Exploring causalities between modal habits, activity scheduling, and multi-day locational practices.

Marc-Edouard Schultheiss, Laboratory of Urban Sociology, EPFL

Conference Paper STRC 2021

STRC | **21st Swiss Transport Research Conference**
Monte Verità / Ascona, September 12 – 14, 2021

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Marc-Edouard Schultheiss

EPFL ENAC IA LASUR
BP 2236 - Station 16
CH-1015 Lausanne

T: +41 78 725 83 34
E: marc-edouard.schultheiss@epfl.ch

Keywords

Modal habits, Multi-day patterns, Activity-travel behavior, Activity space, Mobility motifs

September 2021

Abstract

Despite raising awareness of sustainable behavior and considerable investments in the public transport network and active mobility infrastructure, car use remains the main practice for daily mobility in Switzerland. This work postulates that resistances to change at the individual level annihilate top-down modal shift measures. These resistances are assumed to be rooted in various forms of familiar practices, routines and habits and thereby require multi-day analysis of mobility patterns, going beyond what most mobility census data allows. This research proposes a set of metrics (*complexity*, *home shift*, *regularity* and *proximity)* to better characterize five modal habit profiles and day-to-day regularities in activity-travel behaviors. On the one hand, locational variability addresses the spatial familiarity of individuals' activity space. Measures of recurrent and frequent activity spaces are obtained by mean of centrography and longitudinal spatial analysis. On the other hand, temporal variability addresses the structure of schedules and time-allocation. Results are based on a fine-grained longitudinal travel-diary collected in Switzerland in 2019. The main objective of this paper is to highlight the relations between modal habits and multi-day activity-travel arrangements to better address resistances to change.

1. Introduction

The urban dynamics and transportation planning are usually based on daily snapshots of mobility. Yet, a growing body of literature call for multi-day characterization of mobility. Since every day mobility is mostly repetitive and regular, habits and routines structure the everyday life activity-travel patterns. These temporal and locational regularities participate in the resistance to change and adapt modal practices to greener mobility. Understanding mobility arrangements on a longitudinal dimension can therefore help identifying the attitudes and motivations underlying travel behaviors. Based on the premise of time-geography (Golledge and Stimson 1997), locational and temporal pattern analysis may contribute to targeted city planning and finer operationalization of forecasting models. The goal of this paper is to introduce the building block of multi-day activity-travel analysis by defining activity space metrics as well as measures of the activity structure to further investigate the relations with modal habits. The rest of the paper is structured as follows. Section 2 reviews how habits can be measured with different approached, and how spatial and scheduling regularities are investigated in the literature. Section 3 describes the use case and the data employed to apply the methods that are developed in Section 4. Lastly, Section 5 and 6 discuss the results on profiling modal habit clusters and exploring their locational regularities.

2. Literature review

The temporal and spatial aspects of activity space can be approached by metrics such as frequency of visits, regularity in space and time, and activity scheduling. This forms the premise of the approach of urban rhythm and travel behavior developed by Shönfelder and Axhausen (2010), which relax the traditional hypothesis of static day-to-day scheduling. In very recent research, rhythm has also taken a more sociological perspective. Antonili et. al (2020) call for actions by proposing innovative temporal policies to restructure individual- and social- time, and by extension territories and environments. Bridging the gap between those operational and sociological considerations of rhythm offers promising perspectives both for researchers and practitioners. The approach of multi-day urban rhythm and activity spaces constitute a solid basis for considering the unreasoned aspects of activity-travel behavior. On the one hand, place attachment and spatial familiarity integrates travelers' spatial experience together with cognitive and affective components (Altman and Low 1992). As recently demonstrated by Dubois and Schmitz (2011), spatial familiarity highly depends on frequency of visits to a place ; and can therefore be measured. On the other hand, day-to-day behavioral variability uncovers notions of habits and routines. Scarcely investigated yet by lack of multi-day travel diaries, studying habits and routines unveils latent traits of activity-travel behaviors, such as preferences, attitudes and motivations to change. Vij, Carrel and Walker (2013) explored the repetitive nature of mode choice and variabilities of taste in a six-week travel-diary experiment, and propose measures of *openness* to mode alternatives and travel-time *sensitivity* with respect to multi-day observations. In fact, habitual practices bring stability to behaviours and are constitutive of daily mobility (Buhler 2015). It also strongly influences the aversion to change. From a traveller's perspective, developing habits makes daily life easier as it reduces the cognitive load of decision-making and improves travellers' ontological security (Giddens 1990, 98) and skills to travel (Kaufmann, Bergman, and Joye 2004). This can lead to less effective modal shift policies. In their research on urban rhythms, Schönfelder and Axhausen (2010) show that a full activity-diary periodicity oscillates around 10 days, and that most people have only 6 to 8 reference-locations. In this direction, a growing research stream focuses on Network Theory's pattern identification*,* namely *daily human mobility motifs* (Schneider, Belik, et al. 2013). Considering activity-travel behaviours as a graph has proven high efficiency to measure activity sequence similarities, location history extraction, time-allocation patterns, spatial distribution of travel patterns or space-time profiles (Li et al. 2008; Schneider, Rudloff, et al. 2013; Shen and Cheng 2016; Jiang, Ferreira, and Gonzalez 2017; Su, McBride, and Goulias 2020). Exclusively based on anonymous call detail records, all these researches show that a very limited set of typical daily motif can explain most of the activity-travel behaviour structures.

3. Use case and data

This work leverages the MOBIS study (2019), which tracked 3'700 Swiss residents over 8 weeks in fall/winter 2019. It is one of the few datasets that allows a longitudinal study of Activity-Travel Behaviors which is critical for formalizing travel habit and measures of familiar activity spaces. MOBIS uses mixed data-collection method: participants have to fill a questionnaire (mainly for sociodemographics or declared modal practices) before entering a geotracking phase. Two phases structure the tracking phase. Phase 1 collecting usual behaviors, and phase collecting behaviors impacted by an experiment. The results presented here are based on the first phase of the data collection. Some thresholds applied on daily distances traveled walking as well as weekly occurrence on the different mode use discard outliers and unhabitual practices. Additionally, since the participation can be irregular over the 8-week data collection campaign, respondents with a minimum of 14 days of observation within the 4 first weeks were extracted. This way, all the 2550 respondents remaining (approximatively 70% of the complete dataset) in the sample display some form of regularity in their locational and temporal patterns while remaining a representative population. Lastly, contextual open data is also leveraged, including a territorial typology (OFS 2021) and the OpenStreetMap street-network (2021). Figure 1 gives insights in the project data and introduces spatial clustering algorithms applied to the raw data to identify the frequency of visits to unique locations. This is further discussed in the method section.

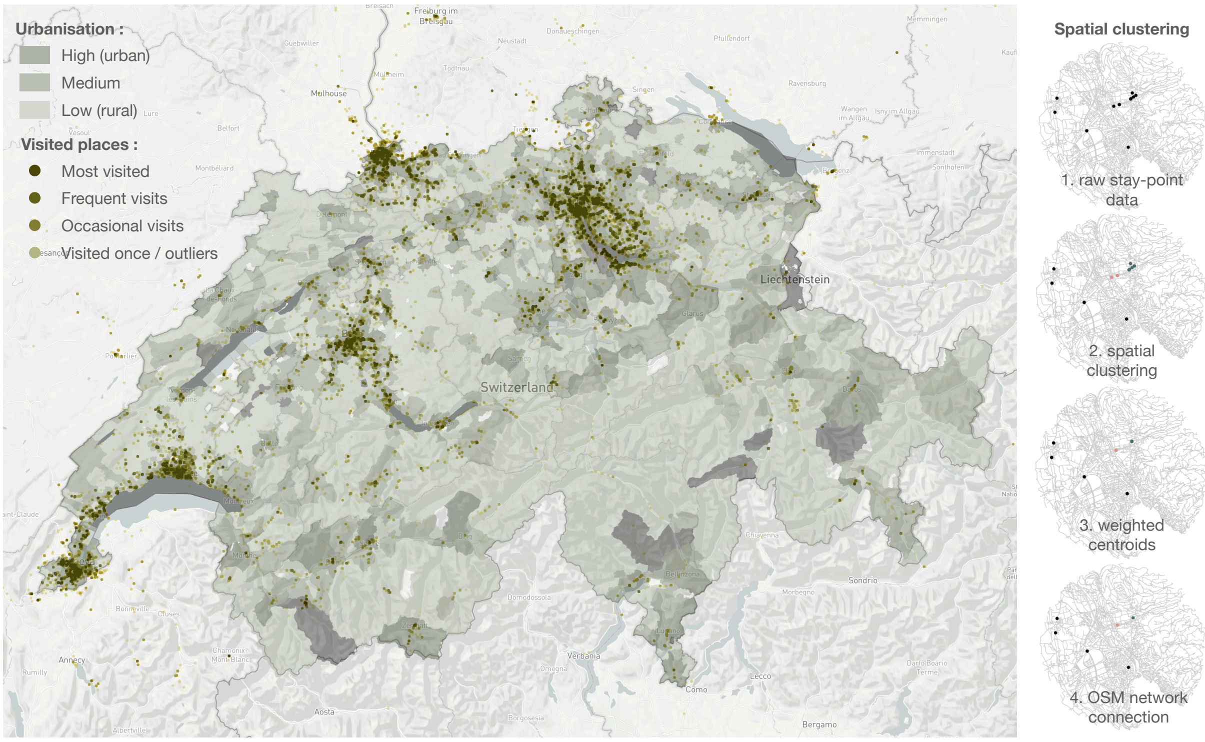

Figure 1 Data insights. On the left – 100'000 multiday activity location after spatial clustering and visit count, scattered on a 3-class urban typology (Federal Office of Statistics). On the right – sample of leisure stay-points scattered on OpenStreetMap (OSM) street network (osmnx python package). Spatial clustering using DBSCAN algorithm. Black dots are outliers i.e. location visited once.

4. Method

This section describes the different methods used in the project. The goal is to explore the causalities between modal habits, and locational and temporal patterns. It is therefore necessary to create analytical objects representing spatial and temporal regularities. First, the mobility motifs are described. They are used to capture the whole daily structure of the activity-travel and its related complexity in a single object. Motifs allow to capture temporal regularity. Secondly, three metrics are derived to capture locational regularity: *proximity*, *regularity* and *home shift*. The second portion of the method concerns the modal habits clustering approach used to create a 5-class typology of travelers based on their modal routines.

4.1 Construction of daily mobility motifs

The daily activity structure of travelers is abstracted as a motif, that is a directed graph in which vertices represent legs between visited places or activity locations, and nodes represent a stay-points. The sequence of stay-point locations within the activity-chain $S^{(i,k)}_{ACT} = \{Act^{(i,k)}_{1}, Act^{(i,k)}_{2}, \ldots, Act^{(i,k)N}_{N\_act}\}$ yields activity-based motifs. The identification of a "central location", here the dwelling is key in the construction of the motifs, since starting and ending the day at the central node is a prerequisite for a valid motif. Variations of the motif construction process have been recently elaborated in other studies (see Jiang, Ferreira, and Gonzalez 2017, 210–15; Su, McBride, and Goulias 2020). The goal is not only to obtain the chaining of the daily mobility motifs, but also to capture the "typical" motifs for each traveler, that is the most recurrent motif over 2-4 weeks of observation. Each daily motif is computed assuming day-to-day independency for a given traveler.

By considering $S^{(i,k)}$ as an ordered categorical sequence of different events over the course of the day, one can compute a motif complexity index. The objective measure of the complexity index of the graph abstracting the motifs is entropy-based. It is a twofold composite index ranging from 0 to 1 taking into account the distribution of events (considered here in terms of relative time allocation $T(Act^{(i,k)}) / T_{TOT}$ to each activity performed i.e. the entropy); and the number of transitions NTr between distinct events, relatively to the total length of the sequence L. Thus, the greater the complexity, the higher the number of trips and the higher the irregularity of out-of-home schedules (see Su, McBride, and Goulias 2020 Table 2 for specific examples). This complexity index is adapted from a biography trajectory complexity index proposed by Gabadinho et al. (2010). Figure 2 displays the 9 most frequent motifs calculated from the sampled data. A "motif 99" aggregates all other detected motifs, and holds only 14% of the day observations.

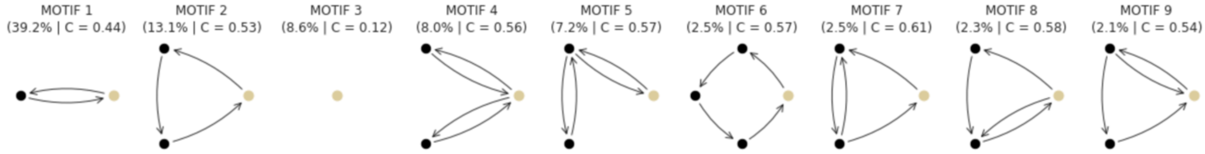

Figure 2 Illustration of the 9 most occurrent activity-based motifs detected in the sampled data. Black dots are unique activity-location tuples, and yellow dot is home location. The percentages are the shares in the population, and "C" denotes the average complexity. Combined, those 9 motifs represent 86% of all motifs.

4.2 Activity space and spatial familiarity

Given a dataset of labelled location in terms of purpose and visit counts over several days, marked point pattern analysis allows the study measures of individuals' action space (Baddeley, Rubak, and Turner 2015). Here, the multi-day period is oscillating between 14 and 28 days as the use case describes. The scarce literature dealing with habitual action space analysis suggests that 7 to 14 days may be sufficient to capture frequently visited places and recurrent activity-travels (Schönfelder and Axhausen 2010). Figure 3 shows a random subsample of nine different activity spaces. The plots display scatters of cartesian coordinates projected on equally scaled axes, but at different zooms. The implementation of centrography and spatial analysis yielded characteristics for describing the activity space, such as the standard deviation ellipse characterizing the space in which individuals are likely to be at any time t, the home and habitual space, the weighted mean center of any visited locations, etc.

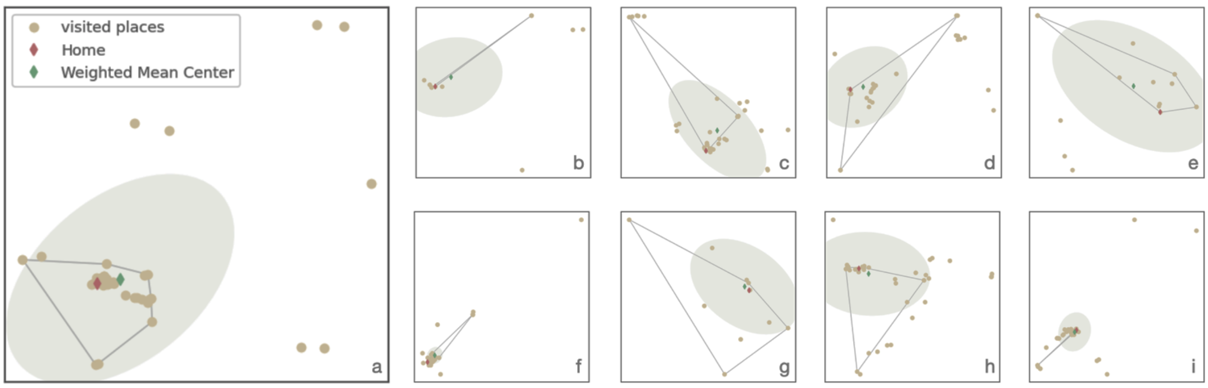

Figure 3 Examples of activity space geometries (one frame per travelers, over eight weeks of observation, sampled from the use case). The beige ellipses (SD ellipses) show the area in which travelers are likely to perform activities given their location history. The grey polygons (convex hulls) delineate the most frequently visited places. Points are at least separated by 300 meters.

On Figure 3, each point represents an averaged longitude and latitude tuple of recurrent visits to the same location. To do so, a density-base clustering algorithm (DBSCAN) was applied to obtain the average location information (in the raw data, the same location e.g. home is generally indicated by several points very close one another due to the inaccuracy of the sensing device). While aggregating the positions, the count of visits is kept. This operation allows to derive the first metric characterizing locational patterns, that is *regularity*. Regularity is the fraction of the number of frequently visited places over all places, including places visited once. A small regularity implies high locational innovation[1], and a regularity that tends to 1 implies that the traveler mostly visits well-known locations. Regularity continuously varies between 0 and 1. Also, the frequency of visits is made categorical to differentiate the most visited places from the frequently visited places, the occasionally visited points, and the places visited once (outlying locations). The second metric characterizing locational patterns is *proximity.* Proximity is the relative dispersion of habitual action space. Interestingly, Figure 3 displays significant differences between the overlaps of the habitual action space (delineated by the hull) and the global action space (delineated by the ellipse). Proximity somehow is a measure of this overlap. For example, a proximity greater than one implies a dispersed habitual activity space (i.e. places frequently visited over a 8-week period are spread on territory) and a close innovation activity space (i.e. places visited once or occasionally are closer to the main home location). Note that proximity is a ratio of standard distances rather than a ratio of surfaces of hulls over ellipses. This, in order to avoid corner cases where frequent locations would be geographically aligned and therefore have a very small area yet very elongated. Such corner case is illustrated in Figures 1.b and 1.i., where the hull surfaces are close to zero while such a location topology is characteristic of long-distance travelers. Empirically, the proximity is generally between 0 and 3. Lastly, the third metric is *home shift*, that is the Euclidean distance between home and the weighted mean center (see Figure 1). Home shift provides a measure of residential isolation. A small home shift means that most activities are done locally, in an area relatively close to the home; and a high home shift implies a remote activity space.

4.3 Modal habits clustering approaches

The modal habits clustering aim at classifying the population according to their multi-day travel and modal practices. To do so, a lot of information is available in the data. For instance, the MOBIS survey asked the participants about their frequency of mode use. Allowed responses were “3 or more times per week”, “2 days per week”, “1 day per week”, “1-3 days per month”, “less than 1 day per month”, or “never”. The considered modes were car, train, local public transport or bicycle. These are declarations from the respondents. Secondly, it is possible to derive the modal practices out of the tracking data to obtain the actual practices and avoid any reporting bias. All the variables used in the modal habits clustering are described in Table 1.

1 Locational innovation refers to the variety seeking of new activity-locations. Here, the multiplicity of places visited once is interpreted as high variety seeking/innovation (for more details, see Schönfelder and Axhausen 2010, 153).

Table 1 Variables used in the clustering of habitual modal practices

Own car	object	categorical	Yes / No / No, but I can arrange to borrow one
GA pass	bool	categorical	True / False
Regional pass	bool	categorical	True / False
½ fare pass	bool	categorical	True / False
No PT pass	bool	categorical	True / False
Frequency car driver (own car)	object	categorical	3+ per week / 2 days per week / 1 day per week / 1-3 days per month / less than 1 day per month / never
Frequency train	object	categorical	3+ per week / 2 days per week / 1 day per week / 1-3 days per month / less than 1 day per month / never
Frequency local PT	object	categorical	3+ per week / 2 days per week / 1 day per week / 1-3 days per month / less than 1 day per month / never
Frequency bike	object	categorical	3+ per week / 2 days per week / 1 day per week / 1-3 days per month / less than 1 day per month / never
Occurrence car	float64	[#trips/week]	average number of car trip recorded per week
Occurrence intra pt	float64	[#trips/week]	average number of local public transport trip recorded per week
Occurrence inter pt	float64	[#trips/week]	average number of inter city public transport trip recorded per week
Occurrence walk	float64	[#trips/week]	average number of walking trip recorded per week
Occurrence cycle	float64	[#trips/week]	average number of cycling trip recorded per week
Distance car	float64	[km/day]	average distance of driving trip recorded per day
Distance intra pt	float64	[km/day]	average distance of local public transport trip recorded per day
Distance inter pt	float64	[km/day]	average distance of inter city public transport trip recorded per day
Distance walk	float64	[km/day]	average distance of walking trip recorded per day
Distance cycle	float64	[km/day]	average distance of cycling trip recorded per day
Duration car	float64	[min/day]	average duration of driving trip recorded per day
Duration intra pt	float64	[min/day]	average duration of local public transport trip recorded per day
Duration inter pt	float64	[min/day]	average duration of inter city public transport trip recorded per day
Duration walk	float64	[min/day]	average duration of walking trip recorded per day
Duration cycle	float64	[min/day]	average duration of cycling trip recorded per day

Several clustering approaches were tested. In a first attempt, the categorical data was discarded to perform a factor analysis followed by an agglomerative clustering. Interestingly, the analysis of the latent factors indicated that walk and intra public transport fall within the same factor and explain about 29% of the variance. The second factor was car use, combining occurrence, distance; followed by a bike use factor and lastly a factor describing inter public transport use. This approach was rejected as the hierarchical clustering yielded unbalanced clusters. Additionally, it appears relevant to keep both the declarative and actual modal practices since habits and routines are particularly subject to attitudes which can lead to reporting bias. The selected clustering approach is the mixed data clustering algorithm *K-prototypes* (Berdat 2020). As further described by Ahmad and Khan (2019), cluster centers are represented by mean values for numeric features and mode values for categorical features. This approach yielded balanced clusters and performs well at differentiating the modal habits.

5. Results

This section develops the results in two parts. In the first part, the modal habit typology – obtained by mean of a mixed-data clustering algorithm – is described. In the second part, the relations between temporal and locational regularities, and the modal habit typology are discussed.

5.1 Profiling the modal habit typology

The clustering of multi-day modal practices yielded five modal habit profiles: exclusive car users (32%), car users (12%), moderate car users (31%), bi-modal users (8%) and multi-modal users (17%). These profiles are a combination of averaged distance, duration and occurrence of each mode of transport, but also dummy and categorical variables, as described in Table 1. On Figure 4 are described each of the profiles in terms of daily time-space patterns, distance-based modal shares, and sociodemographics.

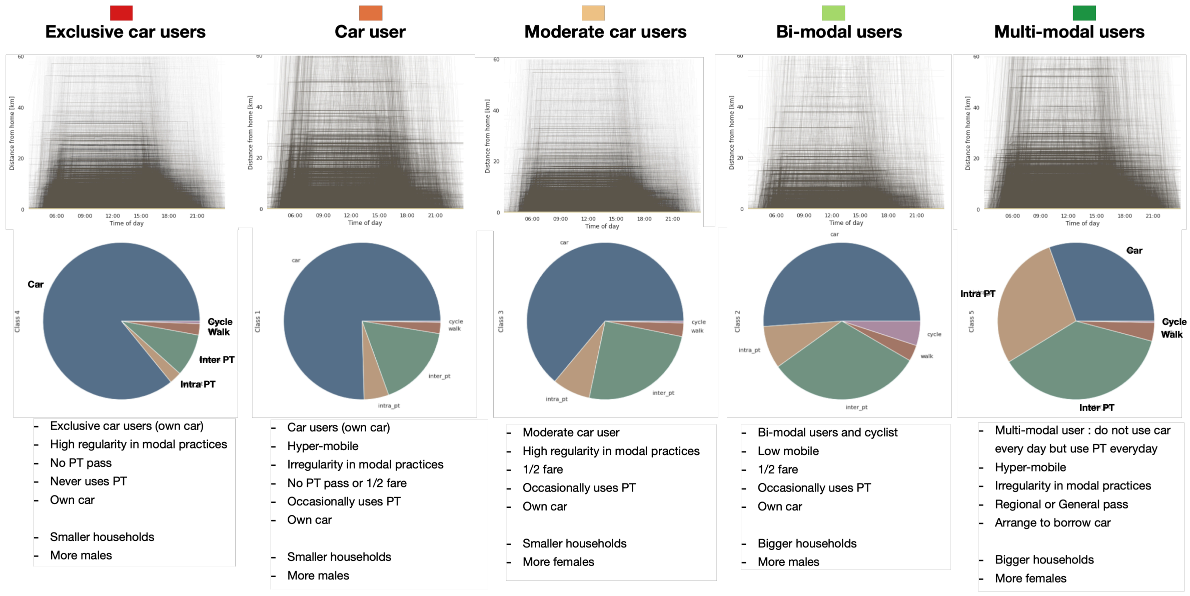

Figure 4 Profiling of the modal habit clusters, with the time-space diagrams, distance-based modal shares and other specific descriptions

Exclusive car users are largely dominated by car use, but also hold a high regularity in modal practices. They generally do not use the public transport system and are characterized by small households (less than three-head households) and mainly constituted of males. In the *car users'* profile, the sociodemographics are similar, but the profile demonstrates higher irregularities in modal habits as well as higher distances traveled on average. *Moderated car users* and *bi-modal users* both occasionally use public transport and display significant spatio-temporal regularities. Interestingly, as the modal split gets diverse, the size of the household tends to get bigger too. In the *multi-modal* profile females are more present, and public transport is preferred on a daily basis. Car is still used but not every day, and the profile displays a particularly high irregularity in the modal practices. This means that the distance, the duration or the occurrence of trips significantly varies from one day to another. The modal habits profiles are dominated by car use as 75% of the population is car-centered.

5.2 Characterize locational patterns

On Figure 5, the modal habit profiles are spatially distributed. Each bin aggregates the home location of the respondents. The majority of modal habit profile within the same bin gives the color of the bin. As a result, the propensity to car use in Geneva city center is higher compared to Bern. The maps display some very clear modal habit preferences distributed in district across the urban territories.

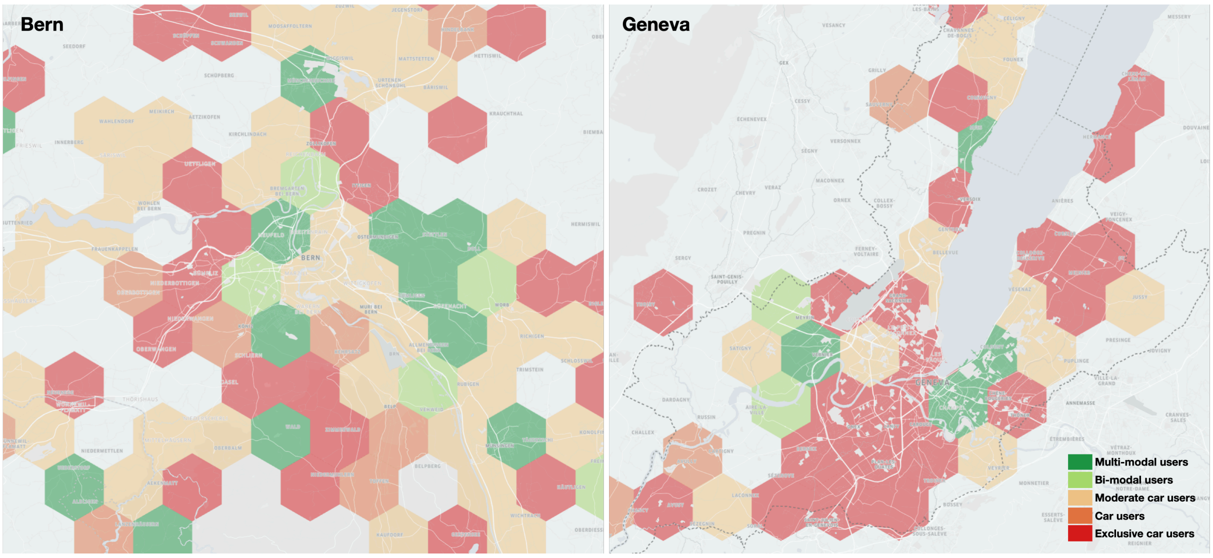

Figure 5 Spatial distribution of the modal habit profiles in the cities of Bern and Geneva (Switzerland). Each hexagonal bin aggregates the dwellers and their modal habit profile

On Table 2, the action space metrics are cross-referenced with the modal habit profiles. The results do not demonstrate the expected result, since the differentiation in action space topologies is not obvious. However, some tendencies emerge that can be counterintuitive. While one of the car most cited advantage often relates to its flexibility and convenience (Kaufmann et al. 2019), the activity space of exclusive car users is characterized by a high proximity, a high regularity and a small home shift. This means that exclusive car users like to visit the same place and close to the dwelling neighborhood. The complexity score and the complexity coefficient of variation are measures of the activity-travel arrangement variations and turbulences. The multi-modal users hold the higher complexity score and the lower complexity coefficient of variation. Thus, the activity scheduling of multi-modal users is complex in a sense that it is made of several change of state, home loops, and various time allocations. But it is also regular over several days of observation.

Table 2 Action space metrics and modal habit profiles

	proximity [-]	regularity [-]	home_shift [km]	complexity [-]	complexity_cv [-]
Exclusive car users	0.57	0.15	7.3	0.51	0.23
Car users	0.58	0.13	11.8	0.54	0.21
Moderate car users	0.53	0.14	10.6	0.51	0.24
Bi-modal users and cyclists	0.51	0.12	8.1	0.52	0.22
Multi-modal users	0.57	0.14	9.6	0.55	0.20

6. Conclusion

This work sets the first building blocks of multi-day activity-travel analysis. A focus is given to the habitual modal practices, which are studied through the lens of locational regularities and activity scheduling patterns. Five modal habit profiles are identified, with different propensities to car use. The mobility motifs abstract the activity-travel arrangements as a single object characterized by the complexity score. Over several days, the complexity coefficient of variations reveals how regular these arrangements can be. The activity space metrics (regularity, proximity and home shift) do not significantly differentiate the modal habit profiles. More research efforts should be put in that direction to better understand the causalities between spatial behaviors and multi-day modal practices. The spatial distribution of the modal habit profiles highlights portions of the territory with respect to the modal preferences. This approach can be useful for targeted urban planning and better addressing the transportation system development.

7. Acknowledgement

This project is fully supported by the *ENAC cluster grant 2020* that fosters multidisciplinary approaches to address urban sustainability. Janody Pougala (co-PI) and Marija Kukic from the TRANSP-OR laboratory (EPFL) actively participated in the discussions of this project. We also thank the IVT group at ETH Zurich for providing the MOBIS dataset.

8. Bibliography

Ahmad, Amir, and Shehroz S. Khan. 2019. “Survey of State-of-the-Art Mixed Data Clustering Algorithms.” *IEEE Access* 7: 31883–902. https://doi.org/10.1109/ACCESS.2019.2903568.

Altman, Irwin, and Setha M. Low. 1992. *Place Attachment*. Human Behavior and Environment Vol. 12. New York (N.Y.) [etc: Plenum Press.

Antonioli, Manola, Guillaume Drevon, Luc Gwiazdzinski, Vincent Kaufmann, and Luca Pattaroni. 2020. *Manifeste Pour Une Politique Des Rythmes*. EPFL Press. https://www.epflpress.org/produit/1001/9782889153503/manifeste-pour-une-politique-des-rythmes.

Axhausen, K.W. 2019. "MOBIS - Mobility Behaviour in Switzerland - Research Project – Funded by Innosuisse and DETEC – In Collaboration with ETH Zurich, University of Basel and Zhaw." 2019. https://ivtmobis.ethz.ch/mobis/en/.

Baddeley, Adrian, Ege Rubak, and Rolf Turner. 2015. *Spatial Point Patterns: Methodology and Applications with R*. Taylor & Francis. https://www.routledge.com/Spatial-Point-Patterns-Methodology-and-Applications-with-R/Baddeley-Rubak-Turner/p/book/9781482210200.

Berdat, Johan. 2020. "Kprototypes." readthedocs.io, release 0.1.2. https://kprototypes.readthedocs.io/.

Buhler, Thomas. 2015. *Déplacements Urbains: Sortir de l'orthodoxie*. PPUR presses polytechniques. https://hal.archives-ouvertes.fr/hal-01136381.

Dubois, Charline, and Serge Schmitz. 2011. "Familiarité spatiale dans deux communes périurbaines belges." *Cahiers de géographie du Québec* 55 (154): 51–65.

Gabadinho, Alexis, Gilbert Ritschard, and Matthias Studer. 2010. "Indice de complexité pour le tri et la comparaison de séquences catégorielles." *EGC 2010* RNTI-E-19: 61–66.

Giddens, Anthony. 1990. *The Consequences of Modernity*. Reprint. Cambridge: Polity Press.

Golledge, Reginald G., and Robert J. Stimson. 1997. *Spatial Behavior: A Geographic Perspective*. The Guilford Press. https://www.guilford.com/books/Spatial-Behavior/Golledge-Stimson/9781572300507.

Jiang, S., J. Ferreira, and M. C. Gonzalez. 2017. "Activity-Based Human Mobility Patterns Inferred from Mobile Phone Data: A Case Study of Singapore." *IEEE Transactions on Big Data* 3 (2): 208–19. https://doi.org/10.1109/TBDATA.2016.2631141.

Kaufmann, Vincent, Manfred Max Bergman, and Dominique Joye. 2004. "Motility: Mobility as Capital." *International Journal of Urban and Regional Research* 28.4: 745–56. https://doi.org/10.1111/j.0309-1317.2004.00549.x.

Kaufmann, Vincent, Juliana González Villamizar, Eloi Bernier, Guillaume Drevon, and Marc Antoine Messer, eds. 2019. *Analyse Des Logiques de Choix Modal Auprès de La Population Active Du Grand Genève*.

Li, Quannan, Yu Zheng, Xing Xie, Yukun Chen, Wenyu Liu, and Wei-Ying Ma. 2008. "Mining User Similarity Based on Location History." In *Proceedings of the 16th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems - GIS '08*, 1. Irvine, California: ACM Press. https://doi.org/10.1145/1463434.1463477.

OFS. 2021. "Atlas Statistique de la Suisse." Office fédéral de la statistique (OFS). 7004424. 2021. https://www.atlas.bfs.admin.ch/maps/13/fr/12359_12482_3191_227/20387.html.

"OpenStreetMap Wiki." 2021. 2021. https://wiki.openstreetmap.org/wiki/Downloading_data.

Schneider, Christian M., Vitaly Belik, Thomas Couronné, Zbigniew Smoreda, and Marta C. González. 2013. "Unravelling Daily Human Mobility Motifs." *Journal of The Royal Society Interface* 10 (84): 20130246. https://doi.org/10.1098/rsif.2013.0246.

Schneider, Christian M., Christian Rudloff, Dietmar Bauer, and Marta C. González. 2013. "Daily Travel Behavior: Lessons from a Week-Long Survey for the Extraction of Human Mobility Motifs Related Information." In *Proceedings of the 2nd ACM SIGKDD International Workshop on Urban Computing - UrbComp '13*, 1. Chicago, Illinois: ACM Press. https://doi.org/10.1145/2505821.2505829.

Schönfelder, Stefan, and Kay W. Axhausen. 2010. *Urban Rhythms and Travel Behaviour. Spatial and Temporal Phenomena of Daily Travel*. Transport and Society. Transport and Society. Ashgate. https://doi.org/10.4324/9781315548715.

Shen, Jianan, and Tao Cheng. 2016. "A Framework for Identifying Activity Groups from Individual Space-Time Profiles." *International Journal of Geographical Information Science* 30 (9): 1785–1805. https://doi.org/10.1080/13658816.2016.1139119.

Su, Rongxiang, Elizabeth Callahan McBride, and Konstadinos G. Goulias. 2020. "Pattern Recognition of Daily Activity Patterns Using Human Mobility Motifs and Sequence Analysis." *Transportation Research Part C: Emerging Technologies* 120 (November): 102796. https://doi.org/10.1016/j.trc.2020.102796.

Vij, Akshay, André Carrel, and Joan L. Walker. 2013. "Incorporating the Influence of Latent Modal Preferences on Travel Mode Choice Behavior." *Transportation Research Part A: Policy and Practice* 54 (August): 164–78. https://doi.org/10.1016/j.tra.2013.07.008.