

1 **IMPACT OF WEATHER ON TRAVEL BEHAVIOR THROUGHOUT THE SEASONS -**  
2 **ANALYSIS OF TWO NATIONAL GERMAN HOUSEHOLD SURVEYS**

3

4

5

6 **Pia Tulodetzki**

7 Email: [pia.tulodetzki@kit.edu](mailto:pia.tulodetzki@kit.edu)

8 <https://orcid.org/0009-0007-3136-165X>

9

10 **Gabriel Wilkes**

11 Email: [gabriel.wilkes@kit.edu](mailto:gabriel.wilkes@kit.edu)

12 <https://orcid.org/0000-0002-1027-2734>

13

14 **Martin Kagerbauer**

15 Email: [martin.kagerbauer@kit.edu](mailto:martin.kagerbauer@kit.edu)

16 <https://orcid.org/0000-0003-4252-7874>

17

18 **Peter Vortisch**

19 Email: [peter.vortisch@kit.edu](mailto:peter.vortisch@kit.edu)

20 <https://orcid.org/0000-0003-1647-2435>

21

22

23 **Affiliation of all authors**

24 Karlsruhe Institute of Technology (KIT), Institute for Transport Studies

25 Kaiserstrasse 12, 76131 Karlsruhe, Germany

26

27

28 Word Count: 6728 words + 3 table(s) × 250 = 7478 words

29

30

31

32

33

34

35 Submission Date: August, 1 2023

**1 ABSTRACT**

2 We study the impact of weather on travel behavior using two large national household surveys  
3 from Germany from 2009 to 2019, and historical weather data from meteorological reanalysis. We  
4 specifically focus on home-based trips for work, education and leisure purposes, analyzing mode  
5 choice in different weather conditions. We find that all parameters studied—temperature, precip-  
6 itation and cloud cover— influence mode choice. The impacts differ between different seasons,  
7 inside the seasons at comparable conditions, and between different socio-demographic groups.  
8 Furthermore, the availability of mobility tools impacts how people react to weather conditions.  
9 Bicycle use is affected most by diverse weather conditions, reaching the highest shares in dry and  
10 warm conditions. The other modes do not change equally, but show different impacts depending  
11 on trip purpose, socio-demographic group and other factors. While we could demonstrate impacts  
12 of weather, future research should be undertaken to account for the possible changes in travel  
13 behavior in recent years.

14

15 *Keywords:* travel behavior, weather, household survey

## 1 INTRODUCTION

2 Travel demand estimation is a crucial element of transportation planning, as it provides valuable  
3 insights for developing efficient transportation systems. The traditional approach to travel demand  
4 modeling relies on estimates for an average day of the year. As we know, some factors, such  
5 as public holidays and school breaks, change mobility on specific days or periods, leading to  
6 variances in travel demand that are difficult to model. Recent advancements in mobility options  
7 (e.g., ride-sourcing, bike-sharing, e-scooter sharing, mobility on demand) have resulted in more  
8 flexible and dynamic travel behavior. The issue of climate change adds another layer of complexity,  
9 as projected increases in temperature and precipitation could impact people's mode choices and  
10 behavior. Therefore, it is crucial to consider the diversity in travel behavior concerning flexibility,  
11 mobility options, and environmental conditions when making informed planning decisions. In this  
12 paper, we want to analyze one environmental condition, which varies significantly throughout the  
13 year in some world regions: the weather. Although global warming pertains to overall climate  
14 changes that occur over a long period, most regions of the world tend to focus on seasonal changes  
15 in weather, such as the typical temperature ranges and precipitation.

16 In this paper, we present an in-depth analysis of the impact of weather on travel behavior  
17 using data from two national household surveys in Germany. We focus on home-based trips, as  
18 they provide individuals with their complete choice set, including the ability to adapt to weather  
19 conditions, such as changing clothes or modifying travel modes. Our analysis considers trip pur-  
20 poses and sociodemographic factors, such as age and gender, to deepen our understanding of the  
21 underlying factors. We analyze how people travel in different weather conditions and seasons,  
22 focusing on the changes in transportation modes. To ensure comprehensive coverage of weather  
23 data, we use data from a weather model that offers historical weather data from a nationwide grid,  
24 providing a detailed and extensive dataset for analysis. This study aims to clarify the effects of  
25 diverse weather conditions, such as temperature, precipitation, and sunshine, which exhibit varia-  
26 tions across seasons. By shedding light on the relationship between weather and travel behavior  
27 in Germany, this study aims to provide transportation planners and policymakers with valuable  
28 insights to enhance the accuracy of travel demand models in an era of changing mobility patterns  
29 and climate variability.

30 We will begin by examining the literature on how weather affects travel behavior. Next, we  
31 describe the data sources and preparation process, combining two household surveys to create a  
32 substantial and diverse database. We then present and analyze our results, focusing on differences  
33 between seasons, and conduct a deeper investigation of the fall season. Finally, the discussion  
34 section elaborates on the findings and identifies potential avenues for further research.

## 35 LITERATURE REVIEW

36 Extensive research has been conducted regarding the impact of weather on individuals' travel de-  
37 cisions, resulting in a substantial body of scientific knowledge. The primary goal of these studies  
38 is to comprehend how different weather conditions impact individuals' mode choices, including  
39 walking, cycling, using public transport (PT), or driving a private vehicle. This information is  
40 of utmost importance for transportation planning and policymaking, especially concerning global  
41 warming. Many different data sources can be used to examine the correlation between weather and  
42 mobility. Essential factors to consider in such analysis include the spatial and temporal resolution  
43 of the weather data, the specific weather parameters, e.g., temperature and precipitation, and the  
44 analyzed period, which primarily depends on the used survey data.

Concerning the survey data, National household surveys offer data on travel behavior over time from a diverse group of people, offering valuable insights into long-term mobility trends and how they are impacted by weather (1–3). Other data sources include traffic count data, mainly used for bicycles (4–6) or the data from smartcards for PT to investigate passenger numbers throughout different weather conditions (7) (Tao 2018), depending on the research focus. Also, the time horizon differs. Some studies focus on particular months or seasons to capture changes in travel behavior, such as Sabir (3) and Kashfi et al. (8), while other studies involve conducting multiple surveys throughout the year to account for weather changes (as done by Böcker et al. (9)). Some studies take a more comprehensive approach and examine travel patterns over a year or longer (as seen in Liu et al. (10)). Because work trips generally show a more stable behavior in the choice of means of transport than, for example, leisure trips, these two purposes are explicitly investigated in some studies. Commuting trips, which are necessary for daily life and less flexible, tend to be less affected by weather than leisure trips, which are typically more flexible and discretionary (11–13). Some studies focus on home-based trips only to investigate choice behavior when having the full option of modes of transportation. Additionally, trips that do not start at home may be influenced by the mode choice done earlier this day, which might reduce the weather influence seen in the data (2, 14, 15).

Spatial resolution and the source of weather data is an essential consideration in weather-mobility studies. Weather data can be obtained from nearby weather stations or measured locally to match individual travel activities (16–18). Typically, the data from the closest weather station is matched with the reported trips, resulting in varying accuracy. It still needs to be discussed if analyzing the weather condition during the journey or considering the daily parameters like mean temperature, maximum temperature, and the sum of precipitation deliver the most precise results. Recent studies show significant results for both time levels, potentially preferring daily data to cover up the overall weather conditions and mitigate e.g. the influence of the daily course (14, 19).

Temperature and precipitation are the most frequently observed weather parameters, followed by wind and sun duration. Regardless of the chosen data basis, it is uniformly evident that the active modes of transport, especially bicycle use, are most influenced by the weather. Bicycles are mainly used in summer and fall and benefit from relatively high temperatures and dryness - the share decreases significantly when temperatures are low (20–22). Weather conditions such as wetness, coldness, and strong winds increase the attractivity of more protected means of transport (23). However, these effects are not linear, e.g., the use of bicycles decreases during hot weather, and the use of cars is significantly lower when there is precipitation in the form of snow (3, 6, 24).

It becomes apparent how complex the issue is when observing how various groups of people respond to weather conditions. Women tend to be more affected by weather conditions regarding mood and satisfaction than men (14, 25, 26). At the same time, young people are more sensitive to lower temperatures and precipitation than older people, particularly for active modes like walking and cycling. In contrast, older people use active modes less under high temperatures (23). Additionally, the location of residence can influence the weather's impact on mode choice, with less dense areas being more sensitive to certain weather conditions, especially for cycling (19, 27).

In light of numerous studies conducted on weather and its impact on mobility in different regions, it can be observed that the findings tend to be location-specific and cannot be generalized to other areas. The sociodemographics of the respondents, the used weather data, the usual weather in the study area, trip purposes, and routines influence the impact of weather on travel behavior.

1        Thus, considering the lack of research in Germany and the use of weather stations instead  
2 of modern weather models, it is imperative to examine the potential of utilizing high-quality data  
3 to isolate the influence of weather on a more comprehensive level. This article aims to contribute  
4 to this dialogue by exploring how contemporary weather combined with two national travel sur-  
5 veys from Germany can provide a more accurate understanding of the effects of weather on travel  
6 behavior.

## 7 **DATA AND DATA PREPARATION**

### 8 **Mobility data**

9        We use the data from travel diaries from two distinct national household surveys conducted in  
10 Germany. The first dataset is the cross-sectional survey "Mobility in Germany" (MiD) conducted in  
11 2017 (28), comprising 960,619 trips. In MiD, individuals reported their trips on a single designated  
12 day throughout the year, allowing for the generation of mobility data covering all seasons and  
13 months. The second dataset stems from the longitudinal survey "German Mobility Panel" (MOP)  
14 conducted between 1994 and 2022 (29), filtered for this study to the lapse between 2009 and 2019,  
15 encompassing 628,371 trips. MOP is a panel survey where individuals record their one-week  
16 trips for three consecutive years. This survey is only conducted during fall (mainly September to  
17 October).

18        The household data went through several filtering criteria to accurately depict the weather's  
19 influence on mobility decisions. The analysis only involves trips where the main mode of transport  
20 is by foot, bicycle, using a car as a driver or passenger, or using public transport (PT). All trips  
21 on days reported by respondents as atypical (such as vacation days, and days out of their usual  
22 surroundings). As the next filtering step, we selected trips highly likely to have originated from  
23 home. For both datasets, only trips where the preceding trip was stated as "towards home" or the  
24 trip was their first trip of the day and the respondents stated to start from home are included. These  
25 filtered datasets ensure that the analysis captures the weather's impact on mobility decisions made  
26 from home and allows for more precise observations and conclusions regarding weather influences  
27 on transportation choices.

28        For all analyses presented in the results, the values are weighted at the person level consid-  
29 ering sociodemographic characteristics of the entire German population.

30        Overall, through this data merging and harmonization, we compiled year-round mobility  
31 data based on MiD, and a particularly large dataset specifically for the fall season by combining  
32 MOP and MiD, which enable the analysis of seasonal disparities, as well as specific patterns during  
33 one season.

### 34 **Weather data**

35        This study uses historical weather data from the ECMWF-ERA5 dataset (30). This is based on so-  
36 called reanalysis, which uses weather models fed with observational data from weather stations,  
37 satellite data, and other environmental information, providing various weather parameters.

38        Our approach differs from most travel studies, which combine reported trips with weather  
39 station data. There are several differences: Instead of limited, singular points of observation, there  
40 is a continuous grid of data points. Therefore, they are less sensitive to place-specific phenomena,  
41 such as a local downpour. Additionally, they contain meteorological parameters not available from  
42 weather stations, such as cloud cover.

43        The ERA5 dataset has a spatial resolution of 0.25 degrees in both latitude and longitude,

1 giving roughly a 31km grid, and is available royalty-free. Three weather parameters—temperature  
 2 2m above ground<sup>1</sup>, total precipitation, and cloud cover—were queried from the dataset for our  
 3 analysis. We processed the data using the Python libraries xarray (31) and cfgrb (32). In ERA5,  
 4 the parameters are available at an hourly resolution. We aggregated and converted them as follows:

- 5 • Temperature: Maximum temperature during the day, converted from Kelvin to degree  
 6 Celsius (°C).<sup>2</sup>
- 7 • Precipitation: Sum of the precipitation among all hours of the day, converted from m to  
 8 mm.<sup>3</sup>
- 9 • Cloud cover: Number of hours per day where cloud cover is lower than 20%.

## 10 **Combining weather and travel data**

11 The trip data needs to be matched with the weather data, considering location and time. In MiD, the  
 12 geometrical center of the individuals' residential postal codes was chosen for the spatial matching.  
 13 In MOP, truncated postal codes and district codes are given, which are intersected and the centroids  
 14 of these units were used. For these locations, the corresponding grid cell from the weather data is  
 15 retrieved. We transformed the trip timestamps from the survey data to Coordinated Universal Time  
 16 (UTC) to match the trip timestamps with the meteorological data.

17 We follow the meteorological classification of seasons, assigning each season to three  
 18 months. For instance, fall is defined as September, October, and November. The analysis is under-  
 19 taken for the trip purposes going to work, going to the place of education and leisure. Therefore,  
 20 we include both the very routinized and more flexible trips.

## 21 **RESULTS RELATED TO SEASONS**

### 22 **Travel behavior by seasons**

23 First, we examine the variations in mode shares across different seasons, see Table 1. Consistent  
 24 with existing literature, work trips exhibit the highest stability in overall mode shares with small  
 25 differences between the seasons. We assume that this is because these trips are characterized by  
 26 strong routines. However, bicycle usage for commuting trips is subject to notable seasonal varia-  
 27 tions, with the share highest in summer at 14.4% and dropping to 10.0% in winter. Interestingly,  
 28 trips made by foot show a distinct pattern, with the highest share occurring during winter at 8.8%,  
 29 suggesting that colder temperatures influence individuals to opt for walking. In contrast, the use  
 30 of car as driver and passenger remains stable throughout the seasons, showing that individuals  
 31 who choose the car for commuting trips maintain their mode choice regardless of the time of year.  
 32 Notably, PT usage shows a slight increase during winter, having a share of 16.5%, compared to  
 33 summer, with a share of 15.2%. It is plausible that individuals who derive pleasure from cycling  
 34 during the warmer seasons partly select walking or using PT as means of transportation during  
 35 the colder months. For education trips the bicycle mode share declines from 23.4% in summer to  
 36 13.4% in winter. Conversely, PT experiences an increase from 24.5% in summer to 32.1% in win-  
 37 ter. The use of modes hardly changes. The observed fluctuations in bicycle and PT mode shares  
 38 emphasize that people who make educational trips switch between bicycle and PT throughout the  
 39 seasons, preferring protected vehicles during spring and winter and bicycles in summer and fall.

---

<sup>1</sup>This is the standard air temperature.

<sup>2</sup>For our readers that are more familiar with values in Fahrenheit (F): 5 °C = 41F, 10°C = 50F, 15°C = 59F, 20°C = 68F, 25°C = 77F

<sup>3</sup>In imperial units: 0.1mm is around 0.004in, 1mm is around 0.04in, 5mm is around 0.2in

**TABLE 1 Modal split of trips in different seasons by purpose**

	Spring	Summer	Fall	Winter
<b>Work</b>				
sample size	20,064	18,375	49,257	12,586
by foot	6.4%	6.3%	7.4%	8.8%
bicycle	13.6%	14.4%	15.6%	10.0%
car as driver	61.7%	61.1%	59.0%	61.1%
car as passenger	3.3%	3.0%	3.9%	3.7%
public transport	15.0%	15.2%	14.2%	16.5%
<b>Education</b>				
sample size	7,651	5,747	13,902	5,609
by foot	23.4%	23.7%	23.8%	22.4%
bicycle	16.5%	23.4%	18.7%	15.2%
car as driver	6.7%	6.6%	6.1%	7.0%
car as passenger	23.7%	22.9%	23.9%	22.8%
public transport	29.8%	23.4%	27.5%	32.5%
<b>Leisure</b>				
sample size	31,998	31,132	71,611	17,234
by foot	33.3%	29.9%	(25.7)%	39.6%
bicycle	14.9%	19.0%	(14.2)%	7.7%
car as driver	26.3%	26.0%	(33.9)%	26.0%
car as passenger	19.1%	18.6%	(18.1)%	19.6%
public transport	6.4%	6.5%	(8.1)%	7.3%

1 Leisure trips show the highest volatility among all trip types, especially for active transport  
 2 modes. Bicycle usage has the highest share during summer, accounting for 19.0% of all trips, but  
 3 drops to 7.7% in winter. Conversely, walking shows the highest mode share during winter at 39.5%,  
 4 while it decreases to 25.7% in fall. These changes indicate that people switch between walking  
 5 and cycling on leisure trips throughout the seasons. In contrast, all other means of transportation  
 6 show stable mode shares for leisure trips, suggesting that these modes are less sensitive to seasonal  
 7 changes. PT slightly increases in winter, maybe due to individuals opting for a protected means of  
 8 transportation in colder weather conditions.<sup>4</sup>

9 Our analysis reveals evident seasonal changes in mode shares, with work and educational  
 10 trips displaying less sensitivity to these variations than leisure trips. The use of car as driver is  
 11 found to be the least influenced by seasons, suggesting that individuals who choose to drive have  
 12 a more routinized behavior, irrespective of the time of year, while active modes of transportation  
 13 vary over the seasons.

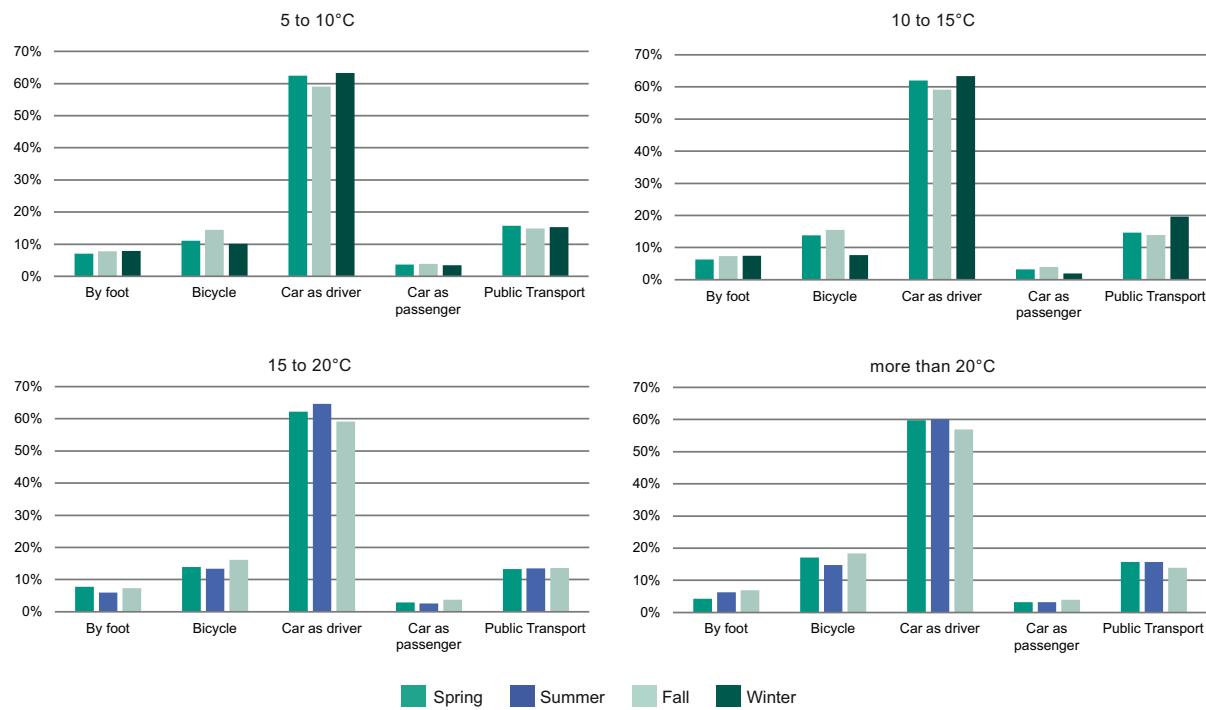
#### 14 **Differentiating the Impact of Seasons and Weather Conditions**

15 After looking at seasonal variations, we aim to explore how people respond to similar weather  
 16 conditions in different seasons. Understanding these dynamics allows a deeper comprehension  
 17 of how weather influences travel behavior and whether they happen on a long-term, seasonal, or

<sup>4</sup>Roundtrips are partially included in leisure in the MID dataset, and are excluded from MOP data. This explains larger differences between fall and the other seasons concerning average modal split, as roundtrips are often undertaken walking, but are excluded to a major proportion in fall due to including the MOP dataset.

1 short-term choice based on the weather of that day. We use categories according to daily maximum  
 2 temperatures, with five-degree Celsius steps ranging from 5 to over 20 °C, and analyze the three  
 3 most relevant seasons for each temperature interval. Due to relatively small samples, we do not  
 4 analyze education trips.

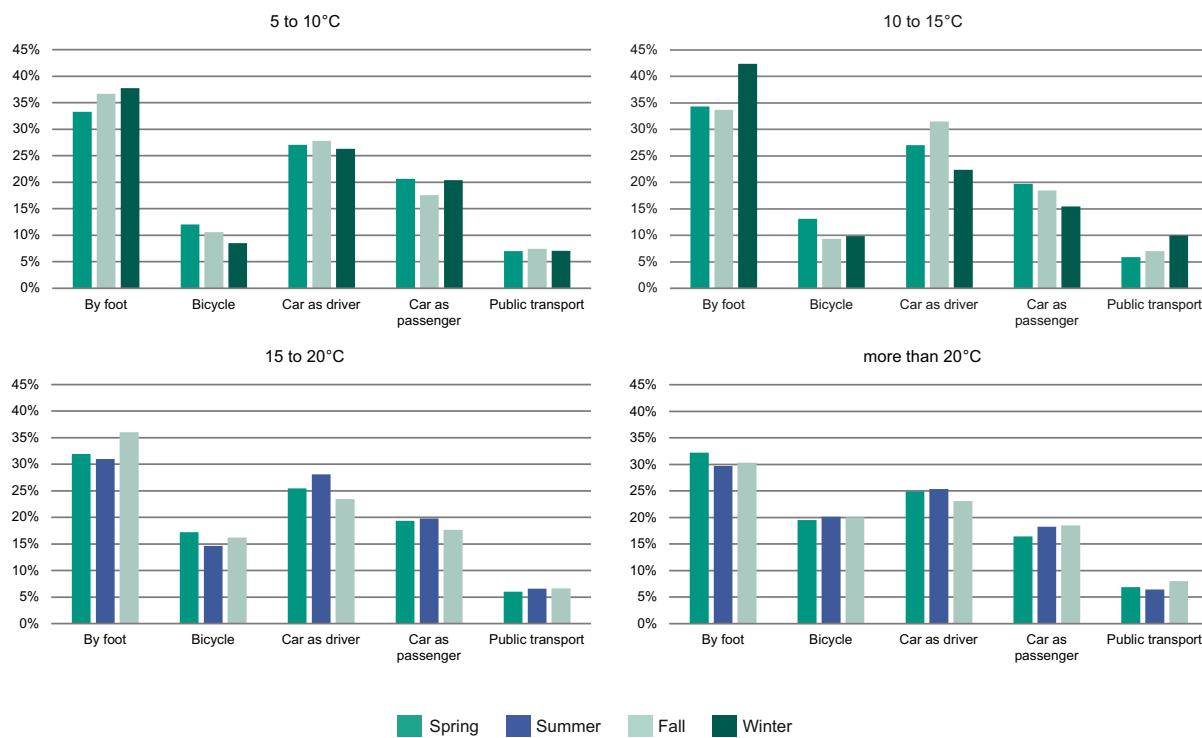
5 Figure 1 presents the modal shares for work trips. For temperatures between 5 and 10°C,  
 6 between spring and winter there is a one percentage point difference in modal shares of bicycles  
 7 (winter: 10.1%, spring: 11.1%). In contrast, during fall, bicycle share is 4 percentage points  
 8 higher than in winter (14.4%). In the 10 to 15°C range, which is a high temperature for winter in  
 9 Germany, the bicycle mode share is 7.7% during winter and between 13.8 and 15.4% for spring  
 10 and fall. Correspondingly, the share of car and PT are especially high during winter. This shows  
 11 that the influence of seasons is larger than temperature. For days in the 15 to 20°C range, active  
 12 modes have the lowest shares in summer, while the car has the highest share in summer. This is  
 13 presumably because these temperatures are considered cold in summer. Conversely, bicycle usage  
 14 is highest during fall, and the shares for spring and summer are nearly identical. For days with  
 15 a maximum temperature exceeding 20°C, the bicycle mode share is 2.3 percentage points higher  
 16 in spring than in summer and 3.5 percentage points higher in fall. This indicates that warm days  
 17 in spring and fall have a higher bicycle mode share than in summer, when warm temperatures are  
 18 more common. Furthermore, PT and car usage as driver show a decrease in fall, indicating that in  
 19 typically colder seasons, people tend to use active transportation more when it is warm outside.



**FIGURE 1 Modal split for work trips in different seasons by temperature level**

20 For leisure trips, we observe even stronger changes, see Figure 2. For temperatures between  
 21 5 and 10°C, the share of leisure trips made by foot is 5.5 percentage points higher in winter (37.7%)

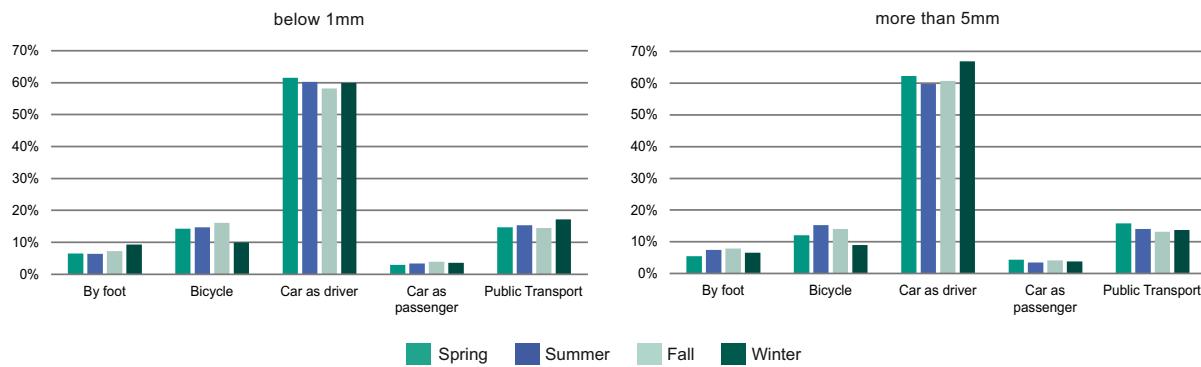
1 than in spring (33.3%). In contrast, bicycle usage shows the opposite trend (12.0% in spring, 8.5%  
 2 in winter). At 10 to 15°C, we observe an increase of almost ten percentage points in leisure trips  
 3 made by foot during winter compared to spring and fall. Here, bicycle usage is highest in spring,  
 4 with 17.1%. It remains on a higher level in winter than in fall, emphasizing that warm weather,  
 5 relative to the typical weather of the season, has a more decisive influence on bicycle usage than  
 6 only the temperature itself. PT usage is highest in winter, nearly doubling the share observed  
 7 in spring. This suggests that people opt for PT during colder months to avoid exposure to cold  
 8 weather conditions. At 15 to 20°C, leisure trips on foot are similar in summer and spring, but there  
 9 is an increase of about five percentage points in fall. Bicycle usage, however, is lowest in summer,  
 10 with 14.6%, despite being the highest in the overall share. While 15 to 20°C maximum is not a  
 11 high temperature for summer, compared to spring, people react with higher bike shares in spring  
 12 than in summer. Interestingly, car usage as a driver is highest in summer, potentially caused by  
 13 the above-mentioned effect. For maximum temperatures exceeding 20°C, bicycle usage remains  
 14 almost the same for all three seasons, suggesting that warm days, irrespective of the season, result  
 15 in a consistent bicycle mode share of around 20%. In conclusion, high temperatures result in the  
 16 lowest overall changes in mode shares between the seasons but create the highest shares of active  
 17 mobility. The same temperatures are perceived differently depending on the season, leading to  
 18 variations in mode choices under similar conditions.



**FIGURE 2 Modal split for leisure trips in different seasons by temperature level**

19 In the following we compare work and leisure trips on days without or with very few  
 20 precipitation (less than 1mm of precipitation throughout the day) to days with more than 5mm of  
 21 precipitation in the different seasons.

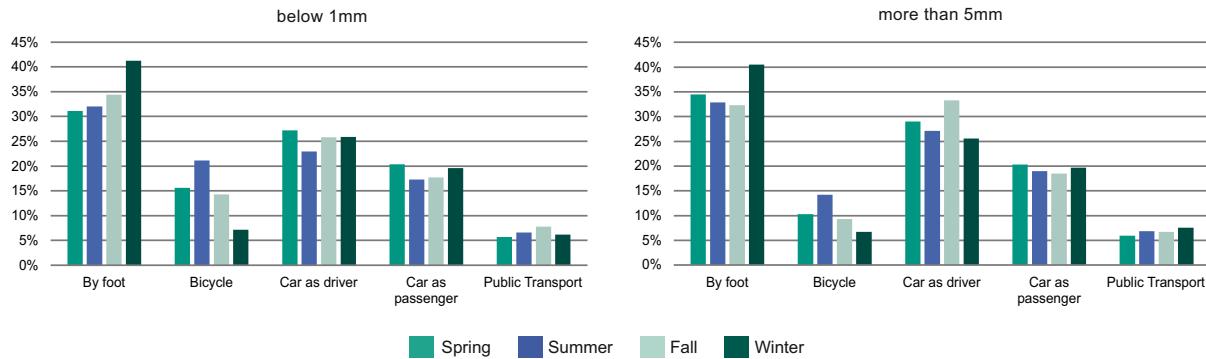
Figure 3 shows the results for work trips. In winter, trips made by foot have the highest share under dry conditions (9.3%), dropping to 6.6% on wet days. Summer and fall show an increase in work trips made by foot with precipitation occurring, potentially due to the higher temperatures during these seasons. Regarding bicycle usage, the share is almost the same on dry days in spring and summer. However, in spring, the share drops by about 2.3 percentage points from dry to wet days, while it increases in summer. Surprisingly, the variation in bicycle shares between dry and wet days in winter is very small (9.9% and 9.1%), indicating that some people use the bike on their work trips regardless of the weather. Car usage as a driver remains roughly stable, with a significant influence of precipitation observed only in winter: In winter, the share of car trips increases by about seven percentage points on wet days, indicating a strong sensitivity to precipitation in the coldest season. Regarding PT, when precipitation occurs, the share drops by about 3.4 percentage points in winter and slightly by about 1.4 percentage points in fall and summer.



**FIGURE 3 Modal split for work trips in different seasons by precipitation**

Concerning leisure trips (see Figure 4), when it is dry, the share of trips made by foot is lowest in spring, with a share of 31.1%, while being at 41.1% in winter. While the share of walking in summer and winter is hardly negatively affected by precipitation, during spring, the modal share of walking increases by 3.3 percentage points and in fall, it decreases by 2.1 percentage points. Bicycle usage is consistently lower in wet conditions by about 5 percentage points in spring and fall, while in summer it is even 7 percentage points lower. In winter, the bicycle share is hardly affected, suggesting that individuals who use the bike in winter are less precipitation-sensitive, just as observed for work trips. Car usage as a driver rises significantly on wet days in fall (from 25.8% to 33.2%) and in summer (from 23.0% to 27.1%).

Overall, the results highlight the varying responses to precipitation and demonstrate the impact of weather conditions on mode choices for work and leisure trips. The effect of precipitation varies throughout the year, mainly for the active transport modes. A particular share of people seems to change their behavior due to the weather. At the same time, there remains a group of less weather-sensitive people, who, e.g., ride their bicycle in winter, and people who do not change their behavior in general, e.g., always driving a car.



**FIGURE 4 Modal split for leisure trips in different seasons by precipitation**

## 1 RESULTS FOR FALL

2 In the following, we analyze further aspects of weather and travel behavior during fall, combining  
 3 also sociodemographic characteristics. The temperature range is always given between 5 and 25°C  
 4 as this is the relevant range for this season in Germany. An introductory remark: as will be seen  
 5 in the tables given, the results are less stable than those for the different seasons - in several result  
 6 rows there are outliers. Therefore, we focus on those results that show a clear pattern or trend.

## 7 Temperature, precipitation and cloud cover

8 At first, we analyze the impact of temperature and precipitation on travel behavior differentiated  
 9 by the three different trip purposes (see Table 2). It can be observed that concerning temperature,  
 10 the modal split of work trips changes most related to the bicycle. With rising temperature, the  
 11 bicycle is used more as a mode of travel (14.4 to 18.1%). Simultaneously, PT and car as driver  
 12 reduce their shares slightly (from 14.8 to 12.8% and from 59.0 to 57.4%, respectively). Concerning  
 13 precipitation, the opposite can be observed: with more precipitation the bicycle share decreases  
 14 (from 16.1 to 14.1%) while the share of car as driver increases (57.9 to 60.7%). PT is affected  
 15 slightly negatively when high levels of precipitation occur (decrease from 14.5 to 13.2%).

16 Trips with education purpose are affected slightly differently. Bicycle share increases with  
 17 rising temperature from 17.7% in the temperature range 5 to 10°C to 27.3% in the temperature  
 18 range 15 to 20°C. However, car as passenger is affected most negatively, decreasing from 17.6 to  
 19 12.9%. Effects of precipitation are similar: increased shares of car as driver and car as passenger,  
 20 however, the bicycle share is affected only at more substantial precipitation levels.

21 Regarding leisure trips, the changes are most dominant with respect to the bicycle: With  
 22 rising temperature, the share of bicycle trips increases from 11.5 to 18.0%. In contrast, car as driver  
 23 and car as passenger decrease slightly. Walking has its highest share at 5 to 10°C range with 28.4%,  
 24 while at higher temperature levels the share is between 24.1 and 25.2%. Concerning precipitation,  
 25 bicycle use decreases by 2.6 percentage points, which is far less than the differences that occur by  
 26 changing temperature. Other modes such as car as driver, car as passenger and walking increase  
 27 slightly.

TABLE 2 Modal split of trips during fall by purposes and weather parameters

	Temperature				Precipitation				Low cloud cover		
	5 to 10°C	10 to 15°C	15 to 20°C	20 to 25°C	<0.1mm	0.1 to 1mm	1 to 5mm	>5mm	<8 h	8 to 16 h	>16 h
<b>Work</b>											
sample size	8,306	15,860	14,211	4,784	17,619	12,529	11,887	6,818	41,035	4,883	2,935
by foot	7.8%	7.4%	7.3%	7.6%	6.8%	7.4%	7.9%	7.4%	7.4%	7.7%	6.9%
bicycle	14.4%	15.5%	16.1%	18.1%	16.1%	16.2%	15.3%	14.1%	15.4%	16.6%	17.4%
car as driver	59.0%	59.2%	59.2%	57.4%	57.9%	58.6%	59.8%	60.7%	59.3%	56.5%	58.1%
car as passenger	3.9%	4.0%	3.8%	4.1%	4.0%	4.0%	3.5%	4.1%	3.8%	4.8%	4.2%
public transport	14.8%	13.9%	13.6%	12.8%	14.5%	14.4%	14.0%	13.2%	14.2%	14.4%	13.5%
<b>Education</b>											
sample size	2,493	4,494	3,731	1,364	5,010	3,507	3,374	1,907	11,698	1,330	770
by foot	16.4%	16.3%	13.5%	16.4%	16.7%	14.3%	16.6%	15.1%	15.9%	13.9%	18.5%
bicycle	17.7%	23.8%	27.3%	21.6%	22.4%	24.1%	22.8%	19.8%	22.8%	23.6%	17.3%
car as driver	11.4%	11.7%	10.1%	10.2%	10.3%	10.0%	11.8%	13.0%	11.2%	9.7%	8.9%
car as passenger	17.6%	14.3%	11.1%	12.9%	13.7%	14.6%	13.6%	15.6%	14.1%	13.1%	17.2%
public transport	36.8%	33.9%	38.0%	38.9%	37.0%	37.0%	35.1%	36.5%	36.0%	39.6%	38.0%
<b>Leisure</b>											
sample size	11,304	23,597	21,128	8,372	28,871	17,471	15,922	8,791	57,531	7,916	5,608
by foot	28.4%	25.2%	24.1%	24.3%	25.6%	25.1%	26.0%	26.1%	25.9%	25.6%	23.4%
bicycle	11.5%	13.1%	15.9%	18.0%	15.2%	14.3%	13.5%	12.6%	13.9%	15.3%	17.0%
car as driver	33.8%	35.3%	34.6%	32.1%	33.6%	33.4%	34.2%	35.8%	34.2%	32.9%	32.9%
car as passenger	18.2%	18.6%	17.7%	17.1%	17.5%	18.9%	18.1%	18.3%	18.0%	17.6%	19.6%
public transport	8.1%	7.8%	7.7%	8.4%	8.0%	8.3%	8.1%	7.2%	8.0%	8.6%	7.0%

1 As an indicator if the weather is (subjectively) pleasant, we use the parameter cloud cover.  
 2 It can be seen that there is a remarkable influence: Comparing days with high and low cloud cover,  
 3 the bicycle share increases from 15.4 to 17.4% for work trips and from 13.9 to 17.0% for leisure  
 4 trips. For all trip purposes, the share of car as driver decreases when low cloud cover prevails.

5 In summary, bicycle use is most affected, for all trip purposes. The highest shares can  
 6 be observed at low precipitation and high temperatures. However, the modes that lose shares are  
 7 distinct between the different trip purposes. For work trips, it is car as driver and PT, for education  
 8 trips it is car as passenger, and for leisure trips it is walking and car as driver and passenger. Cloud  
 9 cover alone also has a visible influence.

## 10 **Influence of mobility tools available**

11 We analyzed our dataset regarding correlations between the weather's influence on modal split  
 12 at work trips, grouped by the availability of car availability, transit pass ownership and bicycle  
 13 ownership (mobility tools). The full results are depicted in Table 3 .

14 Persons that always have a car available increase their share of bicycle from 8.2% to 11.8%  
 15 at higher temperatures. However, this happens only when temperatures reach at least 20°C. At the  
 16 same time, usage of car as driver decreases from around 77 to 74.1%, also walking decreases from  
 17 6.0% to 4.9%. In comparison, people that do "sometimes" have a car available show a change in  
 18 bicycle use from 28.4 to 35.8%, and show a strong increase already at 15°C. Furthermore, they  
 19 seem to change their mode from PT to bicycle. People that do not have a car available hardly  
 20 change their travel mode depending on the temperature.

21 Analyzing the influence of bicycle ownership it can be observed that only those having  
 22 a bicycle change their travel behavior: With rising temperature, the bicycle share increases from  
 23 17.4 to 21.6%. This is at the expense of car as a driver and PT. People without a bicycle do hardly  
 24 change their travel behavior, especially not in a consistent manner.

25 When differentiating people by PT pass ownership, it is remarkable that people having a  
 26 transit pass decrease their PT usage by nearly 7 percentage points (from 69.1 to 62.2%) between  
 27 low and high temperature levels. Simultaneously, the usage of bicycle increases from 8.4 to 13.5%.  
 28 People without a transit pass have a smaller variation of travel behavior: while the bicycle share  
 29 increases with higher temperatures, the differences are smaller (from 16.3 to 19.3%).

30 We also analyzed people that state to be members of car-sharing companies (not depicted in  
 31 the table). They present an especially large variance in travel behavior depending on temperature:  
 32 Bicycle share increases by 23 percentage points, PT decreases by 16 percentage points. However,  
 33 as the samples are relatively small (between 97 and 294 trips), these results should only be seen as  
 34 indicative.

## 35 **Influence of sociodemographic characteristics on weather sensitivity**

36 At last, we analyze people's reactions to weather by age and gender (also depicted in Table 3).  
 37 Concerning gender, we differentiate between male and female, as only these categories are avail-  
 38 able in our data. For simplicity, we differentiate between the age groups "between 18 and 49 years"  
 39 and "50 years and older".

40 Remarkably, male persons of 50 years and older do not show any clear changes in travel  
 41 behavior with changing temperatures. They seem to make nearly the same decisions independent  
 42 of temperature - at least in the temperature levels and the season we are analyzing.

43 Younger men change their behavior over the whole range of temperatures, a pattern of

**TABLE 3 Modal split of trips to work depending on mobility tools and age and gender**

	5 to 10°C	10 to 15°C	15 to 20°C	20 to 25°C	5 to 10°C	10 to 15°C	15 to 20°C	20 to 25°C				
	by mobility tools											
<b>car</b>												
		<b>always available</b>				<b>sometimes or never available</b>						
sample size	6,042	11,691	10,584	3,475	1626	3157	2905	951				
by foot	6.4%	5.1%	5.4%	4.9%	11.3%	12.9%	11.6%	13.5%				
bicycle	8.2%	9.4%	9.5%	11.8%	30.8%	30.3%	34.0%	34.8%				
car as driver	76.7%	77.1%	77.2%	74.1%	15.9%	17.2%	15.7%	17.4%				
car as passenger	3.0%	2.9%	2.4%	3.2%	5.6%	5.6%	6.6%	6.1%				
public transport	5.7%	5.5%	5.5%	6.0%	36.5%	34.0%	32.1%	28.3%				
<b>bicycle</b>												
		<b>bicycle available</b>				<b>no bicycle available</b>						
sample size	6,732	12,755	11,510	3,959	1,474	2,970	2,650	770				
by foot	7.6%	6.9%	7.1%	7.5%	9.3%	9.5%	8.3%	8.2%				
bicycle	17.4%	18.7%	19.8%	21.6%	1.5%	1.6%	1.4%	1.0%				
car as driver	57.7%	57.5%	57.0%	55.9%	64.1%	66.6%	67.8%	64.7%				
car as passenger	3.8%	3.7%	3.4%	3.9%	3.9%	5.2%	5.1%	4.9%				
public transport	13.5%	13.2%	12.6%	11.1%	21.2%	17.1%	17.5%	21.3%				
<b>transit pass</b>												
		<b>owns transitpass</b>				<b>without transitpass</b>						
sample size	1,183	2,433	2,255	731	4,517	8,179	6,549	2,389				
by foot	4.5%	6.9%	7.0%	6.2%	8.5%	8.0%	7.9%	8.3%				
bicycle	8.4%	10.7%	10.3%	13.5%	16.3%	17.1%	17.9%	19.3%				
car as driver	13.1%	14.6%	13.4%	13.6%	67.7%	68.4%	68.9%	65.5%				
car as passenger	4.9%	3.2%	4.8%	4.5%	3.4%	4.1%	3.6%	4.2%				
public transport	69.1%	64.7%	64.5%	62.2%	4.1%	2.3%	1.7%	2.6%				
<b>by age and gender</b>												
		<b>between 18 and 49 years</b>				<b>50 years and older</b>						
<b>female</b>												
sample size	2,106	4,031	3,511	1,312	1,978	3,702	3,475	1,051				
by foot	9.2%	7.1%	8.8%	8.6%	10.3%	8.5%	8.1%	7.6%				
bicycle	13.9%	16.1%	13.7%	17.6%	12.3%	13.4%	13.9%	18.8%				
car as driver	59.4%	57.5%	61.1%	56.5%	55.4%	59.6%	56.6%	54.3%				
car as passenger	4.9%	4.4%	3.6%	3.8%	5.5%	4.6%	4.3%	4.7%				
public transport	12.5%	14.9%	12.9%	13.4%	16.5%	13.9%	17.1%	14.6%				
<b>male</b>												
sample size	2,308	4,286	3,708	1,331	1,868	3,746	3,438	1,067				
by foot	6.3%	6.4%	5.5%	6.3%	6.1%	8.3%	6.6%	7.4%				
bicycle	15.2%	16.7%	19.4%	19.8%	14.6%	14.0%	15.3%	14.8%				
car as driver	59.2%	59.0%	58.7%	57.9%	63.9%	64.1%	61.5%	62.0%				
car as passenger	2.5%	3.3%	3.2%	4.0%	2.8%	3.3%	4.1%	4.0%				
public transport	16.8%	14.6%	13.1%	12.0%	12.5%	10.2%	12.6%	11.8%				

1 decreasing PT and car use can be seen (from 16.8 to 12.0%, and from 59.2 to 57.9%, respectively).  
2 There is an increase from 15.2% to 19.4% in bicycle share from the temperature interval 5 to 10°C  
3 to the interval 15 to 20%. In contrast, among women, a remarkable change of mode choice starts  
4 to set in only at the temperature level of 20 to 25°C with increased bicycle share. Among older  
5 women, this substitutes walking, among younger women no clear substitute is identifiable.

6 At very low temperatures (not depicted in the table), among the older age group, male  
7 people tend to use car more often, while female persons tend to use it less: Between the temperature  
8 levels 0 to 5°C and 10 to 15°C there is an increase in the share of car in modal split of 10 percentage  
9 points among women and a decrease of 3 percentage points among men.

## 10 DISCUSSION

11 In our study, we combined two national household surveys to obtain a large dataset which allows  
12 to analyze the impact of weather on travel behavior. We focused on home-based trips where the  
13 degrees of freedom in mode choice are largest.

14 We found that the same temperature and precipitation generate different modal shares in  
15 the different seasons. Therefore, apparently, similar weather conditions are perceived differently  
16 between seasons. We explain this behavior with the fact that when temperature is relatively high  
17 compared to other days in the same seasons, this might be due to sunshine. Related to this, we also  
18 see a positive impact of having low cloud cover on travel behavior in fall. Thus, having pleasant  
19 days with sunshine may lead to higher use of active modes. However, this possible relationship  
20 needs further research for clarification.

21 We can see that sociodemographic characteristics and the availability or ownership of mo-  
22 bility tools has an impact on the influence weather has on travel behavior. People not always  
23 having a car available, owning a bicycle or owning a transit pass show the largest changes in travel  
24 behavior depending on the weather conditions - shifting from PT to bicycle at higher temperatures.  
25 People not having a bicycle, and also people "never" having a car available hardly change their  
26 travel behavior with changing temperatures. This is probably due to limited alternatives. We as-  
27 sume that nowadays (the data is from 2009 to 2019), this may be different due to an increase in  
28 sharing services.

29 Also, the sociodemographic differences in weather's influence on travel behavior are inter-  
30 esting. Older men react the littlest on changing conditions, thus, when policy wants to change their  
31 behavior, it could make sense to point their attention towards the changing weather conditions and  
32 to re-think their travel behavior. However, further analysis should be undertaken to strengthen this  
33 observation, mainly with more data, as well as with more weather conditions.

34 Precipitation decreases bicycle modal share in all seasons and for all trip purposes. There  
35 are differences in magnitude, having largest impacts for leisure trips. However, as precipitation is  
36 sometimes a relatively local phenomenon, we would like to repeat our analysis with grid zones of  
37 larger resolution, i.e., to have grid zones smaller than 31 km edge length.

38 In recent years there were major changes in mobility: New sharing modes such as bike  
39 sharing and e-scooter sharing have arisen or were scaled up, and due to home-office and video  
40 conferences people can execute their activities more flexibly than before the Covid pandemic.  
41 These changes are not represented in the data we analyzed, as the data is from the years 2009 to  
42 2019. Therefore, it would be useful to repeat the analysis with newer data. Furthermore, in future  
43 research, the possible changes in activities, trip rates and trip lengths should be analyzed.

44 Although we had a large dataset, when analyzing specific weather situations for specific

1 sociodemographic groups the sample quickly gets small. Therefore, there might be a bias if certain  
2 weather situations only occur jointly with other special conditions. It would be promising to use an  
3 even larger dataset. Also further statistical methods such as regression and statistical tests should  
4 be applied to this data.

5       Besides seasons, we used daily maximum temperature, the sum of daily precipitation and  
6 the number of hours with low cloud cover in our study as weather parameters, since in prelim-  
7 inary tests these have shown to be most determining. However, other parameters, such as daily  
8 average temperature or temperature and precipitation at the hour of travel could be meaningful as  
9 well. Testing which parameter or which combination of parameters has most influence should be  
10 analyzed in the future. Also, it may be sound to consider the daytime brightness in combination  
11 with weather. Furthermore, future research should attempt to determine which spatial resolution  
12 of weather and mobility data is required for significant results.

13       Generally, the analysis was undertaken from a European perspective, where the four sea-  
14 sons prevail. Depending on the climate of a place of study, other differentiation criteria would  
15 make sense (e.g., travel behavior in rain seasons vs. dry seasons).

## 16 CONCLUSIONS

17       In our study we analyzed the impact of weather on home-based trips made on 'regular' days,  
18 combining two large household surveys with weather data from a reanalysis model. We could  
19 clearly show that travel behavior is weather-dependent. The influence differs between different  
20 sociodemographic groups and between people with and without certain mobility tools. All three  
21 weather parameters analyzed - maximum daily temperature, sum of daily precipitation and number  
22 of hours of low cloud cover - show variations in travel behavior.

23       In our work, thanks to analyzing these datasets, we could show some new aspects. How-  
24 ever, isolating the exact effects of different parameters is difficult. Therefore, more research needs  
25 to be done to accurately gather them. Furthermore, even larger datasets should be used to analyze  
26 the influences in different circumstances and to have enough data to analyze different sociodemo-  
27 graphic groups.

28       Overall, we do see large variations depending on the weather conditions. As this is rele-  
29 vant for transport planning, we suggest considering it more in travel behavior studies. With large  
30 weather datasets available and the computational ability to handle large datasets, we now have the  
31 possibility to do so. Furthermore, these findings help to develop strategies that consider travel  
32 behavior in new weather conditions, that will occur due to climate change.

## 33 ACKNOWLEDGEMENTS

34       The research was undertaken as part of the project DAKIMO - Data and AI as Enablers for Sustain-  
35 able Intermodal Mobility. This research and development project is funded by the German Federal  
36 Ministry of Education and Research (BMBF) within the "Innovations for Tomorrow's Production,  
37 Services, and Work" Program and implemented by the Project Management Agency Karlsruhe  
38 (PTKA). The authors are responsible for the content of this publication.

## 39 AUTHOR CONTRIBUTIONS

40       The authors confirm contribution to the paper as follows: study conception and design: Pia Tu-  
41 lodetzki (PT), Gabriel Wilkes (GW), Martin Kagerbauer (MK), Peter Vortisch (PV); data col-  
42 lection: GW, PT; analysis and interpretation of results: PT, GW, MK; draft manuscript prepara-

1 tion: PT, GW, MK, PV. All authors reviewed the results and approved the final version of the  
2 manuscript.

1 **REFERENCES**

- 2 1. Böcker, L., T. Priya Uteng, C. Liu, and M. Dijst, Weather and daily mobility in interna-  
3 tional perspective: A cross-comparison of Dutch, Norwegian and Swedish city regions.  
4 *Transportation Research Part D: Transport and Environment*, Vol. 77, 2019, pp. 491–505.
- 5 2. Ton, D., D. C. Duives, O. Cats, S. Hoogendoorn-Lanser, and S. P. Hoogendoorn, Cycling  
6 or walking? Determinants of mode choice in the Netherlands. *Transportation Research*  
7 *Part A: Policy and Practice*, Vol. 123, 2019, pp. 7–23.
- 8 3. Sabir, M., *Weather and travel behaviour*. Ph.D. thesis, Vrije Universiteit Amsterdam,  
9 2011.
- 10 4. Miranda-Moreno, L. F. and T. Nosal, Weather or Not to Cycle. *Transportation Research*  
11 *Record: Journal of the Transportation Research Board*, Vol. 2247, No. 1, 2011, pp. 42–52.
- 12 5. Goldmann, K. and J. Wessel, Some people feel the rain, others just get wet: An analysis  
13 of regional differences in the effects of weather on cycling. *Research in Transportation*  
14 *Business & Management*, Vol. 40, 2021, p. 100541.
- 15 6. Ahmed, F., G. Rose, and C. Jacob, Impact of weather on commuter cyclist behaviour and  
16 implications for climate change adaptation. *33rd Australasian Transport Research Forum*,  
17 2010.
- 18 7. Singhal, A., C. Kamga, and A. Yazici, Impact of weather on urban transit ridership. *Trans-  
19 portation Research Part A: Policy and Practice*, Vol. 69, 2014, pp. 379–391.
- 20 8. Kashfi, S. A., J. M. Bunker, and T. Yigitcanlar, Understanding the effects of complex  
21 seasonality on suburban daily transit ridership. *Journal of Transport Geography*, Vol. 46,  
22 2015, pp. 67–80.
- 23 9. Böcker, L., M. Dijst, and J. Faber, Weather, transport mode choices and emotional travel  
24 experiences. *Transportation Research Part A: Policy and Practice*, Vol. 94, 2016, pp. 360–  
25 373.
- 26 10. Liu, C., Y. O. Susilo, and A. Karlström, Examining the impact of weather variability on  
27 non-commuters' daily activity–travel patterns in different regions of Sweden. *Journal of*  
28 *Transport Geography*, Vol. 39, 2014, pp. 36–48.
- 29 11. Heinen, E., K. Maat, and B. van Wee, Day-to-Day Choice to Commute or Not by Bicy-  
30 cle. *Transportation Research Record: Journal of the Transportation Research Board*, Vol.  
31 2230, No. 1, 2011, pp. 9–18.
- 32 12. Sabir, M., J. Van Ommern, M. J. Koetse, and P. Rietveld, Impacts of weather conditions  
33 on destination choice of leisure trips. *50th Congress of the European Regional Science*  
34 *Association*, 2010.
- 35 13. Liu, C., Y. O. Susilo, and A. Karlström, Investigating the impacts of weather variabil-  
36 ity on individual's daily activity–travel patterns: A comparison between commuters and  
37 non-commuters in Sweden. *Transportation Research Part A: Policy and Practice*, Vol. 82,  
38 2015, pp. 47–64.
- 39 14. Saneinejad, S., M. J. Roorda, and C. Kennedy, Modelling the impact of weather conditions  
40 on active transportation travel behaviour. *Transportation Research Part D: Transport and*  
41 *Environment*, Vol. 17, No. 2, 2012, pp. 129–137.
- 42 15. Liu, C., Y. O. Susilo, and A. Karlström, Measuring the impacts of weather variability  
43 on home-based trip chaining behaviour: a focus on spatial heterogeneity. *Transportation*,  
44 Vol. 43, No. 5, 2016, pp. 843–867.

1 16. Lin, T.-P., Thermal perception, adaptation and attendance in a public square in hot and  
2 humid regions. *Building and Environment*, Vol. 44, No. 10, 2009, pp. 2017–2026.

3 17. de Montigny, L., R. Ling, and J. Zacharias, The Effects of Weather on Walking Rates in  
4 Nine Cities. *Environment and Behavior*, Vol. 44, No. 6, 2012, pp. 821–840.

5 18. Liu, C., Y. O. Susilo, and A. Karlström, Weather variability and travel behaviour – what  
6 we know and what we do not know. *Transport Reviews*, Vol. 37, No. 6, 2017, pp. 715–741.

7 19. Helbich, M., L. Böcker, and M. Dijst, Geographic heterogeneity in cycling under various  
8 weather conditions: evidence from Greater Rotterdam. *Journal of Transport Geography*,  
9 Vol. 38, 2014, pp. 38–47.

10 20. Böcker, L., M. Dijst, and J. Prillwitz, Impact of Everyday Weather on Individual Daily  
11 Travel Behaviours in Perspective: A Literature Review. *Transport Reviews*, Vol. 33, No. 1,  
12 2013, pp. 71–91.

13 21. Thomas, T., R. Jaarsma, and B. Tutert, Exploring temporal fluctuations of daily cycling  
14 demand on Dutch cycle paths: the influence of weather on cycling. *Transportation*, Vol. 40,  
15 No. 1, 2013, pp. 1–22.

16 22. Brandenburg, C., A. Matzarakis, and A. Arnberger, Weather and cycling—a first approach  
17 to the effects of weather conditions on cycling. *Meteorological Applications*, Vol. 14,  
18 No. 1, 2007, pp. 61–67.

19 23. Aaheim, H. and K. Hauge, *Impacts of Climate Changes on Travel Habits: A National  
20 Assessment Based on Individual Choices*. CICERO - Center for International Climate and  
21 Environmental Research, Norway, 2005.

22 24. Cools, M., E. Moons, and G. Wets, Assessing the Impact of Weather on Traffic Intensity.  
23 *Weather, Climate, and Society*, Vol. 2, No. 1, 2010, pp. 60–68.

24 25. Connolly, M., Some Like It Mild and Not Too Wet: The Influence of Weather on Subjective  
25 Well-Being. *Journal of Happiness Studies*, Vol. 14, No. 2, 2013, pp. 457–473.

26 26. Bergström, A. and R. Magnusson, Potential of transferring car trips to bicycle during winter.  
27 *Transportation Research Part A: Policy and Practice*, Vol. 37, No. 8, 2003, pp. 649–  
28 666.

29 27. Phung, J. and G. Rose, Temporal variations in usage of Melbourne's bike paths. *30th  
30 Australasian Transport Research Forum*, 2008.

31 28. Nobis, C. and T. Kuhnimhof, *Mobilität in Deutschland 2017 - Mobility in Germany 2017*.  
32 BMVI, infas, DLR, IVT, infas 360., Bonn, Berlin, 2018.

33 29. Vallée, J., L. Ecke, B. Chlond, and P. Vortisch, *Deutsches Mobilitätspanel (MOP) – Bericht  
34 2021/2022. German Mobility Panel - Report 2021/2022*. Bundesministerium für Verkehr  
35 und digitale Infrastruktur (BMVI), 2022.

36 30. Hersbach, H., B. Bell, P. Berrisford, G. Biavati, A. Horányi, J. Muñoz Sabater, J. Nicolas,  
37 C. Peubey, R. Radu, I. Rozum, D. Schepers, A. Simmons, C. Soci, D. Dee, and J.-N.  
38 Thépaut, *ERA5 hourly data on single levels from 1959 to present*, 2018.

39 31. Hoyer, S. and J. Hamman, xarray: N-D labeled arrays and datasets in Python. *Journal of  
40 Open Research Software*, Vol. 5, No. 1, 2017.

41 32. Russel, I. and B. Raoult, *cfgrib: A Python interface to map GRIB files to the NetCDF  
42 Common Data Model following the CF Convention using ecCodes*, 2023.