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Relationship Between Activities and Multimodal Travel in Everyday Life

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Abstract

Multimodal travel behavior plays a pivotal role in sustainable transport infrastructure design. Unlocking its potential requires a deeper understanding of the underlying mechanisms governing everyday travel. In this study, we investigate the association between activity variability and multimodal travel behavior in Germany using data from the German Mobility Panel. Through descriptive analyses and regression modeling, we explore the activity-related characteristics and contextual factors influencing the adoption of multimodal travel among employees. Our findings reveal that using multiple transport modes positively correlates with engaging in diverse activities. Notably, leisure and shopping activities exhibit a powerful influence on multimodal travel behavior. Moreover, complex travel needs, as indicated by high variations in distances traveled and a more significant number of linked trips, act as additional drivers of multimodal behavior. Furthermore, our results suggest that multimodal travel behavior is more prominent during the transition from weekdays to weekends. These findings contribute to understanding multimodal travel patterns and can inform the development of strategies to promote sustainable and efficient transport systems.

Keywords: Introduction

Over the past two decades, extensive research has focused on the intra-individual variation of transport mode use (Klinger 2017; Kuhnimhof et al. 2006; Molin et al. 2016; Chlond und Lipps 2000), which is directly related to multimodal travel, referring to the use of different transport modes in a given period. This area of study has primarily investigated the factors that determine multimodality and the differentiation of homogeneous behavioral groups (Beckmann et al. 2003; Kuhnimhof et al. 2006; Molin et al. 2016). Numerous studies have explored the impact of sociodemographic factors on multimodality (An et al. 2021; Scheiner et al. 2016; Nobis 2007; Buehler und Hamre 2016). E.g., it was found that retirees are less likely to engage in multimodal travel compared to middle-aged employees and that higher incomes and children within households influence multimodal behavior.

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However, it is worth questioning whether these sociodemographic characteristics themselves determine multimodality. Some authors have identified a correlation between travel patterns and multimodality, suggesting that engaging in many trips supports multimodal travel (Nobis 2007). This implies that multimodality may result from engaging in various activities and utilizing specific transport modes to reach these destinations. Individuals with diverse activities have different travel needs than those who travel infrequently (Hensher und Reyes 2000). These travel needs also influence mode choice, with a greater diversity of activities promoting multimodality, as individuals tend to select the transport mode based on the specific purpose of their trips (Kuhnimhof et al. 2006).

Additionally, the frequency and type of activities individuals participate in vary throughout the week. Previous literature has shown that people behave differently on weekends than on weekdays, partly due to engaging in different activities (Susilo und Axhausen 2014). Working activities predominantly occur from Monday to Friday, while weekends are characterized by leisure and shopping purposes (Lockwood et al. 2005).

Complex individual travel patterns, resulting from various activities and travel needs, may discourage multimodal travel behavior. Individuals might opt for a single mode, such as using a car for all their transportation needs, to simplify their travel decisions. The permanent availability of a private car has been found to decrease multimodal travel behavior.

Spatial conditions and contextual factors of travel can also influence multimodal travel behavior. Urban and rural regions differ regarding the variety of activities available and distance-related accessibility. Although not the focus of this paper, these contextual factors of travel behavior can also affect multimodal behavior.

Given this context, this paper aims to enhance our understanding of the occurrence of multimodal travel behavior by examining the relationship between engaging in various activities, travel patterns, and contextual factors of travel. The Herfindahl-Hirschman Index (HHI) is utilized as a measure of the variation in transport mode usage and participation in activities. The study employs an exploratory approach using data from the German Mobility Panel (MOP) collected between 2015 and 2019. Descriptive analyses are conducted, and a regression model is employed to investigate the occurrence and variation of specific trip purposes throughout a week and their relation to multimodal travel behavior, considering various contextual factors of travel.

The paper is structured as follows: The literature review provides background information regarding multimodality and the variation of both transport mode use and participation in activities. The methods section describes the HHI as a measure of multimodality, the dataset, and the explorative approach using descriptive analysis and a regression model. The results section provides descriptive analyses and the estimation results of the regression model. The discussion deals with the evaluation of both the findings and the limitations of the approach and gives directions to future research. Finally, the conclusion highlights relevant implications for policymakers.

1. Literature review

1.1. Measuring Multimodality

Multimodality can be measured in different ways. A vast body of literature studies individuals who are categorized into modal groups based on their mode choice within a defined period (Beckmann et al., 2003; Chlond & Lipps, 2000; Nobis, 2007). These categorial groups are predefined according to the combined modes, for example the “monomodal car users” (people who only use the car) or the “multimodal car and bicycle users” (people who use the car and the bicycle) (Buehler & Hamre, 2015; Nobis, 2007). Subsequently, the groups are intensely analyzed regarding their travel behavior and socio-demographics. Going beyond, multimodality can be represented by quantitative and continuous indicators reflecting the variability of travel behavior (Diana & Pirra, 2016). People are assigned a value that indicates how strongly they behave multimodally within a defined period. As a result, these indicators provide information on the variation of mode use of individuals but do not specify which modes, in particular, are being varied.

Various indicators exist to measure similarity (Schlich & Axhausen, 2003) or variability (Diana & Pirra, 2016; Mallig & Vortisch, 2017) in a travel-related context. The major problem of such measures is the lack of a generally accepted concept. On the contrary, the advantage of using indicators for multimodality is the possibility of performing more complex analyses by aggregating information. For example, Heinen and Mattioli (2019) investigated trends in multimodality over time by calculating various indicators. Scheiner and Chatterjee (2016) researched key events and their influence on changes regarding multimodal travel behavior.

Besides others, the Herfindahl-Hirschman-Index (HHI) is the most widely applied indicator measuring the variability of transport mode use (Heinen & Mattioli, 2019; Mallig & Vortisch, 2017; Scheiner et al., 2016; Susilo & Axhausen, 2014). Susilo and Axhausen (2014) used the HHI also for activity-travel-location patterns. Diana and Pirra (2016) took a more detailed view of the performance of other multimodality measures such as Gini, Dalton, Aktionson, Entropy, and Herfindal. Although they could not recommend the HHI as the best measure, they confirmed that none of these measures completely outperformed the other. Further, Heinen and Mattioli (2019) concluded that the function of such an indicator, i.e., measuring multimodality as a sophisticated metric is easy to interpret and simple to calculate, is more important than choosing a specific one.

1.2. Variation of Travel and Activity Participation over One Week

For the recording of travel behavior, one week is often chosen as a reference period (Buehler & Hamre, 2015; Hilgert et al., 2018). Since humans are creatures of habit, everyday travel behavior is relatively stable on an individual level. E.g., schools, workplaces and activity frequencies are primarily set for prolonged periods (Gärling & Axhausen, 2003; Janke et al., 2021). However, individuals' travel-activity patterns are also characterized by variability (Hanson & Huff, 1988). The variation in day-to-day travel behavior has been confirmed by several studies (Bayarma et al., 2007; Hanson & Huff, 1988; Heinen & Chatterjee, 2015; Pas & Koppelmann, 1986; Susilo & Axhausen, 2014; Susilo & Kitamura, 2005; Thomas et al., 2019). It can be related to different aspects of travel, e.g. activities, distances traveled, locations, mode choice, or combinations thereof.

Susilo and Axhausen (2014) found that the level of repetition of activity-travel mode choice is highly correlated with the level of repetition of the location of the activity. However, they did not differentiate which mode was used for which activity. Further, Thomas et al. (2019) found a high variation in mode choice for short distances and significantly higher stability regarding mode choice for long travel distances. Multimodal travel behavior is primarily a phenomenon of high-density regions (Buehler & Hamre, 2016; Lavery et al., 2013) with an excellent public transport infrastructure (Klinger, 2017). Thus, the availability of transport modes and the distances of visited destinations are also relevant for the use and variation of transport modes. The influence of various activity spaces on multimodality in total remains unconsidered so far.

In contrast, considering daily trip frequency, individuals with fewer role-related constraints show higher levels of trip frequency. This results in a higher trip variation (Pas & Koppelmann, 1986) and travel mode patterns (Bayarma et al., 2007). The research gap arises because general statements were made about travel behavior without looking at specific activities and their influence on multimodality in detail.

Besides variability, Lockwood et al. (2005) have acknowledged that travel demand modeling often focuses on weekday travel. It is known from the literature that weekend travel is more variable than weekday travel (Schlich et al., 2004; 2003). This results from leisure travel being less stable than other activities. Also, other activity types are performed on weekends than on weekdays and stability in travel behavior on weekdays does not result in stable routines on weekends (Schlich & Axhausen, 2003). Considering single-day characteristics, more leisure activities are performed on Fridays than on other weekdays (Schlich & Axhausen, 2003). Moreover, transport mode use changes when comparing weekdays and weekends (Lockwood et al., 2005). Furthermore, weekend action spaces are generally more varied (Susilo & Kitamura, 2005). To improve modeling, Lockwood et al. (2005) highlight the need for more information regarding travel differences on weekends compared to weekdays, e.g., changes in mode use.

The literature review indicates that there is still a lack of information on the relationship between activity variability and mode use. In this context, a more extended period (more than one reference date) is highly relevant for the research extension. The MOP data are particularly suitable for this purpose.

2. Methods

2.1. Data

This work is based on data from the German Mobility Panel (MOP) of 2015 to 2019. The MOP is a national household travel survey that collects everyday travel data of the German population. Participants fill in a seven-day trip diary and provide additional information on mobility-determining characteristics, such as sociodemographic data. In the trip diary, all trips of a week are reported individually. The transport modes used, the purpose of the trip (categorial), and the distance and duration are reported. Based on the trip purpose, trip chains can be calculated if the trip from an out-of-home activity does not directly lead home. A more extensive description of the MOP can be found in Ecke et al. (2020) and Zumkeller and Chlond (2009). The trip diaries of people aged 18 years or older are used for the analysis. The data basis consists of 13,901 trip diaries filled in by 7,883 people, reporting a total of 206,445 trips. Only the datasets with complete information for all relevant variables are considered for the regression analysis.
Table 1 shows the sample composition by gender, age group, and employment status. The sample used is thus a fairly representative subset of the German population compared to the official statistics of 2015 (Statistisches Bundesamt, 2015). This paper uses weighted data for descriptive analyses, while unweighted data is used in regression modeling. According to Kunert et al. (2012), the sample is used cross-sectionally.

Table 1. Sample composition and diversity of mode use and activities of the sample

	German population*	Sample share
Total	100%	100%
AGE GROUP		
18 - 25 years	10.1%	10.0%
26 - 35 years	14.0%	14.0%
36 - 50 years	23.9%	23.2%
51 - 60 years	19.0%	19.3%
61 - 70 years	13.6%	14.2%
> 70 years	19.4%	19.2%
GENDER		
male	48.5%	48.4%
female	51.6%	51.6%
EMPLOYMENT STATUS		
Trainee		9.1%
Employed: full-time		39.8%
Employed: part-time		15.5%
Homemaker, temporarily unemployed		5.4%
Retired		29.5%
NA		0.7%

*2015 statistics taken from (Statistisches Bundesamt 2015)

2.2. Measuring Multimodal Travel Behavior and Variations of Activities

The facets of multimodality are combined into one concentration measure for the presented work. This is based on the understanding that the more a person uses one transport mode, the higher the concentration of this mode, and the fewer other transport modes are used. In this study, we focus on aggregating data from the MOP (i.e., consolidating it into a novel metric) to maximize the inclusion of information in the analytic framework. Since no single best indicator to display multimodality exists (Diana & Pirra, 2016), the normalized Herfindahl-Hirschman Index (HHI) is chosen as a continuous (outcome) variable to measure both the extent of multimodal travel behavior and the variability of activities in everyday life. This allows us to easily utilize the information that different modes of transportation are used, or activities are performed. Using such an indicator provides an appropriate way of measuring the balance of using mode options and activities in everyday life (Heinen & Mattioli, 2019).

The HHI measures market concentration and has already been used in previous studies on multimodality (Heinen & Chatterjee, 2015; Scheiner et al., 2016; Susilo & Axhausen, 2014). It is calculated over the sum of the squared shares (S) of all categories included (transport modes and activities). The values range from 1/N to N, where N is the number of transport modes or activities. However, the squaring of shares consequently gives higher importance to transport modes or activities with large shares. The initial HHI is normalized following Heinen and Chatterjee (2015) to make the results more comparable. As a result, the values range from 0 (here: multimodality or multi-activities) to 1 (here: monomodal or mono-activities).

$$HHI = \sum_{i=1}^{N} {S_i}^2 \quad (1)$$

$$HHI(n) = \frac{(H-\frac{1}{N})}{(1-\frac{1}{N})} \quad (2)$$

This study calculates the normalized HHI for two cases: transport mode use (HHIM) and activities over one week (HHIA). The first includes the individual's shares of the subsequent modes: walking, bicycle, car, and PT. The latter considers the shares of five different activities: compulsory activities, including travel to work and school, leisure, shopping, service, and other purposes. A high value of the HHIM or HHIA indicates higher degrees of repetition of activities and transport mode use. The maximum value of the index is achieved when only one transport mode is used, or activity is done within a week. Consequently, a low value indicates a mix of regular transport modes or multiple different types of activities in a certain period.

2.3. Research Framework

This study explores the use of different transport modes (e.g., walking, bicycle, car, public transport), known as multimodal travel behavior, and its relation to participation in various activities over one week. Therefore, the methodology of this study represents an exploratory investigation and includes descriptive analyses (D) and a regression analysis (R).

First, an overview of multimodal travel characteristics and their relation to activities and concentration on different time windows within the week is given (D-1). Second, the distribution of monomodal (using only one transport mode over one week) and multimodal (using more than one transport mode) travel behavior for the whole week and compared to weekdays (Mon.-Fri.) and the weekend (Sat.-Sun.) is described (D-2). In addition, the extent of the combination of monomodal and multimodal travel behavior during the week and on weekends is investigated. It is further investigated for which trip purposes and activities transport modes are most likely varied. Based on this differentiated analysis, it is possible to determine the travel purposes for which the greatest "transformation potential" exists. The variation of transport mode use for compulsory activities such as work, school, and leisure activities are investigated separately and cross-sectionally. The descriptive analyses are a relevant preliminary examination to understand how transport modes are varied for different activities.

In previous work, regression models have investigated the relationship between sociodemographic determinants as explanatory variables for multimodal travel behavior (Molin et al., 2016; Nobis, 2007; Scheiner et al., 2016). This study focuses on multimodal travel behavior in terms of activities and contextual factors rather than on which sociodemographic person is behind the observed behavior. Therefore, a multivariate regression model is used to study multimodality, primarily activity-based, using explanatory variables that depart from socio-demography (R-1). The data cannot be included in the model because the spatial information's aggregation level is poor. The variables are described in the following.

The normalized HHIA is applied to reflect the variability of activities within a week. For this, only people who perform trips for compulsory activities (work or school) are considered for the model. For people without such trips, the activity "work" or "school" will not account for diversity, and the HHIA will not cover the full range of the value. To account for an individual's level of mobility the number of activities for different trip purposes is considered. Compulsory activities (work or school), leisure, shopping, service, and other purposes are included in the model to examine to which extent these can explain the probability of being multimodal. Since it is assumed that the level of complexity of travel behavior can hinder or support multimodal travel behavior (Hensher & Reyes, 2000), the number of linked activities within a loop trip are also considered. This describes the number of trips for different purposes taken in a trip chain before the individual returns home (e.g. from home to work to shopping to leisure to home).

Similarly, people who travel within a small radius around their home have different mobility needs than those who travel further distances in everyday life. For this reason, the variation coefficient of trip lengths is calculated. Transport accessibility is also included in the model. It is represented by the dummy variables bike and car availability (regular, occasionally, no). As variables considering the travel, the parking situation (difficult, not difficult) at the place of residence and the walkable accessibility to a rail-bound PT station (yes, no) are also included. Finally, the normalized HHIM represents the dependent variable in this model as a continuous measure of multimodal travel behavior.

3. Results

3.1. Multimodality and Diversity of Activities of the Study Sample (D-1)

Table 2. Diversity of mode use and activities of the sample

	HHI_A	HHI_M	Number of trips per week	Km per week
Total	0.334	0.563	14.0	168
AGE GROUP				
18 - 25 years	0.299	0.529	13.2	185
26 - 35 years	0.257	0.535	16.1	216
36 - 50 years	0.251	0.586	16.2	196
51 - 60 years	0.319	0.591	14.4	180
61 - 70 years	0.404	0.565	12.8	142
> 70 years	0.469	0.546	11.4	97
GENDER				
male	0.336	0.575	14.0	188
female	0.331	0.553	14.3	149
EMPLOYMENT STATUS				
Trainee	0.295	0.481	13.7	180
Employed: full-time	0.267	0.592	15.1	224
Employed: part-time	0.243	0.564	16.6	159
Homemaker, temporarily unemployed	0.422	0.564	13.5	112
Retired	0.464	0.550	11.8	105
NA	0.424	0.572	13.0	101

Table 2 displays the characteristics of the sample regarding the variation of mode use (HHIM) and participation in activities (HHIA). Furthermore, significance tests were made to identify whether HHIm and HHIa differ across groups (but not presented). People with different ages, gender, and employment status are examined. Further, the variables Number of trips per week and Km per week represent the context of travel behavior. Middle-aged people (between 26 and 50 years) show the highest number of trips. The highest diversity of activities also characterizes this group compared to other groups (HHIA~0.25). The behavior of full-time employees is characterized by the highest value of the HHIM (0.59), meaning they are the least multimodal group.

Further, their comparatively low value of the HHIA (0.27) shows their broad diversity of activities. As a result, those people engage in multiple activities. Still, due to their routines in traveling to work, a single mode of transportation will likely become the focus of daily travel. Part-time employees show the lowest values for the HHIA (0.243), meaning their travel behavior depends on multiple and different activities. This indicates that other activities occur besides work, e.g., chauffeuring children and running multiple shopping trips. Their use of different transport modes is more diverse than full-time employees (HHIM~0.56). Their activities might be within close range, where bike use and walking are also comfortable. Trainees are obliged to travel to school regularly. They show less diverse activity patterns (HHIA ~0.30). Since most school attendees still live at home, they are often not responsible for shopping or service trips. However, their multimodal travel behavior is highest among all groups (HHIM ~0.48). In contrast, pensioners and older people show a low number of trips. The variety of activities is also low (HHIA ~0.46), which can be attributed to a lack of regular work trips and potentially also for service trips. Regarding multimodality, this group of people is ranked in the middle (HHIM ~0.56).

3.2. Mono- and Multimodal Travel Behavior for Activities and Across the Week (D-2)

Figure 1 displays mono- and multimodal travel behavior in one week (differentiated by weekends and weekdays) and for different activities. In total, 55% of all respondents only use one transport mode over one week (monomodal). In contrast, 45% use more than one transport mode (multimodals). On weekends, 82% show a monomodal travel behavior. However, in this context, it is essential to consider that the total number of trips made on two weekend days is lower than on five weekdays. Therefore, different modes of transportation are also less likely to be used. Considering five days of weekdays, 38% of the respondents show multimodal travel behavior. Only a third also shows multimodal travel behavior in terms of transport mode usage at the weekend. In addition, 10% of those being monomodal on weekdays use several transport modes at the weekend. This indicates that monomodal people generally tend not to differentiate on their mode choice variation. Simultaneously, multimodal travel behavior occurs to some extent through differences in mode use on weekends and weekdays.

The transport mode used for leisure activities varied for 26% of the sample within a week. In contrast, a changed mode for compulsory activities has only been made by 21% within the week while 79% continuously use a single transport mode for commuting. However, the cross-examination revealed that 17% use one mode for compulsory activities but vary their transport mode for their weekly leisure activities. Also, more than every second person using several transport modes for compulsory activities uses different modes for leisure activities.

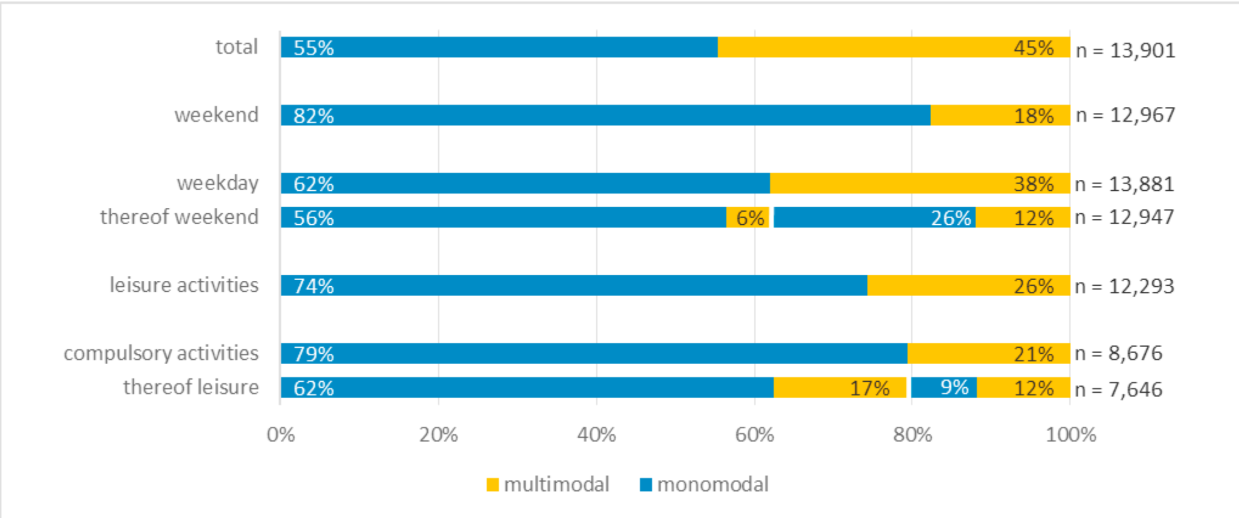

Fig. 1. Share of people with mono- and multimodal travel behavior in the course of one week (differentiated by weekend/weekdays) and related to activities.

3.3. Influence of HHI_A and Contextual Factors on Multimodality (R-1)

The regression model aims to investigate the influence of travel patterns and contextual factors on multimodal travel behavior. Table 3 presents the model estimates, including the variables presented in the methods section. The model is checked for multicollinearity, autocorrelation, and heteroscedasticity. To account for heteroscedasticity, robust standard errors are used. To account for multicollinearity variance inflation factors (VIF) were calculated. Variables with high VIF were not selected from the model. All results are interpreted with care.

The HHIA coefficient is positive, meaning that if a person engages in fewer different activities over one week, this person tends to be less multimodal. The number of compulsory, leisure, and shopping activities has negative coefficients. If the number of shopping activities increases, the HHIM decreases. Accordingly, a person is more likely to be multimodal if more shopping activities are performed. This effect is even higher for the number of leisure activities and less high for compulsory activities.

In contrast, the number of service activities, e.g. taking neighbors to the doctor and other activities, show a positive coefficient. This indicates a more monomodal transport mode use if these activities occur. The model's variation coefficient of trip length shows that a greater variation of kilometers traveled for trips within a week reduces the HHIM. It follows the variation in distance ranges for travel results in a more multimodal travel behavior. Furthermore, the negative coefficient for the number of linked activities within a loop trip indicates that linking tours result in fewer different transport modes.

The analysis is complemented by considering the availability of different transport modes and other travel-related contextual factors. The positive coefficients for bike availability show that people who own a bicycle or an e-bike behave more multimodally. For the analysis of car availability, the coefficients of the dummy variables need to be interpreted in comparison with the reference category: occasional car availability indicates multimodal behavior. In contrast, people with car availability tend to behave less multimodal than those who do not have regular access to a car. Accessibility of a PT station and a problematic parking situation at home also increase multimodal travel behavior.

Summing up, contextual factors of daily lives have varying influences on multimodality. The presented predictors are significant and indicate that multimodality can only be interpreted in a complex context. Finally, the adj. R^2 of 0.315 suggests that the proposed model can explain only a small part of the variance.

Table 3. Model estimates for the influence of activities and contextual factors of mobility on multimodality (HHIM), employees only

Predictors	**Estimates**	**std. Error**	**p**
(Intercept)	0.89537	0.01262	<0.001
HHI_A	0.24985	0.01989	<0.001
Number of compulsory activities	-0.00494	0.00096	<0.001
Number of leisure activities	-0.02339	0.00090	<0.001
Number of shopping activities	-0.01152	0.00112	<0.001
Number of service activities	0.00604	0.00120	<0.001
Number of other activities	0.01046	0.00323	<0.005
Variation coefficient of trip length	-0.08032	0.00504	<0.001
Bike availability [Yes]	0.02262	0.00199	<0.001
Car availability** [Yes, occasionally/in consultation]	-0.09978	0.00756	<0.001
Car availability** [No]	-0.18848	0.00784	<0.001
Accessibility of a rail-bound PT station [Yes]	-0.15127	0.01151	<0.001
Parking situation [difficult]	-0.07881	0.00666	<0.001
Number of linked activities within a loop trip	-0.03920	0.00706	<0.001
Observations	8026		
R^2 / R^2 adjusted	0.316 / 0.315		
** Reference: [Yes, regularly]			

4. Discussion and Conclusion

This study utilized data from the German Mobility Panel (MOP) to examine the characteristics of activity-related behavior in multimodal travel. To assess the concentration of variability in both mode choice and activity participation at an individual level, the researchers employed the Herfindahl-Hirschman-Index (HHI). This index-based approach considers multiple dimensions, such as transport modes and activities, enabling the calculation of average correlations between these variables. A regression model was then employed to gain a deeper understanding of the relationship between multimodality, travel patterns, and contextual factors of travel.

The results suggest that the computed HHIA, which represents the variability of activities, can effectively better contextualize individuals' travel behavior in their daily lives. For multimodal travel behavior, it is crucial to consider whether individuals engage in a wide range of activities or only a limited number. Engaging in a greater variety of activities throughout the week (indicating high variation in activities) is associated with a higher likelihood of exhibiting multimodal travel behavior. Notably, many leisure trips strongly indicate a propensity for multimodal travel behavior.

The results suggest that the variation of activities over one week positively influences multimodal travel behavior. Consequently, it makes a difference for multimodality whether persons indulge in many different activities or only a few. The descriptive results show that employees have more activity variations and are more monomodal than people with another employment status. This observation is confirmed by Hensher and Reyes (2000): the more complex the needs in everyday life, the more likely it is to behave less multimodally, to use the car instead, and to chain trips. Furthermore, people with fewer constraints (e.g. through work-related travel) show more significant intrapersonal variability (Pas & Koppelmann, 1986). Assuming a stable travel time budget, it is unlikely that different transport modes will be used when circumstances are complex: e.g., commuting to work usually involves only one transport mode, which encourages monomodal behavior. Commuting to work as a mandatory activity shapes activity patterns (Hilgert et al., 2018). Moreover, bicycles are unsuitable for all activities due to limited transport capacity, speed, and coverable distance; public transport can also be considered unattractive for chaining trips due to waiting times and transfers.

In contrast, however, the results of this study suggest that more diverse activities in everyday life also lead to increased multimodal behavior. This might result from individuals' mode choice for specific purposes (Kuhnimhof et al., 2006). This is particularly relevant for leisure activities and also for shopping. The number of leisure trips best reflects if a person behaves multimodally. This is a relevant finding for policymakers and opens up the need for additional research. Since leisure travel is the most spatially and temporally variable activity (Schlich & Axhausen, 2003), more detailed information on leisure activities is needed to draw a clear picture of multimodality.

Moreover, it needs to be further considered whether the increase in multimodality due to the number of leisure activities might result from car use (Heinen & Mattioli, 2019). The car is a flexible transport mode, and leisure trips are more elastic and have more degrees of freedom than, e.g., unelastic activities such as work. People might choose the car for their more complex leisure activities for hard-to-reach destinations (Hensher & Reyes, 2000). This is related to a more significant variation in trip length and is also consistent with the findings of this study.

The regression model results suggest that other predictors might explain multimodal behavior more thoroughly than those presented. However, research considering mainly sociodemographic explanatory variables for investigating multimodality also does not show more suitable results concerning model quality (Scheiner et al., 2016). The assumption of a linear relationship between the HHIM and the explanatory variables might further limit the results, since this may not always be true at the individual level. Furthermore, the contra-intuitive results from the descriptive analysis and the regression model might result from heterogeneity within the sample. According to the authors, more detailed analyses are impossible in the analyzed data set with the presented method. Future research should focus on beta regression or generalized linear models (GLMs) for the research question presented in this paper using a normalized HHI. Furthermore, AI-based approaches are also conceivable to address the presented topic in the future. Lastly, this study cannot control, e.g., attitudes, spatial conditions, and weather due to lack of data availability. This may further bias the results but might be highly relevant.

Policymakers should promote policies encouraging individuals to engage in various weekly activities. This can be done by creating a supportive environment that provides opportunities for activities such as leisure, shopping, and cultural events. By promoting diverse activities, policymakers can increase the likelihood of multimodal travel behavior. Policymakers should also prioritize collecting detailed information on leisure activities to better understand multimodal travel behavior. Leisure activities tend to be more variable and have different spatial and temporal characteristics than other activities. By obtaining comprehensive data on leisure activities, policymakers can gain insights into the factors influencing multimodal behavior and design targeted interventions. Lastly, policymakers should support additional research to deepen understanding of the relationship between activity patterns, multimodal travel behavior, and mode choice. This can help identify new insights and inform evidence-based policymaking in the future.

5. Declarations

Availability of data and material

Data is available at https://daten.clearingstelle-verkehr.de/192/

Code availability

R-Code can be made available by the authors upon request.

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