Stability of weekly active days using continuous revealed preference data

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Short summary

This study uses one year of continuous tracking data to explore the stability of individuals' travel behavior over extended periods. The primary objective is to develop a robust methodology for analyzing the stability of travel behavior using continuous tracking data. Specifically, the impact of sociodemographics and life events, such as employment changes, household relocation and childbirth, on weekly active days by purpose. Findings indicate that full-time workers exhibit the most stable patterns in weekly active days, while students display more significant variability, influenced by academic schedules. Life events, particularly changes in employment status, significantly affect travel behavior, with becoming unemployed or starting a job experiencing increased variability. Mobility restrictions also impact weekly active days, with restricted individuals showing reduced activity across all employment statuses. The study provides insights into the complexities of travel behavior stability, emphasizing the importance of considering socio-demographic factors and life events.

Keywords: travel behavior, active days, mobile days, semi-passive data, longitudinal analysis, life events

1 Introduction

Individual choices and variations in personal situations affect behavior and may trigger behavioral change. Substantial short-term variability, as reported by Saneinejad & Roorda (2009) or Cherchi & Cirillo (2014) may become comparatively stable if aggregated into weeks, months, or even years (Pas & Koppelman, 1987). Previous research has further shown a strong association between changes in travel behavior and life events, such as marriage, childbirth, household relocation or job transitions (Clark et al., 2014; Scheiner, 2016; Hilgert et al., 2018; Ahmed & Moeckel, 2023; Moreno, Nouli, et al., 2023). Ahmed & Moeckel (2023) acknowledged that the inability of existing travel demand models to represent habitual travel behavior and slow changes in travel behavior can exaggerate policy sensitivity. Furthermore, they proposed updating travel behavior only after significant changes occurred to the household, the built environment or the network. This assumes that travel behavior remains constant for those individuals who did not experience life events. Against this hypothesis, empirical analyses from Hilgert et al. (2018) found that only 33 % of persons had similar main activity patterns from year to year, acknowledging that some individuals may change their behavior for reasons unrelated to life events.

One of the key mobility variables is how many days individuals engage in out-of-home activities. However, little focus has been placed on weekly active participation in the literature. Ahmed & Moeckel (2023) showed general trends in travel behavior and that the positive and negative impacts of life events on the number of trips by purpose were plausible and within the expected ranges. This was confirmed by Hilgert et al. (2018). Moreno, Nouli, et al. (2023) further analyzed the number of weekly active days by purpose and found that active days are relatively stable across time, especially for unemployed (95%), employed (50%) and students (60%). Mandatory acts were more stable than discretionary acts, and increasing the number of active days for mandatory activities reduce time from discretionary activities. The results also showed the differences by gender on the travel behavior impacts of giving birth and becoming employed/unemployed. Changes to employment status triggered the highest differences on active days for mandatory purposes but little variations on discretionary purposes. Moreno, Nouli, et al. (2023) concluded that half-time employees had more active days for discretionary activities than full-time workers, and students tend to travel fewer days to shop, accompany and other discretionary purposes. Still, they travel for more days for recreational activities. Little surprisingly, the presence of mobility restrictions affected the number of active days even more, with fewer commute and shopping days per week.

Previous studies worked with short-duration mobility panel data (one-week (Hilgert et al., 2018; Ahmed & Moeckel, 2023; Moreno, Nouli, et al., 2023) to four-week travel diaries (Thomas et al., 2019)), which was collected in two consecutive years. In the past decade, the popularity of smartphone devices that carry GPS antennas has revolutionized the tracking of individuals, allowing the cost-effective and less labor-intensive monitoring of large groups of participants for extended periods compared to traditional traditional methods that rely on self-reported data (Prelipcean et al., 2018; Deschaintres et al., 2022). This type of data has found application in various domains, including the calculation of transport appraisal values (Tsoleridis et al., 2022), the modeling of route (Meister et al., 2023) and mode (Dahmen, Weikl, & Bogenberger, 2023) choice based on revealed-preference data and the analysis of the effect of the COVID-19 pandemic on individual mobility (Hintermann et al., 2022).

Against this backdrop, our study aims at investigating the impact of life events on travel behavior using one year of continuous tracking data. To our knowledge, no existing studies utilize this type of data to analyze the effects of life events. The primary objectives of our research are to develop a methodological pipeline to understand the impact of life events on travel behavior, to overcome shortcomings of short-duration travel diaries and to benefit from the potential of long-duration semi-passive data.

2 Methodology

The primary input data for this analysis is the semi-passive data from the *Mobilität.Leben* dataset. This section summarizes how the dataset was generated, the data reduction from semi-passive to weekly active days and the statistical analyses.

The dataset Mobilität.Leben

The *Mobilität.Leben* project was initiated to analyze the impacts on travel behavior of a new transport policy implemented in Germany as a reaction to the high inflation in 2022 and 2023. Initially a 9-Euro-Ticket and a fuel-tax cut were implemented, followed by the Deutschland-ticket (see Figure 1). Both tickets provided unlimited rides on local transit across Germany. The study included a multi-wave survey with over 2,500 participants, of which over 1,100 also recorded their movements with a dedicated GPS-based smartphone tracking app (Loder et al., 2022).

The survey waves included detailed socio-economic, mobility-tool ownership, attitudinal and travel behavior information. While some questions were presented only once, others were repeated across waves to track possible behavioral and life changes. As far as this study is concerned, the work/study status, home-office status and number of cars in the household (hh) were collected in waves 1 and 6, and the hh income, hh size and hh number of children in waves 1 and 5.

The recorded tracking data underwent extensive post-processing to increase its quality and validity, following the approach described in Dahmen, Álvarez-Ossorio, et al. (2023). By aggregating personal details, the data volume was reduced and all privacy-related variables were either aggregated or excluded for further analysis.

Data reduction

The primary variable of analysis is the number of active days per week. It is defined as the number of days a participant carried out at least one out-of-home activity within one calendar week .

Firstly, we summarized whether an individual had at least one track associated with an out-of-home activity. For this analysis, we distinguished between mandatory (work, education) and discretionary (shopping, other known, unknown) activities.

Secondly, we selected participants who annotated their home location in the app. For workers and students, their workplace or education location must be annotated, too, to be included in the final sample.

Thirdly, to capture the effect of life events in long observation periods, we considered participants who were active in the study for at least 181 days (long-term users). Furthermore, to ensure data

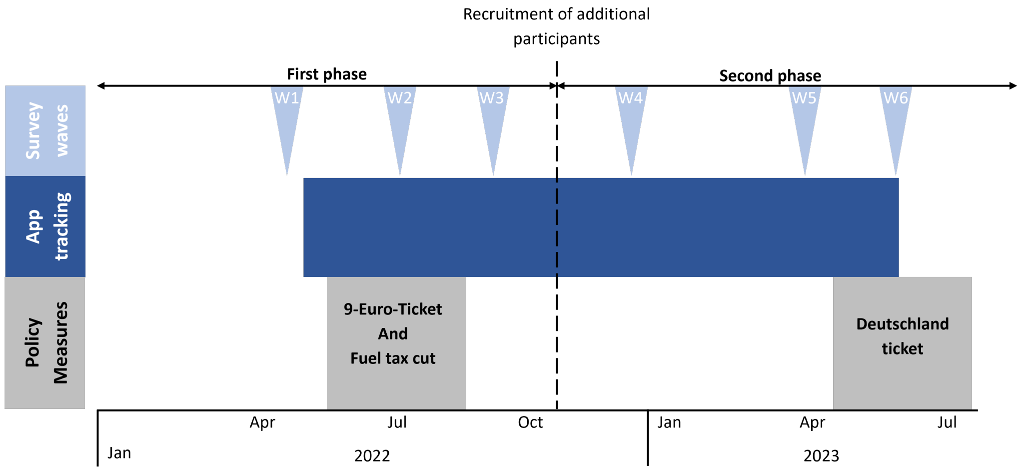


Figure 1: Timeline of the *Mobilität.Leben* project

consistency and minimize the disruptions caused by stays outside of Germany or periods of inactivity, we filtered the weeks an individual was abroad for at least one day or if the application was inactive. Only individuals with complete sociodemographic attributes (gender, age, employment status, household income, household children, household autos and area type) and life events were considered (answered waves 1, 5, and 6).

The initial sample of 65,360 person-weeks was reduced to 10,704 person-weeks (around 16% of the initial sample) while maintaining 355 participants (around 30 % of the initial sample).

Table 1: Sample size before and after data reduction

Users	Person-weeks		Persons	
	N	%	N	%
All participants	65,360	100.00	1,193	100.00
Long-term users with work and home locations	31,179	47.70	567	47.53
Long-term users tracked all weekdays	22,083	33.79	567	47.53
Long-term users in Germany that week	19,564	29.93	565	47.36
Long-term users with sociodemographic and life events	10,631	16.27	355	29.76

Finally, we characterized four types of weeks: 1) Public holiday(s) in workday, 2) Severe rain (at least two days with 10 mm or more of rainfall), 3) Severe snow (at least one day with 10 mm or more of snow) and 4) Normal week. Daily weather data for Munich was obtained from the DWD (German Weather Service) open data portal, including wind, precipitation, snow, temperature, among others.

3 Results

Annual variation (all activities)

Firstly, we analyzed the mean and standard deviation of weekly active days for all individuals by type of week (Figure 2). The mean number of active days per week varied from 5.4 to 6.2 days throughout the year. As expected, the mean values were lower in weeks with public holidays on a workday and in weeks with inclement weather. The standard deviation was larger for weeks with severe weather.

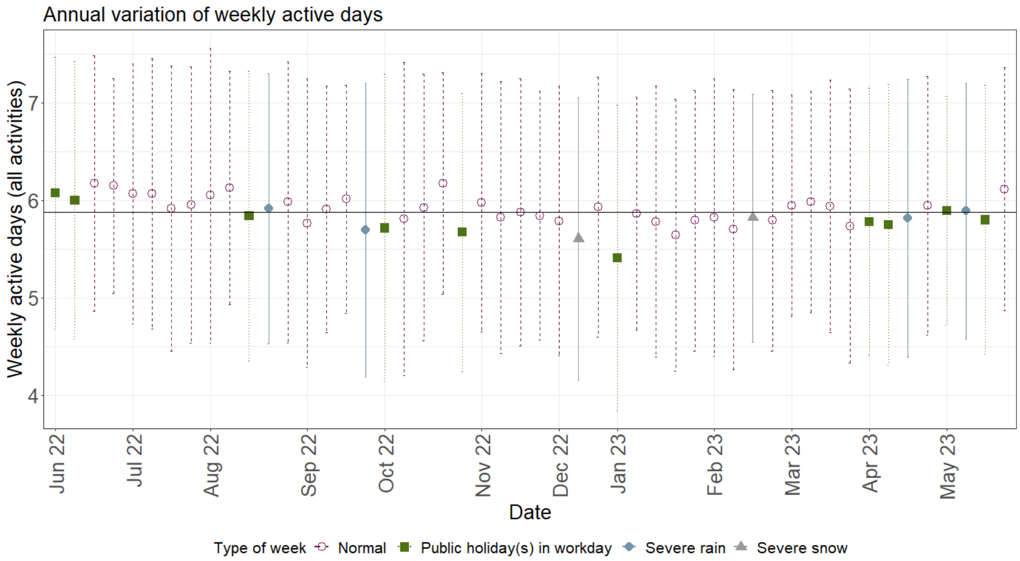


Figure 2: Annual variation of the number of active days (all activities), by week type

Annual variation by employment status

Secondly, we analyzed the annual variation of weekly active days by employment status and purpose (Figure 3). Full-time workers showed the most regular patterns for mandatory, discretionary and all activities. As expected, most full-time workers went to work between 3 and 5 days (Figure 3a). Some probably had the flexibility to work from home for one to two days per week, took vacation or were on sick leave. In most weeks, 10 to 15 % of full-time workers did not perform any mandatory act.

Retirees were the second most regular group for all (Figure 3c) and discretionary activities (Figure 3b), with most participants being active between 5 and 7 days per week. However, some retirees also had weeks with fewer than 2 active days. Some retirees also reported mandatory activities (i.e., work or education).

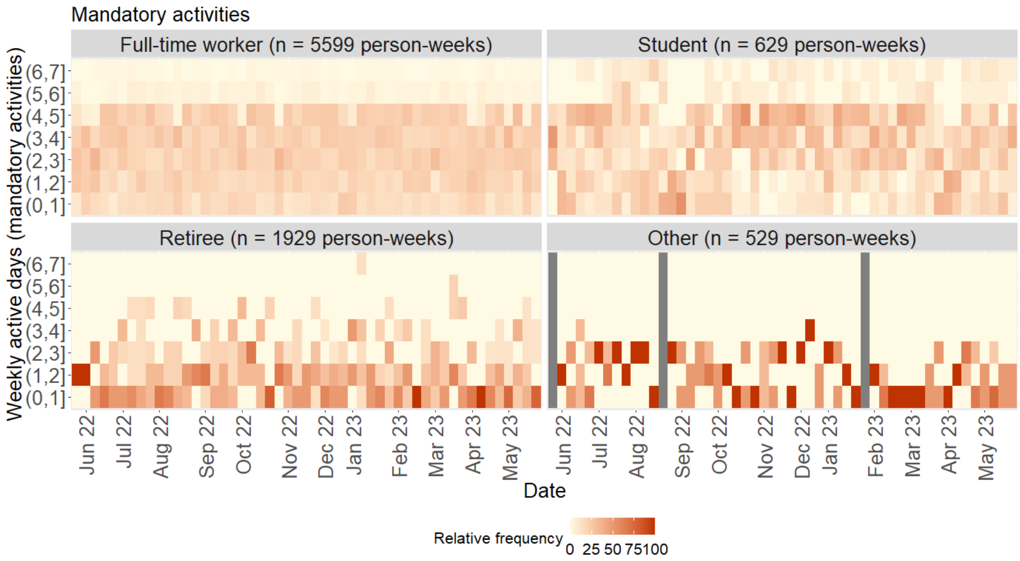
Not surprisingly, students exhibited less regular patterns for mandatory activities. Lecture-free periods (August - September 2022 and March - April 2023) corresponded with fewer active days for mandatory activities, although they were compensated with more discretionary activities. A relatively high share of students (between 15 and 25 %) did not perform any mandatory act in a given week.

Mean weekly active days by employment status

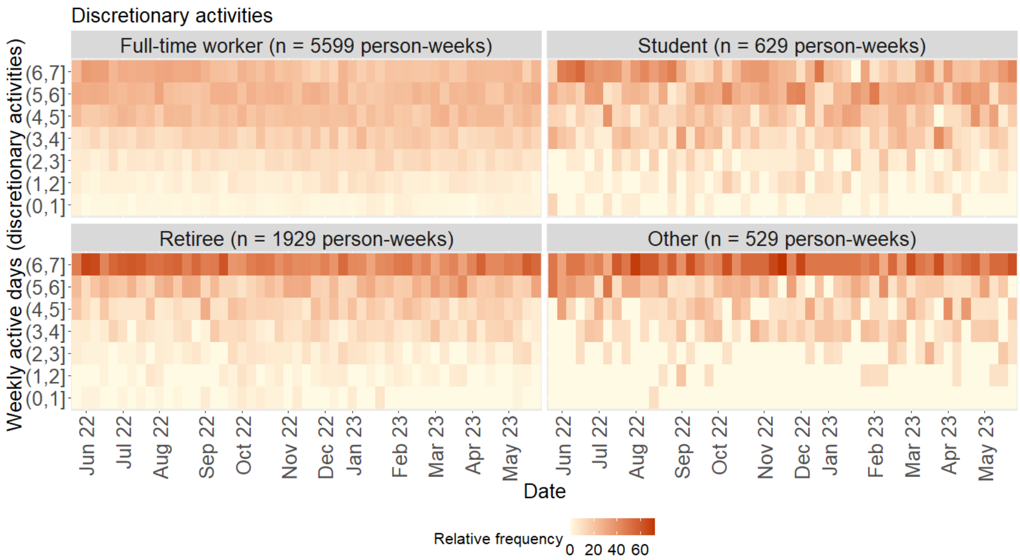
Following the relative frequency analysis, we calculated the mean of weekly active days by employment status and purpose (Figure 4c). Inactive full-time workers and students were defined as individuals who did not perform any mandatory activity in a week.

The mean weekly active days for mandatory acts was close to zero for retirees, others and inactive individuals (Figure 4a). Conversely, full-time workers consistently averaged around 3.4 weekly active days, maintaining a relatively stable mean value. Notably, weeks with a workday holiday decreased mandatory active days, aligning with expectations. In contrast, students displayed more significant variability: mean values for students fluctuated largely, influenced by workday holidays, lecture-free periods and the start of lectures. During the initial two weeks of lectures, mean active days increased from an annual average of 3.8 to peaks of 4.8 weekly active days.

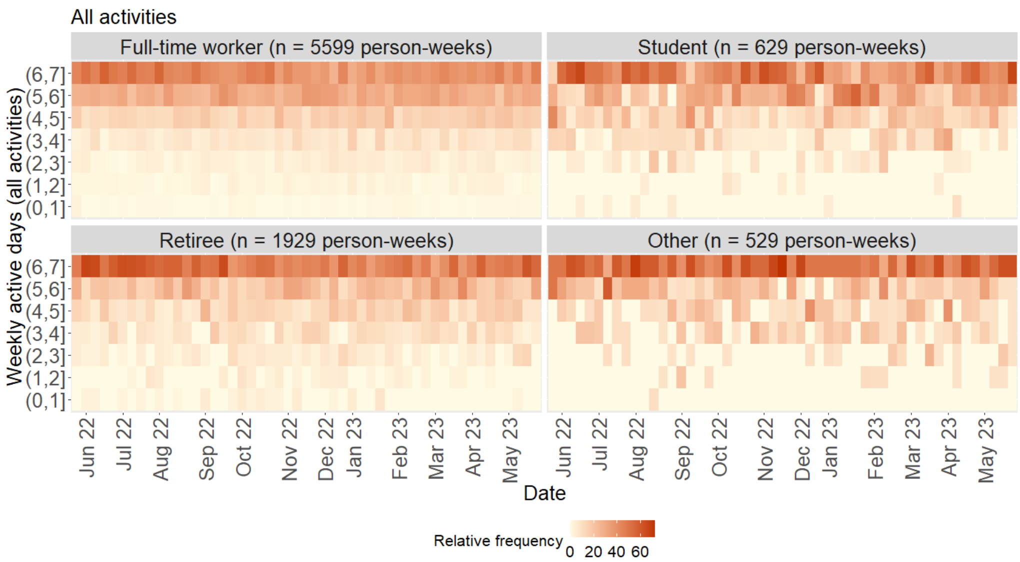
Regarding discretionary activities, results revealed a more stable pattern despite a general trend of fewer activities during winter for full-time workers (Figure 4b). The differences in students' mandatory activities were not reflected in discretionary activities: students engaged more in discretionary activities during weeks with workday holidays, compensating for their fewer mandatory activities. Lecture periods did not emerge as prominently influential in discretionary activities as they did for mandatory activities (Figure 4c).



(a) Mandatory activities

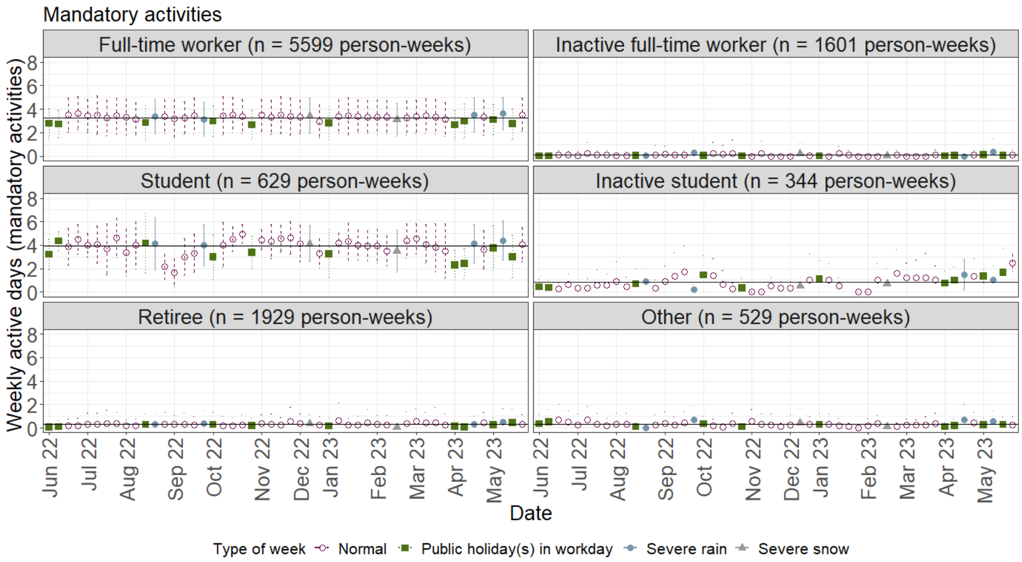


(b) Discretionary activities

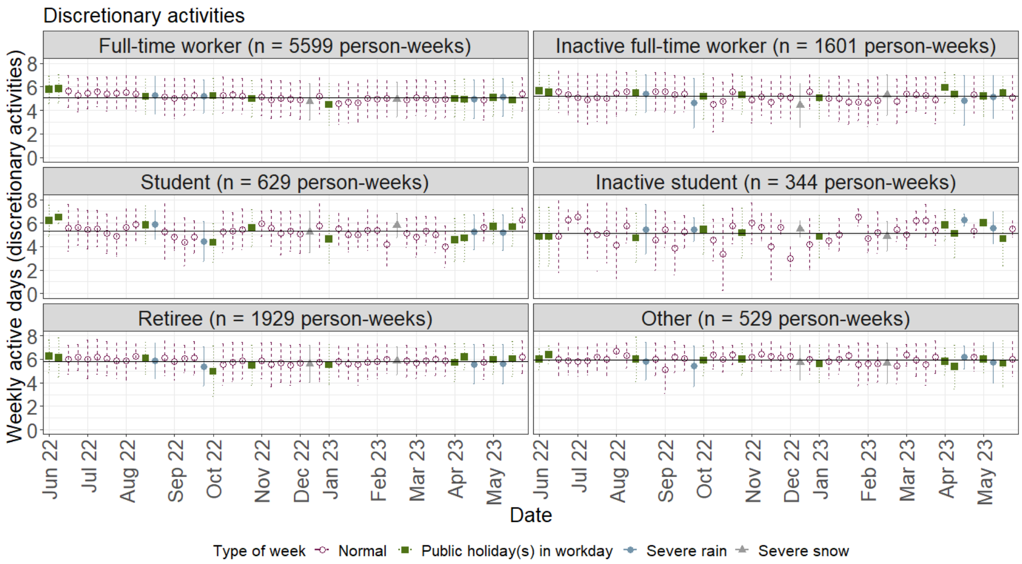


(c) All activities

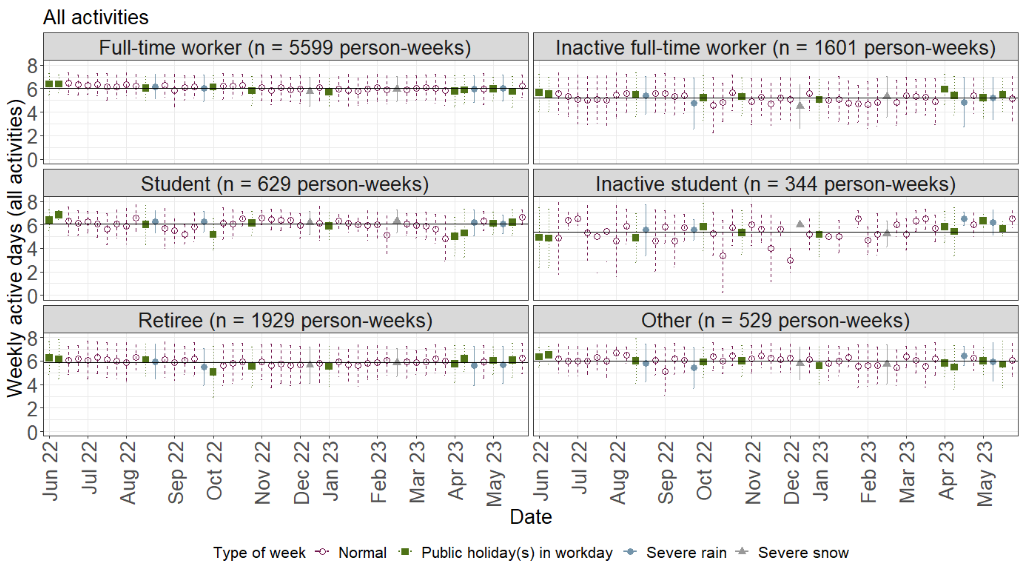
Figure 3: Relative frequency of weekly active days by employment status and purpose



(a) Mandatory activities



(b) Discretionary activities



(c) All activities

Figure 4: Annual variation of the number of active days, by week type, employment status and purpose

Effects of life events

Finally, we evaluated the impact of life events on the mean and dispersion of active days. The coefficient of variation (CV), defined as the ratio of the standard deviation to the mean, was selected as the measure of dispersion. A higher CV indicates higher dispersion on the measurement of the variable. Table 2 summarizes the mean and coefficient of variation by purpose, initial status in wave 1 and if the individual experienced a change in its status in waves 5 or 6 (life event yes/no).

Table 2: Mean and coefficient of variation by purpose and life event occurrence

Initial status	Change	Sample	All activities		Mandatory		Discretionary	
(wave 1)	(wave 5, 6)	size	Mean	CV	Mean	CV	Mean	CV
		Employment status						
Full-time worker	No	181	5.860	0.178	2.708	0.759	5.082	0.260
Full-time worker	Yes	62	5.828	0.193	2.062	0.926	5.181	0.263
Student	No	28	5.682	0.232	3.037	0.640	5.028	0.296
Student	Yes	13	6.283	0.133	2.501	0.869	5.759	0.190
Pensioner	No	53	5.852	0.194	0.285	3.285	5.794	0.199
Pensioner	Yes	1	6.600	0.094	0.644	1.448	6.511	0.107
Other	No	4	6.604	0.058	0.144	4.174	6.599	0.058
Other	Yes	8	5.768	0.165	0.360	1.512	5.695	0.165
		Mobility restriction						
Strongly restricted	-	4	5.021	0.234	0.102	3.886	4.999	0.231
Somehow restricted	-	26	5.544	0.222	1.679	1.722	5.252	0.254
Not restricted	-	317	5.915	0.177	2.126	0.980	5.309	0.241
		Household size						
1 person	No	97	5.907	0.181	2.271	0.806	5.296	0.252
1 person	Yes	5	6.504	0.106	3.664	0.388	5.850	0.179
2 person	No	147	5.875	0.176	1.766	1.274	5.333	0.229
2 person	Yes	4	6.395	0.128	4.047	0.389	5.233	0.228
3 or more	No	93	5.808	0.192	2.214	1.025	5.224	0.254
3 or more	Yes	4	4.678	0.438	2.017	1.332	4.184	0.444
		Household children						
No children	No	262	5.886	0.178	2.042	1.057	5.305	0.241
No children	Yes	3	6.395	0.128	4.047	0.389	5.233	0.228
With children	No	85	5.799	0.200	2.075	1.082	5.259	0.249
		Household income (Euro/month)						
Under 2000	No	43	5.819	0.218	1.856	1.014	5.458	0.257
Under 2000	Yes	7	6.738	0.044	4.273	0.375	6.126	0.144
2000-4000	No	129	5.881	0.177	2.009	1.249	5.270	0.245
2000-4000	Yes	12	6.060	0.165	2.316	0.856	5.625	0.200
4000-6000	No	84	5.866	0.178	2.084	1.092	5.254	0.241
4000-6000	Yes	7	5.680	0.194	2.505	0.912	4.880	0.254
More than 6000	No	62	5.777	0.193	2.021	0.754	5.214	0.248
		Household autos						
One or more autos	No	154	5.812	0.190	1.763	1.322	5.312	0.237
One or more autos	Yes	94	5.858	0.187	2.210	1.036	5.208	0.258
Zero autos	No	96	5.984	0.165	2.437	0.640	5.346	0.239
Zero autos	Yes	6	5.850	0.176	2.218	0.794	5.415	0.225

Employment status and changes in employment status significantly impacted mandatory weekly participation in activities. As expected, full-time workers who discontinued working had fewer weekly mandatory days and increased variability while the weekly discretionary days was higher. Students showed similar results; although the difference in mandatory days was less pronounced, students had substantially more discretionary days on average. Interestingly, retirees had a similar number of weekly active days as full-time workers. A previous study (Moreno, Langer, & Moeckel, 2023) based on survey data concluded that retirees were less active and a substantial share engaged in activities on two or even fewer active days. Semi-passive data could reveal a different behavior, as short trips, usually underreported in traditional household travel surveys, can be recorded.

In agreement with Moreno, Langer, & Moeckel (2023), mobility restrictions significantly affected the results. Individuals with strongly restricted mobility had fewer mandatory activities (around 5 days) compared to those somehow restricted (5.5 days) and not restricted (5.9 days). The sample size was not large enough to account for interactions between employment status and mobility restriction, but generally, mobility restrictions reduced activity for all employment statuses.

The next life events that produced significant differences were household size, childbirth and household income variations. Single-person households who changed to two-person households had more active days and less variability for all activities than other single-person households, as new household members may open the opportunity for more joint activities. Households who increased their income from low to medium also had more activity participation and less variability than households who did not experience the life event. Households without autos were slightly more active than households with autos for all purposes, and households with zero autos who got one car also presented lower activity. It should be noted that the number of these events was relatively low, which could introduce a bias for these results and would require further analysis to evaluate for confounding effects.

4 Conclusions

The results of this paper provide a better understanding of how stable the behavior of individuals is across long periods of time. Occupation status and mobility restrictions were critical factors. Full-time employees were the most stable individuals for mandatory, discretionary and all activities. On the other hand, students presented the least stable patterns, with high seasonal variations of their mandatory activities due to the academic year. Such differences were not too pronounced for discretionary activities, indicating that they maintained activity levels for recreation or shopping. Interestingly, retirees presented relatively stable patterns. Life events impacted this stability: employees who became unemployed increased their variability. On the other hand, students who became employed reduced their variability. The data also showed the impact of mobility restrictions and changes in household size, income and children, although their sample size was limited.

This research also confirmed that passively collected data can correct for the underreporting found in traditional household travel surveys. In contrast to most existing studies on mobile phone data, our dataset included socio-economic data and trip purpose information, allowing us to conduct unprecedented analysis on the stability of travel behavior.

This research only scratches the surface of the stability of travel behavior. Future research will include the time spent out-of-home, the number of trips by mode or recurrence to visit certain areas/points of interest and the use of time series. Furthermore, the data did not allow for distinctions among types of stay beyond mandatory/discretionary. Analysis of shorter periods, without considering the impact of life events, will enable increasing the sample size.

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