Seasonal Trends and Sociodemographic Influences on Long-Distance Trips - A Case Study from Munich

Nico Nachtigall*[1] and Miriam Magdolen[2]

[1]Institute of Automotive Technology, School of Engineering and Design, Technical University of Munich, Germany
[2]Institute for Transport Studies, Karlsruhe Institute of Technology (KIT), Germany

Short summary

This study provides insights into rarely observed long-distance travel patterns of individuals. Collected smartphone tracking data from June 2022 to May 2023 and focused on the Munich metropolitan region allows us to investigate travel behavior and the occurrence of long-distance travel throughout the year. After comprehensive data preparation, long-distance trips are analyzed regarding their occurrence rate and modal share. Furthermore, the influence of various sociodemographic characteristics and car ownership on long-distance travel is investigated. Findings reveal differences in the occurrence of trips, with increased frequency observed during summer, weekends, school holidays, and public holidays. Additionally, the research underscores the impact of sociodemographic factors, particularly household income, leading to elevated levels of long-distance travel activity.

Keywords:
GPS data, Long-distance mobility, Multi-modal transport, Travel behaviour

1 Introduction

Long-distance travel plays a pivotal role in the overall mobility patterns of individuals. From an environmental perspective, the large carbon footprint associated with long-distance travel (Aamaas et al., 2013) is a crucial factor in developing sustainable strategies. Therefore, understanding the patterns of long-distance travel is essential for decision-making in transportation policy and planning. Despite its importance, the level of knowledge in this area is relatively low. Research has focused predominantly on daily commuting and everyday mobility patterns, leaving gaps in the understanding of long-distance travel (Holz-Rau et al., 2014). A major difficulty lies in collecting data on long-distance travel. The more or less sporadic nature of long-distance travel poses a challenge in effectively capturing such trips and journeys (Axhausen et al., 2003). Longitudinal data collection is required to ensure that long-distance events are recorded. However, observing individuals over an extended period of time involves substantial effort and costs. Recent advancements in smartphone-based surveys and passive data collection open new avenues to study long-distance travel patterns in greater detail.

Various factors such as income, education level, age, household composition, and place of residence contribute to different long-distance travel patterns (LaMondia et al., 2014). Further, this type of travel includes various means of transport. In addition to long-distance trains and buses, ships, and airplanes, the car plays a significant role due to its flexibility and easy accessibility. Dargay & Clark (2012) found that car ownership is among a higher income and a higher level of education, related to more of long-distance trips. An analysis of the travel behavior of the German population showed that almost half of the total climate impact of passenger transport is due to car travel (Aamaas et al., 2013). The car can be used universally for everyday and long-distance travel, although for some individuals, one may be more relevant than the other. Especially in urban areas with public transport (PT) as an alternative, it is important to understand how individuals use their cars and whether their long-distance travel behavior can explain car ownership.

In this article, we shed light on the long-distance travel behavior of individuals based on a dataset that contains individual mobility behavior captured through smartphone tracking. With our analyses, we aim to contribute to a comprehensive understanding of long-distance travel behavior, with a special emphasis on car usage and car ownership.

2 Methodology

To observe the occurrence of long-distance mobility in daily mobility routines, we used a GPS tracking dataset with trips of 1,187 participants focused on the metropolitan region of Munich. The tracking time period was between 1 June 2022 and 31 May 2023. The participant's mobility was recorded as GPS traces using a smartphone app, and additional sociodemographic information about the participants was asked in multiple surveys. The data was recorded within the scope of the Mobilität.Leben study (Loder et al., 2024). Several data post-processing techniques have been used to prepare the data for further analysis. To combine the leg-based GPS traces to intermodal trips, legs were joined if the time difference between them was less than ten minutes or the participant labeled the stay with the purpose 'Wait'. Then, the break between two legs was allowed for up to one hour. The mode used for the longest distance within the trip was then chosen as the primary mode of the intermodal trip. To be able to better discuss the presented results, modes detected by the smartphone app were aggregated to the following groups as suggested by Loder et al. (2024):

- *Public transport*: subway, light rail, regional train, train, bus, tram
- *Bicycle*: bicycle, bike-sharing, e-bicycle, kickscooter
- *Individual transport*: car, e-car, motorbike, taxi, uber, carsharing
- *Airplane*: airplane
- *Walk*: walk
- *Other*: boat, other

Mobilität in Deutschland (MiD) reported that mobility behavior highly depends on the area of living (Bundesministerium für Verkehr und digitale Infrastruktur, 2018). The Mobilität.Leben study was focused on the metropolitan area of Munich, but not all participants lived there. To detect the home location, all recorded overnight stays were geo-located. For an overnight stay, we define a stay between two trips if the first trip ends before 9 p.m. and the next trip starts after 7 a.m. at the same geolocation. We used DBSCAN (Ester et al., 1996) with a 30 m epsilon value as the clustering algorithm and chose the centroid of the cluster with the most overnight stays as the home location if the cluster had at least five cluster points. In addition, the participants had the opportunity to label stays as home locations in the smartphone app. This information was used to cross-validate the home location detection we made. The precision rate is greater than 97 %. Only participants with home locations within the local Munich public transport area Münchner Verkehrsverbund (MVV) were chosen for further analysis. In the following, we split the sample into participants with home locations in Munich City and participants with home locations in the surrounding MVV region (which excludes Munich City). In addition, only participants with a tracking period of at least 31 days, a recording time ratio of over 80 %, a recorded coverage ratio of over 99 %, and filled survey information were chosen for further analysis. We calculated the coverage ratio as the ratio between the total tracked distance and the summed gaps between the leg end and the next leg start point. For the following analyses, the legs of 608 participants with, on average, 306 days of tracking history were used. Sociodemographic shares of our sample are shown in Table 1. We additionally combined long-distance trips to long-distance journeys. A journey

Table 1: Sociodemographic share of our sample. All values in percent. Missing values until one hundred percent in employment status are due to missing information.

	Munich City	**Car Owner**	**Households with Children**	**Net Household Income**	**Employment Status**
Sample $n = 608$	79.6	62.2	24.3	$\leq$ 1499 EUR: 12.9 $\leq$ 2499 EUR: 13.8 $\leq$ 3999 EUR: 25.2 $\leq$ 5499 EUR: 18.3 $\geq$ 5500 EUR: 29.8	Student: 16.1 Employed: 71.7 Retired: 8.2

starts with a trip exiting the Munich metropolitan area and ends with a trip returning into the metropolitan area. By this, we can analyze the long-distance travel behavior of the participants both on trip-level and journey-level. To label a trip as long-distance mobility, we used the distance definition of 100 km widely used in the literature (Mattioli & Adeel, 2021).

3 Results and discussion

First, we analyzed the overall occurrence of long-distance trips in our dataset, which is displayed in the upper diagram of Figure 1. We see different trends in our sample. Throughout the year, long-distance trips take place on weekends rather than weekdays, with absolute peaks on public holidays such as Christmas or Easter. In addition, the overall level of long-distance trips is higher during summer (e.g. 06-09.22) compared to winter (11.22-03.23). These seasonal trends can be seen in the bottom diagram of Figure 1. This diagram shows the number of trips per day and tracked participants in the monthly average. We compare the behavior of people living in households with at least one private car with people living in households without a private car as well as people living in the City of Munich with people living in the surrounding MVV region. During the summer months (06-09.22 and 05.23), long-distance trips are nearly equally high in all groups. During the other months, people living in the city of Munich undertook more long-distance trips than those living in the MVV region, except in April 2023. In February and March 2023, the non-car owners undertook slightly more long-distance trips than the car owners. The occurrence of long-distance trips is nearly equal for both groups during the rest of the year.

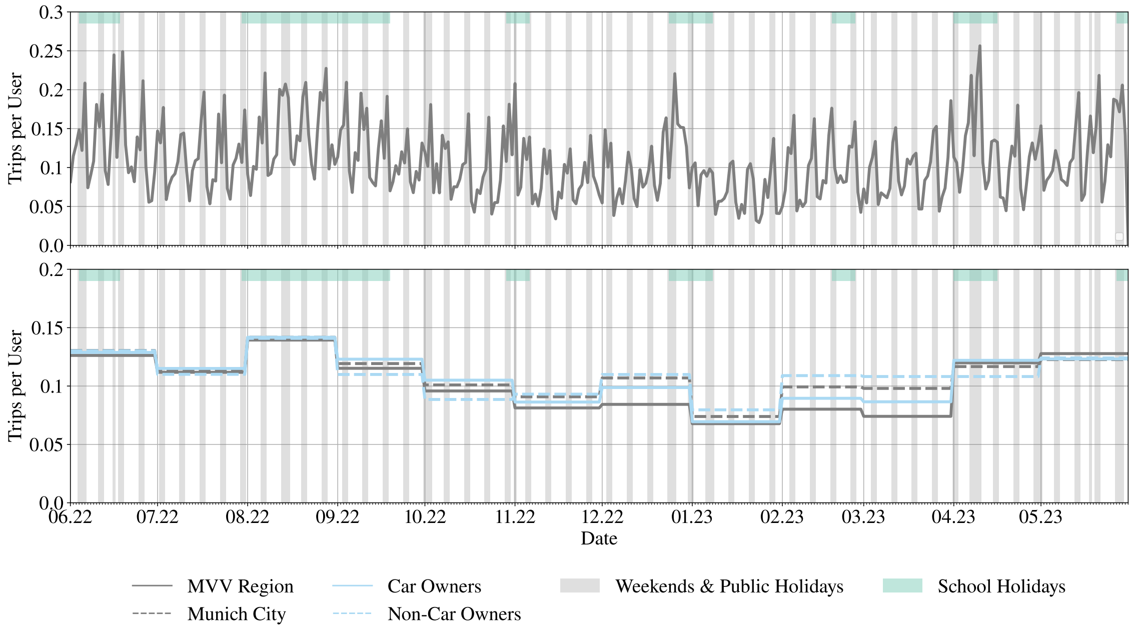

Figure 1: From top to bottom: Long-distance trips per tracked user and day; Long distance trips per day and tracked user on monthly average split in car owners and non-car owners as well as participants with home location in Munich and home location in the surrounding MVV region

The modal share by traveled distance differs significantly between long-distance trips and trips below 100 km in length (Figure 2). The largest difference throughout all groups is for the airplane, with an increase of around 44 percent points. Independent of car ownership, the PT share increases for long-distance trips compared to shorter trips. The difference becomes more apparent when ignoring the traveled kilometers by airplane, bicycle, and walking. Then the modal share for car owners is 31.0 % for PT on trips shorter 100 km and 39.8 % for long-distance trips. The share increase is nearly the same as for the tracked non-car owners. They used in 65.6 % the PT for kilometers made on trips shorter than 100 km and increased the share to 73.9 %. Only participants living in the MVV region used PT slightly less for long-distance trips with 33.2 % for trips below 100 km and 32.4 % for long-distance trips. In all groups, the airplane is an important mode for long-distance trips, while individual transport loses shares to PT in comparison to shorter trips.
One main advantage of the tracking data is, besides the tracking duration, the geo-information about the trips. To analyze the start and end point locations of long-distance trips, we split our

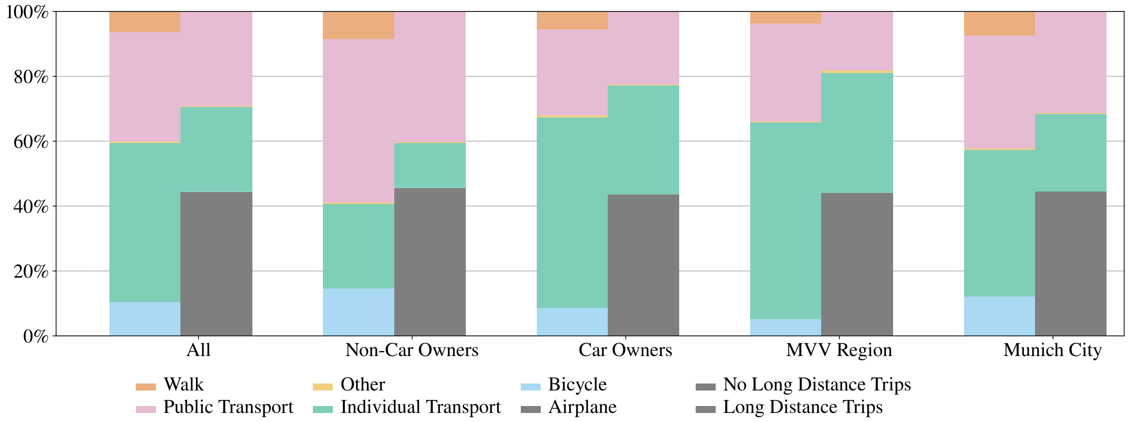

Figure 2: Modal Share by traveled distance for trips below 100 km in comparison to the modal share for long-distance trips.

sample again into car owners and non-car owners. Even though the modal share of both groups is noticeably different, the visited locations with long-distance trips aren't. We aggregated the geo points in regiostar17[1] areas to find differences in areas with lower PT density, but even here, differences were hardly noticeable.

In general, a long-distance trip is part of a longer journey. After identifying journeys in our dataset, we see that one journey contains, on average, 2.5 long-distance trips and has a duration of 4 days. All data shown in Figure 3 refers to the calculated journeys. In the upper part of the figure, for each day over the observation period, the total share of participants traveling on a journey is shown. We distinguish between journeys done with all modes and journeys done by individual transport. It is clearly visible that the share of people on a journey oscillates nearly every week, with the lowest point at the beginning of the week and the highest point on weekends. The share of journeys is, in general, higher in times with school holidays in Bavaria and has three local highs in the second week of the summer holidays, at the Christmas weekend, and at the Easter weekend. The share of journeys done by individual transport follows the same course. The lower part of the figure is split into three different parts. It splits the group of tracked participants by (left) household income, (middle) employment status, and (right) children living in the household. The data visualized is the aggregated share of participants who went on a journey over all days of the tracking period, e.g., on a "median" day with no school holidays 10 % of all employed participants were on a journey. The left diagram shows that when the household income increases, the share of participants on journeys increases. The clearest differences are shown for days in the school holidays. Overall, households earning less than 1499 EUR fall out of the trend. Most likely, the reason for that is our sample. This household group contains 72 % students. Even though students earn most likely less than other households, their journey behavior does not significantly differ from employed people (shown in the middle diagram). Only retired people in our sample have a lower share of journeys on school holidays and weekends. A child living in the household increases the share of journeys on days with school holidays, as shown in the right diagram. On days with no school holidays, the share is slightly lower than for households not having a child.

To transfer the presented results to the whole population of Germany is impossible. Furthermore, even conclusions about the mobility behavior of the inhabitants of Munich must be discussed carefully as all results presented here are observations of our biased sample (more information about the sample consistency is published by Loder et al. (2024)). Nevertheless, due to the long tracking period of one year, the results presented give new insights into the rarely occurring long-distance travel behavior.

4 Conclusions

We used data from a GPS-tracking case study lasting one year with multiple hundred participants to gain insights into the important field of long-distance mobility. Our results showed that long-distance trips fluctuate throughout the year, but certain patterns can be identified for our sample.

[1] `https://bmdv.bund.de/SharedDocs/DE/Artikel/G/regionalstatistische-raumtypologie.html`

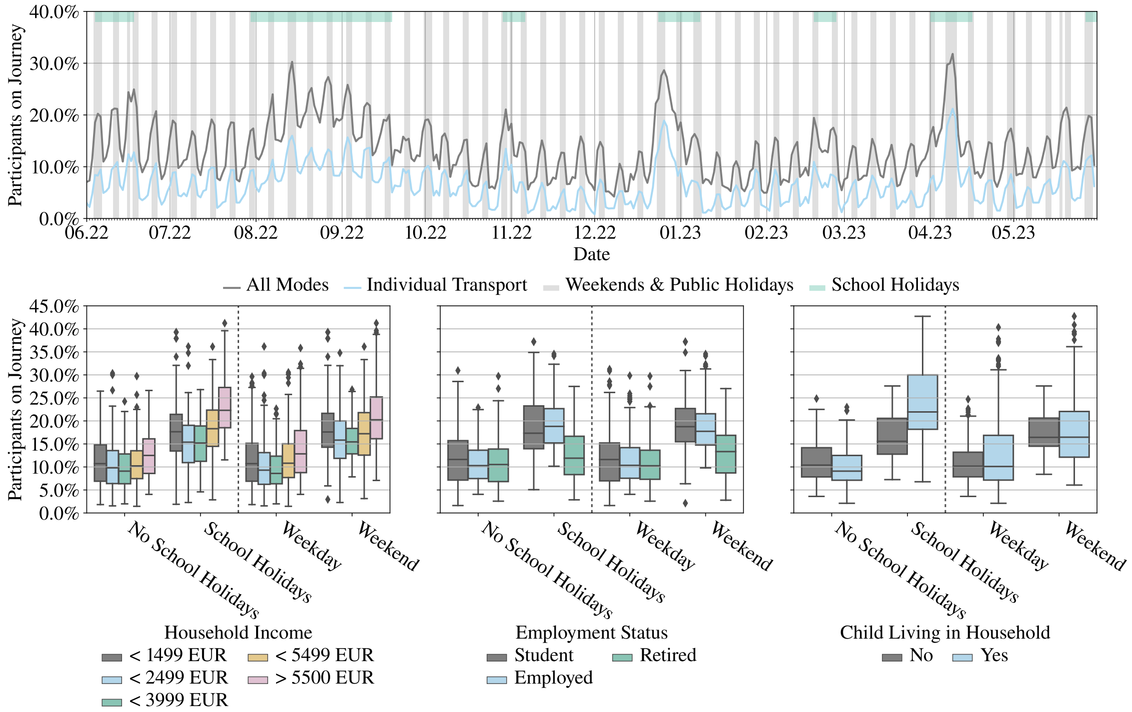

Figure 3: From top to bottom: Share of participants gone for a journey for every tracking day; Share of participants daily gone for a journey, the panel is split by household income (left), employment status (middle), and children living in household (right).

The occurrence is higher on weekends than on weekdays, higher in summer than in winter, and highly increased around public holidays. One learning for traditional travel surveys is, that the timing of the survey matters. The results will highly differ if a survey period is in August compared to January. This is especially important for short observation periods. The modal share for long-distance trips is dominated by airplanes independent of home location (suburban vs city) and car or non-car ownership. For long-distance trips, the share of public transport increased, while the share of individual transport decreased compared to shorter trips.

Our findings show, that an average journey contains more than two long-distance trips and lasts for about four days. How often participants go on a journey is positively related to their household income. Students have quite similar journey behavior to employed participants, and the behavior of retired people is not as much influenced by weekends and school holidays as the other groups are. However, a child living in the household influences the long-distance journey behavior strongly.

Overall, our findings can not be generalized but give detailed and new insights into the long-distance mobility behavior of people living in Germany. Nevertheless, further research is needed to combine our findings with findings about everyday mobility to gain a complete picture of the mobility behavior of people.

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