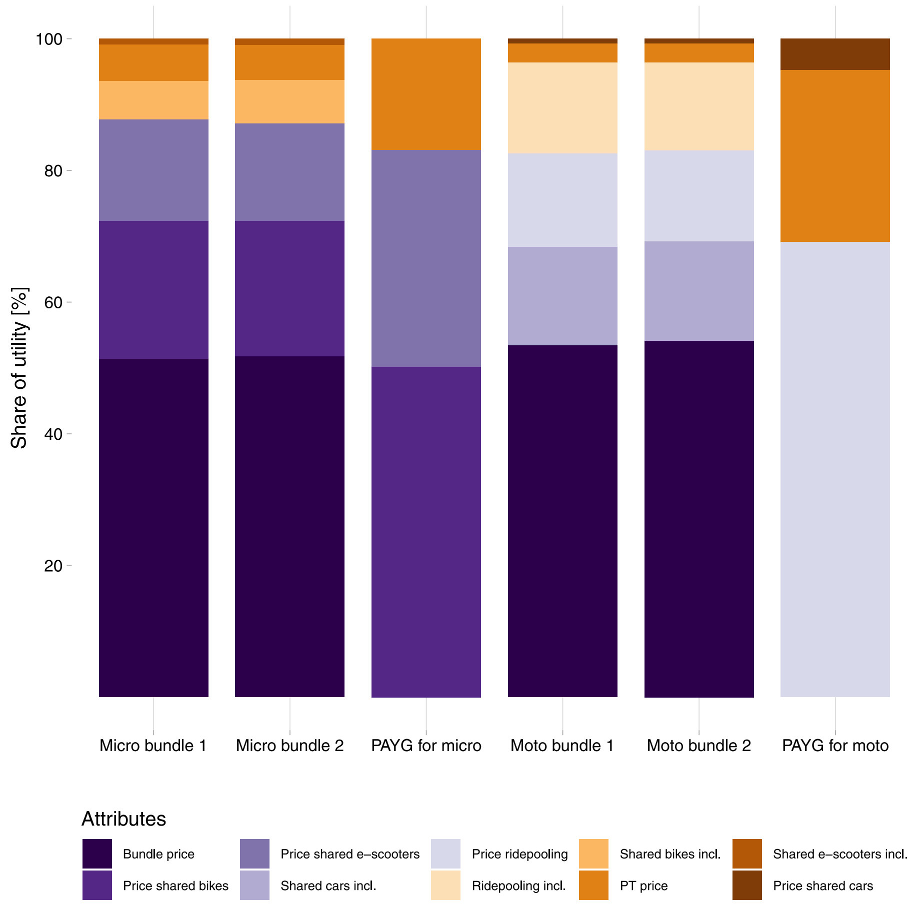


Fig. 7. Partworth, i.e. the importance of each attribute on respondents' utility.

Table 5
Elasticities for bundle attributes and age in case of a +10% increase in the variables.

Variable	MaaS bundle	Elasticity [%]
MaaS bundle price	Micro	−8.65
	PAYG	0.66
	Moto	−14.65
	PAYG	1.12
Price PT trip	Micro	−0.86
	PAYG	0.06
	Moto	−0.88
	PAYG	0.08
Price shared e-scooter	Micro	−2.55
	PAYG	0.20
Price shared bike	Micro	−3.44
	PAYG	0.27
Price ridepooling	Moto	−4.21
	PAYG	0.35
Shared car units included	Moto	4.49
	PAYG	−0.35
Shared ridepooling units included	Moto	4.08
	PAYG	−0.34
Age	Micro	−3.75
	Moto	−4.11
	PAYG	3.47

Table 6
MPE for bundle attributes, city characteristics, respondents' mobility behaviour, and socio-demographics on the choice probability of the modes [%pts.].

Variable	MaaS bundle	Marginal probability effect [%pts.]
PT pass included in MaaS bundle	Micro	5.98
	Moto	6.03
	PAYG	−2.19
Own PT pass	Micro	1.49
	Moto	1.24
	PAYG	−2.73
High shared e-scooter supply density	Micro	5.31
	PAYG	−5.31
High car usage	Micro	−3.30
	Moto	−3.60
	PAYG	6.90
High shared bike usage	Micro	7.95
	Moto	8.82
	PAYG	−16.77
High shared car usage	Micro	7.46
	Moto	8.31
	PAYG	−15.77
Two or more children in household	Micro	8.87
	Moto	9.85
	PAYG	−18.72

experimental designs. While the subscription price is the most important attribute for both bundles, it takes a slightly higher share of the overall utility in the moto (54%) than in the micro case (52%). For micro bundles, the additional prices for shared bikes (21%) and e-scooters (15%) are second and third most important while this is free units for shared cars (15%) and ridepooling as well as its additional price (14% each) for the moto bundles.

The elasticities of a +10% increase in respective variables are shown in Table 5. The elasticity for the monthly subscription price is higher for the moto (−14.65%) than the micro (−8.65%) bundle. The price for a PT trip is similar for both bundles (micro: −0.86%, moto: −0.88%). Concerning the prices of additional units for the shared services, ridepooling shows the highest elasticity (−4.21%), followed by shared bikes (−3.44%), and shared e-scooters (−2.55%). The effect of additional included units in the bundles is higher for shared cars (4.49%) than ridepooling (4.08%). The elasticity of the respondents' age is −4.11% in the moto case and −3.75% in the micro case.

Table 6 shows the MPE for bundle attributes, city characteristics as well as respondents' mobility behaviour and socio-demographics. The PT pass included in the MaaS bundles shows a substantially higher effect (micro: 5.98%pts., moto: 6.03%pts.)

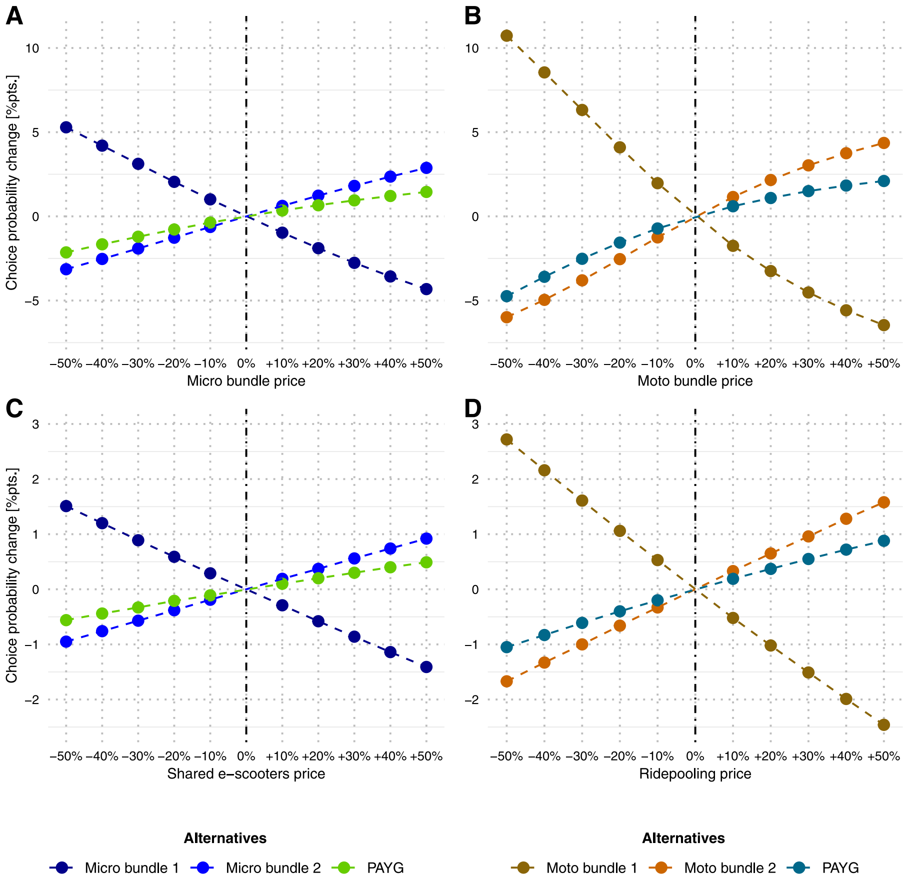


Fig. 8. MPE for bundle prices as well as prices for additional units for shared e-scooters and ridepooling.

than the respondents' own PT pass, which shows a higher effect for micro (1.49%pts.) than moto (1.24%pts.). The effect for PAYG is similar (included in bundle: −2.19%pts., own: −2.73%pts.). With 5.31%pts., a high shared e-scooter supply density (> 4.97 vehicles/1000 inhabitants) also shows a substantial impact on micro bundle choice. The effects of mobility behaviour are larger for the moto than the micro bundle. Car usage shows an effect of −3.60%pts. for moto and −3.30%pts. for micro. The same holds for shared bike (moto: 8.82%pts., micro: 7.95%pts.) and shared car usage (moto: 8.31%pts., micro: 7.46%pts.). Two or more children in the household show a positive effect for both bundles (micro: 8.87%pts., moto: 9.85%pts.).

Fig. 8 shows the MPE for each of the two bundle prices micro and moto as well as those regarding prices for additional units of shared e-scooters and ridepooling (we alter micro or moto bundle 1, respectively). As can be seen from Fig. 8A and B, the effect of increasing bundle prices is greater for the moto than the micro bundle. While decreasing the subscription price of the micro bundle by -50% results in an increase of bundle uptake by +5.3%pts., increasing the price by +50% results in a decrease of bundle uptake of −4.3%pts. (Fig. 8A). For the moto case, these numbers are +10.7%pts. and −6.5%pts. (Fig. 8B). Further, a decrease in bundle price by -50% results in a reduction of selecting the PAYG-option by −2.1%pts. for micro and −4.7%pts. for moto. Turning to Fig. 8C and 8D, we observe that decreasing the price of additional shared e-scooter units in the bundle by -50% generates an additional uptake of +1.5%pts. for the micro bundle. For the moto bundle and the respective ridepooling price, this results in an increase of bundle choice by +2.7%pts.

6. Discussion

We find MaaS bundle choice differing with respect to integrate modes, city characteristics, mobility behaviour, and socio-demographics.

Regarding the bundle attributes, we support and extend previous work: bundle price negatively and included units positively influence respondents' utility (Caiati et al., 2020; Matyas and Kamargianni, 2019a; Jang et al., 2021). However, the importance of these attributes is different regarding the modes integrated. While for shared micro-mobility price is more important than included units, this is vice versa for car-based shared modes. The elasticity of the micro bundle is within the range of what Ho et al. (2021a) find for comparisons with current mobility costs. For moto, the elasticity is larger. Hence, people seem to distinguish by the integrated modes when it comes to their price behaviour.

We find higher car usage to negatively impact bundle uptake, which is similar for micro and moto. Previous work identified car drivers to be less likely and multimodal travellers to be more likely to choose MaaS bundles (Alonso-González et al., 2020; Caiati et al., 2020; Ho et al., 2018). Regarding multimodal behaviour, we find shared mobility usage to increase utility from the MaaS bundles, particularly for shared bikes and cars. Caiati et al. (2020) find a similar effect for carsharing membership. Interestingly, the positive marginal probability effect of shared bike or car usage is in absolute values larger than the negative effect of car usage. Our results support previous findings showing people using shared modes being inclined to use bundles (Caiati et al., 2020; Fioreze et al., 2019; Matyas and Kamargianni, 2021) and particularly could test new modes in bundles (Matyas and Kamargianni, 2019a). We find holding a PT pass increases choice and utility from both bundles (Caiati et al., 2020; Matyas and Kamargianni, 2021) with a higher impact in case of shared micro-mobility. Although COVID-19 cases were at a stable and low level during the data sampling (see Fig. A.1), we might underestimate the positive impacts of PT on bundle choice due to the negative pandemic effects on PT usage.

Our analyses extend previous work by quantitatively investigating the effect of local transport systems' characteristics across several cities on MaaS bundle uptake. We find that cities with very good PT systems and high shared mobility supply show the best preconditions for MaaS bundle usage. The clear positive trend in case of shared micro-mobility might point towards previous findings that these can support local PT systems or vice versa (Radzimski and Dziecielski, 2021; Reck et al., 2021; Cao et al., 2021). The shared e-scooter density can be shown to significantly and substantially contribute to the respondents' utility, underlining their potential key function in local transport systems. The MPE show that the supply density has a comparable effect as the included PT pass. Previous work has found evidence for a plateau-effect in case of shared e-scooters beyond which demand grows at a decreasing rate (Reck et al., 2021). Our results suggest that there also is a threshold-effect for MaaS bundles. Thus, at least for shared e-scooters, the supply density for shared modes needs to reach this threshold in order to make the service attractive enough to potential MaaS bundle users. We do not find these local characteristics to be related to the type of city but to the transport system quality each city provides. Thus, although offering economically viable (shared) services in every city might be difficult, the demand for MaaS bundles can be expected.

In line with previous work, younger respondents choose a bundle more often (Alonso-González et al., 2020; Caiati et al., 2020; Ho et al., 2018, 2020; Matyas and Kamargianni, 2019a; Jang et al., 2021). Previous work found mixed results for the effects of children with Caiati et al. (2020) showing a positive, Alonso-González et al. (2020) a negative, and Ho et al. (2018) a negative effect regarding two or more children. We show a positive effect particularly for two or more children, which is greater in the moto case according to the MPE analysis. This suggests that the flexibility and ease-of-use provided by MaaS bundles is attractive to families, especially so for shared car-based modes that enable transporting children and additional luggage.

7. Conclusions

Drawing on a combination of SP, shared mobility supply, and city data, we analyse the impact of mobility behaviour, transport supply, and socio-demographics on MaaS bundle choice. We integrate shared e-scooters, bikes, and cars as well as ridepooling in the bundles.

Our results indicate that integrating several modes into one bundle may confound important differences towards respondents' choice behaviour. Due to our multi-city approach, we can further draw conclusions based on different transport systems which have implications for policy and practice.

We find evidence for local transport system characteristics and mobility behaviour to significantly and substantially impact MaaS bundle uptake with supply density of shared e-scooters being crucial. Therefore, particularly regarding first- and last-mile trips, PT has to be understood more broadly by including shared modes to allow seamless multi- and intermodal travel.

With respect to the mobility revolution that is sometimes claimed from MaaS and the challenges MaaS providers and transport planners face, our results point at three main aspects for policy and practice: first, offering sufficient free-units for shared car-based modes facilitates customers' adoption while additional costs particularly for shared micro-mobility modes hinder adoption. Second, a very good infrastructure regarding PT and shared mobility supply is key to make MaaS bundles attractive to people, which might reduce car dependence. Third, individuals tend to seek for continuing their (shared) mobility style they have already had but with MaaS bundles, which, if accompanied by respective regulations, could result in higher transport efficiency. MaaS bundles can also be an attractive 'mobility tool' for families. These might find an easy way for the first-/last-mile in shared micro-mobility bundles or an alternative to an expensive private car regarding shared car-based bundles, making MaaS bundles one option for increasing transport justice.

City authorities aiming at increasing shared mobility or MaaS usage need to plan PT and shared modes side by side. This sweet spot between overcoming the threshold and not trespassing the plateau might be difficult to find since respective usage numbers are often available retrospectively only. One solution can be to experiment with shared mobility supply in restricted areas. Especially because this has to be balanced with the PT quality to avoid undesired mode shifts. For PT authorities, integrating shared modes in their offer might be a fruitful approach to cover time- or location-related supply gaps at lower cost or replace low occupancy services by shared modes. Shared mobility providers might want to work with PT authorities more closely as having access to regular PT users might substantially increase their user-base. Thus, infrastructure needs to be there first and people might need an incentive to begin using MaaS bundles. Cities could provide incentives by making MaaS bundles free for some months, particularly when moving there, or by extending the PT service to shared modes and integrate these in bundles. Policy could also rearrange the logic of company cars and make it more attractive to firms to offer MaaS bundles to their employees.

Future research might overcome limitations of this work. To analyse the effects of different transport infrastructures in more detail, one could introduce the same MaaS system in various cities and compare results between these. Adding revealed preference data would give even more insights about what respondents choose when. Our results hold for the groups of respondents in the cities sampled, hence larger cities, regiopolises, and metropolises. Implementing MaaS bundles for people living in rural areas might be more difficult as PT quality is lower and building a high supply density for shared services might be financially challenging. Hence, it would be worthwhile to repeat similar experiments and analyses for data sampled in these regions. This could also integrate real-time vehicle data of shared services and revealed preference data in order to increase the level of detail.

CRediT authorship contribution statement

Konstantin Krauss: Conceptualisation, Methodology, Software, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualisation, Project administration, Funding acquisition. **Daniel J. Reck:** Conceptualisation, Methodology, Validation, Writing – review & editing, Visualisation. **Kay W. Axhausen:** Conceptualisation, Validation, Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. COVID-19 pandemic

See Fig. A.1.

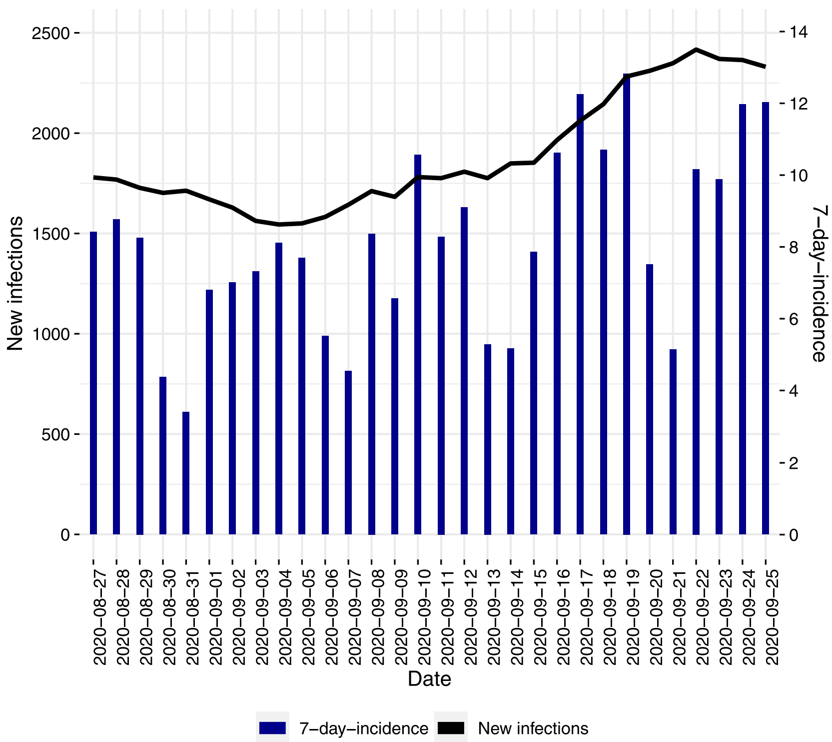

Fig. A.1. New infections and 7-day-incidence regarding the COVID-19 pandemic per day in the time of the survey (RKI, 2022).

Appendix B. Utility functions

For the bundles, we use the following utility functions with *micro* for the bundles including shared e-scooters (ES) and shared bikes (BS) and *moto* including shared cars (CS) and ridepooling (RP), i for the bundle-specific alternatives, n for the respondent, and d for the random Sobol draws.

$$\begin{aligned} U_{micro_i} =& \beta_{PRICE} * bundleprice_{micro_i} + \\ & (\beta_{PTINCL} + \beta_{ptpass} * ptpass_n) * ptincl_{micro_i} + \\ & \beta_{PTPRICE} * ptprice_{micro_i} + \\ & \beta_{ESINCL} * (esincl_i/60) + \beta_{ESPRICE} * (esprice_{micro_i} * 60) + \\ & \beta_{BSINCL} * bsincl_i + \beta_{BSPRICE} * bsprice_{micro_i} + \\ & \beta_{BEHAV_n} + \beta_{SUPPLY_n} + \beta_{SOCIO_n} + \sigma_{micro} * \zeta_{dn}, \\ \text{with} & \\ & \beta_{BEHAV_n} = \beta_{caruse} * caruse_n + \beta_{esuse} * esuse_n + \beta_{bsuse} * bsuse_n + \\ & \qquad \beta_{csuse_n} * csuse_n + \beta_{rpuse} * rpuse_n, \\ & \beta_{SUPPLY_n} = \beta_{ptquality} * ptquality_n + \beta_{essupply} * essupply_n + \\ & \qquad \beta_{bssupply} * bssupply_n + \beta_{city} * city_n, \\ & \beta_{SOCIO_n} = \beta_{age} * age_n + \beta_{female} * female_n + \beta_{child} * child_n + \\ & \qquad \beta_{children} * children_n + \\ & \qquad \beta_{mediumincome} * mediumincome_n + \\ & \qquad \beta_{highincome} * highincome_n, \\ & and\ \zeta_{dn} \sim N(0,1) \end{aligned} \tag{B.1}$$

$$\begin{aligned} U_{moto_i} =& \beta_{PRICE} * bundleprice_{moto_i} + \\ & (\beta_{PTINCL} + \beta_{ptpass} * ptpass_n) * ptincl_{moto_i} + \\ & \beta_{PTPRICE} * ptprice_{moto_i} + \\ & \beta_{CSINCL} * csincl_i + \beta_{CSPRICE} * csprice_{moto_i} + \\ & \beta_{RPINCL} * rpincl_i + \beta_{RPPRICE} * rpprice_{moto_i} + \\ & \beta_{BEHAV_n} + \beta_{SUPPLY_n} + \beta_{SOCIO_n} + \sigma_{moto} * \zeta_{dn}, \\ \text{with} & \\ & \beta_{BEHAV_n} = \beta_{caruse} * caruse_n + \beta_{esuse} * esuse_n + \beta_{bsuse} * bsuse_n + \\ & \qquad \beta_{csuse_n} * csuse_n + \beta_{rpuse} * rpuse_n, \\ & \beta_{SUPPLY_n} = \beta_{ptquality} * ptquality_n + \beta_{cssupply} * cssupply_n + \\ & \qquad \beta_{rpsupply} * rpsupply_n + \beta_{city} * city_n, \\ & \beta_{SOCIO_n} = \beta_{age} * age_n + \beta_{female} * female_n + \beta_{child} * child_n + \\ & \qquad \beta_{children} * children_n + \\ & \qquad \beta_{mediumincome} * mediumincome_n + \\ & \qquad \beta_{highincome} * highincome_n, \\ & and\ \zeta_{dn} \sim N(0,1) \end{aligned} \tag{B.2}$$

For the pay-as-you option, we use the following utility function

$$\begin{aligned} U_{payg} =& \xi_{pooled} * (\beta_{PTPRICE} * ptprice_{payg} + \\ & \beta_{ESPRICE} * esprice_{payg} + \beta_{BSPRICE} * bsprice_{payg} + \\ & \beta_{CSPRICE} * csprice_{payg} + \beta_{RPPRICE} * rpprice_{payg}) \end{aligned} \tag{B.3}$$

Appendix C. Model estimates given different number of draws

See Figs. C.1–C.5.

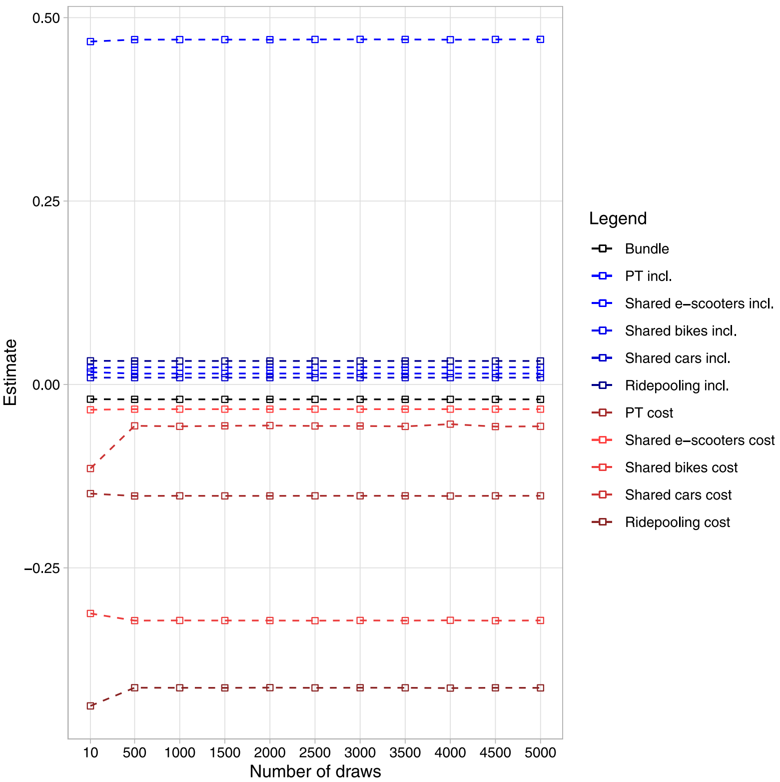

Fig. C.1. Estimates for design attributes given different number of Sobol draws (10 to 5000).

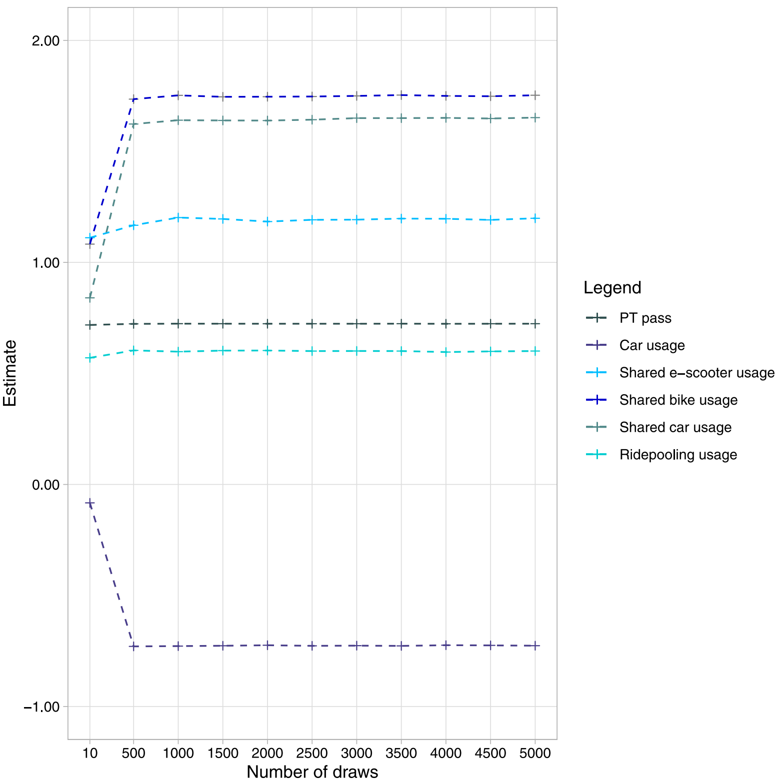

Fig. C.2. Estimates for mobility behaviour given different number of Sobol draws (10 to 5000).

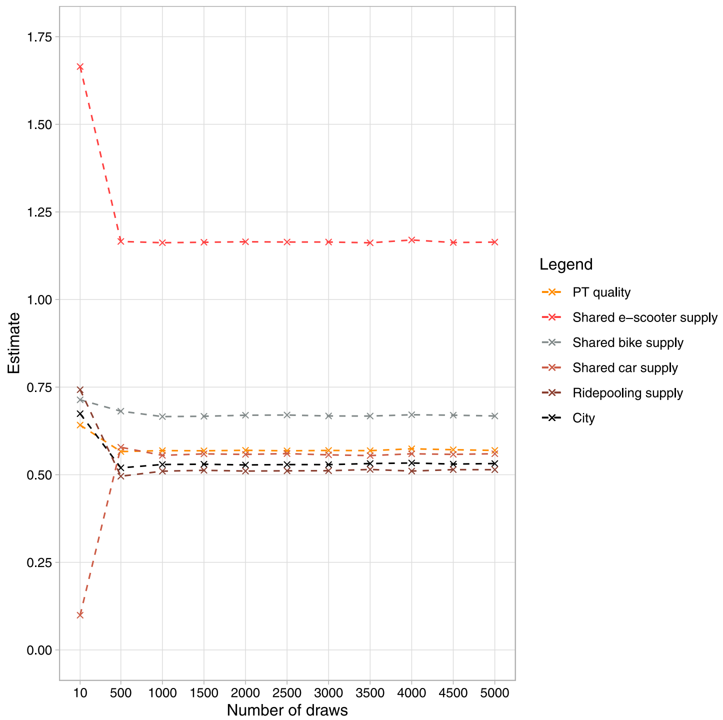

Fig. C.3. Estimates for city characteristics given different number of Sobol draws (10 to 5000).

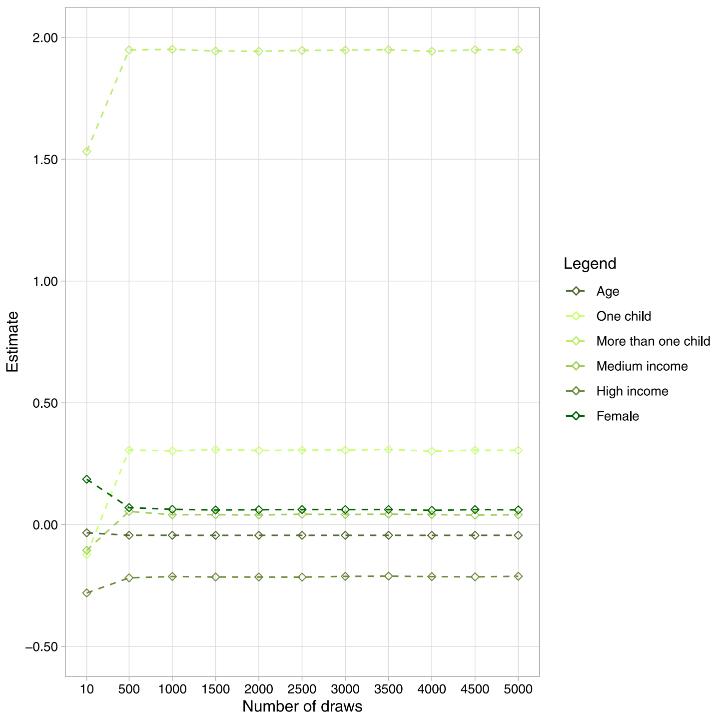

Fig. C.4. Estimates for socio-demographics given different number of Sobol draws (10 to 5000).

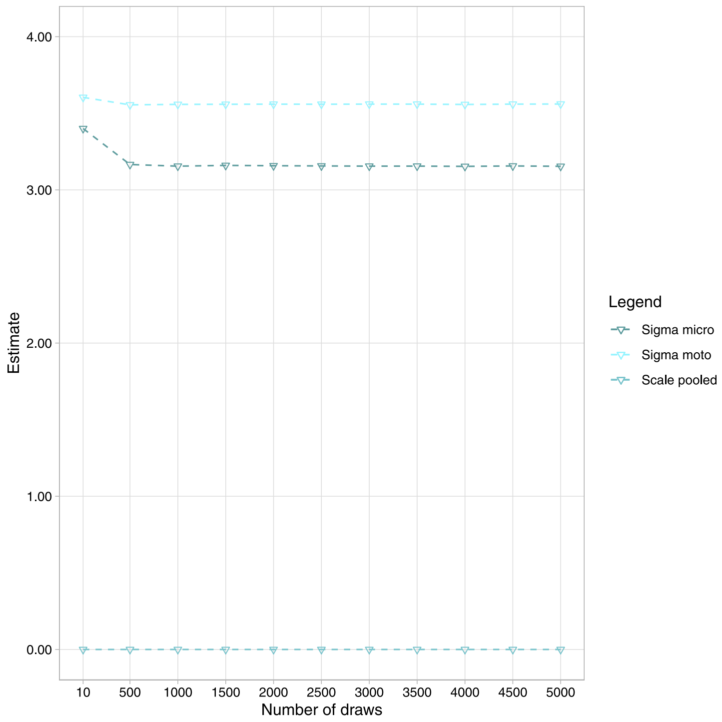

Fig. C.5. Estimates for model design related components given different number of Sobol draws (10 to 5000).

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