**How mobile are persons with mobility restrictions?**
**Analysis of number of days with activities using one-week activity schedules in Germany**

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## SHORT SUMMARY

In Germany, 13% of all residents are disabled and 9.3% are even classified as severely disabled, which includes elderly people with limited mobility as well as physically disabled and mentally disabled people. Persons with mobility restrictions often report on barriers to meet daily needs, which is usually reflected on fewer days to perform out-of-home activities. The objective of this research is to evaluate whether persons with mobility restrictions are less mobile using one-week activity schedules. The results of the models confirm that persons with mobility restrictions are generally less mobile; being statistically significant for work, shop and recreation activities. It was found a significant interaction between occupation status and mobility restriction on the number of mobile days of most activity types, as well as an impact of the number of mobile days for mandatory activities on the number of mobile days for discretionary activities.

**Keywords:** Activity-generation, Mobile, Activity-based models, Disability, Week travel diary, Household travel survey

## 1. INTRODUCTION

Transportation is an important component of reaching amenities such as care facilities, social and family contacts, education, or work, and generally contributes to quality of life (Best et al. 2022). Due to physical, psychological, social, or socio-economic factors, individuals with impeded mobility often face difficulties while travelling. In view of the United Nations' Convention on the Rights of Persons with Disabilities transport research must focus in more detail on barriers and solutions. The convention does not only aim "to promote, protect and ensure the full and equal enjoyment of all human rights and fundamental freedoms by all persons with disabilities" but in its article nine focusses in detail on travel accessibility (United Nations 2006). Pursuing these goals can lead to inclusivity and social justice as parts of transport equity (Litman 2022). The objective of this research is to evaluate whether the persons with mobility restrictions are less mobile than persons without mobility restrictions, in terms of number of days that they perform out-of-home activities, by activity type.

### *The meaning of disabilities*

Disabilities are complex, dynamic, multidimensional, and controversial conditions that involve health conditions following to activity limitations and societal participation restrictions (World Health Organization 2011). They are as diverse as the people who suffer from them and can be short or long term, painful or painless, or even be visible or invisible. By understanding disability as an interaction, not as a characteristic of a person, it is recognized that affected people, are differentiated by factors such as gender, socio-economic status, or origin, which bring with them varying social disadvantages (World Health Organization 2011). In Germany, 13% of all residents are disabled and 9.3% are even classified as severely disabled, which includes elderly people with limited mobility as well as physically disabled and mentally disabled (Statistisches Bundesamt, Wirtschaft und Statistik 2012).

Speaking of the diversity of disabilities, Frye (2019) lists physical, vision, hearing, and cognitive impairments, as well es mental health issues leading to limitations and restrictions in transportation. It is important to understand that both the type of impairment and surrounding environmental factors influence the consequences for affected individuals.

### *Daily mobility for mobility-impaired individuals*

Studies of travel behavior on cognitively impaired persons (Rosenkvist et al. 2009) and those with mobility-impaired persons (Best et al. 2022), studies in different global regions (Frye 2019), in urban or rural areas, or even in differently developed neighbourhoods may differ substantially.

Many countries have laws that guarantee daily accessibility for people with disabilities (Bekiaris et al. 2018). Nevertheless, impaired individuals often report on barriers to meet daily needs. Measures to improve accessibility include information and driver training, pedestrian walkways and street crossings, public transit stops and station infrastructure, public transit vehicles, and appropriate private transportation (World Bank 2013). Best et al. (2022) summarize those as Availability, Accessibility, Accommodation, Affordability, Acceptability, and Awareness. Opposing this are several obstacles impeding the daily commute.

In order to live a qualitative life, people with reduced mobility adapt to the mentioned circumstances. A number of studies have looked at their resulting travel behavior. Schmöcker et al. (2008) focus on shopping trips of elderly and disabled people, stressing the heterogeneity of these individuals and their behavior. As such, Rosenkvist et al. (2009) conduct interviews with cognitively impaired people who they believe are rarely studied. Using data from the UK National Travel Survey, Lucas et al. (2016) found that disabled people travel fewer and shorter distances on average. This can be attributed primarily to the lower number of leisure trips (Jansuwan et al. 2013), which could be a result of lacking accessible social activities (Lucas et al. 2016). Schmöcker et al. (2008) add that the trips also differ in their complexity and that trips are primarily made with a single destination.

Park et al. (2022) conducted a systematic literature review, analysing 115 per-reviewed papers on travel behavior for persons with reduced mobility. They found that people with disabilities take up to 30% fewer trips than people without disabilities. Likewise, a lower amount of non-work trips, increased use of public transportation, cabs, and ridesharing, and in turn, decreased walking distances and car trips were identified. The revirew highlighted that “environmental, social, and system barriers make specific modes unavailable to travelers with disabilities, increase travel time, and eventually decrease their trip frequency” (Park et al. 2022). They concluded that the sum of negative travel experiences “can ultimately lower social inclusion and the quality of life” (Park et al. 2022).

## 2. METHODOLOGY

### *Data source*

To the authors' knowledge, travel behavior in Germany has not previously been studied in relation to persons with mobility restrictions in particular. The 2017 National Travel Survey included one chapter on “Health-related limitations – influence on mobility in an aging society”, which primarily focused on the elderly (Nobis and Kuhnimhof 2018). It is mentioned that 13 percent of the population is affected by health limitations, half of them suffer from mobility restrictions, which is in line with official statistics. They also report that more than 1.5 million people in Germany do not own a car solely for health reasons, affecting travel behavior.

For this study, another important data source for understanding the mobility behavior of the German population, the German Mobility Panel, was used. This large-scale, nationwide survey by the German Federal Ministry of Transport and Digital Infrastructure is conducted every two years and collects information on travel behavior, costs, satisfaction and individual participants. To do this, participants fill out a travel diary on seven consecutive days and provide information on their choice of transportation, reason for travel, travel time and distance. In addition, a household survey is answered about the place of residence and public transport connections, as well as personal questions about age, gender, employment and also mobility restrictions (Vallée et al. 2022). Mobility restrictions were self-reported, without distinguishing by type or degree. Panel data from 2010 to 2019 was analyzed, with a total of 18,700 individual records.

### *Model estimation*

The main dependent variable is the number of days on which an individual perform a given activity (mobile days model). Person was selected as unit of analysis, in line with activity-based models (Hilgert et al., 2018).

The dependent variables are the number of days with a given activity, by activity type and the number of tours per day, by activity type. Therefore, their values could only be non-negative integers (e.g. 0, 1, 2, 3 etc.) and the responses are ordered. Previous approaches using linear regression (Vickerman 1974; Cervero and Kockelman 1997; Seo et al. 2013), multinomial logit models (Hilgert et al. 2018) or nested logit models (Yun and O'Kelly 1997) fail to account for the nature of the dependent variable. Count regression models or ordered logit models could be used instead. Typical distributions for count variables are Poisson or Negative Binomial distributions. The Poisson distribution requires the mean of the count process to be equal to its variance (Washington et al. 2020). If the requirement does not hold, Negative Binomial distributions could be used instead. An excessive number of zeros in the data could mean that it reflects both a normal count and a zero-count process. Models that can handle both states are denominated zero-inflated (Washington et al. 2020).

Preliminary analysis of the data showed overdispersion and a preponderance of zeros for some activity types, such as accompany or education, so zero-inflated negative binomial regression models were initially selected. However, these models could not capture a higher concentration of responses around 5, which reflects the 5-day commute pattern of the majority of full-time employees. To overcome this issue, we selected a two step model: a binomial logit model to model the zero-count state and a ordered logit model to model the count process state.

For each dependent variable, one model per activity type was estimated: work, education, accompany, shop, recreation and other discretionary activities. The models were executed in the R statistical software tool using the pscl package (Zeileis et al. 2008) and the MASS package (Ripley et al. 2023) . Akaike Information Criteria (AIC), correlation between fitted values and simulation values, p-value of the variables and number of parameters were then used to determine the best model by activity type. Furthermore, we compared the observed and estimated number of individuals with zero mobile days to seven mobile days.

In line with most of activity generation models, independent variables included household size, gender, age, occupation status, economic status, car ownership or area type. Individual mobility restrictions were included, as well as their interaction with occupation status. For example, an employed person with mobility restrictions will perform more work activities than an unemployed person with mobility restrictions, but he/she may perform less work activities than an employed person without mobility restrictions.

On one hand, the number of mobile days for mandatory activities could impact the number of mobile days for discretionary activities. Likewise, not all discretionary activities may have the same priority. In this sense, we established a hierarchy among activities: work, education, accompany, shop, recreation and other. The models were estimated in sequence following the hierarchy, and the number of mobile days of higher rank activities were added as explanatory variables to the model.

Independent variables were checked for correlation. Variables with correlation higher than 50% were not considered in the same set of independent variables. Alternative models were estimated with each set of independent variables, and the final model was selected based on goodness of fit.

## 3. NUMBER OF MOBILE DAYS

### *Preliminary analysis*

The preliminary analysis on the number of mobile days by activity type is summarized in Figure 1. Each one of the subfigures indicates the distribution of mobile days by activity type, where blue highlights the share of individuals that did not perform that activity across the whole week, and the darker greens highlight individuals that are highly mobile. Each row and column represent the distribution by occupation status and mobility restriction (MR), respectively.

The top left subfigure we can observe that most of full-time workers without MR do go to work 5 days per week (52 %), compared to 19% that go to work 4 days per week. It is observed that, on an average week, 7% of full time workers do not go to work, either due to vacation or sickness. On the other hand, 98% of full-time worker do not travel for education any day of the week, and 64% do not travel for accompany or other discretionary purposes. There is a higher distribution among how many days do they perform shopping and recreation activities. It is observed than more than half only go for shopping or recreation 2 or fewer times per week, and that only 10% do shop 5 or more time per week. Most individuals distribute such activities either one, two or three days per week (17 - 26 %).

Not surprisingly, part-time employed individuals without MR commute less days than full-time employed, with only 24% of them being mobile 5 days per week (compared to 52%), and between 18 and 22% commuting to work 3 or 4 days per week. Regarding their discretionary activities, part-time employed allocate more days to accompany acts but they show similar distribution of days allocated to shop, recreation and other as full-time employed.

Students present a similar activity pattern as full-time employed to commute for education. However, their distribution of other discretionary activities is different, with fewer days for shopping and accompany. Last but not least, unemployed individuals hardly commute to work or education, and have similar distribution of accompany acts as full-time employed. They allocate more days to shop (only 4% do not shop in the entire week, and more than half shop at least 3 days per week),

The comparison between persons without and with MR shows that, generally, persons with MR do travel fewer days that persons without MR. A notable exception are shop days for students with MR, however the sample size was limited and may lead to non-representative results.

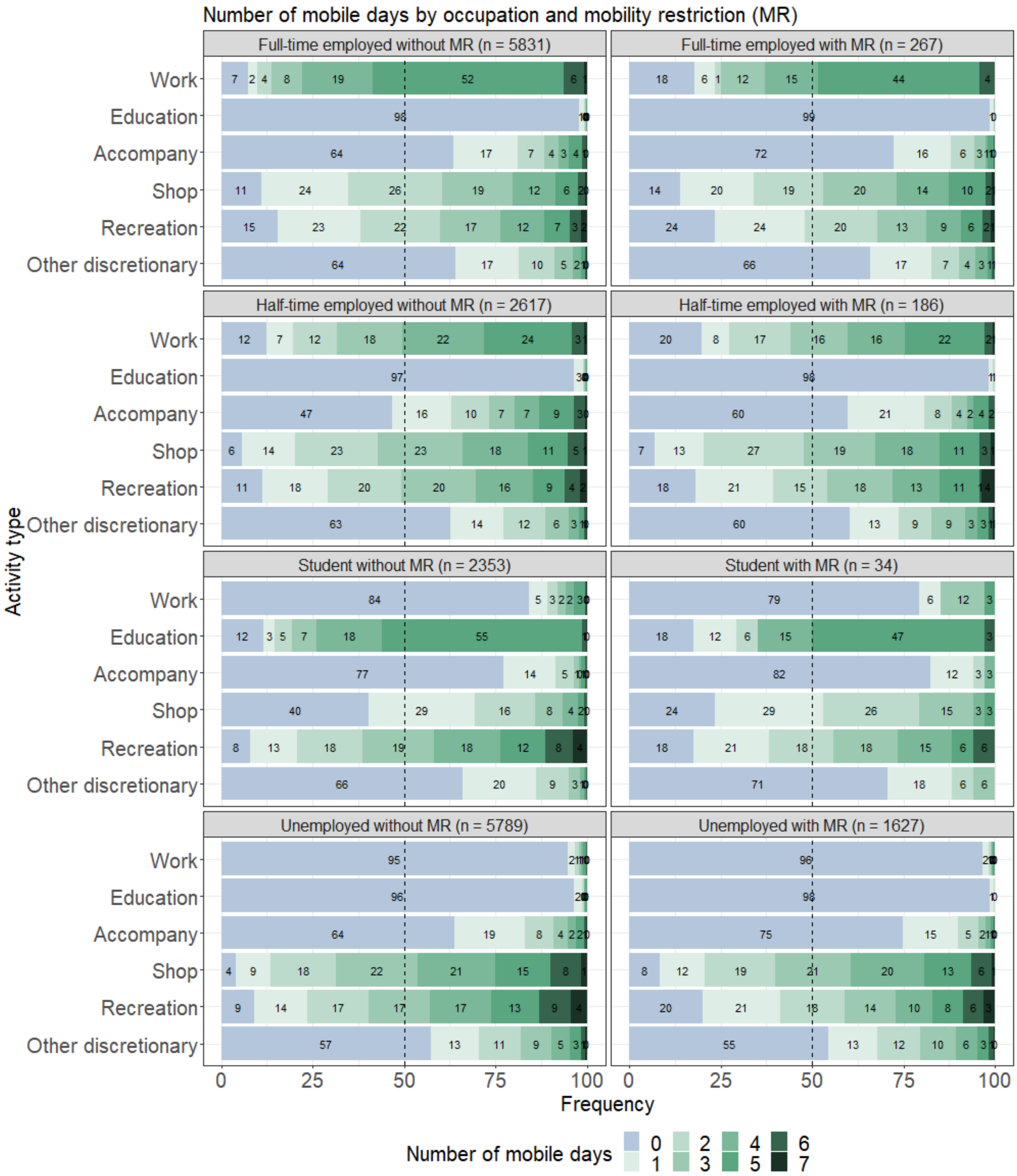


**Figure 1: Number of mobile days per activity type by occupation and mobility status**

## *Model estimation*

The next step is model estimation. As the preliminary analysis showed patterns by occupation status and MR, their interaction term was added for model estimation. Model estimates for the zero-state and count-state are summarized in Tables 1 and 2, respectively. Observed vs. predicted frequencies are shown in Figure 2. As seen in the Figure, the models reproduce the aggregate distribution of number of mobile days by activity type. The distributions show different patterns: from a preponderance of zeros and five mobile days for mandatory activities (work, education), to preponderance of zeros with low mean mobile days (accompany, other discretionary) to skewed distribution with mode equal to two mobile days (shop, recreation).

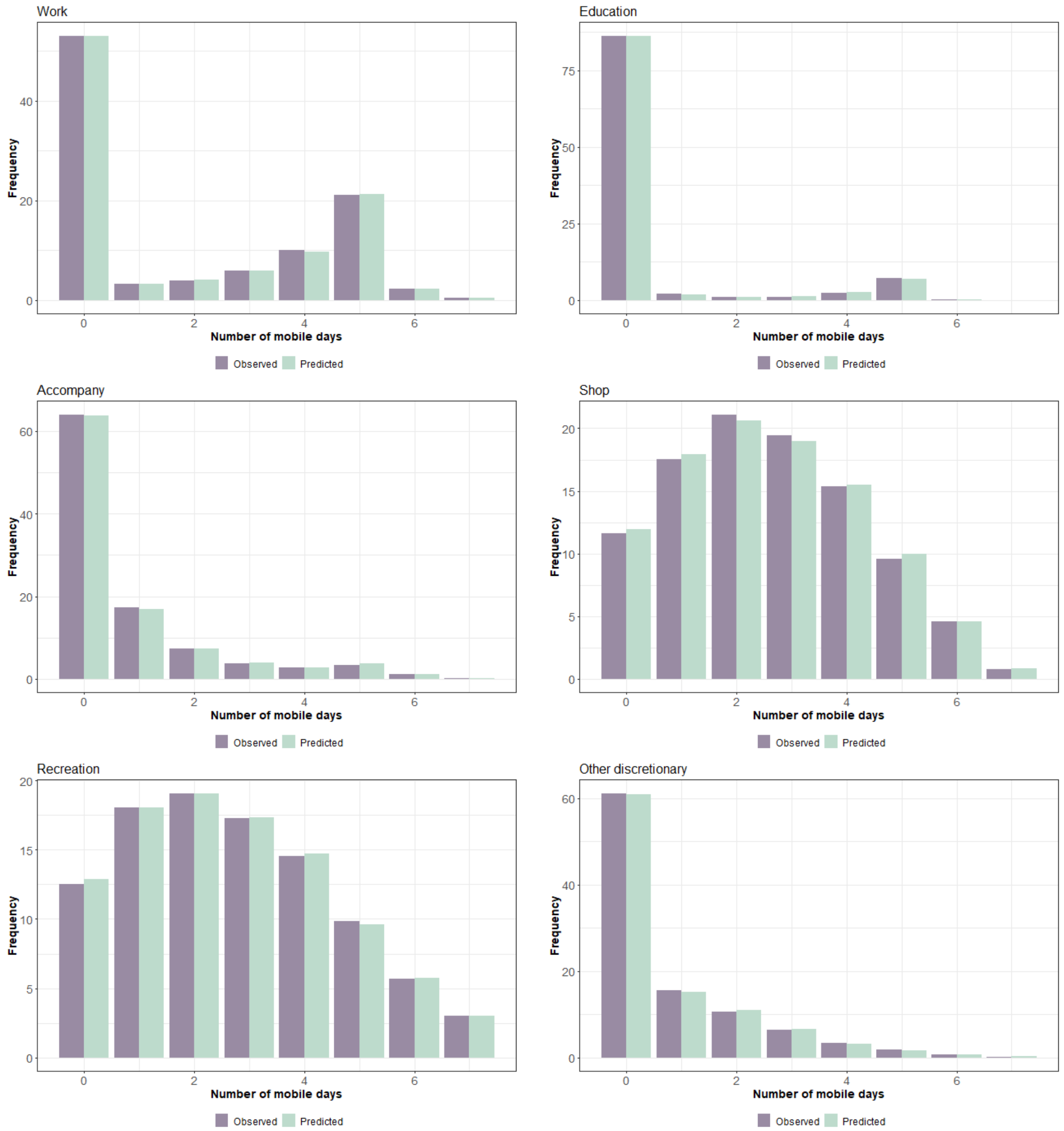


**Figure 2: Number of mobile days per activity type. Observed vs. Predicted**

Table 1 shows the estimates of the zero-state model. This binomial model estimated the likelihood of an individual to perform or not some activity along the week (non-mobile vs. mobile). Positive coefficients indicate higher likelihood of performing the activity compared to the baseline.

Regarding occupation status, the individuals with higher likelihood of not being mobile across the week for commute are students and unemployed; and among unemployed persons, persons with MR. Part-time employed also presented higher likelihood of not being mobile, compared to employed persons. Not surprisingly, students and part-time workers had higher likelihood of conducting at least one education activity along the week. Part-time employees were the most likely to conduct any accompany, shop or recreation activity. We found a distinction based on mobility restriction: unemployed without MR are more likely to be mobile for shop and work activities, while unemployed with MR are less likely to be mobile for the same activities.

Being more mobile for mandatory activities increased the likelihood of not being mobile for discretionary activities, especially for accompany, shop and other. On the other hand, being mobile for accompany increased the likelihood of being mobile for shop, recreation and other; showing a complementary effect. All other variables show intuitive results, as larger households with more children have higher likelihood of doing accompany activities; and individuals aged 60 or older are less mobile than middle-age individuals.

## Table 1: Zero-state model estimation

| Variable | Work | Education | Accompany | Shop | Recreation | Other |
|---|---|---|---|---|---|---|
| (Intercept) | 1.716 | -3.706 | -2.322 | 2.753 | 0.861 | -1.091 |
| Highly agglomerated areas | | -0.219 | | -0.193 | -0.427 | 2.713 |
| Urbanized areas | | | | -0.522 | -0.465 | 2.691 |
| Lower density urban/higher density rural | | | | -0.383 | -0.517 | 2.686 |
| Household economic status: very low | | | -0.184 | -0.217 | -0.658 | |
| Household economic status: low | | | | | -0.224 | |
| Household economic status: very high | | | | | | |
| Household size 2 | -0.281 | | 0.141 | -0.707 | | |
| Household size 3 | -0.185 | | 0.476 | -1.1 | | |
| Household size 4 | -0.185 | | 0.476 | -1.1 | | |
| Household size 5 or more | -0.185 | | 0.476 | -1.1 | | |
| Children per household: 1 | | | 1.135 | | | |
| Children per household: 2 | -0.415 | | 1.576 | | | -0.253 |
| Children per household: 3 or more | -0.853 | | 2.035 | | | -0.293 |
| Adults per household: 1 | | | | | 0.495 | |
| Adults per household: 2 | | | | | 0.502 | -0.124 |
| Adults per household: 3 | | | | | 0.424 | -0.227 |
| Adults per household: 4 | | | | | 0.46 | -0.227 |
| Between 10 und 17 years old | | | -1.67 | -1.424 | 0.773 | |
| Between 18 und 25 years old | | -1.165 | -0.363 | -0.786 | 0.773 | 0.207 |
| Between 36 und 50 years old | | -1.169 | -0.169 | | -0.251 | 0.104 |
| Between 51 und 60 years old | -0.837 | -1.401 | -0.132 | | | 0.088 |
| Over 61 years old | -0.837 | -1.37 | -0.132 | | | |
| Occupation: Student | -3.705 | 5.81 | | -0.455 | 0.255 | -0.286 |
| Occupation: Part-time employed | -0.503 | 0.526 | 0.479 | 0.317 | 0.29 | |
| Occupation: Unemployed | | 1.215 | | | | |
| Mobility Restriction: yes | | | | | | |
| Employed with mobility restriction | -0.908 | | | -0.447 | -0.442 | |
| Unemployed without mobility restriction | -4.916 | | | 0.49 | 0.509 | |
| Unemployed with mobility restriction | -5.34 | | | -0.286 | -0.168 | |
| Student (18 - 60 years old) | | | | | | |
| Unemployed (18 - 60 years old) | | | | | | |
| Part-time employed (18 - 60 years old) | | | | | | |
| Gender: Female | | | | 0.397 | | 0.068 |
| Driver license holder | 1.24 | | 0.969 | 0.341 | | 0.379 |
| Bicycle ownership | | 0.416 | | 0.214 | 0.512 | -0.483 |
| Cars per household: 1 | | | 0.801 | | | |
| Cars per household: 2 | | | 0.732 | | | 0.11 |
| Cars per household: 3 or more | | | 0.771 | | | 0.283 |
| Number of mobile days for work | | | -0.092 | -0.111 | | -0.152 |
| Number of mobile days for education | | | | | | |
| Number of mobile days for accompany | | | | 0.29 | 0.072 | 0.068 |
| Number of mobile days for shop | | | | | 0.165 | -0.064 |

## Table 2: Count-state model estimation

| Variable | Work | Education | Accompany | Shop | Recreation | Other |
|---|---|---|---|---|---|---|
| Highly agglomerated areas | | | 0.186 | -0.284 | -0.428 | 0.432 |
| Urbanized areas | | | -0.211 | -0.532 | -0.455 | 0.329 |
| Lower density urban/higher density rural | | | | -0.484 | -0.39 | 0.554 |
| Household economic status: very low | | | | -0.108 | -0.518 | |
| Household economic status: low | | | | | -0.231 | |
| Household economic status: very high | | | | | | 0.233 |
| Household size 2 | | | 0.382 | -0.256 | -0.143 | |
| Household size 3 | -0.237 | 0.499 | 0.692 | -0.47 | -0.212 | |
| Household size 4 | -0.366 | 0.585 | 0.692 | -0.464 | -0.112 | |
| Household size 5 or more | -0.692 | 0.443 | 0.692 | -0.394 | -0.112 | |
| Children per household: 1 | 0.243 | | 0.888 | | | |
| Children per household: 2 | 0.566 | | 1.234 | | | |
| Children per household: 3 or more | 0.935 | | 1.643 | | | -0.645 |
| Adults per household: 1 | -0.763 | | | | | |
| Adults per household: 2 | -0.88 | -0.302 | | | | |
| Adults per household: 3 | -0.567 | -0.547 | | | | |
| Adults per household: 4 | -0.418 | -0.547 | | | | |
| Between 10 und 17 years old | -2.532 | 3.849 | -0.757 | -1.372 | 0.419 | -0.526 |
| Between 18 und 25 years old | | | -0.757 | -0.356 | 0.519 | -0.411 |
| Between 36 und 50 years old | | | -0.602 | | | |
| Between 51 und 60 years old | -0.201 | -2.325 | -0.816 | | | 0.147 |
| Over 61 years old | -2.092 | -1.896 | -0.816 | -0.265 | | 0.178 |
| Occupation: Student | | | -0.265 | -0.243 | 0.344 | -0.321 |
| Occupation: Part-time employed | | | 0.507 | 0.551 | 0.347 | 0.136 |
| Occupation: Unemployed | | | 0.417 | | 0.516 | |
| Mobility Restriction | -0.189 | | | | | |
| Employed with mobility restriction | | | | | -0.291 | |
| Unemployed without mobility restriction | -1.39 | | | 0.767 | | |
| Unemployed with mobility restriction | -1.864 | | | 0.561 | | |
| Occupation: Unemployed | | | 0.417 | | 0.516 | |
| Student (18 - 60 years old) | -2.253 | 2.49 | | | | |
| Unemployed (18 - 60 years old) | -0.912 | 1.413 | | | | |
| Part-time employed (18 - 60 years old) | -1.028 | | | | | |
| Gender: Female | -0.116 | | 0.205 | 0.071 | | |
| Driver license holder | | | 0.956 | 0.199 | | 0.242 |
| Bicycle ownership | -0.225 | | -0.172 | 0.181 | 0.453 | |
| Cars per household: 1 | | | | | | |
| Cars per household: 2 | | | | | | |
| Cars per household: 3 or more | | | | | | |
| Number of mobile days for work | | | -0.047 | -0.133 | -0.057 | -0.172 |
| Number of mobile days for education | | | | | | |
| Number of mobile days for accompany | | | | 0.103 | | 0.068 |
| Number of mobile days for shop | | | | | 0.069 | 0.058 |
| Number of mobile days for recreation | | | | | | -0.037 |
| 1\|2 | -4.463 | 0.168 | 1.235 | -1.591 | -1.098 | -0.07 |
| 2\|3 | -3.451 | 1.197 | 2.259 | -0.325 | 0.003 | 1.176 |
| 3\|4 | -2.582 | 1.926 | 2.951 | 0.69 | 0.839 | 2.188 |
| 4\|5 | -1.574 | 3.06 | 3.599 | 1.728 | 1.695 | 3.119 |
| 5\|6 | 1.371 | 7.981 | 5.263 | 2.924 | 2.588 | 4.324 |
| 6\|7 | 3.331 | 10.609 | 7.686 | 4.954 | 3.734 | 5.789 |

Table 2 shows the estimates of the count-state model. The ordered logit model provides the probability of an individual to have between one and seven mobile days. Similarly, occupation status and mobility restriction play a role on how many days are mobile. Half-time employed allocate more days for all discretionary activities. Specifically, students tend to travel fewer days for shop, accompany and other, but they do travel more days for recreation activities. As expected, unemployed persons do shop more days per week than full-time employed and commute fewer days per week. Having MR does accentuate the differences even more, with fewer commute days per week and fewer shop days per week than persons without MR.

As for the likelihood of being mobile, an increased number of mobile days for mandatory activities decreased the number of mobile days for discretionary activities. Therefore, increasing the number of mobile days for mandatory activities detracts time from discretionary activities. Regarding number of mobile days for shop, it could be observed that higher mobility for accompany activities do increase the number of mobile days for shop, as well as being female, have driver license or own a bicycle. On the other hand, persons younger than 25 years old or over 70 do travel fewer days for shop.

## 4. CONCLUSIONS

This study presented an analysis on how mobile individuals are, being defined as the number of days per week that they perform activities out-of-home. The analysis has been focused on individuals with mobility restrictions, as they are usually reported as being less mobile. Two main methodological contributions included the analysis of a week-long travel diary as well as the statistical modeling of number of mobile days using a combination of a binomial logit model for the zero-state and an ordered logit model to model the count process state.

The results of this paper provide a better understanding of the individuals who are not mobile across a complete week for a certain purpose. Occupation status and mobility restrictions were key factors to determine how mobile individuals are, as well as the number of mobile days for higher hierarchy activities. Part-time employed individuals allocate more days to accompany acts, as well as shop, recreation and other, compared to full-time employed; and have lower likelihood of not being mobile. Unemployed individuals with mobility restriction do have higher likelihood of not being mobile for work, shop and recreation, and, if they are mobile, they tend to perform the activities in fewer days. On the other hand, unemployed individuals without mobility restriction have higher likelihood of being mobile and also conduct activities in more days per week than employed persons.

This research only scratches the surface on travel behavior of individuals with mobility restrictions. Future research will include the analysis of weekly variability, number of tours per day, distance per tour or mode choice. Furthermore, the data did not allow for distinctions among types of mobility restriction. It would be interesting to evaluate whether the type of disability (visual, cognitive, etc.) does play a role on their activity generation pattern. This may shed more light to uncover the motivations of performing fewer out-of-home activities and whether being less mobile does affect the overall individual well-being. In a broader future research, a survey would be carried out to identify the needs of individuals with mobility restrictions, by type of restriction, and whether their needs are met with their travel behavior.

## REFERENCES

Bekiaris, E.; Loukea, M.; Spanidis, P.; Ewing, S.; Denninghaus, M.; Ambrose, I. et al. (2018): Research for TRAN Committee: Transport and tourism for persons with disabilities and persons with reduced mobility. Brussels: European Parliament, Policy Department for Structural and Cohesion Policies.

Best, Krista L.; Noreau, Luc; Gagnon, Marie-Andrée; Barthod, Corentin; Hitzig, Sander L.; Routhier, François (2022): Housing, Transportation and Quality of Life among People with Mobility Limitations: A Critical Review of Relationships and Issues Related to Access to Home-and Community-Based Services. In *Disabilities* 2 (2), pp. 204–218. DOI: 10.3390/disabilities2020015.

Cervero, Robert; Kockelman, Kara (1997): Travel demand and the 3Ds: Density, diversity, and design. In *Transportation Research Part D: Transport and Environment* 2 (3), pp. 199–219. DOI: 10.1016/S1361-9209(97)00009-6.

Frye, Ann (2019): Disabilty Inclusive Public Transport. In *High Volume Transport Applied Research*.

Hilgert, Tim; Kagerbauer, Martin; Vortisch, Peter (2018): Considering joint trips and activities in week activity schedules. In : TRB 97th Annual Meeting Compendium of Papers. Ed.: Transportation Research Board, Art.-Nr.: 18-01378.

Jansuwan, Sarawut; Christensen, Keith M.; Chen, Anthony (2013): Assessing the Transportation Needs of Low-Mobility Individuals: Case Study of a Small Urban Community in Utah. In *Journal of Urban Planning and Development* 139 (2), pp. 104–114. DOI: 10.1061/(asce)up.1943-5444.0000142.

Litman, Todd (2022): Evaluating Transportation Equity: Guidance for Incorporating Distributional Impacts in Transportation Planning. In *Victoria Transport Policy Institute* 8 (2), pp. 50–65.

Lucas, Karen; Bates, John; Moore, José; Carrasco, Juan Antonio (2016): Modelling the relationship between travel behaviours and social disadvantage. In *Transportation Research Part A: Policy and Practice* 85 (October 2021), pp. 157–173. DOI: 10.1016/j.tra.2016.01.008.

Nobis, Claudia; Kuhnimhof, Tobias (2018): Mobilität in Deutschland - MiD Ergebnisbericht. Studie von Infas, DLR, IVT und infas 360 im Auftrag des Bundesministers für Verkehr und digitale Infrastruktur (FE-Nr. 70.904/15). Bonn, Berlin. Available online at www.mobilitaet-in-deutschland.de.

Park, Keunhyun; Esfahani, Hossein Nasr; Novack, Valerie Long; Sheen, Jeff; Hadayeghi, Hooman; Song, Ziqi; Christensen, Keith (2022): Impacts of disability on daily travel behaviour: A systematic review. In *Transport Reviews*, pp. 1–26. DOI: 10.1080/01441647.2022.2060371.

Ripley, Brian; Venables, Bill; Bates, Douglas M.; Hornik, Kurt; Gebhardt, Albrecht; Firth, David (2023): The MASS package. Available online at https://cran.r-project.org/web/packages/MASS/MASS.pdf.

Rosenkvist, Jenny; Risser, Ralf; Iwarsson, Susanne; Wendel, Kerstin; Ståhl, Agneta (2009): The Challenge of Using Public Transport: Descriptions by People with Cognitive Functional Limitations. In *Journal of Transport and Land Use* 2 (1), pp. 65–80. DOI: 10.5198/jtlu.v2i1.97.

Schmöcker, Jan Dirk; Quddus, Mohammed A.; Noland, Robert B.; Bell, Michael G.H. (2008): Mode choice of older and disabled people: a case study of shopping trips in London. In *Journal of Transport Geography* 16 (4), pp. 257–267. DOI: 10.1016/j.jtrangeo.2007.07.002.

Seo, Sang-Eon; Ohmori, Nobuaki; Harata, Noboru (2013): Effects of household structure and accessibility on travel. In *Transportation* 40 (4), pp. 847–865. DOI: 10.1007/s11116-013-9468-3.

Statistisches Bundesamt, Wirtschaft und Statistik (2012): Lebenslagen der behinderten Menschen. Available online at https://www.destatis.de/DE/Methoden/WISTA-Wirtschaft-und-Statistik/2012/03/lebenslagen-behinderte-032012.pdf?__blob=publicationFile.

United Nations (2006): Convention on the Rights of Persons with Disabilities.

Vallée, Jan; Ecke, Lisa; Chlond, Bastian; Vortisch, Peter (2022): Deutsches Mobilitätspanel (MOP) – Wissenschaftliche Begleitung und Auswertungen Bericht 2021/2022: Alltagsmobilität und Fahrleistung.

Vickerman, R. W. (1974): Accessibility, Attraction, and Potential: A Review of Some Concepts and Their Use in Determining Mobility. In *Environ Plan A* 6 (6), pp. 675–691. DOI: 10.1068/a060675.

Washington, Simon; Karlaftis, Matthew G.; Mannering, Fred L.; Anastasopoulos, Panagiotis Ch (2020): Statistical and econometric methods for transportation data analysis. Third edition / Simon Washington, Matthew G. Karlaftis, Fred Mannering, Panagiotis Anastaspoulos. Boca Raton: Chapman & Hall/CRC (Chapman & Hall/CRC interdisciplinary statistics series).

World Bank (2013): Improving accessibility to transport for people with limited mobility (PLM): A practical guidance note. In *2012*, p. 91.

World Health Organization (2011): World report on disability. WHO Press, World Health Organization. Geneva.

Yun, Dae-Sic; O'Kelly, M. E. (1997): Modeling the day-of-the-week shopping activity and travel patterns. In *Socio-Economic Planning Sciences* 31 (4), pp. 307–319. DOI: 10.1016/S0038-0121(97)00010-4.

Zeileis, Achim; Kleiber, Christian; Jackman, Simon (2008): Regression Models for Count Data in R. In *J. Stat. Soft.* 27 (8). DOI: 10.18637/jss.v027.i08.