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Article

Estimating Weather Effects on Well-Being and Mobility Through Multi-Source Longitudinal Data

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Abstract

Understanding the influence of weather on human well-being and mobility is essential for promoting healthier lifestyles. In this study we employ data collected from 151 participants over a continuous 30-day period in Switzerland to examine the effects of weather on well-being and mobility. Physiological data were retrieved through wearable devices, while mobility was automatically tracked through Google Location History, enabling detailed analysis of participants' mobility behaviors. Mixed-effects linear models were used to estimate the effects of temperature, precipitation, and sunshine duration on well-being and mobility, while controlling for potential socio-demographics confounders. In this work, we demonstrate the feasibility of combining multi-source physiological and location data for environmental health research. Our results show small but significant effects of weather on several well-being outcomes (activity, sleep, and stress), while mobility was mostly affected by the level of precipitation. In line with previous research, our findings confirm that normal weather fluctuations exert significant but moderate effects on health-related behavior, highlighting the need to shift research focus toward extreme weather variations that lie beyond typical seasonal ranges. Given the potentially severe consequences of such extremes for public health and health-care systems, this shift will help identify more consistent effects, thereby informing targeted interventions and policy planning.

Keywords: longitudinal data; data fusion; mixed effects regression; wearable data; weather; environmental health

1. Introduction

Since the advent of the “theory of climates”, most famously articulated by Montesquieu in *The Spirit of Laws* [1], who argued that variations in climate shape people's temperament, behavior, and even political institutions, scholars have long speculated on the influence that meteorological and seasonal dynamics exert on human well-being and behavior. While early theory posited relatively deterministic effects, empirical research over the past decades has yielded a far more nuanced and inconclusive picture. Systematic reviews indicate that meteorological influences are often moderate at best, whereas others report negligible or context-specific strong associations [2,3]. This divergence reflects not only the complexity of human responses to environmental factors but also recurrent methodological and measurement limitations that constrain the reliability of prior findings.

Comparative assessments of systematic reviews have shown that work on temperature and weather effects frequently suffers from deficiencies in protocol registration, risk-of-bias assessment, and reporting transparency, raising questions about the robustness of previous conclusions [4]. Umbrella reviews further highlight that confidence in the existing evidence is often low to critically low, largely due to inconsistent operationalization of outcomes, high heterogeneity across studies, and limited ability to address confounding or interactions [5]. Meta-analyses on ambient temperature and mental health corroborate these findings, showing that although associations can be detected, effect sizes

are highly variable, heterogeneity is substantial, and analytical approaches rarely capture lagged or non-linear effects [2].

Further complications arise when contrasting objective measurements with subjective perceptions. Studies show only weak correspondence between meteorological indicators and self-reported experiences of weather, suggesting that perceptual and reporting biases may distort observed associations [6–8]. Similarly, subjective well-being measures, often collected through self-reported surveys or experience sampling, are prone to recall bias, mood effects, contextual influences, and missing responses, which can lead to inconsistencies between reported and actual states [9,10]. This gap is not trivial, as much of the existing evidence relies on self-reported well-being or retrospective survey data, meaning that discrepancies between experienced and measured conditions could systematically distort effect estimates. The issue is equally salient for mobility, since weather is known to influence transport choices, activity locations, and the use of active versus motorized modes. Yet research demonstrates that self-reported travel adaptations to weather often diverge from mobility patterns captured through GPS or sensor-based tracking, suggesting that individuals may underreport, misremember, or misclassify their behavioral responses to meteorological variation [11,12]. Capturing both places visited, weather conditions, and objective well-being through multimodal, high-resolution tracking is therefore crucial to disentangle actual behavioral and affective changes from perceptual bias, and to generate more credible estimates of the true impact of meteorological variability.

In light of these gaps, we contribute to the growing research on the impact of weather on well-being and mobility through the analysis of longitudinal objective and subjective multi-source data collected as part of an observational study conducted in Switzerland in 2024 [13]. Through the integration of high quality MeteoSwiss weather data, reliable data filtering, and the use of mixed-effects linear regression models, we estimate the effects of weather on several outcomes related to objective and subjective well-being and on distances traveled with different transportation types while controlling for potential socio-demographic confounders. Our work fits in field of environmental health research by demonstrating the feasibility of integrating objective multi-source data to derive practical insights into the effect of environmental factors on humans. Its design mitigates between-person confounding, ensures temporal granularity, and addresses measurement limitations, thereby offering a robust contribution to understanding whether—and to what extent—weather variations shape human well-being and behavioral choices.

The structure of the paper is as follows. Section 2 provides an overview of previous research investigating the relationships between weather, well-being, and mobility choices. Section 3 describes the study protocol, the data used, and the statistical methods that we employed. Section 4 reports the estimates of the weather effects on well-being and mobility that we drew from our sample of observations. Finally, Section 5 provides a critical discussion of the results and of their limitations, while Section 6 summarizes the work and provides insights for future works.

2. Related Work

Previous literature found evidence that atmospheric weather has an effect on both well-being [14] and mobility [15]. Among several well-being outcomes, researchers investigated the relationship between weather and subjective well-being [16,17], happiness [18,19], sleep [20–23], physical activity and sedentary behaviors [24,25], anxiety and depression [26]. However, results are often inconsistent across studies, with authors finding small or non-significant effects [25]. As an example, Feddersen et al. found that warm and sunny days are associated with higher levels of self-reported well-being [17], while Connolly et al. reported that, in regions with hot weather, increase in temperature levels cause a decrease in well-being [16]. Weather effects on well-being during the COVID-19 pandemic were also analyzed, with results reporting no influence of weather on mental well-being during the pandemic [25]. The different results reported in literature on the effects of weather may be due different methodologies in the self-assessment of well-being, with studies involving large cohorts solely relying on self-reported information, which may be affected by recall bias and aggregation over long time

windows [16–19,24–26]. Instead, few studies focused on the use of objective data to measure the impact of weather on well-being. The use of objective measurements allows to reduce the risks of recall bias in self-reported data, and it also allows researchers to collect several measurements of well-being over extended periods of time with less burden posed on study participants, as few to none active tasks are needed. The use of commercial devices for well-being tracking, such as smartwatches and smart rings, allows for the continuous and passive monitoring of objective physiological data through which objective information can then be derived and used for the estimation of weather effects on well-being. An example use of objective data in the sleep domain is from Mattingly et al [20]. In this study, the authors employed a subset of the Tesseract dataset [27] to assess the impact of weather on sleep duration, bedtime, and wake-up times through a year long multimodal study. The authors exploited objective data collected through smartwatches (Garmin Vivosmart 3) and linked them to the weather of participants' homes. Results from this study (216 participants, 51836 observations) indicated small but statistically significant seasonal and weather effects, with bedtimes and wake-up times being later with increasing temperature values, and sleep duration being lower with increasing lengths of the day. Recently, Li et al. [23] reported their analysis on more than 23 millions observations and more than 200 participants, with increasing temperature linked to reduced total sleep time. In a study with an objective measure of physical activity through accelerometers, (127 participants, 720 observations) Sumukadas et al. found day length, temperature, and sunshine to explain 73% of the variance in measured daily activity [28]. In a similar study by Feinglass et al., the authors analyzed the effects of weather on a three-year long study with six weekly measurement waves (241 participants, 4823 observations) and found daylight hours, cold and hot days, and light or heavy rainfall to be associated with lower physical health [29]. Similar results on physical activity were found in several studies using accelerometer-based measurements or steps counts from commercial wearables [24,30,31].

Well-being is not the only domain that was investigated in relationship with weather data. A vast literature corpus deals with the analysis of the effects of atmospheric weather (temperature, precipitation, humidity, ...) on human mobility and transportation mode choices [15]. Climate change, with its consequences on weather, can have tremendous effects on human mobility and transportation choices, and therefore it is necessary to investigate how transport mode choices are influenced by weather to take appropriate actions in time [32]. Similar to what we previously described for well-being, in the mobility domain authors either relied on self-reported information through surveys [33–36] or based their analysis on objective data (e.g., GPS traces provided by smartphones or dedicated trackers, smart cards transactions, ...) [37–41]. Among studies that focused on the use of objective mobility data, Pang et al. built a global dataset based on mobility assessed through data retrieved via social networks and found nice weather (high temperature and moderate pressure) to have a positive impact on human mobility [37]. Lepage et al. integrated data from bike sharing, taxi, and public transport companies to analyze transportation demand under different meteorological conditions [40]. Otim et al. used a total of 2671 GPS trajectories from Beijing to analyze transport mode choices [41]. Even though several studies focusing on the assessment of the effects of weather on mobility make use of objective data, the majority of them are typically cross-sectional, with surveys containing information from each study participant only for a single day/trip, thus failing into capturing intra-subject fluctuations due to weather differences.

3. Materials and Methods

3.1. Study Protocol

We recruited a total of N=294 study participants for a 30-days data collection as part of the project "RENEWAL - Tackling the energy and wellbeing impact of telework practices through multisource data" [13]. We enrolled study participants from six companies and institutions located in Canton Ticino (Switzerland) on a rolling basis from February to May 2024. We requested participants to always wear a Garmin Vivosmart 5 to track physiological data continuously, day and night. We employed Google Location History (GLH) to track trips and locations using Google Takeout to retrieve mobility data. Self-reported information was also provided by participants in different formats. At the start of

the study, they completed an onboarding questionnaire mainly focused on socio-demographics, work-, and leisure-related information. Furthermore, they also filled out the Short Form Health Questionnaire (SF-12), which provides a self-assessment of physical and mental health [42]. Throughout the study, participants received a daily diary asking to self-assess their sleep quality, health, and stress for the day, together with information about their workday, leisure activities, and transport mode choices.

Study participants were thoroughly informed about the study and signed an informed consent before taking part in the study. The study protocol followed the declaration of Helsinki for studies involving human participants [43] and was reviewed by the local ethical committee (SwissEthics Clarification of Responsibility Req-2023-0106). A more detailed description of the study protocol is available in [13].

3.2. Weather Data

We employed MeteoSwiss (<https://opendatadocs.meteoswiss.ch/>) as a weather data source, using the closest weather station to the participants' home as daily source of weather information. A total of 7 weather stations (Acquarossa, Biasca, Cadenazzo, Cevio, Locarno, Lugano, Stabio) were used for the retrieval of weather information, spanning the whole area of Canton Ticino where the study was conducted. MeteoSwiss provides several aggregated weather information for each station. Among them, there is average, maximum, and minimum air temperature at 5 centimeters and 2 meters above ground; average wind speed; relative humidity; total precipitation during the day; absolute and relative sunshine duration. We retrieved all these weather information and linked them to each participant using the weather station closest to their home address. Figure 1 shows the variation of weather across all the available weather stations for the whole duration of the study, for both temperature, precipitation, and sunshine duration. Considering all the available measurements across the weather stations, median (p_{25} , p_{75}) temperature at 2 meters above ground was of 10.5 (7.9,13.6), with increasing temperatures from February (7.5, 6.0 to 9.0) to May (14.4, 12.8 to 15.9). For slightly more than half of the days (53%), the total daily precipitation was lower than 0.1 mm. For the remaining days it was lower than 30 mm (40%), with few exceptions with total daily precipitation greater than 30 mm (7%). March and April were the two months with the highest amount of recorded precipitations across all stations, with the highest being March. Finally, median (p_{25} , p_{75}) sunshine duration was of 191 (2, 413) minutes and, similarly to temperature, increased from February (131, 0 to 320) to April (324, 47 to 544), followed by a decrease in May (131, 11 to 340).

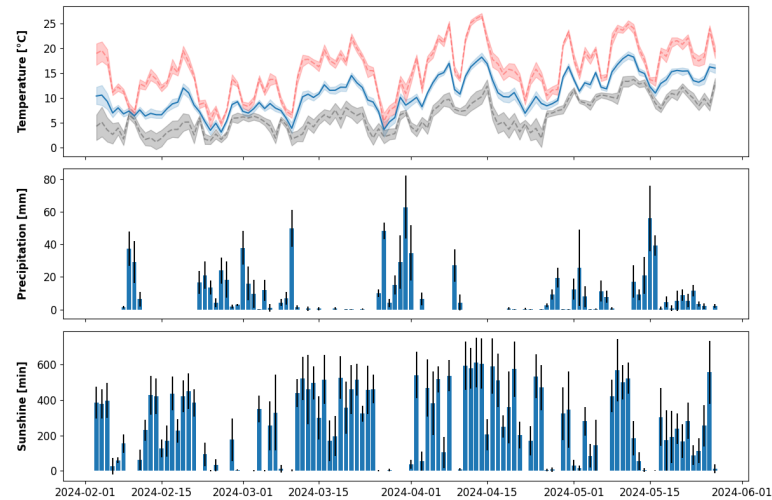


Figure 1. Temperature (top), precipitation (middle), and sunshine duration (bottom) data from the day of the first participant in up to the day of the last participant out. Temperature data are shown as mean (blue solid line), minimum (black dashed line) and maximum (red dashed line), together with the corresponding 95% CI. Precipitation and sunshine duration data are reported as mean (bar height) and standard deviation (error bar). All data refer to the 7 weather stations that were employed for the retrieval of weather data.

3.3. Data Processing

Physiological data were retrieved through Garmin Health API¹. This free service provides, upon direct acceptance from study participants, several data points related to the physiological domain and computed through Garmin proprietary algorithms running on the smartwatch provided to study participants [44]. We processed these data (heart rate, steps, sleep, ...) to extract daily features across several domains related to well-being. Mobility data were instead retrieved from GLH services, that automatically extracts location visits and movements through GPS and network data on smartphones [45–47]. Google does not allow for the automatic retrieval of GLH data through API. Therefore, we instructed study participants to export these data through Google Takeout, and upload the resulting zip file in a dedicated section of the mobile application that was provided to them for the duration of the study [13]. We then processed location data and extracted daily traveling distances according to different modes of transport: active mobility (cycling, running, walking), motor vehicles (car, motorcycle, taxi, ...), and public transport (bus, tram, train).

3.4. Data Filtering

We filtered the collected data to consider only days with reliable data. Filtering was performed using different data sources. First, we considered only weekdays, excluding weekends as they may be characterized by different patterns of activity, mobility, and sleep, and may not be representative of typical behaviors [20,48]. Second, we considered only days in which the total time the vivosmart5 was worn was at least 70% (approximately 17 hours out of 24), so that aggregated features of steps and stress were representative of the majority of the day. Daily wearing time was determined based on heart rate samples, with the assumption that heart rate values are provided only when the smartwatch is placed on the wrist. Then, we considered only those days for which night sleep was automatically tracked by the provided smartwatches, excluding nights with missing sleep data or with manual insertion of sleep times.

In addition to wearing time and sleep, we also accounted for the amount of daily coverage for location data. Daily coverage was computed by resampling the provided GLH location segments (i.e., a movement from point A to point B with a given transportation type) into location bins of 5 minutes, and considering the participant as being in the same static location if the distance between the end of one location segment and the start of the following location segment was lower than 200 meters. This was done with the aim of keeping only days for which participants' locations and travel patterns were known for most of the day, thus justifying the usage of the closest weather station to their home to determine the weather data for each day. We chose to keep only days for which at least 70% of the location was known, using the same threshold that we set for the wearing time of the smartwatch. The use of location data allowed us also to identify travel days, represented by those days in which participants were traveling away from their home. Using this information, we excluded days for which the maximum reported distance from their home was equal to 300 kilometers, suggesting travels away from home for which weather data retrieved from the weather station closest to the home address didn't represent a reliable source of weather information. This traveling threshold was chosen similar to [20], which chose to keep only observations with an average distance from home greater than 320 km. Finally, to further improve the reliability of our estimates employing longitudinal data, we additionally filtered our dataset to consider only study participants for which at least 10 observations were available.

3.5. Statistical Modeling

To examine the effects of whether on well-being and mobility, we used mixed effects linear regression (MELR) models. Since our dataset consists of repeated observations for each participant over

¹ <https://www.garmin.com/health-api>

time, this approach properly accounts for inter-individual variability [49]. The general specification for our MELR models is:

$$y = \beta_0 + \beta_1 \cdot x_1 + \beta_2 \cdot x_2 + \dots + \beta_n x_n + U_i + e \tag{1}$$

where y is the outcome of interest, β_0 is the intercept, $\beta_{1,\dots,n}$ are the coefficients for predictors $x_{1,\dots,n}$, U_i is the random intercept assigned to the i -th participant, and e is the residual error.

We tested hierarchical models including increasing blocks of predictors. First, we built an empty model with no fixed effects (Model 1). Then, we integrated socio-demographics information collected at the baseline as time-invariant predictors for the model (Model 2). At this stage, we included the following time-invariant predictors: age, work organization, sex, having a supervisor role at work, having children, SF-12 mental component score, SF-12 physical component score. The choice of these predictors was based on previous studies which included similar sets of measurements and predictors [20]. The supervisor role was derived based on the computation of the International Standard Classification of Occupations (ISCO), which was derived based on work-related information reported in the onboarding questionnaire. Participants with an ISCO code of "Managers" or "Technicians and Associate professionals" was defined as having a supervisor role. Finally, we added three weather predictors into a final model (Model 3): mean daily temperature, total daily precipitation, and daily sunshine duration. We used the closest weather station to participant's home to assign daily weather information. The choice of these three predictors (temperature, precipitation, and daily sunshine duration) was driven by the choices of *i*) having the same set of predictors across both well-being and mobility domains *ii*) sharing a similar set of predictors with previous related works [20,25]. In our modeling we didn't include wind speed, as we assumed it to have no effect on well-being related outcomes [28]. During the monitoring period, no snow was measured, and therefore was excluded from the modeling.

Statistical modeling of the data was performed on Python 3.13 using the following libraries: pandas [50], scipy [51], and statsmodels [52].

3.6. Outcomes

We focused our analysis on the effects of weather on 11 outcomes related to participant well-being and mobility, which are summarized in Table 1. For well-being, we examined seven health-related features across different physiological domains. In the activity domain, we considered the number of steps taken during the awake cycle as retrieved by the Garmin wearable (from wake-up to bedtime) as well as the percentage of time spent in sedentary behavior during the same time window. Sleep was also assessed through Garmin data, looking at bedtime, wake-up time, and total sleep duration, with weather information from a given day used to predict outcomes on the following night. Stress was examined using three complementary indicators. The first was the self-reported stress level, collected through daily diaries by asking participants "Today, do you feel stressed? Stress refers to a condition in which you feel tense, restless, nervous or anxious, or cannot sleep at night because you are agitated". Answers to this question were recorded on a 5-point Likert scale from 1 (Not at all) to 5 (Extremely). Following Norman [53], this measure was modeled as continuous, albeit originally ordered categorical. The second indicator was the daily average Garmin stress score, which ranges from 0 (no stress) to 100 (extreme stress) and is derived from heart rate and heart rate variability (HRV) measurements [54]. Finally, we considered night recovery, computed as the normalized percentage change in "body battery" a Garmin proprietary metric estimating the body's available energy, during nighttime sleep, which can be considered both as a measure of sleep quality as well as an indicator of stress while sleeping, which could be linked to reduced resting capabilities. For the mobility domain, we analyzed the total daily distance traveled by participants, with transportation modes automatically detected through GLH. Distances traveled by plane were excluded, and we focused instead on three categories: active mobility, motor vehicles, and public transport.

Table 1. Detailed description of the outcomes considered for the MELR analysis, together with their source and scale. *A.U.: Arbitrary Unit.*

Domain	Outcome	Source	Description	Scale	Unit
Well-being	Daily Steps	Garmin	Count of daily steps while awake	≥ 0	Steps
	Sedentary %		% of time in sedentary state while awake	0-100	%
	Bedtime		Bedtime on next night	0-24	Hours
	Wake-up Time		Wake-up on next night	0-24	Hours
	Total Sleep Time		Total amount of sleep hours	≥ 0	Hours
	Night Recovery		Normalized change of body battery while sleeping	0 – 100	%
	Daily Stress		Mean measured physiological stress	0 – 100	A.U.
	Self-Reported Stress	Diary	Perceived stress during the day	0 – 5	A.U.
Mobility	Active Mobility	GLH	Total daily distance traveled with active mobility	≥ 0	km
	Motor Vehicle		Total daily distance traveled with motor vehicles	≥ 0	km
	Public Transport		Total daily distance traveled with public transport	≥ 0	km

For each outcome, we computed the intra-class coefficient (ICC), defined as:

$$ICC = \frac{\tau_{U_0i}^2}{\tau_{U_0i}^2 + \sigma_e^2} = \frac{\text{BP Variation}}{\text{BP Variation} + \text{WP Variation}}$$

where $\tau_{U_0}^2$ is the variance of the estimated random intercepts of the MELR models, σ_e^2 is the variance of the within-person residuals, BP stands for between-person, and WP for within-person [49]. With ICC values ranging from a minimum of 0 up to a maximum of 1, we can determine whether all the variance in the data is longitudinal (i.e., due to within person changes), which results in a ICC of 0, or if it is only cross-sectional (i.e., due to between-person differences), which instead results in a ICC of 1.

4. Results

4.1. Dataset

Our initial dataset was composed of 8820 observations from the whole set of 294 study participants. Upon filtering the dataset with the conditions detailed in Section 3.4, we were left with an analytical sample of 151 participants and 2120 observations. The majority of the participants was male (98, 65%). Median age was of 42 years old, with males being older than females An unbalanced distribution was found for the organization for which participants were working, with a higher proportion for company 5 (59, 51%). Similar proportions were found for having children, with 57% of females and 54% of males reporting having at least one children. Overall, 34% of the included study participants had a supervisory role at work, with a higher proportion of males (39%) than females (25%). The mean (min, max) number of observations per participant was equal to 14 (10, 22).

Figure 2 shows the coordinates of the seven weather stations, together with the location of both home and work addresses for the analytical sample. The median (p_{25}, p_{75}) maximum daily distance between the self-reported home address and the closest weather station, used for linking weather data to participants’ daily measurements, was of 8.9 (5.2, 18.8), with 95% of the available observations having a maximum daily distance from the closest weather station of 48.7 kilometers. To assess the extent to which participants moved away from home while traveling, we also computed the maximum daily traveled distance from their home addresses, and we found a median (p_{25}, p_{75}) distance of 7.6 kilometers (2.8, 19.1). In the analytical sample, participants wore the smartwatch for a median (p_{25}, p_{75}) percentage of time during their awake cycle of 100% (96.44, 100), with a duration of their time spent awake during the day of 16.75 hours (15.92, 17.67). The location of study participants during these days was tracked for a median (p_{25}, p_{75}) number of daily hours equal to 24 (21.5, 24) using a threshold for the distance between two consecutive location segments of 200 meters. The dataset covered 75 days starting from February up to May of the same year (2024), with an available number of observations per day across all study participants of 32 (2.5, 48).

Table 2. Socio-demographics information of the participants available for analysis after after filtering the complete dataset.

	Sex		Overall (N=151)
	F (N=53)	M (N=98)	
Age	42 (32,47)	47 (37,47)	42 (37,47)
SF-12 MCS	43.45 (37.90,51.59)	49.61 (44.30,55.18)	47.91 (41.80,53.04)
SF-12 PCS	55.70 (53.60,57.40)	55.04 (52.00,56.17)	55.30 (52.28,56.59)
Company			
C1, (N, %)	3 (6%)	17	20
C2, (N, %)	3 (6%)	13	16
C3, (N, %)	11 (21%)	12	23
C4, (N, %)	7 (13%)	13	20
C5, (N, %)	23 (43%)	36	59
C6, (N, %)	6 (11%)	7	13
Supervisor role, (N, %)	13 (25%)	38 (39%)	51 (34%)
Having children, (N, %)	30 (57%)	53 (54%)	83 (55%)

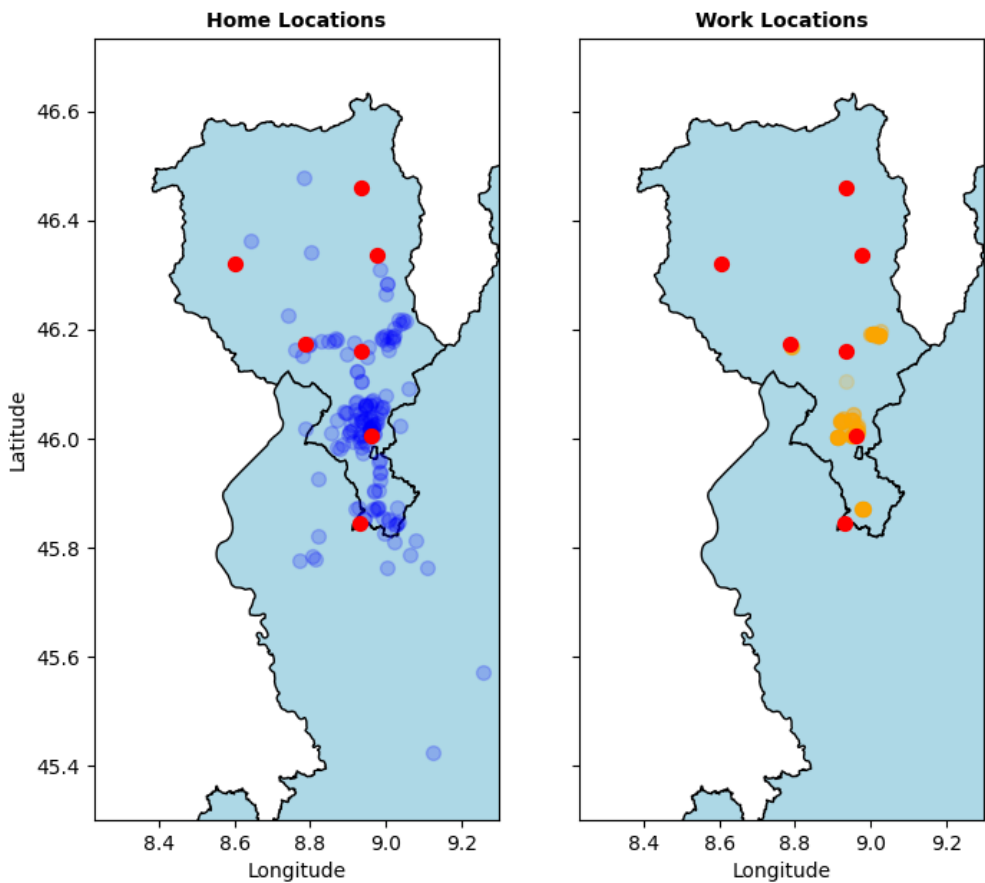


Figure 2. Coordinates of weather stations employed for the retrieval of weather information (red points) and home (left plot) and work (right plot) location coordinates of the subset of study participants used for the analysis.

Table 3 reports the descriptive statistics of the continuous variables (outcomes and weather) measured during the study across all study participants in the analytical sample over time. We assessed also the distribution of the weather changes experienced by by them. For daily temperature, we computed the difference between the maximum and minimum daily mean temperature for each participant, and found a median (p_{25}, p_{75}) difference of 8.9 (7.8, 10.6) degrees. We performed the same analysis for sunshine duration, with a median (p_{25}, p_{75}) difference between the maximum and minimum sunshine duration experience by participant of 10.7 (10.3, 11.8) daily hours. For daily precipitation, we counted the number of days in which the daily total precipitation was greater than

1 mm from midnight to midnight, resulting in a median (p_{25}, p_{75}) number of days of 5 (4, 7) across analytical sample members.

Table 3. Descriptive statistics of the continuous variables. Bedtime and wake-up time are reported as hours from midnight.

		μ	σ	p_{25}	p_{50}	p_{75}
Outcome	Daily Steps	8392.07	3682.85	5782.25	7859.50	10280.00
	Sedentary %	82.12	7.58	77.71	83.17	87.40
	Total Sleep Time [hours]	7.14	1.35	6.35	7.17	7.98
	Bedtime [hours]	-0.48	1.36	-1.40	-0.65	0.30
	Wake-up Time [hours]	6.95	1.31	6.15	6.83	7.52
	Mean Stress [%]	50.71	14.64	40.23	51.51	61.20
	Self-Reported Stress [1-5]	2.47	0.98	2.00	2.00	3.00
	Night Recovery [%]	58.37	27.57	34.74	57.90	83.20
	Active Mobility [km]	2.77	5.81	0.00	0.59	2.63
	Motor Vehicles [km]	31.32	49.92	0.35	16.69	41.39
	Public Transport [km]	8.99	30.86	0.00	0.00	1.85
Weather	Temperature [° C]	11.20	3.17	8.80	11.20	13.00
	Precipitation [mm]	5.56	11.85	0.00	0.00	3.80
	Sunshine [hours]	5.25	4.16	0.34	5.27	9.12

4.2. Weather Effects on Well-Being

4.2.1. Activity

Tables 4 and 5 report the results of the MELR modeling of daily steps and the percentage of time in sedentary state, respectively. The ICC value for daily steps was of 0.378, indicating that around 40% of the variance in the measurements is due to within-person changes over time, with the remaining variance due to between person differences. We didn’t find any significant effect of weather features (temperature, precipitation, and sunshine duration) on the amount of steps per day. Both in the Model 2 and Weather models, the mental (SF-12 MCS) and physical (SF-12 PCS) component of the health assessment carried out at baseline were positively associated with the number of steps per day, with people in better health status (higher MCS/PCS) walking more during the day. Interestingly, one organization (C5) was characterized by a significant positive coefficient, further justifying the inclusion of the company predictor in the modeling.

The additional activity-related outcome that we considered was the percentage of time spent in sedentary behavior during the day. For this outcome, we found an ICC value of 0.475, suggesting that, with respect to daily steps, higher variance can be explained by within-person changes over time. We found a statistically significant effect of the physical health, as assessed by the SF-12 PCS (Model 2: -0.195, 95% CI: -0.340 to -0.053, $p < 0.01$; Model 3: -0.201, 95% CI: -0.345 to -0.057, $p < 0.01$). For weather features, we found increasing temperature (-0.115, 95% CI: -0.218 to -0.012, $p < 0.05$) as well as increasing sunshine duration (-0.093, 95% CI: -0.168 to -0.017, $p < 0.05$) to reduce the percentage of time spent in sedentary behavior, while no effect was found for the level of precipitation during the day.

4.2.2. Sleep

For the sleep domain, Tables 6, 7, and 8 report the MELR coefficients resulting from the modeling of next night total sleep time, next night bedtime, and next day wake-up time, respectively. Total sleep time is measured in decimal hours, while bedtime and wake-up time are reported as hours from midnight. The three sleep time measurements of total sleep time, bedtime, and wake-up time resulted in ICC values of 0.24, 0.42, and 0.35, respectively. These values suggest that variance in bedtime values is characterized by higher between-person differences, while for total sleep time variance is more explained by within-person changes on a day-to-day level.

The results of our modeling of total sleep time show a small significant effect of daily mean temperature on total sleep time (95% CI: 0.6 to 3.0, $p < 0.01$), with an average 1.8 minutes increase per each degree increase in daily mean temperature. Except sex, no socio-demographic predictor was found to be significantly associated with total sleep time. In our results, we found that males slept, on average, 24.2 minutes less than females (Model 2: 95% CI: -39.2 to -9.1, $p < 0.01$; Model 3: 95% CI: -38.9 to -8.9, $p < 0.01$).

The effect of daily temperature that we found for total sleep time disappeared for bedtime (Table 7), for which only socio-demographic factors (age and sex) were found to be significantly associated with sleep onset time. In particular, older participants and females tended to go to bed earlier, with bed time decreasing by about 1 minute for each additional year of age (Model 2 95% CI: -2.0 to -0.06, $p < 0.05$; Weather 95% CI: -1.9 to 0, $p < 0.05$). Females, compared with males, went to bed about 30 minutes earlier (Model 2: -30.5 minutes, 95% CI -48.5 to -12.5, $p < 0.01$; Model 3: -30.7 minutes, 95% CI -48.7 to -12.7, $p < 0.01$).

Moving onto the modeling of wake-up time (Table 8), we found a significant positive coefficient of temperature (2.9, 95% CI: 1.7 to 4.1, $p < 0.001$), and a smaller, but still significant, positive effect of the level of daily precipitation on the wake-up time (0.4, 95%CI: 0.06 to 0.6, $p < 0.05$). These results suggest that the increase in total sleep time due to higher temperatures can be explained with a delay in wake-up time, rather than an anticipation of bedtime. Similar to bedtime, we found a negative association between age and wake-up time, with older people waking up 1.3 minutes earlier for each unit increase in age (Model 2: 95%CI: -2.2 to 0.0, $p < 0.01$; Weather 95% CI: -2.1 to 0.0, $p < 0.01$).

4.2.3. Stress and Recovery

Table 9, 10, and 11 report the MELR coefficients resulting from the modeling of mean stress during the day, self-reported stress level, and next night recovery, respectively. The stress values were those characterized by the highest ICC value, equal to 0.66, with the variance mostly explained by differences between people in the mean stress value. Instead, self-reported stress and night recovery were both characterized by an ICC of 0.37. For the mean stress during the day assessed through physiological data, we found that an increase in mean daily temperature and sunshine duration led to increase levels of measured stress during the day (daily temperature: 0.176, 95% CI: 0.016 to 0.336, $p < 0.05$; sunshine duration: 0.143, 95%CI 0.027 to 0.260, $p < 0.05$). Among socio-demographics predictors, only the SF-12 MCS was statistically significant (Model 2: -0.341, 95% CI: -0.582 to -0.104, $p < 0.01$; Model 3: -0.341, 95% CI: -0.581 to -0.101, $p < 0.01$), with people having higher mental health scores experiencing less stress during the day.

The modeling of self-reported stress value showed similar results for socio-demographics, with increasing mental health status leading to lower daily-self reported values (Model 2: -0.038, 95% CI: -0.049 to -0.026, $p < 0.001$; Model 3: -0.038, 95% CI: -0.049 to -0.027, $p < 0.001$). However, opposite results were found for the effects of weather, with higher temperatures related to lower self-reported stress values (-0.03, 95% CI: -0.045 to -0.016, $p < 0.001$).

Finally, no socio-demographic characteristic was found to be a significant predictor of night recovery as measured through the Garmin body battery feature (Table 11). Among the weather variables, only sunshine duration was significant, with higher sunshine duration leading to lower recovery values (-0.30, 95% CI: -0.597 to -0.004, $p < 0.05$).

Table 4. Results of empty model, socio-demographics model, and weather model predicting the total number of daily steps while awake. For the sake of clarity, coefficients are rounded to nearest integer. Significant coefficients are highlighted in bold. * : $p < 0.05$; ** : $p < 0.01$; *** : $p < 0.001$ MCS: Mental Component Score; PCS: Physical Component Score.

	Daily Steps					
	Model 1		Model 2		Model 3	
	Coef.	CI	Coef.	CI	Coef.	CI
Intercept	8470***	8086 to 8854	8011***	6607 to 9416	7538***	6052.0 to 9024.0
Age			5	-38 to 48	6	-37 to 49
Sex [0=Female]			-439	-1251 to 373	-432	-1242 to 379
Company [0=C1]						
C2			-367	-1856 to 1121	-448	-1936 to 1039
C3			925	-467 to 2317	851	-539 to 2241
C4			728	-681 to 2136	546	-871 to 1964
C5			1422*	190.0 to 2654	1256*	16 to 2495
C6			755	-865 to 2374	742	-875 to 2359
Supervisor role [0=No]			-113	-927 to 702	-118	-932 to 695
Having children [0=No]			-80	-861 to 701	-81	-860 to 698
SF-12 MCS			66**	19 to 112	66**	20 to 113
SF-12 PCS			86**	22 to 150	87**	23 to 151
Temperature					41	-13 to 95
Precipitation					-7	-19 to 6
Sunshine Duration					30	-9 to 70
Marginal R2	0.000		0.062		0.067	
ICC	0.378					

Table 5. Results of empty model, socio-demographics model, and weather model predicting the percentage of sedentary time while awake. Significant coefficients are highlighted in bold.
* : $p < 0.05$; ** : $p < 0.01$; *** : $p < 0.001$ MCS: Mental Component Score; PCS: Physical Component Score.

	Model 1		Sedentary % Model 2		Model 3	
	Coef.	CI	Coef.	CI	Coef.	CI
Intercept	81.989***	81.117 to 82.861	83.995***	80.842 to 87.149	85.487***	82.202 to 88.772
Age			0.021	-0.075 to 0.117	0.018	-0.078 to 0.115
Sex [0=Female]			2.31*	0.488 to 4.132	2.295*	0.475 to 4.114
Company [0=C1]						
C2			-1.014	-4.354 to 2.326	-0.798	-4.137 to 2.54
C3			-2.980	-6.107 to 0.146	-2.817	-5.940 to 0.306
C4			-1.940	-5.103 to 1.223	-1.489	-4.666 to 1.688
C5			-3.839**	-6.605 to -1.073	-3.414*	-6.193 to -0.636
C6			-3.472	-7.109 to 0.165	-3.456	-7.089 to 0.176
Supervisor role [0=No]			-0.148	-1.977 to 1.681	-0.141	-1.967 to 1.686
Having children [0=No]			-1.484	-3.235 to 0.267	-1.482	-3.231 to 0.266
SF-12 MCS			-0.063	-0.167 to 0.042	-0.064	-0.169 to 0.040
SF-12 PCS			-0.196**	-0.340 to -0.053	-0.201**	-0.345 to -0.057
Temperature					-0.115*	-0.218 to -0.012
Precipitation					0.003	-0.021 to 0.026
Sunshine Duration					-0.093*	-0.168 to -0.017
Marginal R2	0.000		0.087		0.094	
ICC	0.475					

Table 6. Results of empty model, socio-demographics model, and weather model predicting total sleep time. Total sleep time is measured in decimal hours. Significant coefficients are highlighted in bold. * : $p < 0.05$; ** : $p < 0.01$; *** : $p < 0.001$ MCS: Mental Component Score; PCS: Physical Component Score.

	Total Sleep Time					
	Model 1		Model 2		Model 3	
	Coef.	CI	Coef.	CI	Coef.	CI
Intercept	7.147***	7.03 to 7.264	7.331***	6.899 to 7.763	7.025***	6.550 to 7.500
Age			-0.009	-0.022 to 0.005	-0.008	-0.021 to 0.005
Sex [0=Female]			-0.403**	-0.653 to -0.152	-0.398**	-0.648 to -0.148
Company						
C2			0.002	-0.456 to 0.461	-0.038	-0.498 to 0.421
C3			0.173	-0.255 to 0.601	0.163	-0.264 to 0.591
C4			-0.086	-0.519 to 0.348	-0.177	-0.616 to 0.262
C5			0.109	-0.269 to 0.488	0.027	-0.357 to 0.410
C6			0.187	-0.311 to 0.686	0.194	-0.303 to 0.692
Supervisor role [0=No]			-0.074	-0.325 to 0.177	-0.069	-0.320 to 0.181
Having children [0=No]			0.052	-0.189 to 0.293	0.050	-0.191 to 0.290
SF-12 MCS			0.001	-0.013 to 0.016	0.001	-0.013 to 0.016
SF-12 PCS			-0.004	-0.024 to 0.015	-0.004	-0.024 to 0.016
Temperature					0.030**	0.008 to 0.051
Precipitation					0.003	-0.002 to 0.008
Sunshine Duration					0.000	-0.016 to 0.016
Marginal R2	0.000		0.036		0.039	
ICC	0.240					

Table 7. Results of empty model, socio-demographics model, and weather model predicting bedtime. Bedtime is measured in decimal hours from midnight. Significant coefficients are highlighted in bold. * : $p < 0.05$; ** : $p < 0.01$; *** : $p < 0.001$ MCS: Mental Component Score; PCS: Physical Component Score.

	Model 1		Bedtime Model 2		Model 3	
	Coef.	CI	Coef.	CI	Coef.	CI
Intercept	-0.481***	-0.628 to -0.334	-0.871**	-1.389 to -0.353	-1.018***	-1.566 to -0.470
Age			-0.017*	-0.033 to -0.001	-0.016*	-0.032 to -0.000
Sex [0=Female]			0.508**	0.208 to 0.808	0.511**	0.211 to 0.811
Company						
C2			-0.271	-0.82 to 0.279	-0.292	-0.842 to 0.258
C3			0.045	-0.469 to 0.559	0.044	-0.470 to 0.558
C4			0.434	-0.086 to 0.954	0.384	-0.140 to 0.909
C5			0.321	-0.134 to 0.775	0.277	-0.181 to 0.736
C6			0.134	-0.464 to 0.732	0.139	-0.459 to 0.737
Supervisor role [0=No]			0.099	-0.201 to 0.4	0.103	-0.198 to 0.404
Having children [0=No]			-0.265	-0.553 to 0.024	-0.266	-0.555 to 0.022
SF-12 MCS			-0.005	-0.023 to 0.012	-0.005	-0.023 to 0.012
SF-12 PCS			-0.017	-0.041 to 0.007	-0.017	-0.040 to 0.007
Temperature					0.017	-0.003 to 0.036
Precipitation					0.002	-0.003 to 0.006
Sunshine Duration					-0.005	-0.020 to 0.009
Marginal R2	0.000		0.093		0.094	
ICC	0.415					

Table 8. Results of empty model, socio-demographics model, and weather model predicting wake-up time. Wake-up time is measured in decimal hours from midnight. Significant coefficients are highlighted in bold. * : $p < 0.05$; ** : $p < 0.01$; *** : $p < 0.001$ MCS: Mental Component Score; PCS: Physical Component Score.

	Model 1		Wakeup Model 2		Model 3	
	Coef.	CI	Coef.	CI	Coef.	CI
Intercept	6.959***	6.827 to 7.092	6.816***	6.357 to 7.275	6.326***	5.832 to 6.819
Age			-0.022**	-0.036 to -0.008	-0.021**	-0.035 to -0.007
Sex [0=Female]			0.089	-0.177 to 0.355	0.097	-0.169 to 0.364
Company						
C2			-0.242	-0.729 to 0.245	-0.308	-0.796 to 0.181
C3			0.196	-0.259 to 0.651	0.184	-0.272 to 0.64
C4			0.269	-0.191 to 0.73	0.121	-0.345 to 0.587
C5			0.374	-0.029 to 0.776	0.241	-0.166 to 0.648
C6			0.292	-0.237 to 0.822	0.306	-0.225 to 0.836
Supervisor role [0=No]			-0.012	-0.278 to 0.255	-0.003	-0.27 to 0.264
Having children [0=No]			-0.22	-0.476 to 0.035	-0.225	-0.481 to 0.031
SF-12 MCS			-0.007	-0.023 to 0.008	-0.007	-0.023 to 0.008
SF-12 PCS			-0.019	-0.04 to 0.002	-0.019	-0.04 to 0.002
Temperature					0.049***	0.029 to 0.069
Precipitation					0.006*	0.001 to 0.01
Sunshine Duration					-0.004	-0.019 to 0.01
Marginal R2	0.000		0.09		0.10	
ICC	0.347					

Table 9. Results of empty model, socio-demographics model, and weather model predicting mean stress value during the day. Mean stress goes from a minimum of 0 (no stress) to a maximum of 100 (high stress). Significant coefficients are highlighted in bold. * : $p < 0.05$; ** : $p < 0.01$; *** : $p < 0.001$ MCS: Mental Component Score; PCS: Physical Component Score

	Mean Stress					
	Model 1		Model 2		Model 3	
	Coef.	CI	Coef.	CI	Coef.	CI
Intercept	50.878***	48.94 to 52.815	47.498***	40.271 to 54.725	45.177***	37.788 to 52.566
Age			-0.016	-0.237 to 0.204	-0.012	-0.234 to 0.209
Sex [0=Female]			-1.07	-5.242 to 3.101	-1.047	-5.229 to 3.134
Company						
C2			3.934	-3.715 to 11.582	3.602	-4.067 to 11.271
C3			4.003	-3.167 to 11.173	3.76	-3.428 to 10.948
C4			5.925	-1.326 to 13.176	5.242	-2.046 to 12.53
C5			4.359	-1.982 to 10.700	3.714	-2.658 to 10.087
C6			7.442	-0.895 to 15.780	7.422	-0.935 to 15.779
Supervisor role [0=No]			-0.588	-4.779 to 3.604	-0.598	-4.799 to 3.604
Having children [0=No]			0.139	-3.868 to 4.146	0.136	-3.880 to 4.153
SF-12 MCS			-0.343**	-0.582 to -0.104	-0.341**	-0.581 to -0.101
SF-12 PCS			0.196	-0.133 to 0.525	0.203	-0.127 to 0.533
Temperature					0.176*	0.016 to 0.336
Precipitation					-0.001	-0.038 to 0.036
Sunshine Duration					0.143*	0.027 to 0.260
Marginal R2	0.000		0.076		0.080	
ICC	0.659					

Table 10. Results of empty model, socio-demographics model, and weather model predicting the self-reported stress value. Self-reported stress goes from a minimum of 1 (no stress) to a maximum of 5 (extreme stress). Significant coefficients are highlighted in bold. * : $p < 0.05$; ** : $p < 0.01$; *** : $p < 0.001$ MCS: Mental Component Score; PCS: Physical Component Score.

	Self-Reported Stress					
	Model 1		Model 2		Model 3	
	Coef.	CI	Coef.	CI	Coef.	CI
Intercept	2.487***	2.385 to 2.588	2.350***	2.004 to 2.696	2.64***	2.272 to 3.008
Age			0.002	-0.009 to 0.012	0.001	-0.010 to 0.011
Sex [0=Female]			0.244*	0.044 to 0.444	0.238*	0.040 to 0.437
Company						
C2			-0.04	-0.407 to 0.326	-0.000	-0.365 to 0.364
C3			0.258	-0.085 to 0.601	0.266	-0.075 to 0.606
C4			0.224	-0.123 to 0.571	0.316	-0.032 to 0.664
C5			0.035	-0.269 to 0.338	0.117	-0.187 to 0.421
C6			0.142	-0.257 to 0.541	0.134	-0.262 to 0.53
Supervisor role [0=No]			-0.031	-0.232 to 0.17	-0.036	-0.236 to 0.163
Having children [0=No]			-0.187	-0.38 to 0.005	-0.184	-0.375 to 0.007
SF-12 MCS			-0.038***	-0.049 to -0.026	-0.038***	-0.049 to -0.027
SF-12 PCS			-0.010	-0.026 to 0.006	-0.010	-0.026 to 0.006
Temperature					-0.030***	-0.045 to -0.016
Precipitation					-0.003	-0.006 to 0.000
Sunshine Duration					0.004	-0.006 to 0.015
Marginal R2	0.000		0.107		0.114	
ICC	0.370					

Table 11. Results of empty model, socio-demographics model, and weather model predicting night recovery. Night recovery is measured as percentage from 0 (no recovery) to 100 (maximum recovery). Significant coefficients are highlighted in bold. * : $p < 0.05$; ** : $p < 0.01$; *** : $p < 0.001$ MCS: Mental Component Score; PCS: Physical Component Score.

	Night Recovery					
	Model 1		Model 2		Model 3	
	Coef.	CI	Coef.	CI	Coef.	CI
Intercept	58.277***	55.438 to 61.117	56.490***	45.6 to 67.379	58.948***	47.438 to 70.459
Age			-0.163	-0.497 to 0.17	-0.166	-0.500 to 0.167
Sex [0=Female]			4.482	-1.813 to 10.777	4.479	-1.825 to 10.783
Company						
C2			2.459	-9.081 to 13.998	2.797	-8.771 to 14.364
C3			3.754	-7.04 to 14.548	4.139	-6.674 to 14.951
C4			0.894	-10.027 to 11.816	1.523	-9.497 to 12.544
C5			-0.579	-10.13 to 8.971	0.056	-9.578 to 9.691
C6			0.727	-11.833 to 13.286	0.810	-11.767 to 13.386
Supervisor role [0=No]			1.535	-4.781 to 7.85	1.587	-4.738 to 7.912
Having children [0=No]			-4.411	-10.463 to 1.641	-4.425	-10.485 to 1.635
SF-12 MCS			0.194	-0.167 to 0.555	0.190	-0.172 to 0.552
SF-12 PCS			-0.048	-0.546 to 0.449	-0.059	-0.557 to 0.439
Temperature					-0.125	-0.531 to 0.281
Precipitation					0.015	-0.078 to 0.109
Sunshine Duration					-0.301*	-0.597 to -0.004
Marginal R2	0.000		0.024		0.027	
ICC	0.373					

4.3. Weather Effects on Mobility

After examining the effects of weather on well-being, we turned to mobility behaviors and patterns. Tables 12, 13, and 14 present the results of the MELR models predicting daily distance traveled by active mobility, motor vehicles, and public transportation, respectively. For all three modes, most of the variance in daily distance was attributable to within-person fluctuations over time, as indicated by ICC values of 0.26 for active mobility, 0.17 for motor vehicles, and 0.12 for public transportation.

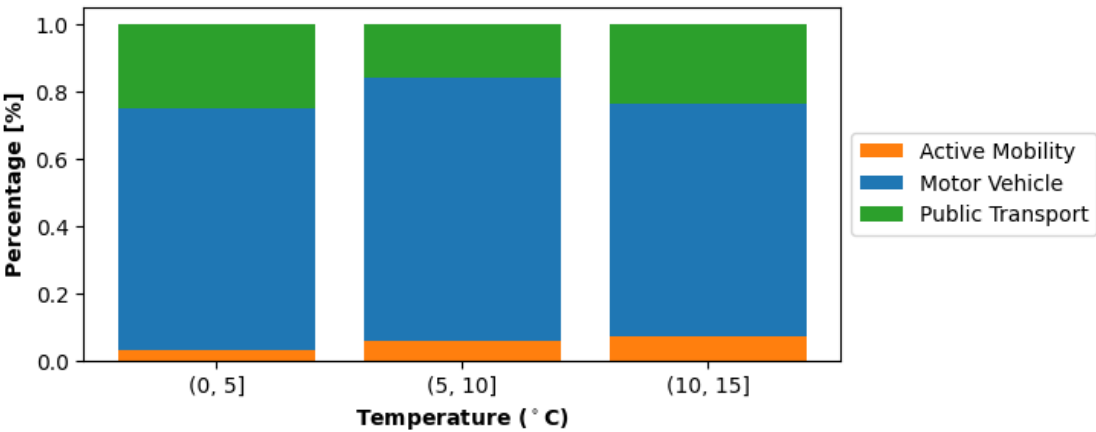


Figure 3. Percentage of daily distance traveled with the three different mobility types (active mobility, motor vehicles, and public transport) with varying mean daily temperatures.

For active mobility (cycling, running, walking), the complete Model 3 revealed significant effects of age, sex, and precipitation. Specifically, older individuals and men covered longer daily distances with active mobility, as indicated by positive associations with age (0.104, 95% CI 0.047 to 0.161, $p < 0.001$) and sex (1.139, 95% CI: 0.065 to 2.213, $p < 0.05$).

We observed a negative association between precipitation and active mobility (-0.022, 95% CI: -0.043 to -0.001, $p < 0.05$), indicating that greater rainfall corresponded to shorter distances covered on foot or by bike. For daily distance traveled with motor vehicles, the model did not reveal any statistically significant effects of weather. Among socio-demographic factors, only the employing organization showed an association with motor vehicle use, while no other predictors were significant.

Finally, for public transportation, Model 3 identified significant effects of both SF-12 PCS and precipitation. Better physical health (i.e., higher scores of SF-12 PCS) was associated with shorter distances traveled by public transport (-0.703, 95%CI -1.079 to -0.326, $p < 0.001$), whereas higher precipitation levels corresponded to greater reliance on this mode of travel (0.123, 95% CI: 0.002 to 0.244, $p < 0.05$).

Table 12. Results of empty model, socio-demographics model, and weather model predicting daily kilometers in active mobility (cycling, running, walking). Significant coefficients are highlighted in bold. * : $p < 0.05$; ** : $p < 0.01$; *** : $p < 0.001$ MCS: Mental Component Score; PCS: Physical Component Score.

	Active Mobility Distance [km]					
	Model 1		Model 2		Model 3	
	Coef.	CI	Coef.	CI	Coef.	CI
Intercept	2.774***	2.255 to 3.292	1.766	-0.097 to 3.629	1.38	-0.651 to 3.412
Age			0.103***	0.046 to 0.161	0.104***	0.047 to 0.161
Sex [0=Female]			1.131*	0.052 to 2.21	1.139*	0.065 to 2.213
Company [0=C1]						
C2			-0.203	-2.180 to 1.775	-0.293	-2.264 to 1.679
C3			0.715	-1.130 to 2.560	0.579	-1.258 to 2.416
C4			-0.808	-2.675 to 1.060	-1.015	-2.898 to 0.869
C5			1.648*	0.015 to 3.281	1.457	-0.189 to 3.104
C6			-0.800	-2.948 to 1.348	-0.841	-2.979 to 1.296
Supervisor role [0=No]			-0.305	-1.386 to 0.775	-0.327	-1.403 to 0.748
Having children [0=No]			-0.308	-1.347 to 0.730	-0.306	-1.339 to 0.727
SF-12 MCS			0.030	-0.032 to 0.092	0.030	-0.032 to 0.092
SF-12 PCS			0.008	-0.078 to 0.093	0.010	-0.075 to 0.095
Temperature					0.029	-0.063 to 0.120
Precipitation					-0.022*	-0.043 to -0.001
Sunshine Duration					0.062	-0.005 to 0.129
Marginal R2	0.000		0.053		0.061	
ICC	0.264					

Table 13. Results of empty model, socio-demographics model, and weather model predicting daily kilometers in motor vehicles (car, motorcycle, taxi). Significant coefficients are highlighted in bold.
* : $p < 0.05$; ** : $p < 0.01$; *** : $p < 0.001$ MCS: Mental Component Score; PCS: Physical Component Score.

	Motor Vehicle Distance [km]					
	Model 1		Model 2		Model 3	
	Coef.	CI	Coef.	CI	Coef.	CI
Intercept	30.729***	26.893 to 34.564	49.26***	36.082 to 62.438	43.307***	28.016 to 58.597
Age			0.08	-0.327 to 0.486	0.091	-0.319 to 0.501
Sex [0=Female]			3.536	-4.117 to 11.189	3.672	-4.048 to 11.392
Company [0=C1]						
C2			-27.850***	-41.872 to -13.827	-28.948***	-43.132 to -14.763
C3			-33.537***	-46.564 to -20.509	-34.438***	-47.592 to -21.284
C4			-29.332***	-42.536 to -16.127	-31.988***	-45.597 to -18.380
C5			-26.410***	-37.956 to -14.863	-28.794***	-40.688 to -16.900
C6			-22.570**	-37.760 to -7.380	-22.722**	-38.045 to -7.400
Supervisor role [0=No]			6.952	-0.691 to 14.595	6.907	-0.803 to 14.618
Having children [0=No]			1.634	-5.742 to 9.010	1.592	-5.847 to 9.030
SF-12 MCS			-0.104	-0.544 to 0.336	-0.104	-0.548 to 0.340
SF-12 PCS			0.200	-0.407 to 0.807	0.214	-0.398 to 0.826
Temperature					0.628	-0.205 to 1.461
Precipitation					-0.112	-0.306 to 0.081
Sunshine Duration					0.194	-0.420 to 0.807
Marginal R2	0.000		0.059		0.062	
ICC	0.172					

Table 14. Results of empty model, socio-demographics model, and weather model predicting daily kilometers in public transportation (bus, train, tram). Significant coefficients are highlighted in bold. * : $p < 0.05$; ** : $p < 0.01$; *** : $p < 0.001$ MCS: Mental Component Score; PCS: Physical Component Score.

	Public Transport Distance [km]					
	Model 1		Model 2		Model 3	
	Coef.	CI	Coef.	CI	Coef.	CI
Intercept	9.144***	7.028 to 11.26	3.300	-4.914 to 11.513	3.149	-6.301 to 12.598
Age			0.172	-0.081 to 0.426	0.171	-0.081 to 0.423
Sex [0=Female]			1.533	-3.238 to 6.303	1.441	-3.310 to 6.193
Company [0=C1]						
C2			4.707	-4.034 to 13.448	4.992	-3.738 to 13.722
C3			4.267	-3.853 to 12.387	4.578	-3.514 to 12.67
C4			5.637	-2.594 to 13.868	6.596	-1.783 to 14.974
C5			12.430**	5.233 to 19.627	13.173***	5.853 to 20.494
C6			0.376	-9.092 to 9.843	0.47	-8.957 to 9.896
Supervisor role [0=No]			-0.447	-5.212 to 4.317	-0.422	-5.166 to 4.322
Having children [0=No]			-2.993	-7.591 to 1.605	-2.963	-7.541 to 1.615
SF-12 MCS			0.064	-0.211 to 0.338	0.069	-0.204 to 0.343
SF-12 PCS			-0.706***	-1.085 to -0.328	-0.703***	-1.079 to -0.326
Temperature					-0.178	-0.700 to 0.344
Precipitation					0.123*	0.002 to 0.244
Sunshine Duration					0.191	-0.194 to 0.575
Marginal R2	0.000		0.042		0.044	
ICC	0.124					

5. Discussion

In this manuscript we reported the study design, methodology and the results obtained when assessing the impact of weather, as measured by mean daily temperature, level of precipitation, and sunshine duration, on ten different outcomes related to well-being (activity, recovery, sleep, and stress) and mobility. For our analysis, we used the dataset collected as part of the RENEWAL study [13], that involved a total of 294 participants for 30 continuous days and for which objective data (i.e., physiological data through Garmin Health API) and self-reported data (i.e., surveys and ecological momentary assessments) were retrieved. Given the longitudinal nature of our dataset, we employed MELR models to analyze how three key weather predictors, namely mean daily temperature, total daily precipitation, and total sunshine duration, affect these outcomes taking into account both intra-person and inter-person differences. To improve the robustness of our analysis, we filtered our daily observations with strict criteria to keep only reliable observations. We considered only weekdays in which the provided smartwatch was worn more than 70% of the time and for which automatic sleep tracking was available. Furthermore, we kept only days with at least 70% coverage in terms of location data, and we excluded days with presumed travels too far away from home (i.e., with maximum daily distance greater than 300 km), similar to what was done in [20]. Our final dataset consisted of 2120 daily observations from 151 participants, spanning the period from February to May 2024, with a median (p_{25} , p_{75}) number of observations available per participant of 14 (10,22).

Our analysis showed modest effects of weather on both well-being and mobility outcomes. For well-being, MELR models found a positive effect of temperature on total sleep time, wake-up time, and physiological stress, while a negative association with temperature was found for self-reported stress values and the percentage of sedentary time during the day. The amount of sunshine during the day positively affected the physiologically measured stress and the percentage of sedentary time during the day, while negatively impacting the recovery during the next night sleep. We didn't find any statistically significant association between weather and bedtime and the total number of daily steps. Our results for wake-up time, are in line with what was found by Mattingly et al. [20] with objective sleep data tracked with Garmin smartwatches. The authors found a modest effect of daily temperature on wake-up time. However, their study was conducted over a longer period of time, with participants enrolled for approximately a year. Therefore, authors were able to include also seasonality among the predictors for MELR models, and seasons resulted significant in the prediction of other sleep-related outcomes (total sleep time, bedtime, and wake-up time). In the same study, in contrast to our results temperature was not found to be associated with total sleep time, which was instead affected by season, with sleep duration decreasing in spring with respect to winter. Similarly, in a recent paper by Li et al. [23] which included automatic sleep tracking through Huawei smartwatches, the authors found total sleep time to be reduced by approximately 10 minutes for every 10° increase in temperature. This contrasting results on sleep-related outcomes may be explained by the limited observation period of our study, with the majority of observations belonging to spring and with little temperature variations. Due to this, we were not able to include seasonality effects in our models, and we instead weather to impact total sleep time and wake-up time, suggesting a shift in wake-up times with increasing temperature, with bedtime remaining unaffected. As far as the activity domain is concerned, our results are in line with previous findings that reported increasing physical activity with increasing temperature and sunshine duration [24,28,29,31]. Our models showed a statistically significant effect of temperature and sunshine duration on the percentage of time spent in active or highly active states (i.e., non-sedentary behavior) but not on the amount of daily steps, suggesting an increasing extent of physical activities not necessarily including walking or running exercises. Interesting, we found opposite results when assessing the impact of weather on stress. In our models, we used two different stress measurements: an objective stress measure, defined as the mean stress value reported by the Garmin smartwatch (i.e., a Garmin proprietary algorithm based on HRV and heart rate analysis [54]) and the self-reported stress value in the daily diaries. While we found warmer days to reduce the self-reported stress value, in line with previous large-scale survey-based studies [17,25],

our analysis showed temperature and sunshine duration to increase the amount of physiological stress as measured through HRV and heart rate, which, to the best of our knowledge, is still unexplored in the available literature. This can be explained by the fact that self-reported and physiological stress are two different representations, with authors finding small to medium effect sizes between self-reported stress and objective physiological stress measures [55]. Furthermore, objective stress measured by Garmin through their proprietary algorithms takes into account also the extent of activity and the recovery phases following it, thus suggesting that warmer and longer days are linked to a greater amount of activity carried out during the day, as confirmed by our results on effects of weather on sedentary behaviors. Finally, for well-being we also assessed the impact of weather on the night recovery, i.e. on the amount of “energy” recovered by the body while sleeping at time and being in a rest state. Our models showed a significant modest and negative effect of the sunshine duration on this outcome.

Moving on to the mobility domain, we assessed the impact of weather on the total daily traveled distance according to three different mobility types: active mobility, motor vehicles, and public transport. We found a statistically significant effect of precipitation on both active mobility and public transport, with a reduced distance traveled by active mobility with increasing precipitation, while the opposite holds for public transport, with increased distances with higher precipitation values. When modeling the distance traveled by motor vehicles, we didn’t find any significant effect of weather. This analysis may suggest an overall stability of distances traveled with motor vehicles, while distance traveled using active mobility transportation types (mainly walking or cycling) are replaced with public transportation in case of higher precipitations during the day. When compared to other studies using objective mobility and location data, Pang et al. found a positive effect of weather on the overall mobility, without differentiating between different types of mobility [37]. Lepage et al. found precipitation to reduce the amount of bikesharing (i.e., indirect measurement of distance traveled with active mobility) [40], while Otim et al. didn’t include precipitation among the predictors for transport mode choices, and found higher temperature to increase the amount of walking share and to reduce bike share [41].

This study does not come without limitations. First of all, when compared to other studies using objective data for well-being and mobility assessments, our dataset is smaller. In the two largest studies assessing the impact of weather on sleep, Mattingly et al. had a total of 51836 observations [20] and Li et al. 23 million observations [23], which are way larger than our 2120 observations. These datasets also span multiple monitoring months, allowing to assess also the effect of seasons rather than only daily weather measurements. Ours, instead, was limited to a short observation period of four spring months during the year 2024, limiting the possibility of studying seasonal effects on the chosen outcomes. In addition to this, our observations were confined in the region of Canton Ticino (Switzerland) and northern Italy, and study participants were mostly office and information workers, thus limiting the generalization capabilities of our results, since other populations (e.g., shift workers) and/or countries with different weather conditions may experience different effects of weather on their well-being and mobility. Furthermore, while on one hand the strict filtering process that we carried out on the dataset left us with a reliable set of observations, on the other hand it may have introduced a bias in the dataset as only the highly compliant participants were left in the analytical sample used for the modeling. Finally, our analysis on mobility distances considered them as a whole during the day, without splitting them into commuting or recreational trips, which could help into better assessing the impact of weather [36]. As an example, Sabir et al. found commuting (recreational) trips to be less (more) affected by weather conditions [33].

Even when considering these potential limitations our results on longitudinal objective and subjective data confirm previous findings in literature for several of the analyzed outcomes (sleep and self-reported stress), while at the same providing new and interesting insights on other outcomes (objective physiological stress and night recovery). The main robustness of our study lays in the use of objective data for the assessment of weather impacts, with the majority of the studies using

self-reported aggregated data. Our analysis also showed that it is possible to use passively collected GLH data for the assessment of weather impact on mobility, potentially allowing for the use of the enormous amount of retrospective GLH data to further refine the results reported in this manuscript. We believe that future improvements on the framework outlined in this paper, with longer observation periods spanning multiple locations, can help assessing the impact of weather on well-being and mobility, driving insights and policies that could prevent severe impacts due to climate change.

6. Conclusions

This paper analyzed 8,820 observations from workers in southern Switzerland to assess how typical weather variations influence individual well-being and mobility using a multi-source objective and subjective data framework. After filtering for reliable weekday data based on wearing time and location tracking, we applied robust mixed-effects models and found small but statistically significant effects of weather on our outcomes. Increasing temperatures were associated with longer total sleep time, delayed wake-up times, and lower self-reported stress, yet objectively measured physiological stress rose with prolonged sunshine and higher temperatures. Likewise, rising precipitation corresponded with reduced distances traveled by active mobility and increased reliance on public transportation. In line with a widespread body of research, these findings confirm that normal weather fluctuations exert significant but moderate effects on health-related behaviors. They highlight the need to shift research focus toward extreme weather variations—such as heatwaves—that lie beyond typical seasonal ranges (e.g. Authors). Given the potentially huge consequences of such extremes for public health and health-care systems, future studies should employ longer tracking periods that integrate both seasonality and extreme weather events into their modeling frameworks. This shift will not only illuminate the full spectrum of weather's impact on individual well-being and mobility but also help in identifying effects that are more consistent in magnitude, thereby informing targeted public health interventions and policy planning.

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Abbreviations

The following abbreviations are used in this manuscript:

GLH	Google Location History
ICC	Intra-Class Coefficient
MELR	Mixed Effects Linear Regression
SF-12 MCS	Short-Form Health Questionnaire Mental Component Score
SF-12 PCS	Short-Form Health Questionnaire Physical Component Score

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