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ScienceDirect

Procedia Computer Science 280 (2026) 560–567

Procedia Computer Science

www.elsevier.com/locate/procedia

The 17th International Conference on Ambient Systems, Networks and Technologies (ANT)
April 14-16, 2026, Istanbul, Türkiye

Modeling Leisure-related Agent-Place Relationships in Agent-based Travel Demand Models

Tim Wörle[a,*], Jan Ellmers[a], Jelle Kübler[a], Martin Kagerbauer[a], Peter Vortisch[a]

[a] *Karlsruhe Institute of Technology, Kaiserstrasse 12, 76131 Karlsruhe, Germany*

Abstract

Understanding spatial behavior is essential for accurately modeling travel behavior, as many activities are repeatedly conducted at a limited set of preferred locations. This paper presents a novel approach for synthesizing agent-specific place relationship networks and integrating them into destination choice modeling within the agent-based framework mobiTopp. Using multi-week activity tracking data from the MOBIS study, we develop sequential models that estimate the number of leisure-related relationships, characterize their behavioral and temporal structure, and assign spatially plausible destinations based on attractiveness and accessibility. The resulting agent-place relationship networks extend conventional short-term destination choice models by embedding long-term spatial preferences. An exemplary analysis of measure sensitivity reveals that incorporating agent-place relationships substantially reduces the responsiveness of agents with strong preferences to accessibility changes, while agents without such relationships remain highly sensitive.

Keywords: Destination choice; Spatio-temporal behavior; Agent-based travel demand modeling

1. Introduction

The places people visit in their daily lives and the distances they travel to reach them significantly shape overall travel patterns and influence additional aspects such as emissions impacts and the space required for transport. Studies show that for longer periods of several weeks a large share of everyday activities occurs only at a few locations, exhibiting a high degree of repetition. Based on travel surveys from different geographical contexts, Schönfelder and Axhausen estimate that, on average, approximately 80 % of all activities take place at the ten most frequently visited activity locations [15]. These include work and educational sites, where repetition is to be expected, but also places associated with other activities to which individuals have an attachment and which form part of their social network. Puhe examined such different types of place relationships with regard to the stability and variability of associated activities and pointed out that the majority exhibit high persistence, with only few being replaceable or adaptable [14].

* Corresponding author. Tel.: +49-721-608-47733.
E-mail address: tim.woerle@kit.edu

This highlights that the nature of a person's relationship to a place interacts with changes in the transport system, and that not every measure can unfold its intended effects, as people tend to maintain their established behavior. Such interrelations can be important when forecasting the impacts of measures in travel demand models.

Different approaches exist to consider a person-specific place network within travel demand models. Horrowitz and Louviere recommend the use of an individual's reported locations as an influencing attribute in the destination choice [6]. Puhe et al. modeled person-place relationships for grocery shopping that included trust in individuals and brands or retail chains [13]. Using the destination choice of an existing simulation and relationship characteristics from a qualitative study, they developed a synthetic relationship network that was subsequently used in further simulations. In these simulations, the characteristics of the relationships influenced the changeability of destination choice. When forecasting the impacts of a car-free city center, varying degrees of mutability were observed. However, the specification of person-place relationships can also be carried out without prior simulation. Kuhnimhof used gravity models to represent routine and non-routine destinations for leisure and shopping purposes, assuming partially stable destination choices for these activity types [8]. Before running the simulation, four to six destinations were selected by evaluating impedance based on home and workplace locations, as well as attractiveness. In the subsequent simulation, these destinations were chosen according to the situation. In a validation simulation over the course of one week, a nearly realistic level of intrapersonal variance in travel performance and a realistic number of visited locations was achieved.

In this paper, we propose an approach for synthesizing agent-specific relationships with places - hereinafter referred to as agent-place relationships (APR) - to represent long-term destination choice in an agent-based travel demand model, using activity-based travel survey data. We show how such APR networks can be incorporated explicitly into the destination choice component of a simulation model and we demonstrate the approach for multiple leisure activity purposes. Moreover, we show exemplarily how the integration of APR affects model sensitivity, highlighting the differences in behavioral responses that emerge when destination choices are constrained by persistent spatial patterns rather than assumed to be entirely flexible.

2. Method

The model concept aimed at a more detailed representation of destination choice builds on the modeling framework of *mobiTopp* [10]. The *mobiTopp* approach models long- and short-term mobility-related decisions. The long-term module generates a synthetic population and models invariant household and person attributes including: generating activity schedules, assigning fixed locations for work and education as well as personal mobility tools such as private car and transit pass. The population synthesis is based on an Iterative Proportional Updating (IPU) procedure that microscopically reproduces the population structure in accordance with real-world distributions [18]. The short-term module conducts destination and mode choice decisions for the simulation period. These decisions are derived from the agents' activity schedules and are determined in interaction with the transport system and other agents. The destination choice model concept presented in this paper extends both the long-term and the short-term modules by adding an APR synthesis and a short-term destination choice component which depends on APR as shown in Figure 1.The long-term module is extended to specifying the extent, spatial reach, and spatiotemporal characteristics of each agent's APR network. This embeds spatial–temporal behavior in the model from a long-term perspective. The characteristics of these APR subsequently affect destination choice decisions probabilistically during the short-term module.

The destination choice component within the short-term module retains its previous overall structure and distinguishes between fixed destinations such as work or education and flexible destinations. Flexible destination choice selects situationally appropriate locations for activities using a probabilistic choice model. The destination choice of leisure activities is stabilized in this model through the integration of APR. The existing influences in the decision model are extended by factors derived from the APR, which increase - but also situationally modulate - the likelihood of specific choices.

2.1. Data

Suitable data for the modeling of APR can be found in activity- and trip-based surveys. In order to model the long-term nature of destination choice behavior it is of particular importance to cover multiple weeks in the observation.

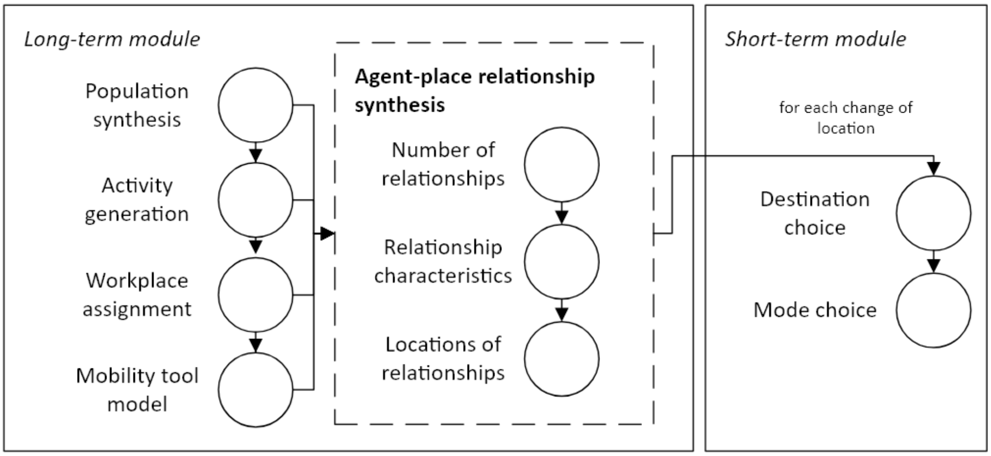

Fig. 1. Overview of adapted mobiTopp modeling framework

The MOBIS study is suitable in this context because it used smartphone-based tracking to collect the travel behavior of eight weeks [12]. It was conducted in 2019 and 2020 and took place in metropolitan areas of Switzerland. The number of complete participants in the study was 3,690. The tracking app detected activities, locations and activity purposes and asked participants to verify and correct these data. Missing information on activity purpose were imputed afterwards. Weekly reminders were sent to support data completion. Compared to manual reporting, the GPS tracking app significantly reduced response burden. The retention rate after eight weeks remained above 80%, indicating the feasibility and user-friendliness of the study.

The following criteria were applied to select the subsamples of participants, activities, and activity locations for the modeling in this research.

- Person participated completely in the study; availability of activity records for at least 42 days
- Place of work or education of a person located within Switzerland or no more than 20 km across the border
- Activity locations no more than 100 km from the place of residence, assuming 100 km limit everyday mobility (many studies set 100 km as a threshold for delimiting long distance travel, e.g. [1])
- At least one home activity per week and on average at least one change of location per day reported
- Less than 5 % missing information on activity purpose per person

After applying these criteria, the processed data set comprises 1,310 participants, 102,400 activity locations, and 226,000 activities. Only six weeks of reported activities are used for the examination as complete weeks are required.

The spatial information of activities in the survey is available based on a 100 meter grid. Unique locations of a person and therefore repetitive destination choice patterns are defined based on this spatial level and the reported activity types. After identifying unique locations, their attractiveness for different leisure purposes is assessed based on Openstreetmap data [7]. The detailed leisure categories were determined by matching activity location data from another survey based on spatio-temporal characteristics. This makes the heterogeneity of leisure activities more visible. Access to these activity locations based on the place of residence, work and education is calculated based on an Openstreetmap network and General Transit Feed Specification (GTFS) data from Swiss Federal Railways.

2.2. Synthesis of agent-place relationships

2.2.1. Number of agent-place relationships

The number of purpose-specific APR determines the extent of an individual's location-based network and directly influences the stability of destination choice behavior in the demand simulation. Therefore, the first model estimates this value. At this stage, all activity locations visited are considered as an APR.

We apply a Zero-Inflated Poisson Regression model to predict a person's number of APR. First, a binary decision - using a binomial logistic regression - determines whether there are any relationships. If this is the case, a count model is applied to estimate the number of relationships (which can still evaluate to zero). We use a Poisson regression as a count model which determines the probability of y_i relationships (c.f. Equations 1 and 2). Here, λ_i denotes the Poisson parameter, which represents a log-linear combination of explanatory variables $X_{k,p}$ and corresponds to the expected value $E[y_i]$ [17]. Another applicable model is the Zero-Inflated Negative Binomial Regression which is expected to better account for the overdispersion due to its greater flexibility compared to the Poisson model.

$$P(y_i) = \frac{e^{-\lambda_i}\ \lambda_i^{y_i}}{y_i!} \tag{1}$$

$$with\ \lambda_i = e^{\beta_k X_{k,p}} \tag{2}$$

where

y_i Number of APR
β_k Parameters of influences of personal characteristics k
$X_{k,p}$ Personal characteristics k of a person p

Both model components account for influences from individual characteristics such as age, gender, employment status, educational level, car availability, and transit pass availability; household characteristics such as household size and the population size of the municipality of residence; and schedule characteristics such as the number of purpose-specific activities over the six-week survey period. The model is applied for each agent and leisure purpose. The dataset from the MOBIS survey used for model estimation comprises 5,240 observations across all leisure purposes.

2.2.2. Characteristics of agent-place relationships

The characteristics of an APR reflect what a person associates with a given place and determine the related behavior. They can describe both the spatiotemporal structure of purpose-specific activities and the underlying behavioral motives. The former captures the frequency, concentration, and timing of behavior, whereas the latter offers an understanding of the reasons why such behavior occurs. In this model, APR characteristics are determined through an analysis of carried-out behavior, which was observed over a six-week period at the respective locations.

The behavior-based preference (BBP) is based on a person's activities performed at a certain location. Equation 3 is evaluated for these activities in total, by weekday and by time of day (in three-hour intervals). This additionally captures to which extent a place preference is tied to a specific temporal context t. For example, weekly meetings, typical activity times or opening hours can thereby be identified. The preference considers all observations except for one in the calculation. Consequently, repeated visits to a place are a precondition for assuming a preference. This is in line with the formation of the mode preferences by Mallig [9].

$$BBP_{t,p,i} = \frac{n_{t,p,i} - 1}{N_{t,p} - 1} \tag{3}$$

where

$n_{t,p,i}$ Number of activities of a person p at a location i for time reference t
$N_{t,p}$ Number of activities of a person p for time reference t

The APR characteristics are assigned probabilistically for complete sets of APR per agent and leisure purpose. This ensures a realistic distribution of stable and variable behavioral patterns that emerge from the distribution of preferences across all APR for a given leisure purpose and person. For example, evenly distributed preferences across several APR result in a generally more variable destination choice behavior than a single strong APR. This assignment considers sociodemographic characteristics such as age, gender, and employment status as they have a pronounced influence on destination choice behavior. The APR are generated based on approximately 4,000 sets across all leisure purposes from an augmented MOBIS survey database. The share of sets exhibiting at least one effective place preference (BBP) with a value greater than zero ranges between 43 % and 64 % (see Table 1).

Table 1. Data for assignment of APR

Leisure category	Number of sets in database	Share of sets with positive place preference
Culture	1,140	63.9 %
Clubs and groups	562	43.1 %
Private visit	1,161	58.8 %
Sport and recreation	1,148	60.0 %

2.2.3. Locations of agent-place relationships

After determining the number and characteristics of APR, each relationship is assigned a concrete location. This resembles destination choice decisions for person-specific place relationships from a long-term perspective. Instead of situational influences, such as current travel time, context-independent indicators are used to explain destination choice behavior, including the attractiveness of a location per leisure purpose and its accessibility (see Equation 4).

$$\begin{aligned} V_{i,p} = {} & (\beta_A + \sum_k \delta_{A,k} X_{k,p} + \sum_t \delta_{A,t} X_{t,b,p}) \ln(A_i + 1) + \\ & \textstyle\sum_m (\beta_{AR,m} + \sum_k \delta_{AR,m,k} X_{k,p} + \sum_t \delta_{AR,m,t} X_{t,b,p} + \sigma_{AR,m,inter} z_{AR,p}) \ \ln(e^{AR_{m,i}} + 1) + \\ & \textstyle\sum_m (\beta_{EA,m} + \sum_k \delta_{EA,m,k} X_{k,p} + \sum_t \delta_{EA,m,t} X_{t,b,p}) \ \ln(e^{EA_{m,i}} + 1) \end{aligned} \tag{4}$$

where

A_i	Attractiveness of grid cell i by purpose
$AR_{m,i}$	Accessibilty of grid cell i from residence r by travel mode m
$AW_{m,i}$	Accessibilty of grid cell i from place of work/education w by travel mode m
$X_{k,p}$	Personal characteristics of a person p
$X_{t,b,p}$	Activity characteristics t of a location relationship l of a person p
$\beta,\ \delta$	Parameters of main and interaction components
$\sigma_{EW,m,inter}$	Interpersonally normally distributed random component
$z_{EW,p}$	Normally distributed random number of person p

Attractiveness is applied in the utility function through a logarithmic transformation which has been recommended in the literature [2]. The underlying assumption is that additional increases in attractiveness yield diminishing marginal effects as attractiveness values grow. Accessibility is based on the utility values derived from a mode choice model. These utility values are transformed using the Euler function and the natural logarithm to ensure nonnegative outcomes and to allow accessibility to approach zero once travel times exceed certain thresholds. It is computed for trips by *car* and *public transport* and from the person's residence and (potential) place of education or employment respectively. All effects of attractiveness and accessibility interact with person-specific and APR-specific attributes. For example, the model captures that individuals with different occupations exhibit varying sensitivities to accessibility and that weekend-specific APR differ structurally in their spatial configuration.

The decision model is specified as a mixed logit model. Unlike a multinomial logit model, it incorporates random utility components within the deterministic utility, represented by a defined distribution whose parameters are estimated within the model. These random components may be specified both interpersonally and intrapersonally to capture unobserved heterogeneity either across individuals or across decisions made by the same individual. In this model, a normally distributed random interpersonal utility component $\sigma_{AR,m,inter}$ is assumed for the accessibility of a destination by car from the individual's residence. This additional random component improves the representation of varying sensitivities among individuals with otherwise similar characteristics. Moreover, this model specification allows for correlation among alternatives, as recommended in the literature [4, 16].

The choice models are estimated using the R package *Apollo* [5]. 30 alternative locations are randomly assigned for each observed activity location. The assignment can choose from all possible locations identified within a maximum distance of 100 km from the place of residence. The dataset used for model estimation consists of approximately 9,300 observations across all leisure purposes. The proportions of the leisure purposes reflect their frequencies in the overall sample, resulting in a relatively small dataset of about 350 observations for club and group activities.

2.3. Short-term destination choice

The modeling approach draws on destination choice behavior observed over a period of several weeks to determine place preferences. The model leverages knowledge of long-term behavior and the dynamics identified therein to explain short-term behavior [11]. General preferences for places are derived to capture overarching affinities for a place and thus spatially stable behavior. In addition, time-specific preferences account for whether a place is consistently visited at particular times of day or on specific weekdays, indicating the presence of spatial–temporal stability in behavior.

The model further incorporates situational attributes such as the attractiveness of a location, its accessibility, the accessibility of the next fixed destination relative to a given place, and the ratio of travel time to total available time until the next fixed activity. These key influences interact with the individual's sociodemographic characteristics. Separate destination choice models are developed for each leisure purpose. Accessibility differs from the long-term destination choice model insofar as it reflects the situational accessibility of a location relative to the current position and the next fixed destination, rather than accessibility from home, work, or educational locations. To keep it simple, this model only considers car-based accessibility but extending it with accessibility by active modes or public transport is reasonable. The model further incorporates the ratio of total travel time between the current location, a potential destination, and the next fixed destination to the remaining time available before the next fixed activity. Values close to one indicate that little time is left for the activity itself, whereas values near zero mean that ample time remains, with only a small proportion consumed by traveling. Studies show that individuals tend to tolerate a stable ratio between activity duration and travel time [3]. The models are specified as multinomial logit models, with the utility function defined in Equation 5. 30 alternative locations are assigned as in the long-term destination choice. However, the assignment prioritizes other APR of a person to make the choice more realistic.

$$\begin{aligned} V_{j,p} = {} & (\beta_A + \sum_k \delta_{A,k} X_{k,p}) \ln(A_j + 1) + (\beta_{ACC,Car} + \sum_k \delta_{ACC,Car,k}\, X_{k,p}) ACC_{Car,i,j} + \\ & (\beta_{ACCFD,Car} + \textstyle\sum_k \delta_{ACCFD,Car,k}\, X_{k,p}) ACCFD_{Car,j,f} + (\beta_{TTR,Car} + \textstyle\sum_k \delta_{TTR,Car,k}\, X_{k,p})\, TTR_{Car,i,j,f,p}) + \\ & \beta_{BBP} BBP_{Total,j,p} + \beta_{BBP,WD} BBP_{WD,j,p} + \beta_{BBP,DT} BBP_{DT,j,p} \end{aligned} \tag{5}$$

where

A_j	Attractiveness of zone j by leisure purpose
$ACC_{Car,i,j}$	Accessibilty by car of zone j from current zone i
$ACCFD_{Car,j,f}$	Accessibilty by car of next fixed destination f from zone j
$TTR_{Car,i,j,f,p}$	Travel time ratio from current zone i to next fixed destination f
$X_{k,p}$	Personal characteristics of a person p
$BBP_{Total,j,p}$	BBP of a zone j and person p
$BBP_{WD,j,p}$	Weekday-dependent BBP of a zone j and person p
$BBP_{DT,j,p}$	Daytime-dependent BBP of a zone j and person p
$\beta,\ \delta$	Parameters of main and interaction components

3. Results

The models described in Section 2.2 are applied within a *mobiTopp* model to validate key characteristics and examine effects on measure sensitivity. While the models focus on leisure purposes, they are combined with existing simple destination choice models for all other activity purposes in order to represent overall daily travel. An existing model of the Karlsruhe region is used. The synthetically generated population comprises approximately 1.47 million inhabitants who, over a six-week period, conduct a total of 226 million activities. The total number of zones amounts to 1,713. Six-week-activity plans are randomly assigned from the MOBIS survey based on sociodemographic characteristics. As the comparative sample of the MOBIS survey only includes persons aged between 18 and 65, only this age group is taken into account in the following evaluations.

We first investigate the extent to which the APR synthesis adequately reproduces the number and structure of APR associated with leisure activities. Therefore, we validate the generated APR for each agent with respect to their number and distance to residence per leisure purpose (see Table 2). The distributions of the synthetically generated relationships and those observed in the MOBIS survey are generally consistent. For example, club and group activities show substantially lower numbers of relationships than the other leisure purposes, and the distributions align very closely. The remaining leisure purposes also exhibit appropriate distributional patterns. When comparing the distance to the place of residence, more pronounced differences become apparent. Further calibration of the models would be necessary here.

Table 2. Comparison of APR metrics in model and survey

Metric	Leisure category	Synthesis			Survey		
Quartile		Q1	Q2	Q3	Q1	Q2	Q3
Number of relationships	Culture	6	9	14	4	7	11
	Clubs and groups	1	2	3	1	2	3
	Private vists	5	9	15	5	8	13
	Sports and recreation	4	6	10	4	6	10
Distance to residence	Culture	6.4	13.7	25.3	3.1	7.6	18.4
	Clubs and groups	4.7	10.5	20.7	2.2	5.4	12.3
	Private vists	4.9	10.2	18.5	3.4	9.7	24.5
	Sports and recreation	8.1	16.7	29.2	3.9	10.5	27.2

The effect of the modeled APR characteristics on the changeability of destination choice behavior is examined using a measure that alters the accessibility of two selected leisure destinations. We assume that car travel times to these destinations increase by ten minutes, due to changes in parking supply and access management. Two simulations were conducted for this scenario: a baseline destination choice model is compared to a model including the BBP. We analyze the relative change in activity counts within the affected traffic zones.

At both locations, the number of activities decreases by 67 to 74 % in the baseline model. The decrease is slightly higher for agents with an APR at the respective location as they live closer on average. In comparison, the model including BBP results in a substantially lower decrease for agents with APR. A higher share of agents maintain their behavior on average. Agents without relationships react almost as strongly as in the baseline model.

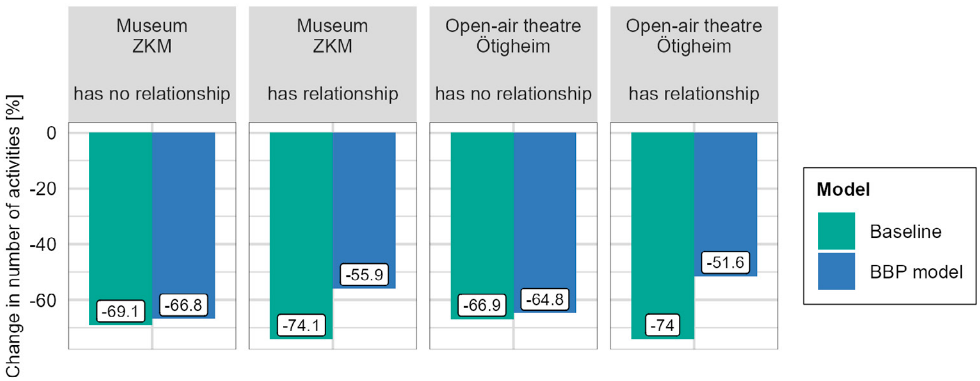

Fig. 2. Measure sensitivity of destination choice at selected locations

4. Discussion

This research demonstrates a novel approach for synthesizing an agent-specific place relationship network, enabling the representation of long-term spatial preferences within an activity-based demand simulation. By using commonly available activity-based survey data, the proposed method generates both the typical locations and their relationship characteristics, thereby extending traditional destination choice modeling with behaviorally grounded, person-specific spatial structures. The synthesis procedure itself is sequential and integrates an initial set of interdependent models. While this structure provides a practical and modular framework, it also offers substantial potential for refinement. Future work could incorporate more behaviorally sophisticated models at each step, and the approach could benefit from explicit integration with choice set formation and action space modeling. Such extensions would likely enhance the theoretical grounding and empirical robustness of the synthesized relationship networks.

Several challenges remain. First, the approach requires multi-week survey data to capture the spatial repetition of activities and identify stable APR. These types of longitudinal mobility datasets are still rare, which limits broader applicability. Second, the model region, the estimation data, and the validation data stem from different geographic contexts, introducing spatial inconsistencies and the need for further calibration. Although this study assumes that the urban regions are sufficiently comparable for a pilot application, this assumption warrants closer investigation in future research. Third, the method rests on the assumption that observed spatial stability implies lower changeability in destination choice. While theoretically plausible, this relationship must be empirically validated, particularly in the context of policy-sensitive simulations.

Acknowledgments

The authors thank Kay W. Axhausen for providing the tracking data stemming from the MOBIS study.

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