

1 **MODELING VARIABILITY AND STABILITY OF TRAVEL BEHAVIOR IN A**
2 **LONGITUDINAL VIEW USING THE AGENT BASED MODEL MOBITOPP**

3 Martin Kagerbauer (corresponding author)
4 Institute for Transport Studies, Karlsruhe Institute of Technology (KIT)
5 Kaiserstrasse 12, 76131 Karlsruhe, Germany
6 Tel: +49 721 6084 7734
7 Email: Martin.Kagerbauer@kit.edu

8 Nicolai Mallig
9 Institute for Transport Studies, Karlsruhe Institute of Technology (KIT)
10 Kaiserstrasse 12, 76131 Karlsruhe, Germany
11 Tel: +49 721 6084 4119
12 Email: Nicolai.Mallig@kit.edu

13 Peter Vortisch
14 Institute for Transport Studies, Karlsruhe Institute of Technology (KIT)
15 Kaiserstrasse 12, 76131 Karlsruhe, Germany
16 Tel: +49 721 6084 2255
17 Email: Peter.Vortisch@kit.edu

18 Manfred Pfeiffer
19 IVT Research GmbH
20 Quadrat M4, 10, 68161 Mannheim, Germany
21 Tel: +49 621 150308 40
22 Email: Pfeiffer@ivt-research.de

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1 ABSTRACT

2 The current travel behavior in Germany shows an increasing tendency to intermodal and multi-
3 modal trips. It is more common for the population to use different travel modes in different situa-
4 tions. During a longer period (e.g. one week) it is more likely for people to use more than one
5 travel mode. The association of the Stuttgart Region (Verband Region Stuttgart) commissioned
6 an agent-based travel demand model (mobiTopp) to simulate the travel behavior of all inhabit-
7 ants of the Greater Stuttgart Region. The multi agent-model mobiTopp models, based on a
8 household travel survey, all trips of the 2.7 million inhabitants in the course of one week with all
9 their origins and destinations, all modes, departure and arrival times as well as a variety of other
10 information. Due to the longitudinal character of the model, it is possible to analyze the stability
11 and variability of people's travel behavior. The results of mobiTopp are comparable with a
12 household travel survey of the entire population of the planning area. The results of the model,
13 which have a high spatial (zones) and temporal (minutes) resolution, enable us to include differ-
14 ent aspects in the analyses such as time and space dynamics, intra- vs. interpersonal relations as
15 well as multimodal travel behavior and stability and variability of destination and mode choices.

1 INTRODUCTION

2 Travel behavior, especially in industrialized countries, is becoming more varied. Travelers in-
3 creasingly use more than one mode of transport during one trip (intermodality) as well as in the
4 course of several days (multimodality) (1; 2). These changes in travel behavior also affect how
5 we model travel demand. In order to reflect multimodality on the person level in a model, a trav-
6 el demand model is needed which simulates the stability and variability of travel behavior of
7 agents over a longer period (e.g. one week).

8 The Greater Stuttgart Region has updated its database to develop the Regional Transport
9 Plan and for further planning strategies. Data collected in a household travel survey on travel
10 behavior constitutes a representative basis for the Region's travel demand model. In addition, a
11 region wide macroscopic travel demand model was developed to simulate traffic loads during an
12 average working day. In order to simulate travel behavior consistently under future conditions on
13 the level of individuals, a microscopic longitudinal travel demand model using the agent-based
14 model *mobiTopp* has supplemented this macroscopic model.

15 An agent-based view allows for consistency and plausibility testing of individual travel
16 behavior. Furthermore, *mobiTopp* simulates individual agents with different daily routines and
17 time budgets. An essential advantage of that model is the opportunity to simulate the heterogene-
18 ity of travel behavior, in particular concerning stability and variability of destination and mode
19 choices of persons.

20 The data for the multi-agent travel demand model in the Greater Stuttgart Region was
21 taken from a longitudinal household travel survey in the course of one week consisting of the
22 persons living in about 5,000 randomly drawn households in that same region. The survey period
23 of one entire week provides data that allows analyzing and subsequently modeling variability
24 and stability of mode choices in an agent-based model simulating the travel behavior of all 2.7
25 Mio inhabitants of the region in the course of one week. The model simulates all trips of the in-
26 habitants including destinations and transport modes chosen including temporal and spatial in-
27 terdependencies of these choices. Each simulated person respectively agent with specific socio-
28 demographic and socio-economic characteristics is matched with an empirically observed travel
29 pattern. Thus, each person shows its own consistent behavior. This microscopic database is built
30 by synthesizing all households and persons within the model area. Together with their individual
31 activity patterns in the course of one week, they constitute a complete description of travel be-
32 havior of all inhabitants within the region. The contextual consistency of households and persons
33 offers a crucial advantage compared to other models, as specific issues can be examined within
34 their causal correlations.

35 The microscopic demand simulation results in a travel demand file comprising all agents
36 comparable to a database gained from a complete 7-day-survey within the planning area. Thus,
37 we have data from a synthetically generated complete household travel survey, which one can
38 analyze in all possible ways (e.g. multimodal travel behavior, interdependencies within the
39 households, etc.).

1 This paper describes the setup and estimation of the destination and mode choice models
2 in a longitudinal perspective as well as the steps of the agent-based model *mobiTopp*. The focus
3 lies on analyzing and modeling variability and stability of travel behavior in the course of one
4 whole week in a spatial and temporal perspective.

5 In order to investigate the destination and mode choice in a longitudinal perspective some
6 disaggregated travel demand models have been applied. Generally, the models used for the anal-
7 ysis of travel behavior represent the choice behavior of individual travelers. Discrete choice
8 analysis is the methodology used to analyze and predict travel decisions. For a review of the the-
9 oretical and practical aspects of discrete choice models in the area of travel demand see (3), for
10 example. Alternative discrete choice model forms are logit, nested logit, generalized extreme
11 value and probit, as well as more recent developments such as Hybrid (Mixed) Logit and the
12 Latent Class choice model (4–8). In the present context binary logit and discrete choice models –
13 both enhanced by some “dynamic components” – have been used to model variability and stabil-
14 ity of destination and mode choice behavior in the course of one week.

15 The travel demand model *mobiTopp* (9) is suitable to model stability and variability in
16 destination choice and mode choice because it uses an analysis period of one week. Other mod-
17 els, e.g. ALBATROSS (10), CEMDAP (11), CT-RAMP (12), FAMOS (13), SACSIM (14),
18 TAPAS (15), TransMob (16), typically use only an analysis period of one day, which is obvious-
19 ly too short to observe stability or variability in the individual travel behavior. The only excep-
20 tion is MatSIM (17), which has been extended to an analysis of one week (18); however, this
21 extension is still prototypical.

22 **RESULTS OF THE HOUSEHOLD TRAVEL SURVEY WITHIN THE GREATER** 23 **STUTTGART REGION ON DESTINATION AND MODE CHOICE**

24 In 2009/2010, a large longitudinal household travel survey was conducted in the Greater
25 Stuttgart Region, asking participants for information on their travel behavior for a period of sev-
26 en consecutive days (one-week travel survey). Because of day-to-day variability of individual
27 travel behavior, this multi-day survey method provides more detailed information on different
28 aspects of individual travel behavior than a one-day survey

29 **Database: Travel survey in the Greater Stuttgart Region 2009/2010**

30 The present analyses are based on a travel survey of the inhabitants of the Greater Stuttgart Re-
31 gion commissioned by the association of the Stuttgart Region during the years 2009/2010. The
32 travel survey was conducted as a household survey designed similar to the German Mobility
33 Panel (MOP) (19; 20): All persons aged 6 years and older within a selected household fill in a
34 trip diary to report on their travel behavior during the course of seven consecutive days (one
35 week travel survey).

36 The survey was carried out between September 2009 and April 2010, the main survey
37 times being outside of the holiday seasons during fall 2009 (mid-September to mid-December)

1 and spring 2010 (mid-January to mid-April). The participants of the survey are 6 years and older
 2 and the characteristics for the total sample drawn for the survey are:

3	• Number of households surveyed:	5,567
4	• Number of persons surveyed:	12,999
5	• Number of person days recorded:	90,993
6	• Number of person days without mobility:	12,276
7	• Number of trips recorded:	275,913
8	• Number of “tours” (trips from home):	122,745

9 A detailed description of the survey and sample design as well as the methods used for
 10 weighting and expansion can be found in (21). The following analyses bases on unweighted data.

11 **Destination choice in the course of one week**

12 Descriptive analyses show that destinations for trips with a determined purpose are not
 13 chosen independently. There is rather a tendency – more or less strong, depending on the trip
 14 purpose – to choose repeatedly the same destination or destination zone. An increase in the num-
 15 ber of leisure trips per week, for example, also shows an increase in the number of different des-
 16 tinations; the latter however is smaller. A reason for this is probably that the more leisure activi-
 17 ties a person undertakes, the higher the probability that a destination will be chosen again during
 18 one week.

19 Based on the data of the household survey for trips within a reporting period of 7 days a
 20 dynamic destination choice model in the course of one week was designed, which also takes into
 21 account the importance of habitual behavior (stability) when choosing destinations. The model is
 22 a regression model, which simulates on the trip level the probability for a repeated choice of a
 23 destination already chosen before (replication of a previous destination choice) in relation to cer-
 24 tain influencing factors. For technical reasons the model considers only “first” or “new” choices
 25 of a destination instead of measuring replications of previously chosen destinations (is the desti-
 26 nation chosen for the first time, i.e. it is a “new” destination). Within a specific trip purpose the
 27 destination (or destination zone) of trip k of a person is defined as “new”, if it hasn’t already
 28 been chosen for the trips numbered 1 to $k-1$. In order to estimate statistically the probability
 29 model, a binary attribute “trip destination “new” (yes/no)” has to be defined in the database for
 30 each trip of each different trip purpose a person makes. This attribute is the dependent variable in
 31 the regression model (binary logit-model) and is not defined for the first trip of a person within a
 32 particular trip purpose.

33 The following trip or person attributes proved to be significant:

- 34 • Serial number of the trip (of the specific purpose) – „Tripno“
- 35 • Origin of trip (home, work, education / other) – „Origin“
- 36 • Type of community the person lives in (state capital Stuttgart / major or medium re-
 37 gional center / other type of community) – „community“

38 The attribute “type of community” can be seen as a proxy variable characterizing the dif-
 39 ferent size (“layout”) of zones, which are defined as potential destinations for trips.

1 An exemplary glance at the logit model for the trip purpose „shopping for everyday
 2 needs” shows that the probability P for the choice of a “new” destination (thus a variability in
 3 travel behavior) depends primarily on the serial number of the trip (Tripno), i.e. how many trips
 4 of this type (trip purpose) the person has already made during that week. All three influencing
 5 factors Tripno, community and origin (in this order) are significant determinants for the „proba-
 6 bility of choosing a new destination“ P. The estimated values for the parameters are shown in
 7 Table 1.

8 **Table 1 Estimated values for parameters of the binary logit model for the choice of a new**
 9 **destination for trip purpose „shopping for everyday needs“ during the course of one week**

Analyses of Maximum-Likelihood-Estimation								
Parameter		DF	Estimate	Standard error	95% Confidence limits		Chi-Square	Pr > Chi Sq
Intercept		1	-1.5931	0.0855	-1.7606	-1.4256	347.41	<.0001
Tripno	2	1	1.6735	0.0824	1.5121	1.8350	412.74	<.0001
Tripno	3	1	0.9400	0.0853	0.7729	1.1071	121.59	<.0001
Tripno	4	1	0.6220	0.0922	0.4413	0.8027	45.51	<.0001
Tripno	5	1	0.4107	0.1056	0.2038	0.6176	15.14	<.0001
Tripno	6 and more	0	0.0000
Origin	Other	1	0.3201	0.0416	0.2385	0.4016	59.21	<.0001
Origin	Home/Work/ Education	0	0.0000
Community	City of Stuttgart	1	0.8287	0.0475	0.7356	0.9217	304.83	<.0001
Community	Major/medium regional center	1	0.2220	0.0507	0.1226	0.3215	19.14	<.0001
Community	Other community	0	0.0000

10
 11 By means of the odds ratio the impact of the influence of each of the three factors can be
 12 demonstrated. Thus, the chance of choosing a “new” destination is ceteris paribus more than
 13 twice as high (factor 2.29) for inhabitants of the state capital Stuttgart compared to inhabitants of
 14 other community types in the Region:

$$15 \quad \exp(0.8287)/\exp(0) = 2.29$$

16 This result can be attributed primarily to the different resolution regarding the subdivision
 17 of zones. The City of Stuttgart is subdivided into many small zones, whilst the number of zones
 18 is much lesser for the other communities.

19 The “probability to choose a new destination” significantly decreases with increasing se-
 20 rial number of the trip (stability of travel behavior). Therefore, it would be an inadmissible sim-
 21 plification to model trip destination choices as independent activities. The above-described mod-
 22 el has been estimated for 10 different trip purposes.

1 **Mode choice in the course of one week**

2 The choice set of different modes used in this work consists of the following modes:

- 3 • Walking
- 4 • Bicycle
- 5 • Car driver
- 6 • Car passenger
- 7 • Public transport.

8 For the database we use, the “transport mode” is an attribute for which multiple answers
9 are not admissible. The method used defines one main mode of transport for the trip, not consid-
10 ering a combination of modes. As the travel data refer to a 7-day reporting period, it is possible
11 to examine the mode choice behavior of persons not only during one day but also in the course of
12 one week. This allows for more detailed analyses on multimodality, which are important for
13 modeling mode choice behavior.

14 Descriptive analyses showing trips of persons in their temporal sequence reveal that
15 mode changes are not very frequent. This can be attributed to the fact that a mode choice usually
16 occurs only from one “tour” to the next, not however from one trip to the next within the same
17 tour. This leads to the assumption that a mode choice model should ideally be dynamic, meaning
18 that the mode used for the “current” trip depends essentially on the mode that the same person
19 used for the trip immediately preceding the current trip.

20 The choice probabilities for the five transport mode options are calculated using two dis-
21 crete-choice-models (conditional logit):

- 22 • Model 1: mode choice for the first trip of that week starting from „home“
- 23 • Model 2: mode choice for the second and all further trips of that person during the
24 week

25 Model 1 determines the starting position of each person concerning mode choice; Model
26 2 simulates how the mode choice of that person develops for each consecutive trip. Concerning
27 the aforementioned dynamic approach, the mode used for the previous trip is, in Model 2, an
28 essential determinant for the mode choice of the current trip.

29 The following illustrates for both Models 1 and 2 the general (trip, person and household
30 specific) factors and the factors varying for the different alternatives which we found out to be
31 most significant factors determining mode choice.

32 Household and person specific factors:

- 33 • Type of household (single persons household, 2 adults, household with children,
34 others) – „hhtype“
- 35 • General availability of car (yes, no, sometimes) – „caravail“
- 36 • Transit pass for public transport (yes, no) – „transpass“
- 37 • Person groups (pupils 6-9 years, pupils 10 years and older, education, students,
38 working/employed persons up to 40 years, working/employed 41 years and older,
39 unemployed, retired) – „pgroup“
- 40 • Commuting distance (in km) – „comkm“

1 Trip specific factors:

- 2 • Day of the week (weekday, Saturday, Sunday) – „wdaytyp“
- 3 • Short trip distance ≤ 1 km (yes, no) – „shorttrip“
- 4 • Trip purpose (work, education, business, shopping, leisure, round trip, service,
- 5 personal, in model 2 also trip back home) – „purpose“
- 6 • Parking pressure (time to find a parking space in min.) within the destination zone
- 7 – „parkpress“
- 8 • Trip length (distance) (in km) – „dist“

9 Factors varying for the different alternatives

- 10 • Travel time (in min.)
- 11 • Travel costs (in cent) per km

12 Travel costs are “specific” travel costs per km due to a high correlation between travel
 13 time (minutes) and travel costs (cents). The variable “comkm” (commuting distance) defines the
 14 distance traveled on the first trip to work or education (if applicable).

15 In Model 2, the mode used for the previous trip („modelast“) of the agent is added as a
 16 dynamic factor within the model.

17 The results of our testing of the conditional logit-model for mode choice of the mode
 18 used for the first trip of the week (on Monday) starting from home is shown in Table 2 left. In
 19 the conditional logit-model, only factors varying for the different alternatives (here: travel time
 20 and travel costs) are considered as explanatory variables. Other (trip specific) determinants (e.g.
 21 trip purpose) must be modeled as interaction effects with mode choice.

22 **Table 2 Conditional logit-model for mode choice of the mode used for the first trip (left)**
 23 **and the second and consecutive trips the of the week starting on Monday**

Conditional logit-model for mode choice of the mode used for the first trip of the week (on Monday) starting from home Type-3-effect analysis				Conditional logit-model for mode choices of the second and consecutive trips starting Mon-day Type-3-effect analysis			
E ffect	DF	Wald Chi-Square	Pr > ChiSq	E ffect	DF	Wald Chi-Square	Pr > ChiSq
mode	4	28.6370	<.0001	mode	4	1390.9763	<.0001
Travel time	1	33.2577	<.0001	Travel time	1	1047.4362	<.0001
Travel costs per km	1	137.7236	<.0001	Travel costs per km	1	2595.8491	<.0001
mode*caravail	8	561.7754	<.0001	mode*modelast	16	81515.6516	<.0001
mode*transpas	4	1139.9950	<.0001	mode*caravail	8	2543.7086	<.0001
mode*purpose	28	732.6141	<.0001	mode*transpas	4	4028.9460	<.0001
mode*wdaytyp	8	4.0098	0.8562	mode*purpose	32	12692.3094	<.0001
mode*hhtyp	12	130.8115	<.0001	mode*wdaytyp	8	815.9866	<.0001
mode*pgroup	28	169.1050	<.0001	mode*hhtyp	12	596.0980	<.0001
mode*parkpress	4	416.0658	<.0001	mode*pgroup	28	874.4959	<.0001
mode*dist	4	288.2756	<.0001	mode*parkpress	4	4705.7832	<.0001
mode*comkm	4	22.1580	0.0002	mode*dist	4	3618.5895	<.0001
mode*shorttrip	4	477.9181	<.0001	mode*comkm	4	118.5816	<.0001
				mode*shorttrip	4	9274.1202	<.0001

1 The Chi-Square-Values show a rough estimation of the impact each factor has. In this
2 model, the possession of a transit pass for public transport has the largest impact on mode choice
3 – followed by trip purpose and car availability. Mode choice also depends on trip length or if it is
4 a short trip ($\leq 1\text{km}$) or how difficult it is to find parking space in the destination zone.

5 As the number of conditional parameters in the logit-model is very large (110 param-
6 eters), we will renounce on a detailed illustration. The estimates for the parameters variable travel
7 time (-0.0102) and travel costs (-0.0282) shall serve as an example. The more travel time and
8 travel costs per km increase, the smaller the probability to choose this mode. The odds ratio is
9 thus less than one for both factors:

10 0.990 for the factor travel time ($\exp(-0.0102) = 0.9899$) and

11 0.972 for the factor travel costs per km ($\exp(-0.0282) = 0.9722$).

12 This means: an increase of travel time of 1 minute or an increase of the specific travel
13 costs of 1 cent/km respectively leads to a decrease of the probability this mode is chosen of 1.0
14 % or 2.8 % resp. (indicating the change in percent of the probability this mode is chosen, not the
15 absolute change of the probability this mode is chosen in percent).

16 Other parameter estimates also show situations as expected. E.g., an increase in car avail-
17 ability leads to

- 18 • increasing proportion of trips where the mode car driver is chosen
- 19 • decreasing share of trips for which other modes are chosen (walking, public transport,
20 car passenger, bicycle).

21 Table 2 right shows the results of the discrete choice model supplemented by the variable
22 “mode used for the previous trip” for the second and each consecutive trip during the course of
23 one week.

24 The additional variable “modelast” in this model shows by far the strongest influence on
25 mode choice for the current trip. This means the probability for a certain chosen mode depends
26 largely on the mode chosen for the previous trip. The addition of this variable to the model sig-
27 nificantly increases the number of parameters to be estimated (to 130 parameters); however, it
28 also improves the quality of the model fit. The parameter estimates not shown here for reasons of
29 space allow for estimations of the mode choice probabilities for each of the transport modes
30 available. These estimates are used in the agent-based model.

31 **MODELLING PROCESS WITH MOBITOPP**

32 mobiTopp is an agent-based travel demand model, in which each person within the planning area
33 is modeled as a virtual person, a so-called agent. Travel demand is simulated chronologically
34 over the course of one week, all agents carrying out their activities and the necessary trips simul-
35 taneously. For each activity, a destination choice decision and a mode choice decision is mod-
36 eled. The result of the simulation is a file containing all trips during the week including all attrib-
37 utes such as starting time, travel time, mode used, trip purpose, etc.

1 mobiTopp runs in two phases: an initialization phase, in which long-term decisions are
2 modeled, which remain stable during the entire simulation, and a simulation phase, in which all
3 travel behavior is simulated and in which trip related decisions are modeled.

4 **Initialization phase**

5 The population is synthesized consecutively for all zones. For each zone within the plan-
6 ning area marginal distributions for variables on household and person level are defined and a
7 random sample is taken from the travel database out of the survey, the sample corresponding as
8 closely as possible to the margins. The sample is chosen on household level, i.e. complete
9 households are chosen including all persons living in those households. This ensures that the
10 household context is consistent. Based on 12 different household types (household size by num-
11 ber of cars available in the household), the necessary number of households is randomly drawn
12 from the data of the travel survey. A household is chosen as a whole, meaning that all persons of
13 the household and some characteristics of their activity programs (weekday, purpose, durations,
14 planned beginning) are included.

15 Households are selected randomly as follows: based on the distribution of households
16 (household size by car availability) and persons (age group by sex, employment status) within
17 the traffic zones, a probability of being selected is calculated for each household of the survey
18 data. Based on those probabilities the necessary number of households is then randomly selected.
19 This means for each of the twelve household types the predetermined number of households is
20 randomly drawn from the data of the travel survey (stratified random sample with replacement).
21 When the household is drawn, all persons belonging to that household from the travel survey
22 including their socio-demographic attributes are allocated to represent the household in the mod-
23 el. This also includes the commuting distance to work or education as well as the activity pro-
24 gram reported in the travel survey. Knowing the commuting distance for work and education
25 corresponding to the activity program enables us to assign compatible locations for work and
26 education in a later step (see below). Thus the spatial circumstances of the households are en-
27 sured. The allocation of car ownership (number of cars available in the household) is also trans-
28 ferred from the data of the survey to the household in the model.

29 The model does not simulate a destination choice for destinations, which are chosen fre-
30 quently such as work or education during the simulation phase. These destinations are allocated
31 during the population synthesis and remain consistent throughout the entire simulation. The dis-
32 tribution of destinations for work and education is taken from commuter matrices, which can be
33 gained from data of the Federal Employment Agency and similar sources. For the Greater
34 Stuttgart Region model, these matrices were taken from the existing macroscopic travel demand
35 model. Depending on the employment status, the following types of destinations are determined:
36 work place, primary school, secondary school, vocational school, university, other education. For
37 each of these destination types the number of persons per zone is taken from the commuter ma-
38 trix. The numbers of persons are scaled so that they correspond to the number of persons in the
39 zone. Afterwards, the destination zones are allocated to the persons, so that the commuting desti-

1 nations correspond as best as possible to the reported commuting distances from the travel sur-
2 vey. This means that persons who reported a short distance receive a short commuting distance
3 in the model and vice versa. This is to ensure that the activity programs of the persons are com-
4 patible with their commuting distances. At the moment we are working on the implementation of
5 a syntactical generation of the activity program, but this was not part of this project.

6 A logit-model is used to allocate transit pass possession on the person level. The logit-
7 model was calibrated on the basis of the variables administrative district, profession, car availa-
8 bility, sex and cars per person in the household.

9 **Simulation phase**

10 During the simulation phase all agents carry out the activities of their activities programs.
11 The simulation is carried out chronologically in time steps of one minute over the period of one
12 complete week. Agents who have terminated an activity in the current time step select the next
13 activity in their activity program and make a destination choice for that activity concerning the
14 purpose of the activity. Based on the modes available the agent then makes a mode choice for the
15 trip and finally makes the trip. If the agent starts his trip from home and chooses the mode car
16 driver for the trip, the cars available in the household are reduced by one car. Agents who have
17 completed a trip within the current time step now start their activity. If an agent has just returned
18 home, the car is returned to the household's car pool and is available for other agents of the same
19 household. The agents consider the household circumstances in that way. When all agents termi-
20 nating an activity or a trip within the time step have acted, the next time step begins and the
21 agents are determined who will start or end an activity during that next time step. Travel time
22 and travel distance of all modes are taken from a macroscopic travel demand model. Travel times
23 vary over the day and have been calculated by static traffic assignment of all trips starting in the
24 respective period.

25 **Destination choice**

26 The destination choice takes into account that some destinations are visited frequently.
27 The model distinguishes between activities (work, education) which usually take place at the
28 same destination (activities with fixed destinations) and activities with principally flexible desti-
29 nations (e.g. leisure, shopping), for which however the same destination can be chosen repeated-
30 ly. The destination choice model thus takes place in two phases. In the first phase the decision is
31 made if a destination is chosen another time or if a new destination is chosen (longitudinal model
32 of destination choice as mentioned above) and then the destination is chosen in the second phase.

33 In the case of activities with fixed destinations, the destinations determined during the
34 initialization phase are used. In the case of activities with flexible destinations the model checks
35 if an activity of the same purpose has already been made during the week. In case of the first
36 activity of a certain type (purpose), a destination zone is selected from all zones of the model by
37 use of a destination choice model based on a gravitation model.

1 In case of one or more activities of the same purpose have already been carried out during
 2 the week, the longitudinal destination choice model determines whether a previously chosen des-
 3 tination shall be chosen again or if a new destination shall be chosen. In case the longitudinal
 4 model determines that a previously used destination shall be chosen, the destination choice mod-
 5 el chooses one of all those destinations that have already been chosen for that purpose. If the
 6 longitudinal model determines that a new destination shall be chosen, then the destination choice
 7 model chooses a new destination among all destinations not yet used for that purpose.

8 The destination choice model is based on a gravitation model approach and takes into ac-
 9 count the opportunities offered within the potential destinations, travel times, travel costs as well
 10 as available transport modes. The model does not only consider the travel time and travel costs to
 11 the potential destination but also the travel time and costs from the potential destination to the
 12 next fixed destination similar to the approach used in (22).

13 For a person located in zone i the probability to choose cell j as a destination is described
 14 in Equation 1.

15 Equation 1: Destination Choice

$$16 \quad p_{ij} = \frac{G_{jz}^{\alpha_z} \cdot e^{\beta_z(t_{ij}+t_{jp})+\gamma_z(c_{ij}+c_{jp})/I}}{\sum_{k=1}^N G_{kz}^{\alpha_z} \cdot e^{\beta_z(t_{ik}+t_{kp})+\gamma_z(c_{ik}+c_{kp})/I}}$$

17 Where G_{jz} is the number of opportunities for purpose z in zone j , t_{ij} and c_{ij} are the travel
 18 time and the travel costs for a trip from zone i to zone j , p is the cell containing the next fixed
 19 destination (work, education, home) and I determines the monthly household income divided by
 20 the number of persons of the household. α_z , β_z , γ_z are the model parameters for purpose z .

21 The model parameters are estimated for each purpose using a logit-model: for each cho-
 22 sen destination, 100 not selected alternatives are randomly chosen. The model is calibrated on
 23 this basis.

24 Mode choice

25 mobiTopp uses a logit-model as mode choice model. Model 2 as described above is used to take
 26 into account that mode choice is not always independent of modes used for the previous trip.
 27 Availability of transport modes is also considered.

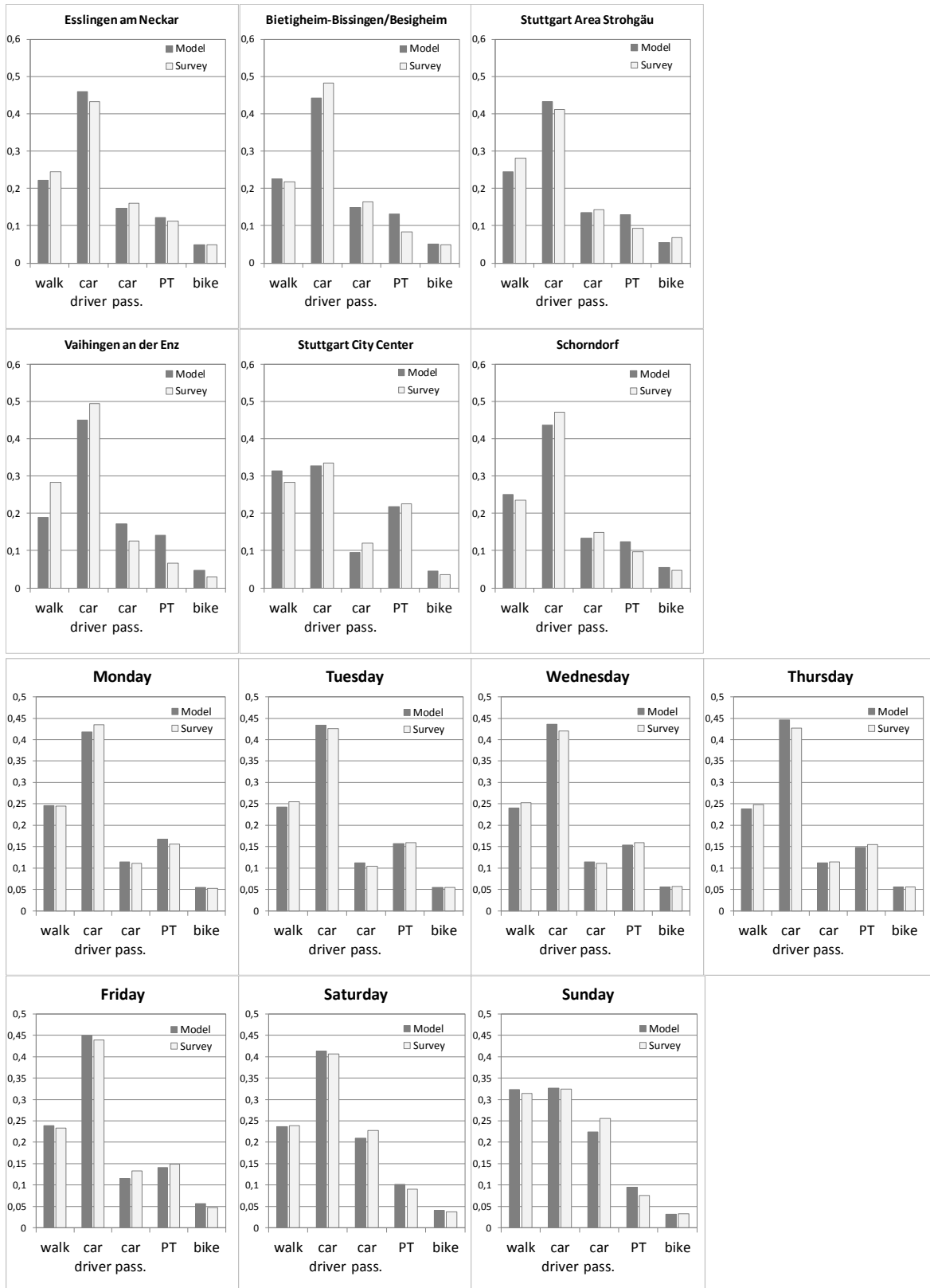
28 The mode choice model distinguishes whether it is the first trip of the agent of that week
 29 or if it is a further trip. If it is the first trip of the week, the mode choice model for the first trip
 30 (Model 1) is used, because there is no information available about previously used transport
 31 modes. To make the model as realistic as possible, not all modes are available at all times: if a
 32 person is at another destination than home and the trip to reach that destination was not made by
 33 car, then the car will not be available at that destination. In the model, the full choice set (car
 34 driver, public transport, walk, bicycle, car passenger) is available only if the agent is at home and
 35 a car is currently available. If the agent is not at home, the choice set includes modes available
 36 according to the mode used for the previous trip. If the mode used for the last trip was car driver,
 37 then the only available mode is car driver. If the last mode used was the bicycle, only the bicycle

1 is available. If the modes used previously were walk, public transport or car as passenger, the
2 choice set consists of the three modes walk, public transport and car as passenger. Here we use
3 the simplifying assumption that the option to ride as car passenger is always available.

4 **RESULTS OF THE LONGITUDINAL SIMULATION**

5 The simulation results of the mobiTopp model are used for a variety of analyses (e.g. distribution
6 of trip lengths according to purpose, employment status, weekdays, purpose and employment
7 status, employment status mode or trip lengths, modal split according to employment status, pur-
8 pose, household size, etc.). The possibilities are as varied as with analyses of a travel survey,
9 except that the data from the model can be analyzed more in depth.

10 The following examples show analyses after model calibration referring to spatial and temporal
11 aspects indicating mono- and multimodal travel behavior and thus showing stability and variabil-
12 ity in travel behavior. Figure 1 shows the modal split according to the hometown of persons and
13 weekdays. The dark bars show the data modeled with mobiTopp, the light bars show data from
14 the survey.



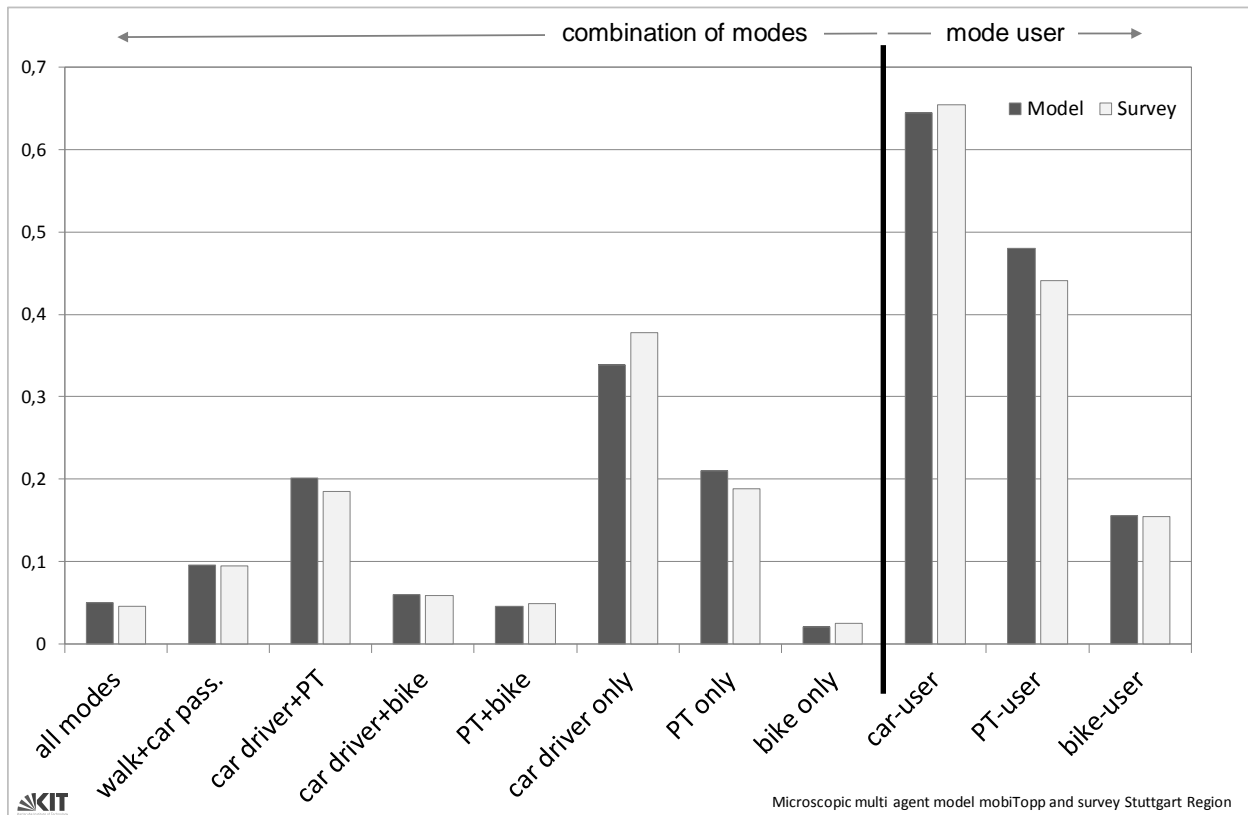
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3 **Figure 1: Modal split by home locations and weekdays**

1 As expected, on the one hand the results show different mode choice behavior in urban
 2 areas (e.g. City of Stuttgart) and more rural or suburban areas (e.g. Vaihingen/Enz), e.g. in the
 3 use of public transport. These differences in behavior reported in the survey correspond to the
 4 results of the model simulation. On the other hand, modal split for the entire Greater Stuttgart
 5 Region by weekday (Monday to Sunday) corresponds to the data produced by the model. The
 6 weekdays Monday to Friday are relatively similar, while Saturday and especially Sunday show a
 7 different modal split.

8 Figure 2 shows analysis of mode use behavior of persons in the Greater Stuttgart Region.



10 **Figure 2: Multimodal travel behavior in the Greater Stuttgart Region**

11 The left part of Figure 2 shows the use of different mode combinations of all persons in
 12 the course of one week. The right part of the figure shows the user groups of modes who have
 13 used the particular transport mode at least once, no matter whether other modes used as well.

14 The stability of mode use of individuals reporting a monomodal mode choice is well re-
 15 flected by the model. For example, in the Greater Stuttgart Region, a high share of persons only
 16 use car. However, there is also a high share of multimodal mode use, which corresponds to a
 17 high variability in mode choice of individuals. These analyses can be further differentiated ac-
 18 cording to socio-demographic attributes for the mode users as well as for a variety of other crite-
 19 ria.

1 SUMMARY AND OUTLOOK

2 The agent-based model mobiTopp simulates the travel behavior of each person within a
3 planning area over the period of one week including mode and destination choices. Due to the
4 longitudinal aspect of a simulation period of one week, the model considers the variability and
5 stability of destination choice and mode choice of every individual person (resp. agent) depend-
6 ing on sociodemographic issues as well as chosen destinations and modes.

7 In order to model the destination choices, we developed algorithms to describe variability
8 and stability of destinations chosen within the course of one week. The mode choice model simu-
9 lates mode choice routines in the course of one week. It considers not only persons who show a
10 monomodal and thus very stable mode choice behavior, but also persons who make multimodal
11 mode choices and thus show high variability in their travel behavior. The output of the multi-
12 agent model is a file, which is similar to a complete household survey and allows for analyses on
13 household, person and trip level. The microscopic data allow for a great variety of analyses, such
14 as:

- 15 • Differentiated analyses of spatial (e.g. travel of inhabitants of a planning area or parts
16 of the area (neighborhoods)) and temporal (e.g. use of transport modes during differ-
17 ent times of day or during the week) aspects.
- 18 • Identification of user groups for specific transport modes for targeted marketing
19 campaigns, identification of mode use patterns (multimodal persons, occasional users
20 of public transport, captives (user groups who use public transport always or never))
- 21 • Identification of costs for travel, e.g. on household level.
- 22 • Modelled data – unlike data gained from household surveys – are not subject to data
23 privacy and can be passed on.

24 With the mobiTopp model, research can be conducted to calculate measures and scenari-
25 os, which have effects on the individual decisions and potentially result in behavior changes, e.g.
26 toll charges, e-mobility, cohort and age effects etc. The model furthermore allows for a descrip-
27 tion of user patterns for cars and charging procedures by modeling individual persons and cars.

28 REFERENCES

- 29 1. Institut für Mobilitätsforschung (ifmo). *Mobilität junger Menschen im Wandel - multi-*
30 *modaler und weiblicher*, 2011.
- 31 2. Lanzendorf, M., and R. Schönduwe. *Wandel mobilitätsbezogener Wert-orientierungen*
32 *junger Erwachsener? Stand der Forschung - Studie im Auftrag des Instituts für Mobili-*
33 *tätsforschung (ifmo)*, Goethe Universität, 2010.
- 34 3. Ben-Akiva, M. E., and S. R. Lerman. *Discrete choice analysis: Theory and application to*
35 *travel demand*. MIT Press, Cambridge, 1985.
- 36 4. Ben-Akiva, M. E., ed. *Structure of passenger travel demand models // Travel demand fore-*
37 *casting*. Transportation Research Board National Research Council, Washington, DC, 1974.

- 1 5. Ben-Akiva, M., and Boccara B. Discrete choice models with latent choice sets. *International*
2 *Journal of Research in Marketing*, No. 12, 1995, pp. 9–24.
- 3 6. Ben-Akiva, M., and D. Bolduc. Multinomial probit with a logit kernel and a general para-
4 metric specification of the covariance structure, 1996.
- 5 7. McFadden, D. *Modeling the choice of residential location - in Spatial Interaction Theory*
6 *and Planning Models*, ed. by A. Larlqvist, L. Lundqvist, F. Snickars, and J. Weibull, North-
7 Holland, Amsterdam, 1978.
- 8 8. McFadden, D., and K. E. Train. Mixed multinomial logit(MNL) models for discrete re-
9 sponse. *Journal of Applied Econometrics*, 2000, pp. 447–470.
- 10 9. Mallig, N., M. Kagerbauer, and P. Vortisch. mobiTopp – A Modular Agent-based Travel
11 Demand Modelling Framework. *Procedia Computer Science*, Vol. 19, 2013, pp. 854–859.
- 12 10. Arentze, T. A., and H. Timmermans. A learning-based transportation oriented simulation
13 system. *Transportation Research Part B: Methodological*, Vol. 38, No. 7, 2004, pp. 613–
14 633.
- 15 11. Pinjari, A. R., N. Eluru, S. Srinivasan, J. Y. Guo, R. B. Copperman, I. N. Sener, and C. R.
16 Bhat. CEMDAP: Modeling and Microsimulation Frameworks, Software Development, and
17 Verification. In *TRB 87th Annual Meeting Compendium of Papers*, Washington, D.C., 2008.
- 18 12. Davidson, W., P. Vovsha, J. Freedman, and R. Donnelly. CT-RAMP family of activity-
19 based models. In *Proceedings of the 33rd Australasian Transport Research Forum (ATRF)*,
20 2010.
- 21 13. Pendyala, R. M., R. Kitamura, A. Kikuchi, T. Yamamoto, and S. Fujii. Florida Activity Mo-
22 bility Simulator: Overview and Preliminary Validation Results. *Transportation Research*
23 *Record: Journal of the Transportation Research Board*, No. 1921, 2005, pp. 123–130.
- 24 14. Bradley, M., J. L. Bowman, and B. Griesenbeck. SACSIM: An applied activity-based model
25 system with fine-level spatial and temporal resolution. *Journal of Choice Modelling*, Vol. 3,
26 No. 1, 2010, pp. 5–31.
- 27 15. Hertkorn, G., and P. Wagner. The application of microscopic activity based travel demand
28 modelling in large scale simulations. In *World Conference on Transport Research (WCTR)*,
29 Istanbul, Turkey, 2004.
- 30 16. Perez, P., R. Wickramasuriya, V. L. Cao, N. Huynh, and M. Berryman. Transmob: an agent
31 based simulation of transport demand and residential mobility in South East Sydney. In *So-*
32 *cial Simulation Conference*, 2014.
- 33 17. Raney, B., and K. Nagel. *An Improved Framework for Large-Scale Multi-Agent Simulations*
34 *of Travel Behavior*, 2004.
- 35 18. Horni, A., and K. W. Axhausen. *MATSim Agent Heterogeneity and a One-Week Scenario*,
36 ETH, Eidgenössische Technische Hochschule Zürich, IVT, Institut für Verkehrsplanung und
37 Transportsysteme, 01.01.2012.

- 1 19. Kagerbauer, M., and S. Bricka. Panel, Continuous, and Cross-Sectional Travel Surveys –
2 Germany's Experience. In *TRB 94th Annual Meeting Compendium of Papers*, Washington,
3 D.C., 2015.
- 4 20. Zumkeller, D., and B. Chlond. Dynamics of Change: Fifteen-Year German Mobility Panel.
5 In *TRB 88th Annual Meeting Compendium of Papers*, Washington, D.C., 2009.
- 6 21. Verband Region Stuttgart. *Begleituntersuchungen zur Fortschreibung des Regionalver-*
7 *kehrsplans – Band 1: Mobilität und Verkehr in der Region Stuttgart 2009/2010. Regionale*
8 *Haushaltsbefragung zum Verkehrsverhalten*. Schriftenreihe Verband Region Stuttgart, Stutt-
9 gart, 2011.
- 10 22. Wassmuth, V. *Modellierung der Wirkungen verkehrsreduzierenden Siedlungskonzepte.*,
11 Karlsruhe, 2001.