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Discrete Continuous Travel Mode Choices based on Simulated Travel Demand: a MDCEV Model Application

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Abstract

The significantly higher level of detail of agent-based travel demand models (ABM) compared to aggregate models stands in contrast to their high simulation times. Once fast model responses are necessary, the application of ABMs may pose run time challenges. For such purposes, a condensation of ABMs' sensitivities and saturation effects regarding travel mode choice is required, which - as shown in this paper - is achieved by a multiple discrete continuous extreme value model (MDCEV). The application case of this method is a serious game which enables decision-makers and citizens low-threshold access to a better understanding of interrelations within the urban mobility system. The mode choice model for the serious game is estimated on the basis of the simulated travel demand patterns of an ABM. The comparison of the model application with the ABM reference results attests a good ability to reproduce the current travel demand, even for different types of traffic. Also modal shift reactions on policy interventions reveal a high level of consistency. v

Keywords: Multiple Discrete Continuous Extreme Value Model; Discrete-continuous travel mode choice; Serious game

1. Introduction

Serious games - i.e., games whose main purpose goes beyond entertainment - are regarded as appropriate instruments to enable decision-makers and citizens low-threshold access to a better understanding of complex systems or the impacts of interventions (see, e.g., Krath et al. (2021) or Ghodsvali et al. (2022)). The challenge in developing such instruments lies in the requirement of representing relationships in a scientifically sound manner, while abstracting from the complexity of the considered contexts.

In this tension, the current paper presents an approach to apply the travel mode choice of an agent-based travel demand model (ABM), which considers travel behavior at the individual level, to a serious game in which only aggregated relationships are modeled.

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Research on travel mode choice has been quite extensive, and with increased computational power, the applied models have become more advanced over the last decades. Implemented in ABMs, travel mode choice models generate highly detailed results by considering travel behavior at the level of individuals. The application of such models requires high efforts in data collection and model estimation, and may involve long run times for simulations.

For application in a serious game, however, the requirements of the travel mode choice model are different compared to those for typical planning processes in transportation, where as many details as possible are to be taken into account and the eventual simulation time is of lower importance. A serious game requires a particularly low simulation run time and shall be applicable to a wide range of different scenarios and policy measures in the present context. It shall enable its users to comprehend the effects of urban transport policy measures in a game environment and can be applied to address different user groups, such as stakeholders (e.g., shop owners, civic associations), urban transport planners, students, or interested citizens. The serious game is intended to show the effects, dependencies, possibilities, and boundaries of urban transport policy options and entails a scoring system for environmental, social, and economic aspects.

Consequently, for application in a serious game, a mode choice model is needed with a more aggregated view on interrelations and a lower level of detail. Thus, a simplified level of modeling is required to ensure the serious game's usability and direct responsiveness. Furthermore, it is necessary to embed the mode choice model in broader application contexts with linkages to other models (i.e., demography, transport infrastructure/ supply, vehicle fleet).

For such an application area, both methodology and data of the agent-based mode choice model require aggregation, which implies reducing the scope of modeling from the microscopic to the macroscopic level. Such research – i.e., the application and aggregation of data and methodology of detailed models for the development of fast and simplified models at aggregated level – corresponds to the creation of "meta-models", for which several examples exist at the European level: for instance, the EXPEDITE and SUMA foresight meta-models (de Jong et al., 2004; Van Grol et al., 2006) were developed by integrating European transport demand forecasts with national forecasts. The TRANSVISIONS foresight meta-model was used to identify possible paths towards a post-carbon society through a back-casting approach. The HIGH-TOOL model (Szimba et al., 2018) represents a high-level strategic European policy assessment tool whose modules for passenger demand, freight demand, demography, economy, environment, vehicle stock, and safety are simplified representations of detailed European models.

In this context, the approach presented in the current paper entails an existing complex travel mode choice model to be reduced to its essential functions. This implies developing an approach to distill the detailed model sensitivity towards policy measures. Hence, the scientific challenge lies in the reduction of complexity of the travel mode choice model while preserving as much as possible both the essential interrelationships of behavior and similar model sensitivities for various optional policy measures. The aim of this paper is to develop a method for the creation of such a model and to test its applicability in an exemplary use case.

Specifically, the ABM *mobitopp* is used as an input for the travel mode choice model of the serious game. *mobitopp* simulates travel behavior at the level of residents' trips within one week (Mallig et al., 2013). Each trip represents the result of multiple discrete choices, taking into account the traveler's characteristics as well as the trip context and activities. To preserve the travel mode choice of *mobitopp* as much as possible in the context of a computationally simplified model as part of the serious game, the application of the *multiple discrete continuous extreme value model* (MDCEV) is considered to be suitable. The MDCEV model approach is able to operate with multiple discreteness (Bhat, 2005), which occurs once all travelers' discrete mode choices are aggregated. With this method, the simulation output of *mobitopp* - i.e., travel demand by mode choice - is aggregated from the level of individual trips to OD pairs with aggregated characteristics serving as an input for the *MDCEV* estimation. Thereby, this research investigates whether MDCEV models are applicable for capturing discrete-continuous travel mode choice.

This research is structured as follows: Section 2 explains the applied method while illustrating the model structure as well as the database and estimation process. It further refers to the state of knowledge focusing on the factors influencing travel mode choice and the modeling of discrete continuous travel demand choices. It also reviews and interprets the estimation results. Section 3 demonstrates the application of the models and their validation regarding replication ability and model sensitivity. The last section summarizes research contributions and future challenges.

2. Method

The model to be developed requires multiple characteristics to be applicable to the serious game. First, the model has to operate at the level of OD-pairs allowing for a spatial allocation of effects. Second, the model has to take into account multiple modes of transport and determine their total transport demand. Third, the model still has to include the heterogeneity related to sociodemographic, spatial and transport supply characteristics as much as possible. Last, the model needs to be sensitive to measures in an appropriate dimension.

The method developed correspondingly is shown in Figure 1. Simplifying a complex travel mode choice model of an agent-based framework with its extensions regarding situative mode availability and level of service cannot be done by just rearranging its functions. Instead, this is done by using its simulated results to derive interrelationships between travel demand and independent factors. Therefore, a set of ABM simulations is run to create an extensive database which subsequently is aggregated and enriched by sociodemographic, spatial, and transport supply characteristics (see Section 2.1). This step is supported by a literature review on the main determinants of travel mode choice (see Section 2.2). On the basis of this database, a model concept is created, under further consideration of findings of research into models for discrete-continuous decisions (see Section 2.3 and 2.4). This model concept represents the basis for application in a serious game. Based on the simulated data of Section 2.1, multiple models are estimated (Section 2.5). These models are applied both for the status quo, and a scenario using a forecasting algorithm. Their results are validated by comparison with the original ABM simulation results, thus investigating the models' replication ability (see Section 3.1) and sensitivity (see Section 3.2). Thus, their usability within the serious game is ensured and further recommendations on the design of such models can be derived.

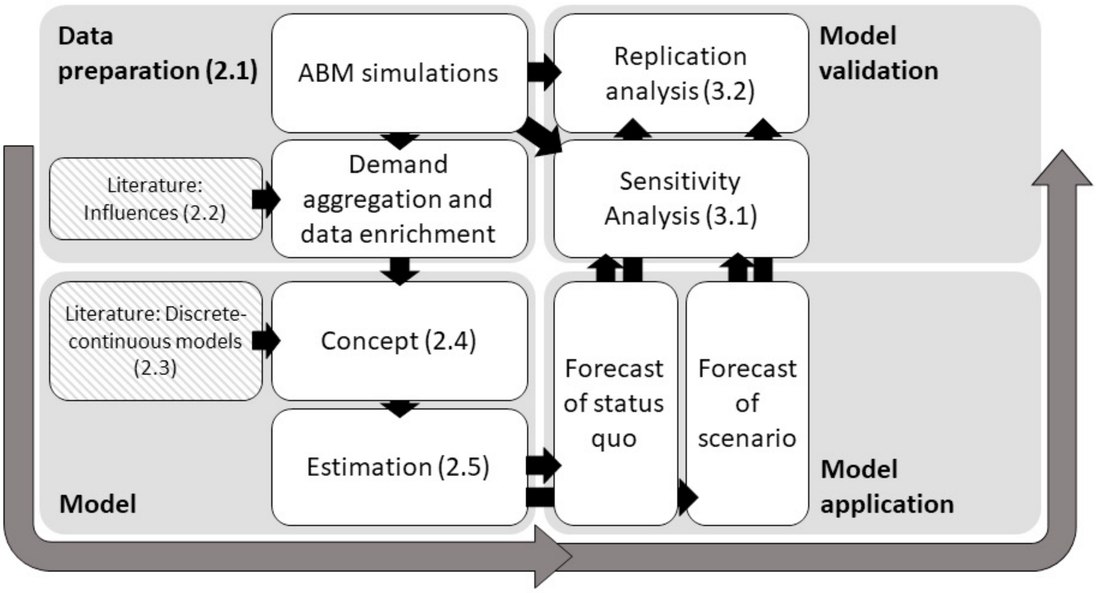

Fig. 1: Overview

2.1. Database and Estimation Process

The following section describes the data basis applied for the process of simplification. The simulated travel demand in this research originates from an ABM of the Karlsruhe region located in the southwest of Germany. The model was set up in the ABM simulation framework *mobiTopp* (Mallig et al., 2013). The model simulates agents' behavior for a whole week by creating individual activity plans and then chronologically deciding the destination and travel mode of a trip between the activities minute by minute for all agents simultaneously. The model sets up individual environments for agents regarding their fixed destinations (i.e., workplace and place of education), decides on mobility tools such as car ownership and transit pass, and controls the availability of travel modes within the households (i.e., private car) and within the services (i.e., carsharing, bikesharing, etc.).

The depicted area consists of urban and rural areas interconnected by a comparably well-developed public transportation system. In total, the population consists of about 1.9 million inhabitants belonging to about 880,000 households. The study area has a diameter of about 100 kilometers and is split into 2,400 traffic analysis zones. During the simulation period of one week, all agents conduct over 50 million trips.

For the modeling of this research, the simulated travel demand for each travel mode is aggregated at the city district level for the urban area of Karlsruhe and at the multi-municipal level for the surrounding region, resulting in 1539 OD pairs. These only include OD pairs having the city districts at least as an origin or as a destination. The considered travel modes are private car, car as passenger, walking, cycling, public transportation and carsharing. The travel demand of a typical weekday is considered. For each OD pair, attributes are assigned based on the origin district or as an attribute of the OD pair to characterize related circumstances of travel as well as spatial and demographic information. A literature review on factors influencing travel mode choice (see Section 2.2) is conducted to identify the most important attributes which can be used to explain travel mode choice. The resulting attributes on the district level include age distribution, occupation distribution, household composition regarding the presence of children, population density, vehicle and transit pass ownership, carsharing membership, and carsharing vehicle density. The attributes of the OD pair include travel times and costs for the respective travel mode and the share of travel purposes work, education and shopping. All attributes stem from the original ABM and are appropriately summarised. For example, the travel times and costs of previous microsimulation trips are aggregated to create a weighted value. These attributes are later used as determinants of travel mode choice within the developed model.

Further, a selection of these attributes is varied within in different ABM simulation runs. One aim of the simplified model to be estimated is to capture detailed measure sensitivity. With the database solely consisting of status quo data, the effects of measures were only observable through the model-based comparison of different OD pairs. Hence, the database for the later estimation is extended with simulated results of multiple ABM scenarios. A total of 17 scenarios were set up with varying travel times and costs of car and public transportation, carsharing supply, vehicle ownership, and transit pass ownership. These scenarios depict (combinations of) different measures within the transport sector to which the model must be sensitive. The resulting database consists of 27,702 observations each related to an OD pair and a simulation run with 106 omitted due to missing travel demand.

2.2. *Factors influencing travel mode choice*

The following section summarises the state of knowledge on influencing factors on travel mode choice in everyday travel. Over the last decades, exclusive and model-based analyses have comprehensively investigated travel mode choice behavior. In the case of ABM, the choice of travel mode is mainly determined by the travelers' characteristics and travel mode-associated issues, such as travel time, travel costs, etc. Individual characteristics include age, gender, employment type, or income. While most of the previous work relating to this paper differs in the referenced trip modes, trip purpose, geographic scope as well as used method, we want to highlight the main contributing factors likely to affect mode choice behavior at a city-district or city level.

Level-of-service (LOS) is often measured by the mode-specific attributes of travel time and travel cost, among various others such as comfort, reliability, etc. (Lawrence Frank et al., 2007; Al-Salih and Esztergár-Kiss, 2021). Travel time components generally include in-vehicle time, out-of-vehicle time, walking, and waiting time. As travel time, correlating to travel distance, increases, mode choice tends to move for the benefit of public transportation and private car. In contrast, active trip modes such as foot and bicycle trips prevail (Wang and Ross, 2018). The time valuation can differ across the respective travel modes. A minute of walking or bicycle time implies marginally more onerousness than a minute of driving or transit time (Rajamani et al., 2003). The effect of travel costs on private car and public transportation usage is negative. In contrast, car users give less importance to variations in travel costs than users of public transportation (La Paix et al., 2022). According to Bai et al. (2017), a ten percent decrease in public transportation costs seems to have a more substantial effect on the share of public transportation than a ten percent increase in private car costs.

Several studies have proven that car ownership has a positive impact on car usage and a negative on non-motorized travel modes. This effect is consistent through travel distance classes, thus reducing trips on foot for shorter trips and public transportation for longer (Scheiner, 2010; Kim and Ulfarsson, 2008; Chen et al., 2008). Further, increasing individuals' age was linked with decreased walking and bicycle rides, while the probability of choosing the car increased simultaneously. A similar link is identified for families with children (Kim and Ulfarsson, 2008). A contrary behavior is shown by university students, who favor non-motorized travel modes and public transportation according to several studies (Georgina Santos et al., 2013; Cattaneo et al., 2018; Jacques et al., 2011). One of the underlying reasons is the ownership of a transit pass, which can potentially increase the probability of commuting by transit and decrease the probability of driving alone (Zhou, 2016). Consumers' experience of using carsharing appears to significantly influence households' mode choices, increasing the probability of using diversified travel modes (e.g., bikesharing and taxi) and decreasing the likelihood of choosing to use privately owned travel vehicles such as private cars (Zhou et al., 2020; Martin and Shaheen, 2011; Barrios and Godier, 2014).

In addition to socioeconomic and -demographic factors, some studies consider land use types and urban forms as determinants of modal choice behavior. Accordingly, high population density, along with a high traffic volume and lack of parking space, implies higher ownership costs for private cars and thus reduces the share of trips taken by private cars (Wang and Ross, 2018). Such areas further have the potential to contribute to the success of carsharing since they translate to more potential members within walking distance of a carsharing vehicle (Barrios and Godier, 2014). In addition, the motivation to promote public transportation grows, implicating a rise in its attractiveness to the user. Due to short travel distances resulting from high population density, many trips are made by foot or by bicycle (Souche, 2010; Schwanen, 2002; Dargay and Hanly, 2004).

2.3. Discrete continuous choices in transportation research

In order to explain the travel mode choice in the simulated database, taking into account the interrelationships with transport supply, demography, and spatial structure, an appropriate model has to be developed.

Most decisions in the field of transportation are taken on an individual level. Furthermore, as most surveys collect the behavior of individuals and hence single choices of, among others, activity, destination, and travel mode, most of the research analysis is done one the individual level as well. It is especially interesting to understand the characteristics of the situation and person and their influence on the decision. Both traditional discrete choice approaches (Ben-Akiva and Bierlaire, 1999; de Dios Ortúzar and Willumsen, 2011), as well as newer machine learning approaches (Hagenauer and Helbich, 2017), enable both analysis and prediction of discrete decisions. However, some research exists taking an aggregate perspective.

Linear regression is mainly used for trip generation within travel demand models. Some research exists to model travel demand with a spatial dimension: Varagouli et al. (2005) collected multiple travel data sets and surveys to compile the overall travel demand and analyzed independent spatial variables using linear regression to be able to forecast travel demand.

The former assumes linear dependencies and becomes more problematic when modeling the interaction between multiple travel modes, which cannot be accounted for. For the joint estimation of tour-based travel mode choice and travel distance decisions Liu et al. (2022) applied a copula-based discrete continuous model to account for the dependency of these decisions. A similar approach was able to identify self-selection in the choice of the residential neighbourhood in combination with daily household vehicle miles traveled (Bhat and Eluru, 2009). Rashidi and Koo (2016) addresses the dependency of travel mode choice, travel party decision, and expenditure decision with a joint multinomial logit–trip expenditure hazard-based function.

Multiple discrete continuous extreme value models (MDCEV), first proposed by Bhat (2005), have been used to analyse and model travel mode decisions in different cases. Meister et al. (2022) set up an MDCEV model with a mixing error structure to model urban travel mode choice in terms of weekly vehicle miles traveled during different time segments of the COVID pandemic in 2020 and 2021. The model depicts travel mode choice and respective distances on an individual level and includes personal background, availability of mobility tools, and weather conditions besides the control of the time segments. Similarly, Bhaduri et al. (2020) analyzed the effects of the pandemic in its early stages on weekly trip frequencies by travel mode in India. They highlight the ability of the model to simultaneously get insights into the "extend of change in frequency of using different modes." The advantage of the model is the assumption of a "diminishing marginal utility as the level of consumption of any particular alternative increases," leading to satiation effects (Bhat, 2005).

2.4. Model concept

The model applied in this research has to cope with an existing travel demand between districts on the origin-destination (OD) level and aims to forecast aggregated travel mode choice based on characteristics of an OD pair and both districts. Existing research also uses only the characteristics of districts or a whole municipality. However, approaches reach their limits when it comes to forecast measures on the network level, such as measures leading to travel time reduction. They are intended to analyze factors influencing travel mode choice. The requirements for this model encompass both a discrete decision of which travel modes occur generally and what proportion of travel demand they account for. An appropriate model sensitivity and satiation effects must be incorporated into the model framework.

The MDCEV model provides the possibility of multiple discreteness and was introduced by Bhat (2005) with the example of modeling time use decisions of individuals. Most of the applications of the model (i.e., among others, consumer choices, vehicle ownership, and usage - c.f. Meister et al. (2022)) refer to discrete continuous choices of individuals. In contrast, this research sees an OD pair as the individual and the observed travel demand by travel mode as the discrete-continuous choice.

The MDCEV model's utility maximization problem with a budget condition formulated by Palma et al. (2021) is defined as:

$$Max_{x_m} \sum_{m=1}^{M} \frac{\gamma_m}{\alpha} \psi_m ((\frac{x_m}{\gamma_m} + 1)^{\alpha} - 1) \tag{1}$$

$$s.t. \sum_{m=1}^{M} x_m = B \tag{2}$$

where

x_m	amount of alternative m consumed
γ_m	satiation parameter for each alternative m
ψ_m	marginal baseline utility of alternative m
α	further satiation component
B	budget

γ_m and ψ_m are linear combinations of multiple influencing attributes providing the possibility to make utility and satiation dependent on attributes of the decision maker and the alternatives. The higher both values are the lower is the satiation and the higher is the utility of consuming an alternative compared to another. Depending on the formulation of the model it allows for corner solutions leading to a zero consumption of a certain good respectively a non-usage of a certain travel mode. α represents a second satiation component, but according to Bhat (2008) "it leads to serious empirical identification problems and estimation breakdowns when one attempts to estimate both γ and α parameters for each good". For this research the γ_m-profile was chosen as its forecasting algorithm is more efficient (Pinjari and Bhat, 2010; Palma et al., 2021). In this case, it exists one $alpha$ parameter for all alternatives.

For the estimation of the models the authors applied the R package *Apollo* (Hess and Palma, 2019). The forecasting algorithm originally formulated by Pinjari and Bhat (2010) and extended by Palma et al. (2021) for the case without an outside good is also applied in this research.

For this case of this model, an observation corresponds to the travel demand on an OD pair for a typical weekday. The alternatives are represented by the six available travel modes walking, cycling, car as driver, car as passenger, public transportation and carsharing. Thus, a corner solution with zero travel demand of a travel mode can occur, when the utility is evaluated too low.

2.5. Estimation results

Based on the described database, multiple estimations of continuous travel mode choice are conducted. It should be kept in mind that only effects can be modeled that have been accounted before in the ABM simulation.

As a reference for the main models, a base model *V0* is estimated solely containing the *alternative specific constants* ($delta_m$) and γ_m parameters. The first essential model *MDCEV V1* extends *V*0 with the level of service parameters (LOS) for each mode and subsequently *MDCEV V2* adds further 48 population and travel-related parameters, where the authors mainly focus on for interpretation. Adding further parameters significantly improves both the log-likelihood and the Bayesian Information Criterion (BIC), ensuring a still effective model. The extensions of the model are tested by applying the likelihood ratio test, whereas the null-hypothesis was rejected (Train, 2009). In the base model, all $delta_m$ are negative for all modes compared to the car reference reflecting the car as the mode used most often. Moving to *MDCEV V1* and *MDCEV V2*, positive changes can be observed for all modes except carsharing, which is enabled by further differentiation of choice through additional parameters. All the level of service parameters are significant and negative. Comparing *V1* and *V2*, time coefficients mainly become more negative, whereas the influence of cost becomes smaller. Some influences captured in the LOS parameters in *V1* can be better explained by other district- or OD-related parameters. This can substantially change the model sensitivity regarding measures reducing or increasing travel time and costs. Looking at saturation parameters γ_m of *MDCEV V2*, carsharing reveals to be the travel mode with the least saturation, followed by cycling and walking. Driving the private car is, in this model, the most saturated travel mode. The estimation results are shown in Table 1 and Table 2. The latter only contains parameters of *MDCEV V2*.

A higher proportion of heterogeneity of aggregated travel mode choice can be explained by incorporating further aggregated information on the city district and OD level. As shown in Section 2.2, the integrated attributes characterizing the population, the spatial structure and travel in general help to understand travel mode choice.

The ownership of private vehicles significantly raises the utility of the private car in these districts. Compared to all other modes, its share increases at the cost of all others, almost equally considering the parameters. Still, the private car competes more with travel modes commonly used on longer distances. This probably leads to higher shifts from public transportation and car as passenger.

The ownership of a transit pass acts as an indicator of multimodal travel behavior. A higher share mainly benefits public transportation, carsharing, walking, cycling, and riding, which is in line with, a.o., Zhou (2016). The influences depend on the type of traffic: for internal OD pairs mainly carsharing and walking profit, whereas for OD pairs to and from the city public transportation, carsharing, riding, and cycling profits. The transit pass ownership correlates with the carsharing membership. This might explain, why the bicycle is rated weaker regarding transit pass ownership. Significant positive influences by the latter can be observed in the simulation for cycling and carsharing itself. Also, the density of carsharing vehicles offered within the district correlates positively with the choice of carsharing, verifying the importance of carsharing vehicle availability for the successful diffusion of carsharing. A higher availability lowers the probability of all vehicles being in use and thus results in a higher reliability, and the higher density makes carsharing more accessible.

The inhabitants are classified into four age groups representing the share of children, young adults, middle-aged adults, and the elderly. Due to the high correlation of the share of children, families, and private cars, all modes entail disadvantages compared to the car in the case of children's travel. This confirms the results of Kim and Ulfarsson (2008) that the share of families is associated with the presence of private cars. The share of children and the share of households with children correlate to a high degree in the model, whereas the latter was kept out of the estimation. Another noticeable aspect is the popularity of bicycles and transit for young adults among all age groups. The gap to the reference car is for this age group the lowest. Assuming a solid representation of students in this category, the results of Georgina Santos et al. (2013), Cattaneo et al. (2018) and Jacques et al. (2011) stating that students favor non-motorized travel modes and public transportation would get confirmed. The ABM does not treat students differently because of their occupation, but only because of their age in combination with the purpose. As both of these attributes

Table 1: Estimation results

Model	MDCEV V0	MDCEV V1	MDCEV V2
LL	-465,372.9	-437,614.3	-425,751.2
BIC	930,868.5	875,443.4	852,340.9
Parameters	12	21	69
	Estimates		
α_{base}	-13.74**	-17.17**	-13.02**
γ_{car}	0.54**	0.52**	0.30**
$\gamma_{pedestrian}$	8.71**	0.98**	0.79**
$\gamma_{passenger}$	0.65**	0.59**	0.57**
$\gamma_{bicycle}$	3.23**	1.06**	1.01**
$\gamma_{transit}$	0.80**	0.65**	0.55**
$\gamma_{carsharing}$	1.72**	1.76**	1.26**
δ_{car}	0.00	0.00	0.00
$\delta_{pedestrian}$	-6.44**	0.01	11.11**
$\delta_{passenger}$	-2.41**	-2.23**	4.27**
$\delta_{bicycle}$	-3.81**	-0.62**	4.11**
$\delta_{transit}$	-1.11**	0.22**	6.33**
$\delta_{carsharing}$	-6.43**	-5.34**	-7.25**
$\delta_{travelt,car}$	-	-0.009**	-0.013**
$\delta_{travelt,pedestrian}$	-	-0.047**	-0.051**
$\delta_{travelt,passenger}$	-	-0.040**	-0.047**
$\delta_{travelt,bicycle}$	-	0.065**	-0.054**
$\delta_{travelt,transit}$	-	-0.027**	-0.029**
$\delta_{travelt,carsharing}$	-	-0.003	-0.010**
$\delta_{cost,car}$	-	-0.287**	-0.182**
$\delta_{cost,transit}$	-	-0.175**	-0.156**
$\delta_{cost,carsharing}$	-	-0.369**	-0.074**
σ	1.00	1.00	1.00

level of significance ** 5 % , * 10 %, $\alpha = 1/(1 + \exp(-\alpha_{base}))$

Table 2: Estimation results of MDCEV V2 - further attributes

Parameter	Pedestrian	Passenger	Bicycle	Transit	Carsharing
$\delta_{m,privatevehicles/inh.}$	-3.16**	-3.38**	-2.97**	-3.15**	-2.83**
$\delta_{m,transitpasses/inh.,intra.}$	0.46**	-1.82**	-0.66**	-0.55**	0.57**
$\delta_{m,transitpasses/inh.,outg.}$	-3.06**	1.62**	-0.59**	0.20**	5,79**
$\delta_{m,transitpasses/inh.,incom.}$	-3.06**	2.47**	0.79**	0.65**	2.25**
$\delta_{m,csmembers/inh.}$	-	-	2.14**	-	3.04**
$\delta_{m,csvehicledensity}$	-	-	-	-	0.10**
$\delta_{m,shareagelower19y.}$	-15.05**	-4.58**	-9.03**	-8.18**	-3.64**
$\delta_{m,shareage20-29y.}$	-5.40**	-4.44**	-1.74**	-4.17**	-
$\delta_{m,shareage30-49y.}$	-4.51**	-8.01**	-3.16**	-6.45**	-
$\delta_{m,shareageabove64y.}$	-9.80**	-4.98**	-5.32**	-6.40**	-1.70**
$\delta_{m,populationdensity}$	-0.03**	-0.04**	-	0.01**	0.06**
$\delta_{m,shareofworktrips}$	-3.27**	-0.90**	-3.08**	0.85**	1.15**
$\delta_{m,shareofshoppingtrips}$	6.17**	-7.94**	3.54**	-3.08**	-
$\delta_{m,shareofeducationtrips}$	-0.70**	0.50**	1.41**	5.31**	1.22**
$\delta_{m,inner-cityODpair}$	-2.98**	0.66**	-	-	1.76**

level of significance ** 5 % , * 10 %

are considered in the model, the share of students is removed in *MDCEV V2*. Moreover, the share of the elderly pushes non-motorized modes significantly down. It can also be assumed that the underlying reason for the negative influence on carsharing can be the presence of private cars among the elderly, the complexity of carsharing, or simply the aversion to it. In the ABM simulation, the memberships are distributed accordingly reflecting this influence.

Higher population densities shift public transportation and carsharing above the reference mode indicating higher resistance for private vehicles due to a shortage of space and higher accessibility with other travel modes. Walking and cycling are expected to be more popular in dense areas. The authors assume an overlapping of effects with other parameters as they observe a substantial negative correlation with $\delta_m shareage20-29y.$ and $\delta_m shareage30-49y.$ capturing positive effects.

Trip purposes are separated in share of work, shopping, education, and leisure trips. The latter serves as a reference. Because of the relatively long distances taken to work, parameters of travel modes associated with shorter distances, such as walking, car as passenger, and cycling, are negative, whereas public transportation and carsharing are favored. The latter highlights observable use cases of carsharing, namely trips to work and education places. However, the share of shopping trips correlates strongly with active transportation modes like pedestrian and bicycle, indicating shorter distances and higher supermarket accessibility, respectively. Among the shown trip purposes, traveling with public transportation and car as a passenger is most likely for trips to the educational institution. The bicycle also has its highest purpose-related popularity for shopping.

The parameter for an inner-city OD pair serves for the compensation of different sizes of traffic analysis zones. It correlates positively with car as passenger and carsharing, while the effect on walking is significantly more substantial towards the opposite. The influences described can be found in Table 2. For a better interpretation, the distribution of ownership rates and shares of age groups is shown in Figure 2 as the value of parameters and the continuous attributes need to be interpreted together. For example, the parameters regarding transit pass and car ownership of the alternative pedestrian have a similar size, but because of the generally higher car ownership, this substantially has a higher impact on the utility.

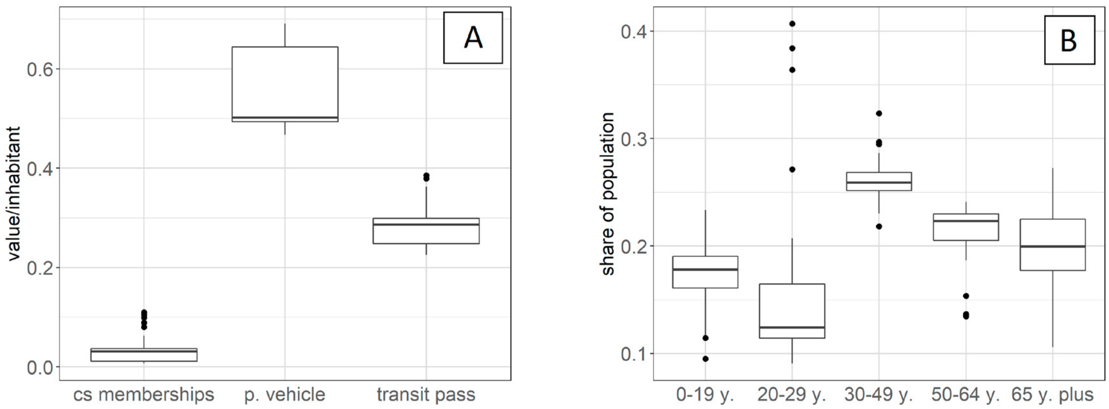

Fig. 2: (A) mobility tool ownership; (B) share of age groups.

3. Model application and validation

The resulting models are applied to a test database consisting of the status quo ABM simulation and another scenario that was not part of the estimation database. The validation of the model includes both its ability to reproduce current travel demand and its measure sensitivity respectively its predictive abilities.

3.1. Analysis of replication ability

Both models estimated (i.e., *MDCEV V1* and *MDCEV V2*) need to be compared to the ABM simulations to assess their ability to replicate present travel mode choice and predict shifts in travel demand due to changes in population and transport infrastructure-related measures. For this purpose, a scenario is set up differing from the simulations being used in the estimation database. This scenario includes a reduction in public transportation travel times, a further expansion of carsharing and bikesharing services, and an increase of transit passes and carsharing memberships in the population. The former is assumed to be achieved through privileging over other modes in local traffic and acceleration through improving the infrastructure and is limited to local public transportation.

All applications of MDCEV models apply the algorithm of Palma et al. (2021) and are based on the respective ABM travel generation and destination choices resulting from the actual population and transport infrastructure. This secures comparability of results in total. Nevertheless, some effects cannot be accounted for: mainly because the improved accessibility and reduced costs of public transportation agents travel longer distances in the ABM simulation. These longer trips are more likely to be outside the districts' central study area and are therefore cut out of the current consideration. These effects might interact with observed shifts.

Different forecasting results can be observed for the different models for the replication of status quo. Compared to the reference ABM simulation, *MDCEV V2* performs better than the simpler model *V1* as a result of the further consideration of the peculiarities of particular districts (see Table 3). Only minor differences can be observed by looking at the smaller share of cycling and a higher share of driving for the city-internal OD pairs. Both models perform pretty well for the other OD pairs with a slighter lead of *MDCEV V2*. Even travel modes accounting for only small shares of modal split (e.g., carsharing) occur in the forecasts and do not disappear because of too many corner solutions. A similar observation can be made for the forecast for the scenario. It should be kept in mind that the forecasts applying the MDCEV models are spatially more aggregated and therefore loose some information. The results are shown in Figure 3.

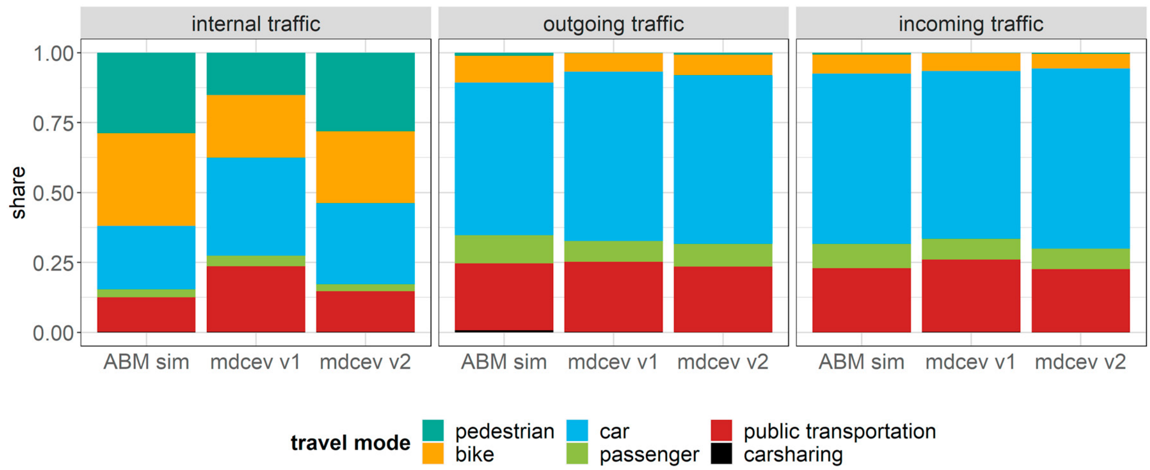

Fig. 3: Modal split of trips in ABM simulation and forecast of MDCEV V1 and V2 for status quo by type of traffic

Table 3: Replication ability of MDCEV V1 and MDCEV V2 for status quo

Mode-specific coefficient of determination	MDCEV V1	MDCEV V2
R^2_{Car}	0.815	0.982
R^2_{Bike}	0.983	0.984
$R^2_{Pedestrian}$	0.972	0.983
$R^2_{Transit}$	0.471	0.881
$R^2_{Passenger}$	0.431	0.902
$R^2_{Carsharing}$	0.301	0.736
R^2_{Total}	0.662	0.911

3.2. *Analysis of sensitivity*

The application of the models in a serious game especially requires a realistic calculation of measure effects selected by the player. Regarding the modal shift in the ABM simulation, the measures and changes in the population mainly benefit public transportation, carsharing, and cycling depending on the type of traffic (c.f. Figure 4). Carsharing mainly increases for outgoing traffic from the city, and cycling increases especially within the city.

The forecasting results of *MDCEV V1* can only account for improving the public transportation system, because share of transit pass and carsharing ownership are not considered in the utility function. Therefore, all other travel modes than public transportation receive lower shares, not depending on the type of traffic. An increase in carsharing or cycling can consequently not be observed. However, the shifts in public transportation match the reference results with only slight differences. Thus, the shifts in the ABM simulation are well captured by the travel time reduction, while the influence of transit pass and carsharing ownership rates overlap with the parameter.

The forecasting results of *MDCEV V2* are of more interest as the replication of the status quo was found to be of higher quality. Some effects can be explained appropriately; others reveal difficulties mainly resulting from the simplification of the model. The shift of carsharing is found to almost match the results of the ABM simulation for all types of traffic leading to the conclusion that the integrated parameters can evaluate the improvements of carsharing service and related memberships appropriately. Shifts of the bicycle can also be modeled even though the forecast is higher than the reference ABM forecast. Nevertheless, the positive influence of multimodal behavior indicators like transit pass ownership and carsharing membership can be observed. The quality of public transportation forecast depends on the type of traffic. For the longer distances of the outgoing and incoming traffic, the shifts match the ones of the ABM simulation comparatively well. But there are some problems with the internal traffic where public transportation is valued too badly. This comes along with a positive shift for walking. Even though the type of traffic-specific parameters are added for transit pass ownership in the model, the effects are not yet sufficiently integrated for the city-internal traffic. This leads leads to a weak valuation of replication ability for public transportation (see Table 4). Further problems can be observed regarding car passenger being valued as too high, mainly due to growing transit pass ownership. This probably leads to the higher negative shift of the car as a driver that can be observed on the OD pairs crossing the city border. The authors expect the influences leading to this positive effect on car passenger not to be causally dependent on transit pass ownership rate, but on other factors not implemented in the model. Further parameters would be required to improve the model results, especially the model sensitivity. Only integrating the attributes in the model changing in the scenario probably leads to a lower quality of the replication of the status quo by this model. Further, the influences may overlap with influences of other attributes leading to biases. For example, a correlation exists between carsharing membership and younger adults, and by leaving out the effect of age, the influence of the membership would be overestimated.

Generally, *MDCEV V1* shows some advantages regarding the shifts of public transportation and car as passenger due to its simple integration of effects, whereas *MDCEV V2* better captures shifts of the car as driver, cycling and carsharing. This is clearly visible in Table 4. For a better understanding of Figure 4, it should be noted that internal traffic makes up a larger share of the total travel demand. With the overall coefficient of determination being lower for *MDCEV V2* than for *MDCEV V1* the former has more problems in predicting shifts for this type of traffic.

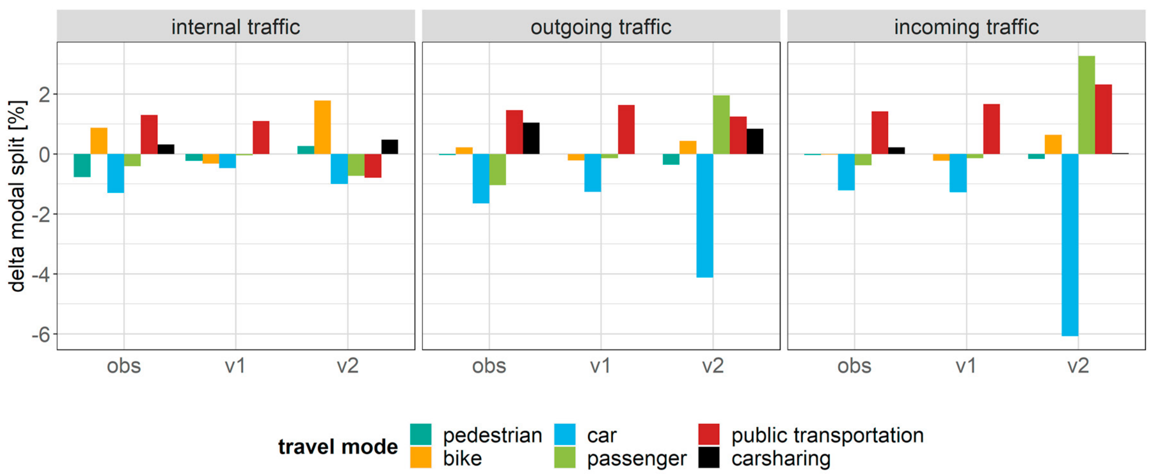

Fig. 4: Changes in travel demand status quo - scenario by type of traffic

Table 4: Replication ability of MDCEV V1 and MDCEV V2 for the sensitivity of the ABM simulation

Mode-specific coefficient of determination	MDCEV V1	MDCEV V2
R^2_{Car}	0.6752	0.7578
R^2_{Bike}	0.4385	0.5009
$R^2_{Pedestrian}$	0.8949	0.8619
$R^2_{Transit}$	0.5911	0.0039
$R^2_{Passenger}$	0.2443	0.0163
$R^2_{Carsharing}$	0.283	0.3293
R^2_{Total}	0.5212	0.4117

4. Conclusion

This research is motivated by a growing need for better communication tools, e.g. in the form of a serious game. It is expected to build a bridge from the modeling to decision-makers or the general public. At the same time, the authors are aware that this is a specific use case. The complexity of ABM and especially their sluggishness, if fast responses on forecasting scenarios are necessary or helpful, impedes their application. Therefore, a condensation of model functionalities and saturation effects regarding travel mode choice is chosen by applying a MDCEV model to the simulated travel demand of ABM for different scenarios.

The estimated MDCEV models indicate various significant effects between different travel modes and specific attributes, namely sociodeomographic, spatial and infrastructure-related attributes. These effects were implemented before in the ABM - still, they can be observed after the transformation. They further mostly match the findings from the literature. Their interpretation is not always intuitive as they reflect aggregated influences and not individual preferences. One of the notable results is the mode choice behavior of children and the elderly, who were similarly dependent on the car and averse to other modes. The importance of carsharing on longer distances and the positive relationship between transit pass ownership and carsharing membership are other eye-catching results. Meanwhile, the effects of population density remain surprisingly very low, indicating possible correlation effects with other parameters, e.g., carsharing membership and transit pass ownership. Presumed effects on students' travel behavior have been indicated by the enormously positive relationship between educational trips and transit share. This research therefore exemplary shows that MDCEV models can capture the determinants of mode choice pretty well.

The comparison of the MDCEV model applications with the reference results of ABM simulation attests a good ability to replicate the current status quo of travel demand, even for different types of traffic. And even in comparing modal shifts, most effects can be rated as good. Some weaknesses appear regarding the shift of specific travel modes and influence the shifts to other travel modes. While the detailed MDCEV model *V2* performs better in replicating the status quo of the ABM simulation, the simpler model *V1* achieves better results in replicating the total modal shift. This is mainly because difficulties occur in the detailed model in processing the effects on the internal traffic's public transportation share. At the same time, this certain type of traffic also represents a major part of the total travel demand. Therefore, if possible, the authors recommend validating the model sensitivities of the MDCEV concerning observed effects that might not be plausible, even though the model shows a significant effect. By integrating both influences of population and mobility tools and spatial interaction with these attributes, unrealistic effects can probably be avoided. Further, impacts on saturation parameters γ_m could be integrated to secure spatially differentiated saturation effects. To summarise, this research exemplary provides insights in the forecasting abilities of MDCEV models regarding mode choice and hereby contributes to the use cases of this type of discrete-continuous choice model.

The resulting models and their evaluation are case-specific in both their regional behavioral characteristics and the simulated database for estimation. Observable interrelationships of behavior and the data preparation may be different for other cases. This research is only intended to test the applicability of the method in a specific context. The overall travel demand of an ABM is highly practical when such a model is at hand as it provides both spatial distribution and further information about travelers and circumstances of travel. Looking at the database for the estimation, other options are conceivable. Other applications of the approach could use mobile phone data as an input for travel demand, as detailed information on the OD level can be provided. Attributes, such as population distribution and vehicle ownership, are easily accessible. Only the purpose-related attributes on the OD level need to be changed to district-specific attributes, such as trip generation and trip attraction.

An alternative to relying on an existing agent-based travel demand model and transferring it to a macroscopic scale for the serious game application is to develop a macroscopic model from scratch, which, however, requires substantial development efforts and lacks the possibility of considering all mode choice behavior patterns at the micro level (e.g., mode availiability in the ABM simulation). Another alternative can be seen in applying the ABM mode choice model in the serious game by only covering a certain proportion of the travel demand. This would lead to lower simulation times and is a common practice for getting faster results. However, an ABM mode choice model is more difficult to connect with other neighbouring models that cover other developments (e.g., demography). Forecasts based on ABM simulations allow a higher degree of the interrelation of travelers' behavior and reactions to developments and measures leading to more accurate results than the simplified models presented in this research. Still, this aggregated model approach can be used to evaluate effects of changes in transport supply on mode choice behavior faster for the use within, e.g., a serious game for stakeholders or the public. This requires further model components to not only account for changes in mode choice. This might allow for improved and more flexible communication of forecast results in different use cases while strengthening the comprehensibility and credibility of planning tools in the transport sector to other interest groups.

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