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# A Tour-Based Multimodal Mode Choice Model for Impact Assessment of New Mobility Concepts and Mobility as a Service

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ABSTRACT

Mobility as a Service (MaaS) and new mobility concepts mutually inspire each other, provide alternatives for the private car-oriented transport system as we know it, and will offer more mobility choices in a single journey than ever. This multitude of mobility choices however poses challenges in modeling the travelers' mode choices in travel demand prediction models. To address these challenges, this paper develops a multimodal tour-based mode choice model as part of an activity-based demand model. By explicitly modeling access and egress modes, this choice model creates multimodal mode chain sets on a tour level based on restrictions with respect to personal vehicle ownership, MaaS subscription ownership and vehicle states, and subsequently makes mode choices for every traveler.

For the creation of these mode chain sets, we introduce the concept of mode categorization. We propose seven mode categories that include both private and shared mobility concepts. This categorization makes sure that modes are mutually sufficiently different in nature, so that reasonably unbiased mode chain choices can be made. Furthermore, the reduction to seven categories enables the study of large scenarios, while the introduced categories still represent new and already existing modes well.

We illustrate the potential of the model by simulating travel demand in the Metropolitan region Rotterdam-The Hague. The results show that our model is capable of making plausible mode choices in the presence of MaaS and new mobility concepts, and can be used to assess the impact of mobility hubs where access and egress mode choice is important.

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# 1. Introduction

We are witnessing the development of new transport technologies, such as connected vehicles using 5G, level 3, 4 or 5 automatic vehicles, and mobile app-based car-sharing or ride-sharing services. *Mobility as a Service* (MaaS) combines all these technologies and services, thus offering a tailored mobility package for individual travelers (Jittrapirom, Caiati, Feneri, Ebrahimigharehbaghi, González and Narayan, 2017; Hesselgren, Sjöman and Pernestål, 2020). In the context of this paper, we assume that MaaS offers travelers full freedom to choose any traffic mode at any time.

On the one hand, MaaS promotes including multiple modes in a single trip (called *multimodal mode*) by the use of mobility hubs and the use of multiple (multimodal) modes in a tour (called multimodal mode chain). On the other hand new mobility concepts (such as the electrical vehicle, autonomous car, shared bike, Uber) also stimulate the development of MaaS (Milakis, van Arem and van Wee, 2017; Snelder, Wilmink, Van Der Gun, Bergveld, Hoseini and Van Arem, 2019; Wright, Nelson and Cottrill, 2020). This paper develops a methodology to study multimodal mode choice, explicitly including the modes brought forth by MaaS and new mobility concepts, in the context of activities and related trips that people make during a day. Throughout this paper, we refer to a series of trips starting and ending at home as a *tour*.

Owing to its flexibility, robustness and efficiency to model complex travel behavior (Miller, 2018), *Activity-based modeling* (ABM) offers a highly suitable methodology for quantifying the impact of MaaS and new mobility concepts. There is a growing body of literature on this approach: for example Narayan, Cats, van Oort and Hoogendoorn (2019) have investigated ride-sourcing for car and public transport in Amsterdam, while Hörcher and Graham (2020) did a study on car ownership with subscriptions to alternative modes. Furthermore, Matyas (2020) studied the opportunities and barriers for a modal shift via interviews about people's attitudes towards MaaS. In Snelder et al. (2019), an explorative iterative model has been developed to study the impact of automated driving and shared mobility using a network fundamental diagram. In Ciari, Schuessler and Axhausen (2012), car-sharing demand has been modeled in MATSim, an open-source multi-agent transport simulation framework (Horni, Nagel and Axhausen, 2016). We also note that Franco, Johnston and McCormick (2020) have modeled the demand of ride-sharing services, which is also fundamental for the implementation of MaaS, in MATSim. The above-mentioned studies in the first place show that there is ample potential for MaaS and new mobility concepts. Importantly, however, their focus has predominantly been on unimodal trips, thus ignoring the pivotal role multimodal modes play in MaaS. Another omission of the existing literature is that one typically does not align the trips that people make during a day, leading to possibly inconsistent mode choices within a tour.

MaaS and new mobility concepts stimulate the use of multimodal modes. Several studies have stated that mass public transport (PT) is essential for MaaS and suggest to shape complementary services to it (Basu, Araldo, Akkinepally, Biran, Basak, Seshadri, Deshmukh, Kumar, Azevedo and Ben-Akiva, 2018; Matyas and Kamargianni, 2018), such as taxis (Wang and Ross, 2017), a car-sharing system (Mounce and Nelson, 2019), or on-demand mobility (Salazar, Rossi, Schiffer, Onder and Pavone, 2018). Furthermore, Creemers, Bellemans, Janssens, Wets and Cools (2015); Olvera, Guézéré, Plat and Pochet (2015); Himmel, Zaunbrecher, Ziefle and Beutel (2016) have analyzed access and egress mode choice based on surveys in the context of PT-based multimodal mode choice. We also mention Krajzewicz, Heinrichs and Beige (2018), where an agent-based demand model is used to study multimodal mobility behavior, considering multimodal modes on a trip level, but only with PT as a main mode. On the operational side, Zgraggen, Tsao, Salazar, Schiffer and Pavone (2019) have developed a routing algorithm to optimize coordination between new mobility concepts and public transit, while Wright et al. (2020) has presented a journey planning app where carpooling and public transport are connected. Although these studies do foster the use of multimodal modes within a trip by considering multimodal mode choice, they still do not check the consistency of mode choices within a tour. Moreover, many of these studies focus on single new mobility concepts, while MaaS typically requires the incorporation of a wide range or mixture of concepts.

A relatively low number of studies explicitly checks the consistency of modes within a tour. For instance, one model approach which actively does this is the supernetwork approach. In this regard, we mention the works of Arentze and Timmermans (2004); Liao, Arentze and Timmermans (2010); Fu and Lam (2014); Liao (2016), where multi-state supernetworks have been developed to model activity location, time, duration, (multimodal) mode and route choice simultaneously, based on least-cost path choices. The supernetwork approach can also consider household joint activity choices simultaneously Vo, Lam, Chen and Shao (2020). This approach is very powerful, as witnessed by the fact that it is amenable to extension, see e.g. the study of Li, Liao, Timmermans, Huang and Zhou (2018), which incorporates free-floating car sharing as an alternative mode. Next to the supernetwork approach, another useful approach in the literature is that of discrete choice models (DCM) for mode choice. For example, the stand-alone tour-based mode choice model developed by Vovsha, Hicks, Vyas, Livshits, Jeon, Anderson and Giaimo (2017) also explicitly checks for consistency of modes within a tour. The supernetwork and the DCM approaches are mutually different in nature, both having their advantages. On one hand, the supernetwork approach is much more flexible in that it can incorporate all kinds of new modes simultaneously based on a 'unified path choice' approach. On the other hand, the DCM approach offers more flexibility to include mode specific advantages via alternative specific constants and non-observable utility via error terms in the underlying utility functions of the choice models. Furthermore, its parameters can be estimated based on stated and/or revealed preference data. In the present paper, we focus on the second of these two approaches. To the best of our knowledge, the models known in literature following the DCM approach only consider single new modes or a limited combination of new modes. With the advent of MaaS, however, it is important to include all new modes and mode combinations within a single model, motivating why in our paper we strive to do this.

We proceed by detailing the contributions of our work. In the first place, we develop a multimodal tour-based mode choice model, as part of an activity-based demand model called ActivitySim (ActivitySim, 2015), where on the trip level multimodal modes are considered. The underlying model creates multimodal mode chain sets on a tour level, based on restrictions with respect to personal vehicle ownership, MaaS subscription ownership, vehicle availability and vehicle locations. By imposing these restrictions, it enforces mode consistency throughout the whole tour. Subsequently, for each tour, inspired by the mechanisms presented in Miller, Roorda and Carrasco (2005); Vovsha et al. (2017), the multimodal mode chain having the highest utility is chosen. As a second contribution, our paper introduces the concept of mode categorization: modes with similar properties are placed in a single mode category and afterwards considered as the same mode. This alleviates selection bias as a result of modes being similar in nature (i.e., it reduces the problem of similar modes having higher likelihood to be chosen). In our specific case, we introduce seven categories that cover many new mobility concepts such as micro-modalities (e.g., bike, scooter) and on-demand PT. Both private and shared mobility concepts are considered, and all the multimodal mode alternatives are based on combinations of those seven modes/mode categories. As an additional benefit, this mode categorization reduces the computational complexity due to the smaller number of mode alternatives, and as a result the smaller total number of multimodal mode combinations. It renders our model numerically efficient: it can handle cases with large-scale multimodal mobility corresponding to up to millions of travelers. To substantiate this claim, we present, as a last contribution, a study for a large-scale instance that focuses on the Rotterdam-The Hague area in the Netherlands. It demonstrates the potential of our methodology, explicitly including multimodal modes and mode consistency within tours, for assessing the impact of MaaS, mobility hubs and new mobility concepts.

The remainder of this paper is organized as follows. Section 2 explains the details of the compartments our methodology consists of. In Section 3, we provide a large-scale numerical experiment that illustrates the potential of our approach. Finally, Section 4 presents the conclusions, discussion, and recommendations for future research.

## 2. Methodology

Because our model can be interpreted as a component of an activity-based model (ABM), we start by explaining how our model interacts with ActivitySim. First, a population is synthesized as pointed out in Klunder (2019). ActivitySim then makes long-term decisions, taking into account the number of cars each household owns, parking availability, work/school locations, etc. Next, the daily main activity purpose of each person is determined considering the interaction with other household members. After this, each individual makes decisions on the number of tours to be undertaken that day, and the number of stops in each tour including the start time, duration, the destinations and modes of each trip in the tour. The trip mode chosen at this stage is not final, but it will be considered by our model as the main mode of the uni- or multimodal mode to be chosen. In particular, our new tour-based mode chain choice model subsequently determines access and egress modes to generate a feasible trip mode combination for the tour.

In the next subsection, we detail the mode categorization of seven main modes as will be applied in the numerical experiment of Section 3. We argue that this categorization covers most of the traditional as well as new mobility modes. Afterwards, we derive multimodal mode alternatives from these seven main modes, which enables us to explain how our multimodal mode choice model works.

### 2.1. Mode categorization

We now describe the unimodal mode alternatives included in our ABM. In doing so, we introduce the notion of mode categorization, meaning that modes from different categories should be seen as different in nature. The main

| Category | S (in km/h) | W | VS (in PCU) | PC | Example |
|---|---|---|---|---|---|
| Micro5 | $\leq 5$ | MM | $\leq 0.25$ | $< 1$ | walk (WA) |
| Micro15 | $5 - 20$ | MM | $0.25 - 0.5$ | $< 1$ | bike (B) |
| Micro25 | $20 - 30$ | MM | $0.25 - 0.5$ | $< 1$ | e-bike (EB) |
| Private | $> 30$ | $\geq$ car | $> 0.5$ | $1 - 8$ | car (C) |
| Shared private | $> 30$ | $\geq$ car | $0.25 - 0.5$ | $1 - 8$ | CP |
| Shared on demand | $> 30$ | $\geq$ car | $\leq 0.25$ | $1 - 8$ | DRT |
| Shared traditional | $> 30$ | $\geq$ car | $\leq 0.25$ | $> 8$ | PT |

**Table 1**
Overview feasible mode categories

goal of this categorization is the reduction of selection bias at the mode choice selection stage of the model, as we will explain in greater detail later in this section. The underlying categories can be chosen in many ways, in line with the analysis that needs to be performed. To illustrate, we have identified seven different modes categories depending on the speed, weight, vehicle space per person, and passenger capacities, where it is noted that most of the traditional travel modes as well as new mobility modes fit into these categories. An advantage of using mode categories instead of single modes is that new modes can easily be added to the model as long as they fit within one of the seven categories. Per aspect, we distinguish between the following elements:

- Speed (km/h): $\text{S} \in \{\leq 5, 5 - 20, 20 - 30, > 30\}$;
- Weight: $\text{W} \in \{\text{MM}, \geq \text{car}\}$;
- Vehicle space per person: $\text{VS} \in \{\leq 0.25, 0.25 - 0.5, > 0.5\}$;
- Passenger capacity: $\text{PC} \in \{< 1, 1 - 8, > 8\}$.

The vehicle space per person is defined as the space a person occupies compared to a passenger car unit (PCU). Pedestrians and people in public transport fit for instance in the first class ($\leq 0.25$ PCU), cyclists in the second class ($0.25 – 0.5$ PCU), and car drivers in the third category ($> 0.5$ PCU). As a result, there are $4\times2\times3\times3 = 72$ combinations. However, not all the combinations are valid. Below we list all *infeasible* combinations, with an argumentation:

- $\{\text{W} \geq \text{car}\}$ & $\{\text{S} \leq 30\}$: a vehicle that weighs at least as much as a car should drive faster than 30 km/h.
- $\{\text{W} \geq \text{car}\}$ & $\{\text{PC} < 1\}$: a vehicle that weighs at least as much as a car should have capacity for one or more passengers.
- $\{\text{W} \geq \text{car}\}$ & $\{\text{PC} > 8\}$ & $\{\text{VS} > 0.25\}$: the passenger capacity exceeding 8 implies that the vehicle space should be in the category '$\leq 0.25$'.
- $\{\text{W} = \text{MM}\}$ & $\{\text{PC} \geq 1\}$: micro-modalities do not have space for passengers.
- $\{\text{W} = \text{MM}\}$ & $\{\text{S} > 30\}$: micro-modalities will not move faster than 30 km/h.
- $\{\text{W} = \text{MM}\}$ & $\{\text{VS} > 0.5\}$: micro-modalities do not take that much space.
- $\{\text{W} = \text{MM}\}$ & $\{\text{S} > 5\}$ & $\{\text{VS} \leq 0.25\}$: assuming that the speed of anyone with a means of micro-modality transport is higher than 5 km/h, the vehicle space per person is higher than a quarter of a PCU.
- $\{\text{W} = \text{MM}\}$ & $\{\text{S} \leq 5\ \}$ & $\{\text{VS} > 0.25\}$: micro-modalities moving at such low speeds typically take less space than the quarter of a passenger car unit.

Eliminating the invalid combinations, seven mode categories remain; see Table 1. The last column provides, for each category, a representative example, which we will now comment on. We will use the abbreviations presented in this table in the remainder of this paper. The walk mode (WA) has a speed less than 5 km/h. The bike (B) mode corresponds with a travel mode with a speed between 5 and 20 km/h, thus covering (non-motorized) scooters as well. For the e-bike (EB) mode the speed is between 20 and 30 km/h, so that it also covers e-scooters. The car mode (C) effectively represents a transportation mode with speeds over 30 km/h (which can be electric or even autonomous). Here, both private and shared (e-)bikes and cars are considered. Car passengers (CP) can ride a private car with someone else from their household, or use a shared car (such as a taxi). Demand responsive transport (DRT) includes minibuses, shared taxis or shuttles of which the passenger capacity is smaller than the capacity of traditional public transport. Conventional public transport (PT) includes bus, tram, metro, and train.

The categorization example that we show in this paper was chosen based on expert judgement so as to distinguish between modes as much as possible. It could happen, however, that mode categorization, although it reduces selection bias significantly and enables efficient, tractable computation, may lead to heterogeneity issues. That is, travellers may still have different personal preferences regarding two modes which are placed in the same category. The categorization may therefore be further optimized to diminish these issues as much as possible, while retaining the positive effects of selection bias reduction and computational efficiency; cf. Section 4.

## 2.2. Multimodal mode alternatives

We continue by explaining the multimodal mode alternatives that we consider. Each multimodal mode contains an access mode, a main mode and an egress mode, so that there are $7 \times 7 \times 7 = 343$ multimodal mode alternatives. To model multimodal modes, we have introduced two types of hub locations. A hub is a place where travelers change their travel mode within a trip, i.e., travelers use a unimodal mode to travel from an origin to a hub location and then switch to another travel mode to continue their journey. The two hub types are C-PT and C-B hubs. For each origin-destination zone pair, hubs are first selected where the maximum cycle distance to/from the hubs is 3 km, the maximum distance for PT is 10 km, and the minimum car distance is 20 km. Then, the best hub is selected based on shortest travel distance. However, not all multimodal modes are valid. We use the following rules to select the valid multimodal modes:

1. Each of the seven unimodal modes are valid access, main or egress modes.
2. For all unimodal modes, walk is implicitly used as access and egress mode, because it is always necessary to walk a short distance to, e.g., your bike, car, or PT stop.
3. When WA, B or EB is used as main mode, the access and egress mode can only be WA.
4. If a traveler owns a MaaS subscription and he/she chooses to use B, EB or C, we let this traveler use a shared bike, shared e-bike or shared-car, even in case he/she owns these vehicles privately as well.
5. Transfers within public transport are possible, but not considered as a mode switch.
6. In scenarios without MaaS, cars should return home at the end of a tour.
7. In scenarios without MaaS, bike or e-bike should return home or can stay at hubs/stations at the end of a tour.
8. In scenarios without MaaS, when the car is the main mode, the access or egress mode should be WA. This simplification ensures that only one hub is used.
9. In scenarios without MaaS, B and EB cannot be used as egress mode in a sub-tour.
10. At a C-PT hub, C/CP can switch to PT or DRT mode, while PT or DRT can switch to C/CP mode.
11. At a C-PT hub, DRT can switch to PT, while PT can switch to DRT mode.
12. At a C-B hub, C/CP/DRT can switch to B/EB mode, while B/EB can switch to C/CP/DRT.
13. travelers can change their travel mode only once within a trip (walking excluded). To ensure that a multimodal mode always has one access mode, one main mode and one egress mode, either the access or egress mode is WA. B-PT-B is an exception. (Due to lack of service data we have not included EB-PT-EB; conceptually it is no problem to add this option once this data is available.)
14. C is only considered as main mode. This is because in The Netherlands, Park+Ride facilities are located at the edges of cities, so people typically prefer to use PT or B for the last part of their trip CROW-KpVV (2008). Hence, C is not used as an access and/or egress mode in this paper.

The non-MaaS related rules are based on the large-scale travel survey OViN/ODiN (see CBS (2018)), while the MaaS-related rules are based on the judgement of stakeholders. Based on the considerations provided above, we end up with just 32 multimodal modes (out of the possible 343). They are provided in Figure 1.

It is worth stressing that our modeling framework is highly flexible. In principle, it can also include various other multimodal modes, thus also multimodal modes using C as access/egress mode, or multimodal modes that do not include WA. In the next section, we explain how to calculate the utility of multimodal modes.

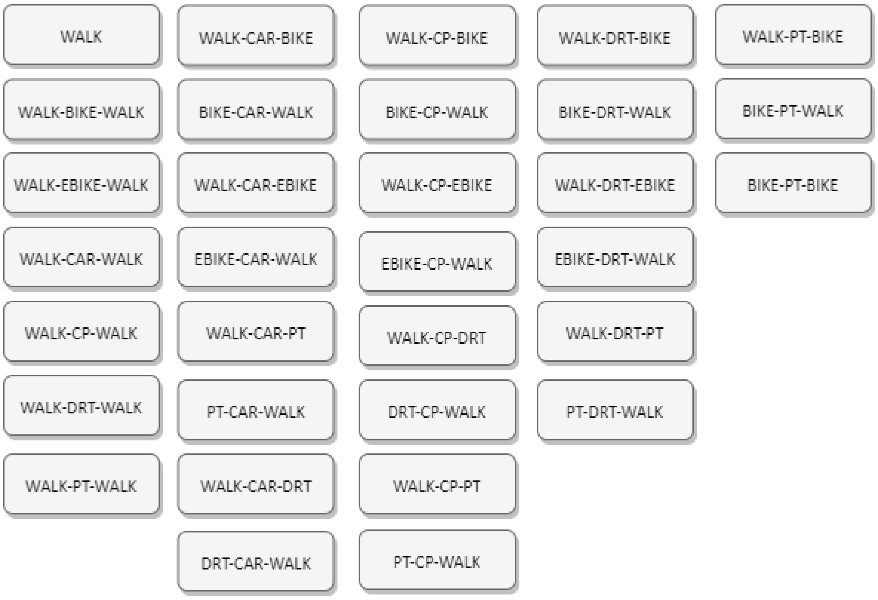


**Figure 1:** Selected multimodal modes

## 2.3. Multimodal mode utility calculation

We now discuss the calculation of utilities of the multimodal mode alternatives. In particular, the utility function of multimodal modes is derived from the utility functions of unimodal modes. It covers socio-demographic attributes, travel times and costs.

The socio-demographic attributes include age, gender, driving license, household number of cars, household income, household composition, education level and activity type; there are $N$ attributes, with $\mathrm{C}_j$ denoting the value of the $j$-th attribute. The parameters for these attributes and the mode alternative specific constant (ASC) are set equal to the parameters of the main mode of the trip. Intuitively, it would feel natural to also include the socio-demographic attributes and ASC of the access and egress mode in the utility function. This would however entail a comprehensive estimation of the associated coefficients, because these are not known in the literature. By including only the attributes of the main mode, we can use already known estimations based on unimodal modes, while we expect them to model the utility reasonably well.

The utility contributions of the search time (ST), travel time (TT), operational cost (O), start-up cost (SU), parking cost (P) are summed over the access, main and egress mode. Furthermore, a multimodal mode will consist of two transfers, from access mode to main mode and from main mode to egress mode. Hence, the utility contribution of the hub transfer time ($\mathrm{T}_{\text{transfer}}$) is summed over these two transfers. In addition we include terms $\mu_{\text{multimodal}}$ and $\eta_{\text{multimodal}}$ that represent the errors made in computing the utility of the multimodal mode of the trip. In line with Miller et al. (2005), the first term $\mu_{\text{multimodal}}$ is specific to the mode and traveler. It models the personal preference with respect to a mode, and is not resampled whenever the same mode/traveler combination is regarded for a different trip (both within a tour or across multiple tours), so as to enforce consistency. The second term $\eta_{\text{multimodal}}$ is not only specific to the model and traveler, but also to the actual trip. This term models any other random effects, and is resampled also when the same mode/traveler combination is considered for a different trip. We assume both of these terms to follow a normal distribution, each with mean zero and appropriately chosen variance. In summary, the utility function of the multimodal mode thus becomes:

$$
\begin{aligned}
U_{\text{multimodal}} = \mathrm{ASC}_{\text{main}} + \sum_{j=1}^{N} \beta_{j,\text{main}} \mathrm{C}_j + \sum_{i \in \{\text{acc,main,egr}\}} \beta_{\text{tt},i}(\mathrm{ST}_i + \mathrm{TT}_i) + \sum_{i \in \{\text{acc,main,egr}\}} \beta_{\text{cost},i}(\mathrm{O}_i + \mathrm{SU}_i + \mathrm{P}_i) \\
+ \sum_{i \in \{\text{acc}-\text{main},\text{main}-\text{egr}\}} \beta_{\text{tt,walk}} \mathrm{T}_{\text{transfer},i} + \mu_{\text{multimodal}} + \eta_{\text{multimodal}} \qquad (1)
\end{aligned}
$$

Here, $\beta_{\text{tt},i}$ is the coefficient corresponding to travel time of the access, main and egress mode respectively (indexed by $i \in \{\text{acc}, \text{main}, \text{egr}\}$); the coefficients $\beta_{\text{cost},i}$ and $\beta_{\text{tt,walk}}$ are defined analogously. The transfer time at hubs is a constant: for C-B hubs it is set to 5 minutes, and for C-PT hubs to 8 minutes based on the public transport transfer times reported in Schakenbos and Nijenstein (2014). The transfer mode is assumed to be WA.

The travel time and travel cost differ for private and shared vehicles. It depends on the combined value of three personal attributes which one should be used: driving license, car ownership and MaaS subscription. If a person owns a MaaS subscription and has a driving license the utility of a car is computed using the attributes for shared vehicles even if she/he also owns a private vehicle. Otherwise the attributes of private vehicles are used. For bike or e-bike, it works similarly except for the fact that a driving license is not required.

It is worth noting that the utility function of a multimodal mode is based on that of a traditional unimodal mode. In fact, the utility function of a non-shared unimodal mode is given by

$$\begin{aligned} U_{\text{unimodal}} = \text{ASC}_{\text{main}} &+ \sum_{j=1}^{N} \beta_{j,\text{main}} \text{C}_j \\ &+ \beta_{\text{tt,main}} \text{TT}_{\text{main}} + \beta_{\text{cost,main}} (\text{O}_{\text{main}} + \text{SU}_{\text{main}} + \text{P}_{\text{main}}) + \mu_{\text{unimodal}} + \eta_{\text{unimodal}} \end{aligned} \tag{2}$$

The differences that can be observed between (1) and (2) stem from the difference in nature between multimodal and traditional unimodal modes. For example, (2) does not include terms for the access and egress modes, as a unimodal mode only consists of a single (main) mode. Next to this, traditional unimodal modes do not include search times and transfer times, which is why they are not represented in (2) either.

## 2.4. Choice model

After the utility calculation, a multimodal mode choice is generated through the following two steps.

⋆ Step 1: *generate multimodal mode chain sets.* Using the 32 multimodal modes, we generate valid multimodal mode chain sets for each tour type by taking into account the long-term decisions made in an earlier stage of the ABM. In particular, we consider vehicle ownership and availability restrictions of the travelers. We also factor in mode consistency on a tour level. Vehicle ownership here should be interpreted as a combination of car, bike and e-bike ownership: there are 8 combinations ranging from not owning a vehicle to full ownership of all three vehicles. For each ownership combination, we calculate all valid multimodal mode chains of different tour types consisting of 2 trips, 3 trips, 4 trips without sub-tour, 4 trips including a sub-tour or 5 trips. In the settings we considered, these tour types typically cover the vast majority (more than 98% according to OViN data CBS (2018) between 2013 and 2015) of all tours. For other tour types the model chooses one of the seven unimodal modes. We apply the rules with respect to mode ownership, mode availability in the tour, locations where vehicles should be returned and mode allowance as explained in Zhou, Dorsman, Snelder, Mandjes and de Romph (2020) in combination with the following rules for the situation without MaaS:

1. C is a valid main mode in an inbound trip when the egress mode is walk;
2. C is a valid main mode in an outbound trip when the access mode is walk;
3. B/EB is a valid access mode or egress mode in inbound and outbound trips (where it is recalled that (e-)bikes can be left at hubs/stations).

For instance, in a scenario without MaaS, if a tour consists of a trip from home to work and a trip from work back to home, the combination WA-C-B from home to work and B-C-WA from work to home is valid, whereas WA-C-B combined with B-PT-WA is not valid because the privately owned car has not returned home.

The description above is based on the condition that the travelling person does not have a MaaS subscription. If he/she does, then we relax all constraints on the mode choice per trip. This means that the traveler can pick up shared cars or bikes on all locations where they are available. Hence, the number of possible multimodal mode chains is simply the full combination of all 32 modes for each tour type.

⋆ Step 2: *select a multimodal mode chain from the set of valid multimodal mode chains.* To make a multimodal mode chain choice, we regard the set of valid mode chains as generated by step 1 corresponding to the individual's vehicle ownership, tour type and the main modes of the trips within the tour. Subsequently, we calculate the total utility of each multimodal mode chain in this set for the complete tour, by adding together the utilities of the (unimodal or multimodal) modes corresponding to each trip within the tour; cf. Equation (1). The multimodal mode chain having the highest utility will then be the selected multimodal mode chain. It is worth emphasizing that in this approach, we do not compute probabilities of which mode chain set should be selected. Due to the normally distributed error terms in (1) and (2), these probabilities would not allow for a manageable closed-form expression in this case. Rather, we select mode chain sets directly by checking which one corresponds to the highest utility. Due to the presence of the normally distributed error terms in the utility functions, stochasticity is however involved, so that this approach should not be mistaken with a deterministic approach. In fact, since the uncertainty in the utility functions is represented by a normally distributed component, the current approach is reminiscent of the multinomial probit choice model.

## 3. Illustrational example

In this section, we demonstrate how the ABM, that includes our tour-based multimodal mode choice model, can be used to simulate the travel demand. This we do by means of a large-scale numerical experiment, corresponding to the metropolitan region Rotterdam–The Hague (MRDH) in the Netherlands. In our setup we explicitly include, in the way discussed in the previous section, the scenario that MaaS and new mobility concepts are available. The type of results that we obtain illustrates the added value of our approach for assessing the impact of MaaS and new mobility concepts, and is as such an indispensable tool facilitating future policy evaluation.

As mentioned, first a population synthesizer (Klunder, 2019) has been used to generate a population. It contains, per individual, the home location, household situation, gender, driving license, education level, student public transport card, income level, roots of the individuals, bike type, vehicle type and urbanization level. For this illustrational case, we focus on the population of the cities of Delft, Pijnacker, Nootdorp and Zoetermeer, being located between the two major cities in the MRDH area (Figure 2). There are 278698 people (131466 households) living in this area in the year of 2016. 16% of the population is younger than 15, 15% is between 15 and 25, 26% is between 25 and 45, 27% is between 45 and 65 and 16% is older than 65.

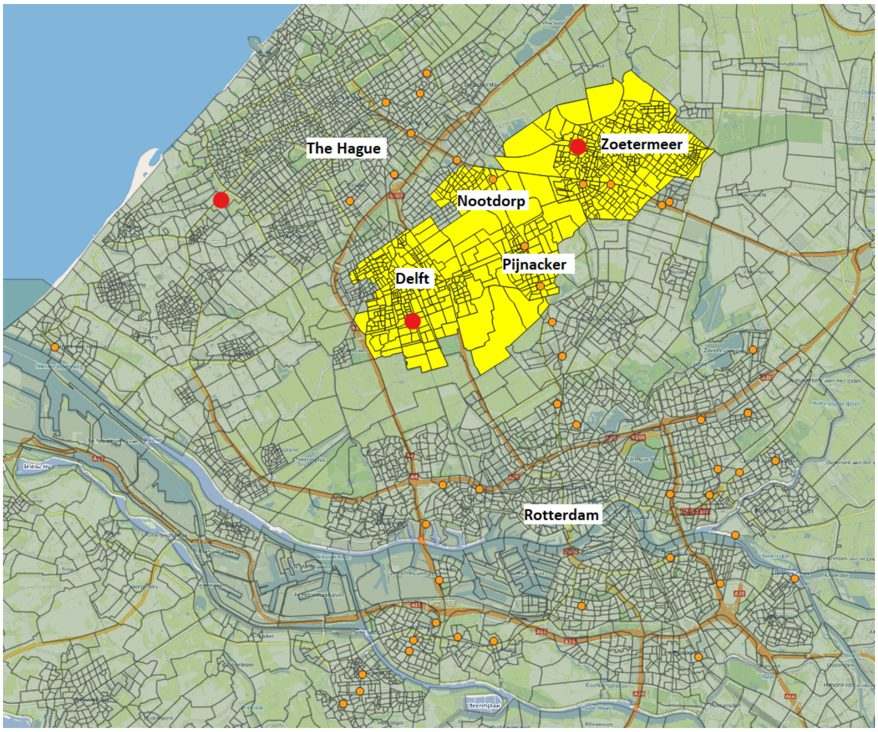


**Figure 2:** Population living area (in yellow) between The Haag and Rotterdam, the orange and red points are hubs

The MRDH road network includes access roads besides the main roads, while outside MRDH only the main roads have been included. The network also contains hubs (depicted by the blue points in Figure 2), where travelers can transfer from car to (e-)bike or from car to PT and vice versa.

For each origin-destination pair, the level of service data (including distance, travel time and cost for the seven main modes directly) has been derived using the values presented in Table 2. Where applicable, the source of these

| Name | Value | Source |
|---|---|---|
| Average time to search shared bike | 1 min | |
| Price for shared bike | 0.00 €/min | |
| Start-up cost of shared bike | €1.925 | OV-fiets |
| Area where shared bike is allowed | Everywhere | |
| Factor speed (shared) e-bike | 1.5 | 25 km/h: 15 km/h |
| Price shared e-bike | 0.3 €/min | Felyx scooter |
| Search time for car sharing | 5 min | |
| Price car sharing | 0.1 €/min | Greenwheels |
| Start-up cost car sharing | 0 | Greenwheels |
| The area allowed for car sharing | Everywhere | |
| Factor speed car-sharing car | 1 | |
| Waiting time car passenger in shared-vehicle (e.g. Taxi) | 5 min | |
| Price car passenger in shared-vehicle | 0.35 €/min | |
| Start-up cost of car passenger in shared-vehicle | €3.00 | Uber |
| PCU value car passenger in shared-vehicle | 1 | |
| Area allowed for car passenger in shared-vehicle | Everywhere | |
| Factor speed DRT | 1 | |
| Waiting time constant DRT | 0 | |
| Price DRT per min | 0 | |
| Start-up cost DRT | €3.00 | |
| PCU value for shared on demand | 0.2 | Assumed 5 passengers |

**Table 2**
List of input parameters used in level of service

numbers are mentioned in the table. If no source is mentioned, these numbers are assumption-based. If a shared mode happens not to be available at the origin or not allowed at the destination, then a very high impedance is imposed to ensure that the mode will not be selected (i.e., the model will assign a very low utility to this mode).

Parking rates per zone have been obtained in RDW (2015). While in practice parking rates tend to vary between days and over time, we have used a simplified approach in which parking rates are fixed (i.e., the rates of Tuesday afternoon 15.00h). The hourly parking rates in a zone are calculated as weighted averages of all parking places in the corresponding zone. We assume in our study that parking at hubs is free (but evidently the experiments can also be performed for situations with parking fees).

## 3.1. Model parameters

Since some unimodal and multimodal modes are at the moment hardly ever used, it is not possible to estimate all model parameters. In our case, we therefore decided to restrict the estimation to all unimodal modes for which sufficient data is available; here we rely on the large-scale travel survey OViN/ODiN (CBS, 2018) in the Netherlands for the years 2013–2017. The model parameters for DRT are inherited from the car passenger mode. The model parameters for the EB mode are based on those of the B mode. The utilities for the multimodal modes are computed using the parameters of the unimodal modes as explained by Equation (1). While we deem these numbers to be representative, setting up a detailed estimation of model parameters pertaining to MaaS and/or new mobility concepts is outside of the of this paper. In this respect, it should be kept in mind that our primary objective here is to demonstrate the kind of scenario evaluation that can be performed with our approach.

## 3.2. Scenario description

Table 3 gives an overview of all scenarios that we considered in our illustration case. The reference scenario, scenario 1, disables the DRT mode (demand-responsive transport), so there are six unimodal modes. There are also no shared services, so people cannot rent a shared car or shared (e-)bike or use the DRT services. In all other scenarios the DRT mode is enabled.

In the scenarios having '16.5% MaaS' in their names, we assume that 10% of the people younger than 15 or older than 65 have a MaaS subscription, while 20% of the people between 15 and 65 have a MaaS subscription. As a result, on average 16.5% of the population has a MaaS subscription. In any of the MaaS scenarios, having a MaaS subscription

| # | Scenario name | MaaS subscription% | Run multimodal mode chain model | Parking cost w.r.t. normal | Operation Cost w.r.t. normal |
|---|---|---|---|---|---|
| 1 | Reference | 0% | No | 1.0 | 1.0 |
| 2 | 16.5% MaaS | 16.5% | No | 1.0 | 1.0 |
| 3 | 100% MaaS | 100% | No | 1.0 | 1.0 |
| 4 | 16.5% MaaS + MM | 16.5% | Yes | 1.0 | 1.0 |
| 5 | 100% MaaS + MM | 100% | Yes | 1.0 | 1.0 |
| 6 | 16.5% MaaS + MM + Parking 200% | 16.5% | Yes | 2.0 | 1.0 |
| 7 | 100% MaaS + MM + Cost 50% | 100% | Yes | 1.0 | 0.5 |
| 8 | 100% MaaS + MM + Cost 20% | 100% | Yes | 1.0 | 0.2 |
| 9 | 100% MaaS + MM + Cost 20% (excepts cars) | 100% | Yes | 1.0 | 0.2 |

**Table 3**
Scenario overview; 'MM' stands for multimodal.

implies that a person can use a shared car/bike/e-bike, or use a shared taxi, minibus or other shared mode, which does not belong to the traditional public transport modes (bus, tram, metro, train). In the scenarios having '100% MaaS' in their names, 100% of the population has a MaaS subscription. In scenarios 2 and 3 multimodal trips are excluded. These scenarios show how MaaS and new mobility concepts can be included as main modes in a mode choice model, the numerical results providing an indication of the potential of shared mobility concepts and DRT. Scenarios 4 and 5 do include multimodal modes, so as to assess the added value of modeling access and egress modes and show the potential of hubs. In scenario 6 the parking costs have been increased, to study whether hubs in these circumstances are used more intensively to avoid higher parking costs. In scenarios 7 and 8 the operational cost of all modes have been reduced in order to study its effect on the mode choice. In scenario 9 this has also been done, except for the shared car mode. This way, one can quantify the possible impact of a flexible cost mechanism to further reduce car usage.

### 3.3. Scenario results

Using an ActivitySim implementation, which includes the model described in this paper as the multimodal mode choice component, we have simulated the aforementioned nine scenarios. Each of these scenarios took about 5 hours to run on a server (CPU: Intel Xeon(R) 2.4GHz, Memory: 128 GB). We now proceed by discussing the numerical findings pertaining to the various scenarios. The modal split effects are shown in Figure 3. In scenarios 1 and 2, WA and B are the dominant modes because the main destinations are in the city centers. In scenario 2 the share of DRT trips is 7%, which is relatively high given the fact that the DRT mode is available for only 16.5% of the population; compared to scenario 1, these DRT trips mainly stem from WA and CP. There is also a modest (order of 1%) increase in e-bike trips. When everybody owns a MaaS subscription, in scenario 3, the total share of C trips decreases from 22.4% to 18% while the share of EB trips increases from 4% to 8%. So MaaS prompts people to choose the EB mode (instead of C). This also results in a significant decrease in the total number of car kilometres: this number goes down by as much as 7%.

In scenario 4, 3.3% of all trips use multimodal modes (such as combinations of C, PT and B/EB). Among those trips, 89% uses the C-PT hubs and 11% uses the C-B hubs. In particular, the share of trips using C-B hubs with private car and bike is only 0.05%. This low percentage is in line with our expectation because currently, the share of park and ride is also very low: in the OViN 2016 data, just 0.02% of all trips in the Netherlands uses a C-B hub.

In the extreme scenario 5, the total share of C trips reduces from 22.4% to 13%. Those C trips are mainly shifted to e-bikes and multimodal modes. This results in an increase by a factor of 2 of e-bike trips (to 7.9%), and an increase of multimodal mode use (to 10.7%). This shift can be explained by the fact that shared mobility concepts make it easier to use multimodal modes and do not impose any restrictions with respect to mode availability. The higher travel time via a hub is compensated by a reduced cost, recalling that car parking at hubs is free (as was assumed in Section 3.2) and that the cost for a shared e-bike is also relatively low (as can be seen in Table 2).

In scenario 6 the parking cost has been increased by 100%, relative to scenario 4. The total number of trips using a car has decreased from 20.8% to 20.1%. This small change can be explained by the fact that the daily parking costs are on average low for private car travelers. However, the number of trips using a private car, whose destinations are

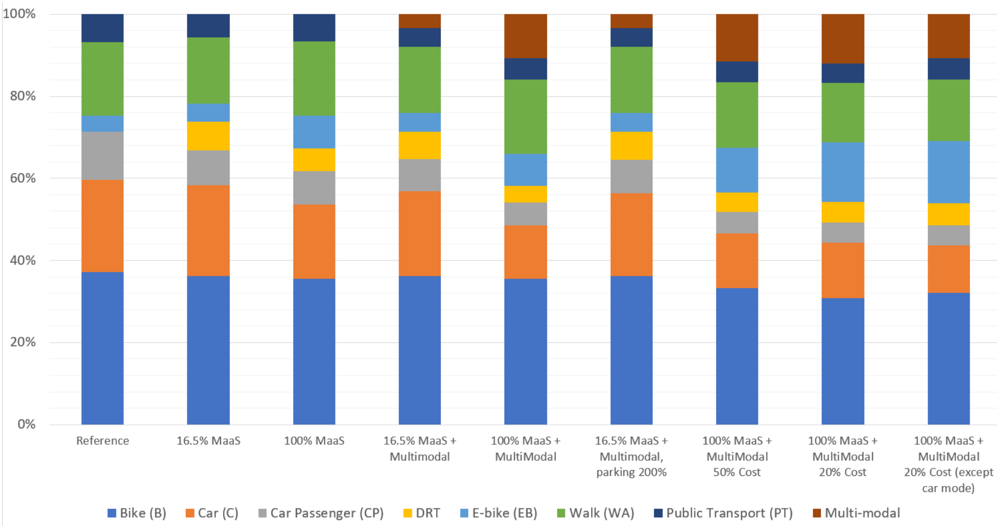


**Figure 3:** Modal split in different scenarios. Sharing and non-sharing trips are aggregated, and multimodal mode trips are aggregated.

the three most visited paid parking zones, has reduced by 10.6% (from 2590 to 2316), which is again in line with what could be expected. Based on the modal splits observed for scenarios 5 and 6, we can claim that the mode choice is sensitive to MaaS subscription ownership and parking cost.

In scenario 7 and 8 the operational cost has been decreased to 50% and 20%, respectively, with respect to scenario 5. Compared to 7.9% of e-bike trips in scenario 5, the percentage of e-bike trips increases: it becomes 10.9% in scenario 7 and 14.5% in scenario 8. These trips have primarily shifted from bike trips and walk trips. The multimodal trips have also slightly increased to 11.6% and 12%, respectively, compared to 10.7% in scenario 5 due to the overall lower cost.trave

In scenario 9, again all operational costs have been decreased to 20%, but this time except for the private and shared car modes. The total car trips percentage decreases to 11.5% compared to 13.5% in scenario 8. Those car trips have mainly shifted to other unimodal modes.

We continue, in Figure 4, by analyzing the resulting trip length distribution of a few multimodal modes of scenario 4, normalized by the total number of trips per mode. Clearly, C-PT hubs are used for longer trips than the trips C-B hubs are used for. The top 3 most visited hubs are the hubs located on the boundaries of the cities Delft, Zoetermeer and The Hague (the three red circles in Figure 2). This makes sense, as travelers prefer to switch from C to B/EB or PT to enter the cities and switch back to C when leaving the cities.

As a further sanity check, we zoom in on one specific hub ('Kralingse Zoom', located near the highway pass through Rotterdam), particularly focusing on the W-C-B mode. Figure 5 shows the origins and destinations of travelers using this hub. When considering scenario 4 instead of the reference scenario 1, on average the traveled distance increases by 2.1 km and the travel time by 10 minutes. This may be surprising, as there seems to be no incentive for a shift to a mode having higher travel distance or travel time. However, there are no parking costs involved when transferring at a hub. As a result, the utilities of the W-C-B mode and the car mode are in general close to each other. Because of traveler heterogeneity, modeled by the error terms, multimodal modes such as the W-C-B mode will be chosen in scenario 4, as compared to the reference scenario. The average extra 2.1 km travel distance can be covered by bike: when a bike is used as access/egress mode for PT the average cycle distance is between 1-3 kilometers (Jonkeren, Harms, Huibregtse and Bakker, 2018), thus confirming the plausibility of our results.

### 3.4. Sensitivity analysis

There are two normally distributed error terms incorporated into the utility function, so as to represent the unobserved utility; see Equation (1). For both normal distributions, we choose 0 as mean without loss of generality, and an adjustable $\sigma$ as standard deviation. In our calculations, we picked $\sigma$ such that the standard deviation of the sum of the two error terms equals 50% of the average absolute utility of all modes.

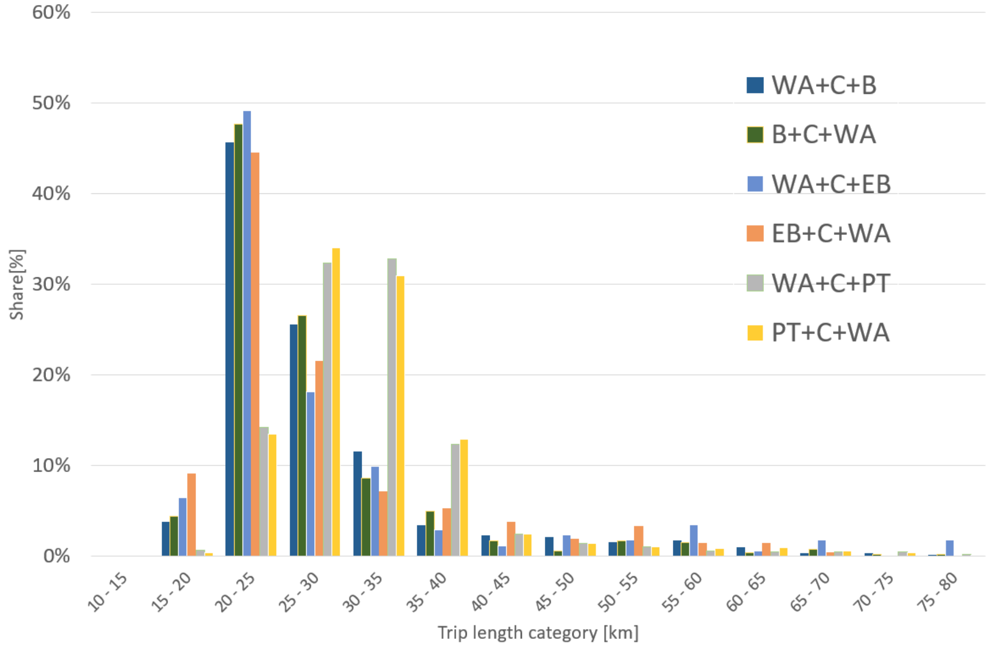


**Figure 4:** Trip length distribution for WA+C+B/EB, WA+C+PT


**Figure 5:** Trip origins (yellow blocks) and destinations (light red blocks) using the same hub (red point) by the WA+C+B mode.

We have in addition run experiments where $\sigma$ was set so that the standard deviation of the combined error terms was equal to only 10% of the average absolute utility. In this case, in scenario 4, the percentage of multimodal trips reduced from 3.3% to 1.5%. Hence, with a small standard deviation, the multimodal modes are unattractive compared to the unimodal modes. This can be explained by the fact that the mode having the highest utility is selected, and generally the utilities of unimodal modes are higher than that of multimodal modes. This experiment quantifies the impact of $\sigma$ on the modal split; in general, an appropriate value of $\sigma$ can be identified e.g. by using survey data.

## 4. Conclusion and discussion

In this paper, we presented a novel tour-based multimodal mode choice model for the impact assessment of new mobility concepts and Mobility as a Service. It includes mode consistency restrictions with respect to personal vehicle ownership, MaaS subscription ownership and vehicle states. We also introduced the concept of mode categorization. More specifically, we showed that a categorization into seven main modes includes most of the traditional modes and new mobility concepts like micro-modalities and on-demand public transport. Other new modalities can be added to the framework as well, and the model can deal with both shared and non-shared modalities. The categorization helps to reduce selection bias, while it induces numerical efficiency: our model is able to handle large scenarios up to millions of inhabitants. A possible drawback of categorization, however, could be that it introduces heterogeneity issues. That is, travellers could still have different personal preferences regarding two modes in a single category, leading to anomalous choice behavior. Solving these heterogeneity issues is a topic for further research. That is, by selecting different aspect elements than those chosen in Section 2.1, or even choosing different aspects, this issue may be reduced to a minimum. With this model, insight in the expected impact of new mobility concepts and Mobility as a Service on mode choice can be obtained. Moreover, it can be used to analyze the accessibility of hub locations in the future.

Since the multimodal mode choice model has been integrated in an ABM, the impact of new mobility concepts and MaaS on trip activities and destination choice can also be explored. However, this requires a connection with a multimodal traffic assignment. Such a connection would also make it possible to assess the impact of changes in mode choice on travel times which in turn can affect activity, destination and mode choice. Since this paper does not integrate our model in a multimodal assignment model, only first-order impacts have been presented, which implies that some effects might have been slightly overestimated, especially in congested areas. Therefore, we recommend to integrate our model within a multimodal traffic assignment model.

Concerning the multimodal mode alternatives, we have assumed them in this study to include just a single main mode. However, one may reason that there may be more than one main mode used within a single trip. For example, think of a park and ride service, which uses both a car and a public transport mode. Although inclusion of multiple main modes in a multimodal mode alternative is no problem from a modeling point of view, this will aggravate the computational complexity because of the exponential increase in the number of mode combinations. This is a point for further research.

Next, in the current study, in the utility calculation of the multimodal mode alternatives only the ASC and the socio-demographic attributes of the underlying main mode are considered. The reason behind this is that in this way, previously estimated coefficients of these attributes in a unimodal setting could be used. This however leads to the possibly undesirable effect that personal preferences on the various access or egress modes are not taken into account. To include these modes, a comprehensive estimation of coefficients in a multimodal setting is required. A possible approach could be that of dynamic discrete choice modelling studied by Hasnine and Habib (2018).

Finally, when making multimodal mode choices, the model either requires the traveler to fully use their private vehicles or shared vehicles, without allowing a mixed use of private and shared vehicles. This can be improved by adjusting the mode consistency check in such a way that mixed use is also possible or by introducing a rule-based approach: e.g. when a private vehicle is available in the tour, the private vehicle is included in the choice set and otherwise the shared vehicle is included in the choice set. Moreover, mobility packages (Esztergár-Kiss and Kerényi, 2020) and the type of sharing services such as free-floating or station-based sharing also affects the multimodal mode choice patterns (Kopp, Gerike and Axhausen, 2015). Since we have assumed free-floating services in a situation with MaaS, the model can be improved by including station-based sharing.

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