

1 **STABILITY AND VARIABILITY IN DESTINATION CHOICE FOR LEISURE**
2 **ACTIVITIES**

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1 ABSTRACT

2 Empirical research has shown that people's daily life consists of highly stable, repetitious behaviors
3 as well as of significant sequences of variability. This does not only concern activity patterns, but
4 also refers to travel mode and destination choice. Within travel demand modelling, destination
5 choice is dependent on capturing the mechanisms that lead to behavioral stability or variability in
6 order to point out the changeability of destination choices. This research addresses the modeling
7 of destination choices of different leisure purposes by considering spatio-temporal relationships
8 towards certain destinations by using a longitudinal data set. Three dimensions of heterogeneity are
9 accounted for: the inter-travel-purpose, the inter-traveller and the intra-traveller-related dimension.
10 Considering these, the developed destination choice model estimated with the six-week Mobidrive
11 study contains a differentiation between five sub-purposes of leisure, assumes latent classes among
12 the respondents revealing different preferences. Furthermore, the study accounts for both spatial
13 and temporal destination choice patterns of individuals. The classes reveal destination choice
14 behavior to be different between individuals having both stable and variable preferences and further
15 reacting differently to accessibility and attractiveness. While it is applied to leisure travel, the
16 proposed model including additional components is applicable to all travel purposes in an agent-
17 based travel demand framework.

18

19 *Keywords:* destination choice, heterogeneity, latent classes, stability and variability

1 INTRODUCTION

2 The current state of the transport sector is expected to experience fundamental transitions, triggered
3 by policy responses to climate change, the emergence of digital and autonomous technologies as
4 well as by a presumed change of travellers' behaviors. The development and the adaption of a
5 transport system enabling a high degree of mobility and to encourage both an efficient and low-
6 emission transport system is a key challenge. A transformation, however, implies that relatively
7 stable, highly routinized user behaviors need to be altered, in terms of the modes being used but
8 also in terms of the distances travelled. Considerable research exists that deals with the habitualiza-
9 tion of mode choice behavior, while less scientific debate comprise the the stability and variability
10 of destination choices. However, to understand and assess the dynamics mentioned above, it is re-
11 quired to understand the mechanisms of stability or the willingness to change destination choices.
12 The paper at hand will therefore try to contribute to this debate by highlighting stability effects in
13 leisure destination choice.

14 A significant part of daily life and the overall traffic volume is taken up by leisure travel. For
15 example, the latest version of the German national household travel survey "Mobility in Germany"
16 (2017) accounts for a share of 28 % of trips and 34 % of distance travelled (1). This tightly exceeds
17 the total of commuting and business trips in both measures. Further, leisure activities are part of
18 every everyday life not depending on age or occupation. This makes statements on the willingness
19 to change destination choice based on socio-demographic attributes even more challenging. Thus,
20 leisure travel is important to consider for the development of traffic volume. The importance to
21 consider general travel indicators of leisure travel has been highlighted by several authors (2, 3).

22 Travel demand models aim at quantifying the extent to which policy interventions or tech-
23 nological innovations will contribute to changing travel demand. They provide the possibility of
24 planning infrastructure by considering multiple overlaying interactions of measures and external
25 developments. One precondition for its suitability to forecast future behavior is seen in its ability
26 to realistically reproduce existing behavior patterns with its causalities.

27 Within travel demand modeling, travellers have to choose destinations for a given set of
28 activities to locate trips appropriately in space and time. Destination choice is thus a crucial step for
29 generating realistic model results. The sheer amount of possible locations in space for recreation
30 (and other purposes) is very challenging to model. Therefore, strategies are needed to reduce the
31 amount of available destinations to a manageable size. Strategies to do so include deterministic
32 and probabilistic approaches (an overview is given by Thill, Pagliara and Timmermans (4, 5)).
33 In summary, most approaches perceive spatial and time budget factors as the most fundamental
34 determinants for destination choice. However, it does seem a bit arbitrary to apply this assumption
35 to all destination choices alike (6, 7).

36 Another challenge is seen in the heterogeneity of the travel purposes themselves. Describ-
37 ing the attractiveness of a destination for a broad class of travel purposes is not without problems,
38 if no further information is available about what exactly a person is aiming at. For example, it does
39 make a difference for the attractiveness of a destination, if someone wants to go swimming or if
40 that same person wants to see a friend. While this is already difficult to consider in a data set, it is
41 proposed to restrict destinations to an "awareness-set" of locations being known to the traveller (6).
42 In line with this reasoning, some strategies take into account cognitive aspects, such as familiarity
43 with or emotional aspects towards certain locations (7, 8).

44 Either way, destination choice modelling is dependent on capturing the mechanisms that
45 lead to behavioral stability or variability. Empirical research has shown that people's daily life

1 consists of highly stable, repetitious behaviors as well as of significant sequences of variability (9–
2 11). It has been emphasized that decision-making is not always rational in the sense that there is a
3 systematic weighing up of pros and cons of different alternatives. Instead, even after infrastructural
4 interventions, travellers tend to stick to routinized behaviors (12).

5 Against this backdrop, the aim of this research is to contribute to modeling destination
6 choices by considering spatio-temporal relationships of individuals in a longitudinal perspective.
7 We will therefore outline the importance of a non-rational perspective on destination choices in
8 everyday leisure travel and collect destination choice model approaches being able to account for
9 spatial and temporal patterns of destination choice on an inter- and intra-personal level. For the
10 formulation of an own model approach, we analyze the variation of leisure destination choices
11 based on a longitudinal travel survey. This is followed by the development of a destination choice
12 model applicable in agent-based travel demand models (AB TDM) accounting for observed spatial
13 and temporal stability. Hereby, heterogeneity of choices is analyzed by different latent classes of
14 stable and variable destination choice behavior. The destination choice model is applied for leisure
15 purposes, but conceptualized for all travel purposes. The paper concludes with recommendations
16 for further research needs to improve the understanding and models of destination choice for long-
17 term and short-term planning horizons.

18 LITERATURE REVIEW

19 The state of knowledge is provided for empirical research on stability and variability in travel
20 behavior with a focus on destination choices and discusses current approaches to destination choice
21 modeling.

22 Variability of travel behavior

23 The availability of longitudinal data has helped to reveal spatio-temporal patterns of activity and
24 destination choice. Today, several studies are available showing that people's daily lives are char-
25 acterized by recurrent activities and destinations as well as by sequences of greater variability
26 (9, 13). By using multi-week survey designs it is possible to observe clusters and periodicity of
27 activities and destinations on specific days or at specific times being previously unobserved in
28 cross-sectional surveys (e.g. weekly soccer training, which is practiced on the same day every
29 week). Studies suggest that up to 70% of everyday trips follow routine destination choices (14).
30 Hanson and Huff (15) defined core stops for each individual based on their occurrence on rep-
31 resentative days and the total frequency. They classified 65 % respectively 83 % of individuals
32 having recreation stops or shopping stops as a core stop. These can be regarded as an anchor point
33 in everyday life. Looking at possible combinations between purpose and destination, Schlich and
34 Axhausen (13) observe only a small share of combinations occurred within the six-week survey
35 period supporting the suggestion of routine destination choices for certain purposes.

36 Only a small share of destinations of about 17 % of all observed destinations within the
37 survey are located within a radius of 1 kilometer around home locations. This share is larger when
38 it comes to out-of-home-leisure destinations (3). This finding supports the assumption of travellers
39 having a larger activity space for leisure travel. Furthermore, destination choice is linked to obliga-
40 tory destinations such as the location of workplace or education institutions, as well as other highly
41 stable activity patterns. This influences the time frames, in which other destination choices have to
42 be accommodated, potentially leading to further stability mechanisms for destination choices that
43 are widely assumed to be discretionary. (14, 16) Empirical research indicates clearly that variable

1 behaviors are more likely to occur on weekends, whereas Fridays differ slightly to other working
2 days (13). Further, there is more spatial extension on Fridays and on weekends (14). Especially
3 for leisure purposes, the longitudinal perspective of the survey reveals that new destinations are
4 visited more frequently on the weekends, indicating a higher variability (3).

5 Hanson and Huff (9) assume a systematic, cyclical, temporal variability of travel behavior.
6 But it is also important to separate systematic from random effects. The literature highlights both
7 the temporal and spatial dimension of behavior. The flexibility regarding the choice of destinations
8 for different purposes depends on both.

9 Destination Choice Modelling

10 Looking closer at destination choice, individuals can be recognized as being driven by certain
11 needs: supermarkets allow people to take care of their weekly grocery purchases and local recre-
12 ation areas serve as places for spending leisure time. Consequently, the structure of an area is
13 one important criteria for assessing its attractiveness. Travel demand models use attractiveness as
14 a measure to model destination choices of people by using spatial interaction models (17). Gen-
15 erally, they combine impacts of access or distance and impacts of scale or size in relative terms
16 (18).

17 Various models are available for destination choice, whose task is to link the attractiveness
18 of a destination (or traffic cell) with the effort required to overcome space (resistance). Cascetta
19 et al. (19) provide an overview over different destination choice models. Destination choice is more
20 difficult to model than other choice decisions, since there is a disparately larger set of alternatives
21 available (6, 20, 21)). Consequently, choice set formation is regarded as a possibility to limit the
22 opportunities and to only consider recognised destinations of individuals. Spatial and temporal
23 aspects are seen as key determinants in limiting possible destinations (4, 5, 22). But as Hanson
24 and Huff (23) set the requirements to appropriately model destination choice to be "sufficiently
25 detailed and complete to distinguish habitual from non-habitual behaviors", only using subsets of
26 destinations might not be enough to distinguish between stable and variable patterns in destination
27 choice.

28 The assumption of destination choices being not independent from each other is brought
29 up, among others, by Tardiff (24) and Miller and O'Kelly (25). Their model approaches applied
30 on shopping destination choice therefore include both a time dependency between choices by ei-
31 ther integrating time-specific parameters or by exploring the influence of past choices on present
32 choices. The latter involves the problem of missing information for the first trips and aging for the
33 on-going survey (25). The results show a decreasing influence of objective attributes like accessi-
34 bility and attractiveness by incorporating time dependency. The assumption of relationships being
35 relevant for destination choices has been investigated by Puhe et al. (26) by using a qualitative
36 research design. The observed stability of shopping destination choice as a result of a relationship
37 to a specific store respectively the owner or a relationship to a brand were applied to a simulated
38 shopping travel demand of one week and their changeability was tested in the model.

39 Other approaches of modeling destination choice provide a broader scope and operate on
40 an aggregate level and are included because of their consideration of spatial and temporal depen-
41 dency of destination choices. The problem of spatio-temporal correlation has been addressed by
42 Zhang et al. (27) applying a Bayesian approach incorporating spatio-temporal random fields to ob-
43 served destination choices of taxis. For capturing both inter and intra-segment heterogeneity in a
44 destination choice model Mehadil Orvin and Rahman Fatmi (28) combined a latent class approach

1 with continuous distributions of parameters within the classes and applied it to dockless bikeshar-
2 ing data to analyze the influence of spatial and infrastructural attributes of the destination zone.
3 However, these approaches are dependent on a large amount of aggregated data, which is difficult
4 to receive across all travel modes. Further, the approach is missing the individual perspective and
5 therefore hardly applicable in AB TDM.

6 METHOD

7 Based on these findings, the aim of this research is the analysis of destination choices in a longi-
8 tudinal travel survey through discrete choice modelling. The resulting models thereby are aimed
9 at being applicable in an AB TDM framework to not only understand stability and variability in
10 destination choice but also to incorporate observed behavior in forecasting models.

11 In this research we limit the analysis to the frequent leisure purposes being asked in the
12 Mobicdrive study (14). These include *active sports, cultural activities, club meetings, meeting*
13 *friends and gardening.*

14 Data Description

15 The Mobicdrive survey was conducted in spring and fall 1999 and covers the population of Karl-
16 sruhe and Halle, two medium-sized cities in Germany. Respondents reported their travel behavior
17 for six consecutive weeks enabling a deeper insight into rhythms of daily life and longitudinal
18 dimensions of different travel related choices. The sample for the city of Karlsruhe includes
19 geocoded locations of home, workplace and all destinations visited. Its sample size is compar-
20 atively small what leads to limitations (29). Not many longitudinal studies exist yet that provide
21 the data needed for answering the research questions. To test the approach we accept potential
22 hazards resulting from an old data set.

23 General travel indicators like average trip frequency, distance and duration for all purposes
24 match with German-wide results of the German mobility panel of the same year (3). This can be
25 observed even though the sample only contains an urban population. Leisure trips were reported to
26 be more frequent, which was explained with the intensive supervision of the survey. The sample is
27 characterized by a higher share of employees, a higher income and a more frequent car ownership
28 than in the average population of the considered region (13).

29 The longest distances among the sub-categories of leisure were observed for cultural ex-
30 cursion, meeting friends and relatives and nature excursions (3).

31 Stability of destination choice can be analyzed when looking at recurring choices over
32 time. An analysis therefore is only appropriate, when there is a certain number of observations
33 per destination and purpose. The distribution of frequency of destinations by leisure purpose is
34 shown in Figure 1. Based on this analysis the sub-purposes *active sports, disco/pub/restaurant,*
35 *garden/cottage, group/club meeting* and *meeting friends* were selected for further analysis. It
36 should be noted that having a garden plot outside someones home is quite common among the
37 German population, at least in urban settings and among certain population segments. However,
38 other leisure purposes may become of interest, when the length of observation increases due to
39 observation methods reducing the burden to the respondent such as GPS tracking.

40 A detailed differentiation between *group/club meeting* and *active sports* could not be done
41 by the author. We expect potential overlapping of the data sets and respective model effects as e.g.
42 soccer training can be seen as both a *group/club meeting* or an *active sports* activity. The same
43 applies to meeting friends, which could overlap with the purpose *disco/pub/restaurant* and it is not

1 clear if people responded consistently or which instruction they were given.

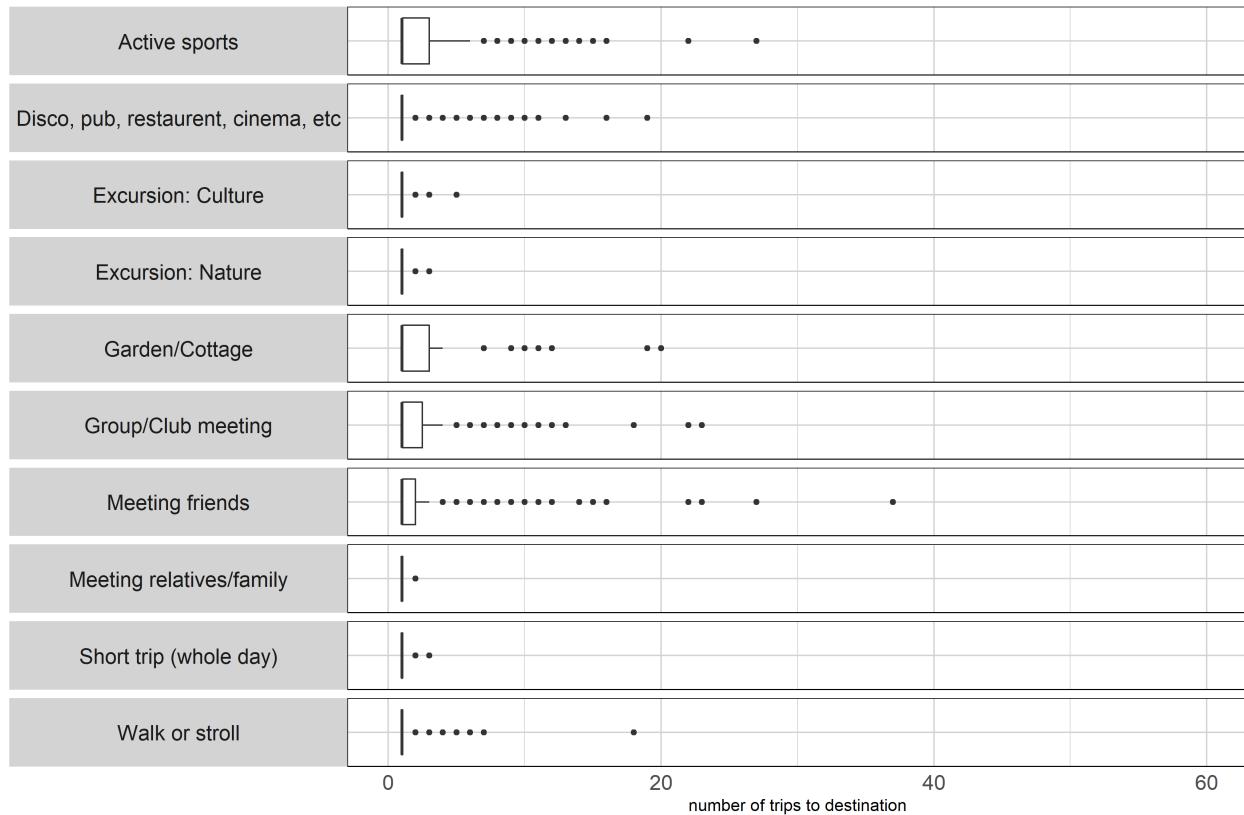


FIGURE 1 Frequency of visits of destinations by leisure trip purpose

2 A further important information is the distribution of visits on different destinations. Schön-
 3 felder and Axhausen (14) already pointed out, that only few destinations make up for a major
 4 proportion of trips. This can be further differentiated looking at the variation of destinations by
 5 sub-categories of leisure purposes (cf. Figure 2). The variation hereby captures the share of the
 6 destination most frequently visited among all trips of this purpose of a person.

7 The analysis reveals a higher variation for purposes like *meeting friends* and *disco/pub/restaurant*.
 8 At the other end of the scale, there are more stable purposes like *group/club meetings* and the visit
 9 of an own garden plot or cottage appear. The analysis confirms the finding of other studies de-
 10 scribed in section 3.1 that both stable and variable behaviors exists.

11 Model Formulation

12 With this expectation in mind and based on the data set described, multiple destination choice
 13 models for different leisure purposes are set up to analyze influencing factors on decision-making.
 14 The trips are restricted to the geocoded trips of the population of Karlsruhe. The data set is not
 15 limited to a certain kind of trip chain, but covers all trips or trip chains that include leisure travel.
 16 Consequently, all situations where a person chooses a location for a leisure purpose are considered.
 17 The choice set for the estimation of the destination choice model is reduced to 10 alternative
 18 destinations including the chosen alternative, a set of other destinations that have been chosen
 19 at different points in time and random destinations that have not been chosen at all. When a

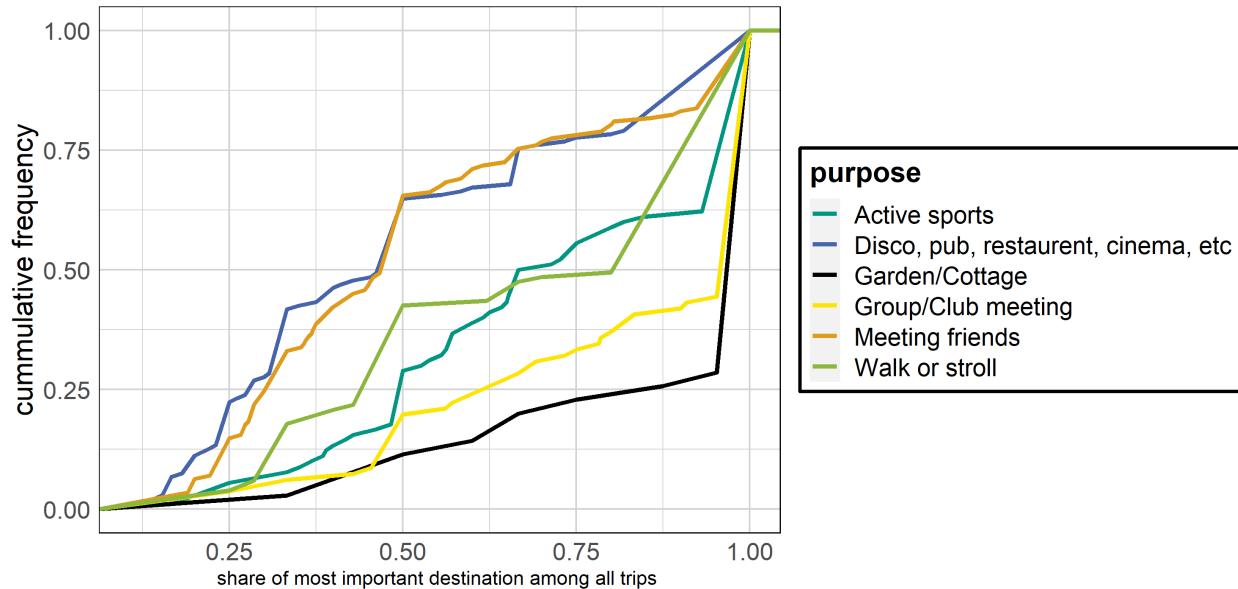


FIGURE 2 Variation of destinations by leisure trip purpose

1 respondent generally visits only few locations, this results in more non-visited destinations in the
 2 choice set, because the number of other destinations chosen depends on what was observed in the
 3 data. Consequently, the choice set formation is aware of the activity space for leisure purposes of
 4 an individual respondent.

5 The attributes are assigned both on the origin - destination level of traffic analysis zones
 6 (TAZ) and on the destination level relating to certain geocodes. The following attributes are used
 7 for the estimation:

- 8
- 9 • *acc* - a logarithmic utility of pedestrian travel time indicating a higher accessibility with
 10 higher values - assigned on TAZ level
- 11 • *attr* - a measurement of attractiveness by collecting POI relevant for the purpose and
 12 weighting number and size to a value of trip attraction (cf. Klinkhardt et al. (30)) -
 13 assigned on TAZ level
- 14 • *share freq* - the share of visits to this location among all visits of the decision maker for
 15 this purpose - assigned on geocode level
- 16 • *HHI weekd.* - the Herfindahl Hirschman index of a location and the decision maker for
 17 weekdays - assigned on geocode level
- 18 • *HHI dayt.* - the Herfindahl Hirschman index of a location and the decision maker for
 19 different times of the day classified in three-hour-intervals - assigned on geocode level

20 The Herfindahl-Hirschman-index (HHI) is a measure for variability of observations (see
 21 e.g. the explanation of Susilo and Axhausen (31)). The indicator is used in this case to describe
 22 the temporal variability respectively stability of visited destination over the week or over different
 23 times of the day. A high index thus reflects a high stability regarding weekdays or daytimes,
 24 whereas a high parameter shows a higher preference for temporally stable destinations. A specific
 25 club meeting only occurring at one destination and happening always at a certain day of the week

1 can be seen as an example for a high index.

2 The term preference in the context of this research does not distinguish between the rea-
3 sons for showing a likeliness for certain attributes of a destination. Based on the available data set
4 the authors are not able to identify obligations regarding specific destinations or simply an affec-
5 tion to location or individuals at the location. Only stable and variable patterns are observed and
6 correlation to the actual choice is worked out.

7 All destination choice models were estimated by using the package *Apollo* (32). Both a
8 simple multinomial logit and a more complex latent class approach are chosen. The latter includes
9 heterogeneity through a "discrete parameter variation" (33) in combination with a class allocation
10 model analyzing deterministic influences of attributes on the probability. Therefore it is not ob-
11 servable to the analyst, whether an individual respondent falls into a specific class. That carves out
12 certain taste classes regarding the addressed decision. For a detailed explanation of the latent class
13 model see Greene and Hensher, Hensher et al. (33, 34). The latent class models are estimated by
14 applying the starting value search to better reach the global optimum.

15 MODEL RESULTS AND INTERPRETATION

16 In a first step, different destination choice models are estimated to present general differences
17 between the leisure purposes. General model results are comparatively good: depending on the
18 purpose, a high proportion of heterogeneity can be explained. This is only possible as *share freq*
19 is already known and acts like a preference for certain destinations. Nevertheless, this influence
20 differs among the purposes. Among the more stable leisure purposes as a result of the general
21 preference are *garden/cottage* and *meeting friends*. *Active sports* and *club meetings* are less sta-
22 ble. However, as the low variation (cf. Figure 2) suggests, *group/club meetings* take place at
23 more temporal stable destinations indicated by both HHI parameter values. This counts as well
24 for the daytime HHI of *garden/cottage* activities, pointing out to destinations being preferred that
25 are mostly visited at a similar time of day. In general, daytime stability is of higher importance
26 than weekday stability except for meeting friends suggesting typical regular weekdays for these
27 activities. The accessibility is of lower importance for the choices but still has a significant influ-
28 ence, being highest for *active sports* and *club, pub, restaurant*. The measured attractiveness is only
29 weakly significant in few cases. An overview of the MNL model results can be found in Table 1.

TABLE 1 MNL estimation results

Purpose	R ²	acc	attr	share freq	HHI weekd.	HHI dayt.
meeting friends	0.35	0.002**	0.04*	6.56**	0.59**	0.49**
club meeting	0.71	0.003*	-	5.71**	0.80*	1.13**
active sports	0.54	0.004**	-	5.69**	0.77**	0.89**
disco, restaurant	0.33	0.005**	-	6.06**	0.32*	0.88**
garden/cottage	0.89	0.003**	-	6.47**	0.34	4.59**

level of significance ** 5 % , * 10 %

30 The MNL model results provide average insights in the influences of destination choice for
31 different leisure purposes. For the observation of both variable and stable choice patterns latent
32 classes are assumed among the respondents and included in the model by applying the latent class

1 approach with a class allocation model. As a result of the low number of individuals, a maximum
2 of two classes can be observed in the data set.

3 Cultural activities in *clubs, pubs, restaurants or cinemas* are visited in different patterns
4 by different people. The results in Table 2 reveal a more stable and a more variable class. The
5 more stable class is characterized by being attracted by locations that are typically visited by the
6 decision-maker. Furthermore, this class shows a preference for destinations visited with a high
7 stability regarding both daytime and weekday. The more variable class reveals a higher preference
8 for closer destinations and is less bound to specific destinations. Additionally, the locations are
9 visited on different weekdays, whereas the daytime appears highly stable - even more stable than
10 for those of the other class. The attractiveness of the location measured by the number and size of
11 respective POI has a negative effect on being chosen, indicating a preference for locations without
12 a cultural agglomeration and not attracting a large number of people. Regarding the size of the
13 classes the more stable class includes about two thirds of the sample whereas a significant effect
14 of the age on class allocation can be recognized: respondents with an age between 18 and 40 years
15 have a substantially higher probability to be part of the more stable class.

16 The destination choice for *meeting friends* also contains a higher degree of inter-individual
17 heterogeneity. Both classes are influenced to a similar degree by *share freq* whereas this does
18 not hold for the temporal indicators: the larger class consisting of about 87 % of the sample has
19 an additional preference for point in time related destinations regarding weekdays and daytime.
20 This does not count for the smaller class, which prefers more temporal variable destinations for
21 meeting friends. A second major difference can be observed in the valuation of accessibility of
22 both classes. The temporally more variable class (LC 2) strongly prefers a better accessibility by
23 foot. This indicates that they seem to have more friends in close proximity. In the context of the
24 urban sample of the survey it reflects meeting friends within the same or close city districts and less
25 in other municipalities. It exists a slightly non-significant effect of students to be more likely in
26 this second class which can be a plausible explanation of the more geographically dense network
27 of friends in this class. The general frequency of visiting relatives is comparatively low and the
28 related distance is quite high, leading to the conclusion that a higher share of respondents did not
29 grow up within the survey area. It seems relatively reasonable to argue that joined *group/club*
30 *meetings*, locations for education or workplaces are geographically more oriented towards the city
31 center than towards the neighbouring municipalities. However, it is generally more likely that
32 friendship relations depend more on homophily than on geographical proximity (35). For other
33 experiences with friendship destination choice, see e.g. Chen et al. (36).

34 *Group and club meetings* itself are expected to be both spatially and temporally stable due
35 to typical locations like clubhouses, fire departments or church buildings for these activities. Still,
36 the results do not support this assumption at first glance. The influence of *share freq* in both
37 classes is average. The first class consisting of about three quarters of the sample has a significant
38 preference for temporally stable destinations being visited only at certain weekdays and daytimes.
39 The second class contrarily does prefer destinations being visited on different days of the week
40 which can be transferred to multiple meetings a week at the same location. Further, the influence
41 of accessibility for this class is higher than for the first class. This might indicate the fact that
42 club meetings are often located at destinations, which are accessible to as many people as possible.
43 However, participating in a specific club can still be driven by other rationales than accessibility
44 ratings. The result of a general stability of destinations being only average can be interpreted as
45 a share of respondents having different group/club meetings for different purposes (e.g. music

1 education and volunteer youth work), but are stable in their location and relationship.

2 Destination choice behavior regarding *active sports* further differs inter- and intra-individually
3 in different dimensions. There exists a major share of individuals being more variable regarding
4 the spatial choice for doing sports while still revealing some patterns of destinations that are only
5 visited at certain days. Daytime does seem to be less important which is contrary to the MNL
6 results. Although, there is a smaller class of about 27 % of the sample showing a high spatial
7 stability for doing *active sports*. The choice is further influenced by a high weekday stability of
8 destinations. Looking at the influence of accessibility there is no substantial difference between
9 both classes. But the attractiveness complements the existing picture of the classes: the first class
10 prefers locations with sport facilities like gyms, pools, sports fields and parks. The second class
11 clearly behaves in the opposite way by preferring locations without these facilities. Individual
12 sports activities like running and cycling often take place outside the built environment, which is
13 not covered by the attractiveness measure used here. Interestingly, the spatial and temporal stabil-
14 ity is very high for these respondents. An example can be a weekly running appointment in a close
15 forest.

16 The destination choice for *gardening* revealed problems to find a significant second class
17 within the data set. The observed share of respondents in the second class is below 1 % leading
18 to insignificant results. A larger sample might eventually enable more accurate insights in hetero-
19 geneity of destination choices of gardening and staying at a cottage. For this analysis the results
20 of the MNL can be used for the interpretation. A highly stable choice behavior becomes apparent,
21 especially regarding location and daytime. This is no surprise as most people have one specific
22 garden or cottage for regular visits.

23 The results provide deeper insights into the destination choice behavior for leisure pur-
24 poses, which can be used in forecasting under certain circumstances. The application of the models
25 in AB TDM would require a previous simulation of relationships consisting of location, their gen-
26 eral preference based on the observed frequency and the observed temporal stability for all agents
27 and the respective travel purposes. These relationships can be observed in longitudinal travel data.
28 The sample of the survey used in this research reaches its limits regarding sample size and number
29 of individuals. Other survey methods like GPS tracing provide lower barriers for participating in
30 longitudinal surveys as they significantly reduce the effort of reporting. For example, Molloy et al.
31 (37) reached a sample size of more than 3,500 respondents participating eight weeks in their survey
32 and a still considerable share participating even longer.

33 The observed relationships towards certain destinations can be assigned randomly or by
34 applying estimated choice models to the agents in the simulation. Present approaches for choice
35 set formation or travel-probability fields (cf. Beckmann et al. (38) or Schönfelder and Axhausen
36 (14)) can help for the selection. It would still be required to account for uncertainty and enable the
37 choice of a destination that has never been observed before as specific constraints can cause the
38 inappropriateness of many other destinations. Thill (4) points out this dimension of the choice set
39 formation by pointing out that the analyst is external to the choice process.

40 Further information on the reasons, commitment and alternatives for chosen specific activi-
41 ties and destinations can be implemented in a survey. Cullen and Godson (39) proposed simple
42 questions as an addition to reported trips asking whether the respondent could have done an activi-
43 ty at another time or another destination. This research has also inspired a series of surveys that
44 study the ad hoc nature of activities and respective destinations, e.g. by Doherty (16). Looking at
45 the changeability of stable destination choice patterns this information is important to understand

TABLE 2 Latent class estimation results

Purpose: Disco, pub, restaurant, ...	LC 1	LC 2
<i>share</i>	0.67	0.33
acc	0.001**	0.058**
attr	-	-0.38**
share freq	7.92**	4.49**
HHI weekd.	0.55**	-0.32
HHI dayt.	0.69**	1.92**
Purpose: Meeting friends	LC 1	LC 2
<i>share</i>	0.87	0.13
acc	0.001**	0.008**
attr	-	-
share freq	6.58**	6.23**
HHI weekd.	0.82**	-
HHI dayt.	0.85**	-
Purpose: Club meeting	LC 1	LC 2
<i>share</i>	0.74	0.26
acc	0.001	0.038*
attr	-	-
share freq	5.72**	5.36**
HHI weekd.	1.37**	-
HHI dayt.	0.97**	1.23**
Purpose: Active sports	LC 1	LC 2
<i>share</i>	0.73	0.27
acc	0.007*	0.01**
attr	0.06**	-0.71**
share freq	5.43**	13.61**
HHI weekd.	0.94**	2.85*
HHI dayt.	0.78**	0.57**

level of significance ** 5 % , * 10 %

1 the causalities. Puhe et al. (26) states that "changeability is not a matter of frequency only", but
 2 depends on the type of relationship. In the case of grocery shopping, both trust in person and
 3 trust in brands result in different degrees of changeability. This perspective can also be transferred
 4 to other purposes. Imagine, for example a person having a relationship to a football club. This
 5 person would not choose a different destination, just because it is more attractive in an objective
 6 point of view. Rather, the changeability of the destination depends on the motivation of this person
 7 has to continue the relationship with that specific club (40). However, addressing such issues in
 8 quantitative survey designs appears relatively challenging.

1 CONCLUSION

2 This research address the modeling of destination choices by considering spatio-temporal rela-
3 tionships of individuals towards certain destinations with a longitudinal perspective. The state of
4 knowledge on destination choice behavior coincidentally points out that travellers only recognise
5 a certain number of possible destinations. Further, there exist both variable and stable patterns of
6 choices being being dependent on the specific travel purpose, at least to a certain extend. Existing
7 model approaches to account for spatial and temporal patterns of destination choice on an inter- and
8 intra-personal level are collected. They agree on a further need for an extended consideration of
9 such patterns within modelling frameworks. Mainly, three dimensions of heterogeneity occur: the
10 inter-travel-purpose, the inter-traveller and the intra-traveller related dimension. Based on these,
11 the developed destination choice model estimated with the six-week Mobicdrive study contains a
12 differentiation between all sub-purposes of leisure, assumes latent classes among the respondents
13 revealing different preferences and accounts for both spatial and temporal influences on destination
14 choices. With further model components the model is applicable in an AB TDM and provides a
15 framework integrating more realistic destination choice patterns in travel demand forecasts.

16 Nevertheless, for capturing destination choice heterogeneity for a whole population, a
17 larger sample of longitudinal destination choices is fundamental. The significant interpersonal
18 class allocation parameters are rare for this data set and the number of observed classes is limited.
19 Further, only an urban population is covered which still leaves open how observed patterns shape
20 in other geographical contexts.

21 It should be mentioned that the presented analysis and the consecutive destination choice
22 model framework cover only correlations. Causal mechanisms of stability and changeability are
23 not incorporated. It is striking, that there is a relatively large number of studies available describing
24 and measuring the extent to which everyday life patterns are stable or variable. Though, other than
25 for mode choice behavior, there is hardly any analysis available systematically exploring the causes
26 of stability or its changeability. It has thus remained largely unanswered which conditions favor
27 persistent stability of destination choice behavior or under which conditions people are willing
28 to change established habits. However, this knowledge is needed to assess the the transforming
29 potential of new technologies, transport services or restrictive policy interventions.

30 In social psychology, habitual behavior is a key topic being under investigation. Although
31 there is still disagreement about its conceptualization and measurement, literature agrees on ha-
32 bitual behavior following a kind of script or a rule of behavior triggered by certain cue stimuli.
33 Thus, the behavior performed may have been originally decided intentionally, but with increasing
34 repetition under the same (or similar) conditions, the traveller does not reconsider the reasons for
35 action. Moreover, several studies highlight that people have persistent social relationships to peo-
36 ple, things and places (12, 40–42). Following up on these aspects could be a worthwhile approach
37 to the study and modeling of changeability.

38 The problematic of a more stable destination choice caused by a more habitual behavior is
39 seen its higher resistance to changes (13, 43). Consequently, stronger changes would be required
40 to make up for this.

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1 AUTHOR CONTRIBUTIONS

2 The authors confirm contribution to the paper as follows: study conception and literature review: T.
3 Woerle and M. Puhe; data preparation: T. Woerle; analysis and interpretation of results: T. Woerle,
4 M. Puhe and P. Vortisch; draft manuscript preparation: T. Woerle. All authors reviewed the results
5 and approved the final version of the manuscript.

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