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Modeling Tour-Based Mode Choice in Agent-Based Travel Demand Models

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Abstract

Mode choice in travel demand models is commonly predicted on a trip-by-trip basis, assuming that individuals choose a mode independently for each trip. This sequential structure neglects that travelers often anticipate subsequent trips within a tour and select modes to maximize overall tour-level utility. As a result, trip-based models may generate unrealistic behavior. This paper proposes and evaluates a tour-based mode choice approach that can be integrated into an agent-based travel demand model. Using household travel survey data from northern Germany, three model variants are estimated and compared: a standard trip-based model, a trip-based model incorporating tour attributes, and a two-step tour-based model distinguishing between fixed and flexible modes. The results show that integrating tour information substantially improves behavioral plausibility. Bicycle use on long-distance tours decreases to more realistic levels, fixed-mode decisions become more consistent, and anticipatory return-trip behavior is better represented. The two-step tour-based model performs best, demonstrating clear advantages over trip-based structures. Overall, the findings indicate that tour-based mode choice modeling enhances the realism of travel demand simulations and provides a promising foundation for further extensions, including subtours and integrated destination–mode choice frameworks.

Keywords: tour-based; mode choice; agent-based modeling; ABM; travel demand; logit model, transport

1. Motivation

In travel demand modeling, mode choice is typically predicted sequentially. Thus, in the classic four-step modeling framework, first, the destination is selected, followed by choosing the most suitable mode of transportation for the particular trip. Once the scheduled activity is complete, the next destination and mode of transportation are selected in the same stepwise fashion. However, this sequential decision-making structure can produce behavior that substantially deviates from real-world patterns because it only partially considers future trips and the future availability of modes of transportation. In reality, however, individuals often choose a mode for the first trip of a tour in anticipation of subsequent trips, aiming to maximize their overall tour-level utility. For example, if no public transit connection is

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available for the return trip after an activity, it is unlikely that public transit would be chosen for the initial trip — even if the outbound connection is convenient. Therefore, disaggregated agent-based models allow for methods to model mode choice at the tour-level in a behaviorally realistic manner. Thus, in this paper, we present a methodological approach for estimating a tour-based mode choice model, compare it to a trip-based approach and demonstrate how such a model can be integrated into the agent-based travel demand modeling framework *mobiTopp*.

The remainder of the paper is structured as follows. Section 2 provides an overview of literature on mode choice modeling. Section 3 introduces the data sources used in the analysis. The methodological approach is detailed in Section 4, while results are presented in Section 5 and discussed in Section 6.

2. Literature

Mode choice is a fundamental component of travel demand modeling. To develop models that are policy-sensitive and realistic, it is essential to represent the actual decision-making process underlying mode choice as accurately as possible. The literature describes a wide range of disaggregated approaches, which can broadly be classified as trip-based or tour-based. According to Ortúzar and Willumsen [15], a tour is defined as a sequence of trips that begins and ends at the same location. Bastarianto et al. [2], however, adopt a narrower definition in which a tour must start and end specifically at the home location.

Most models follow a trip-based approach, for example Asensio [1], Ben-Akiva and Richards [3], de Dios Ortuzar [6], or Hasnine et al. [8], where all trips are modeled sequentially without information on future trips of the same tour. Although these models can be easily integrated into a traditional four-step modeling framework, they may not capture realistic behavior throughout tours [7, 14].

A simplified tour-based approach, in contrast, can be implemented by considering only the choice of a single tour mode [7]. While this approach allows the characteristics of the entire tour to be taken into account, it is limited to representing purely unimodal tours. Nevertheless, this approach is used for example by Bastarianto et al. [2] or Cirillo and Axhausen [5], and is justified by the fact that the vast majority of tours are conducted using a single mode only.

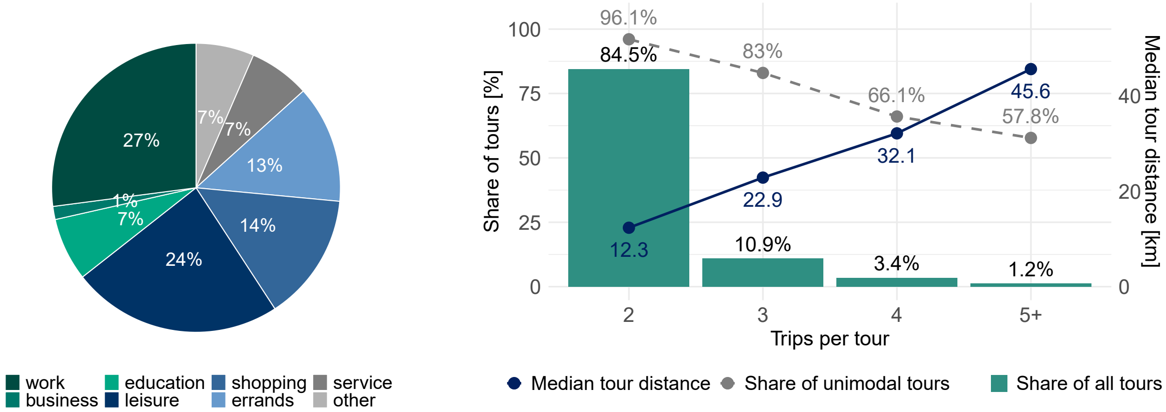
Building on this concept, the stand-alone two-stage modeling approaches have been developed [16]. In these models, the choice of a main tour mode is determined first. Subsequently, the mode for each individual trip within the tour is estimated, typically incorporating the previously chosen main tour mode as an explanatory variable [4]. Zhou et al. [17] develop a two-stage intermodal tour-based mode choice model, where similar modes are categorized to mitigate selection bias and reduce computational complexity. Another advanced approach by Vovsha et al. [16] employs a recursive, dynamic-programming-based enumeration algorithm combined with shortest-path principles to efficiently generate all feasible mode sequences within a tour, thereby eliminating the need for a two-stage modeling framework.

3. Data

We use data from the national household travel survey *Mobility in Germany 2023* [9]. The dataset contains information at the person, household, and trip level, with trip records additionally providing alternative travel times for modes of transportation that were not chosen in the observed situation. For the analysis, we restrict the sample to the federal states of Hamburg, Lower Saxony, and Schleswig-Holstein in the north of Germany. After applying this regional filter, the dataset comprises approximately 63,000 individuals from 33,000 households, accounting for a total of 161,000 trips.

For the purpose of this study, we conducted a rigorous data-cleaning process, retaining only those trips that were part of fully reported tours and for which alternative travel times were available. In addition, we restricted the set of considered modes of transport to car (driver and passenger), bicycle, walking, and public transit. These steps resulted in a final dataset comprising 46,000 trips in 21,000 tours.

As illustrated in Figure 1a 35% of all tours of the final dataset are work- or education-related, while 24% are carried out for leisure activities. Another 14% are shopping tours, and 13% are for errands, leading to 7% each for service and other trip purposes. Figure 1b, shows that 84% of the reported tours consist of two trips — one from home to a destination and one returning home. An additional 11% comprise three trips, while the remaining 5% include more than three trips. The median tour distance, however, increases steadily with the number of trips per tour. Conversely, as the number of trips per tour grows, the share of unimodal tours decreases.



(a) Tour main purposes

(b) Tour length with corresponding median tour distances and share of unimodal tours

Fig. 1: Overview of tour characteristics in the final data set

4. Method

Based on the dataset introduced in the previous section, several *multinomial logit (MNL) models* are estimated and applied to the output of the agent- and activity-based travel demand model *mobiTopp*. The aim is to compare three different mode choice implementations, as illustrated in Figure 2: (1) a trip-based model, (2) a trip-based model augmented with tour attributes, and (3) a two-step tour-based model. All three approaches consider the fixed modes car as driver and bike, as well as the flexible modes car as passenger, walking, and public transit. Fixed modes imply that the chosen mode cannot change throughout a tour, whereas flexible modes can be combined freely within a tour.

Section 4.1 describes the model estimation procedure, followed by an introduction to the agent-based travel demand model *mobiTopp* in Section 4.2.

4.1. Model estimation

MNL models, originally introduced by McFadden [13], can be estimated using Equation 1. The probability P that individual i on trip t selects mode m is given by the exponential of the systematic utility of mode m divided by the sum of exponentials of the utilities of all available modes of transport.

$$P_{m,i,t} = \frac{e^{V_{m,i,t}}}{\sum_{j=1}^{J} e^{V_{j,i,t}}}. \tag{1}$$

The models are developed iteratively by sequentially incorporating trip-, tour-, and sociodemographic attributes, and excluding those that do not significantly enhance model performance, leading to three consecutive configurations, presented in Figure 2. The trip-based approach (1) represents the most commonly used method for modeling mode choice. It includes trip-related attributes — such as travel time, travel cost, and trip purpose — in addition to individual and household characteristics. The modeling is sequential. Thus, if a fixed mode of transport — e.g., a car — is selected for the first trip of a tour, it must be used for all subsequent trips. The trip-based approach with tour attributes (2) extends this by also incorporating tour-level indicators, including the number of trips within the tour, the overall tour distance, and the minimum and maximum trip distances of the tour. However, the modeling remains sequential. In the two-step tour-based approach (3), mode choice is separated into two steps. First, the model from (2) is applied to all trips of a tour to determine whether the tour is undertaken with a fixed mode of transport, or whether the mode choice is flexible. To derive the utility of the flexible option, the maximum utility across all flexible modes for each

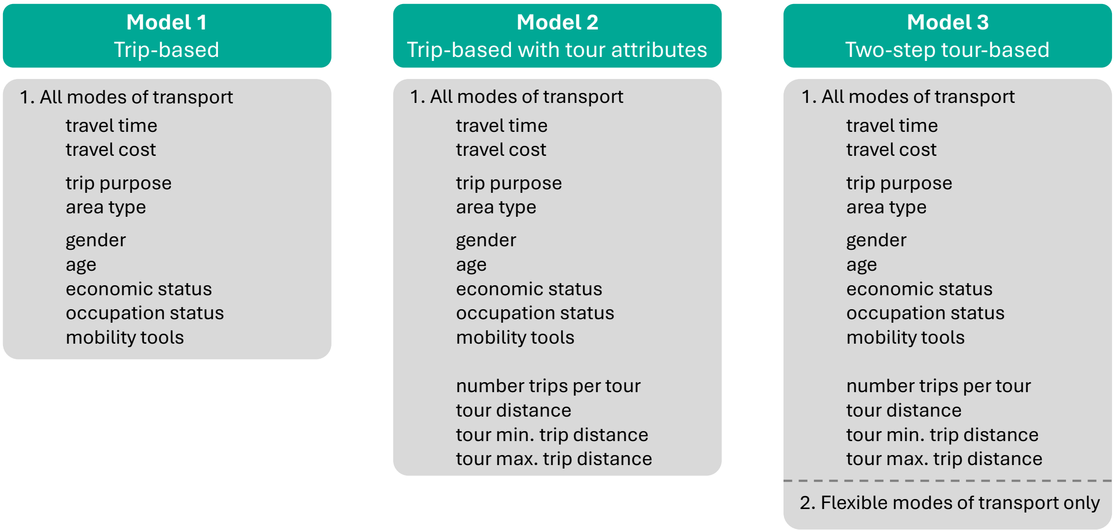


Fig. 2: Overview of estimated models

trip of a tour r is used to compute the overall tour utility, as stated in Equation 2. If a fixed mode is selected, with utility given from Equation 3, the mode choice is complete. If the tour is classified as flexible, a second trip-based mode choice step is performed, but only among the flexible modes $m \in M_{\text{flex}}$: walking, car as passenger, and public transit. The workflow for the tour-based estimation is shown in Figure 3.

$$V_{i,r}^{\text{flex}} = \sum_{t \in r} \left(\max_{m \in M_{\text{flex}}} V_{m,i,t} \right) \tag{2}$$

$$V_{m,i,r}^{\text{fix}} = \sum_{t \in r} V_{m,i,t}, \quad m \in M_{\text{fix}} \tag{3}$$

4.2. *mobiTopp framework and model application*

The agent- and activity-based travel demand model *mobiTopp* [10, 11, 12] for the city of Hamburg simulates peoples's behavior over one week, capturing their mobility patterns with high spatial and temporal resolution. Figure 4 shows the two consecutive modules of *mobiTopp*.

In the Long-Term Module, a synthetic population is generated. Individual agents are created along with their household context and relevant socio-demographic attributes. Households are assigned a geographic reference for their place of residence. Mobility tools are allocated at either the individual or household level. Further, long-term decisions, such as workplace locations, are modeled, and weekly activity schedules are generated for all agents.

The Short-Term Module subsequently simulates the population's travel demand over the entire week, including both destination and mode choice. The excerpt of the model used for this study contains 89.4 million trips in 37.4 million tours, which are executed by 3.8 million persons.

In this study, the three mode choice models were applied to the output of the *mobiTopp* short-term module. Mode choice is therefore recalculated externally using a slightly simplified approach and destination choice is given exogenously. Nevertheless, the recalculation remains consistent with the overall logic of mobiTopp, especially with respect to the distinction between fixed and flexible modes: If a fixed mode — car as driver or bicycle — is chosen for the

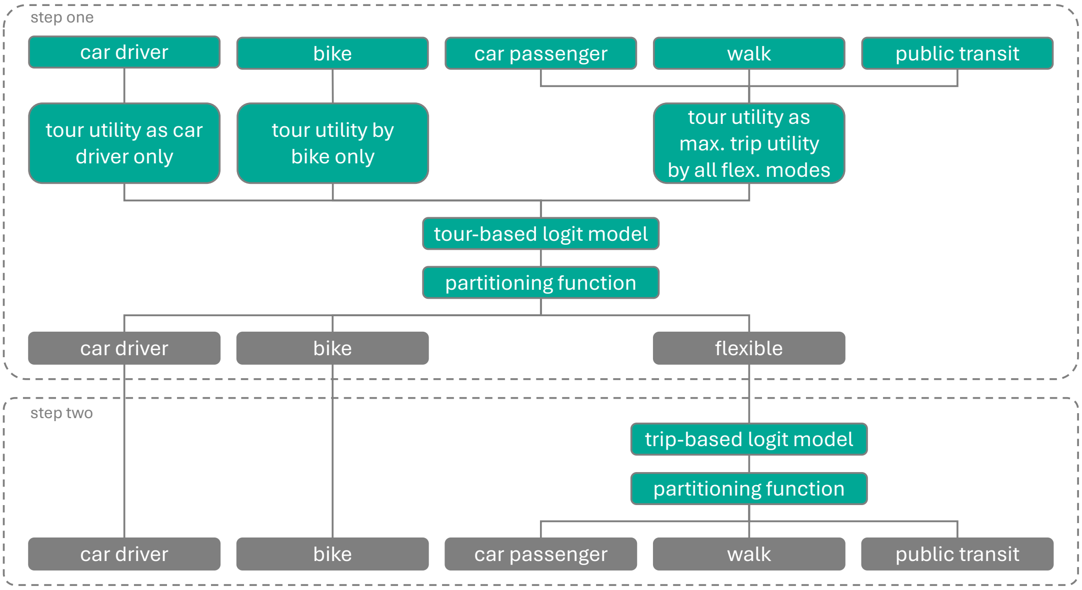


Fig. 3: Flow of two-step tour-based mode choice

first trip of a tour, it remains the only available mode for all subsequent trips of that tour. Conversely, if neither car nor bicycle is selected for the first trip, these modes are no longer available for the remainder of the tour. In this case, only flexible modes (walking, public transit, and car as passenger) may be used.

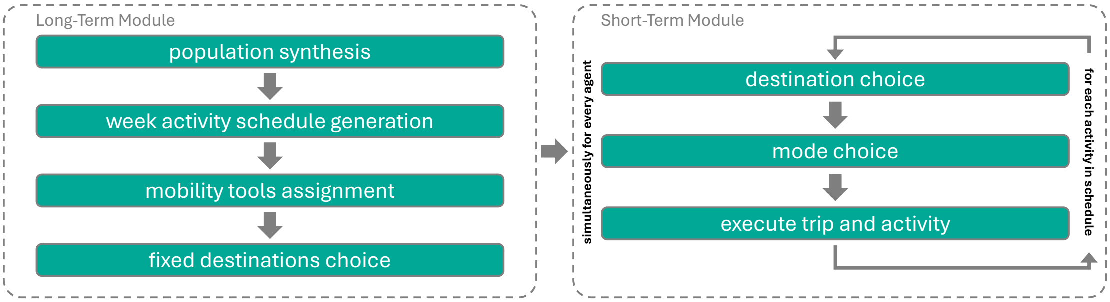


Fig. 4: Flow of the travel demand model *mobiTopp*

5. Results

While the trip-based approach (1) yields only an adj. $R^2 = 0.26$ against observed shares (adj. $R^2 = 0.46$ against equal shares), incorporating tour attributes in approach (2) increases the adj R^2 to 0.29 (adj. $R^2 = 0.46$ against equal shares). For flexible tours only, the adj. R^2 reaches 0.48 (adj. $R^2 = 0.50$ against equal shares). When interpreting these results, it is important to note that only a simple MNL structure was implemented to clearly illustrate the tour-based effects and to demonstrate the overall feasibility of the concept.

The improvements observed in the model estimation constitute only one part of the overall advancements. More importantly, the revised modeling approaches allow for a more behaviorally realistic representation of tour-level decision-making. To assess these effects, all three models were applied to the output of the *mobiTopp* short-term module, and their outcomes were analyzed at both the tour and trip level.

Table 1 shows the summary statistics of the utilities generated across the three models. It becomes evident that the range of utilities is considerably smaller in the two approaches with tour attributes, and that Model 3 in particular yields a substantially higher average utility compared to Models 1 and 2.

Table 1: Summary statistics of total utilities across the three modeling approaches

Model	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Model 1	-279.0	-20.1	-8.9	-4.9	7.0	244.0
Model 2	-200.4	-18.8	-8.8	-3.4	6.7	241.6
Model 3	-197.6	-10.8	-4.3	2.3	10.2	236.2

With respect to the distribution of trip lengths, all three models produce comparable results for walking and public transit. However, in the two-step approach (3), with increasing trip distance, the share of car as driver trips increases and the share of car as passenger trips decreases compared to Models 1 and 2, as shown in the top row of Figure 5. The largest difference appears in bicycle use. In Model 3, bicycle use drops sharply and disappears entirely at approximately 30 km — corresponding more closely real-world behavior. These improvements already begin to emerge in Model 2, where including tour attributes increases behavioral plausibility. Model 3 reinforces these patterns even further, demonstrating the advantages of explicitly modeling anticipatory, tour-level decision-making. The differences remain when considering the total distance of the tour, see the bottom row of Figure 5. In the baseline model, bicycle is frequently chosen for tours with total distances of more than 50 km, mostly because it was selected for the first trip of the tour. Incorporating tour parameters in Model 2 significantly reduces this unrealistic pattern, and Model 3 yields the most plausible results. Further, walking continues to appear in long-distance tours, which is reasonable: since walking belongs to the flexible set of modes, agents may switch from walking to public transit within the same tour.

The advantages of tour-based modeling become particularly evident when considering trips beyond the first within each tour. During daytime hours, the public transit mode share decreases by 8 % from Model 1 to Model 3. At night, when transit services are more limited, this difference increases to 20 %, reflecting travelers' anticipation of reduced service availability and longer expected travel times. These effects — especially pronounced during nighttime travel on the urban periphery — are captured in Model 3 but not in Model 1.

It is important to emphasize that no calibration against observed mode shares or aggregate statistics was performed. The intention of this study is not to provide a fully calibrated operational model, but rather to demonstrate the conceptual and behavioral improvements achieved through incorporating tour-level logic into mode choice modeling.

6. Discussion

The results demonstrate that incorporating tour-level information into mode choice modeling substantially improves behavioral realism compared with a purely trip-based approach. However, several methodological considerations and opportunities for further development arise from this work.

A first challenge concerns destination choice. In many applications, destination and mode choice interact, as individuals adjust destinations based on anticipated mode availability. Since this study focuses solely on mode choice, destinations were treated as exogenous. Extending the approach to a joint destination–mode choice framework would be a valuable direction for future research.

Moreover, the current implementation does not explicitly account for subtours, such as going to a restaurant for lunch during work. Subtours are common in real-world, and incorporating them would not require fundamental methodological changes. The logic used for main tours can be directly applied to subtours, suggesting that tour-based modeling can be extended without conceptual difficulty.

The comparison of the three modeling approaches shows that integrating tour information improves performance even within a sequential trip-based structure. However, the two-step tour-based framework produces the most behaviorally plausible results. This suggests that once tour-based modeling is adopted, distinguishing between fixed and

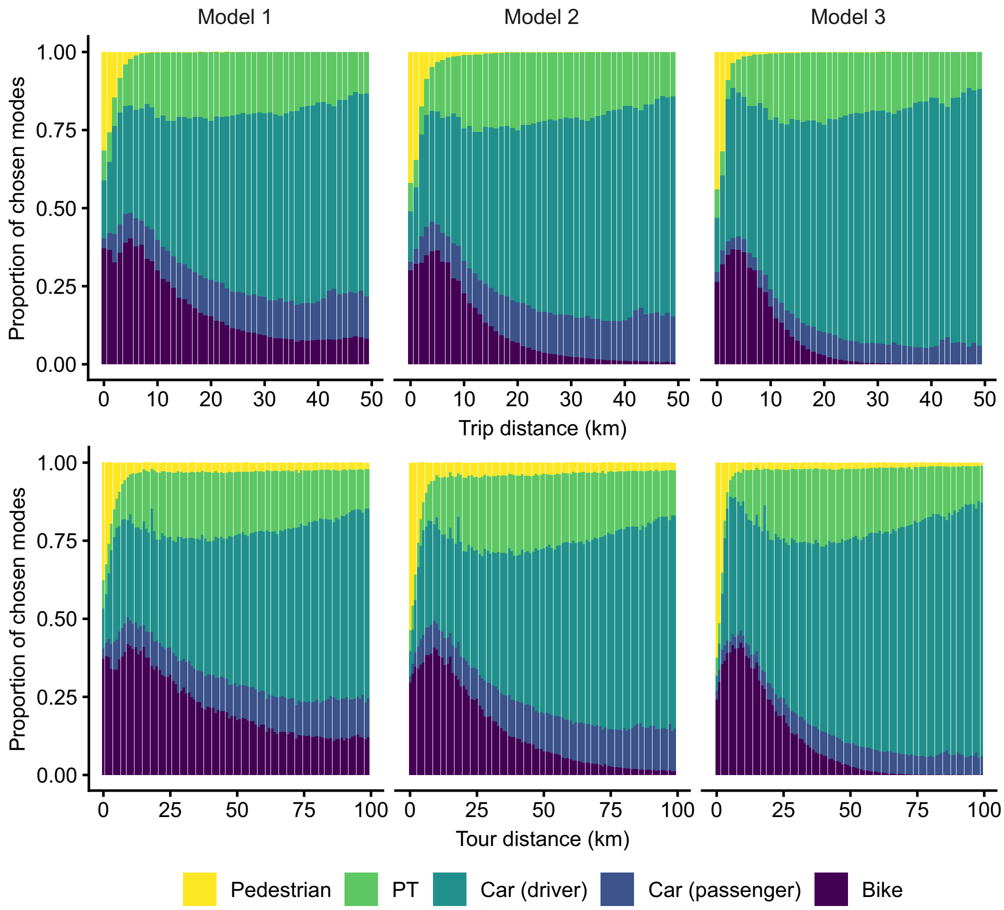


Fig. 5: Trip-based mode share by trip distance (top row) and by tour distance (bottom row) in the three approaches

flexible modes at the tour level is more effective than merely adding tour attributes to a trip-based model. The advantages also extend to out-and-back tours, where anticipatory return-trip behavior can be represented more realistically.

Also, only relatively simple MNL models were estimated in this study. Their purpose was to isolate and illustrate the conceptual differences between trip-based and tour-based approaches. In practical applications, more advanced model structures would typically be employed, potentially further improving predictive performance.

For simplicity, the model used here only contained a small set of modes. When other modes such as ride-pooling and bike-sharing are of interest, they can be integrated easily. It is expected that a tour-based approach brings further benefits in this case.

Finally, future work should specify how the tour-based approach can be operationalized within *mobiTopp*. Explicit modeling of fixed modes would particularly benefit from a tour-level framework, since availability constraints for car and bicycle use stem from decisions made at the start of a tour. The improvements observed here indicate that such an integration could substantially enhance the behavioral realism of travel demand models.

7. Conclusion

This study demonstrates that incorporating tour-level decision structures into mode choice modeling leads to substantially more realistic behavior than a purely sequential, trip-based approach. Using data from the German national travel survey and implementing three different model variants within the *mobiTopp* framework, we show that even modest extensions — such as adding tour attributes to a trip-based model — yield meaningful improvements. The two-step tour-based formulation, however, provides the clearest behavioral advantages by explicitly representing anticipatory decisions and the constraints associated with fixed modes such as car and bicycle.

The empirical results confirm that tour-level modeling mitigates several well-known inconsistencies of trip-based mode choice, such as unrealistic persistence of fixed modes on long-distance tours and implausible mode choice for the first trip of a tour. The approach improves model behavior not only for complex tours with multiple trips, but also for simple out-and-back patterns, where anticipatory return-trip considerations matter. These findings indicate that tour-based choice structures offer clear advantages, especially when differentiating fixed and flexible modes.

The study was intentionally based on simple MNL specifications to isolate conceptual differences rather than optimize predictive accuracy. In operational practice, more advanced model structures and traditional calibration procedures would further enhance performance. Future research should examine how the proposed tour-based approach can be fully integrated into the *mobiTopp* destination and mode choice modules, and how subtours and joint destination–mode interactions can be incorporated. Overall, the results underscore that tour-based mode choice modeling represents an important step toward more behaviorally realistic and policy-sensitive travel demand simulations.

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