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Seasonal Trends and Sociodemographic Influences on Long-Distance Trips - A Full Year of GPS Tracking Data from Munich

Nico Nachtigall[1], Miriam Magdolen[2], Markus Lienkamp[3]

[1] corresponding author nico.nachtigall@tum.de, Institute of Automotive Technology, School of Engineering and Design, Technical University of Munich (TUM), Germany; 0000-0002-8591-2126
[2] Institute for Transport Studies, Karlsruhe Institute of Technology (KIT), Germany; 0000-0003-0452-2474
[3] Institute of Automotive Technology, School of Engineering and Design, Technical University of Munich (TUM), Germany; 0000-0002-9263-5323

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Abstract

This study provides insights into the rarely observed long-distance travel patterns of individuals. Collected smartphone tracking data from June 2022 to May 2023, 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, the recorded modal share and the share of observed long-distance trips are compared with the findings of a German travel survey to investigate the benefits of the dataset. Long-distance trips are further analyzed in terms of their occurrence rate and modal share throughout the year. Furthermore, the influence of various sociodemographic characteristics and car ownership on long-distance travel is explored. The primary usage of privately owned cars is also analyzed. Our 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 and age, on elevated levels of long-distance travel activity. Our research indicates that a significant share of car owners in the urban area use the car primarily for long-distance trips.

1 Introduction

Understanding long-distance travel behavior is crucial for developing effective transport policies and sustainable mobility solutions. Although long-distance travel accounts for a relatively small proportion of all travel, it is responsible for a significant proportion of the total travel distances and associated emissions (Aamaas et al., 2013; Schulz et al., 2024; Wadud et al., 2024). As evidenced by recent data, the recovery of travel demand to pre-pandemic levels underscores the relevance of studying long-distance travel. For instance, in Germany, tourist travel recovered in 2023 after a sharp drop during the coronavirus pandemic. With 250.6 million journeys in 2023, the demand almost recovered to the level of 2019 (260.5 million), while during the pandemic, the level was much lower (2020: 146.2 million) (Statistisches Bundesamt, 2024). Overall, the recovery of travel demand has been observed worldwide, and even higher demands are expected to follow (Gössling et al., 2021; Mattioli et al., 2023).

At the same time, long-distance travel remains less studied compared to everyday travel, primarily due to the significant challenges in data collection but also due to a lack of interest among policymakers and research funders. Long-distance travel requires longitudinal data to accurately reflect the infrequent and often irregular nature of such journeys in individual behavior (Aultman-Hall et al., 2015). The availability of this kind of data for this article provides new insights into long-distance travel by capturing long-distance travel events and analyzing the seasonal and weekday/weekend variation in individual and collective longitudinal mobility behavior.

Long-distance travel plays a pivotal role in individuals' overall mobility patterns. While long-distance trips comprise only a small share of all trips, they account for large parts of the distances traveled (Gerike and Schulz, 2018). In Germany, for example, only 1.7 percent of all trips have a minimum distance of 100 km, but these trips account for about 46 percent of the traveled distances (Schulz et al., 2024). Similar results were found in Great Britain: Less than two percent of the journeys exceed a minimum distance of 50 miles, but they explain more than 30 percent of the distances traveled (Dargay and Clark, 2012). Most recent results for England show that this interrelation still exists, as about three percent of all trips have a minimum distance of 50 miles, but they account for about 60 percent of the distances traveled (Wadud et al., 2024). Moreover, when considering the resulting greenhouse gas emissions from passenger travel, the study shows that almost 70 percent is contributed by long-distance travel.

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 (Gerike and Schulz, 2018; Holz-Rau et al., 2014). The more or less sporadic nature of long-distance travel poses a challenge to effectively capturing such trips and journeys (Malichová et al., 2022). 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 (Aultman-Hall et al., 2015; Axhausen et al., 2003).

In this article, we use a new longitudinal dataset to shed light on the long-distance travel behavior of 532 individuals. The data, collected by Loder et al. (2024) from June 2022 to May 2023, focusing on the Munich metropolitan region, and contains GPS-based individual mobility behavior captured through a smartphone application. We examine the comprehensive dataset obtained from several different dimensions. First, we investigate the mode choice of long-distance travel and its relationship to car ownership and home location. These calculations provide an overview of the relationship between the availability of modes and their use in long-distance travel. We then explore the travel behavior over an entire year and provide valuable insights into the temporal dynamics and seasonal trends of long-distance travel. Only through such long-term analyses is it possible to reliably record the rarely occurring long-distance travel and investigate temporal and seasonal trends. In our research, we differentiate between car owners and non-car owners and split the sample into participants living in an urban and a more rural area to investigate the impact of these different influencing factors on seasonal trends in long-distance travel. Furthermore, we examine the impact of other sociodemographic characteristics to improve the understanding of long-distance travel patterns as a basis for policy recommendations. Lastly, we quantify the importance of long-distance travel on car usage by car owners in the urban area of Munich. Understanding this influence is essential for providing appropriate, more sustainable, and less space-consuming alternatives to private car use.

This article is structured as follows: In the next section, we provide an overview of current research on long-distance travel, the methods used, and highlight the special role of the car as a mode of transport. In Section 3, we introduce the datasets used, the methodology applied to match the data, and explain the post-processing techniques used to process the GPS dataset further. The results are presented in Section 4. The final section discusses our findings, identifies the limitations of our research, and indicates possibilities for further research. The article concludes with a summary of our findings.

2 Literature Review

A substantial aspect of studying long-distance travel is its definition. To date, no standardized definition of long-distance travel exists, which makes it challenging to compare data and information from different data sources. While most studies in transportation research use distance-based criteria, e.g., a minimum distance of 100 km (LaMondia et al., 2014; Mattioli and Adeel, 2021; Schulz et al., 2024; Wadud et al., 2024), some studies use an overnight criterion or focus on specific purposes, such as holiday travel (Christensen, 2018; Gerike and Schulz, 2018; Große et al., 2019). While researchers and studies are divided regarding their definitions of long-distance travel, they are in agreement regarding the identified factors influencing long-distance travel behavior. It was shown that various factors such as gender, occupation, education level, income, age, place of residence, and household composition contribute to long-distance travel behavior (Czepkiewicz et al., 2020; Dütschke et al., 2022; Holz-Rau et al., 2014; LaMondia et al., 2014; Mattioli et al., 2023). A recent study from Germany shows, in line with the mentioned literature, that people who are male, employed, highly educated, and have a high income travel more kilometers in long-distance travel than their counterparts (Magdolen et al., 2022; Schulz et al., 2024). Further results show that middle-aged groups (25 to 55 years) have a higher demand for long-distance trips than younger or older age groups (Magdolen et al., 2022). Regarding household composition, it was found that having children is related to fewer international and overnight journeys (LaMondia et al., 2014). Research also indicates that residents of urban areas engage in more long-distance travel compared to their counterparts in suburban or rural regions (Czepkiewicz et al., 2020; Ottelin et al., 2014; Reichert and Holz-Rau, 2015), and living near a large airport is related to a higher demand for air travel (Mattioli et al., 2021). Residents from more rural areas show higher car use in everyday travel than their counterparts living in urban areas. However, when it comes to long-distance travel, people living in urban areas show a higher travel frequency and cause more emissions (Dütschke et al., 2022). A few studies also suggest intra-urban variations, with individuals in densely populated districts exhibiting distinct long-distance travel patterns (Czepkiewicz et al., 2018). Such variations might be explained by residential choice and psychological or 'lifestyle' factors such as a cosmopolitan attitude (Czepkiewicz et al., 2020; Große et al., 2019).

All these characteristics related to long-distance travel result in an unequal distribution of the overall long-distance travel demand. Only a small part of the population belongs to frequent long-distance travelers, whereas large parts do not or seldom participate in long-distance travel (Büchs and Mattioli, 2021; Schulz et al., 2024). Regarding emissions resulting from travel, the inequality becomes even more substantial, which is mainly due to air travel (Gössling and Humpe, 2020; Mattioli et al., 2023), but can also be seen for car travel (Klein and Taconet, 2024). As mentioned, however, most studies rely on cross-sectional data with limited observation periods, e.g., one-day trip diaries, or retrospective data collection over a limited period, e.g., the last three months. Longitudinal data is necessary to understand seasonal trends and the variation in individual long-distance travel behavior. It remains of interest how sociodemographic characteristics such as variation in mode use can be related to variations in long-distance travel behavior.

2.1 *Methods to capture and analyze long-distance travel*

Many national household travel surveys aim to collect data on long-distance travel with a retrospective approach, e.g., asking about overnight trips in the last three months (Gerike and Schulz, 2018). However, retrospective data over longer periods are influenced by recall effects, especially by frequent travelers, which result in a loss in accuracy and reliability (Aultman-Hall et al., 2015; Christensen, 2018). In addition, long-distance travel is highly dependent on temporal conditions. The demand for long-distance travel varies depending on the season, e.g., summer vs. winter, and the type of day (weekdays, weekends, and public holidays) (Axhausen et al., 2003). Therefore, the long-distance travel captured in surveys varies with the chosen observation period. While earlier attempts with annual survey periods had difficulties with low response rates and fatigue (Aultman-Hall et al., 2015), there is a prospect of improved data collection: Advancements in smartphone-based surveys and passive data collection open new avenues for studying long-distance travel patterns in greater detail (Malichová et al., 2022). A smartphone application to analyze long-distance travel was used by Malichová et al. (2022). However, due to the study design and the short observation period of on average seven days for each participant, only an excerpt of long-distance trips could be detected. Furthermore, no detailed analysis based on sociodemographic characteristics or seasonal trends could be made. Based on mobile phone data, Janzen et al. (2018) investigated long-distance travel in France and compared their results with those of a national travel survey to investigate the true number of long-distance travel events. However, they did not investigate seasonal trends, modes of use, or exclude international trips. Molloy et al. (2022) used a smartphone application for several months to study mobility behavior, but they did not focus on long-distance travel. To the best of our knowledge, we provide the first insights into individual long-distance travel based on a longitudinal GPS tracking smartphone application.

2.2 *Car use in long-distance travel*

Long-distance travel includes various modes of transportation. In addition to long-distance trains, buses, and airplanes, the car plays a significant role due to its individuality, flexibility, and easy accessibility. The dominance of the car as the main mode in long-distance trips is also shown in the study of Wadud et al. (2024) for England. For the German population, it was determined that about 45 percent of the distances traveled within long-distance trips (including air travel) are traveled by car (Schulz et al., 2024). Another 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). In a study analyzing travel data from an app-based survey in eight European countries, it was found that in 66 percent of the captured long-distance trips, the car was the main mode (including car as a driver and car as a passenger) (Malichová et al., 2022). However, the authors highlight that it is not clear if people decide to use the car as a means of transportation because of its characteristics, e.g., convenience, flexibility, door-to-door travel, or because the car is the only option. Travel at the destination, e.g., flexibility in the selection of locations to visit, can lead to a preference for traveling by private car (Bursa et al., 2022). In addition, sociodemographic characteristics are related to the frequency of car use in long-distance travel. Compared to singles or young couples, families with children choose the car more often as a means of transport for holiday travel (Böhler et al., 2006). The importance of analyzing the overall mobility behavior of individuals, including everyday and long-distance travel behavior, becomes evident in several studies focusing on car use and air travel. It was found that some people, mainly living in dense urban areas, show a low level of car use in everyday travel, but at the same time show a high demand for air travel (Ottelin et al., 2014). Thus, in everyday life, they behave in a comparatively environmentally friendly manner, but in long-distance travel, they are high emitters (Mattioli et al., 2023). Further, it was shown that people may reveal similar everyday travel patterns, but are different in their long-distance travel (Miriam Magdolen et al., 2022), which highlights the necessity to analyze the overall travel behavior of individuals. An indication that car ownership is not only relevant for everyday travel patterns was detected by Dargay and Clark (2012), who found that car ownership is among higher income and a higher level of education, is related to more long-distance trips. In a study of residents in Greater Copenhagen, it was found that car ownership was positively related to a higher number of weekend and holiday trips (Große et al., 2019); however, in this study, these effects were not shown to be significant.

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 as an alternative, it remains of interest to understand how individuals use their cars every day and especially in long-distance travel, and how the latter is related to car ownership.

Based on the reviewed literature, we define four research questions for this publication: What is the proportion of long-distance travel in the total travel behavior collected in longitudinal tracking data? Do seasonal trends exist in long-distance travel? Do sociodemographic characteristics such as employment status, age, household income, household size, and children living in the household influence the time of occurrence of long-distance travel? What is the significance of cars in the context of everyday and long-distance mobility, and does the area of living influence this significance?

3 Data sources and methodology

In this article, we analyze a recent longitudinal GPS dataset focusing on long-distance travel. We compare the findings with a large German travel survey to highlight the insights gained from this new dataset. In this section, we introduce the datasets and clarify the methodology used for data processing and matching of the two datasets.

3.1 Datasets

The GPS dataset was collected with a smartphone application in 2022 and 2023. As a comparison, we use the survey-based Mobilität in Deutschland (MiD) dataset from 2017, which is a national household travel survey in Germany. The datasets are introduced in more detail in the following sections.

GPS Dataset

To observe the daily mobility routines of individuals and the occurrence of long-distance travel, we used a GPS tracking dataset with trips of 1,187 participants focused on the metropolitan region of Munich. A media campaign was used to recruit the participants. Everyone was free to register, but needed to be aged 18 or older. The tracking period was between 1 June 2022 and 31 May 2023. The participants' mobility was recorded as GPS traces using a smartphone app called Mobilität.Leben. The app was a white-label third-party solution from MOTIONTAG and has also been used by Loder et al. (2024). Additional sociodemographic information about the participants was collected in multiple surveys. With the smartphone app, the participants could voluntarily correct the detected mobility behavior. The options included assigning a different mode to a recorded leg, joining two different legs to one, and labeling a leg as completely wrong. The smartphone app also automatically recorded stays between different legs. The participant could assign a purpose to the recorded stay during the post-processing step. The data was captured within the scope of the Mobilität.Leben study (Loder et al., 2024). In total, 2,795,945 monomodal legs have been recorded.

German travel survey - Mobilität in Deutschland

The German Travel Survey (MiD) from 2017 (Bundesministerium für Verkehr und digitale Infrastruktur, 2018) was conducted between June 2016 and September 2017 as a national travel survey to gain a representative overview of the everyday mobility behavior of the German population. The participants were selected at the household level and filled in a one-day mobility diary. Municipalities were able to set a special focus by ordering a larger sample from their region. Together with the other municipalities united in the Münchner Verkehrsverbund (MVV) region (region of Munich's regional transportation network), the city of Munich decided to order this enhanced data collection. In this way, a representative view of the mobility behavior of people living in the MVV region is available (Belz et al., 2020). For the German-wide study, 316,361 people participated and reported 960,619 trips. The (MVV) region had 29,353 participants, who reported 90,031 trips. The German-wide dataset is called *MiD Germany,* and the regional (MVV) dataset is called *MiD MVV* in the following.

3.2 GPS dataset - Data preparation

We used several data post-processing techniques to prepare the GPS dataset to be able to compare the data with the German travel survey and for further analysis. The different steps are visualized in Figure 1.

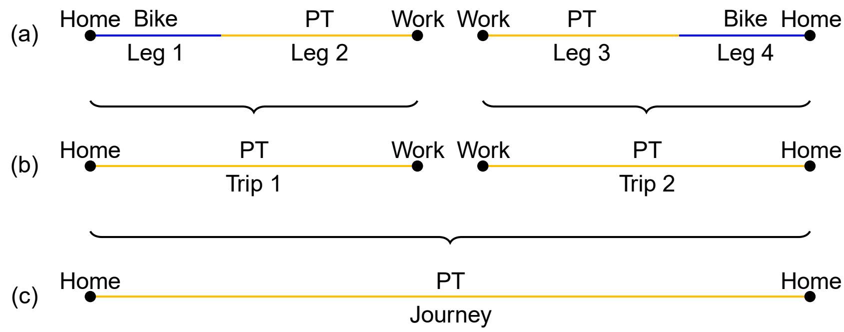


Figure 1. From top to bottom: (a) the original state without post processing the data contains only mono-modal legs (PT: public transport); (b) combining multiple legs to a trip (e.g. from home location to work location); (c) combination of multiple trips to a journey (from home location to home location)

State (a) shows the original state of the used smartphone app offered as a data dump from the smartphone app provider. We joined the different legs to an intermodal trip if the time difference 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, resulting in state (b). For some analyses made for long-distance trips, we decided to join several trips to a journey (c). A journey always starts at a participant's home location and ends there again at the next visit. The mode used for the longest distance within a journey was assigned to the journey. If a journey contains at least one long-distance trip, we define it as a long-distance journey. To label a trip as long-distance, we used the distance definition of 100 km, which is widely used in the literature (Mattioli and Adeel, 2021). The used smartphone application can automatically detect many different modes, and additional ones could be chosen by the participants in the post-processing, which are marked in the following listing. Not every participant did this post processing step. To minimize the impact of a wrong mode detection on the analysis, we aggregated modes into the following groups:

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

MiD Germany 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 defined a stay between two trips if the first trip ended before 9 p.m. and the next trip started after 7 a.m. at the same geolocation. We used DBSCAN (Ester et al., 1996) with a 30 meter 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 was greater than 97 percent. The detected home locations of all participants in Germany are shown in Figure 2 (left), whereas participants with home locations within the MVV area were chosen for further analysis.

In the following, we split the sample into participants with home locations in Munich City and those with home locations in the surrounding MVV region (excluding Munich City). In addition, only participants with a tracking period of at least 31 days, a recording time ratio of over 80 percent, a recorded distance coverage ratio of over 99 percent, and filled survey information were chosen for further analysis. We calculated the distance coverage ratio between the total tracked distance and the summed gaps between the leg end and the next leg's start point. For the following analyses, the legs of 614 participants were used. Their home locations are displayed in Figure 2 (right).

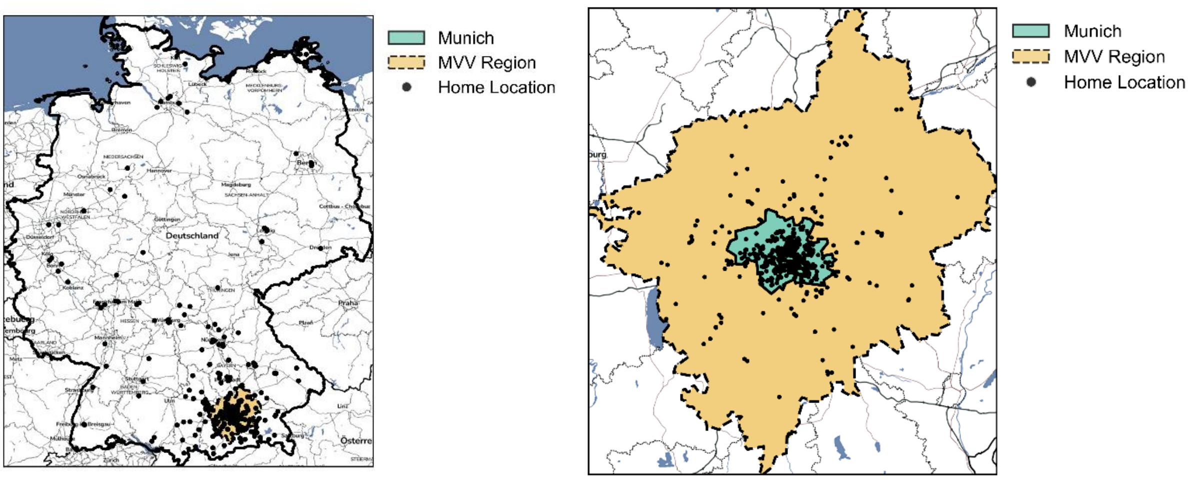


Figure 2. Home locations of participants. Left: Home locations of participants living in Germany. Right: Home locations of all participants were analyzed further.

3.3 *Matching the MiD data and GPS dataset*

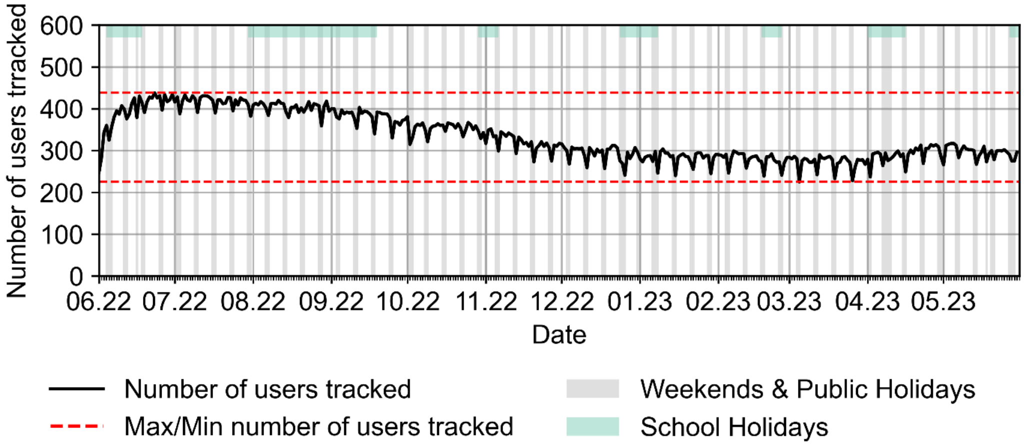
Our main research interest in this article is the long-distance mobility recorded in the GPS dataset. As described earlier, the sample is biased, and the results will not become representative and reliable even when we apply different weighting techniques. Therefore, we decided to use the representative MiD survey and sample participants from it to investigate the benefits of the GPS tracking technique compared to the travel survey-based method used in the MiD.

The sample in the GPS dataset was biased and only located in the Munich Metropolitan region. To find a corresponding sample in the MiD data, we matched the 614 participants we selected from the GPS dataset person-wise with participants of the MiD MVV sample. In this way, we only compared the mobility of people living in the MVV region. The matching was performed considering parameters widely used in the literature for sample weightings, such as age, gender, education level, and employment status (Bundesministerium für Verkehr und digitale Infrastruktur, 2018; Ecke et al., 2023). Furthermore, we decided to add household size, the information about children in the household, car ownership in the household, and the home location as matching parameters as we analyze the mobility behavior based on these characteristics in Section 4.

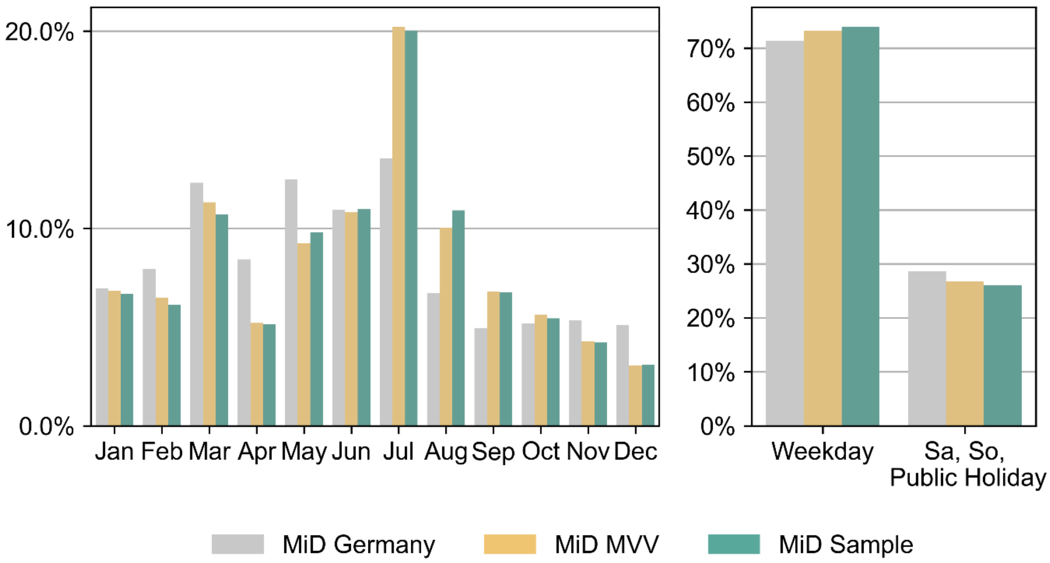
With the matching approach, 532 out of the 614 participants in the GPS dataset are directly represented by 8345 participants in the MiD MVV dataset. This means that we could find at least one participant in the MiD MVV with the exact same sociodemographic characteristics for each of the 532 participants in the GPS dataset. A one-to-many connection was possible. The other participants in both datasets have no direct representative and are neglected in the further analysis. As the main objective of this article is the knowledge gained from the GPS dataset, we define weighting factors for the matched MiD MVV participants such that the sum of all weighting factors of the matched MiD MVV participants representing one GPS dataset participant is equal to one. The weighting factor of participants within one group is equal. The resulting sample is used for further analysis. The matched and weighted MiD dataset is called *the MiD sample,* and the GPS dataset containing just matched participants is called the *GPS dataset* in the following sections.

3.4 *Seasonal characteristics of the datasets*

The selected sample of the GPS dataset is not constant over the full recording period, as visualized in Figure 3a. The ramp-up phase in June 2022 is because the sample acquisition started on short notice in the second half of May 2022 (Loder et al., 2024). In the second half of June 2022, the maximum number of parallel-tracked participants reached 438. Due to a slow drop-off rate, a minimum of 225 participants were reached in March 2023. At this time, a new advertisement round started and slightly increased the number of tracked participants. We offered two rounds of a small financial incentive (30€ and 20€) for participation in the form of a voucher during the year. On average, participants were tracked for 227 days. Also, the samples of the three MiD datasets are distributed throughout the year. The distributions of the one-day travel diary are shown in Figure 3b.



(a) Number of tracked participants over the tracking period in the GPS dataset.



(b) Left: Distribution of participation in the various MiD studies throughout the year; Right: Distribution between weekdays and weekends, including public holidays.

Figure 3. Distribution of samples over the year.

3.5 Sociodemographic characteristics of the sample

Due to the experimental design, the sample of the used GPS dataset is biased. The resulting sample distribution over the used matching parameters is shown in Table 1, in comparison to the official data for the population of Munich and the MVV region. Compared with the official data, it is visible that the sample from the GPS dataset is too young and too well-educated. Furthermore, students are over-represented by 10.2 percentage points, and retired people are underrepresented by 13.0 percentage points. Participants living in a two-person household are overrepresented by 18.6 percentage points, while participants living in a household with four or more people are underrepresented by 13.8 percentage points. The share of households with car ownership and households with children matches the official statistics quite well. At the same time, participants living in Munich are over-represented by 19.0 percentage points in contrast to participants living in the surrounding MVV region. Due to the performed matching process, the sociodemographic characteristics of the MiD sample are identical to those of the GPS dataset.

Table 1. Sociodemographic characteristics of the matched GPS dataset (n=532), the weighted MiD sample dataset (n=8345), and the official statistics for Munich and the MVV region; All values in percent

	GPS dataset and matched and weighted MiD sample	Official statistics Munich + MVV region
Age		Zensus 2011 (Statistisches Bundesamt, 2022a)
18 - 29 years	26.5	18.1
30 - 39 years	23.1	17.4
40 - 49 years	18.4	20.6
50 - 59 years	19.2	15.1
60 - 69 years	8.8	13.1
70+ years	4.0	15.7
Household income		
< 1500 EUR	12.4	-
1500 EUR - 2499 EUR	12.4	-
2500 EUR - 3999 EUR	25.6	-
4000 EUR - 5499 EUR	19.0	-
> 5500 EUR	30.6	-
Gender		Zensus 2022 (Statistisches Bundesamt, 2022b)
Female	48.3	50.8
Male	51.7	49.2
Divers	0.0	0.0
Education level		Zensus 2022 (Statistisches Bundesamt, 2022b)
Secondary School (Hauptschule)	0.9	-
Secondary School (Mittl. Reife)	15.8	-
High school diploma (Abitur)	9.8	-
University degree	73.5	36.2
Employment Status		MiD (Bundesministerium für Verkehr und digitale Infrastruktur, 2018)
Student	15.2	4.8
Employed	72.9	61.4
Retired	8.7	21.7
Other	3.2	12.1
Household size		Zensus 2022 (Statistisches Bundesamt, 2022b)
1	24.8	23.7
2	44.7	26.1
3	12.0	18.0
4	18.4	32.2
Children in household		MiD (Bundesministerium für Verkehr und digitale Infrastruktur, 2018)
Yes	24.8	20.0
No	74.8	80.0
Car ownership in household		MiD (Bundesministerium für Verkehr und digitale Infrastruktur, 2018)
Yes	66.7	69.0
No	33.3	31.0
Home location		Zensus 2022 (Statistisches Bundesamt, 2022b)
Munich	78.8	49.8
MVV	21.2	50.2

4 Results

In this section, we first present the overall recorded mobility results with the GPS dataset in comparison with the recorded mobility behavior of the matched and weighted MiD sample, calculated as described in Section 3, as well as the overall MiD results for Germany. A more detailed analysis was then made for the observed mobility behavior in the GPS dataset to give a comprehensive view of the long-distance mobility behavior.

4.1 *Modal share*

In the GPS dataset, we recorded 532 participants' 1,155,236 monomodal legs, combined them to 475,967 trips, including 14,500 long-distance trips (trips above 100 km), and combined them further to 149,404 journeys, including 6,034 long-distance journeys. The matched MiD sample dataset recorded for 8,345 participants 32,351 trips, including 749 long-distance trips.

The number of daily recorded trips per active participant (at least one recorded trip) is in all three datasets, with 3.7 trips per day in the MiD Germany dataset, 3.9 trips per day in the MiD sample dataset, and 4.1 trips per day in the GPS dataset, comparable to high. The average traveled distance varies at 46 km per day in the MiD Germany dataset, 54.2 km in the MiD sample dataset, and 80.3 km in the GPS dataset. When excluding long-distance trips, the average traveled distance per day in the MiD sample dataset is 33.2 km, and in the GPS dataset, 29.5 km. We observe long-distance trips in all three investigated datasets, but the share is different. The lowest share is in the MiD Germany dataset at 1.5 percent. In the MiD sample, the share of long-distance trips is 2.0 percent, and the highest share is in the long-term GPS tracking dataset at 3.0 percent. The average traveled distance, when only long-distance trips are included, is in the MiD sample at 21.0 km, which is less than half of the average distance in the GPS dataset at 50.6 km.

The recorded share of kilometers traveled in association with long-distance trips in the MiD Germany dataset is 29.3 percent, and the share in the GPS dataset is 63.7 percent, as shown in Figure 4. The results from the MiD sample indicate, at a share of 38.5 percent, that the matched sample traveled more long-distance trips than the average population of Germany (shown in Figure 4), but the share of kilometers traveled in long-distance trips is still 25 percentage points lower than the share of the GPS dataset sample.

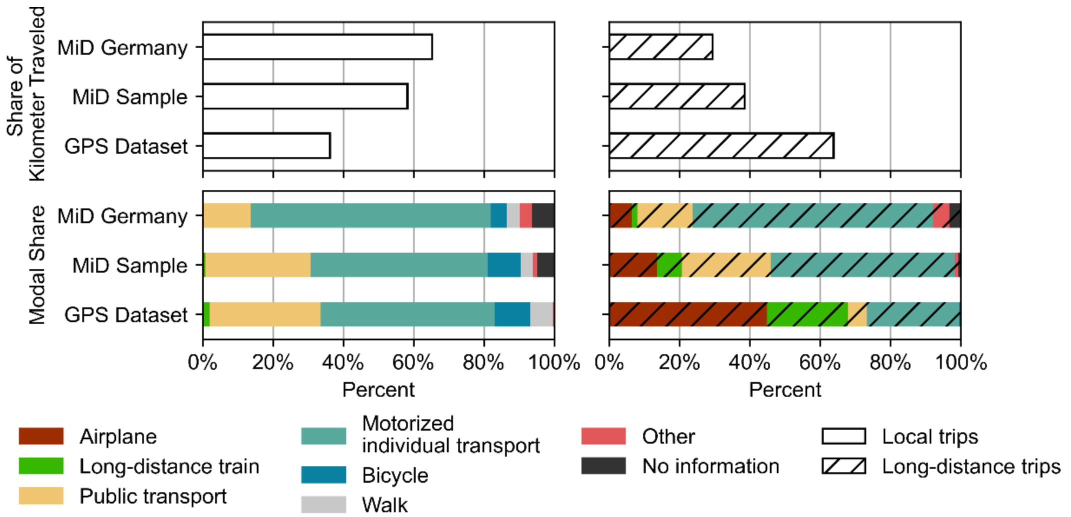


Figure 4. Left top: Share of kilometer recorded associated with local trips for the three analyzed datasets; Right top: Share of kilometer recorded associated with long-distance trips; Left bottom: Distance-based modal share for recorded local trips; Right bottom: Distance-based modal share for recorded long-distance trips; The groups of aggregated modes are defined in Section 3.2

The distance-based modal share for local trips is in the MiD sample with a share of 50.4 percent for motorized individual transport, 9.3 percent for bicycle usage, and 30.1 percent for public transport, nearly equivalent to the modal share of the GPS dataset (49.5 percent, 10.1 percent, and 31.6 percent).

The modal share for long-distance trips varies significantly. The main difference is the modal share for airplane travel, which is in the MiD sample at 13.4 percent, clearly below the 44.7 percent recorded in the GPS dataset. The share of public transport is at 25.3 percent in the MiD sample, clearly higher than the 5.3 percent recorded in the GPS dataset. The share of long-distance trains is reversed at 7.1 percent in the MiD sample and 23.1 percent in the GPS dataset. The share of motorized individual transport is at 52.4 percent in the MiD sample, more than 26.4 percent in the GPS dataset.

The modal share depends not only on the survey design but also on several sociodemographic characteristics. Figure 5 shows the modal share observed in the GPS dataset. The participants are split into car owners and non-car owners. Additionally, the influence of the home location is investigated by splitting the participants into groups, which have their home locations in Munich, and those who live in the surrounding MVV region.

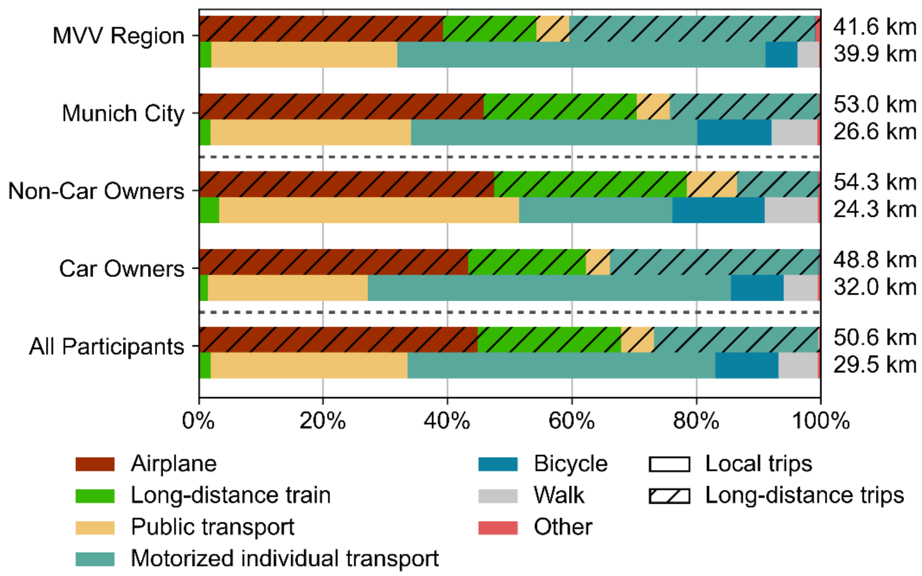


Figure 5. Modal share by traveled distance for local trips in comparison to the modal share for long-distance trips observed in the GPS dataset; Distances on the right: Average distance per tracked day and participant associated with the two trip categories.

The modal share by traveled distance differs significantly for all groups between long-distance trips and local trips. The largest difference among all groups is for the airplane, which is irrelevant for local trips but plays a major role in long-distance trips. It is noticeable that car owners have a lower share of airplane travel at 43.3 percent in comparison with non-car owners at 47.5 percent. Also, participants who live in Munich have a higher airplane share at 45.8 percent compared with participants who live in the surrounding MVV region at 39.3 percent. The higher airplane shares might explain the higher average travel distances per day associated with long-distance trips for non-car owners and participants in Munich.

Independent of car ownership, the motorized individual transport share decreases for long-distance trips compared to local trips. The difference becomes more apparent when ignoring the kilometers traveled by airplane, bicycle, and walking. Then the modal share for car owners is 68.3 percent for motorized individual transport on local trips and 59.6 percent for long-distance trips. The share decrease is nearly the same as that of tracked non-car owners. They used in 32.3 percent the motorized individual transport for kilometers made on local trips and decreased the share to 25.0 percent for long-distance trips. Only participants living in the MVV region used motorized individual transport slightly more at 65.0 percent for local trips and 66.0 percent for long-distance trips.

4.2 *Seasonal trends in long-distance mobility*

We analyzed the overall occurrence of long-distance trips in the GPS dataset during the year, displayed in the upper diagram of Figure 6. We see different trends in the GPS dataset sample. Throughout the year, long-distance trips increase by 73.1 percent on weekend days compared to 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 6. This diagram shows the daily trips of the tracked participants on a monthly basis. We compare the behavior of people living in households with at least one private car with people living in households without a private car and people living in the city of Munich with people living in the surrounding MVV region. During the summer months (06-08.22), all groups made nearly equally many long-distance trips. During the winter months (11.22-03.23), people living in Munich undertook more long-distance trips than those living in the MVV region. Between November 2022 and March 2023, the non-car owners undertook slightly more long-distance trips than the car owners, and fewer in September and October 2022.

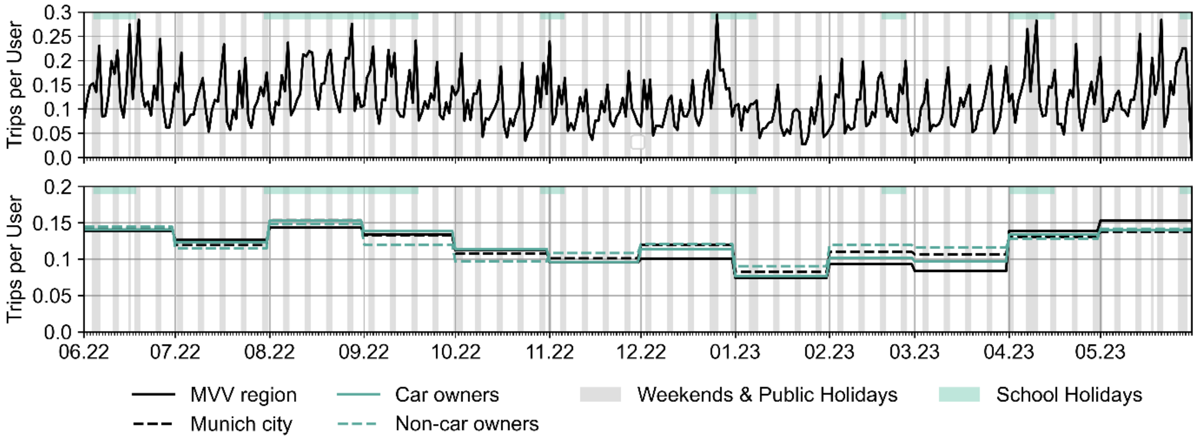


Figure 6. From top to bottom: Long-distance trips per tracked user and day; Long-distance trips per day and tracked user on a monthly average split in car owners and non-car owners, as well as participants with home location in Munich and home location in the surrounding MVV region

One main advantage of the tracking data, besides the tracking duration, is the geo-information about the trips. To analyze the start and end point locations of long-distance trips, we split the GPS dataset sample into car owners and non-car owners. We aggregated the geo points in regiostar17 (BMDV, 2011) areas to find differences in areas with lower public transport density, but differences were hardly noticeable. We follow that even though the modal share of both groups is different (Figure 5), the locations they visited for long-distance trips within Germany do not seem to be different.

In general, a long-distance trip is part of a longer journey. After identifying long-distance journeys in the GPS dataset (methodology in Section 3.2), we see that one long-distance journey contains, on average, 2.5 long-distance trips and lasts for four days. On average, a long-distance journey was recorded every 33 days for every participant who made at least one long-distance journey. The average distance of a journey was 881 km, and the median distance was 374 km. Seventeen participants did not take any long-distance journeys during the tracking period.

All data shown in Figure 7 refers to the calculated journeys. For each day during the observation period, the total share of participants traveling on a journey is shown. The share of all participants is shown in the bottom figure. The group is split into participants living in households with car ownership (middle figure) and those living without a car (top figure). We distinguish between long-distance journeys taken in different main modes. Starting with the bottom figure, it is 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 generally higher during school holidays in Bavaria. There are three local highs in the second week of the summer holidays, Christmas and Easter. The share of journeys done by motorized individual transport follows the same course. The share of participants on a long-distance journey by public transport does not show as many seasonal effects as the long-distance journeys by motorized individual transport. Especially during the Bavarian summer school holidays, the share does not increase significantly compared to the time before. The same holds for the peaks on Christmas and Easter. The share of participants on a long-distance journey by airplane does not oscillate by week. The highest peak is during the Bavarian summer school holidays, at nearly five percent. The overall level for airplane long-distance journeys was higher in 2022 than in 2023.

Comparing car owners and non-car owners, the seasonal trend and the share of participants on long-distance journeys are comparable. Car owners mainly use motorized individual transport as the main mode of transport for long-distance journeys, whereas non-car owners use long-distance trains. The share of participants traveling by long-distance train does not vary as much as that of motorized individual transport for both groups. Non-car owners increasingly use motorized individual transport in the second half of the Bavarian summer school holidays, Christmas and Easter, as well as some probably randomly distributed weekends during the year, such as the third weekend in January 2023. Car owners' motorized individual transport usage for long-distance journeys follows the overall long-distance journey trend.

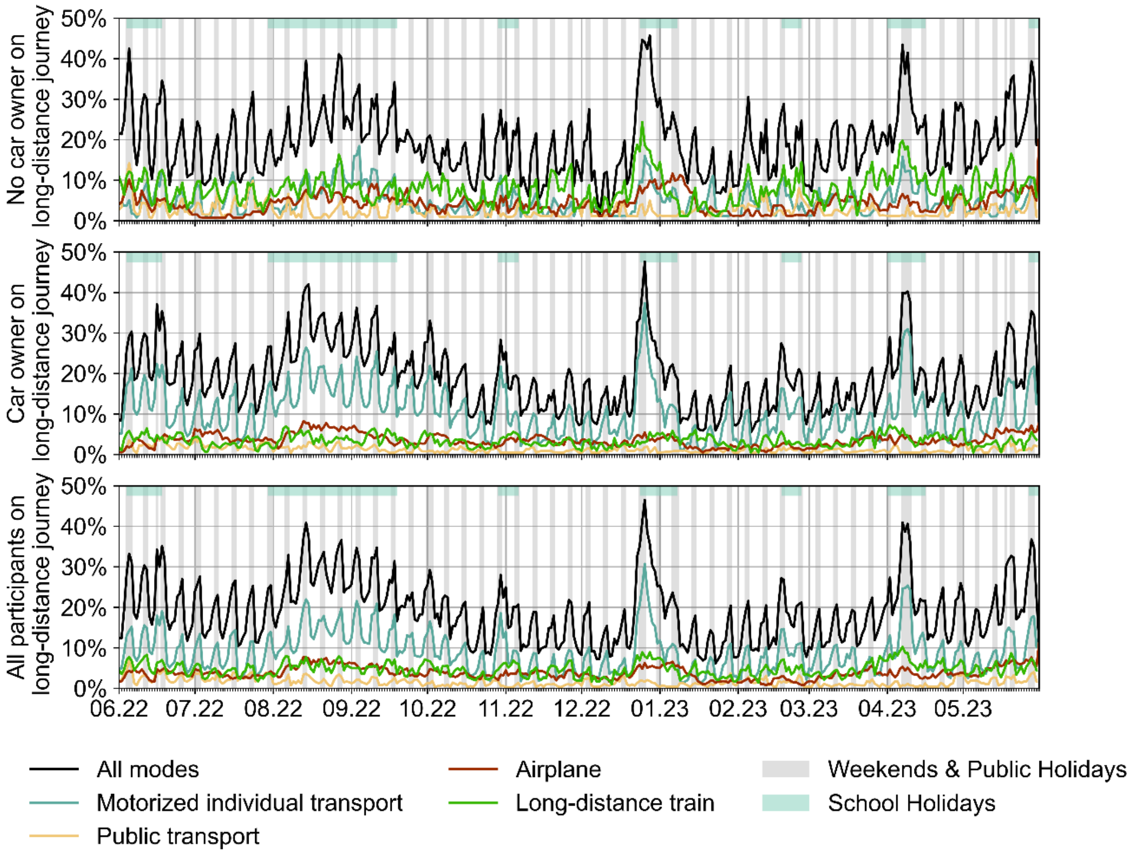


Figure 7. Seasonal share of participants on long-distance journeys by mode; Top: Car owners; Middle: Non-car owners; Bottom: All participants

4.3 Influence of sociodemographic and residential factors on long-distance mobility

Besides seasonal effects, sociodemographic factors play a role in the occurrence of long-distance journeys. Figure 8 visualizes the share of the GPS dataset sample on a long-distance journey on weekdays, weekends, Bavarian school holidays, and non-school holidays on average throughout the year. The sample is split into several groups based on sociodemographic factors. We calculated the significance with an ANOVA test (Girden, 1992). The results are documented in Table 2. We chose an alpha level of 0.5 percent.

Our results indicate that the home location of participants in our GPS dataset had no significant influence on the occurrence of long-distance journeys, whether on weekdays/weekends or school holidays/non-school holidays.

At least one child living in the household has no significant influence on long-distance journeys on weekdays and weekends, but it does on the occurrence during school holidays and non-school holidays. It is visible in Figure 8 that participants who have a child living in the household travel less during non-school holidays in comparison to participants who have no child living in the household. During school holidays, it is the opposite. The same results can be observed for the household size. Household size has a significant influence only during school holidays. A participant living in a household with four or more people is more likely to go on long-distance travel during school holidays than a single person.

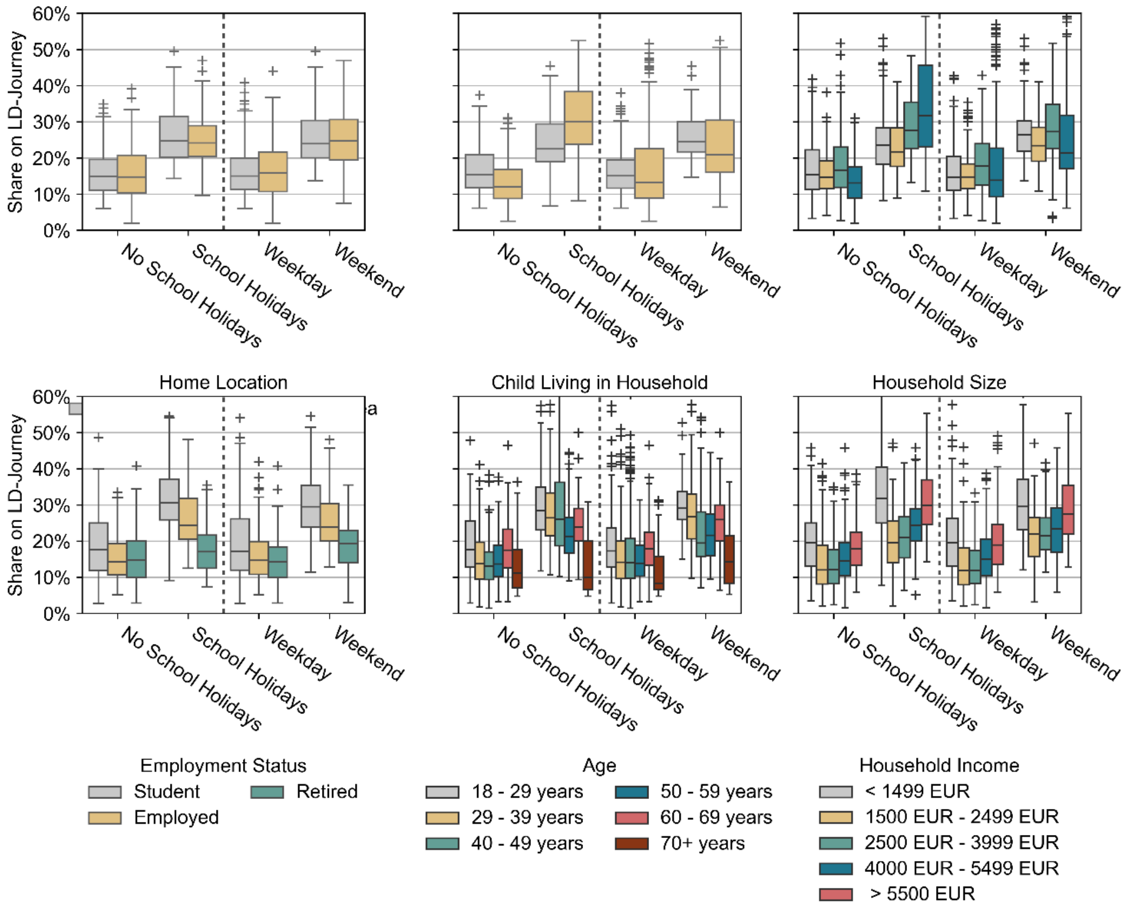


Figure 8. Share of participants on long-distance (LD) journey by different sociodemographic characteristics

A significant influence on the share of participants on long-distance journeys is the employment status during school holidays and weekends. Retired participants maintain nearly the same share of long-distance values, independent of weekend/weekday or school holidays/non-school holidays, while students and employed participants have an increased share on weekends and during school holidays. During the week and times with no school holidays, the share of all three groups is on the same level.

Age is a significant influencing factor in our sample for all four time ranges. Participants older than 70 are significantly less likely to go on long-distance journeys than all younger participants. However, the share does not continuously decrease with age. During non-school holidays, the youngest group (18 - 29 years) and the participant group aged 60 - 69 years have the highest share. The youngest group is in all time ranges the group with the highest share of long-distance journeys. The group aged 60 - 69 years also has a high share on weekdays. On weekends, the group aged 29 - 39 years has the same share as the youngest group, and during school holidays, all three groups between 18 and 49 years have a share on the same level, while the other groups have a lower share.

Household income also has a significant influence on the occurrence of long-distance journeys in all four time ranges. It stands out that participants belonging to the lowest income group have the highest share of long-distance journeys in all four time ranges. This group consists of 78.6 percent of students who have a higher share of long-distance journeys than all other groups. For all other income groups, it is held that with higher income, the share of long-distance journeys increases.

We also investigated the influence of car ownership in the household, but it had no significant influence.

Table 2. ANOVA results for the share of participants on long-distance journeys. DF: Degree of freedom; Sum SQ: Sum of squares; Mean SQ: Mean of squares

		DF	Sum SQ	Mean SQ	F	p
Weekday	Home Location	1	0.0002	0.0002	0.0114	0.9151
	Child Living in Household	1	0.0000	0.0000	0.0010	0.9744
	Household Size	3	0.0783	0.0261	1.5232	0.2075
	Employment Status	3	0.0981	0.0327	1.9130	0.1264
	Age	5	0.2941	0.0588	3.5051	0.0040
	Household Income	5	0.4941	0.0988	6.0264	0.0000
	Car Ownership	1	0.0000	0.0000	0.0013	0.9715
Weekend	Home Location	1	0.0033	0.0033	0.1040	0.7472
	Child Living in Household	1	0.0785	0.0785	2.4469	0.1184
	Household Size	3	0.2002	0.0667	2.0906	0.1005
	Employment Status	3	0.3606	0.1202	3.8009	0.0102
	Age	5	0.8115	0.1623	5.2555	0.0001
	Household Income	5	0.7031	0.1406	4.5231	0.0005
	Car Ownership	1	0.0069	0.0069	0.2159	0.6424
No School Holidays	Home Location	1	0.0016	0.0016	0.0760	0.7830
	Child Living in Household	1	0.2412	0.2412	11.5787	0.0007
	Household Size	3	0.1780	0.0593	2.8305	0.0379
	Employment Status	3	0.0776	0.0259	1.2228	0.3007
	Age	5	0.3724	0.0745	3.6031	0.0033
	Household Income	5	0.3998	0.0800	3.8787	0.0018
	Car Ownership	1	0.0187	0.0187	0.8848	0.3473
School Holidays	Home Location	1	0.0002	0.0002	0.0064	0.9365
	Child Living in Household	1	0.4994	0.4994	13.7365	0.0002
	Household Size	3	0.7030	0.2343	6.4915	0.0003
	Employment Status	3	0.5237	0.1746	4.7908	0.0027
	Age	5	0.8397	0.1679	4.6680	0.0004
	Household Income	5	1.2346	0.2469	7.0100	0.0000
	Car Ownership	1	0.0255	0.0255	0.6836	0.4087

4.4 *Airplane usage for long-distance travel*

We recorded 224 (42.1 percent) participants on at least one long-distance journey by airplane, and if participants used the airplane at least once, they went on average every 179 days on a journey by airplane. When extrapolating our findings to one year, every participant took an average of 0.86 airplane journeys. In our sample, people living in Munich travel, on average, more often by airplane than people living in the surrounding MVV region. In an additional analysis, we investigated the influence of the distance between the airport and the home location and the frequency of airplane trips, but we could not find a correlation.

The median airplane journey lasts six days, but the journey duration is not uniformly distributed. Sociodemographic characteristics correlated with the duration of a journey with the main mode airplane are shown in Figure 9. We observe that the median duration of a journey by airplane for participants belonging to the highest two income groups is 5.2 days, while the median duration of participants in the lowest income group is 9.5 days. Participants in the group of retired people (small sample size) have a median duration of airplane journeys of 9.2 days and students of 9.5 days, while employed participants have a median duration of 5.5 days. Participants with children in the household had a median travel time of 4.6 days, which is significantly shorter than 7.1 days, which is the median duration of an airplane journey for participants without children.

In the limited sample of about 200 people who made airplane trips, no strong differences in the frequency of air travel were revealed between socio-demographic factors (income, children, and employment status).

4.5 Car usage for long-distance travel

While car ownership does not significantly influence the frequency of long-distance journeys, we investigate whether car owners use the car primarily for long-distance travel. To better understand car usage, we compare the average number of kilometers traveled by participants on local trips per day and on long-distance trips per day. This comparison is shown in Figure 9. We differentiate between participants living in a household that owns a car and participants who live in a household that does not own a car. We further split the sample into households living in Munich and in the surrounding MVV region.

Figure 9. Classification of journeys with airplane by duration and allocation according to various social characteristics of the travelers; n = Number of recorded airplane journeys.

The majority of participants (64.5 percent) use motorized individual transport for less than 10 km a day for local trips. The share of non-car owners using motorized individual transport for less than 10 km a day associated with local trips is 96.8 percent, significantly higher than the share of car owners, which is 47.1 percent. But still, nearly half of all tracked car owners use motorized individual transport for less than 10 km a day on average. The share is even higher at 53.7 percent for participants living in Munich and owning a car.

Considering distances associated with long-distance trips, a majority of 58.3 percent drove more kilometers in long-distance trips than in local trips. This share is at 62.3 percent, even higher for participants living in Munich and owning a car, and significantly lower (46.1 percent) for people living in the surrounding MVV region.

In the following, we define participants using the car primarily for long-distance journeys as those who use motorized individual transport on average less than 10 km a day for local trips and use motorized individual transport on average for more kilometers a day associated with long-distance journeys as for local journeys (the resulting area is colored in Figure 10. The share of participants affected by this definition is 43.4 percent. Only 21.6 percent of participants living in a household with a car in the MVV region are under this definition. Of those who live in Munich and own a car, 41.4 percent use their car mainly for long-distance trips.

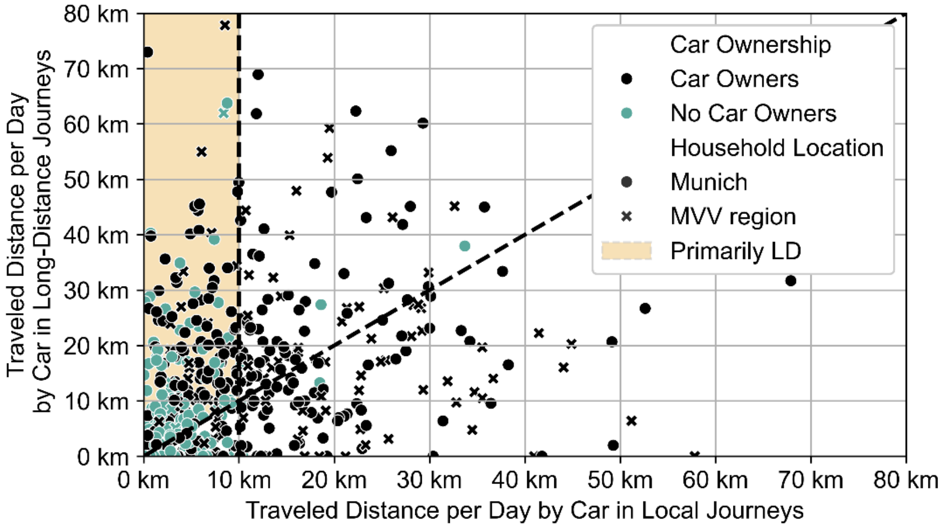


Figure 10. Average traveled kilometers by motorized individual transport and day for every participant associated with long-distance (LD) and local journeys.

5 Discussion and conclusion

This article provides insight into the seasonal trends, sociodemographic influences, home location, and the impact of car ownership on long-distance travel. The dataset primarily analyzed is a GPS tracking dataset with an observation period of one year and a focus on the metropolitan region of Munich. The majority of participants have been constantly tracked over many weeks and months. We assume the vouchers were not the only reason for the long participation. Molloy et al. (2022) reported a quite similar behavior in a comparable smartphone application, in which many participants were still providing information on their mobility behavior even months after the official end of the study. Based on that, we assume that people also like to record their mobility for themselves and want to follow the analysis of their behavior in the app, or that the app did not bother them that much to uninstall it. The observed sample in the GPS dataset is highly biased. However, the sociodemographic characteristics are compared with official statistics, indicating that the sample is mainly too young, too well educated, and lives in too small households. The sample size is too small for applying weighting algorithms to calculate representative results for the metropolitan region of Munich. To still be able to classify the results in long-distance travel, a matching approach at the level of the participants is used to compare the results of a German one-day travel survey with the results of the GPS dataset.

5.1 *Key findings*

When only considering local trips, the mobility findings in the MiD sample and the GPS dataset are nearly equivalent. For long-distance trips, the GPS dataset observed more than twice the number of traveled kilometers in comparison to the one-day travel survey. These findings correspond to Janzen et al. (2018), who discovered that in a one-day travel diary, long-distance trips are underrepresented by approximately half compared to the number of long-distance trips captured in cell phone data. Our results show that for the observed GPS dataset sample, the majority of kilometers (63.7 percent) traveled are associated with long-distance travel, which points out the need to investigate long-distance mobility behavior in detail.

A reason for a significantly higher share of observed kilometers traveled in long-distance journeys is airplane travel. The average number of journeys by airplane is 0.86 journeys per year and participant, which is higher than the value of 0.75 journeys determined in a recent study (Magdolen et al., 2022). Due to the mobile phone switching to flight mode, it is not certain that the smartphone application for recording the trips could detect all trips, and the number could be even higher. The biased sample could explain these high numbers, as the socio-demographic equivalent sample in the MiD survey also has a higher share of airplane travel in comparison to the representative MiD Germany sample. The GPS dataset sample is also mainly located in Munich, and our research shows that participants living in the Munich urban area have a higher share of kilometers traveled by airplane than participants living in the more rural MVV region. This is in line with the findings of previous studies on long-distance travel of urban residents (Czepkiewicz et al., 2018; Czepkiewicz et al., 2020; Ottelin et al., 2014). Other than Enzler (2017), we did not observe a correlation between the distance from the home location to the airport and more long-distance airplane journeys. We assume that the geographical region of analysis in the GPS dataset is too small, and the accessibility of the Munich airport is not fundamentally different from most home locations, , as the Munich airport is not located in the city center. The findings of Mattioli et al. (2023) indicate that sociodemographic characteristics could influence the frequency of airplane trips. We were not able to find differences in household income, children in the household, or employment status on the frequency of airplane travel. Our small sample size and/or the not sufficiently long observation period could be the reason for that.

In the GPS dataset, we observe that non-car owners exhibit a higher proportion of kilometers traveled by airplane compared to car owners. This suggests a substitution of motorized individual transport for long-distance travel, as the number of long-distance trips is approximately equal between the two groups. These findings are interesting, as Mattioli et al. (2021) could not find this correlation for the inhabitants of England, but Ottelin et al. (2014) did for the inhabitants of Finland. These contrasting results make it clear that further research is still needed in this area.

The different mode shares for long-distance trips of participants living in Munich compared to participants living in the MVV region indicate that the home location influences the mode choice for long-distance trips. A reason for the higher share of kilometers traveled by long-distance trains for the participants living in Munich could be the higher accessibility to the Munich main train station, which is the main starting point for long-distance trains in the region. This assumption is based on the findings of Reichert and Holz-Rau (2015), who find this correlation in their data.

Our results show that car ownership does not influence the occurrence of long-distance journeys significantly, but that car ownership has an impact on the used modal share and the traveled distances. This distinguishes our results from findings in Great Britain (Dargay and Clark, 2012) but agrees with more recent results from the Greater Copenhagen region (Große et al., 2019). In our study, participants who own a car have a significantly higher share of motorized individual transport for long-distance trips than participants who don't own a car. These results are consistent with the findings of Reichert and Holz-Rau (2015) regarding the correlation between reduced car usage for local trips and a corresponding decrease in car usage for long-distance travel.

We also found out that 41.4 percent of the observed participants living in Munich and owning a car mainly use it for long-distance trips. This finding indicates that long-distance travel could be an important reason for car ownership in urban areas. The chosen thresholds to identify car use primarily for long-distance trips (Subsection 4.5) have no common sense in the community yet. Therefore, we would like to keep them open for discussion.

Besides the home location and the car ownership status, seasonal effects and sociodemographic characteristics also influence long-distance travel. We observed more long-distance trips during summer than winter and more on weekends than weekdays. The peak time is on weekends during the Bavarian summer holidays, Christmas, and Easter. How often participants go on a journey is positively related to their household income, which is consistent with the findings of (Reichert and Holz-Rau, 2015; Schulz et al., 2024). An exception is the analyzed GPS sample, which is the lowest income group and mainly consists of students. Students have quite similar travel behavior to the employed participants, which matches the findings of Dargay and Clark (2012). We assume that the combination of low income and high travel activity of the students is explainable with relatively low living costs in comparison to employed participants, some irregular income sources that the students did not report, and journeys to their former home towns, e.g., to visit family and friends, during weekends and semester breaks.

Several surveys (Böhler et al., 2006; Dargay and Clark, 2012; Reichert and Holz-Rau, 2015) have shown that children in the household are related to a lower number of long-distance journeys. Our results show this effect at all time periods except school holidays, which indicates the need for long-lasting mobility recordings to figure out if this correlation is correct.

The participant's age significantly influences the share of long-distance journeys. The youngest group, which consists mainly of students, has the highest share of long-distance trips, while the middle-aged have a lower share in comparison. Several other studies (Hubert and Potier, 2003; LaMondia et al., 2014; Mattioli and Adeel, 2021) have investigated the influence of age on long-distance travel and have highlighted the relevance.

5.2 Learnings from longitudinal data collection

The main learning from the longitudinal data collection that is highly relevant for traditional travel surveys is that the timing of the survey matters. The results for long-distance trips will differ significantly if the survey period is in August compared to January. This is especially important for short observation periods.

Different socioeconomic factors influence the occurrence of long-distance trips throughout the year. When, e.g., not including school holidays in the observation period, it might occur that children living in the household seem to reduce long-distance trips disproportionately.

Airplane trips occur quite irregularly, which makes it necessary to observe a long time horizon to analyze the correlation between the frequency and sociodemographic characteristics. We have already been able to show this in an initial approach, but the sample for air travel is still very limited. The investigation should be continued with a larger and longer lasting sample size.

Continuous data collection via smartphone allows mobility to be tracked at the individual level over an extended period of time, thus allowing the capture and examination of variations in individual mobility behavior. The recording of long-distance travel events is therefore not dependent on retrospective survey designs that are influenced by the memory of the respondents and do not need to be limited, e.g., to the last three trips, to reduce the respondent burden. Furthermore, it is not necessary to define long-distance travel in advance when conducting a survey. Rather, different definitions can be applied during the analysis of the longitudinal data, for example, based on the number of overnight stays, the minimum distances traveled, or the use of certain means of transport. While most traditional travel surveys consider either every day travel or long-distance travel, the longitudinal survey allows both to be examined together. This is relevant, for example, for a better understanding of car use, since this means of transport is important for both every day and long-distance travel. Our results indicate that a high share of people living in urban areas use their car primarily for long-distance journeys. This is especially important to consider for policymakers who decide about the usage of public space and design mobility alternatives for private cars.

5.3 Limitations and future work

While the data collected and used in this study hold major potential and our results provide new insights, our study is subject to some limitations. First, the GPS dataset used is biased, as shown in Table 1. The sample is mainly too young, too well-educated, contains too many students, and the two-person household is over-represented. It follows that the presented results are also biased and not representative. This study should be seen as a first attempt that demonstrates the potential of the data collection approach and shows the possibilities for analyzing long-distance travel that arises from a tracking survey. In this sense, the study can be seen as a feasibility study using the Munich metropolitan region as an example. It is important to note that tracking studies always have to deal with achieving representativeness. A survey with representative participation of the population would be desirable in order to draw general conclusions about travel behavior.

All our results shown for the GPS dataset are based on methods to detect the home location of the participants, the combination of different legs to trips, and the combination of trips to journeys as described in Subsection 3.2 with the chosen thresholds. To the best of our knowledge, the chosen thresholds lead to the most trustworthy results for the chosen smartphone application, but a fundamental analysis of these thresholds is necessary. We recommend a detailed analysis of different smartphone manufacturers with the used smartphone application. The automatic mode detection is precise, but errors can not be eliminated completely. This limitation could be improved by combining a traditional one-day travel diary with the tracking application or by requiring more corrections from the participants via the smartphone application.

The primary home location is detected with the methodology described in Subsection 3.2, but we neglect the possibility of a second home location. Reasons for a second home location could be, for example, a holiday house, a different location for work and family, or a move during the observation period. Many users marked multiple locations as their home locations in the used smartphone application. Not all of them were real home locations, but rented holiday flats or longer visits to the homes of friends. This might have happened because the smartphone application did not provide the possibility of marking a stay as a holiday location, and for some people, the best option was to mark the holiday flat as a home location. This should be improved in upcoming versions of the smartphone application to gain more insight into, for example, the correlation between the ownership of holiday houses and long-distance travel.

Studying and understanding air travel is particularly interesting due to the high greenhouse gas emissions. We recommend an extended sample size and/or an extended observation period for a more detailed analysis of airplane travel.

We could not differentiate between business and leisure travel in the provided GPS dataset. This differentiation would provide a deeper understanding of the travel purposes, which is necessary to develop more sustainable travel options for long-distance trips. An improvement would be to include a corresponding response option in the smartphone application for the participants.

Overall, our findings can not be generalized but give detailed and new insights into the long-distance mobility behavior of people living in Germany.

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Author Statement

Nico Nachtigall: Conceptualization, Methodology, Data Curation, Validation, Writing - Original Draft, Writing - Review & Editing, Visualization

Miriam Magdolen: Conceptualization, Validation, Writing - Original Draft, Writing - Review & Editing

Markus Lienkamp: Resources, Writing - Review & Editing, Supervision, Funding acquisition

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Conflict Of Interest (COI)

There are no conflicts of interest.

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