ON THE VARIATION IN MODE CHOICE BEHAVIOR IN AGENT-BASED TRAVEL DEMAND MODELS

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ABSTRACT
Past research shows that individual mode choice preferences and, thus, taste variation of mode choice play an essential role and are observable even for one day. Both multi- and monomodal behavioral patterns with different degrees of mode choice variation are the subject of investigation. Hence, agent-based travel demand models (AB-TDMs) must account for this taste variation, which is expected to affect model sensitivity. To assess the impacts of mode choice model configuration on the resulting variation, we apply an approach based on mixed logit models and implement them in an AB-TDM simulation. We analyze the mode choice behavior regarding variation indicators for the simulation period of one day and one week and compare it to observed behavior.

We show that classic MNL models cannot appropriately account for mode choice variation in AB-TDM, both for one week or one day. We show that mixed model approaches can bridge this gap by better capturing heterogeneity and suggest using mixed models in an agent-based context. This prevents models from overestimating multimodal mode choice behavior.

Keywords: variation of travel mode choice, agent-based travel demand modeling, multimodal, travel patterns, mixed logit

INTRODUCTION

Travel behavior shows constant changes when looking at the past decades. The reliance of young people solely on the private car is decreasing while public transportation and bicycle use are rising, and multimodal travel patterns (use of several transport modes in everyday life) can be observed more often (*1, 2*). Findings further suggest that generations preserve their learned habits at young ages for their adult life. These habits lead to rising car availability in the older generations nowadays as they acquired related behavior in the 60's and 70's (*2*). However, young people (age 36 and younger) tend to show a higher multimodal behavior coupled with generally higher flexibility and trip intensity, looking at the example of Germany (*2*). Further, it is a predominantly urban behavior (*3*).

More complex travel patterns on the one hand and new mobility services like car and bike-sharing on the other require a more differentiating view on travel behavior regarding its variation. This process considers both inter- and intra-personal variation in activities during the week (*4*) and the variation in used travel modes on similar dimensions. Variation of travel behavior is closely related to the topic of multimodality. The variation of used travel modes observed over a defined period reveals whether a person is focused on a single mode and is therefore characterized as monomodal or whether multiple modes are used to characterize a multimodal travel behavior. The temporal dimension of variation is essential for this classification of behavior observed in surveys. Typically, the distinction is conducted for the behavior of a single week (*3*). Still, substantial differences in variation are already observable for a day (*5*).

Today's decisions in transport and city planning depend on a solid understanding of decisions and interactions in the transport network. Travel demand models (TDMs) offer a way to depict current conditions in traffic and forecast the effects of transportation-related measures. Typically, when using TDM for assessing infrastructure in practice, only the average weekday and sometimes only the busiest hours with the highest level of traffic need to be analyzed. Travel behavior in its aggregation is regarded as relatively stable over time. Following this assumption, modeling one typical weekday allows for conclusions on other weekdays.

However, inter and intra-personal variation cannot be analyzed when only traffic volumes are modeled without any individual-specific reference. New application fields of TDM, especially with the rise of agent-based travel demand models (ABM), opened up and enabled named analysis by forecasting individual travel behavior. They set the foundation for individual mode choice preferences, generating the observable variation of travel behavior. It raises the question of whether models can reproduce variation of travel mode choice appropriately, which can be observed in travel surveys.

From the perspective of choice analysis, these preferences are reflected in inter- and intrapersonal taste heterogeneity. Preferences in travel behavior create a multitude of travel patterns. They are either determined by life circumstances or by attitudes (*6, 7*). Whereas life circumstances can be considered partly through socio-demographic variables, considering preferences not observable to the analyst in agent-based travel demand models (AB-TDM) is more complicated and done less often in applied demand forecasting. An exemplary approach analyzing mode-specific preferences is using Integrated Choice and Latent Variable (ICLV) or Hybrid Choice models (HCM). Another approach is to introduce inter- or intrapersonal variance for specific influences in addition to influences of, e.g., age or income. This randomness captures preferences that are not observable to the analyst and are not yet covered. Preferences in simple Multinomial Logit (MNL) models have a fixed value for all individuals with equal characteristics. Mixed Multinomial Logit (MMNL) and Latent Class (LC) models allow for further inter- and intrapersonal variation and, therefore, extended individual preferences. Especially MMNL models are recommended for taste variation, repeated choices, and substitution patterns (*8*). Still, their number of applications in AB-TDMs is relatively small compared to MNL and Nested Logit (NL) models, which can be related to its higher complexity and the need for "highly-trained analysts" (*8*).

The multitude of options for modeling travel mode choice raises the question of to what extent both single-day or multi-day AB-TDM with varying degrees of considering travel mode preferences can reflect today´s changed behavior and reach realistic degrees of mode choice variation. Hence, in this paper, we pursue two goals. We aim to map out the necessity to account for appropriate variation in travel mode choice and, therefore, mono- and multimodal behavior in AB-TDMs. We then apply a method to account for preferences in AB-TDMs and show the effects using multiple simple mode choice models. A consecutive validation of the forecasting abilities is done by comparing simulated travel patterns and their mode choice variation with the German Mobility Panel (MOP). The validation is done for the simulation time of a single day and a whole week. The aim is primarily to reproduce observed mode choice behavior and not to test the resulting model sensitivity, which is the subject of further research.

This paper is structured as follows. First, we continue with the analysis of the current literature focusing on the analysis, measuring, and modeling of mode choice variation. Second, we introduce the AB-TDM framework applied in this research, focusing on the mode availability model. Third, we describe model formulation and estimation. Fourth, we present the results of our variation analysis. We close this paper with a conclusion of our work and an outlook for further research.

LITERATURE

This section gives an overview of the current literature regarding three related topics. We first analyze the empirical findings of variant preferences in travel mode choice behavior. We then present indices to measure variation, followed by a summary of model approaches accounting for heterogeneity in travel mode choice. We highlight Mixed Multinomial Logit (MMNL) models as one promising method and give an overview of the applications of these approaches in travel demand models.

Empirical basis: Variation of travel behavior

Variation of travel behavior is relevant at different levels. Inter-personal variation stems from understanding differences between activity profiles or travel behavior of multiple individuals. In contrast, intrapersonal variation is defined by the fact that individual needs and desires to travel vary from day to day or trip to trip (*9*). However, socio-demographic characteristics and level-of-service attributes of transport supply can hardly explain these types of variation only, especially regarding the intrapersonal variation. The general intrapersonal variation is high, whereas this is not due to systematic intrapersonal variation between different days (*10*).

Both types of variation in travel mode choice are mostly accounted for through the analysis of mono- or multimodal groups. A vast body of literature studies individuals categorized into mono- and multimodal groups based on their travel mode choice on all trips within an observation period (*3, 11*). This can, among others, be found in the report of the German National Household Travel Survey *Mobility in Germany* (*12*). Multimodal behavior, by its definition, implies using at least two modes of cycling, driving, and riding public transport (PT) during the observation period of a week. This analysis does not consider using other travel modes, such as walking or sharing. Walking is expected to be used by all people and therefore not taken into account (e.g., access/egress to PT, short trips). In 2017, the two largest groups were only-car-users (~45%) and car-and-bike-users (~21%) (*12*). Carrel et al. (*13*) provides a definition for a six-week-analysis accepting, e.g., up to 10% of trips conducted with other modes when specifying a "quasi-unimodal auto user." Consequently, definitions depend on the modes considered and the observation period.

Variation of mode choice can further be differentiated in variation for repeated trips such as working trips and variation for different trips (*14*). Repeated choices of the same location relate to habits regarding travel mode choice, whereas a higher variation for new destinations can be expected. For example, Carrel et al. (*13*) found a higher share of monomodal groups for working tours within their sample. This suggests the importance of activity purposes for the mode choice variation.

The literature also highlights the inter- and intra-personal variation in activities and time use over a certain period (*4*). A substantial variation in travel mode choice can already be explained by the variation of activities over the week (*13, 15*).

Indices for measuring travel mode variation

Most surveys consider mainly the person-specific frequency by travel mode when analyzing stability. As shown before, multimodal groups built upon this analysis enable an understanding of the stability of mode choice behavior. However, Mallig and Vortisch (*16*) found stability to be measured in terms of frequency of use and changes of use and specific periodic repetitions of subsamples of mode combinations. Different indicators were tested on correlation to enable an exhaustive picture of mode choice variation using only as many indicators as needed. Therefore, it has been suggested to keep only one frequency-based and one sequence-based indicator when analyzing multimodal behavior or calibrating a TDM to an appropriate degree of variation.

Frequency-based indicators can be found in many studies: Streit et al. (*2*) used an indicator looking at the number of modes used during one week, weighted by the number of trips of the most frequently used mode. Thomas et al. (*14*) expressed both intrapersonal variation of mode choice of repeated and different trips by looking at the most frequently used mode and setting it in relation to all trips or to all trips to a specific location. The resulting variation is given by the total share of the not most used modes. Both indicators can be analyzed based on the number, distance, and duration of trips by mode (*2*). Kuhnimhof (*17*) developed the indicator MIX to take not only the total variation of mode use into account but also to relate it to the number of choices (i.e., trips or tours) of the period and the number of available choice options. This leads to an improved analysis of travelers with only a few choices. Still, Mallig and Vortisch (*16*) found minor weaknesses in the specific differentiation. The HHI is a measure of market concentration and, therefore, can be used as an adequate indicator. Several studies have already used the Herfindahl-Hirschman Index (HHI) as a measure for variation in travel mode choice (e.g., Mallig and Vortisch, Rhoades, Heinen and Chatterjee (*16, 18, 19*)).

Sequence-based indicators enable a different analysis of travel mode choice, specifically considering the sequence and order of decisions. Mallig and Vortisch (*16*) propose a pair-based and a run-based indicator. The former looks at pairs of subsequent decisions in mode choice, the latter at the "maximum contiguous subsequence of the same mode" (*16*).

Mode choice variation structures in travel demand models

The variation in travel behavior has already been recognized and considered in travel demand modeling. Today, most travel demand models are based on one-day travel surveys. They form the basis of transportation policy in many countries (*20*). A fundamental assumption of these models based on one-day travel surveys is that behavior adapts immediately to new circumstances and that, for example, trips are highly repetitive in the short term. However, these assumptions do not hold in reality. Recent work shows apparent differences between the results of cross-sectional and longitudinal models (*21*). Especially to better represent new mobility concepts that aim at using different alternatives, longitudinal data are needed to analyze the inter- and intrapersonal dynamics of travel mode usage. In addition, the models assume that individuals know the complete set of alternative travel modes, have complete information and consciously reflect their choice based on respective level-of-service attributes (*22*).

Numerous model approaches exist that address taste variation in travel mode choices based on longitudinal data by choice of discrete choice model. MMNL models offer the possibility of incorporating random taste heterogeneity in the model without linking it to an observed attribute in the data (*23*). These "error components capture unobserved correlation across travel mode choice decisions made by the same individual" (*22*). This usually leads to an improved likelihood and better model fit on the one hand and more complex estimating processes on the other hand. Carrel et al. (*13*) used discrete mixtures as a combined latent class and mixed logit model to integrate latent preferences and taste heterogeneity into a travel mode choice model. Thereby, they characterized different modality styles, which has been suggested before by Kuhnimhof et al. (*5*). Both the results of the descriptive analysis and the resulting three-class-solution of the latent class model suggest the presence of quasi-unimodal auto users, a transit and bike-oriented multimodal class, and a more auto-oriented multimodal class. When restricting the data for the estimation to only two days, it became more challenging to observe similar classes and apply the same model structure. Another implicit integration of preferences through latent classes representing different modality styles was done by Vij et al. (*22*). The analysis revealed an auto-oriented, a transit-oriented, and a multimodal class. Based on an MMNL model accounting for error components for all available modes, Thomas et al. (*14*) found substantial variation for all trips and purpose-specific trips. Cherchi et al. (*15*) set up different MMNL models accounting for respondents' correlation over the same weekdays, a single week, and the whole observation period analyzing the 6-week travel diary *Mobidrive*. Extending the correlation significantly improved the results, whereby the correlation for the same weekdays appeared to be more critical. All cases successfully captured a larger proportion of heterogeneity in their models. Still, to the authors' knowledge, no application of these models was made to test whether they can reproduce different levels of variation through modality styles in simulation frameworks.

Explicit integration of preferences in travel mode choice is commonly used to explain travel behavior and modality styles. Paulssen et al. (*24*) included preferences in commuting mode choice via latent variables in a mixed ICLV framework and explained a high level of variation in travel mode choice. Nevertheless, a simulation was not conducted because the information on preferences in the population for simulation is difficult to simulate.

A different approach of model-based accounting for mode choice variation is the state-dependent consideration of past behavior. Thereby, models assume an influence of prior decisions on the present. Kuhnimhof (*17*) estimated a tour-based travel mode choice model considering the previous mode used, the previous mode used on the same routine tour, and a commuting mode influence as independent variables. The routine tour influence was an essential factor indicating a stable preference for repeating trips. Mallig and Vortisch (*25*) tested different approaches to include various degrees of short-term stability within a tour and long-term stability over the week by accounting for the previous use of modes. By comparing the standard cross-sectional mode choice model with the extended longitudinal model, they found the cross-sectional approach to overestimate multimodal mobility styles and to underrate patterns with low variation in travel mode choice. While both approaches successfully integrate stability in travel mode choice, they have the limitation of missing information for a traveler's first trip in the simulation period. Specific situations in the beginning and the subsequent mode choice influence travel behavior, potentially leading to extreme behavior.

In a joint reflection of both areas Mallig (*26*) compared eight approaches to account for variation. He tested four state-dependent approaches considering previously used modes: including the previous mode, checking whether the previous mode is the same, checking which modes have been used among all previous uses, or counting the previously used modes. The MMNL approach was also tested using random parameters for constants in the utility function interpreted as individual preferences for specific modes. Finally, incorporating empirical preferences, i.e., the relative usage frequency over the survey period, into the utility functions was tested by including the preference for the single evaluated mode or all mode preferences. The MMNL approach turned out best when comparing the simulated and empirical variation indicators closely followed by the model with empirical preferences. The state-dependent approaches were shown to estimate monomodal behavior better but to underestimate persons with higher variation in travel mode choice.

Achieving realistic levels and distributions of travel mode choice variation is not an end but also affects its forecasting abilities. Studies found that different model approaches lead to varying model sensitivities regarding forecasting. Mallig and Vortisch (*25*) found that models are too sensitive and identified a need for further incorporation of mode preferences within models to receive reasonable forecasts, especially when assessing measures in transport infrastructure and supply. Vij et al. (*22*) highlight the role of varying time sensitivity for policies. Their observed latent classes, respectively, their modality styles covered both sensitive and insensitive classes regarding level-of-service attributes. Improved forecasting has been observed by Provencher and Bishop (*27*). Their study compares a standard MNL model, a latent class, and two MMNL models regarding their forecasts of fishing catch rates. However, there is no clear indication of MMNL and LC models being superior to standard MNL models regarding all indicators tested.

METHODOLOGY

In this section, we first describe the applied AB-TDM, its key characteristics, and its framework *mobiTopp* with a focus on the existing approaches to account for different degrees of behavioral variation in mode choice. This is done in the context of the later analysis, which also investigates whether this AB-TDM's control of mode availability and variation of life circumstances and activity profiles is already sufficient for achieving an appropriate level of mode choice variation. We then present the MMNL models of our approach by summarizing the data used in this research and the subsequent model estimation.

Study and simulation context

For this research, the authors use an AB-TDM of the Karlsruhe region. The area includes the city of Karlsruhe and its neighboring counties in the southwest of Germany, inhabited by approximately 1.9 million residents. It comprises urban and rural areas interconnected by a comparably well-developed public transportation system.

The AB-TDM is set up in the framework *mobiTopp* (*28, 29*), an extendable modeling framework which, e.g., allows to incorporate MMNL choice models. Furthermore, *mobiTopp* simulates a population's activities and trips over one week, which is required to observe variation in travel mode choice better. Especially the latter led to the choice of this framework.

The model framework already accounts for mode choice variation in the long-term perspective by controlling mobility tools and mode availability. It further provides a foundation for inter- and intrapersonal variation through activity schedules and the probabilistic nature of the used choice models. The used survey population pool for the synthetic population provides a natural interpersonal variation of life circumstances as the synthesized population inherits the reported variation from a (weighted) survey. Subsequently, the activity schedule generator *actiTopp* synthesizes weekly activity schedules based on these life circumstances and provides inter- and intrapersonal variation of activities during the week (*30*). Furthermore, a person's mobility tools (i.e., cars, season tickets, sharing memberships) influence the availability of modes and, therefore, the mode choice behavior during the simulation contributing to behavioral stability. The influence of mobility tools on mode choice can be direct by determining the availability of a specific mode (e.g., non-members cannot use bikesharing, or cars can only be used by one household member (group) simultaneously). It can also be indirect if mobility tools are considered in the utility function of a choice model (e.g., if carsharing members show a higher probability of choosing other modes such as bicycle).

In the short-term perspective, the set of available modes depends on the current location and the previous trip(s). The basic model distinguishes two situations: trips starting at home and intermediate trips on a larger tour. When starting at home, the car and bike can only be used if a respective vehicle is currently in the household. Furthermore, people can only use cars with a driver's license. Agents that have already started a tour with a fixed mode (i.e., car, bike, pedelec, station-based carsharing) are forced to take the vehicle with them until they return home (resp. carsharing station). Conversely, fixed travel modes cannot be used during tours starting with a flexible mode. Once a destination is selected, the available modes can be filtered; e.g., if the estimated distance of a tour exceeds a car's maximum range, it is considered unavailable for that trip. This mode availability model provides stability and consistency of an individual agent's behavior within the context of a tour.

In summary, the long-term module models long-term decisions or agents' properties that stay consistent throughout the simulated week (e.g., income, work destination, season ticket) and contribute to improved accounting for interpersonal heterogeneity. By further establishing behavioral variation in the form of activity schedules and restricting the choice set of mode choice at locations and within tours, the short-term module contributes to intrapersonal stability.

Data and model estimation

The data used in this study for the estimation of the travel mode choice models consists of two cross-sectional surveys, both containing reported travel demand of the study area of the travel demand model. The first survey is the nationwide *Mobility in Germany* (*12*) containing a useful sample for the local region, and the other is a local household travel survey of Karlsruhe, Germany. Both surveys mount up to a total sample of about 29,200 trips. They are enriched by information on the available mode alternatives and their level of service as locations of start and destination are recorded. The data is limited to responses of one day, limiting the explanatory power for the weekly perspective. However, Kuhnimhof (*17*) showed that structures of mode choice variation are already observable within 24 hours and could estimate and simulate these. This supports the usability of the present sample for the purpose of incorporating taste heterogeneity in a travel mode choice model and analyzing travel mode choice variation in the simulated forecasts. The authors, therefore, decided to take both the daily and weekly perspective regarding the later analysis of variation regarding mode choice in the simulated data.

To account for preferences and taste variation in mode choice behavior, we estimated different types of trip-based MMNL models. As described in the literature section, applying individual-specific random taste parameters instead of using fixed values allows to account for interpersonal preferences. The models focus on interpersonal heterogeneity because extending the models to account for unobserved intrapersonal heterogeneity leads to a substantial increase in estimation time and was not found to significantly improve of choice prediction accuracy by Krueger et al. (*31*).

The model setup contains four different models: a simple MNL model only containing the deterministic influences of sociodemographic characteristics, an MMNL model with normally distributed random taste parameters as the alternative-specific constant (MMNL 1), a second MMNL model with additional correlation parameter between these random tastes (MMNL 2) and a third MMNL model with Johnson-SB distributed random parameters for the constants. All models consider the travel modes car as a driver, car as a passenger, public transportation (PT), walking, and cycling. For the general structure of an MMNL, the authors refer to McFadden and Train (*23*). The varying alternative-specific constants of the models are in the following referred to as mode preferences. The estimation was done by testing 25 sets of starting values to avoid local optima. Further, to avoid correlation in drawn sequences for the five distributions in the case of using Halton draws, we used Modified Latin Hypercube Samples (MLHS) with 300 draws for each distribution (*32*). For the estimation of all models, we used the Apollo package for R (*33*).

In the field of transport, primarily distributions for different travel time sensitivities are of interest (*34*). Hess and Axhausen (*35*) analyze different distributions on their effects. We transfer this knowledge to our application of the alternative-specific constants. By choosing a normal distribution, we use its simpler applicability and average flexibility. By the choice of the Johnson SB distribution, we make use of its high flexibility in terms of asymmetry and its boundedness. By allowing for correlations between distributions, we extend its ability to capture interrelationships between travel modes.

The sociodemographic components of the utility functions of the models are limited to only a few person-specific attributes. They consider age, occupation, gender, income, and the ownership of a season ticket as effects on the general preference. The baseline in all models is represented by a 30-to-49-year-old male with low or average income, not-occupied, and without a season ticket. Their estimates are not shown in the following section as they are not the focus of this research. Additionally, improvements by considering tours in the choice model and by accounting for travel purposes were not used in these models to keep the manageability. The utility functions of all models can be found in Equation 1 to 4.

$$MNL : U_m = \mu_{asc,m} + \beta_{LOS,m} * X_{LOS,m} + \beta_{SOZ,m} * Y_{SOZ,m} \tag{1}$$

$$MMNL1 : U_m = \mu_{asc,m} + \sigma_{asc,m} + \beta_{LOS,m} * X_{LOS,m} + \beta_{SOZ,m} * Y_{SOZ,m} \quad (2)$$

$$MMNL2 : U_m = \mu_{asc,m} + \sigma_{asc,m} + \sigma_{asc,mXm} + \beta_{LOS,m} * X_{LOS,m} + \beta_{SOZ,m} * Y_{SOZ,m} \quad (3)$$

$$MMNL3 : U_m = a + \frac{b}{1 + e^{\mu_{asc,m} + \sigma_{asc,m}}} + \beta_{LOS,m} * X_{LOS,m} + \beta_{SOZ,m} * Y_{SOZ,m} \quad (4)$$

where

m	travel mode
X_{LOS}	Level-of-service attributes of travel mode (i.e., travel time [min], travel cost [€], pt access time [min], # transfers [-])
Y_{SOZ}	Sociodemographic attributes of individuals (i.e., age, gender, occupation, income, seasion ticket ownership)
$\mu_{asc,m}$	mean of normal distribution | shape parameter of Johnson SB distribution
$\sigma_{asc,m}$	standard deviation of normal distribution | shape parameter of Johnson SB distribution
$\sigma_{asc,mxm}$	standard deviation of distribution correlating with other travel modes
a	offset parameter of Johnson SB distribution
b	range parameter of Johnson SB distribution

RESULTS

For the presented analysis, different models were tested on their ability to capture taste heterogeneity of travel mode choice and to reproduce variation of travel mode choice appropriately. In the setup process of the models, we took all empirical results as well as experiences of comparable estimations into account. By integration into the existing travel demand model (see section 4.1), the performance of the models is assessed by comparing key indicators of the literature (see table 3.2) in simulations and survey data. For the comparison, the German Mobility Panel (*36*) is chosen as it provides a considerable sample size for the travel whole week and every year. As it does not provide a specific sample for the application area, the survey data is filtered on spatial area types matching the survey areas (i.e., large and medium-sized cities and small-town areas in urban regions as well as central and medium-sized cities in rural regions).

Mode Choice Models

Viewing the different mode choice models reveals an improving model fit for the more complex models with a large improvement when accounting for taste heterogeneity in MMNL1 and a slight improvement when accounting for correlation of the mode-specific random parameters (MMNL2). MMNL1 represents the most effective model as the additional parameters in MMNL2 do not improve the likelihood enough to reach a better BIC. For this research, the accounting correlation is desired, whereas the authors keep the model in the analysis. The model estimation results using the Johnson SB distribution show a similar model fit to those using the normal distribution. Multiple models were estimated having a better model fit than the one presented, but they were not chosen because of positive travel time or cost parameters. The results of the estimation are shown in Table 1.

TABLE 1: Estimation results of general parameters

	MNL	MMNL 1	MMNL 2	MMNL 3
LL	-27,827.02	-20,860.69	-20,829.11	-20,839.93
Rho Square	0.364	0.523	0.524	0.524
BIC	56,157.82	42,245.74	42,285.39	42,275.24
Paramter	Estimates			
$\mu_{asc,walk}$	1.06**	3.67**	3.43**	-1.08**
$\mu_{asc,bike}$	-0.62**	-1.55**	-1.86**	-2.32**
$\mu_{asc,card}$	0.00	0.00	0.00	-1.41
$\mu_{asc,carp}$	-2.19**	-4.36**	-4.17**	-1.11**
$\mu_{asc,pt}$	-2.30**	-4.41**	-4.23**	-5.75**
$\sigma_{asc,walk}$	-	3.10**	2.38**	0.12**
$\sigma_{asc,bike}$	-	7.48**	7.65**	-1.47**
$\sigma_{asc,card}$	-	6.17**	6.22**	0.46**
$\sigma_{asc,carp}$	-	4.65**	5.43**	1.67**
$\sigma_{asc,pt}$	-	3.53**	-1.27**	-4.99
a walk	-	-	-	39.63**
b walk	-	-	-	-139.21**
a bike	-	-	-	6.77*
b bike	-	-	-	-131.99**
a car d	-	-	-	16.06**
b car d	-	-	-	-79.81
a car p	-	-	-	1.05**
b car p	-	-	-	-16.58**
a pt	-	-	-	-3.51**
b pt	-	-	-	-17.62
$\sigma_{asc,walkXpt}$	-	-	-1.96**	-
$\sigma_{asc,walkXcarp}$	-	-	1.39**	-
$\sigma_{asc,walkXcard}$	-	-	-0.88**	-
$\sigma_{asc,bikeXpt}$	-	-	0.58**	-
$\sigma_{asc,bikeXcarp}$	-	-	1.47**	-
$\sigma_{asc,bikeXcard}$	-	-	1.74**	-
$\sigma_{asc,ptXcarp}$	-	-	-0.94**	-
$\sigma_{asc,ptXcard}$	-	-	-0.96**	-
$\sigma_{asc,carpXcard}$	-	-	2.83**	-
$\beta_{traveltime,walk}$	-0.13**	-0.24**	-0.25**	-0.24**
$\beta_{traveltime,bike}$	-0.16**	-0.29**	-0.29**	-0.28**
$\beta_{traveltime,card}$	-0.21**	-0.37**	-0.36**	-0.37**
$\beta_{traveltime,carp}$	-0.22**	-0.38**	-0.39**	-0.39**
$\beta_{traveltime,pt}$	-0.04**	-0.07**	-0.07**	-0.07**
$\beta_{accesstime,pt}$	-0.10**	-0.17**	-0.17**	-0.17**
$\beta_{transfer,pt}$	-0.59**	-1.23**	-1.30**	-1.21**
$\beta_{cost,card}$	-0.18**	-0.11*	-0.15**	-0.15**
$\beta_{cost,pt}$	-0.46**	-0.66**	-0.69**	-0.73**

level of significance ** 5 % , * 10 % — Table excludes sociodemographic parameters

In the MNL, some influences are averaged out because this model does not allow for taste heterogeneity. Hence, allowing for taste heterogeneity in the MMNL models, the deterministic components of these models becomes more important compared to the MNL, which is equivalent to an increasing scale. This counts for time and cost coefficients as well as for the socio-demographic attributes. The latter are not presented in this study as their interpretation is not in the focus. All estimated socio-demographic parameters show the expected signs.

Of particular interest is the observed correlation between the travel mode preference distributions. Walking reveals a significant positive correlation with the car as passenger, but negative correlation towards public transportation and the car as driver. This may be associated with the higher walking rates of travellers without a driver's license or a car available. Cycling shows positive correlation to all other modes except walking which revealed to be not significant. The positive correlation supports the supplementary use of the bicycle as it is for most travellers limited to certain purposes and ranges and therefore requires the use of other travel modes. This is supported by Nobis and Kuhnimhof (*12*) denoting car-and-bike users as the most important multimodal segment. In contrast, public transportation and the use of the car, both as driver and passenger, compete on similar trips whereas their correlation is found to be negative (see Thomas et al. (*14*) for comparison). Finally, using the private car as driver and passenger has a high positive correlation which may be due to the reason that different members of a household can take different roles while being on the way by car. The estimated effects lead to the mode preference distribution when applied to all agents of the AB-TDM shown in Figure 1. The comparison of the distributions should only be done in terms of shape and not in terms of values as the latter are not comparable for different models. These preferences include values of the distribution and the socio-demographic influences. The distributions of both the bicycle and car as driver reveal the widest distribution of preferences. The distribution of public transportation and walking preferences is substantially more narrow leading to less extreme preferences and usages.

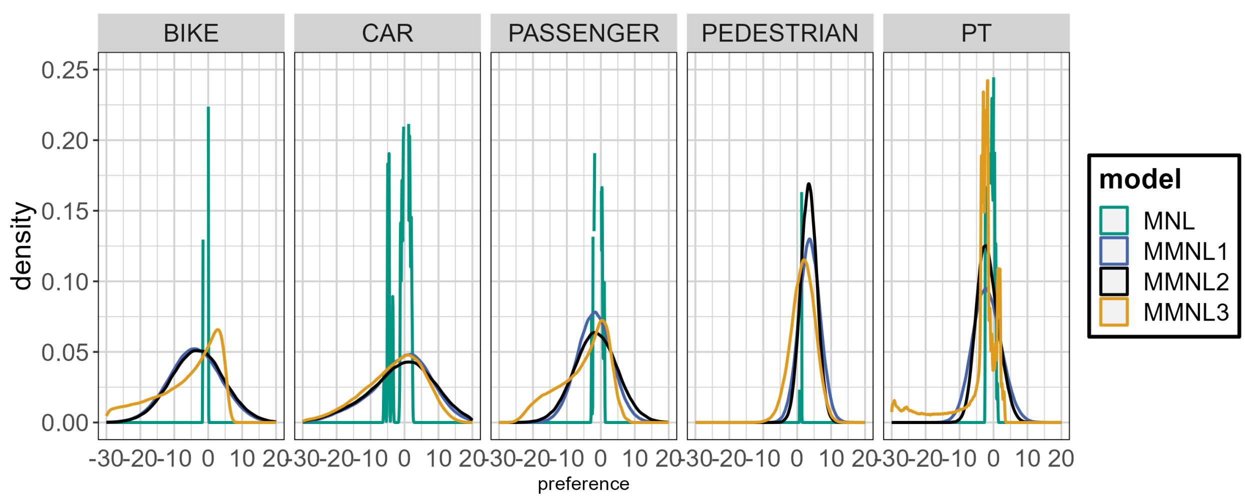

FIGURE 1: Individual preference distribution for different travel modes based on random and fixed taste components

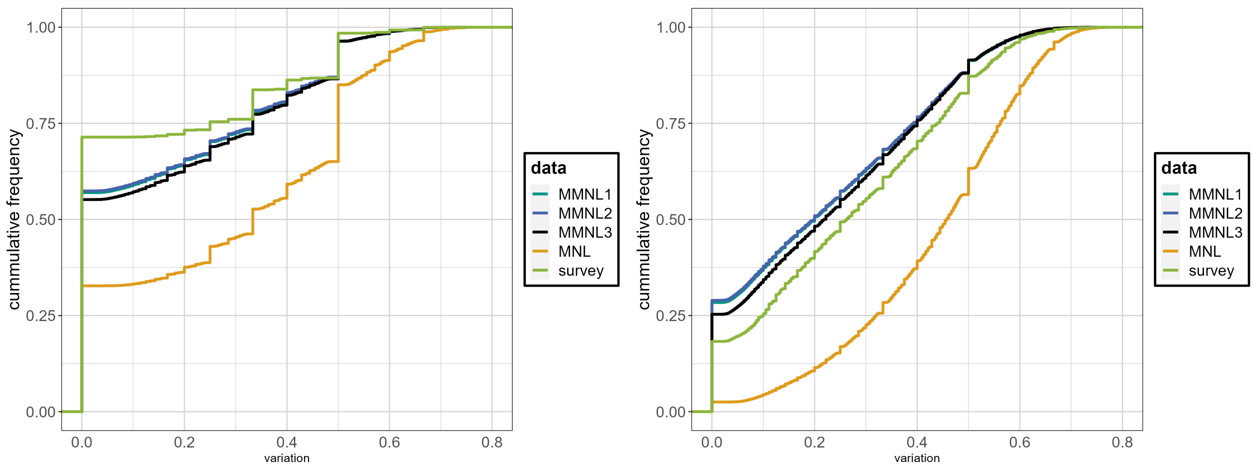

FIGURE 2: Comparison of (a) variation per day ; (b) variation per week

Simulation-based analysis of variation

The general mode choice results in terms of trips per travel mode are similar in all models and only differ up to 1% from each other. The mode choice models described are further analyzed on the observable variation of travel mode choice decisions in the AB-TDM *mobiTopp*. Both distributions of variation indices as well as the assignment to modal groups are important for an appropriate assessment of variation. The authors compare both results of the daily and weekly assessments. The chosen indicators found in the literature are:

- frequency-based
  - variation index by Thomas et al. (*14*) for different and repeated trips
  - Herfindahl-Hirschman Index (HHI) by Rhoades (*18*)
- sequence-based
  - number of runs by Mallig and Vortisch (*16*)

The variation indicator as used by Thomas et al. (*14*) specifies the share of trips not conducted with the most frequently used mode of a traveler. A higher value, therefore, represents a higher variation of mode choice. Hereby, a higher variation is observed on the week level: the day-based analysis results in a share of about 70 % monomodal users and the week-based analysis results in a share of about 20 % monomodal users in the survey. The MNL model overestimates the variation in both cases significantly. All MMNL models either slightly underestimate the stability per day or overestimate the stability per week. Distributions of variation are shown in Figure 2.

A similar result can be taken from the comparison of different distribution of the HHI. A higher value for HHI implies a lower variation of mode choice. Therefore, the HHI is lower in the week-based analysis. Again, the MNL model overestimates the degree of variation in both temporal perspectives and the MMNL models are closer to the results based on the survey analysis (see Figure 3).

The only sequence-based indicator included again confirms the gained stability through the integration of random taste heterogeneity. The number of runs, i.e., the number of subsequences with the same travel mode in relation to the total number of trips, indicates higher levels of variation for lower values. The implementations of MMNL models lead to lower values of *# runs*. The weekly perspective reveals lower values for the indicator, suggesting that on a daily basis,

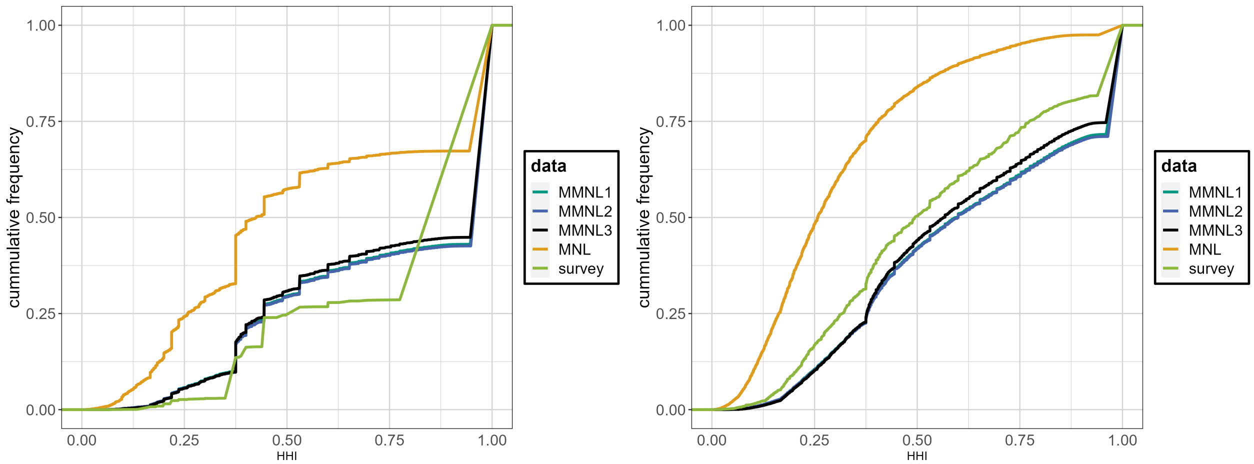

FIGURE 3: Comparison of (a) HHI per day ; (b) HHI per week

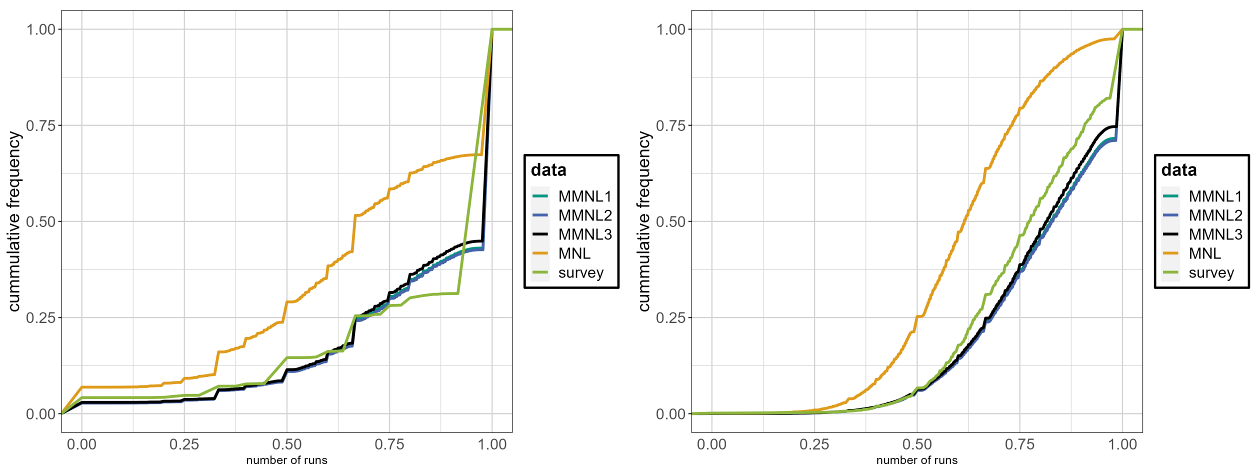

FIGURE 4: Comparison of (a) # runs per day ; (b) # runs per week

comparably long runs up to the total 24 hours are passed using almost only one mode. The results are presented in Figure 4.

The analysis of modal groups is presented in Figure 5. It is based on the simulation data only. The groups are differentiated comparable to the groups of the MiD (see 3.1) and exclude car as passenger and walking. As the survey data of the MOP represents the German average for the selected spatial typologies but the travel behavior of the residents of the application area is significantly different from this shown by the higher share of cycling and public transportation, a comparison is not reasonable.

Modal groups of different simulations still confirm the results gained in the analysis of the continuous indicators and the findings of Mallig and Vortisch (*25*): a not-consideration of stability leads to a higher share of multimodal travelers. This is already relevant for the day-based level of analysis. Especially travelers using the car as driver, public transportation and the bicycle appear much more often in the MNL simulation.

Depending on the indicator, the day-based analysis reveals that the model meets the degree of variation observable in the survey fairly well. Hereby, the indicator using the number of runs

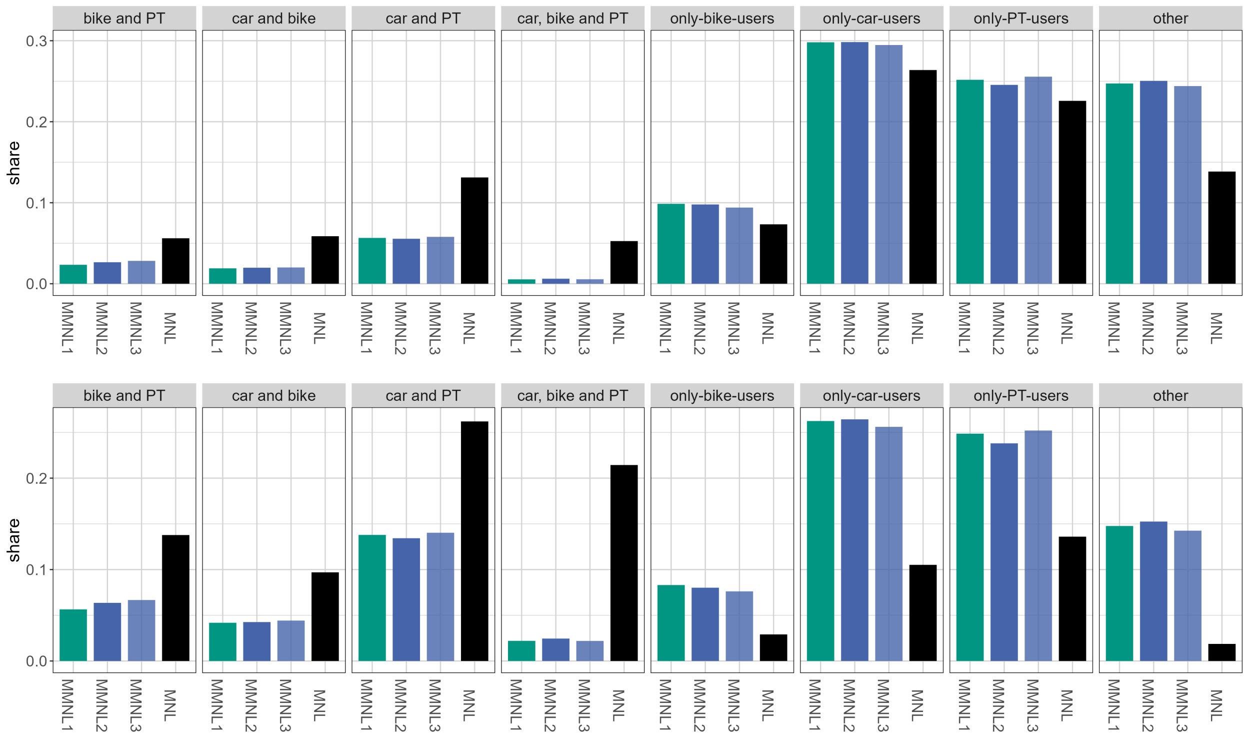

FIGURE 5: comparison of different multimodal travel patterns (a) per day ; (b) per week

denotes the best match. This confirms the expected degree of variation estimated upon the 24 hour survey. The week-based results therefore have a marginally too high stability integrated which can be addressed by using survey from a total week.

Looking at the different models, the MMNL3 results match the survey the best. This indicates the importance of flexible distributions in the model design. The differences between the different MMNL models with and without correlation between the random components reveal only slight differences. This is in line with the only marginal increase in model fit through the extension. Especially the continuous indicators for variation do not differ noticeably. However, modal groups reveal slight differences comparing both MMNL models but do not allow further interpretation. Still, the role of correlation could become more critical when analyzing variation on a pair-based level. Only having a conventional MNL combined with the implementation accounting for mode availability and consistency within tours is found to not capture the variation realistically.

CONCLUSION

The research presented addresses the importance of more detailed modeling of travel mode choice variation in AB-TDM. Therefore, the foundation was set aggregating existing literature on empirical assessments of behavior's variation, its indicators and existing state of research in modeling and forecasting. A need to account for random taste variation in travel mode choice is found to be of high relevance, especially in long-term simulations for multiple days or a week. Some examples already integrating such model components already exist and indicate an improvement of models regarding forecast sensitivity and incorporation of appropriate levels of variation.

In this work, we present an application of modal preferences through MMNL models in travel mode choice to extend the knowledge on their use in AB-TDMs. The models were integrated into an existing AB-TDM setup with the software *mobiTopp* for the Karlsruhe region. The use of AB-TDM and especially of this model framework allows to incorporate already short-term stability, particularly within tours by accounting for the general and situational availability of travel modes and respective constraints. Through a further integration of mode preferences, an additional improvement was reached regarding both the travel mode variation in the daily and weekly consideration. The indicators suggest a more stable travel mode choice behavior than traditional mode choice models. This matches the results of the survey the simulation data was compared to.

As a result, the authors recommend accounting in more detail for mode preferences and non-systematic taste heterogeneity for both AB-TDM with a simulation period of only one day as well as of one week. This leads to a better simulation of monomodal and multimodal travel behavior. By affecting the agents' sensitivity to switch to other travel modes as a result of measurements, an improvement of forecast quality can be expected.

Further improvements can be gained by an additional sequence-based integration of stability as proposed by Mallig and Vortisch (*25*) or Kuhnimhof (*17*). Nevertheless, as suggested in the literature, travel mode choice is always based on the mobility demand stemming from activities and the respective desired locations. Accounting for variation on this level of the simulation already facilitates the explanation of variation in travel mode choice. This is especially relevant for patterns observable over longer periods than one week. Still, further integration raises the need for better data (*4*). This concerns especially surveys with a period of at least one week or longer, panel surveys and, at the same time, the possibility of georeferencing to understand patterns in relation to the locations visited and to add attributes of all mode alternatives for the modeling (*15*). Still, it should be mentioned that the number of papers has already increased in recent years (*17*). However, the more the issue of variation is considered in modeling, the more important it is to study the stability of behavioral patterns over time (*22*). Here, a stronger longitudinal approach is necessary to model the developments of travel behavior over multiple decades.

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AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: study conception and design: Tim Woerle, Lars Briem, Jelle Kübler, Michael Heilig; model setup and estimation: Tim Woerle, Lars Briem, Jelle Kübler, Michael Heilig; analysis and interpretation of results: Tim Woerle, Jelle Kübler, Michael Heilig, Lisa Ecke, Martin Kagerbauer, Peter Vortisch; draft manuscript preparation: Tim Woerle. All authors reviewed the results and approved the final version of the manuscript.

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