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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. Seven mode categories are proposed, which 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. The potential of the model is illustrated 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.

Keywords MaaS · New mobility concepts · Multimodal trips · Tour-based · Mode choice

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Introduction

We are witnessing the development of new transport technologies, such as connected vehicles using 5 G, 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 et al. 2017; Hesselgren et al. 2020). In the context of this paper, MaaS is assumed to offer travelers full freedom to choose any traffic mode at any time.

On 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 and Uber, also stimulate the development of MaaS (Milakis et al. 2017; Snelder et al. 2019; Wright et al. 2020).

To assess the full potential of MaaS and new mobility concepts, it is crucial that multimodality including transfers at hubs can be modelled. Furthermore, it is required that flexible and consistent mode choice within tours can be considered. At the same time, restrictions regarding vehicle ownership and availability of modes for different trips in a tour must be taken into account.

There is a growing body of literature that focuses on impact assessment of MaaS and new mobility concepts using activity based models and discrete choice models (see e.g. Narayan et al. (2019); Becker et al. (2020); Diogu (2019)). However, their focus has predominantly been on unimodal trips or the use of a single mode throughout a complete tour. In contrast, multimodal mode choice has been extensively studied in e.g Basu et al. (2018); Mounce and Nelson (2019); Saprykin et al. (2022)), but these studies do not check the consistency of mode choices within a tour. The consistency of mode choice on a tour level has explicitly been considered in some studies using discrete choice modelling approaches (e.g Adnan et al. (2016); Vovsha (2017); Becker et al. (2020)). It is worth noting, though, that none of these studies consider multimodal trips, or equivalently, the use of multiple modes within a single trip. An important reason why multimodal trips are not considered is that the inclusion of these trips in tours with multiple trips results in a huge choice set, especially when many new modes are considered. Multi-state supernetwork approaches (e.g Li et al. (2018)) can consider multimodal trips within tours. However, these methods have only considered one new mode and they are hard to apply to large realistic networks due to their computational complexity and due to the difficulty to estimate and calibrate their parameters. To the best of our knowledge, a tour-based multimodal mode choice model that is able to include multiple new mobility concepts and transfers at hubs (i.e. multimodal modes) in large-scale realistic networks, while considering restrictions regarding ownership and availability of modes in a tour, has not yet been developed so far.

This paper overcomes this gap in the literature, by developing a methodology to study multimodal mode choices, 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. Since mobility hubs are required to use multimodal modes, this work thus also pays attention to mobility hub modelling. The contributions of this work can be summarized in the following way. In the first place, we develop a multimodal tour-based mode choice model, as part of an activity-based demand model called ActivitySim (Gali et al. 2008), 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, a probit model is used to select the multimodal mode chain having the highest utility. 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 a higher likelihood to be chosen). In our specific case, seven categories are introduced that cover many new mobility concepts such as micro-modalities (e.g., bike, scooter) and on-demand public transport. 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, as a last contribution, an illustration example is presented that considers 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.

Throughout this paper, a tour is understood to be a series of trips starting and ending at home. A trip can consist of multiple legs. We use the term multi-modality in the meaning of intermodality for trips in which different modes are used for different legs of a trips (e.g. cycling as access mode, public transport as main mode and walking as egress modes). Finally, hubs are locations where people can change modes between different legs within a multimodal trip.

The remainder of this paper is organized as follows. In Sect. "Literature review" , relevant literature is presented on unimodal trip modelling, multimodal trip modelling and tour modelling. Section "Methodology" explains the details of the compartments our methodology consists of. In Sect. "Illustrational example", we provide a large-scale numerical experiment that illustrates the potential of our approach. Finally, Sect. "Conclusion and discussion" presents the conclusions, discussion, and recommendations for future research.

Literature review

This section presents literature on different modelling aspects that are relevant to assess the impact of MaaS and new mobility concepts. First, activity-based and discrete choice modelling approaches are presented that assess the impact of MaaS and new mobility concepts for unimodal trips. Subsequently, we discuss studies that do consider multimodal trips, but disregard consistency of mode choice at the tour level. Finally, we review literature that focuses on impact assessment of MaaS and new mobility concepts on tour level.

Unimodal trip modeling

Owing to its flexibility, robustness and efficiency to model complex travel behavior, *Activity-based modeling* (ABM) offers a highly suitable methodology for quantifying the impact of MaaS and new mobility concepts (NMC) because it works on the personal level and user-centricity and personalisation lay actually in the core of MaaS and NMC (Miller

2018; Franco et al. 2020). There is a growing body of literature on this approach: for example Narayan et al. (2019) have investigated ride-sourcing for car and public transport in Amsterdam using MATSim, an open-source multi-agent transport simulation framework (Horni et al. 2016). Several other studies have also used MATSim. Ciari et al. (2012) estimated the car-sharing demand, taking into account individual travel behavior, activity patterns, and mode choice. Becker et al. (2020) found that a MaaS scheme with shared mobility may slightly decrease travel times and cost, while substantially reducing energy consumption. Zwick and Axhausen (2020) analyzed on-demand ridepooling while Segui-Gasco et al. (2019) evaluated the impact of different automated mobility-on-demand (AMoD) scenarios from travelers, operators and city's perspective using MATSim and IMSim. Together with MATSim, the TASHA model (Miller et al. 2005) has been used to study the effect of transit-oriented infrastructural investments and transport policies in the Greater Toronto Area (Diogu 2019). SimMobility (Adnan et al. 2016), another ABM model, has been used to study the advantages and challenges of AMoD compared to mass transit systems (Basu et al. 2018). In the study of Parsa et al. (2020), POLARIS (Auld et al. 2016) is used to predict changes in average daily traffic under the connected and autonomous vehicles technology in the Chicago metropolitan area.

Discrete choice models (DCM) have also been used outside activity-based models to assess the impact of MaaS and new mobility concepts. The study of Snelder et al. (2019) applied a multinomial logit model to analyze the impact of automated driving and shared mobility in The Netherlands. A study in Finland (Ratilainen 2017) used choice modeling to identify the most important factors that affect traveler's choices on MaaS packages as well as their willingness to pay for those factors. It shows that current public transport users are most interested in the use of MaaS packages. Using a latent class choice model (LCCM) to identify user groups with different personal preferences in Greater Manchester, Matyas and Kamargianni (2021) has shown significant heterogeneity of users' preferences on MaaS monthly subscription. Higher-income and education-level people tend towards larger subscriptions. Similarly, Alonso-González et al. (2020) also used LCCM, and they found that individuals usually having a multimodal pattern have the highest inclination for future MaaS adoption while unimodal car users are the least likely to adopt MaaS. Finally, we mention Hensher et al. (2022, 2023), which use advanced discrete choice models to build a commuter mode choice model.

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 or only unimodal modes in a tour, 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.

Multimodal trip modeling

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 et al. 2018; Matyas and Kamargianni 2018), such as taxis (Wang and Ross 2017; Saprykin et al. 2022), a car-sharing system (Mounce and Nelson 2019), or on-demand mobility (Salazar et al. 2018). Franco et al. (2020) studied demand responsive transport (DRT) with mass transit in the multimodal journeys. Furthermore, Creemers et al. (2015); Olvera et al. (2015); Himmel et al. (2016) have analyzed access and egress mode choice based on surveys in the context of PT-based multimodal mode choice. We also mention Krajzewicz et al. (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 et al. (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.

Tour modeling

A relatively low number of studies explicitly check the consistency of modes within a tour. Some tour based discrete mode choice models use simplified main tour modes and conditional trip-level mode choices, such as DaySim (Bradley et al. 2010), CT-RAMP (Davidson et al. 2010) and SimMobility (Adnan et al. 2016). The choice set explodes when the number of trips in a tour increases. Therefore, TASHA (Miller et al. 2005) uses a simulation procedure to get the mode choice probability. There are also models that handle all feasible tour mode combinations. For example, the stand-alone tour-based mode choice model developed by Vovsha (2017) explicitly checks for consistency of modes within a tour. CEMDAP (Bhat et al. 2004) also models this but only for simple tour combinations. Besides, Hasnine and Habib (2018) proposed a tour-based mode choice mode using dynamic discrete choice models, but only two- and three-trips tours are handled. Although these tour-based mode choice models check for consistency of mode choices within tours, they do not consider multimodal trips withing tours.

Supernetworks are able to consider multimodal trips within tours. In this regard, it is also important to consider the works of Arentze and Timmermans (2004); Liao et al. (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 et al. 2020). This approach is very powerful, as witnessed by the fact that it is amenable to an extension (e.g. the study of Li et al. (2018)) that incorporates free-floating car sharing as an alternative mode. However, as far as known to the authors, these approaches have not yet been applied to large realistic networks due their computational complexity and due to the difficulty to estimate and calibrate the parameters.

Conclusions literature review

Although different modelling approaches have been developed and applied to assess the impact of MaaS and new mobility concepts, a tour-based multimodal mode choice model that is able to include multiple new mobility concepts and transfers at hubs (i.e. multimodal modes) in large-scale realistic networks, while considering restrictions regarding ownership and availability of modes in a tour does not yet exist.

The discrete choice modelling (DCM) and supernetwork 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. The present paper focuses on a discrete choice modelling approach.

Methodology

Our model can be interpreted as a component of an activity-based model (ABM). As such, we wish to implement the model in an activity-based travel-demand modelling package that already contains all other components required to run the ABM as a whole. For purposes of practicality, this software package should be available on an open-source basis and be able to handle vast amounts of data. Next to this, the end user should be able to alter the utility function without changing the source code. As ActivitySim (cf. Gali et al. (2008)) satisfies all these requirements, we have opted to implement our model as a component of ActivitySim. An explanation of how our model interacts with ActivitySim is now in order. First, a population is synthesized as pointed out in Snelder et al. (2021). 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.

The next subsection details the mode categorization into seven main mode categories, which are also used in the numerical experiment of Sect. "Illustrational example". We argue that this categorization covers most of the traditional as well as new mobility modes. Afterwards, multimodal mode alternatives from these seven main modes are derived, which enables us to explain how our multimodal mode choice model works.

Mode categorization

We now describe the unimodal mode alternatives included in our ABM. In doing so, the notion of mode categorization is introduced, meaning that modes from different categories should be seen as different in nature. The main goal of this categorization is the reduction of selection bias at the mode choice selection stage of the model, as will be explained 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, seven different modes categories will be identified 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): s $\in \{\leq 5, 5--20, 20--30, > 30\}$;
- Weight: w $\in$ { mm , $\geq$ car };
- Vehicle space per person: vs $\in \{\leq 0.25, 0.25 - 0.5, > 0.5\}$;
- Passenger capacity: 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 $4 \times 2 \times 3 \times 3 = 72$ combinations. However, not all the combinations are valid. Below all *infeasible* combinations are listed including an argumentation:

- {w $\geq$ car} & {s $\leq$ 30}: a vehicle that weighs at least as much as a car should drive faster than 30 km/h.
- {w $\geq$ car} & {PC < 1}: a vehicle that weighs at least as much as a car should have capacity for one or more passengers.
- {w $\geq$ car} & {PC > 8} & {VS > 0.25}: the passenger capacity exceeding 8 implies that the vehicle space should be in the category '$\leq$ 0.25'.
- {W = MM} & {PC $\geq$ 1}: micro-modalities do not have space for passengers.
- {W = MM} & {s > 30}: micro-modalities will not move faster than 30 km/h.
- {W = MM} & {VS > 0.5}: micro-modalities do not take that much space.
- {W = MM} & {s > 5} & {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.
- {W = MM} & {s $\leq$ 5 } & {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. The abbreviations presented in this table are used 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

Table 1 Overview feasible mode categories

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

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 shown 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, travelers 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. Sect. "Conclusion and discussion".

Multimodal mode alternatives

Now that unimodal mode alternative are explained, it remains to explain the multimodal mode alternatives. 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, two types of hub locations are considered. 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. The following rules are used to select 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, this traveler uses 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, EB-PT-EB is not included; 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 Centraal Bureau voor de Statistiek (2018)), while the MaaS-related rules are based on the judgement of stakeholders. Based on the considerations provided above, just 32 multimodal modes remain out of the possible 343. They are provided in Fig. 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, it is explained how to calculate the utility of multimodal modes.

Multimodal mode utility calculation

It is left to consider 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.

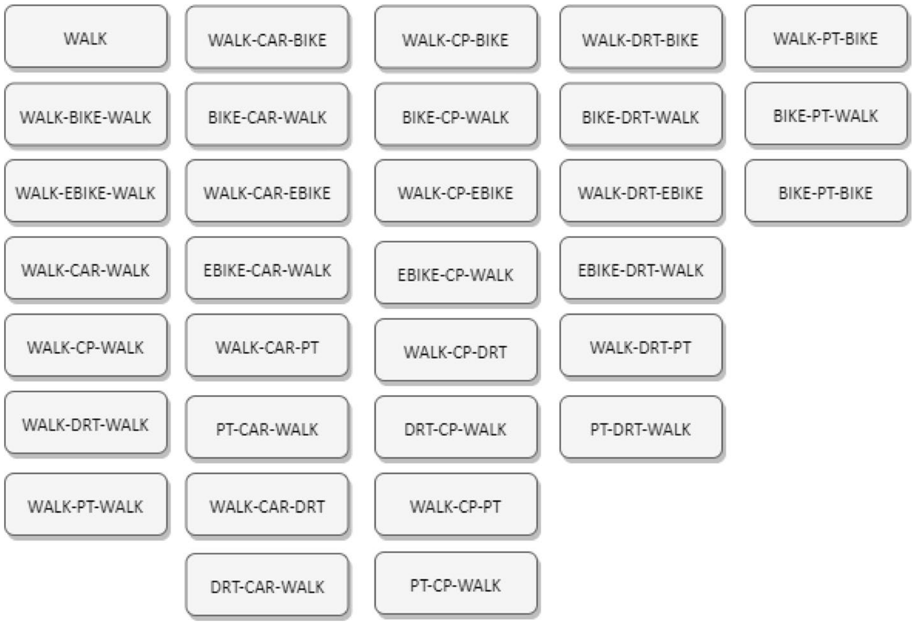

Fig. 1 Selected multimodal modes

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 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, already known estimations based on unimodal modes are used, while they are expected 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 (T_{transfer}) is summed over these two transfers.

As for the inclusion of error terms in the utility function, we apply the error term structure adopted in Miller et al. (2005) and in doing so expand it to a multimodal setting. This work advocates the use of two error terms, only one of which is resampled between trips. Translating this to our setting, this means that we include terms $\mu_{\text{multimodal}}$ and $\eta_{\text{multimodal}}$ in the utility function that represent the errors made in computing the utility of the multimodal mode of the trip. 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. That is, by not resampling this number, it is ensured that throughout the decision making for different trips, each traveler retains its personal preferences concerning mode choice.

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, which can vary between trips, even though the same traveler/mode combination is considered. As a result, in contrast to $\mu_{\text{multimodal}}$, $\eta_{\text{multimodal}}$ is resampled when making a choice for a different trip, even though the same mode/traveler combination is considered. Both of the error terms are assumed to follow a normal distribution, each with mean zero and appropriately chosen variance.

In summary, the utility function of the multimodal mode thus becomes:

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

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

It is also noteworthy that the above-explained error term structure of Miller et al. (2005) is beneficial for use in our setup because of the fact that the sum of the two error terms $\mu_{\text{multimodal}}$ and $\eta_{\text{multimodal}}$ is again normally distributed. This is due to the property that the sum of normally distributed random variables is again normally distributed. Furthermore, when the utility of the mode choices in a complete tour needs to be calculated, typically the utilities of the mode choices for the individual trips are added up. Due to the same property, the aggregate error term of the utility on a tour level is again normally distributed. As a result, the choice model resolves to a multinomial probit model, which is a widely used in this context. The choice model is further commented on in the following section.

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, valid multimodal mode chain sets are generated for each tour type by taking into account the long-term decisions made in an earlier stage of the ABM. To this end, vehicle ownership and availability restrictions of the travelers are considered. 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, all valid multimodal mode chains of different tour types are generated consisting of 2 trips, 3 trips, 4 trips without sub-tour, 4 trips including a sub-tour or 5 trips. In the settings considered, these tour types typically cover the vast majority (more than 98% according to OViN data (Centraal Bureau voor de Statistiek 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 et al. (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 traveling person does not have a MaaS subscription. If he/she does, then all constraints on the mode choice per trip are relaxed. 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, the total utility of each multimodal mode chain in this set is calculated for the complete tour, by adding together the utilities of the (unimodal or multimodal) modes corresponding to each trip within the tour; cf. Eq. (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, there is no computation of probabilities concerning 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, as is usual in a probit model such as this one, mode chain sets are selected 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.

Illustrational example

In this section, it is demonstrated how the ABM, that includes our tour-based multimodal mode choice model, can be used to simulate the travel demand. This is done 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 are obtained 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 (Snelder et al. 2021) 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 (Fig. 2). The output of this population synthesizer yielded a population of 278,698 inhabitants, together making up 131,466 households for the year of 2016. Of this generated population, 16% of this 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.

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 red and orange points in Fig. 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 concerning current-day modes and the results in Snelder et al. (2021) on future modes. Where applicable, the source of these numbers are mentioned in the table. If no source is mentioned, these numbers are assumption-based. If a shared mode

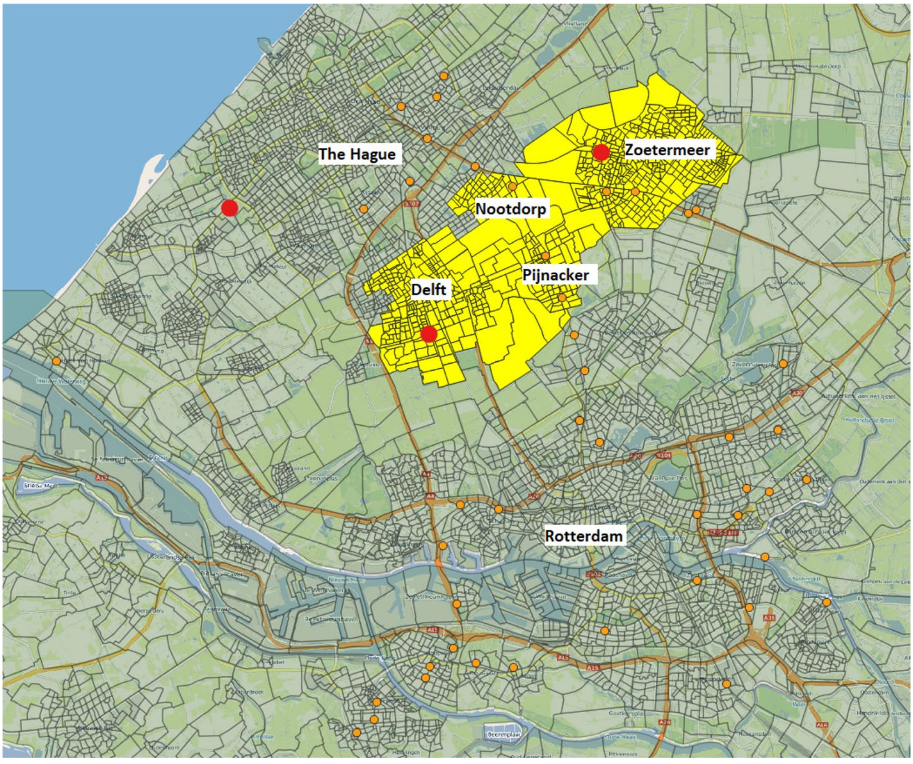

Fig. 2 Population living area (in yellow) between The Hague and Rotterdam, the orange and red points are hubs. (Color figure online)

Table 2 List of input parameters used in level of service

Name	Value	Source
Shared bike:		
Price for shared bike	0.00 €/min	OV-fiets (NS Reizigers 2023), Mobike (Micromobiliteit.nl 2023), Donkey Republic (Frederik 2023)
Start-up cost of shared bike	€1.925	OV-fiets, Mobike, Donkey Republic
Factor speed (shared) e-bike	1.5	25 km/h: 15 km/h
Price shared e-bike	0.3 €/min	Felyx scooter (Felyx 2023)
Car sharing		
Price car sharing	0.1 €/min	Greenwheels (Greenwheels 2023)
Start-up cost car sharing	€0	Greenwheels
Factor speed car-sharing car	1	
Price car passenger in shared-vehicle	0.35 €/min	
Start-up cost of car passenger in shared-vehicle	€3.00	Uber (Uber Technologies, Inc 2022)
PCU value car passenger in shared-vehicle	1	
DRT		
Factor speed DRT	1	
Waiting time constant DRT	0	
Start-up cost DRT	€3.00	Uber
PCU value for passenger in DRT vehicle	0.2	Assumed 5 passengers

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). It may strike as odd that several prices are set at zero. For example, the time-dependent price for the shared bike is set to 0 euro per minute. This is however not an unreasonable assumption, as shared bikes are usually hired per day in The Netherlands.

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 (Centraal Bureau voor de Statistiek 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 Eq. (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 scope 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.

Table 3 Scenario overview; 'MM' stands for multimodal

#	Scenario name	MaaS subscription%	Run multi-modal 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% (except car)	100	Yes	1.0	0.2

Scenario description

Table 3 gives an overview of all scenarios that are considered in our illustration case. All the assumptions related to the scenarios are summarized in Appendix A2. 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, it is assumed 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 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.

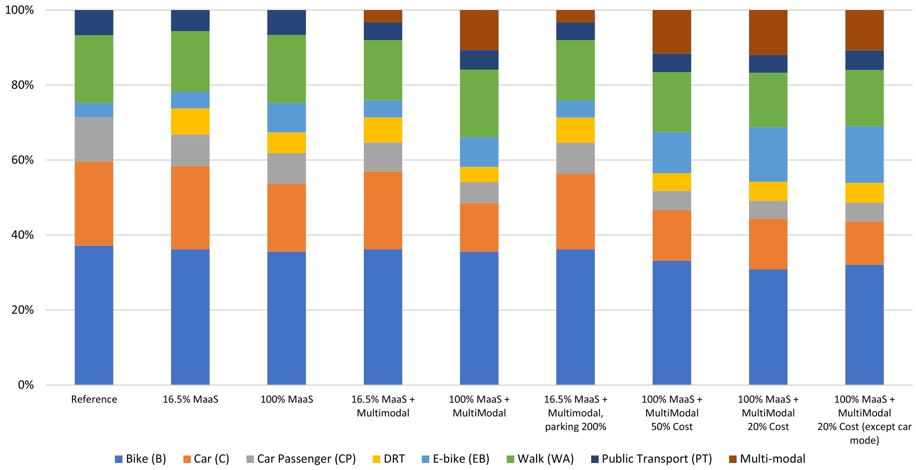

Fig. 3 Modal split in different scenarios. Sharing and non-sharing trips are aggregated, and multimodal mode trips are aggregated

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 h to run on a server (CPU: Intel Xeon(R) 2.4GHz, Memory: 128 GB). This section discusses the numerical findings pertaining to the various scenarios. The modal split effects are shown in Fig. 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 Sect. "Scenario description") 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 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, one can conclude 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 Fig. 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 Fig. 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 WA-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 min. This may be surprising, as there seems to be no

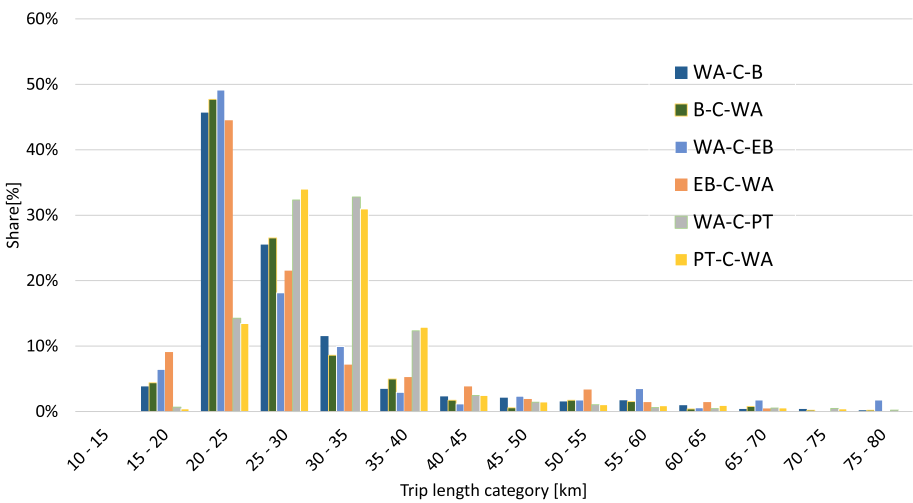

Fig. 4 Trip length distribution for WA-C-B/EB, WA-C-PT

Fig. 5 Trip origins (yellow blocks) and destinations (light red blocks) using the same hub (red point) by the WA-C-B mode. (Color figure online)

incentive for a shift to a mode having higher travel distance or travel time. However, it should be stressed that in Scenario 4 no parking costs are involved when transferring at a mobility hub, so that leaving the car at the hub and traveling further with e.g. bike is an attractive option. This makes that the (explained) utilities of the WA-C-B mode and the car mode are in general very close to each other, despite the longer travel distance and/or time of the WA-C-B mode. Due to the utilities being close to each other, the error terms $\mu_{\text{multimodal}}$ and $\eta_{\text{multimodal}}$ play a large role in the ultimate decision of the individual traveler. As a result, due to the heterogeneity of the travelers, not only car is chosen often as a mode in Scenario 4, but also modes that are multimodal. These multimodal modes are not chosen in the reference scenario 1. Therefore, since multimodal modes such as the WA-C-B mode usually incur a larger travel distance and time to reach a destination than unimodal modes, it is conceivable that the average traveled distances and average incurred travel times are larger in scenario 4 than in scenario 1. According to (Jonkeren et al. 2018), when a bike is used as access/egress mode for PT, the average cycle distance is between one and three kilometers. The additional average of 2.1 kms incurred in scenario 4 can thus be covered by bike, adding to the plausibility of our results.

Personal preference for the use of multimodal modes

To get an impression of which groups of the traveling public have a personal preference for multimodal modes given the ownership of a MaaS subscription, the results of scenario five werea nalyzed further. In this scenario, each traveler holds a MaaS subscription. While only regarding trips undertaken using a multimodal mode, education, income and age of the travelers were tracked since they are important factors affecting people's choice of using MaaS according to Matyas and Kamargianni (2021). The results show that low-educated people (36%) and people with low or middle-level household incomes (78.6%) are the main MaaS users. This is not surprising, since these travelers may not own private vehicles and the MaaS subscription is assumed to be offered for free. Regarding age, the majority of the multimodal mode users are between 25 and 65 years old (62.2%). This can be explained by the fact that the main travel purpose of these trips is for work (38.1%), which is most relevant for this age group. Note that we assumed that the parameters in the utility function are the same for all groups of travelers. It is recommend to estimate user group specific parameters in follow-up research and to study how that would affect the results.

Sensitivity analysis

As mentioned in Sect. "Multimodal mode utility calculation", there are two normally distributed error terms incorporated into the utility function, so as to represent the unobserved utility; see Eq. (1). Without loss of generality due to the alternative-specific constants, both distributions are assumed to have a zero mean. Furthermore, we have assumed both error terms to have the same variance. In particular, the value of this variance is determined such that the standard deviation (i.e., the square root of the variance) of the sum of the two error terms equals 50% of the average absolute utility of all modes.

In addition, experiments were run where the value of the variance 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 the variance on the modal split. In general, one must conclude that an appropriate value of the variance must be identified e.g. by using survey data.

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, it was shown that 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, travelers 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 Sect. "Mode categorization", 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.

Concerning the multimodal mode alternatives, these are assumed 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 the 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 modeling studied by Hasnine and Habib (2018).

Furthermore, 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 upon by extending the model with an additional choice model, which decides when a traveler uses a shared or a non-shared mode, in case the traveler has access to both. Such a choice model would need to be based on data concerning personal preferences of travelers. Moreover, mobility packages (Esztergár-Kiss and Kerényi 2020) and the type of sharing services such as free-floating or station-based sharing also affect the multimodal mode choice patterns (Kopp et al. 2015). Since free-floating services were assumed in a situation with MaaS, the model can be improved by including station-based sharing.

As mentioned above, incorporation of a choice model on whether to use a shared or non-shared mode requires additional data on personal preferences. In this spirit, it should also be mentioned that there are many other points where accuracy could be improved even further if data were available on the personal preferences of travelers. Then, utility functions could be personalized by having the attributes depend on these data. One may for example think of personal preferences regarding future modes, for which hardly any data is available currently, or the willingness to use MaaS. It should be mentioned, though, that data on personal preferences regarding current-day modes are available. Hence, it is currently possible to include personal preferences regarding current-day modes in the model.

A non-trivial process of parameter estimation is required to this end, which is outside the scope of the current paper. The same holds when one would be interested in applying the model to regions outside of the Netherlands. In this case, while the model can be applied fully analogously, the OViN data cannot be used anymore. As such, this inevitably requires the estimation and subsequent calibration of relevant coefficients in the utility functions based on local survey data.

Other than applying the model to other regions, there are many ways in which the model can be used to obtain useful insights. For example, as eluded to at the start of Sect. "Illustrational example", the illustrational example mainly considers pricing schemes which are based on a pay-per-use principle. The model may however also be used to study the impact of other types of pricing schemes, for example, those generating revenue by letting the travelers pay for holding a MaaS subscription. This again requires additional data on personal preferences. In this regard, the options are endless: all kinds of 'business models' can be considered.

We proceed by commenting on the scaling capabilities of the model. As reported at the start of Sect. "Scenario results", a scenario in the illustrational example took about five hours to run using code which was not optimized for speed. While not the focus of this paper, this calculation time can be reduced drastically. When one would optimize the code, one is able to handle large traffic systems within a reasonable amount of computation time; cf. Zhou et al. (2023). On top of this, if the GPU of a computer would be exploited for multi-threaded purposes in the spirit of our study Zhou et al. (2019), the computation time would be reduced even further. As mentioned in that paper, this way the computation time can be sped up by a factor up to 50. Thus, by taking these steps, the current model is amenable for use in analyzing large regions. As another idea of increasing the speed of the model, one may think of reducing the number of mode alternatives by excluding combinations of modes as a multimodal mode based on the location of the traveler. Indeed, considering the locations of the travelers, one may restrict the available multimodal modes available to them even further than done in this paper by considering the availability, accessibility and affordability at the traveler's location. This was however not incorporated in this paper, so as to show the applicability of our model to larger areas including cities, where typically (almost) all modes are available.

Finally, this work takes network congestion into account by basing the travel times on level-of-service data. While we expect this to be reasonably accurate, one may wonder whether the feedback from a network assignment model can be incorporated into the current travel demand model. While this may lead to improvements, incorporating such a 'feedback loop' presents methodological challenges and merits a study on its own.

Appendix: Assumptions

In this section, the assumptions made in the paper are summarized. We distinguish between the assumptions made in the methodological part of the paper and the assumptions made in the scenario modeling. The assumptions in the former category, which also include the rules set up in Sect. "Multimodal mode alternatives", are compiled in Sect. "Assumptions in the methodology". The remaining assumptions pertaining to the modeling of the scenarios are listed in Sect. "Assumptions in the scenarios".

Appendix 1: Assumptions in the methodology

- Each of the seven unimodal modes is a valid access, main or egress mode.
- For all unimodal modes, walk is implicitly used as the access and exit mode, because it is always necessary to walk a short distance, for example, to the bike, car, or PT stop.
- When WA, B or EB is used as the main mode, the access and egress mode can only be WA.
- 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.
- Transfers within public transport are possible, but not considered as a mode switch.
- In scenarios without MaaS, cars should return home at the end of a tour.
- In scenarios without MaaS, bike or e-bike should return home or can stay at hubs/stations at the end of a tour.
- 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.
- In scenarios without MaaS, B and EB cannot be used as egress mode in a sub-tour.
- At a C-PT hub, C/CP can switch to the PT or DRT mode, while PT or DRT can switch to C/CP mode.
- At a C-PT hub, DRT can switch to PT, while PT can switch to DRT mode.
- At a C-B hub, C/CP/DRT can switch to B/EB mode, while B/EB can switch to C/CP/DRT.
- 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 not a problem to add this option once these data are available.)
- 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.
- For the situation without MaaS, C is a valid main mode in an inbound trip when the egress mode is walk;
- For the situation without MaaS, C is a valid main mode in an outbound trip when the access mode is walk;
- For the situation without MaaS, 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).
- Both error terms $\mu_{\text{multimodal}}$ and $\eta_{\text{multimodal}}$ in the utility function are assumed to follow a normal distribution, each with mean zero and appropriately chosen variance.
- The transfer time at hubs is a constant: for C-B hubs it is set to 5 min, and for the C-PT hubs to 8 min according to the public transport transfer times reported in Schakenbos and Nijenstein (2014), which considers these parameters in the Netherlands.
- The transfer mode is assumed to be WA.
- There are no constraints for travelers to use any available modes if they own a MaaS subscription.

Appendix 2: Assumptions in the scenarios

In the scenarios considered in the illustrational example, the following assumptions were made.

- Average time to search for shared bike is 1 min.
- Average time to search for a car sharing possibility is 5 min.
- The waiting time for the car passenger in a shared vehicle (e.g., taxi) is 5 min.
- The use of shared bikes, car-sharing, and being a car passenger in a shared vehicle is allowed everywhere: there are no restrictions for shared modes based on location..
- There is no other cost for the DRT mode except the start-up cost.
- The parking rates per zone assumed in the scenarios are those reported 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., we picked the rates of Tuesday afternoon at 3PM). The hourly parking rates in a traffic analysis zone are calculated as weighted averages of all parking places in the corresponding zone.
- Parking at hubs is considered to be free of charge.
- Holding a MaaS subscription is free of charge.
- It is assumed that 10% of the traveling public younger than 15 or older than 65 hold a MaaS subscription, the percentage of the public between 15 and 65 years old holding a MaaS subscription reads 20%. As a result, on average 16.5% of the population has a MaaS subscription.
- Holding a MaaS subscription implies that a traveler 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).

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