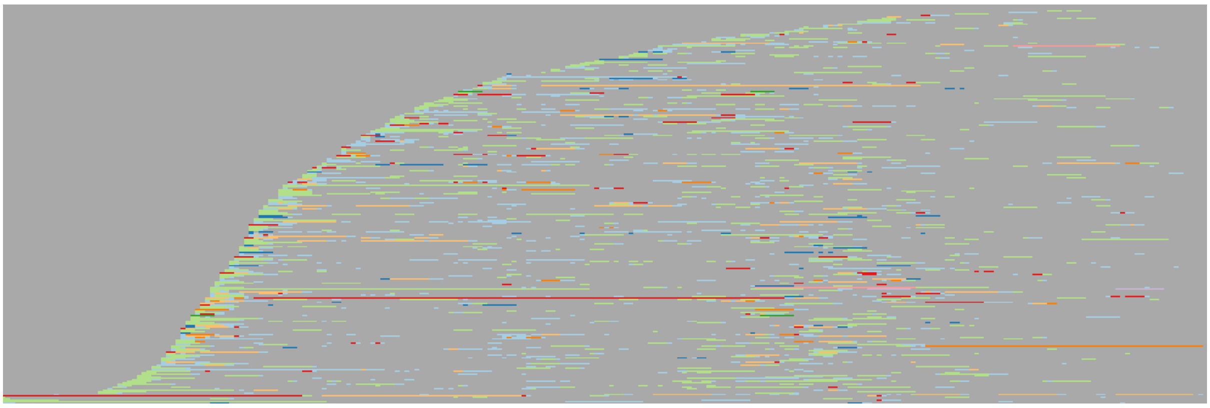

How did COVID-19 shift time use patterns in Switzerland?

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Abstract

This report uses GPS tracking data to determine the cause and the magnitude of time use pattern shifts during the COVID-19 pandemic in Switzerland. The impact of COVID-19 related restrictions and health risks, weather conditions, and socio-demographics on travel behavior are investigated simultaneously. Initially, trajectory sequencing is performed to convert the GPS data into sequences, which can be used for descriptive analysis and serve as inputs for the subsequent analysis. Secondly, Multi-Dimensional Sequence Alignment Method is performed to calculate the inter-personal and intra-personal variation of travel activities. Cluster analysis and discrepancy analysis are then performed to determine the time-variant and time-invariant factors that cause travel behavior shifts. Lastly, the panel effects regression model is used to determine the combined effect of all parameters on travel behavior. The analysis shows that COVID-19 had a significant impact on travel behavior, and this impact differs between the first and the second wave. More restrictions and higher health risks would make people travel less, stay at home more, grow preference of private transport means over collective means, and make the difference of travel patterns across all individuals more similar. Days of the week, precipitation level, gender, age, income range, education level, employment status, and public transport pass ownership have prominent impacts on intra-personal activity pattern, whereas days of the week, precipitation, temperature, age range, and public transport ownership influence inter-personal activity patterns more. This report would help policy makers understand the effectiveness of the restrictions, under what conditions people performed out-of-home activity, and the changes that are likely to persist after the lockdown, therefore, assist them for better transportation planning policies in the post-pandemic and better restriction policies for a pandemic in the future.

Keywords

COVID-19, Time Use Patterns, Activity-Travel Sequence, Multi-Dimensional Sequence Alignment Method, Panel Effects Regression Model

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1 Introduction

Since the COVID-19 pandemic started, the Swiss government introduced various measures according to the COVID-19 situation development to contain the spread of the virus. The measures applied often introduced restrictions to movements, shopping, sporting and cultural leisure activities, such as tight border entry requirements, participant number cap and limited open hour of restaurants, cinemas, theaters, etc, ban on night leisure venues, as well as recommendations for social distancing and work from home when possible (Federal Office of Public Health, 2021b). Consequently, the pandemic has a significant impact on the patterns of daily time use, as individuals cannot perform many activities due to restrictions or concern over contagion.

Some existing studies tried to identify the impact of COVID-19 on mode and purpose time use patterns (Abdullah *et al.*, 2021; Parady *et al.*, 2020; Hunter *et al.*, 2021; Irawan *et al.*, 2021; Shamshiripour *et al.*, 2020; Hara and Yamaguchi, 2021; Parker *et al.*, 2021; Shakibaei *et al.*, 2021; Liu *et al.*, 2021; Anwari *et al.*, 2021; Jiao *et al.*, 2021; Apple, 2021; Google, 2021; Department for Transport, 2021), whereas some others focused more on how socio-demographics differentiated travel behavior during the pandemic (Politis *et al.*, 2021; Jiao and Azimian, 2021). On top of the COVID-19 development and socio-demographics, days of the week, the temperature of the day and the precipitation level also influence the travel behavior to different extent Brum-Bastos *et al.* (2018); Xianyu *et al.* (2017). Therefore, it is desirable to consider the COVID-19 situation, socio-demographics, days of the week and the temperature of the day simultaneously for a more comprehensive view on the travel behavior during the pandemic.

This report uses GPS tracking data collected by IVT at ETH Zurich and WWZ at the University of Basel, which spans over the pre-pandemic, the first wave, the post-lockdown and the second wave, together with socio-demographic information of each participant, COVID-19 risks and development, and weather conditions for each recorded day. Firstly, we analyzed descriptively the development of time-of-the-day and day-of-the-week patterns throughout the pandemic, then determined the factors that affected the mode and purpose patterns using cluster analysis, Multi-Dimensional Sequence Alignment Method and statistical tests, and lastly modeled the main drivers using Panel Effects Regression Model.

By determining how each factor influenced the patterns of daily time use, this research provides an insight into how people reacted to the restrictions limiting personal freedom coupled with a high level of health risks on a global scale, and how this reaction changed with time. This research fills the current literature gap, as it is the first known project that uses longitudinal GPS data to determine the travel behavior shifts during different stages of the pandemic development, considering a variety of socio-demographic information, the days of the week and weather conditions. It will help policy makers have a better idea of how people react to restrictions, the effectiveness of restrictions, the reasons behind activity shifts during a pandemic, the conditions under which people are willing to perform out-of-home activities and the behavioral changes that are likely to persist after a pandemic, therefore ameliorating their decision-making for post-pandemic transport policies and potential future national emergencies.

2 Literature Review

2.1 Research Background

The pandemic has a significant influence on patterns of daily time use, and it offers an unprecedented opportunity to study the impact of national-wide restrictions on individual travel behavior. The data from these studies were collected using online surveys (Abdullah *et al.*, 2021; Parady *et al.*, 2020; Abdullah *et al.*, 2020; Anwari *et al.*, 2021; Politis *et al.*, 2021; Jiao and Azimian, 2021; Shamshiripour *et al.*, 2020; Irawan *et al.*, 2021) or GPS data (Hara and Yamaguchi, 2021; Hunter *et al.*, 2021; Liu *et al.*, 2021; Engle *et al.*, 2020; Jiao *et al.*, 2021) to determine the impact of the outbreak on different aspects of travel behavior.

Among studies that collected data using online surveys, Abdullah *et al.* (2021); Parady *et al.* (2020) and Abdullah *et al.* (2020) used questionnaire surveys to determine the influence of COVID-19 policies on mode and purpose pattern, in which the former two were conducted in Pakistan and Japan respectively, and the last study used social media and emails to reach out to people around the globe. Their results indicate that the pandemic significantly affected mode, purpose, trip distance, and trip frequency, people shifted from public transport means to private and non-motorized transport means and the main purpose shifted from work or study to shopping (Abdullah *et al.*, 2021, 2020). Abdullah *et al.* (2020) performed an additional analysis on socio-demographic factors that affected mode choice and found that gender, mobility ownership and employment status played a role. Politis *et al.* (2021) concentrated on the correlation between socio-demographics and travel pattern shifts during the pandemic in Greece, they showed that trip frequency was significantly correlated with gender and income during the lockdown, which was not observed before the outbreak. Jiao and Azimian (2021) focused on the impact of socio-demographics on the trip made by public transport (PT) and for visiting stores, and found that age, gender, ethnic background, education level, employment status, household size, income level, and health condition significantly affected public transport usage and store visiting. Parker *et al.* (2021) focused on how the outbreak affected frequent public transport riders in the US and suggested that the pandemic had a more significant effect regarding travel behavior on frequent PT riders compared to non PT riders, as most PT riders performed fewer PT trips due to concern over infection risk, and income had an influence on this behavioral shift since low-incomers had fewer mode choices, forcing them to use PT to move around. Shamshiripour *et al.* (2020) used preference-revealed preference (SP-RP) surveys in Chicago Metropolitan Area to investigate how people's daily routines were affected by the outbreak, and whether these changes would persist after the end of the pandemic. They found that people grew a preference for work from home, online shopping, and private transport means during the pandemic, and the former two are likely to persist after the end of the pandemic.

Many other studies used GPS data to determine travel behavior shifts during the pandemic (Hara and Yamaguchi, 2021; Hunter *et al.*, 2021; Liu *et al.*, 2021; Engle *et al.*, 2020; Jiao *et al.*, 2021). Engle *et al.* (2020) used GPS data from February to March 2020 in the US to estimate the impact of COVID-19 related restrictions and risks on individual mobility and suggested that both restrictions and risks would decrease mobility, especially in densely populated and older counties. Hara and Yamaguchi (2021) used location data from the mobile terminal network during the first wave across Japan, to investigate how people reacted to the "state-of-emergency" declaration from the Japanese government. They concluded that the number of inter-regional trips reduced significantly, people tried to avoid areas with high population density and the travel behavior returned to normal state slowly after the declaration was lifted. Hunter *et al.* (2021) used mobility data from mobile devices from February to June 2020, covering more than 1.6 million individuals across the US, to determine the walking pattern during the pandemic, and found out that walking activities reduced significantly during the pandemic, especially utilitarian walking, whereas recreational walking increased and surpassed the pre-pandemic level. They also noted that walking patterns in areas where people relied on PT heavily and low-income areas were more affected by COVID-19 restrictions. Jiao *et al.* (2021) employed mobility data and employment status in Houston to study traffic patterns between March and November 2020, and found that the traffic pattern was strongly affected by the COVID-19 incident rate from the previous week, PT usage decreased and unemployment played a significant role in foot traffic during the study period. Liu *et al.* (2021) used GPS data from January 2020 to January 2021 across the US to determine the pattern of necessary activities during the pandemic, which were quantified by determining the connections between trip characteristics, income level, and supermarket density. They found that the lockdown measurement had a less significant impact on trip distance and frequency than the individual financial situation and accessibility to essential services.

All the papers mentioned above that studied the combined effect of the COVID-19 pandemic and detailed socio-demographics employed survey data. Nevertheless, people receiving surveys often over-report or under-report their trip duration and frequency, as well as neglect to report some performed trips (Bricka *et al.*, 2012; Stopher and Shen, 2011; Wolf *et al.*, 2003). These features introduce imprecision to the travel diary, making the data only applicable to a limited level of details. GPS data surmounts these restraints, as it tracks the performed activities automatically, making the data more precise and more detailed on trip location and exact start and finish time of movement (Zhao *et al.*, 2015; Chen *et al.*, 2010). However, the studies that employed GPS data did not include extensive socio-demographic information when analyzing the behavioral shifts during the pandemic, not to mention the effect of the days of the week and weather conditions. Xianyu *et al.* (2017); Brum-Bastos *et al.* (2018) and Cools *et al.* (2010) argued that socio-demographics, weather conditions, and days of the week affect the travel behavior before the pandemic, making it desirable to consider these variables when studying behavioral shifts after the outbreak. This paper fills this gap, as we will consider all three types of variables simultaneously, together with COVID-19 related restrictions and risks, to determine the factors that caused behavioral shifts.

2.2 Methodology Background

Sequence Alignment Method (SAM) was originally developed by Sankoff and Kruskal (1983) in molecular biology to compare uni-dimensional DNA and RNA sequences. Abbott (1995) expanded the SAM in social science and opened up possibilities for applying this method in other domains. Later on, Wilson (1998) applied the SAM for comparing daily activity patterns in transportation research. The SAM is advantageous in determining similarity between sequences of activities as it considers simultaneously the difference in the list of activities and the difference in the order in which the activities happen (Moiseeva *et al.*, 2014). In order to expand the SAM to multi-dimensional sequences, Joh *et al.* (2002) proposed the Multi-Dimensional Sequence Alignment Method (MDSAM) that takes the interdependencies of each dimension into account. Several studies applied the MDSAM for determining travel patterns. Moiseeva *et al.* (2014) used the MDSAM to investigate the reasons behind longitudinal patterns shifts, and concluded that the inter-personal distance is higher than the intra-personal distance, and both distances are influenced by socio-demographics. Dharmowijoyo *et al.* (2017) and Xianyu *et al.* (2017) employed the MDSAM to calculate intra-personal and inter-personal distance, which were then used as the dependent variables in the panel effects regression model.

Cluster analysis is a statistical technique for determining patterns of the dataset, by grouping samples with similar features together into a homogeneous subset (Boccard and Rudaz, 2013; Roessner *et al.*, 2011). Schlich (2003) and Ding and Zhang (2016) applied cluster analysis to find travelers with similar travel behavior. Brum-Bastos *et al.* (2018) used cluster analysis to identify the effect of weather conditions on travel behavior, using Ward's algorithm to partition the days with similar weather conditions into groups with help of Calinski-Harabaz Index (CHI), and using Kruskal-Wallis test and Levene's test to determine whether the difference in time use of each mode and purpose was statistically significant.

Panel data refers to a dataset that carries information on how the data evolved over time for each entity (Stock and Watson, 2020). Depending on the data type, a fixed effects model or a random effects model can be applied to deal with the panel data (Croissant and Millo, 2008). The fixed effects model assumes that the time-invariant parameters do not play a significant role in the data, whereas the random effects model considers between-individual heterogeneity, meaning that it also examines time-invariant parameters in the model (Stock and Watson, 2020; Fávero and Belfiore, 2018). Xianyu *et al.* (2017) used the panel effects regression model to determine how day-of-the-week and socio-demographics influence inter-and intra-personal distance, and proved that weekday sequences are more similar to other weekdays than weekends, and socio-demographics impact the sequence variation significantly (Xianyu *et al.*, 2017). This study should also observe these trends. Dharmowijoyo *et al.* (2017) used the panel effects regression model to investigate how activity pattern is influenced by trip characteristics, socio-demographics, city configuration, and personal health condition, and found that an individual's travel pattern is strongly affected by the patterns of other household members, and unemployed individuals have more predictable travel patterns than employed ones. These two papers combined the MDSAM with panel effects regression model to determine how time-variant and time-invariant parameters affect travel behavior.

These papers demonstrated the possibility of combining MDSAM with cluster analysis and panel effects regression model to determine the reasons behind mode and purpose shifts, as well as daily travel pattern variation, considering both time-variant and time-invariant variables. However, these papers did not investigate the impact of a pandemic on travel behavior. This study would show whether the findings from these papers would still be valid in a pandemic, as well as providing a new perspective into the MDSAM in transportation analysis.

3 Methodology

3.1 Trajectory Sequencing

Initially, the raw data was converted into sequences, which served as input for the MDSAM. By definition, a sequence is an ordered array of characters from the list that represents successive states (Abbott and Tsay, 2000). In the sequence analysis method, each state is given a specific letter from a finite list of alphabets (Idury and Waterman, 1995). In this study, eight dimensions were being considered: mode, purpose, KOF Stringency Index, daily increase, daily hospitalized, daily deceased, precipitation, temperature. Therefore, eight sets of unique alphabets were generated.

Table 1 and Table 2 show the alphabets for mode and purpose in this study, as well as all possible modes and purposes that were recorded by the GPS tracking application. Table 3 shows the precipitation and temperature discretization utilized in this study. The scale was adopted from the Federal Office of Meteorology and Climatology MeteoSwiss (2021), in which the precipitation represents the daily precipitation in millimeters and the temperature represents the free-air temperature two meters above ground level in Celsius. The COVID-19 related parameters considered for this study include the daily increase of confirmed cases, daily hospitalized individuals, daily deceased individuals, and the KOF Stringency-Plus Index. The KOF Stringency-Plus Index was developed by Pleninger (2021) to quantify the stringency of COVID-19 measurements implemented by the federal and cantonal government in Switzerland, taking into account 11 dimensions related to public life restrictions. The COVID-19 data of daily increase, hospitalized and deceased cases were taken from Federal Office of Public Health (2021a), recorded on a national level. Table 4 shows the discretization of COVID-19 related parameters discussed above, in which the ranges were defined by observing the COVID-19 development in Switzerland for the entire time horizon.

An example of an 8-dimensional sequence for one individual over a 30-minute interval with a 5-minute time step is depicted in Fig. 1. This type of multi-dimensional sequence is generated for each day of each individual at a 5-minute time interval outside 01:00 to 05:00, and at a 30-minute time interval between 01:00 to 05:00. This difference of time step is to account for night hour activities, during which all individuals tend to have a high level of behavioral similarity (Schlich, 2003).

Table 1: Alphabets for Mode

Letter	MA	MB	MC	MD	ME	MF	MG	MH	MI
Description	Walk	Bike	Car	Motorbike	Airplane	Bus	Train	Tram	Boat

Table 2: Alphabets for Purpose

Letter	Description
PA	Home
PB	Work
PC	Leisure
PD	Shopping
PE	Other
PF	Study
PG	Errand
PH	Co-Working
PI	Education
PJ	Assistance
PK	Home Office
PL	Wait
PM	Unknown

Table 3: Alphabets for Weather Conditions

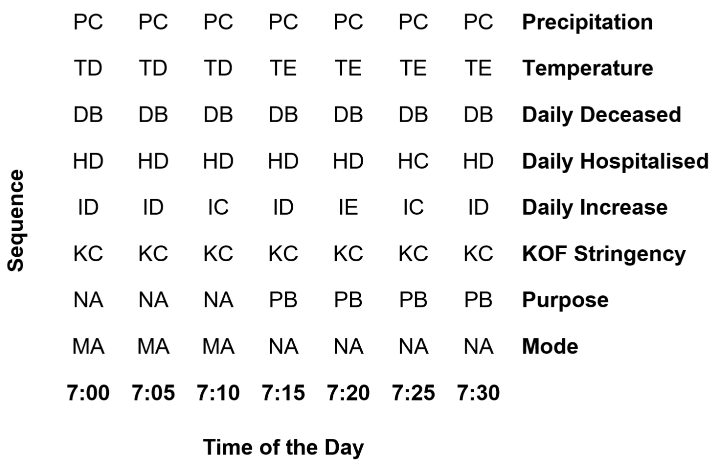
Precipitation [mm]			Temperature [Celsius]		
Letter	Description	Range	Letter	Description	Range
RA	Dry	0	TA	Very Cold	<0
RB	Very Slight	0 - 2	TB	Cold	0 - 10
RC	Slight	2 - 4	TC	Cool	10 - 15
RD	Low Moderate	4 - 6	TD	Comfortable	15 - 20
RE	Moderate	6 - 10	TE	Slightly Warm	20 - 25
RF	Heavy	10 - 20	TF	Warm	25 - 30
RG	Very Heavy	20 - 40	TG	Hot	30 - 35
RH	Violent	> 40	TH	Very Hot	>35

Source: Adopted from the scale used by the Federal Office of Meteorology and Climatology MeteoSwiss

Table 4: Alphabets for COVID-19 Related Parameters

KOF Stringency Index		Daily Increase		Daily Hospitalized		Daily Deceased	
Letter	Range	Letter	Range	Letter	Range	Letter	Range
KM	0	IM	0	HM	0	DM	0
KA	1 - 40	IA	1 - 500	HA	1 - 40	DA	1 - 10
KB	40 - 45	IB	500 - 1000	HB	40 - 80	DB	10 - 20
KC	45 - 50	IC	1000 - 1500	HC	80 - 120	DC	20 - 30
KD	50 - 55	ID	1500 - 3000	HD	120 - 160	DD	30 - 40
KE	55 - 60	IE	3000 - 4500	HE	160 - 200	DE	40 - 50
KF	60 - 65	IF	4500 - 6000	HF	200 - 240	DF	50 - 60
KG	65 - 70	IG	6000 - 6500	HG	240 - 280	DG	60 - 70
KH	> 70	IH	> 7500	HH	> 280	DH	> 70

Figure 1: An Example of an 8 Dimensional Sequence with 5-Minute Intervals



3.2 Multi-Dimensional Sequence Alignment Method (MDSAM)

The core concept of SAM is to utilize 'insertion', 'deletion' and 'substitution' to find the minimum sum of operating costs that equalize two sequences (Joh *et al.*, 2002). A smaller distance between two sequences means a higher similarity between them, and vice versa (Gauthier *et al.*, 2010). In this analysis, the Optimal Matching (OM) distance was employed to calculate the similarity between sequences. According to Gabadinho *et al.* (2011b), the OM method requires two arguments: the insertion/deletion cost and a substitution matrix. The cost of insertion and deletion used in this analysis is 1, meaning that substitution has cost 2, since substitution can be regarded as a combination of insertion and deletion (Schlich, 2003). The substitution-cost matrix used for this method was the transition rates between states of the sequence data. According to Gabadinho *et al.* (2011b), the substitution-cost matrix has dimension $n \times n$, where n is the number of state in the alphabet and element (i, j) corresponds to the substitution cost between state i and j. The substitution cost was calculated by Eq. (1) given that $p(i|j)$ represents the transition rate between state i and j, corresponding to the probability of observing state j at time $t + 1$ and state i at time t.

$$2 - p(i|j) - p(j|i) \quad i \neq j \tag{1}$$

The OM distance was calculated recursively using Eq. (2), in which each row returns a possible OM score of two sub-sequences (Gauthier *et al.*, 2010). $C_{S_iS_j}$ is the distance between i^{th} term of sequence I and j^{th} term of sequence J, i.e. the substitution cost. d represents the costs of deletion/insertion, and $F(i, j)$ represents the optimal OM distance of the first i characters of sequence I and the first j characters of sequence J (Gauthier *et al.*, 2010).

$$F(i, j) = min \begin{cases} F(i-1, j-1) + C_{S_iS_j} \\ F(i-1, j) + d \\ F(i, j-1) + d \end{cases} \tag{2}$$

3.3 Context-Aware Similarity Analysis (CASA)

The context is properties to be analyzed for similarity analysis, and in CASA, only certain contexts are used for comparing the similarity between entities (D. Hossein Zadeh and Reformat, 2013). In this study, the R language package "TraMineR" was used for the sequence analysis (Gabadinho *et al.*, 2011a).

3.3.1 Cluster Analysis

In order to determine the effect of weather and COVID-19 related parameters on travel behavior, clustering analysis was used in this analysis. For each weather and COVID-19 related parameter, days within the same range specified in Table 3 and Table 4 were grouped in the same cluster. For each cluster, two types of distribution were determined for further analysis: 1) the proportion of time spent per day on each mode and purpose for each individual, 2) the average inter-personal and intra-personal distance from the MDSAM for each day of each individual. Kruskal-Wallis test and Levene's test were then performed to determine the significance of the differences in median and variance respectively (Riffenburgh, 2006). Assume that a statistical significance of Kruskal-Wallis or Levene's test is sufficient evidence to prove that different groups have different travel behavior, hence concluding that the corresponding parameter affects travel behavior (Brum-Bastos *et al.*, 2018).

3.3.2 Discrepancy Analysis

Discrepancy analysis can help identify the relationship between socio-demographics and travel behavior (Brum-Bastos *et al.*, 2018). The method employed here evaluates the association between groups of individuals based on socio-demographics by determining the share of discrepancy and p-value, using their discrete covariate and dissimilarity matrix (Gabadinho *et al.*, 2021). The share of discrepancy is calculated by Eq. (3), SS_B represents the between sum of squares and SS_T represents the total sum of squares (Studer *et al.*, 2011).

$$R^2 = \frac{SS_B}{SS_T} \tag{3}$$

3.4 Panel Effects Regression Modeling

In order to examine the combined effect of COVID-19 pandemic development, weather, and socio-demographics on travel behavior in Switzerland, panel effects regression model, especially the random effects model, was used to find the correlations between these factors and travel pattern variations. Eq. (4) shows the model used for this analysis.

$$Y_{i,t} = \alpha + \sum_{w=1}^{W-1} \beta_w W_{tw} + \sum_{p}^{P} \gamma_p P_{itp} + \sum_{c}^{C} \sigma_c T_{itc} + \sum_{s=1}^{S} \delta_s X_{is} + u_{it} + \epsilon_{it} \tag{4}$$

The dependent variable $Y_{i,t}$ to be predicted in this model denotes four different values for each day t of each individual i: 1) Intra-personal distance mean; 2) Intra-personal distance standard deviation; 3) Inter-personal distance mean; 4) Inter-personal distance standard deviation. The intra-personal distance and inter-personal distance is calculated by the MDSAM, using mode and purpose sequences. The intra-personal distance mean and standard deviation are obtained by extracting the travel sequences for each day of the week of each individual, calculating the 7×7 dissimilarity matrix for each recorded week, then determining the mean and standard deviation of each row or column of this matrix, resulting in a 7×1 vector in which each value shows how far on average and how varied one day's activity pattern is from all other days of the week of the same week. A higher mean implies the corresponding day's activity pattern is more different compared to other days of the week, and a higher standard deviation reveals that the patterns of the days of the week are more heterogeneous, meaning that the individual's weekly pattern is more different from each other and the weekday-weekend difference is likely to be larger. The inter-personal distance mean and standard deviation are calculated by taking the travel sequences of all individuals for each day, computing a distance matrix for that day, in which each value represents the distance between travel patterns of two individuals, and finding the mean and standard deviation of each row or column, showing how different one individual's travel behavior is to all the others for that day. A higher inter-personal distance mean indicates that an individual performed more different patterns than others, whereas a higher standard deviation suggests that more individuals performed significantly different activities than other individuals.

The first term α in the Eq. (4) is the regression constant. The component $\sum_{w=1}^{W-1} \beta_w W_{tw}$ captures the effect of days of the week, parameter β_W represents $W - 1$ days of the week (one day of the week is taken as reference, $W - 1 = 6$), and W is a variables of binary vector, in which $W_{t1} = 1$ means day t is a Monday. The component $\sum_{p}^{P} \gamma_p P_{itp}$ denotes the COVID-19 effect, in which P is a binary vector indicating the COVID-19 variables p for day t of individual i and γ_p is the corresponding parameters for variable P. In this analysis, the COVID-19 variables can be interpreted in two ways: 1) solely by phase, which is a variable that takes into consideration the public life restrictions imposed by the government and COVID-19 infection risks simultaneously; 2) a combination of variables introduced in Table 4. Note that only KOF stringency index and daily increase are employed here, as daily increase, daily hospitalized, and daily deceased are covariate. $\sum_c^C \sigma_c T_{itc}$ demonstrates the weather effect, including daily precipitation and daily average temperature, in which σ_c is the parameter of weather attribute c, and T is variable of binary vector. $T_{itc} = 1$ if day t of individual i has weather condition specified by c. The fifth element explains the effect of social-demographics, where x_{is} is the s-th attribute of socio-demographics and δ_s is the corresponding parameter. Lastly, u_{it} and ϵ_{it} are between-entity error and within-entity error respectively.

4 Data and Descriptive Analysis

4.1 Data Description and Manipulation

4.1.1 Movement Data

The data used in this study is an extension of the MOBIS study, a collaboration project on mobility behavior in Switzerland between ETH Zurich, the University of Basel, and the Zurich University of Applied Sciences, 3,700 participants were invited to participate in the MOBIS study between September 2019 and January 2020, and the GPS tracking data was collected through the tracking app, Catch-my-Day [1] (Molloy *et al.*, 2020b). Note that only individuals who use a car for at least two days a week could participate in the MOBIS study, making the sample further away from the Swiss population (Molloy *et al.*, 2020a). Among these invited participants, GPS tracking data for 3690 individuals are available. However, since the pandemic started in Switzerland, which is the main focus period for this study, 1671 individuals tracked their travel behavior for at least one day.

In order to have a more detailed look at the behavioral shift of individuals throughout the pandemic, subsets of the individuals and their recorded days are selected such that: 1) the selected individual is not in the treatment group "Pricing" so that their travel behavior was not influenced by monetary rewards during the MOBIS study; 2) the individual tracked for at least seven or 14 consecutive days in each of phase 1, 2, 4, 5, 6, 7 and 8, in which each phase corresponds to a COVID-19 situation described in Table 5 and Table 6. Phase 3 is not included here, as it corresponds to the post-MOBIS study, and many participants stopped tracking their travel behavior in this phase. After applying these requirements, two subsamples were obtained: 1) Scenario 1 with 275 individuals who tracked for at least seven consecutive days for each of the required phases; 2) Scenario 2 with 142 individuals who tracked for at least 14 consecutive days for each of the required phases. The first seven or 14 tracked days in each required phase for each selected individual were utilized for this analysis. These two scenarios shed light on different aspects of the analysis, as scenario 1 includes more individuals, giving it a more in-depth look at the effect of socio-demographics on travel behavior, whereas scenario 2 includes more days for each individual, making it more suitable for analysis that requires more data points. A description of the time periods covered by the subsamples and corresponding average daily temperature, daily COVID-19 cases and stringency index are given in Table 7 and

[1] Based on Motion-Tag's SDK Molloy *et al.* (2020b)

Table 8.

Table 5: Interpretation of Phase

Phase	Start Date	Description
1	First 28 days of tracking	Control phase of the MOBIS study
2	Second 28 days of tracking	Treatment phase of the MOBIS study
3	End of Phase 2 till 2020-03-02	Post-MOBIS
4	2020-03-02	Pandemic starts in Switzerland
5	2020-05-11	Post lockdown
6	2020-07-06	Masks required on all public transport
7	2020-10-19	Start of the second wave
8	2020-11-12	Expansion of sample with additional panel

Table 6: Interpretation of Phase (cont.)

Phase	Description with Respect to COVID-19 Risks
1	
2	No COVID-19 – No restrictions to public life
3	
4	Highest stringency index with medium COVID-19 risks
5	High stringency index with low COVID-19 risks
6	Low stringency index with low COVID-19 risks
7	Medium stringency index with high COVID-19 risks
8	Medium-high stringency index with high COVID-19 risks

Table 7: Selected Periods and Corresponding Characteristics for Scenario 1

Phase	Earliest Date	Latest Date	Average Mean Temperature	Average COVID-19 cases	Average Stringency
1	03/09/2019	01/12/2019	11	0	0
2	02/10/2019	04/01/2020	8	0	0
4	20/03/2020	10/05/2020	7	834	72
5	11/05/2020	03/07/2020	12	30	69
6	06/07/2020	18/10/2020	19	141	36
7	19/10/2020	08/11/2020	10	6041	47
8	12/11/2020	12/12/2020	7	4815	60

Table 8: Selected Periods and Corresponding Characteristics for Scenario 2

Phase	Earliest Date	Latest Date	Average Mean Temperature	Average COVID-19 cases	Average Stringency
1	03/09/2019	05/12/2019	11	0	0
2	02/10/2019	07/01/2020	7	0	0
4	20/03/2020	10/05/2020	8	746	72
5	11/05/2020	04/07/2020	14	26	67
6	06/07/2020	07/10/2020	19	123	36
7	19/10/2020	11/11/2020	10	6952	49
8	12/11/2020	11/12/2020	5	4381	60

Table 9 and Table 10 shows the descriptive analysis of each scenario, as well as the corresponding term from Swiss Mobility and Transport Microcensus (MTMC) as a reference. The MTMC is obtained by filtering individuals in a household with a car and those aged below 66 years old. The filter "the household owns a car" is used to approximate the requirement to participate in the MOBIS study, which specifies that each individual must drive for at least two days a week. Overall, more individuals in the sub-samples received higher education, are employed, are from smaller households, and are from high-earning groups, compared to the Swiss average.

4.1.2 Contextual Data

In this study, three types of contextual data, namely COVID-19 related development, weather, and socio-demographics, were considered to determine the reasons behind travel behavioral shifts recorded by GPS tracking data. The COVID-19 and weather-related parameters are introduced in Table 4 and Table 3, and socio-demographic information is recorded for each participant, including their age, gender, Swiss citizenship, educational level, employment status, income, household size, mobility ownership and characteristics of mobility tools.

Table 9: Description of Scenario 1 Sample Compared to the Swiss MTMC

Variable	Value	% dataset	% MTMC
Age	19 - 29 years	7.27	17.27
	30 - 39 years	11.64	16.32
	40 - 49 years	25.45	29.9
	50 - 59 years	36.36	25.49
	60 years or older	19.27	11.03
Gender	Male	50.55	49.06
	Female	49.45	50.94
Education	Mandatory	4.36	14.94
	Secondary	45.45	52.01
	Higher	50.18	33.05
Occupation	Employed	78.55	63.65
	Student/Apprentice	2.18	2.87
	Unemployed/Household duties	10.91	30.52
	Search for a job	NA	0.73
	Retired	3.64	2.23
Household Size	1	14.91	4.05
	2	41.45	23.89
	3	18.55	20.05
	4	18.91	32.65
	5 or more	6.18	19.37
Household Income	Under 4,000 CHF	2.55	3.76
	4,001 – 8,000 CHF	29.82	22.62
	8,001 – 12,000 CHF	30.18	22.15
	12,001 – 16,000 CHF	15.64	11.08
	More than 16,000 CHF	12.73	8.04
	Not Provided	9.09	32.35

Source: Federal Office of Statistics (2017)

4.1.3 Data Processing

The GPS tracking data includes the start and finish time of each recorded mode and purpose for each individual, with a minimum time resolution of one second, classified as "Track" and "Stay" depending on whether the individual is moving or staying at the same place, respectively. "Track" and "Stay" correspond to mode and purpose respectively. The GPS data was converted into two sets of sequences: mode sequence and purpose sequence. Each sequence represents the mode or purpose pattern of one day for an individual, and

Table 10: Description of Scenario 2 Sample Compared to the Swiss MTMC

Variable	Value	% dataset	% MTMC
Age	19 - 29 years	8.45	17.27
	30 - 39 years	11.27	16.32
	40 - 49 years	28.17	29.9
	50 - 59 years	30.99	25.49
	60 years or older	21.13	11.03
Gender	Male	54.93	49.06
	Female	45.07	50.94
Education	Mandatory	2.82	14.94
	Secondary	44.37	52.01
	Higher	52.82	33.05
Occupation	Employed	78.87	63.65
	Student/Apprentice	0.70	2.87
	Unemployed/Household duties	11.27	30.52
	Search for a job	NA	0.73
	Retired	3.52	2.23
Household Size	1	14.79	4.05
	2	42.25	23.89
	3	16.20	20.05
	4	21.83	32.65
	5 or more	4.93	19.37
Household Income	Under 4,000 CHF	2.82	3.76
	4,001 – 8,000 CHF	29.58	22.62
	8,001 – 12,000 CHF	33.10	22.15
	12,001 – 16,000 CHF	13.38	11.08
	More than 16,000 CHF	11.97	8.04
	Not Provided	9.15	32.35

Source: Federal Office of Statistics (2017)

each element of the sequence represents the main activity that was performed during the corresponding time interval of that time interval. In this study, each day was discretized into 30-minute time intervals between 01:00 and 05:00 and 5-minute time intervals for the rest of the day. Night hours were treated with care, as shorter intervals with longer sequences would result in a greater distance between two sequences, thus the element is given a higher weight if shorter time intervals are used, meaning that having the same time interval for night hours would result in a higher similarity between different days since most individuals stay at home during night hours (Wilson, 1998; Schlich, 2003). The 30-minute time interval for night hours decreases similarity between sequences and puts more focus on periods where people move around more.

The converted sequence for each day was combined for inter-personal and intra-personal analysis. Overall, the mode sequences are 91% empty, the purpose sequences are 22% empty, and the combined mode and purpose sequences are 15% empty for Scenario 1, whereas for scenario 2, these values are 91%, 17% and 11% respectively.

The COVID-19 related data and weather data have a minimum time resolution of one day. The daily temperature profile was generated by combining two half sine waves, using the daily maximum, average, and minimum temperature, whereas the rest of the dimensions shown in Fig. 1 have a repetitive value for each day that matches the length of mode and purpose sequences. This repetition is reflected in Fig. 1, in which the sequences of precipitation, daily deceased, daily hospitalized, daily increase, and KOF stringency index have the same value for each time step of the same day.

The subsequent analysis is divided into two streams: stream 1 covering Mondays to Fridays and stream 2 covering Saturdays to Sundays, as days of the week have a crucial effect on day-to-day variability of mode-purpose pattern, with Mondays to Fridays having a more similar pattern to each other than to Saturdays and Sundays, as shown by e.g. Xianyu *et al.* (2017). Each stream is analyzed separately to determine the possible reasons behind the behavioral shift in each stream.

4.2 Sample Weighting

As described in Section 4.1.1, the socio-demographics of the selected sub-samples deviate from that of the Swiss population. Therefore, sample weighting is necessary to reach a meaningful model that can represent the Swiss population adequately. Iterative Proportional Fitting (IPF) is commonly employed for weighting individuals (Schatzmann and Axhausen, 2021). In the subsequent analysis, the R package 'anesrake' is used for weighting the data. The algorithm embedded in this package is the American National Election Studies algorithm, and the weight of each individual in the subsamples is adjusted by three socio-demographic variables (gender, age, household size), using values indicated in the MTMC column of Table 9 and Table 10 (Pasek, 2018).

The distribution of weights for both scenarios is shown in Table 11.

Table 11: Summary of Weights

Scenario 1					
Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
0.1956	0.4252	0.7105	1.0000	1.3541	4.8382
Scenario 2					
Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
0.1438	0.3834	0.7539	1.0000	1.0910	4.3573

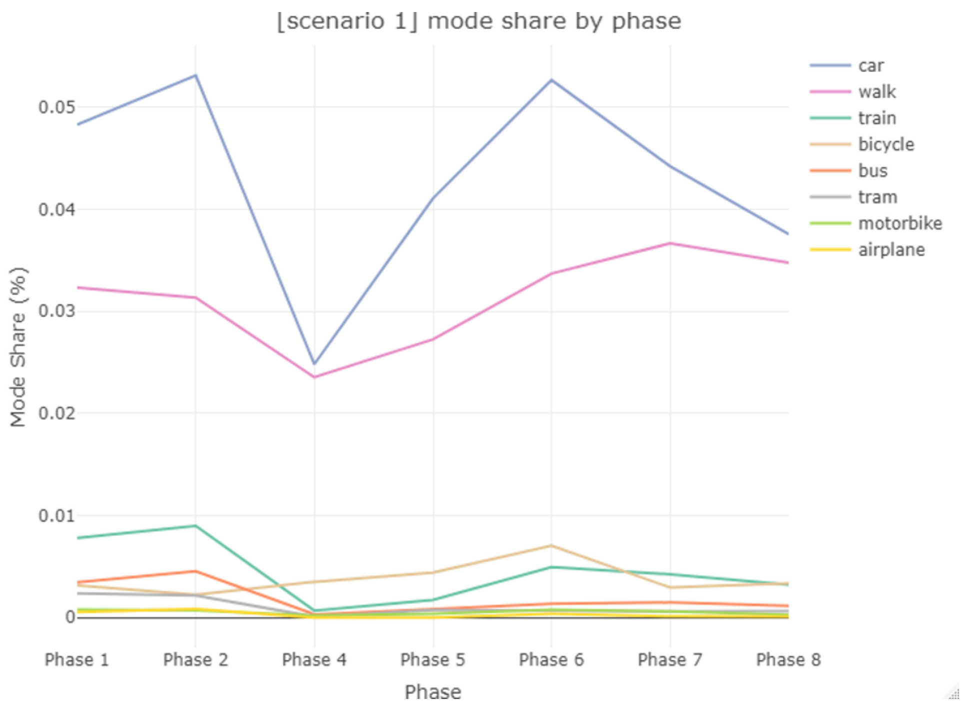
4.3 Descriptive Analysis

An overview of the impact of the COVID-19 development in Switzerland on each mode and purpose is shown in Fig. 2 and Fig. 3 respectively. The parameter "phase" is adopted here to represent COVID-19 profiles, as it integrates the COVID-19 related restrictions and development, making it more suitable for describing the COVID-19 situation than parameters in Table 4.

As presented in Fig. 2, all the modes were affected by phase to different extents. During the first wave (phase 4), the percentage of time spent in cars almost halved and the time spent in public transport approached zero percent, compared to the pre-pandemic level. The time share of walking decreased by roughly one-fourth, whereas the time spent on bicycles increased slightly. As the restrictions eased and the infection rate decreased (phases 5 and 6), the mode share of car, bicycle, and walk increased, among which the share of car reached the same level as and the share of walk attained a higher level than pre-pandemic level. The time share of public transport also increased, albeit not reaching a level that is close to the pre-pandemic time use. As the second wave hit (phases 7 and 8), the time use of cars showed a similar trend as the first wave. However, some patterns in the second wave differed from the first wave. Firstly, the share of walking increased instead of decreased. Secondly, the time use of public transport was not affected by the second wave considerably, as the share of public transport decreased, but not to zero percent. Lastly, the use of bicycles decreased in the second wave. This difference could be due to the weather condition, as the second wave corresponds to fall/winter, making it less pleasant to cycle.

Fig. 3 shows that as the COVID-19 situation worsened (phases 4, 7, and 8), individuals spent more time at home and less time for leisure, and as the COVID-19 situation improved (phases 5 and 6), the share of home and leisure returned to the pre-pandemic

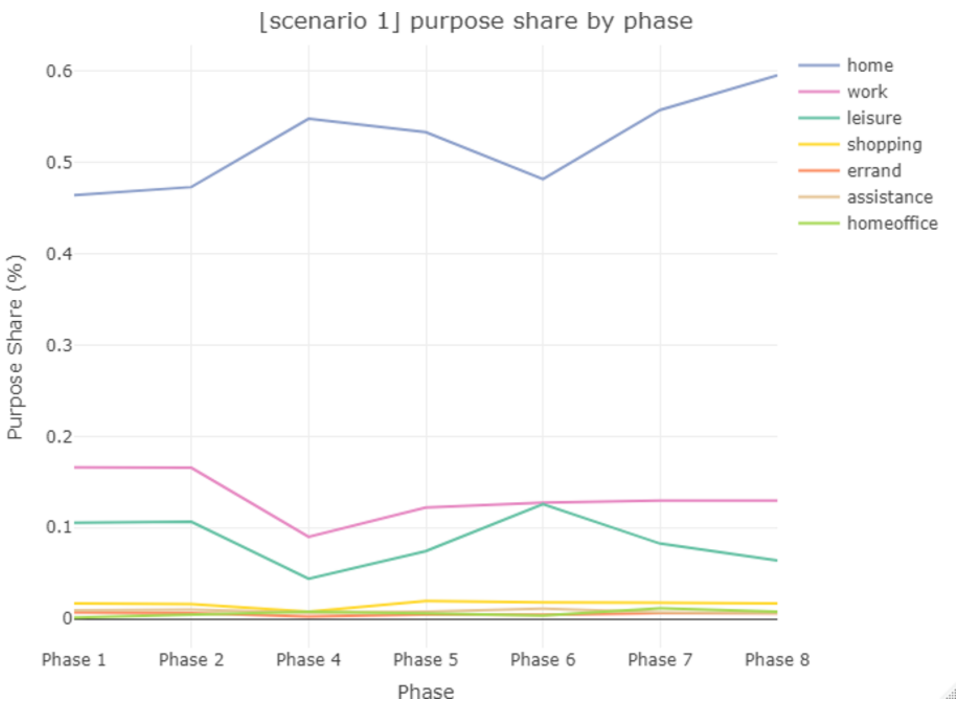
Figure 2: Mode Share by Phase



level. The pattern was different for work and shopping activities. During the first wave, the percentage of time spent at work and on shopping was almost halved compared to pre-pandemic. The reduced share of work and shopping could be due to the "work from home" advice from the government and the shortage of goods supply during the first wave. As the lockdown eased (phases 5 and 6), the share of work increased, albeit not to the pre-pandemic level, and the share of shopping returned to the same level as the pre-pandemic level. The share of work and shopping did not decrease significantly during the second wave. The reason could be that in-person working was not as restricted in the second wave as in the first wave, and after the first wave, the supply of goods was sufficient, making the shopping activity closer to pre-pandemic norms. On top of this, shopping is an essential activity, making it less likely to be influenced strongly by restrictions (Department of Health and Social Care, 2021).

Fig. 4 and Fig. 5 illustrate the impact of precipitation on mode share and purpose share. Fig. 4 demonstrates that heavier rain would make people drive more, walk less and cycle less, and the rain level did not affect the use of public transport significantly. As displayed in Fig. 5, purposes were not strongly affected by precipitation level. This could mean

Figure 3: Purpose Share by Phase



that individuals would perform the tasks they have planned, regardless of precipitation condition, but possibly with different modes. It is worth noting that the precipitation level was recorded daily, but the rain is likely to be concentrated in a certain period, rather than spread out over the entire day. In this case, the participants might delay their activities rather than cancel them at once. This possibility cannot be studied here due to the restriction embedded in the data.

The daily average temperature also influenced the travel pattern. Fig. 6 shows that as the temperature increased, individuals drove more or cycled more, whereas the other mode types were not influenced by temperature considerably. Fig. 7 shows a clear purpose pattern under different temperature profiles: as the temperature got higher, people spent less time at home, more time for leisure activities, whereas the other purposes were not affected as much by the temperature. This phenomenon is intuitive, as people tend to go out of the home more when the temperature is higher, whereas work is not affected by temperature greatly, as it is a must-do activity. Similar to the precipitation data, the temperature data is also recorded on a daily basis. However, this constraint does not have as big an impact on travel behavior as precipitation, since the daily average temperature

Figure 4: Mode Share by Precipitation Level

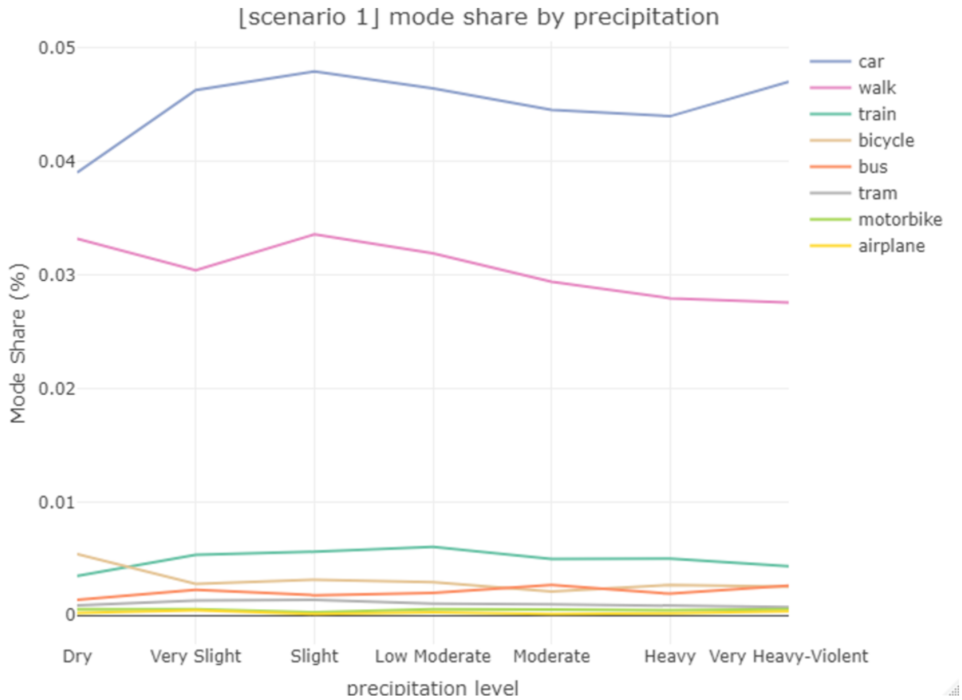


Figure 5: Purpose Share by Precipitation Level

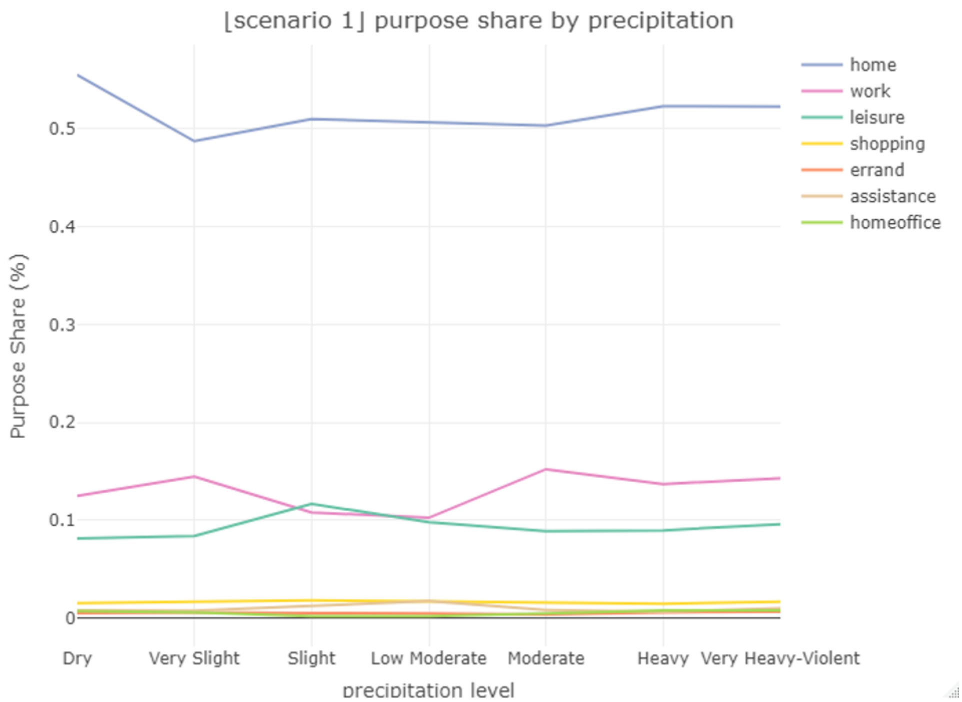
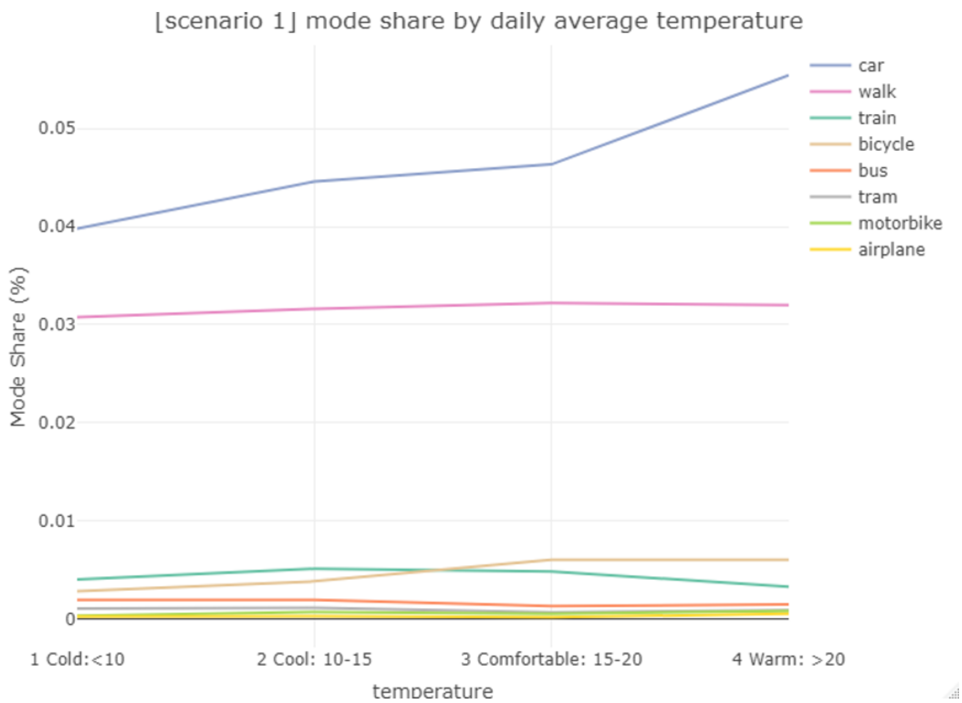


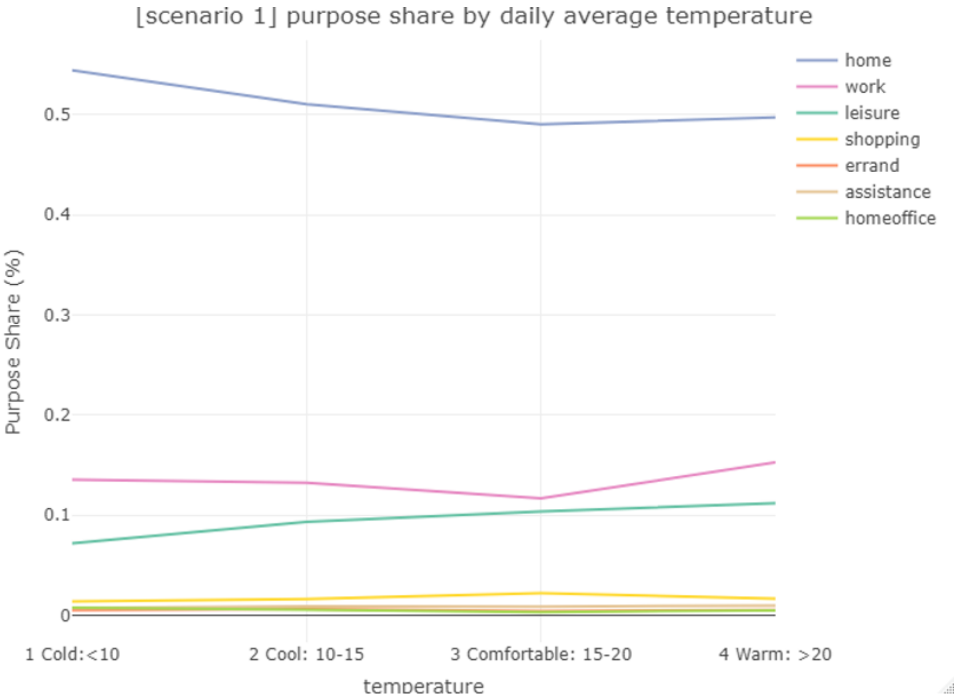
Figure 6: Mode Share by Daily Average Temperature Level



is a good indicator of the temperature level of a day, and temperature would not vary as much as precipitation during one day.

The effect of socio-demographics on mode and purpose share is recorded in Table 12 and Table 13. The mode share data shows that females spent less time in cars than males. Self-employed and unemployed participants spent less time in cars, and retired individuals spend more time in cars than employed individuals. Self-employed participants walk more than people in another occupation status. Individuals with higher income levels drove more and cycled more. The purpose share data shows that the older generation spent more time at home and less time at work, whereas younger generations spent more time for leisure and shopping activities. Females spent more time at home and shopping, and less time at work and leisure than their male counterparts. Self-employed individuals spent more time at home, much less time at work, less time on leisure, and more time on shopping than people from another occupation status. Student and unemployed individuals spent longer hours on leisure activities. Individuals from a bigger household size stayed at home more and at work less, possibly due to family duties. Lastly, participants with high income spent more time on leisure activities compared to others.

Figure 7: Purpose Share by Daily Average Temperature Level



In order to determine how the COVID-19 pandemic changed the time of the day and the day of the week travel patterns, the state distributions of mode and purpose pattern for each day were generated. The Section 4.3.1 and Section 4.3.2 illustrate the pattern of Mondays and Saturdays through different phases of the pandemic. Mondays represent stream 1 patterns, whereas Saturdays represent stream 2 patterns. Within each stream, the mode and purpose patterns are similar to each other. The state distribution of all the other days of the week is given in Appendix A.

4.3.1 Trajectory Sequencing Results of Stream 1 (Mondays - Fridays)

Fig. 8 shows the state distribution of mode patterns on Mondays of all individuals. Compared to the pre-pandemic (phases 1 and 2), the mode pattern in the first wave (phase 4) was much less varied: the use of airplanes was not observable and the use of public transport, including bus, train, tram, and boat, reduced significantly throughout the day. The state distribution of walk increased throughout the day, especially in the evenings. The distributions of car and bicycle also increased throughout the day. This trend was likely due to the preference for personal transportation over collective transportation

Table 12: Mode Share in % of Time Based on Demographics

Variable	Value	Car	Walk	Train	Bicycle
Age	20 - 29 years	3.8	3.0	0.8	0.3
	30 - 39 years	4.6	3.3	0.6	0.2
	40 - 49 years	4.1	3.4	0.3	0.4
	50 - 59 years	4.6	2.8	0.5	0.4
	60 years or older	4.0	3.5	0.4	0.3
Gender	Male	4.8	3.1	0.5	0.5
	Female	3.9	3.1	0.4	0.3
Education	Mandatory	4.4	3.2	0.4	0.4
	Secondary	3.6	3.0	0.2	0.4
	Higher	4.3	3.0	0.5	0.3
Occupation	Employed	4.5	3.1	0.5	0.4
	Self-Employed	3.3	4.0	0.4	0.4
	Student	3.9	3.5	0.3	0.4
	Retired	5.2	3.2	0.2	0.5
	Unemployed	3.7	2.8	0.9	0.1
	Other	2.5	2.8	0.5	0.4
Household Size	1	4.7	2.8	0.5	0.3
	2	4.4	3.1	0.4	0.3
	3	4.3	3.2	0.5	0.5
	4	3.8	3.1	0.4	0.5
	5 or more	4.6	3.8	0.8	0.3
Income Level	Under 4,000 CHF	3.6	2.7	0.3	0.2
	4,001 – 8,000 CHF	4.3	2.8	0.4	0.3
	8,000 – 12,000 CHF	4.2	3.3	0.6	0.4
	12,001 – 16,000 CHF	4.2	3.0	0.4	0.4
	More than 16,000 CHF	5.1	3.2	0.3	0.6
	Not Provided	4.1	3.8	0.5	0.3

during the first wave due to infection concerns. As the restriction eased and the confirmed cases decreased (phases 5), the pattern of car and walk got closer to the pre-pandemic level, the distribution of public transport increased, albeit still much less than the pre-pandemic. The use of bicycle continued to increase, reaching levels greater than the pre-pandemic, possibly due to the higher average temperature in this phase. As the situation continued to improve and the government introduced mandatory masks on public transport (phase 6), the state distribution of car and walk got closer to the pre-pandemic level, and the use of public transport continued to increase throughout the day, but not reaching the same level as the pre-pandemic. Mode airplane was observable again in this phase, likely due to

Table 13: Purpose Share in % of Time Based on Demographics

Variable	Value	Home	Work	Leisure	Shopping
Age	20 - 29 years	48.8	13.6	9.4	2.5
	30 - 39 years	49.0	14.8	11.2	3.0
	40 - 49 years	53.7	13.2	7.3	1.2
	50 - 59 years	50.9	15.5	8.3	1.3
	60 years or older	56.0	8.3	8.8	1.5
Gender	Male	50.3	15.6	9.0	1.3
	Female	54.2	11.0	8.1	1.9
Education	Mandatory	52.1	13.5	8.5	1.7
	Secondary	55.6	14.6	6.4	0.7
	Higher	52.0	12.9	8.9	1.6
Occupation	Employed	50.8	15.5	8.5	1.5
	Self-Employed	64.0	2.0	6.7	2.1
	Student	54.8	2.6	12.0	1.3
	Retired	51.1	14.7	8.9	1.1
	Unemployed	51.1	4.4	10.9	0.9
	Other	57.4	3.4	10.5	5.5
Household Size	1	50.4	17.1	7.4	1.0
	2	51.4	13.3	9.9	2.0
	3	52.3	11.6	8.3	1.6
	4	55.1	12.3	7.6	1.2
	5 or more	52.6	11.8	6.7	1.5
Income Level	Under 4,000 CHF	47.5	11.5	11.2	9.9
	4,001 – 8,000 CHF	52.3	15.0	8.8	1.1
	8,000 – 12,000 CHF	53.1	12.6	7.3	1.3
	12,001 – 16,000 CHF	52.4	14.1	7.7	1.3
	More than 16,000 CHF	47.9	14.7	11.1	2.2
	Not Provided	56.2	7.0	9.7	1.8

relaxed international travel restrictions. During the second pandemic (phases 7 and 8), the state distribution of car was similar to the first wave. However, there were two differences compared how people reacted in the first wave. First, the share of public transport was not as affected as it was in the first wave, since it did not decrease much from phase 6. Second, the mode airplane was still observable in the second wave, as international travel was not banned. Another point to note is the share of bicycle decreased in phases 7 and 8. These phases also correspond to colder weather and it indicates that the use of bicycle might be more affected by the temperature, rather than by COVID-19 development.

Figure 8: State Distribution of Mode Patterns on Mondays

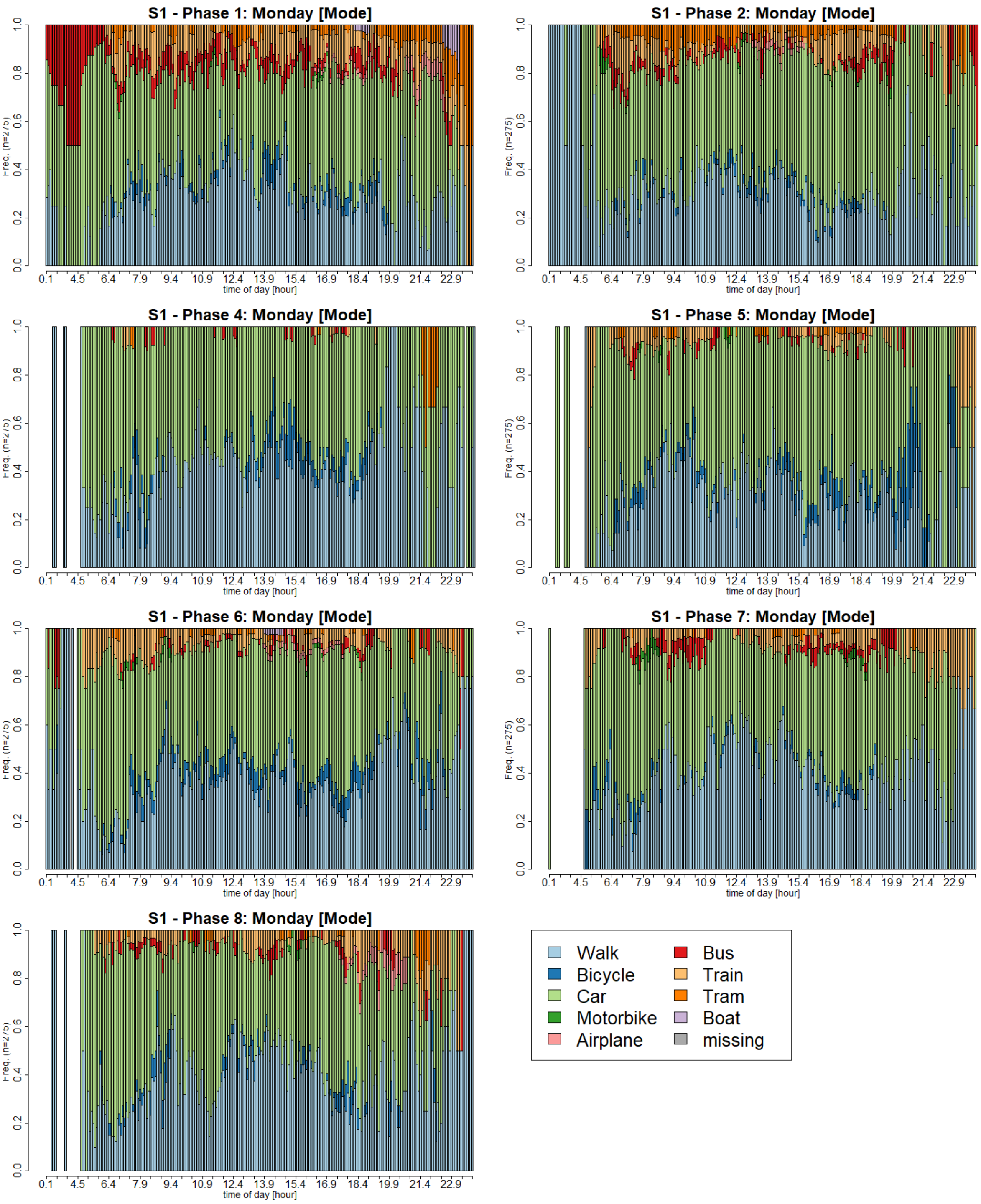


Fig. 9 presents the state distribution of mode and purpose patterns on Mondays of all individuals. The graph from the first wave (phase 4) shows that a significant share of purpose work reduced during the working hours, from around 07:00 to 17:00, whereas the share of purpose home during this period increased notably. The share of purpose leisure reduced throughout the day, especially after work, from 17:00 onward, as a significant proportion of time spent on leisure activity shifted to home activity. Purpose shopping also reduced throughout the day, possibly due to the shortage of supply of goods during the first wave. This indicates that out-of-home activities decreased significantly during the first wave. During the post-pandemic (phases 5 and 6), the share between purpose home, work, and shopping slowly returned to the pre-pandemic level, and purpose leisure reached a larger share compared to the pre-pandemic, possibly because many people had summer holidays during this period and were eager to go out of their home after the long lockdown. Since the second wave hit, the share of purpose home increased, but not to the same level as in the first wave. During the after-work period, the share of purpose leisure also decreased, possibly due to the restrictions of closed leisure venues. Another point to note is the purpose shopping. The share of shopping did not decrease significantly as in the first wave. This indicates that the out-of-home activities were not as affected in the second wave as in the first wave.

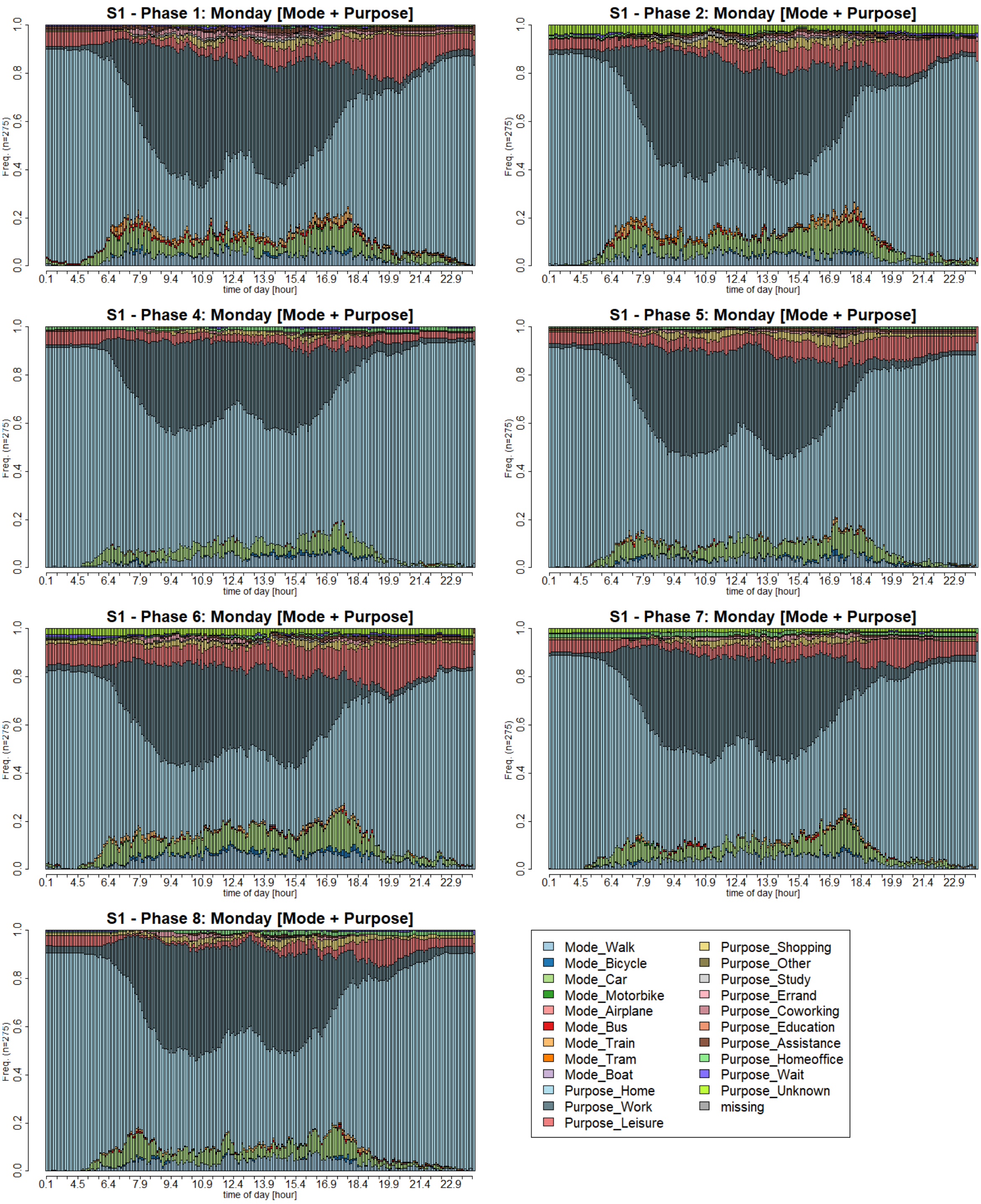
Fig. 9 also gives additional information on the time share of all modes throughout the day. According SBB (2015), the peak hour in Switzerland is 06:00 to 08:59 and 16:00 to 18:59, Mondays to Fridays. Before the pandemic, people traveled around throughout the day, with a higher share of time spent on modes during the peak hours, lower share between the morning and evening peak hours, gradually decreasing share after evening peak hours. During the first wave, the share of modes almost halved throughout the day, and the share during peak hours was not significantly different from between morning and evening peak hours anymore. After evening peak hours, the share of modes quickly decreased to near 0%, instead of gradually. In the post-lockdown (phase 5), the state distribution of modes increased throughout the day, but the role of peak hour was still not as prominent, as the share was relatively constant throughout the peak hours and working hours. As the situation improved further (phase 6), the state distribution of modes became very similar to the pre-pandemic level again. During the second wave (phases 7 and 8), the state share of mode decreased again, following a similar trend to the first wave, in terms of peak hours and post evening peak hour patterns. However, the role of peak hours was more apparent in phase 8, as the state share of modes during peak hours was slightly higher than off-peak hours. This trend reveals that throughout the pandemic, those who needed to travel did not have a strong time-of-the-day limitation during weekdays, and these individuals were freer to travel throughout the day, not heavily limited by peak hours. It also indicates that during the evening off-peak hours, people would travel less with more restrictions and higher COVID-19 risks, possibly also due to the closure of leisure venues.

4.3.2 Trajectory Sequencing Results of Stream 2 (Saturdays - Sundays)

The development of state distribution for mode patterns for weekends from phase 1 to phase 8 is similar to that described for Fig. 8, whereas for purpose patterns, some differences can be observed. As shown in Fig. 10, before the pandemic started, work accounted for very little share throughout the day, leisure accounted for a significant share of out-of-home activity, especially after 09:00, and the share of leisure activities continued to grow until night hours. The share of shopping activities was also much more observable during daytime (approximately 09:00 to 19:00) compared to stream 1. During the first wave (phase 4), the share of leisure and shopping reduced significantly, in which the share of leisure activities seemed more uniform throughout the day, and the share of shopping activity was still observable during the daytime, but it had a higher share in the morning (before 12:00) than in the afternoon. In the afternoon, the share of shopping reduced, whereas the share of leisure increased slightly. In the post-lockdown) (phase 5), the share of both leisure and shopping increased during the day, with shopping reaching a similar level to pre-pandemic. In phase 6, the share of shopping and leisure continued to rise. However, unlike the pre-pandemic pattern, the shopping activity was more concentrated in the morning, whereas the leisure activity was more concentrated in the afternoon. Since the beginning of the second wave, especially in phase 7, the share of shopping activity was not as affected as in phase 4, whereas the share of leisure decreased from phase 6 level, albeit not by an as significant amount as in phase 4. A higher share of shopping in the morning and a higher share of leisure in the afternoon could still be observed. In phase 8, the share of leisure decreased slightly, and the shopping activity was no longer more concentrated in the mornings but spread throughout the day.

In terms of the combined state distribution of mode and purpose, as shown in Fig. 10, the mode share did not have two peaks during the peak hours anymore, as weekends are off-peak hours (SBB, 2015). However, a higher share of mode can be observed during the daytime throughout all the phases. This share decreased during phase 4 and increased further back to a level that is similar to the pre-pandemic in the post lockdown. The share of mode reduced again since the start of the second wave, but this decrease was not as significant as in the first wave. In the evenings (from 19:00 onward), a share of modes can

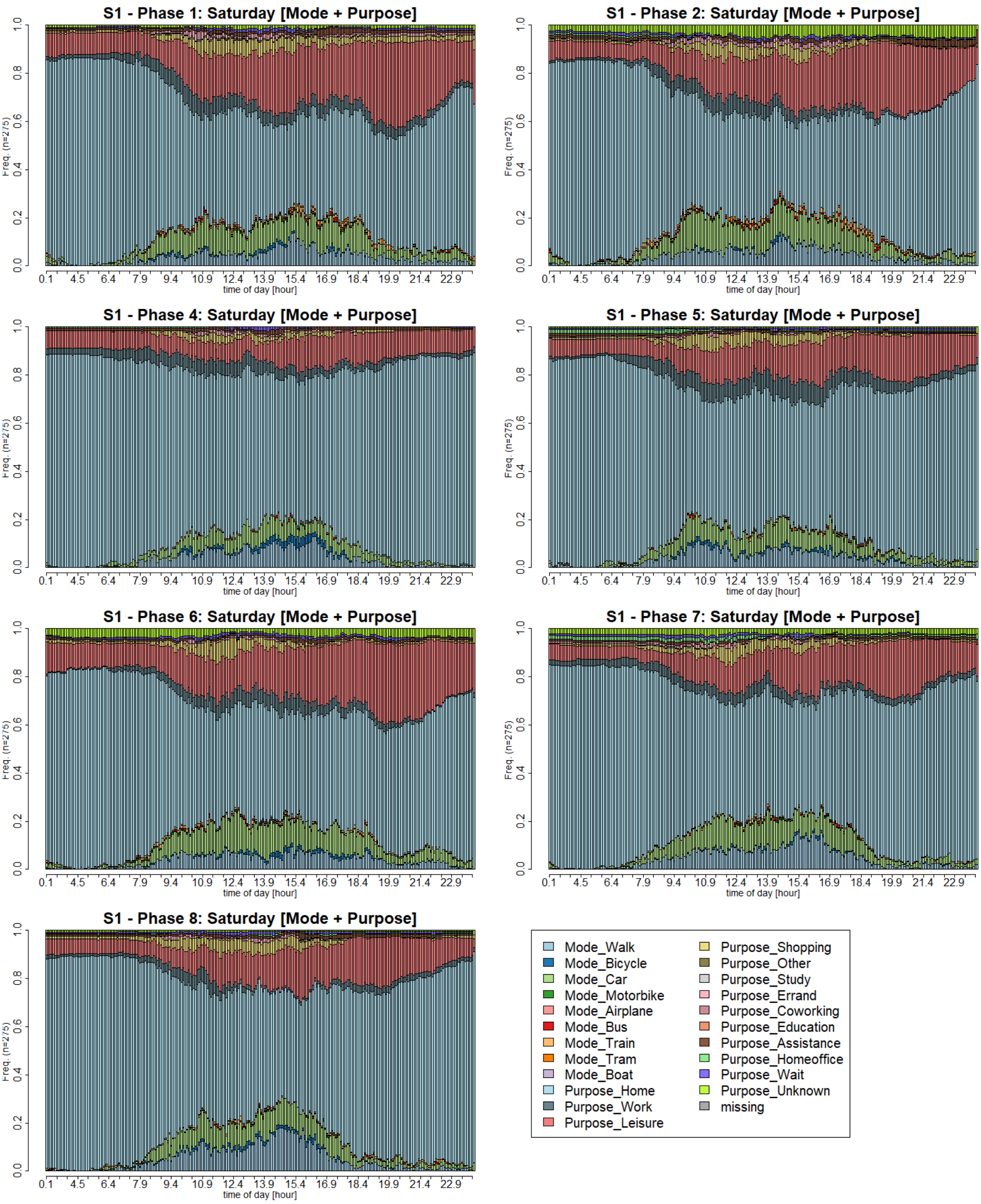
Figure 9: State Distribution of Mode and Purpose Patterns on Mondays



still be observed before the pandemic, meaning that people were still traveling around in the evenings. In the first wave, the share in the evening reduced to 0% quickly. This share increased in post-lockdown (phases 5 and 6), reaching a similar level to the pre-pandemic level, then decreased again as the second wave hit, but not by as much as in phase 4.

In summary, both the first wave and second wave reduced the share of out-of-home activity, but the first wave had a bigger impact, as it had the most stringent restrictions. The second wave had less influence on both mode and purpose, possibly due to more relaxed restrictions in place, and people got used to the pandemic, making them not as skeptical in performing different activities as in the first wave. It should also be noted that with few restrictions to public life and minimal health risks due to the spread of COVID-19 during the post-lockdown, the mode and purpose share did not reach the same level as pre-pandemic, showing the persistent impact of COVID-19 on travel behavior.

Figure 10: State Distribution of Mode and Purpose Patterns on Saturdays



5 Context-Aware Similarity Analysis and Results

5.1 Cluster Analysis

Cluster analysis was performed to determine the effect of COVID-19 development and weather on each mode and purpose, as well as the inter-and intra-personal distance. The result from scenario 2 is shown here, as it includes more days, making it more advantageous for analyzing the impact of COVID-19 and weather. In the subsequent analysis, parameter "phase" is used to represent the effect of COVID-19 restrictions and risks, as specified in Table 5 and Table 6. The effect of KOF Stringency Index, Daily Increase, Daily Hospitalized, and Daily Deceased will also be discussed briefly. Daily average temperature and daily precipitation are used to represent the temperature profile and precipitation profile of each day respectively.

As specified in Section 3.3.1, there are two types of cluster analysis. For the first type, the corresponding distribution of time share for each mode and purpose, grouped by phase, daily precipitation for phase 1, and daily average temperature for phase, illustrated as box plots, are given in Appendix B. Note that the distributions for daily precipitation and the daily average temperature are generated for each phase to minimize the influence of the COVID-19 pandemic on the determination of the effect of weather on travel behavior. The Kruskal-Wallis test and Levene's test are performed to determine if the difference between the distributions of each cluster was statistically significant from each other.

5.1.1 COVID-19 Development

Table 14 shows that phase had an impact on all modes and purposes during weekdays, as all the p-values are significant to at least 0.05. During the weekends, however, mode motorbike and purpose work were not affected by phase, as both Kruskal-Wallis test and Levene's test do not show statistical significance in these two cases. For purpose work, it is likely due to the low share of work activities during weekends, as shown in Fig. 10. For those who needed to work before the pandemic, such as cashier, police, doctor, nurse (Department of Health and Social Care, 2021), it is also likely that their job required physical presence during the pandemic, which could mean that the pandemic would not change their job pattern significantly.

Table 14: P-Values from Cluster Analysis for Mode and Purpose, Grouped by Phase

	Stream 1		Stream 2	
Statistical Test	Kruskal-Wallis	Levene's	Kruskal-Wallis	Levene's
Car, Train, Bicycle, Bus	0.0000	0.0000	0.0000	0.0000
Walk	0.0000	0.0014	0.0000	0.0001
Tram	0.0000	0.0000	0.0000	0.0191
Motorbike	0.0399	0.0133	0.2978	0.1080
Airplane	0.0000	0.0002	0.0083	0.0005
Home, Leisure, Errand	0.0000	0.0000	0.0000	0.0000
Work	0.0000	0.0000	0.1292	0.8948
Shopping	0.0000	0.0000	0.0048	0.0000
Assistance	0.0000	0.0022	0.1859	0.0000
Homeoffice	0.0000	0.0000	0.0807	0.0000

Appendix C.1 presents additional cluster analysis results, in which p-values are calculated by comparing the mode and purpose pattern of each phase to all the other phases separately, showing how the patterns of modes and purposes changed from phase to phase. This provides additional information on how the pandemic development influenced each mode and purpose over time.

Firstly, the mode pattern of stream one will be discussed. The time use patterns of both mode car and walk were affected significantly by phase. The p values of walking in phases 6, 7, and 8 was not statistically significant compared to phase 1, suggesting that the second wave did not impact the time spent on walk significantly. For bicycles, the time spent using bicycles for phases 4, 7, and 8 was not significantly different from phase 1. This indicates that the first wave and second wave did not influence the usage of bicycles. Regarding public transport, the time use pattern throughout the pandemic did not identify to that in pre-pandemic. However, the second wave had a smaller impact on it, as many terms in phases 7 and 8 are not statistically significant compared to phase 6. This pattern suggests that the pandemic altered the use of public transport, but the impact was different for the first and the second wave, and the use of public transport in the second wave was less than the pre-pandemic level, but not different from the post-lockdown.

Secondly, the purpose pattern of stream one was investigated. The time spent at home was strongly affected by phase. The result for home suggest that people spent different amounts of time at home depending on the restrictions and risk level. For phases 7 and 8 (second wave), the p-values for home were not statistically different from each other, implying that people spent a similar amount of time at home for the second wave. The time spent at work was also significantly affected by phase. Throughout the pandemic, the time spent at work did not show similarity to the pre-pandemic level. However, time spent in phases 7 and 8 showed similarity to phase 6, implying that the second wave did not have as big an impact on the time spent at work as the first wave. The time spent on leisure activities in phase 7 was not statistically significant from phase 5, suggesting that the second wave did not affect the time spent on leisure as much as the first wave. For purpose shopping, the corresponding cluster analysis suggests that the time use was only affected during the first wave (phase 4), whereas after the first wave, the time share was similar to the pre-pandemic level. This implies that the out-of-home activities were mainly affected by the first wave, and the second wave did not have as big an impact as the first wave.

The time spent on each mode for stream 2 was similar to that in stream 1. As for the purpose for stream 2, the main difference from stream 1 was the time use of purpose work. Similar to explained above, work activity was not affected by phase at weekends significantly, since all P values are not statistically significant in this case.

Appendix C.3 shows the result of cluster analysis for each COVID-19 related parameter, i.e. KOF stringency index, daily increase, hospitalized and deceased, separately. The results are similar to the description above, further consolidates the use of phase as the appropriate factor to describe the COVID-19 situation.

Subsequently, the inter-and intra-personal distance was calculated for type 2 analysis, as specified in Section 3.3.1. The mean and variance were calculated from the distance, similar to that described in Section 3.4 for calculating the dependent variables. The results are given under Appendix C.2 for reference. The intra-personal mean and variance in stream 1 were strongly affected by phase, as all terms are statistically significant. It suggests that individuals had different weekly travel patterns for each of the phases. In stream 2, the intra-personal distance mean for phase 8 is similar to phase 6 and 7, whereas the variances are statistically significant. This result implies that the weekly activity patterns performed by each individual in the second wave did not vary significantly from before the start of the second wave, and the within-week pattern of the distance between each day of the week and the other days of the week shifted. The P-value between phases 5 and 6 is statistically insignificant for inter-personal mean and significant for intra-personal variance, suggesting that in these two phases, the distance between individuals' activity patterns did not change, but more individuals performed very different travel patterns than others. For stream 2, the inter-personal distance was strongly affected by phase, with all terms being statistically significant, suggesting that the distance between individuals' activity patterns shifted from phase to phase.

5.1.2 Daily Precipitation

Table 15 suggests that precipitation affected the time use of mode car in phases 5, 6, and 7. These phases correspond to a time with better temperature conditions, meaning that people were likely to spend more time outdoors. In this case, precipitation could make people drive instead of walk if there is heavy rain. Mode walk showed statistical significance in all phases except phase 6, implying that walk was more affected by precipitation than other types of mode. This observation aligns with Cools *et al.* (2010). Phase 6 also corresponds to the summer with the lowest COVID-19 risks and restrictions, and it is possible that the rain was periodical instead of continuous in this period of time, making it not as important when deciding to walk. Furthermore, many people were eager to go out after the lockdown, which could have contributed to this anomaly. The use of public transport was affected by precipitation to some extent, especially in phase 4. However, it could be erroneous, as the time spent on public transport reduced dramatically in this phase.

In terms of purpose, the result suggests that precipitation influenced the percentage of time spent at home for most phases. For purpose work, the rain did not seem to affect phase 4 and phase 8. The reason could be that for those who had to work in the first and second wave, their jobs often required physical presence, were less flexible, hence less affected by the weather condition. Time share by leisure and shopping was generally not affected by precipitation, except phases 5, 7 and 8. This effect could be due to the limited amount of permitted indoor leisure activities during these periods, and consequently, people performed more outdoor activities. However, outdoor activities were more dependent on the precipitation. The result of stream 2 is shown in Appendix C.4 for reference. The patterns for stream 2 are similar to stream 1, with one noticeable difference for purpose work. Precipitation did not show statistical significance in phases 2, 4, 5, 7, and 8 during the weekends. One explanation is that for those who had to work during weekends, they needed to be present at their workplace, hence the weather was not an important factor.

Table 15: P-Values from Cluster Analysis for Mode and Purpose, Grouped by Daily Precipitation, Stream 1

Term	Test	P1	P2	P4	P5	P6	P7	P8
Car	K-W	0.3526	0.1725	0.4355	0.3796	0.0429	0.8820	0.9663
	L	0.4956	0.4252	0.6607	0.0017	0.2828	0.0396	0.5873
Walk	K-W	0.0004	0.0175	0.0000	0.0005	0.7312	0.0018	0.0608
	L	0.0518	0.0689	0.2714	0.0000	0.4701	0.0024	0.4997
Train	K-W	0.0414	0.2140	0.0587	0.3618	0.6137	0.9558	0.3265
	L	0.7837	0.6631	0.9713	0.9381	0.0816	0.5369	0.3561
Bicycle	K-W	0.0298	0.1680	0.0379	0.0000	0.2394	0.0001	0.4699
	L	0.5859	0.7266	0.1728	0.0001	0.7107	0.0012	0.6700
Bus	K-W	0.5147	0.4544	0.0007	0.8769	0.0816	0.3824	0.4406
	L	0.7005	0.6606	0.0051	0.7731	0.5204	0.5221	0.0149
Tram	K-W	0.0293	0.2145	0.9604	0.3301	0.1683	0.5745	0.6337
	L	0.1536	0.7378	0.9402	0.0519	0.3730	0.5783	0.8419
Motorbike	K-W	0.7784	0.5171	0.9932	0.4459	0.3604	0.2007	0.9280
	L	0.7725	0.6965	0.9914	0.7968	0.3761	0.7726	0.9626
Airplane	K-W	0.5263	0.3898	NA	NA	0.0939	0.7102	NA
	L	0.4938	0.4468	NA	NA	0.1785	0.2961	NA
Home	K-W	0.7471	0.2984	0.0001	0.0859	0.0597	0.2594	0.0227
	L	0.0526	0.6612	0.0897	0.7126	0.0062	0.8920	0.6743
Work	K-W	0.7091	0.4154	0.4020	0.0270	0.0486	0.0435	0.3357
	L	0.5796	0.0162	0.6758	0.0288	0.3084	0.0184	0.8336
Leisure	K-W	0.3822	0.7110	0.5419	0.0005	0.6940	0.3177	0.7774
	L	0.5475	0.5137	0.1575	0.0132	0.4886	0.0952	0.0483
Shopping	K-W	0.6047	0.8585	0.1336	0.5151	0.2681	0.4572	0.2117
	L	0.7128	0.3629	0.4284	0.0002	0.0299	0.9319	0.0624
Errand	K-W	0.0743	0.7686	0.9298	0.4677	0.4568	0.1580	0.3063
	L	0.0168	0.6835	0.9952	0.5178	0.6949	0.2091	0.7336
Assistance	K-W	0.1652	0.3986	0.8972	0.0013	0.1984	0.9270	0.5191
	L	0.1655	0.8555	0.9670	0.0278	0.2569	0.9501	0.7313
Homeoffice	K-W	0.2766	0.4832	0.9179	0.9575	0.9424	0.8910	0.8165
	L	0.0556	0.2906	0.8553	0.8942	0.9266	0.7510	0.7396

*K-W represents Kruskal-Wallis test and L represents Levene's test
**P represents Phase

5.1.3 Daily Average Temperature

Table 16 demonstrates the effect of temperature in stream 1, and it suggests that the temperature profile changed the time use of modes and purposes. For mode walk, statistical significance was present in phases 1, 2, 4, 5, and 6. For mode bicycle, phases 1, 4, 5, 6, and 7 showed statistical significance. These two modes require direct contact with the ambient, which could be why the individuals were more affected by the temperature. For public transport and car, the temperature had a limited impact on the time use pattern. In terms of purpose, temperature seemed to affect the purpose work more than others, as statistical significance could be observed in phases 1, 2, 4, 5, 6, and 8 for purpose work. Statistical significance is observed in phases 1, 2, 5, and 6 for leisure, in phases 1, 2, and 4 for home, and in phase 6 for shopping. It suggests that leisure activity was more dependent on temperature during low-risk and low-restriction periods, and shopping activity was hardly affected by temperature. For stream 2, as presented in Appendix C.4, the effect of temperature was similar to stream 1, particularly for mode walk, bicycle, public transport. In terms of public transport, most p-values for train and tram did not show statistical significance, with the exception of bus, with statistically significant p-values for phases 2, 5, 6, and 8. This result suggests that the usage of the bus was more affected during weekends than weekdays. For purpose home, statistical significance can be seen in phases 1, 2, 5, and 6. It implies that in the post-lockdown, the temperature was more important for time-use patterns of home activities on the weekends than on weekdays. For work, phases 1, 4, 6, and 8 shows significance, indicating that temperature has a lower degree of influence of on weekends than on weekdays. Similar to stream 1, leisure and shopping were not strongly affected by temperature. In summary, the temperature was a more important factor for purpose work during weekdays, and for purpose home during weekends.

The influence of weather on inter-and intra-personal distance mean and variance is illustrated in Appendix C.4. The results suggest that except phase 5, precipitation and temperature had an impact on both inter-and intra-personal distance. The intra-and inter-personal mean and variance for phase 5 were not statistically significant, implying that weather did not change an individual's weekly pattern, nor the distance between individuals' activity patterns.

Table 16: P-Values from Cluster Analysis for Mode and Purpose, Grouped by Average Temperature, Stream 1

Term	Test	P1	P2	P4	P5	P6	P7	P8
Car	K-W	0.9828	0.2795	0.0051	0.4009	0.7654	0.1917	0.9573
	L	0.6864	0.9711	0.0185	0.0662	0.0159	0.4325	0.2735
Walk	K-W	0.0005	0.0254	0.0005	0.0549	0.3980	0.4247	0.5789
	L	0.0041	0.1847	0.1220	0.0005	0.0002	0.1072	0.4006
Train	K-W	0.7281	0.4651	0.2869	0.0608	0.0129	0.0101	0.2649
	L	0.6697	0.6555	0.2406	0.3080	0.0014	0.3879	0.5533
Bicycle	K-W	0.0736	0.9851	0.1366	0.0000	0.0503	0.0026	0.8139
	L	0.5417	0.7422	0.0142	0.0000	0.0009	0.0051	0.8223
Bus	K-W	0.6032	0.5347	0.3557	0.8023	0.8640	0.8395	0.5559
	L	0.3558	0.6685	0.4450	0.2663	0.1049	0.9031	0.5507
Tram	K-W	0.1669	0.0575	0.8933	0.0017	0.1753	0.9714	0.4473
	L	0.8881	0.8600	0.4834	0.0038	0.1758	0.9869	0.3383
Motorbike	K-W	0.2244	0.3197	0.0160	0.2183	0.2432	0.6554	0.8818
	L	0.2788	0.2156	0.0879	0.1702	0.5699	0.5974	0.9171
Airplane	K-W	0.2364	0.9087	NA	NA	0.9936	0.9839	NA
	L	0.2780	0.9895	NA	NA	0.9936	0.8551	NA
Home	K-W	0.0217	0.0266	0.0003	0.5462	0.9349	0.3085	0.7623
	L	0.1403	0.6383	0.1468	0.6008	0.3382	0.1352	0.7625
Work	K-W	0.5262	0.2514	0.0318	0.0035	0.0008	0.6384	0.0989
	L	0.0651	0.0827	0.0139	0.0027	0.0001	0.5665	0.2138
Leisure	K-W	0.0055	0.0575	0.6127	0.0200	0.0000	0.1214	0.3965
	L	0.2405	0.0460	0.5558	0.1895	0.0024	0.9391	0.9675
Shopping	K-W	0.6485	0.6870	0.6968	0.5724	0.0523	0.4184	0.3363
	L	0.8410	0.4874	0.7419	0.5158	0.4162	0.9594	0.5207
Errand	K-W	0.0248	0.0035	0.3472	0.5309	0.1836	0.6599	0.5146
	L	0.0174	0.2643	0.9123	0.0536	0.6289	0.8146	0.3985
Assistance	K-W	0.0000	0.0330	0.8650	0.3156	0.7245	0.8554	0.3543
	L	0.5226	0.0842	0.5112	0.4171	0.6200	0.7251	0.3983
Homeoffice	K-W	0.0334	0.0002	0.0544	0.5912	0.4951	0.9132	0.7630
	L	0.0003	0.0004	0.0197	0.6325	0.6308	0.9655	0.5980

*K-W represents Kruskal-Wallis test and L represents Levene's test
**P represents Phase

5.2 Discrepancy Analysis

Discrepancy analysis was applied to determine the effect of socio-demographics on travel behavior. It was calculated based on results from MDSAM, taking into account all eight dimensions shown in Fig. 1. The result from scenario 1 is displayed here, as this sample includes more individuals. The result of discrepancy analysis, as presented in Table 17, indicates that the travel behavior was not affected by household size, and the rest of the socio-demographic parameters affected the travel behavior to some extent.

In stream 1, gender, age, education, and employment status showed statistical significance before the pandemic hit Switzerland. In the first wave, gender and age no longer showed significance. The reason could be that education level and employment status could affect the job type, and the job type was crucial in deciding whether one individual had a higher chance of working in person or working from home. Those who needed to work in person in the first wave would have a different daily pattern than those who did not need to. Right after the lockdown (phase 5), only income had statistical significance. Income is another factor related to job type, and it indicates that in the first part of post-lockdown, job type still played a crucial factor in the difference in travel behavior between the participants. In phase 6 and phase 7, only gender showed statistical significance, and job type was no longer important. The reason why gender shows significance could be that more leisure activities were expected for phase 6, which corresponds to the summer holidays, however, time spent on leisure activities is affected by gender, as females tend to spend less time on leisure activities than males (Payne, 2017). In phase 8, age, education, main employment, and income showed statistical significance. The reason behind it could be the same as in the first wave.

In stream 2, fewer factors affected travel behavior compared to stream 1. In the pre-pandemic, only age and employment showed statistical significance. Table 13 indicates that older people spent more time at home and less time at work, making age a significant factor. Employed individuals might have a routine and spent their weekends on certain activities compared to their counterparts, making employment a decisive factor. In phase 4, gender, education, and employment were statistically significant. It indicates that during the first wave, gender and job type would differ participants' travel choices during weekends. In phase 5, education and income showed statistical significance, and in phase 6, only employment status was significant. The significant factors from phases 5 and 6 show links to job type, meaning that job type might be a crucial factor in the post-lockdown travel behavior at weekends. In phase 7, gender and education were both significant. In phase 8, education level and income were statistically significant, which are both related to job type. This pattern means that gender, job types and age had statistically significant impact on travel behavior during the pandemic, which was also suggested by Politis *et al.* (2021) and Jiao and Azimian (2021).

Table 17: P-Values from Discrepancy Analysis for Socio-Demographics

	Stream 1						
	P1	P2	P4	P5	P6	P7	P8
Gender	0.049	0.212	0.607	0.744	0.020	0.010	0.582
Age	0.004	0.051	0.132	0.239	0.701	0.364	0.081
Education	0.016	0.181	0.009	0.144	0.700	0.224	0.001
Main Employment	0.002	0.001	0.013	0.411	0.229	0.601	0.015
Income	0.316	0.205	0.951	0.091	0.255	0.402	0.032
Household Size	0.764	0.689	0.736	0.970	0.387	0.915	0.783
Total	0.001	0.001	0.027	0.272	0.051	0.264	0.001
	Stream 2						
Gender	0.267	0.855	0.039	0.582	0.578	0.069	0.834
Age	0.290	0.005	0.113	0.189	0.581	0.680	0.314
Education	0.605	0.106	0.003	0.085	0.304	0.067	0.001
Main Employment	0.336	0.065	0.019	0.648	0.082	0.922	0.150
Income	0.351	0.597	0.863	0.019	0.490	0.338	0.078
Household Size	0.274	0.679	0.415	0.401	0.467	0.986	0.454
Total	0.070	0.010	0.016	0.107	0.155	0.604	0.002

6 Model Estimation and Results

Fig. 11 and Fig. 12 shows the distribution of the two types of dependent variables calculated by MDSAM. The inter-personal distance was higher than the intra-personal distance, as inter-personal distance ranged between 280 to 400, whereas intra-personal distance ranged between 200 to 320. This observation aligns with the result found by Moiseeva *et al.* (2014).

Fig. 11 shows that the intra-personal distance was considerably higher at weekends compared to weekdays for all the phases, which was also confirmed by Xianyu *et al.* (2017). The figure also indicates that the phase played a vital role in the intra-personal distance. The distance in phases corresponding to high stringency index and high COVID-19 risks (phases 4, 7, and 8) had a generally lower intra-personal distance, and vice versa. The intra-personal distance throughout the pandemic did not reach the same level as in the pre-pandemic, even in phase 6, with the lowest stringency index and lowest risk. It is also worth noting that the difference between average weekday and weekend intra-personal distance was much lower in the first wave than the pre-pandemic difference, suggesting that people performed more similar activities throughout the week in this period. In the post-lockdown, the difference increased. However, in the second wave, this difference was higher than the difference in the first wave. This trend means that individuals performed more distinguished activities between weekdays and weekends during the post-lockdown, and the second wave did not have an as influential impact on this difference as the first wave.

Fig. 12 shows that the inter-personal distance did not exhibit the same pattern between weekdays and weekends as the intra-personal distance. However, the general trend by phase was similar to intra-personal distance. The average inter-personal distance decreased as stringency index and risk level became higher (phases 4 and 8), and vice versa. It suggests that different individuals performed activities that were more similar to each other in phases 4 and 8, and as the situation improved, individuals started to perform tasks that were more distinct from each other. The pattern for inter-personal distance differed from the intra-personal distance pattern in the post-lockdown period. In phase 6, the inter-personal distance reaches a similar level to the pre-pandemic, whereas for intra-personal distance, it did not reach the same level throughout the pandemic.

Intra-personal distance shows the variation of one day's activity pattern from another

Figure 11: Average Intra-Personal Distance by Days of the Week

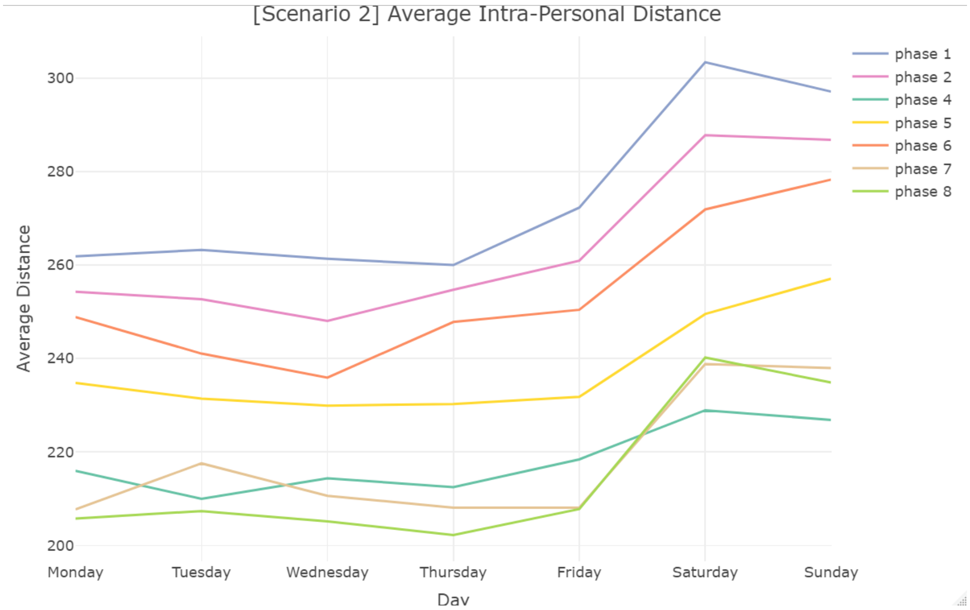
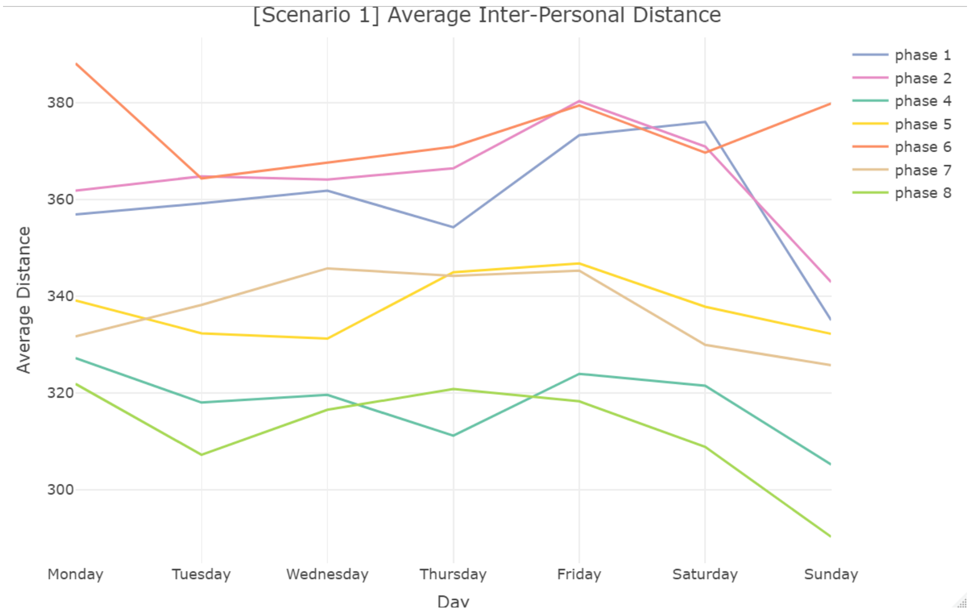


Figure 12: Average Inter-Personal Distance by Days of the Week



day of the same week. A higher intra-personal distance between two days signifies that these two days have very different travel patterns, a higher distance mean indicates that this day's pattern is very different from all other days of the week, and a higher standard deviation reveals that the weekly pattern of that individual is more varied from day to day. Inter-personal distance is obtained for each day. The inter-personal distance between two individuals indicates the variation between the travel patterns of these two individuals. A higher inter-personal distance between two individuals suggests that these two individuals performed very different activity patterns, a higher distance mean represents that the individual performs more different activities from others and a higher distance standard deviation indicates that some people in the sample had drastically different activity patterns than others.

The intra-personal distance is calculated separately for each individual, implying that it shows the difference in each individual's travel pattern, making it more suitable for determining the effect of socio-demographics on travel patterns. On the other hand, since the inter-personal distance mean takes the average of the distance to all other individuals, the effect of socio-demographics on travel patterns is weakened in this averaging process. Therefore, a sample with more individuals should be chosen for the analysis using intra-personal distance, to maximize the effect of socio-demographics on travel patterns, and a sample with more days for the inter-personal distance, to minimize the influence of averaging on socio-demographic information. Therefore, scenario 1 was adopted for intra-personal distance analysis, and scenario 2 for inter-personal distance analysis. The corresponding results of modeling is given in Table 18 and Table 19 for intra-personal distance analysis, and in Table 20 and Table 21 for inter-personal distance analysis. Note that reference on different variables has been tested and the results were consistent to the results presented here, indicating the stability of the model.

6.1 Intra-Personal Distance

The results from Table 18 and Table 19 suggest that intra-personal distance was affected by both time-variant and time-invariant factors. Similar to the pattern described for Fig. 11, the intra-personal distance mean was similar during weekdays and higher during weekends. Similar patterns to Fig. 11 can also be observed for phase. Compared to phase 1, all the coefficients for the phase were negative, meaning that the intra-personal distance reached the maximum at phase 1. The coefficient for distance mean also indicates that the

Table 18: Estimation Result for Intra-Personal Distance Using Panel Effects Regression Model

Term (Reference) Variable	Mean Coefficient (P value)	Standard Deviation Coefficient (P value)
Intercept	321.464*** (0.000)	182.683*** (0.000)
Days of the Week (Monday)		
Tuesday	-5.136* (0.026)	-1.679 (0.140)
Wednesday	-6.498** (0.005)	-1.605 (0.157)
Thursday	-4.955* (0.033)	-1.273 (0.266)
Friday	2.233 (0.345)	-2.441* (0.036)
Saturday	23.187*** (0.000)	0.245 (0.830)
Sunday	20.396*** (0.000)	1.105 (0.338)
Phase (Phase 1)		
Phase 2	-12.518*** (0.000)	-5.922*** (0.000)
Phase 4	-47.580*** (0.000)	-0.966 (0.437)
Phase 5	-36.069*** (0.000)	-9.449*** (0.000)
Phase 6	-18.949*** (0.000)	-0.875 (0.568)
Phase 7	-48.050*** (0.000)	-17.532*** (0.000)
Phase 8	-61.889*** (0.000)	-20.522*** (0.000)
Daily Precipitation (No Rain)		
Very Slight	6.061*** (0.000)	4.040*** (0.000)
Slight to Low Moderate	6.724** (0.007)	2.497* (0.041)
Moderate	4.583 (0.109)	3.447* (0.014)
Heavy	-3.630 (0.152)	0.845 (0.498)
Very Heavy to Violent	-4.919 (0.162)	1.987 (0.251)
Daily Average Temperature (<10C)		
10 - 15C	-0.440 (0.793)	-1.593. (0.054)
15 - 20C	3.555 (0.210)	-1.505 (0.281)
20 - 30C	0.868 (0.835)	-4.215* (0.040)
Gender (Male)		
Female	-10.138* (0.046)	-8.141** (0.003)
Age (Below 40)		
40 - 49	-27.612*** (0.000)	-11.772*** (0.001)
50 - 59	-20.067** (0.002)	-8.499* (0.015)
Above 60	-6.870 (0.424)	-2.482 (0.593)
Income (Below 8000CHF)		
8,001 - 12,000CHF	-12.137* (0.029)	-7.790** (0.009)
Above 12,000CHF	13.173* (0.026)	6.780* (0.033)

Table 19: Estimation Result for Intra-Personal Distance Using Panel Effects Regression Model, Cont.

Household Size (Size 1)		
Size 2	-23.116. (0.053)	-11.379. (0.078)
Size 3	-8.745 (0.470)	-7.904 (0.227)
Size 4 or More	-13.580 (0.239)	-8.703 (0.163)
Education Level (Mandatory and Secondary)		
Higher	-12.351** (0.009)	-2.276 (0.371)
Employment Status (Unemployed)		
Employed	15.635* (0.016)	4.845 (0.169)
PT Pass (without PT pass)		
Subscription (exclude Half Fare)	7.095 (0.160)	4.856. (0.075)
Half Fare	1.060* (0.817)	1.179 (0.634)
Mobility Ownership		
Own a Car	-20.614 (0.033)	-6.078 (0.243)
Own a Bicycle	10.274 (0.248)	4.466 (0.353)
Own a Motorbike	-3.044 (0.630)	-3.847 (0.260)
Car Size (Medium)		
Small	-10.699 (0.106)	-4.066 (0.256)
Big	-6.685 (0.231)	-6.647* (0.027)
Car Year (2012)		
Before 2010	4.330 (0.506)	6.276. (0.074)
After 2015	-4.861 (0.410)	-3.990 (0.210)
Bike Type (E-Bike)		
Regular Bike	-8.510 (0.302)	-5.537 (0.213)
Overview		
Total Sum of Squares	78143000	17856000
Residual Sum of Squares	67913000	16452000
R-Squared	0.100	0.034
Adjusted R-Squared	0.098	0.031
P value	0.000	0.000
Effects		
	std.dev (share)	std.dev (share)
idiosyncratic	72.350 (0.809)	35.850 (0.777)
individual	35.110 (0.191)	19.230 (0.223)

Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

weekly activity patterns were more similar to each other throughout the pandemic than the pre-pandemic. Phases 4, 7, 8 had notably smaller coefficients for distance mean than other phases, suggesting that during the first wave and the second wave, individuals' weekly travel patterns were much less varied than the pre-pandemic and post-lockdown levels. The distance standard deviation reached a minimum at phase 8, followed by phase 7 and phase 5, suggesting that the weekly activities were much less varied, and individuals performed activities that were more similar between weekdays and weekends in the second wave. Daily average temperature and precipitation level had limited effect on intra-personal distance. Compared to no rain scenario, only very slight rain and slight to moderate rain scenarios showed statistical significance, and both terms increased intra-personal distance mean and standard deviation. It implies that each individual performed activities more differently on days with these precipitation profiles than on dry days. For temperature profiles, the coefficients show that a higher temperature would reduce the intra-personal distance standard deviation. Therefore, individuals would perform more homogeneous weekly activity patterns with lower differences between weekdays and weekends when the temperature is higher.

The coefficients also present the effect of socio-demographics on intra-personal distance. Females had lower intra-personal distance mean and standard deviation than their male counterparts. It suggests that females performed more similar and homogeneous activities across different days of the week, and the difference between weekday and weekend activities was less obvious. People belonging to the age range 40 to 49 years old had lower mean and variance compared to younger generations. A possible explanation is that individuals from this range tended to have a weekly routine, hence their travel activities were more similar and more homogeneous to each other across the week. People who have a higher salary or are employed had higher intra-personal distance mean and standard deviation, meaning that their weekly pattern was more different from each other and the difference between weekday-weekend activity patterns was more apparent than their counterparts. In terms of education level, individuals with higher education levels showed lower intra-personal mean, possibly due to the job type or employment status that could be related to education level. Lastly, individuals with half-fare subscriptions had a higher intra-personal mean, compared to those without any subscription. The cause could be that half-fare subscriptions enable a higher degree of freedom in terms of available mobility options, and individuals would be more likely to use public transport in combination with cars to conduct activities.

In summary, among time-variant variables, days of the week and COVID-19 development showed the biggest impact on the intra-personal distance, and daily precipitation level and daily average temperature showed less influence. Socio-demographics also exerted a significant impact on travel behavior. For example, the coefficient of age was of the same magnitude as days of the week, and gender and income had more influence on travel behavior than weather conditions.

6.2 Inter-Personal Distance

Table 20 and Table 21 suggest that inter-personal distance was mainly influenced by time-variant variables. The days of the week column shows that compared to Mondays, Fridays had a higher inter-personal distance mean and slightly lower standard deviation, whereas Sundays had a lower mean and a higher standard deviation. It indicates that on Fridays, activities performed by each individual were more different from all other individuals than on Mondays to Thursdays and Saturdays, but the individuals' distances to others were less varied, meaning that fewer individuals performed activities that were significantly different from others. It can be due to the notable share of leisure activities after work on Fridays, as shown in Section 4.3.1, and the pattern related to leisure activities is likely to differ from person to person. On Sundays, the activity patterns of each person were more similar to other people, but there were more individuals who performed drastically different patterns than others. The COVID-19 development also had a notable impact on inter-personal distance, similar to the features in Fig. 12. As the situation deteriorated, individuals had more similar activity patterns to each other. As the situation improved, especially in phase 6, the mean was much higher than the pre-pandemic level, meaning that the travel patterns of all individuals were more different in this phase than in phases 1 and 2. In the first wave (phase 4), the standard deviation was much higher than the pre-pandemic, indicating that some individuals performed significantly different travel plans than others. In the second wave, the coefficients of mean and standard deviation were lower than that in phase 4. This trend indicates that people's travel patterns were more similar to others and less people performed drastically different activities than others in the second wave than the first wave. The weather also affected the inter-personal variation. Coefficients from precipitation revealed that with little to medium level of rain, the distance mean was higher. This phenomenon is possibly because when the rain is not too heavy, people tend to choose a more varied mode of transport and purpose type depending on their perception of the precipitation level, making the inter-personal distance mean higher. A higher temperature would also increase the coefficient for mean and decrease that for standard deviation. This shows that individuals performed more different activity plans than each other, but fewer had very different patterns than others at a higher temperature.

Table 20: Estimation Result for Inter-Personal Distance Using Panel Effects Regression Model

Term (Reference) Variable	Mean Coefficient (P value)	Standard Deviation Coefficient (P value)
Intercept	373.209*** (0.000)	106.085*** (0.000)
Days of the week (Monday)		
Tuesday	0.411 (0.843)	-2.620*** (0.001)
Wednesday	6.249** (0.003)	-2.091** (0.006)
Thursday	5.642** (0.007)	-1.397. (0.067)
Friday	14.777*** (0.000)	-3.366*** (0.000)
Saturday	3.998. (0.055)	3.995*** (0.000)
Sunday	-13.975*** (0.000)	16.370*** (0.000)
Phase (Phase 1)		
Phase 2	4.373* (0.041)	1.230 (0.115)
Phase 4	-39.512*** (0.000)	18.949*** (0.000)
Phase 5	-21.651*** (0.000)	9.550*** (0.000)
Phase 6	31.661*** (0.000)	9.757*** (0.000)
Phase 7	-31.541*** (0.000)	11.616*** (0.000)
Phase 8	-45.543*** (0.000)	11.498*** (0.000)
Precipitation (No Rain)		
Very Slight	16.365*** (0.000)	-1.748*** (0.001)
Slight to Low Moderate	7.201*** (0.001)	-0.670 (0.390)
Moderate	6.298* (0.016)	0.557 (0.559)
Heavy	4.547. (0.063)	-0.157 (0.861)
Very Heavy to Violent	-1.643 (0.669)	-0.410 (0.770)
Daily Average Temperature (<10C)		
10 - 15C	6.086*** (0.000)	-1.446* (0.011)
15 - 20C	3.257 (0.165)	-3.013*** (0.000)
20 - 30C	0.292 (0.935)	-4.553*** (0.001)
Gender (Male)		
Female	-15.727. (0.057)	1.198 (0.608)
Age (Below 40)		
40 - 49	-10.667 (0.315)	1.136 (0.705)
50 - 59	-8.607 (0.410)	2.059 (0.486)
Above 60	-28.341* (0.041)	7.952* (0.042)
Income (Below 8000CHF)		
8,001 - 12,000CHF	6.992 (0.414)	-1.950 (0.420)
Above 12,000CHF	5.525 (0.575)	-3.248 (0.244)

Table 21: Estimation Result for Inter-Personal Distance Using Panel Effects Regression Model, Cont.

Household Size (Size 1)		
Size 2	-3.429 (0.851)	1.606 (0.756)
Size 3	-24.942 (0.172)	7.147 (0.166)
Size 4 or More	-22.042 (0.208)	4.961 (0.317)
Education Level (Mandatory and Secondary)		
Higher	-2.860 (0.704)	2.521 (0.236)
Employment Status (Unemployed)		
Employed	-6.588 (0.542)	-2.967 (0.331)
PT Pass (without PT pass)		
Subscription (exclude Half Fare)	24.364** (0.001)	-6.838** (0.001)
Half Fare	14.061. (0.082)	-2.419 (0.290)
Mobility Ownership		
Own a Car	-5.677 (0.700)	0.082 (0.984)
Own a Bicycle	5.549 (0.696)	-3.473 (0.387)
Own a Motorbike	-16.601. (0.071)	2.492 (0.339)
Car Size (Medium)		
Small	-8.225 (0.435)	2.135 (0.474)
Big	6.098 (0.489)	-0.517 (0.836)
Car Year (2012)		
Before 2010	1.392 (0.892)	0.568 (0.845)
After 2015	-10.084 (0.269)	3.163 (0.220)
Bike Type (E-Bike)		
Regular Bike	-9.484 (0.477)	3.001 (0.426)
Overview		
Total Sum of Squares	67739000	8699800
Residual Sum of Squares	58989000	7859800
R-Squared	0.120	0.106
Adjusted R-Squared	0.117	0.103
P value	0.000	0.000
Effects		
	std.dev (share)	std.dev (share)
idiosyncratic	65.720 (0.747)	23.710 (0.834)
individual	38.200 (0.253)	10.570 (0.166)

Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

The impact of socio-demographics on inter-personal distance was limited. Firstly, gender affected the inter-personal travel pattern. Females tend to have lower inter-personal distance mean, implying that females performed travel patterns that were more similar to other females, whereas males have more varied travel patterns among each other. Secondly, for people aged over 60 years old, the coefficient of mean was much lower and the coefficient of standard deviation was higher than their younger counterparts. In other words, people aged over 60 years old had more similar travel patterns, but more people performed very different activities than the rest of the individuals in this group. Lastly, individuals holding a public transport subscription would have a higher inter-personal distance mean and a lower standard deviation. This is possibly because people with subscriptions would use public transport more often, which introduces more varied travel patterns, making the inter-personal mean higher. However, these individuals would also tend to use public transport more, making fewer among them having vastly different patterns than the rest.

In conclusion, COVID-19 development had the most notable impact on inter-personal distance, followed by the daily precipitation level and the days of the week. Days of the week were not as important for inter-personal distance as for intra-personal distance. Socio-demographics were not as prominent for inter-personal distance as for intra-personal distance. Nonetheless, gender, age, and PT pass had significant impacts on the inter-personal distance, since their coefficients were much higher than many time-variant variables.

These results further consolidate the necessity of this project, as socio-demographics, weather conditions and days of the week showed significant impact on travel behavior during the pandemic, and their combined effect would provide a more detailed and complete look at the causes of travel behavior shift during the pandemic.

6.3 Additional Modeling Results

Lastly, separate variables related to COVID-19 development were used in the model, instead of using phase, to determine how each variable affected the travel behavior. "KOF Stringency Index" and "Daily Increase" were used to represent the COVID-19 situation. The results for both intra- and inter-personal distance are very similar to Table 18, Table 19 and Table 20, Table 21. The difference lies in the COVID-19 related variables, and this part of the results is given in Table 22.

For intra-personal distance, among statistically significant terms, all stringency index and

Table 22: Estimation Result for Intra- and Inter-Personal Distance Using Panel Effects Regression Model, Using KOF Stringency Index and Daily Increase to Describe COVID-19 Development

Intra-Personal Distance		
Term (Reference) Variable	Mean Coefficient (P value)	Standard Deviation Coefficient (P value)
KOF Stringency Index (KOF Stringency Index = 0)		
1 - 40	6.197 (0.649)	-7.976 (0.234)
40 - 45	-26.403*** (0.000)	-13.542*** (0.000)
45 - 55	-36.042*** (0.000)	-10.314*** (0.000)
55 - 60	-40.072*** (0.000)	-12.548*** (0.000)
60 - 65	-44.917*** (0.000)	-11.733*** (0.000)
65 - 70	-10.969 (0.421)	-17.140* (0.011)
>70	-26.340. (0.056)	-10.612 (0.118)
Daily Increase (Daily Increase = 0)		
1 - 500	-18.410 (0.172)	10.717 (0.106)
500 - 1500	-13.400 (0.332)	13.207. (0.052)
1500 - 4500	-14.826** (0.003)	-5.369* (0.031)
4500 - 6000	-11.635* (0.011)	-5.097* (0.023)
6000 - 6500	-12.369* (0.010)	-3.437 (0.147)
Inter-Personal Distance		
KOF Stringency Index (KOF Stringency Index = 0)		
1 - 40	8.617 (0.247)	14.216*** (0.000)
40 - 45	-33.920*** (0.000)	11.290*** (0.000)
45 - 55	-38.859*** (0.000)	11.893*** (0.000)
55 - 60	-55.084*** (0.000)	10.658*** (0.000)
60 - 65	-52.853*** (0.000)	14.498*** (0.000)
65 - 70	-43.508*** (0.000)	12.920*** (0.000)
>70	-62.050*** (0.000)	26.851*** (0.000)
Daily Increase (Daily Increase = 0)		
1 - 500	19.551** (0.007)	-3.897 (0.140)
500 - 1500	20.719** (0.009)	-10.925*** (0.000)
1500 - 4500	2.486 (0.510)	-1.057 (0.441)
4500 - 6000	9.547** (0.005)	-1.565 (0.201)
6000 - 6500	11.340** (0.006)	-3.332* (0.027)

daily increase greater than 0 decreased the intra-personal distance mean and standard deviation. Therefore, any restrictions or health risks would make each person have more similar travel patterns throughout the week and make the difference between weekday and weekend patterns less observable. The distance mean coefficient of the KOF Stringency Index reached a minimum at interval 60 - 65, and second-lowest at interval 55 - 60. These two intervals of stringency index mainly correspond to phase 8. In terms of daily increase, the coefficient for distance mean and standard deviation reached a minimum at interval 1500 - 4500, which also correspond with the risk development at phase 8. The combined stringency between 60 - 65 and daily increase between 1500 - 4500 would make the intra-personal distance mean to reach the minimum possible level due to COVID-19 development. This aligns with the observation made for Table 18, in which the intra-personal distance was at the lowest level in phase 8.

For inter-personal distance, a stringency index greater than zero would decrease the inter-personal distance mean but increase the standard deviation, whereas, for daily increase, all daily increase greater than zero would increase the mean but decrease the standard deviation. Therefore, restrictions or risks would make people travel more similarly to each other, and increase the probability of having some individuals performing extremely different travel patterns. The smallest coefficient of distance mean for KOF stringency index was interval > 70. The largest coefficient for daily increase was interval 500 - 1500. Both terms correspond to the feature of phase 4, and a combined coefficient would be -41.331. The coefficients corresponding to phase 8, as described above, would return a combined coefficient of -50.379. However, interval 1500 - 4500 for daily increase was not significant here, but even with the interval above it (4500 - 6000), the combined coefficient would still be -43.306, smaller than that from phase 4. Hence, the inter-personal distance would reach the minimum at phase 8, which aligns with the data shown in Table 20.

The complete results for intra- and inter-personal distance using KOF stringency index and daily increase, instead of phase, are shown in Appendix D for reference. The results of Table 22 further suggest that phase is a better description for COVID-19 development. The use of separate variables would cause confusion, as the coefficients were not intuitive. One would expect that higher stringency index or daily increase would decrease the inter-personal and intra-personal distance, as higher restrictions and risks would force people to stay at home more, making the travel pattern more similar across all individuals. However, the in results in Table 22 contradicts this expectation. The reason is that the individuals behaved differently during the first wave and the second wave, and the first wave had a higher stringency index whereas the second wave had a higher daily increase. This difference between waves can be more easily observed by classifying the COVID-19 development by phase.

7 Conclusion and Discussion

This report tries to answer what factors contributed to shifts in time use patterns and how the corresponding factors change travel patterns during the COVID-19 pandemic, by using a subset of GPS data recorded in the MOBIS-COVID-19 study. Firstly, the data is converted into sequences using trajectory sequencing. The sequences are utilized to descriptively analyze the weekly and daily time use patterns of modes and purposes, and how COVID-19-related variables, weather-related variables, and socio-demographics shifted the patterns. Secondly, cluster analysis is performed to determine whether the difference caused by one factor on the time use difference of each mode and purpose is statistically significant, giving an initial idea of how the COVID-19 variables and weather factors affect the travel patterns. Thirdly, the Multi-Dimensional Sequence Alignment Method is applied to determine the inter-personal and intra-personal distance, taking into consideration eight different factors: mode, purpose, KOF Stringency Index, daily increase, daily hospitalized, daily deceased, temperature, and precipitation. Cluster analysis and discrepancy analysis are then employed to determine whether each of the factors contributes to changes in the intra-personal and inter-personal distance patterns. Lastly, the panel effects regression model is used to determine the development of intra-personal and inter-personal distance, which are calculated using MDSAM with dimensions mode and purpose, and to analyze the reasons behind behavioral shifts during the pandemic.

This study is the first to look at time use at such a fine resolution using GPS data from MOBIS-COVID19, and the first known COVID-19 related study that uses GPS data to determine the combined effect of COVID-19, socio-demographics, weather conditions and days of the week on the travel behavior changes during the pandemic. This report investigates the factors that contributed to changes in travel behavior throughout the studied time frame. It started by considering the influence of each factor separately and ended with a analysis that simultaneously considered all the factors for an overview of the combined effects of various variables on travel behavior change. The result shows that the COVID-19 pandemic development was the most important factor that caused the travel behavior shift during the pandemic. As more restrictions being imposed and higher health risks developed, people showed a tendency to travel less, stay at home for a longer period, prefer private transport means over collective means, perform similar activity patterns to other individuals, and have more similar weekly travel patterns. As the situation improved, the travel behavior slowly shifted back toward the pre-pandemic level. The time use pattern was also different for the first wave and the second wave. In the second wave, individuals performed more out-of-home activities than the first wave, and the preference for private transport was not as prominent as in the first wave. On top of the effect of COVID-19 development, days of the week, precipitation, temperature, and socio-demographics also influenced the individuals' travel patterns significantly.

This project is heavily restrained by the available data. Most participants in the MOBIS study did not continue to record their daily travel patterns during the pandemic, and among those who recorded, most individuals did not provide enough data to work with for this project. Although the GPS data is advantageous here, as it allows automatic identification of mode and purpose, enabling large-scale automatic data collection, there are also some errors in the collected data, such as unknown and misidentified activities. One example is purpose "leisure". As can be observed on Fig. 9 and Fig. 10, many individuals performed leisure activities throughout night hours. This could be due to misidentification by the application, or the individual staying overnight at someone else's place, which was then identified as leisure. In both cases, the leisure activity was mislabeled. Another example is the amount of missing data. Even by populating the missing and unknown purpose data using machine learning, there were still many unknown purposes. From the trajectory sequencing, the combined mode and purpose sequences still had around 12 % data that were not filled. These shortages of GPS data could cause errors in the analysis. On top of that, the weather data was not complete. In this analysis, the average weather data from nearby areas, through mapping the nearby postcodes of each postcode, was taken in case of missing weather data. The precipitation data given is based on one day, which also introduces errors in determining the effect of precipitation on travel behavior, since rain event often happens over a short period of time, in which case the individuals are more likely to postpone or cancel their travel schedule, depending on their perception of the precipitation level and duration. Therefore, it would be interesting to consider the rain distribution of each day when investigating the effect of precipitation on mode and purpose patterns.

For future analysis, it would be interesting to integrate the location data provided in the GPS data set in the analysis, to help determine the change of trip location, duration, length, and frequency during the pandemic. The possibility of populating the data set should also be considered to expand the number of qualified individuals. This is especially true during the first and second waves, as many people stayed at home for a few days in a row, and the GPS tracking could be disabled in this case. It is worth noting that the data set was expanded in phase 8, and more individuals started to participate in this study. This additional source of data opens up the possibility to use this expanded data set to determine how travel behavior is changed from the second wave onward, adding in the possibility of the effect of vaccination on travel behavior at an individual and collective level. Two possible scenarios to consider are: 1) how each individual changed their travel behavior after being administered the first and the second injection and 2) how the overall travel behavior shifted with vaccination rate. One fundamental constraint of the data set is because the MOBIS study requires individuals to use cars for at least two days a week. This requirement filtered out individuals who heavily relied on public transport or other forms of transport before the pandemic, such as walking or bicycling. However, these individuals could present remarkably different travel patterns than participants in the MOBIS study. Therefore, it would be interesting to determine how these individuals changed their travel behavior during the pandemic, as enclosed spaces, such as buses, trains, and trams would increase the infection rate, making these individuals more affected by the COVID-19 development than people with access to cars. Lastly, the possibility of using a more advanced model, such as the closed-form multiple discrete-continuous extreme value choice model with multiple linear constraints proposed by Mondal and Bhat (2021), should be explored.

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A State distribution of Mode and Purpose

This section shows all the plots generated for Section 4.3.1 and Section 4.3.2.

A.1 Mode

This section includes the state distribution of mode on Tuesdays, Wednesdays, Thursdays, Fridays, Saturdays and Sundays. The plots are generated by phase.

Figure 13: State Distribution of Mode Patterns on Tuesdays

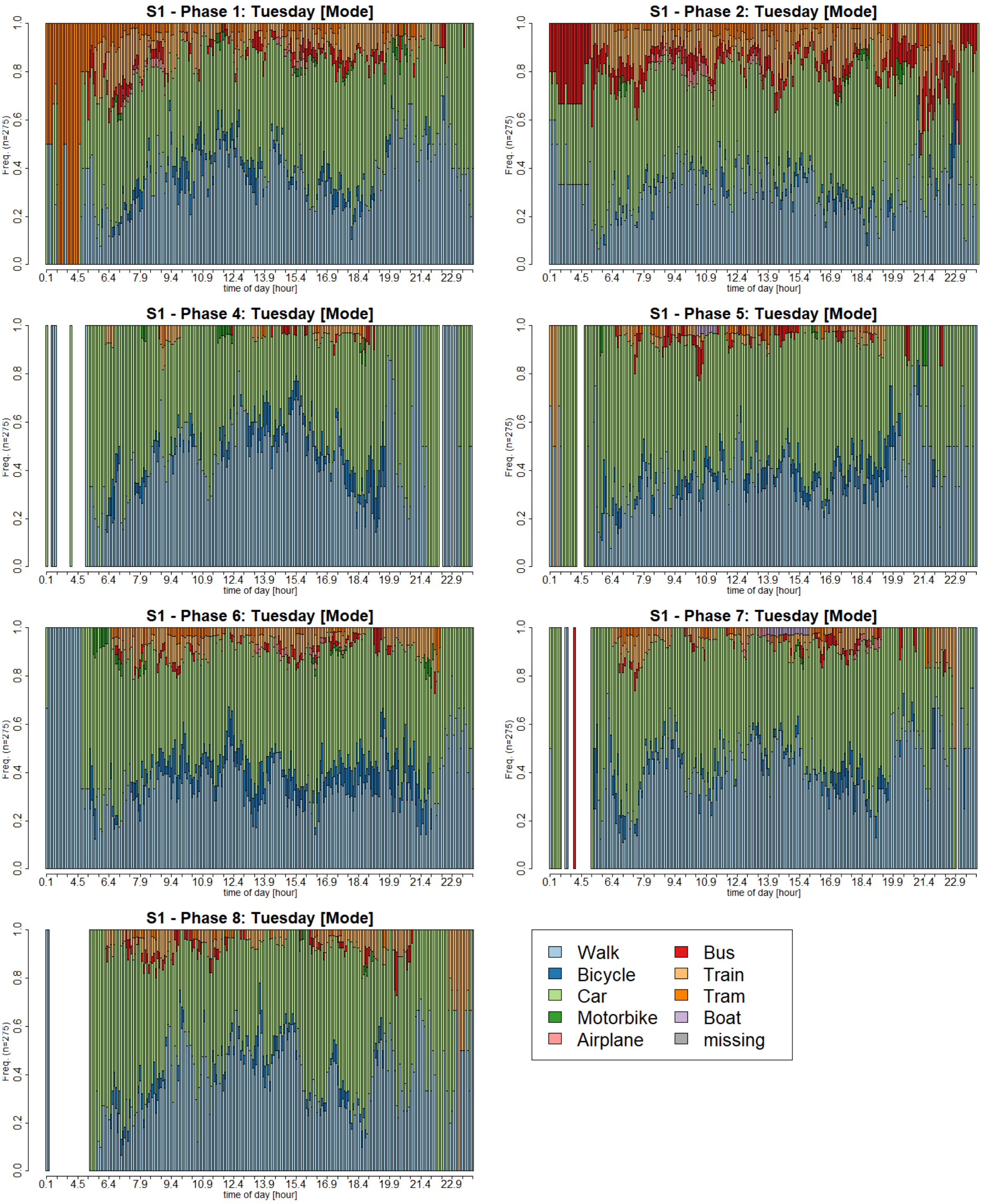


Figure 14: State Distribution of Mode Patterns on Wednesdays

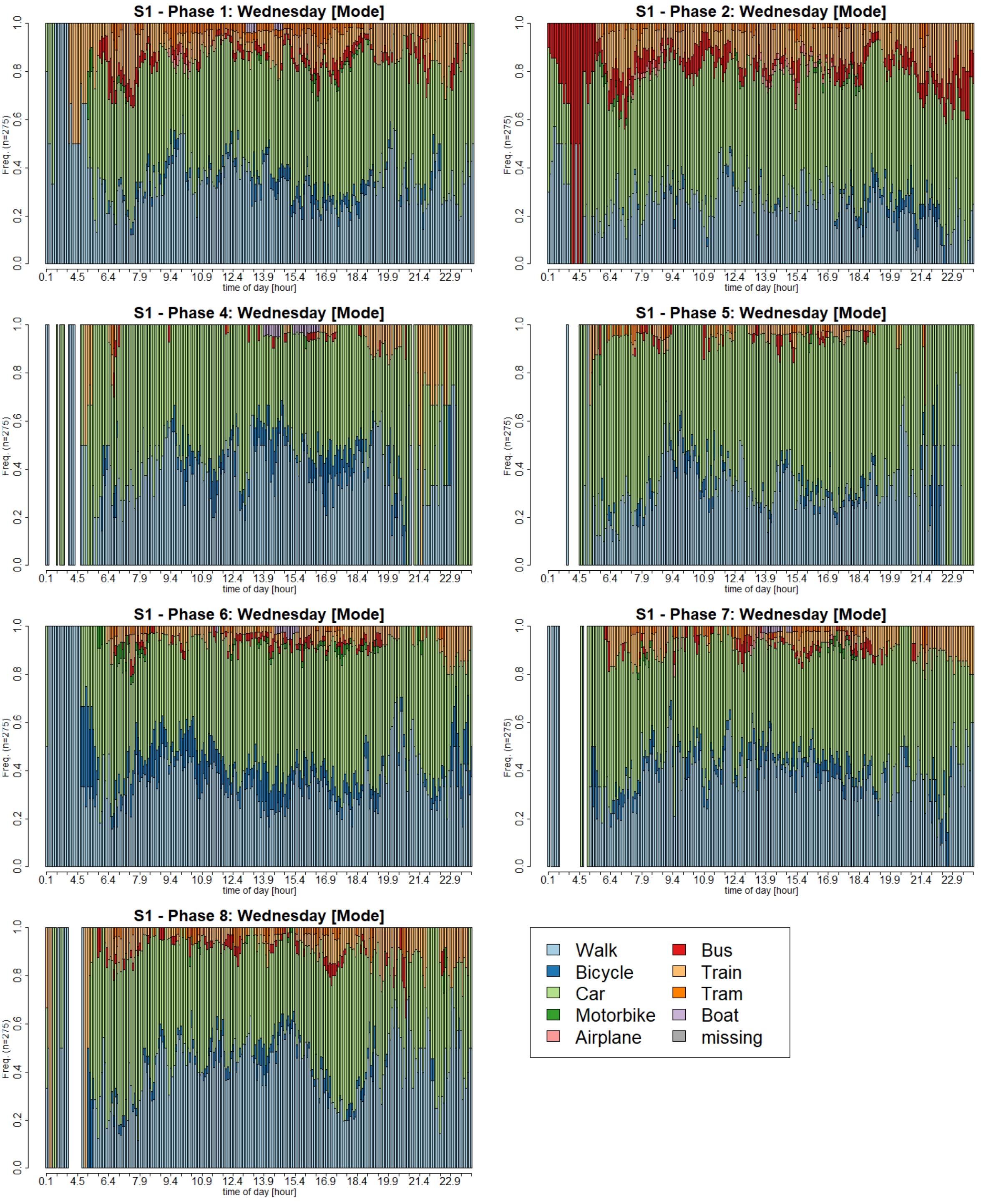


Figure 15: State Distribution of Mode Patterns on Thursdays

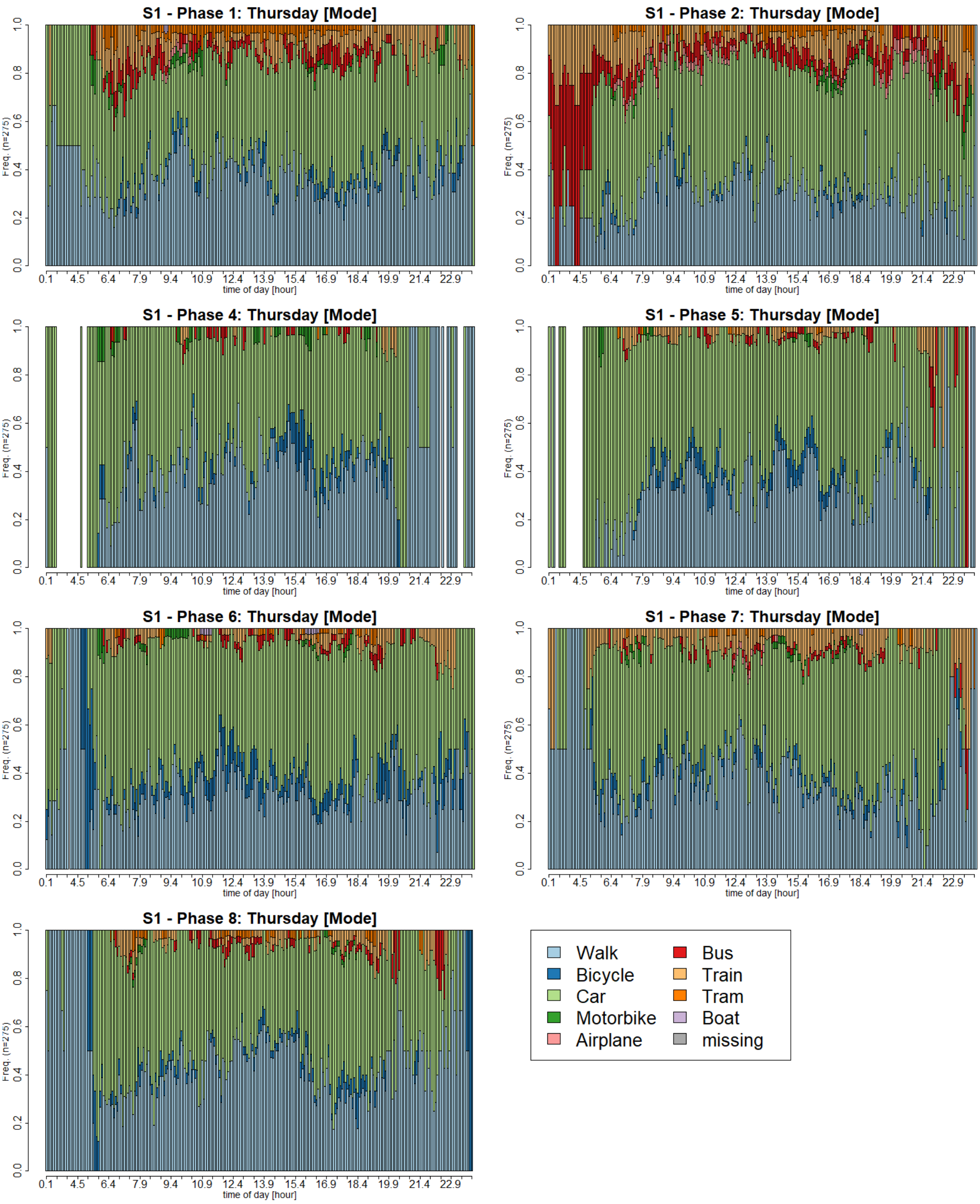


Figure 16: State Distribution of Mode Patterns on Fridays

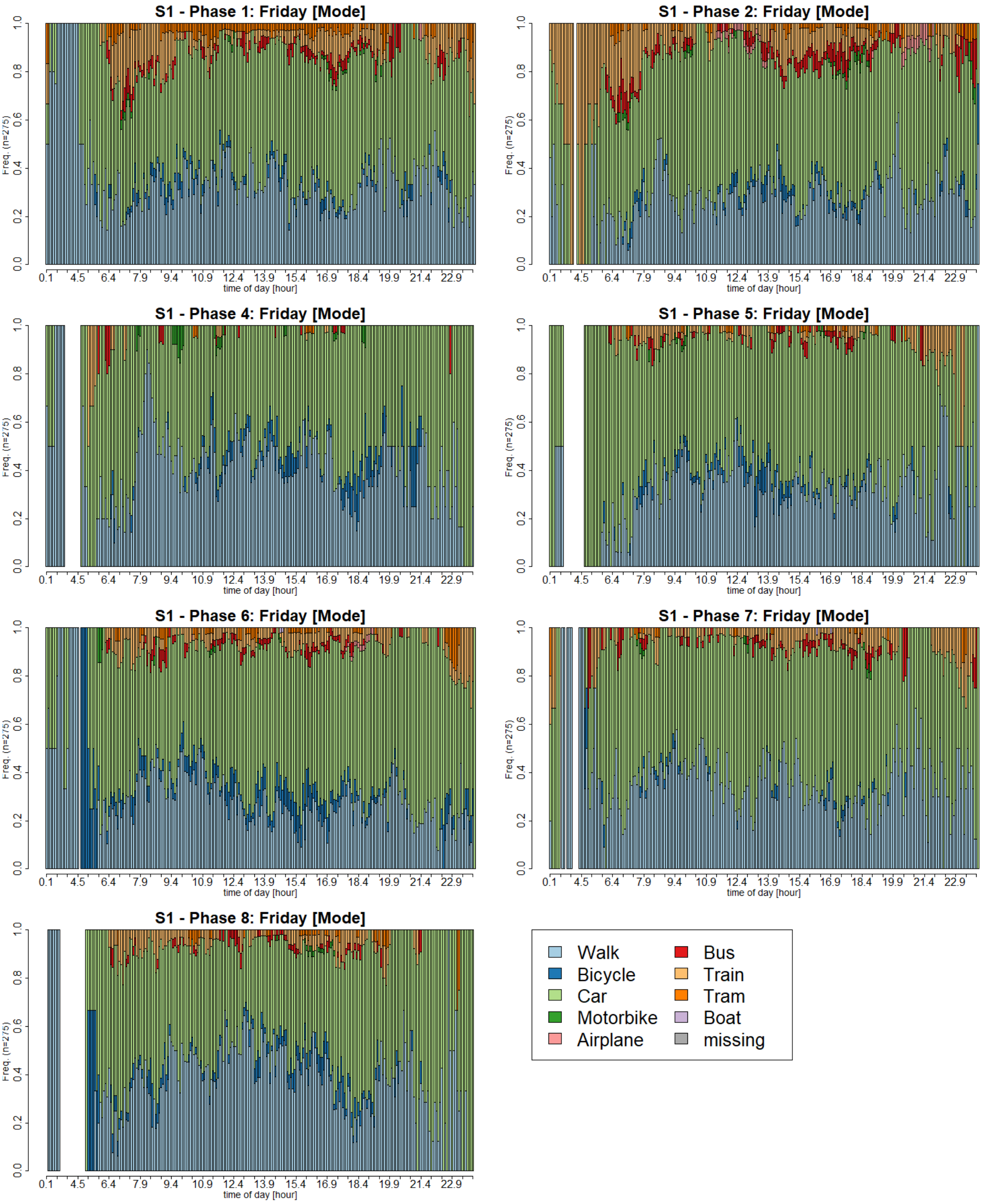


Figure 17: State Distribution of Mode Patterns on Saturdays

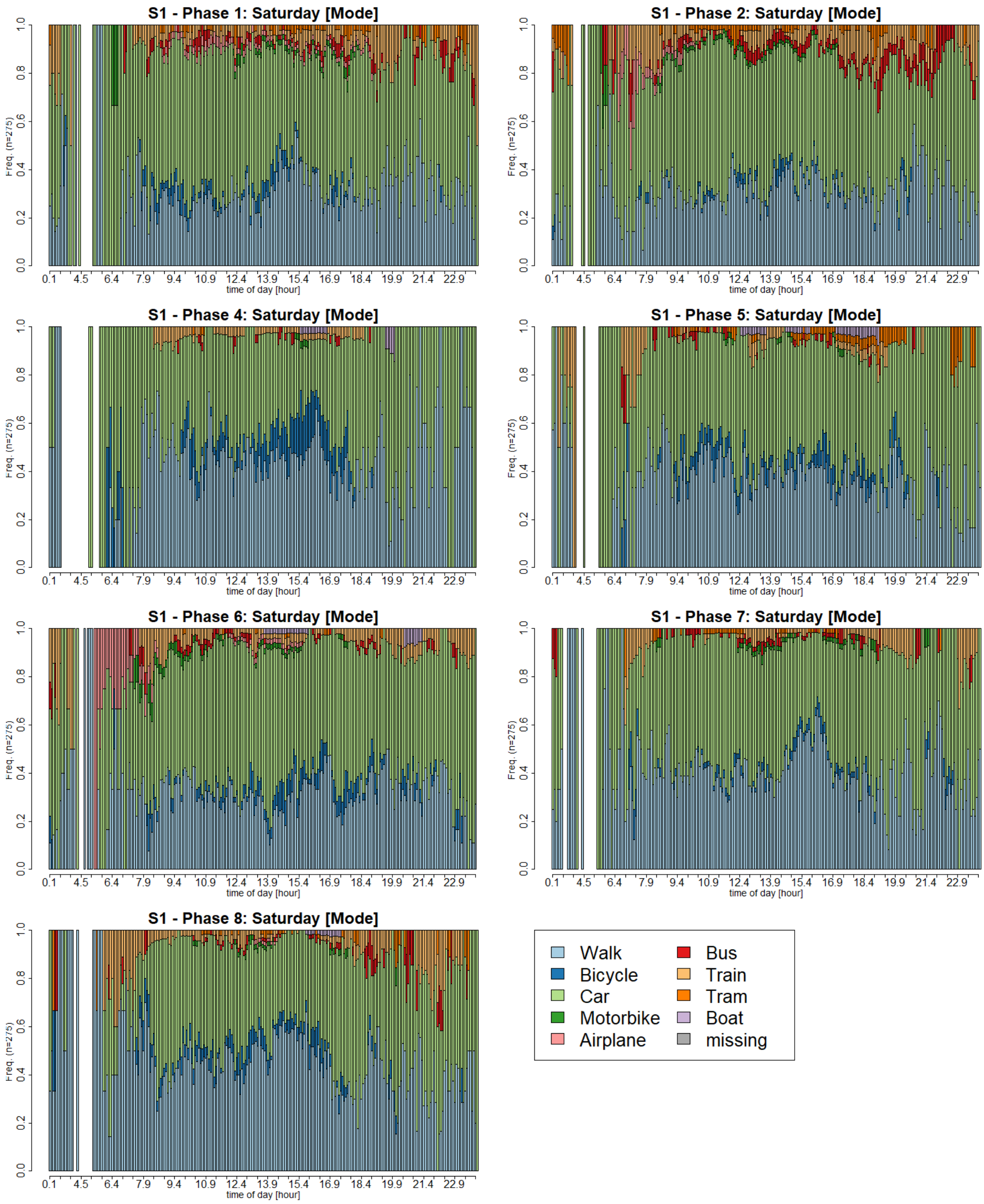
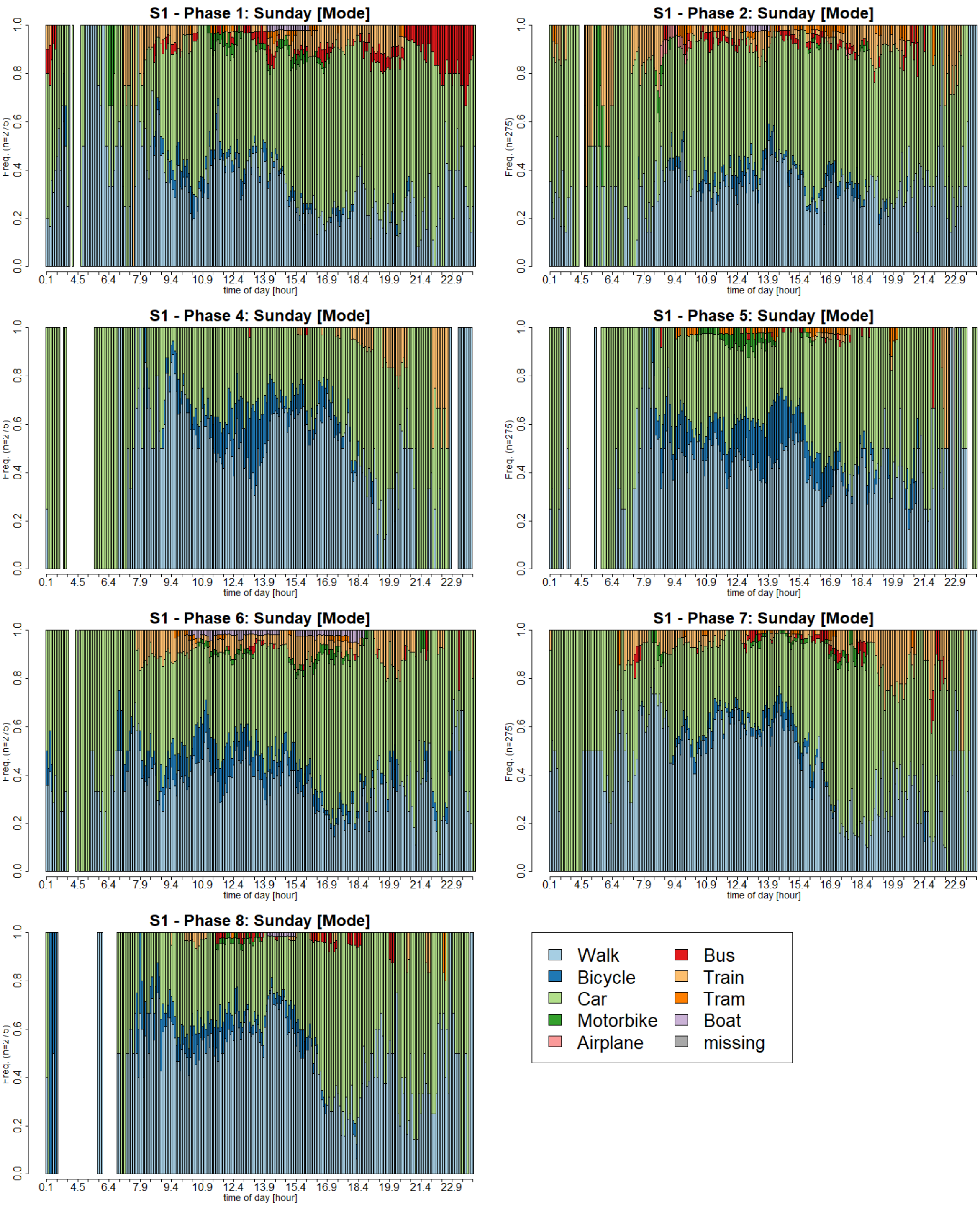


Figure 18: State Distribution of Mode Patterns on Sundays



A.2 Mode and Purpose

This section includes the state distribution of combined mode and purpose on Tuesdays, Wednesdays, Thursdays, Fridays and Sundays. The plots are generated by phase.

Figure 19: State Distribution of Mode and Purpose Patterns on Tuesdays

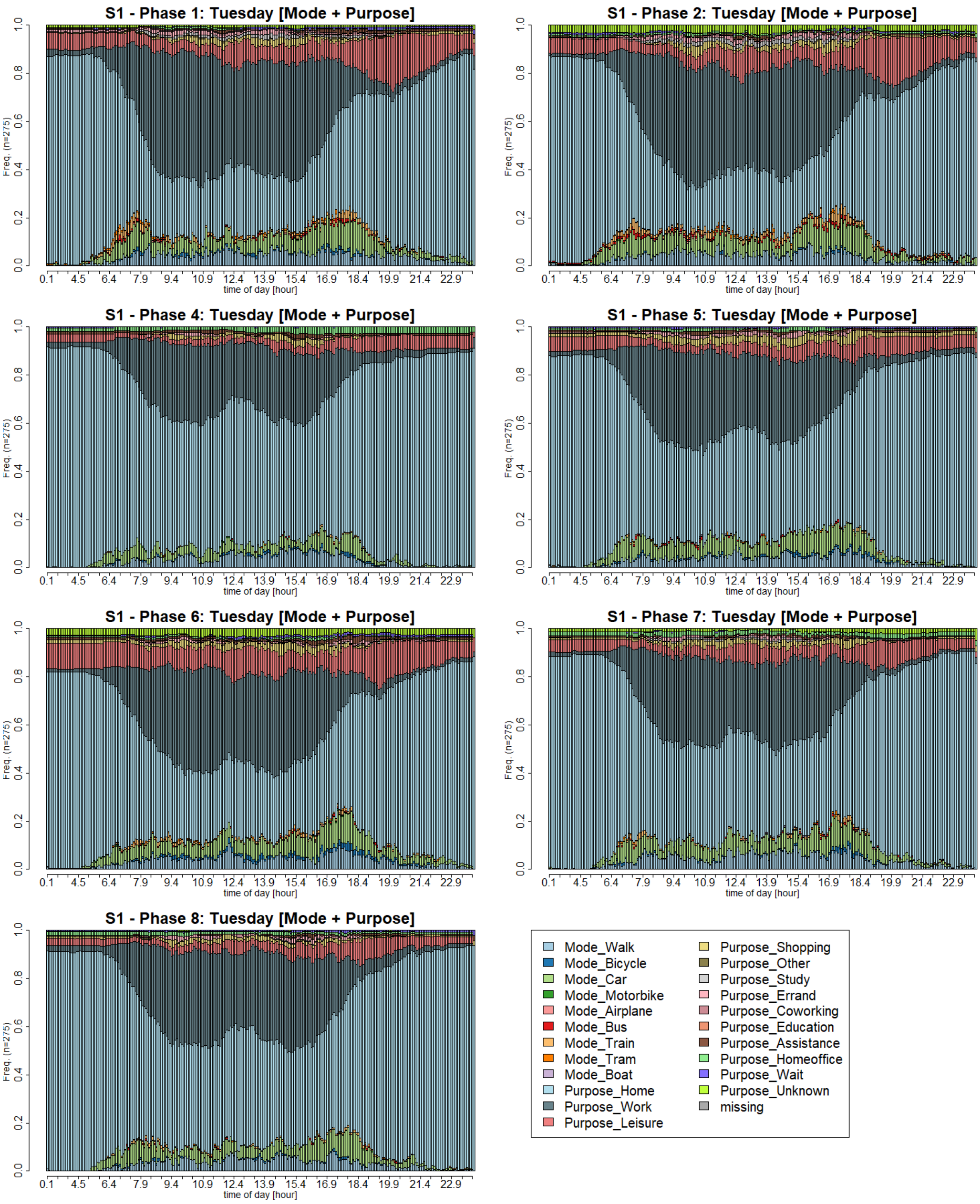


Figure 20: State Distribution of Mode and Purpose Patterns on Wednesdays

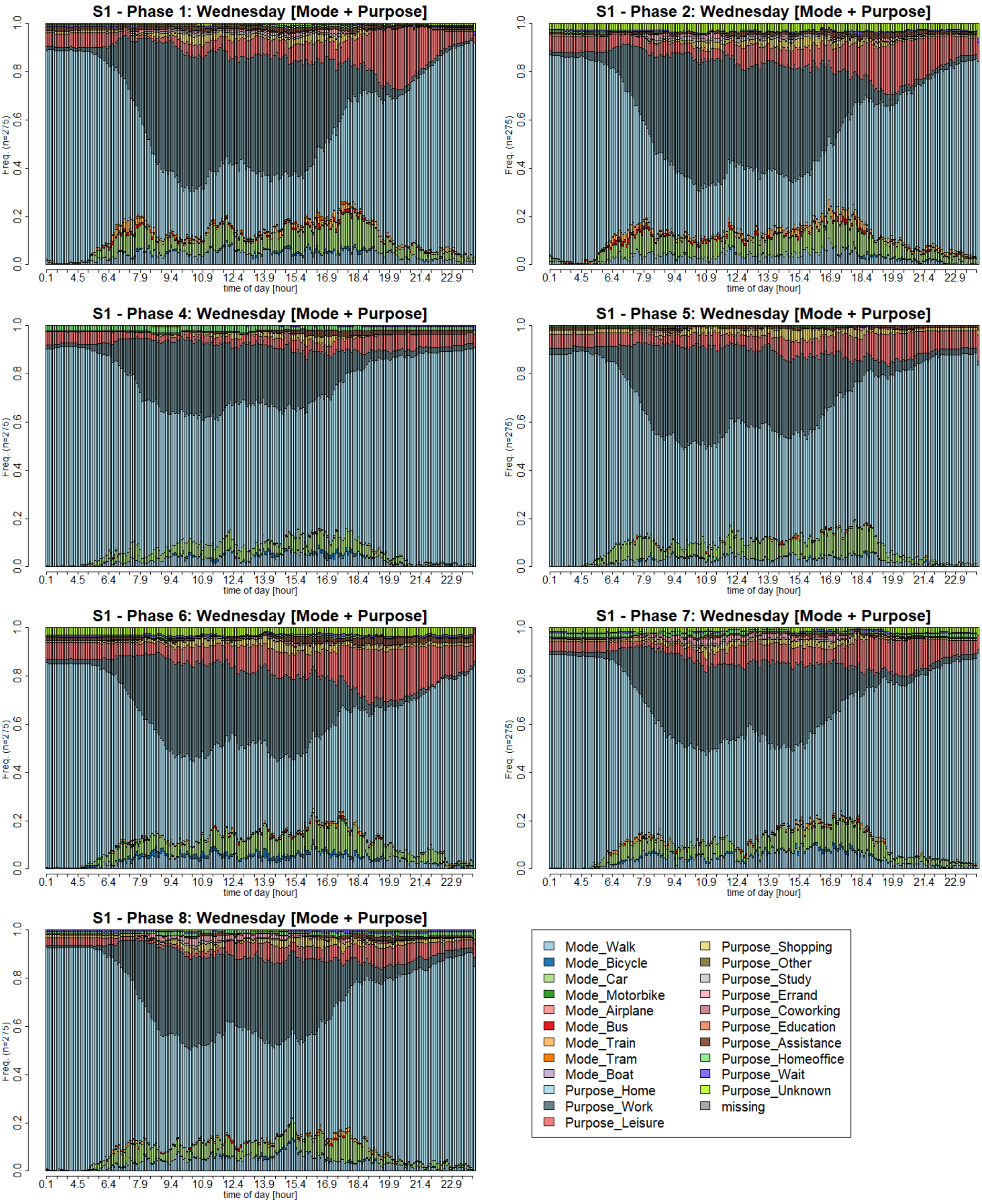


Figure 21: State Distribution of Mode and Purpose Patterns on Thursdays

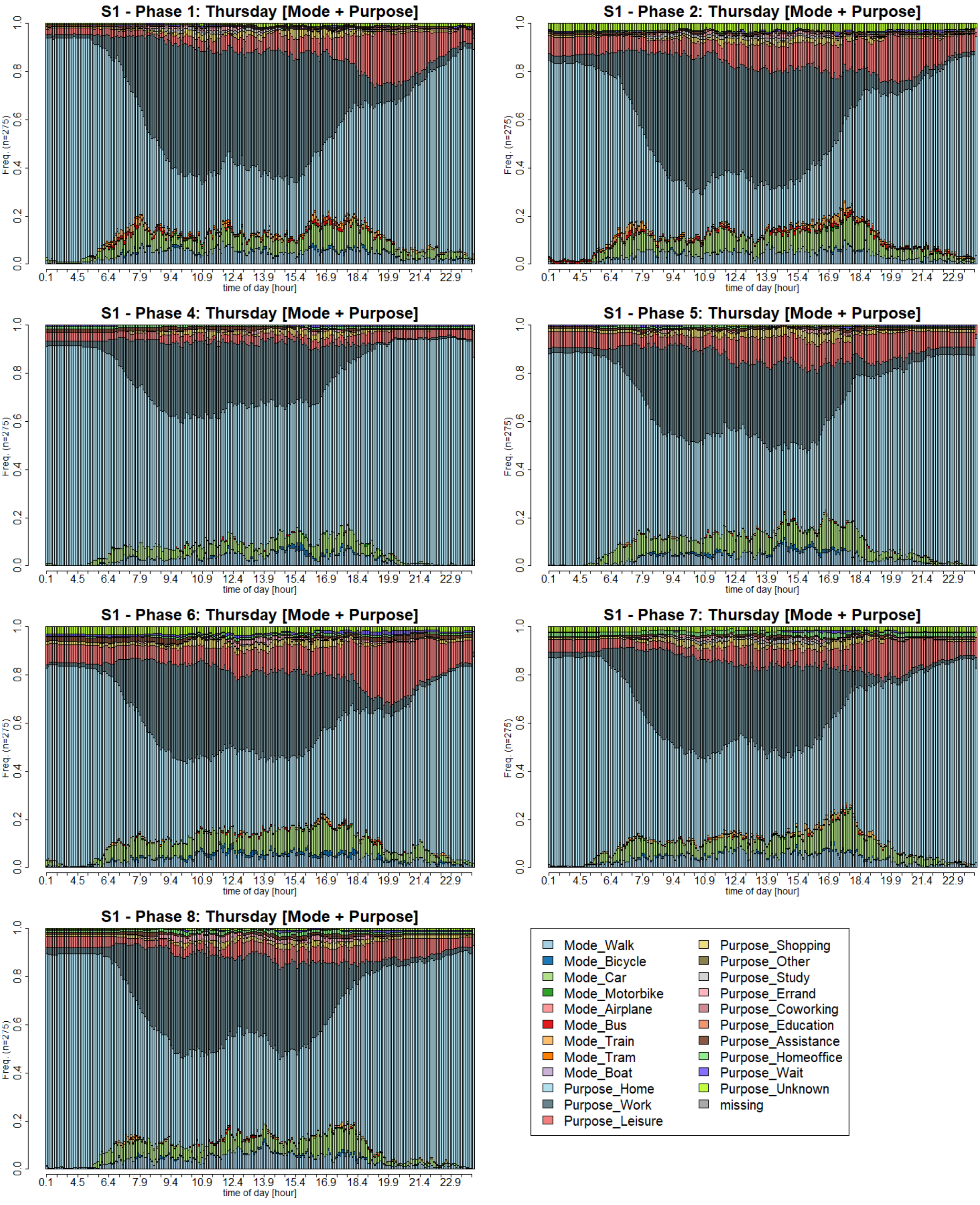


Figure 22: State Distribution of Mode and Purpose Patterns on Fridays

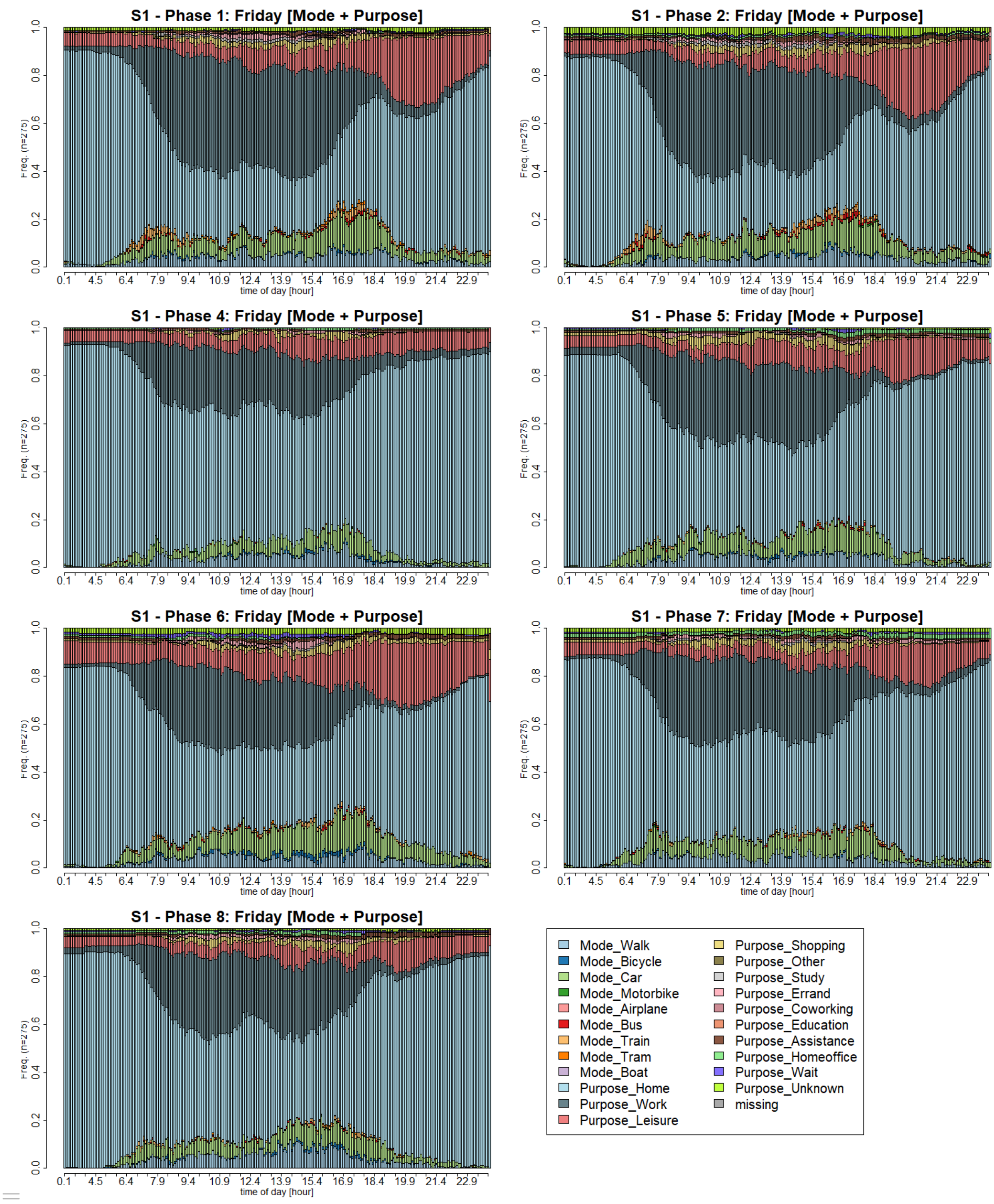
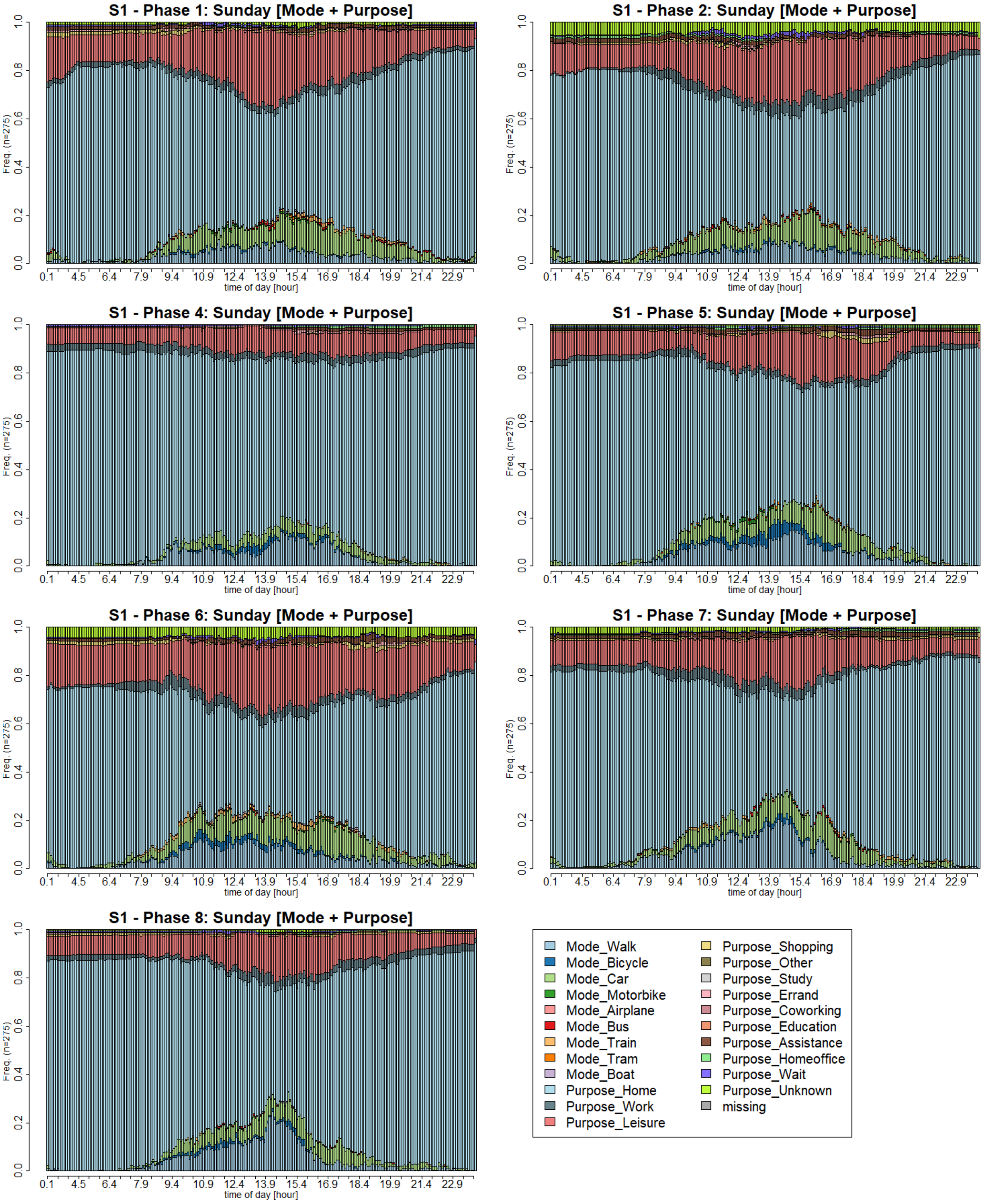


Figure 23: State Distribution of Mode and Purpose Patterns on Sundays



B Box Plot of Mode and Purpose

This section is a supplement for Section 5.1. The box plots show the distribution of time use for each cluster. Statistical tests were performed to determine whether the difference between each cluster is statistically significant.

B.1 Box Plot by Phase

This section includes box plots grouped by phase.

Figure 24: Box Plot of Mode Share by Phase, Stream 1

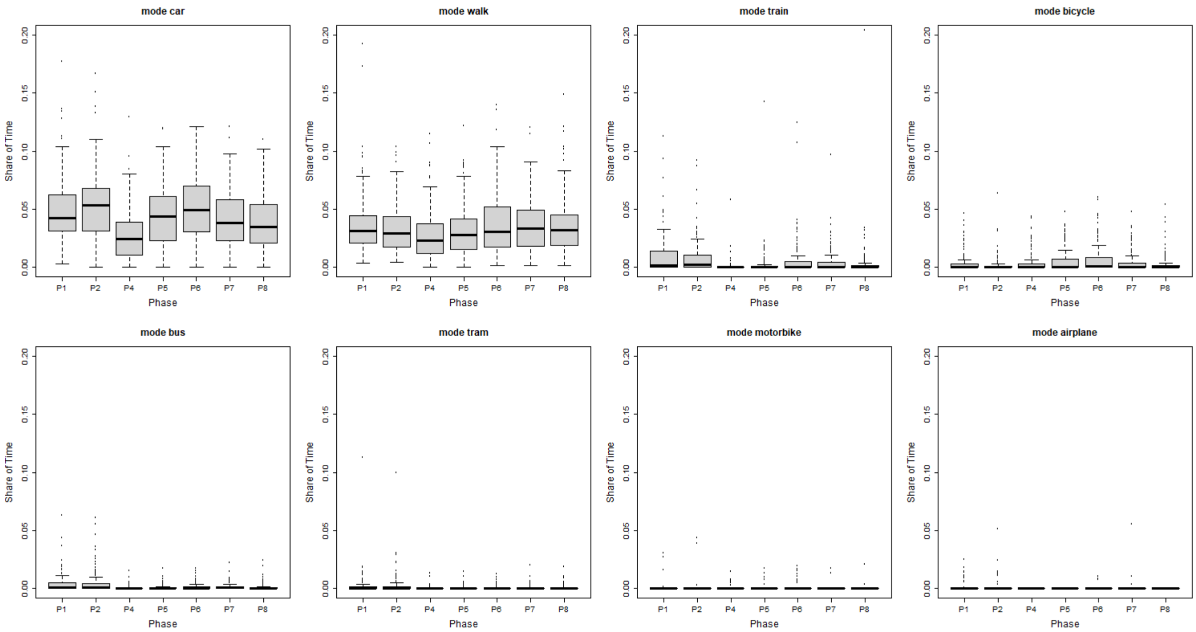


Figure 25: Box Plot of Purpose Share by Phase, Stream 1

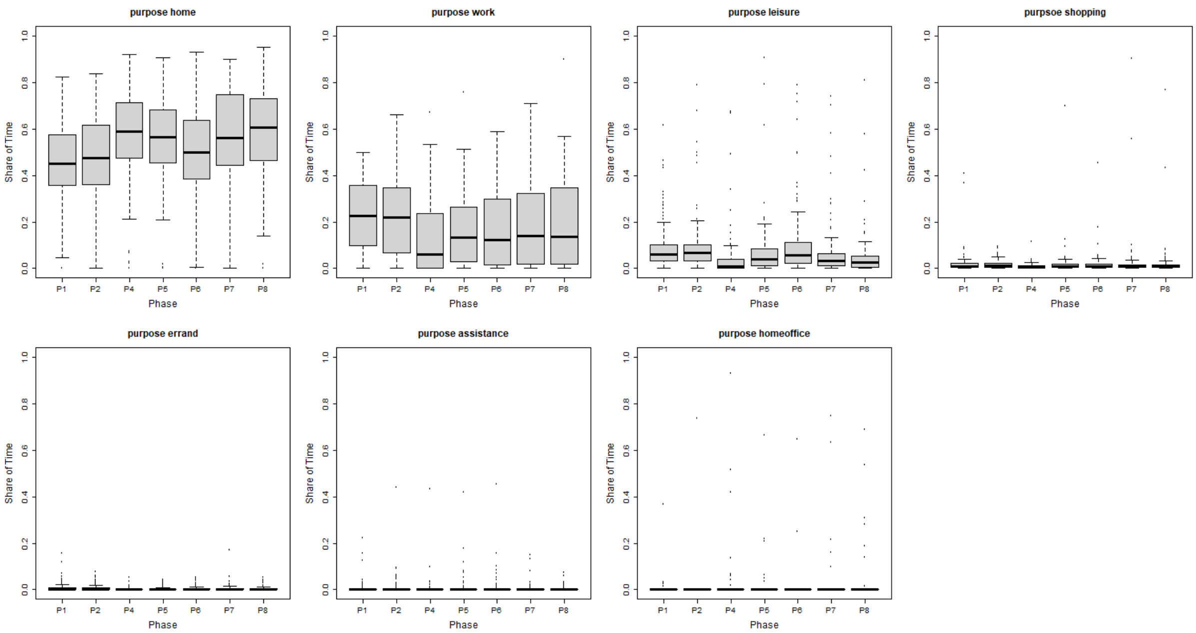


Figure 26: Box Plot of Mode Share by Phase, Stream 2

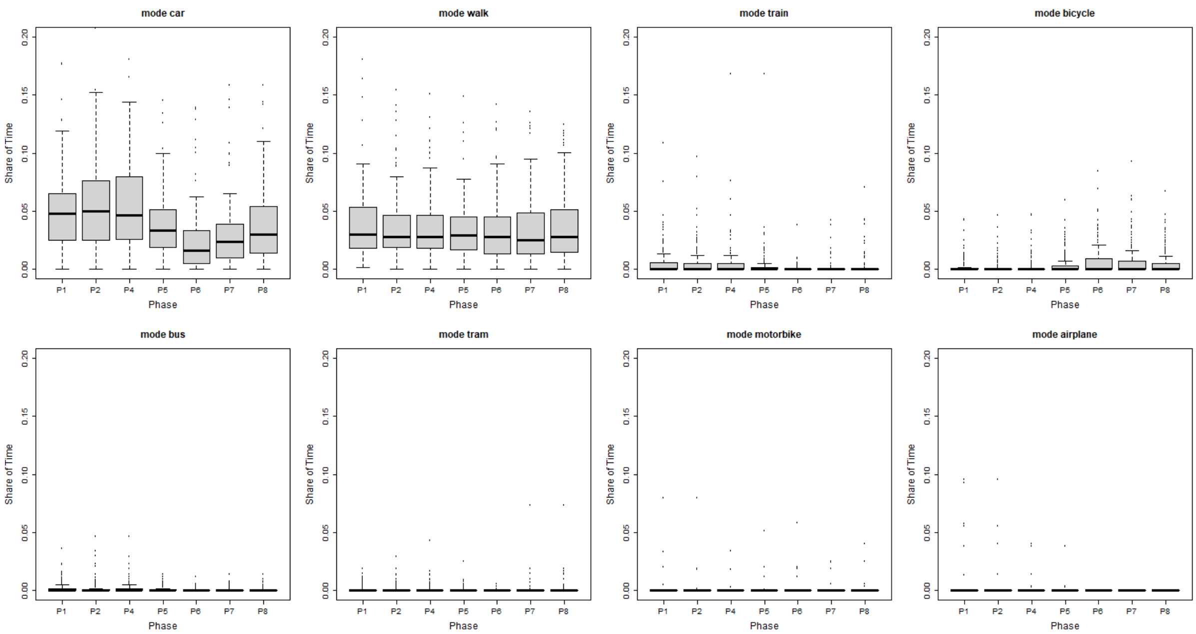
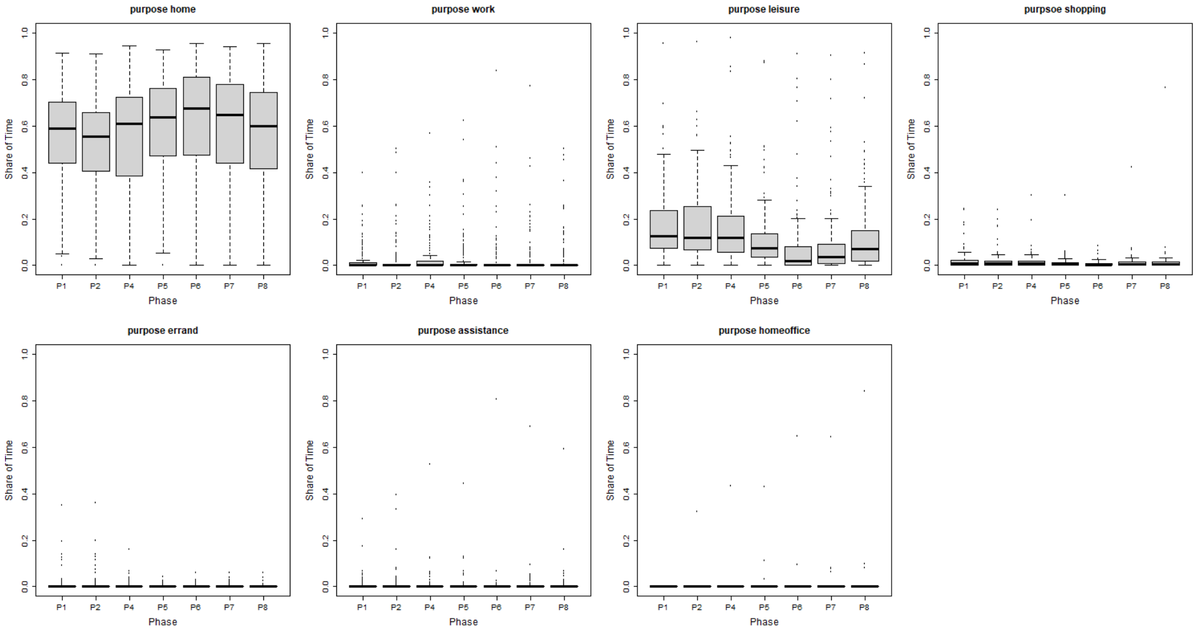


Figure 27: Box Plot of Purpose Share by Phase, Stream 2



B.2 Box Plot by Daily Average Temperature [Phase 1]

This section includes box plots grouped by average temperature in phase 1.

Figure 28: Box Plot of Mode Share by Average Temperature, Phase 1, Stream 1

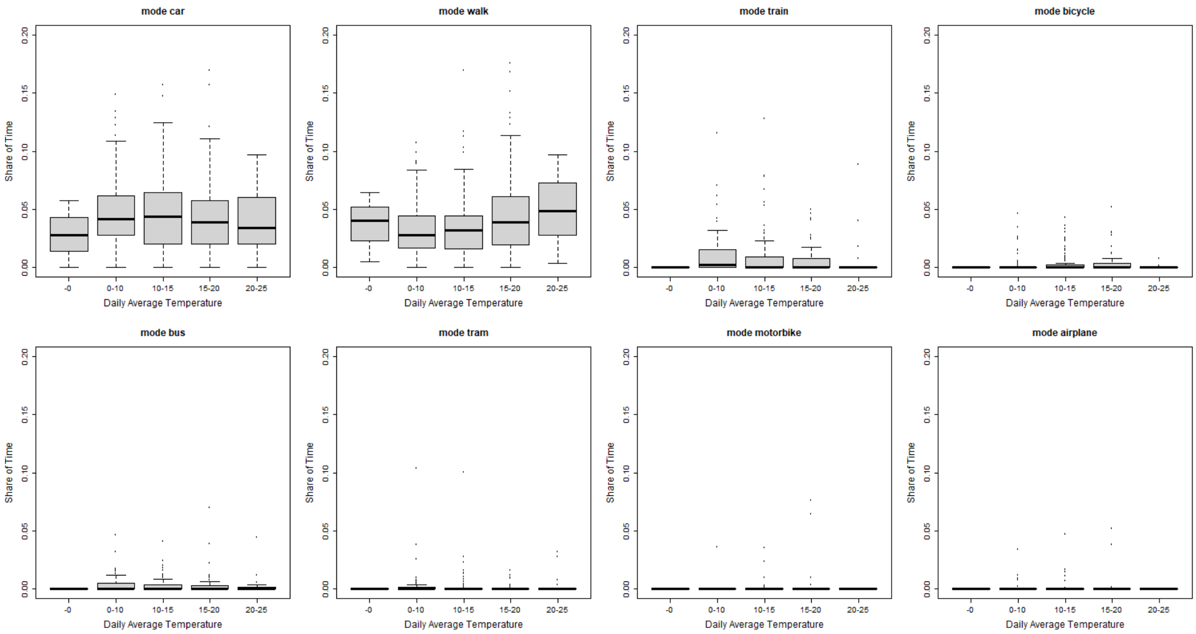


Figure 29: Box Plot of Purpose Share by Average Temperature, Phase 1, Stream 1

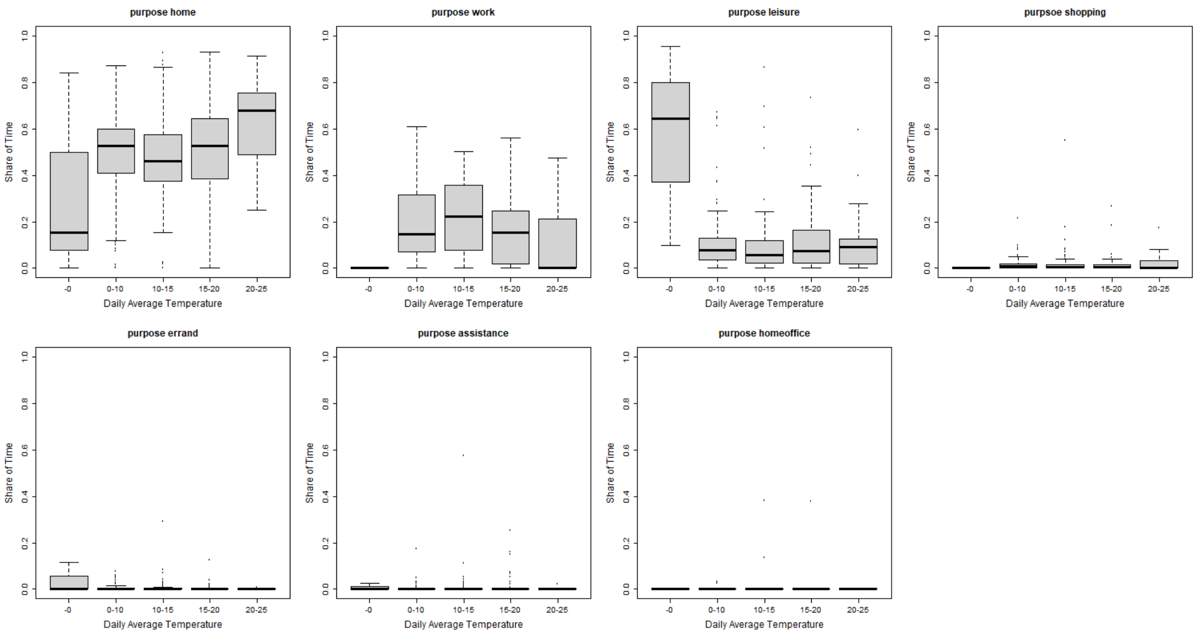


Figure 30: Box Plot of Mode Share by Average Temperature, Phase 1, Stream 2

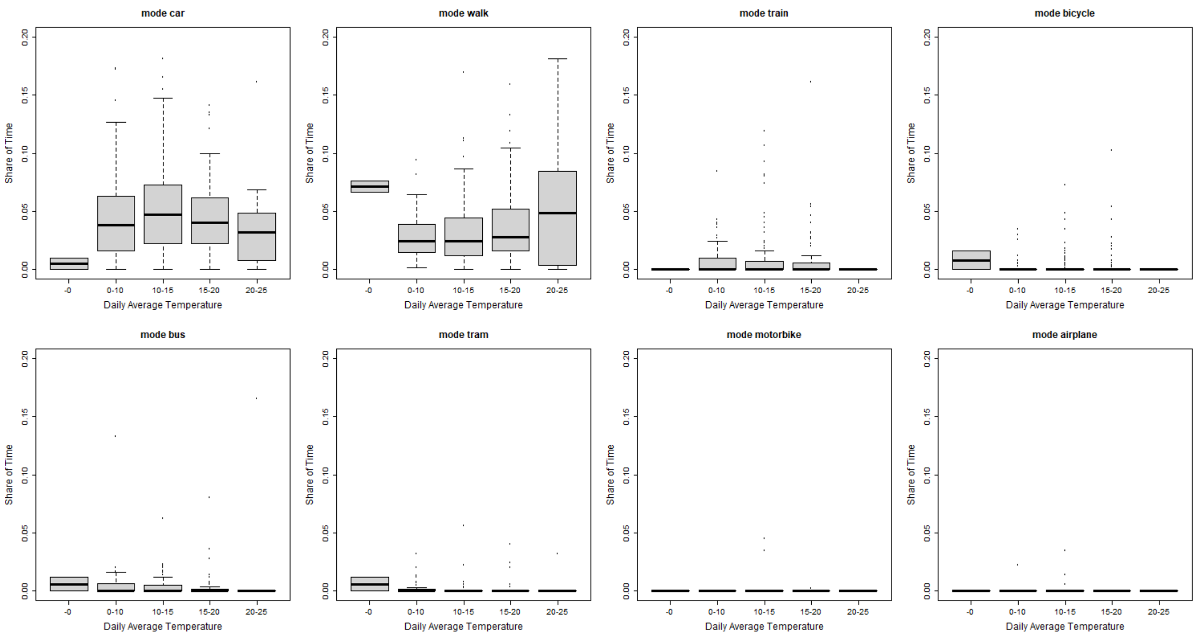
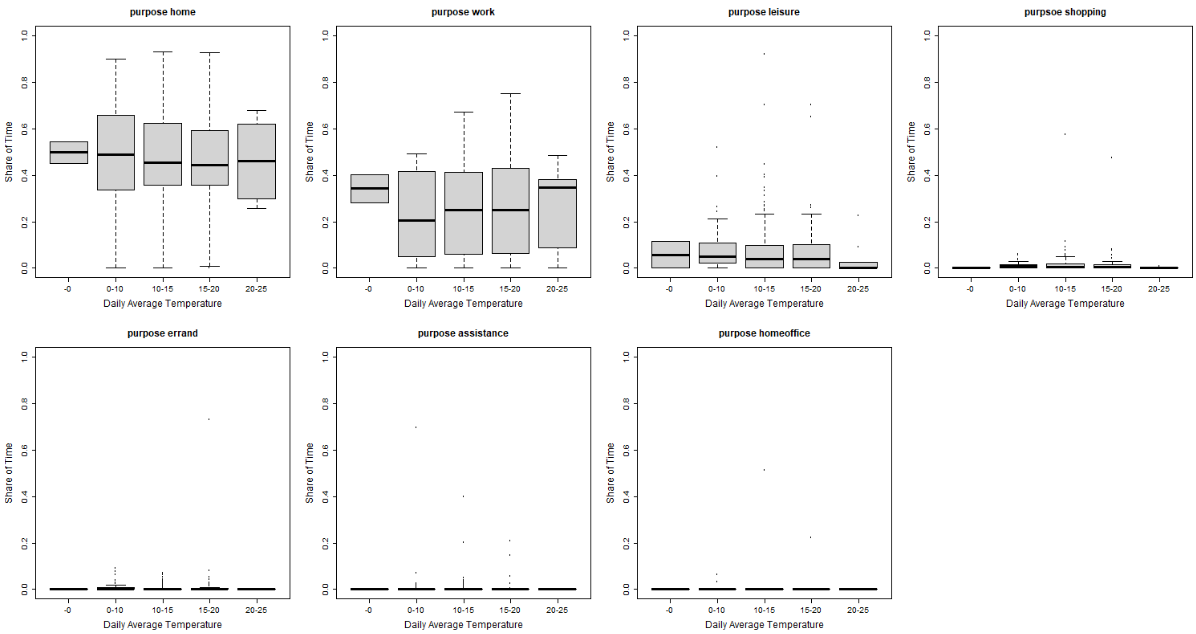


Figure 31: Box Plot of Purpose Share by Average Temperature, Phase 1, Stream 2



B.3 Box Plot by Daily Precipitation [Phase 1]

This section includes box plots grouped by precipitation level in phase 1.

Figure 32: Box Plot of Mode Share by Daily Precipitation, Phase 1, Stream 1

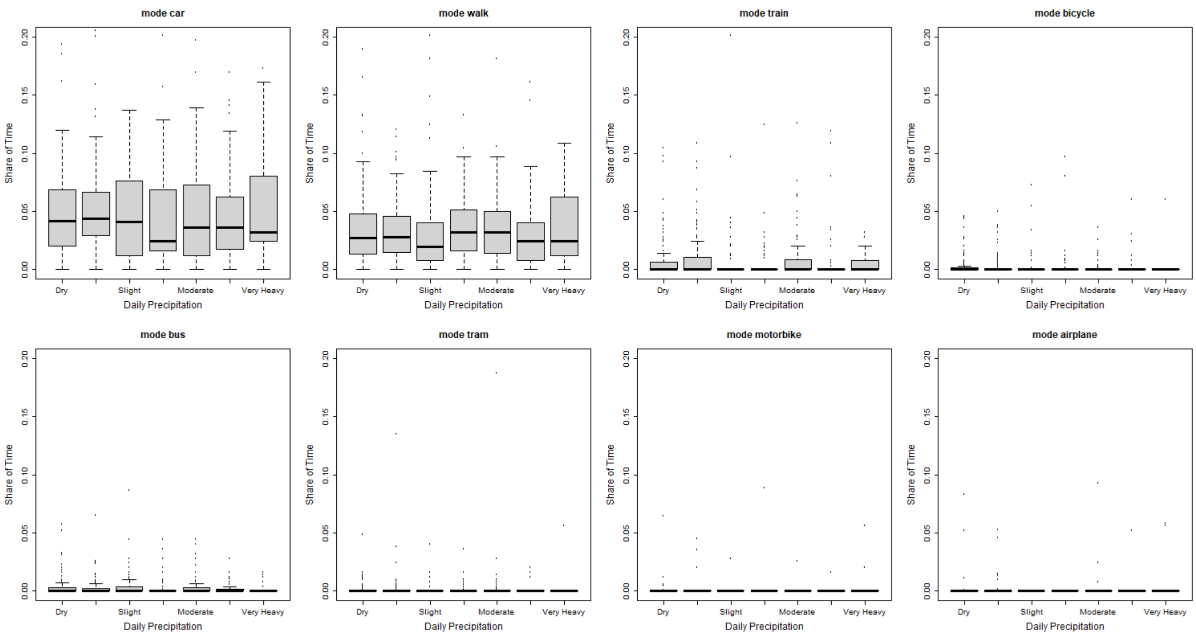


Figure 33: Box Plot of Purpose Share by Daily Precipitation, Phase 1, Stream 1

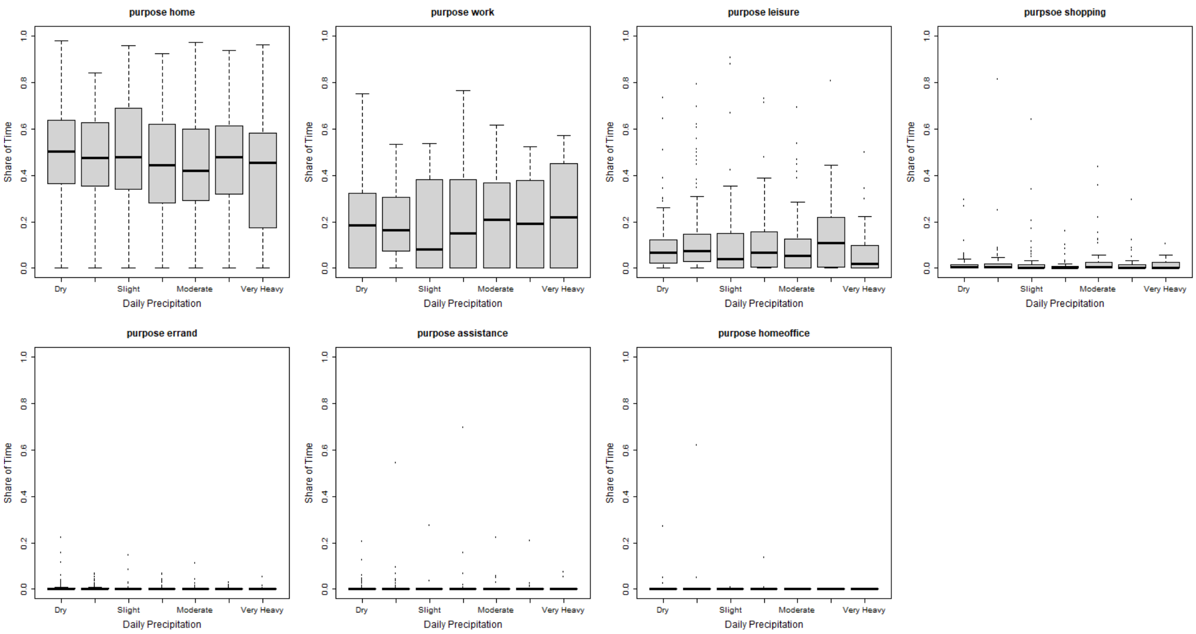


Figure 34: Box Plot of Mode Share by Daily Precipitation, Phase 1, Stream 2

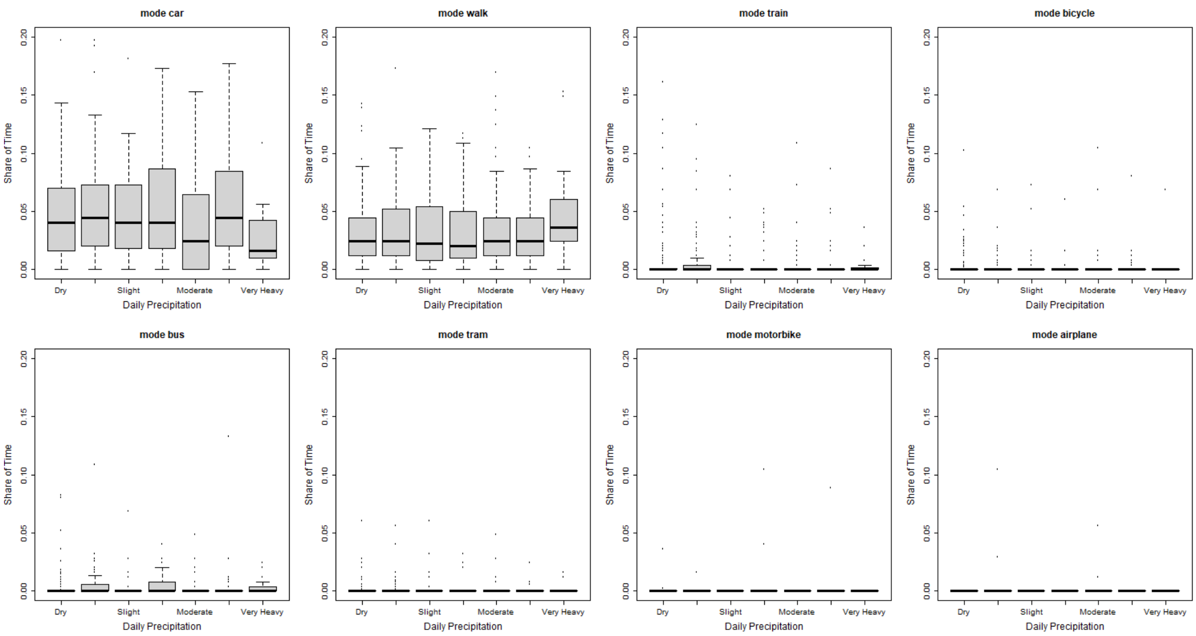
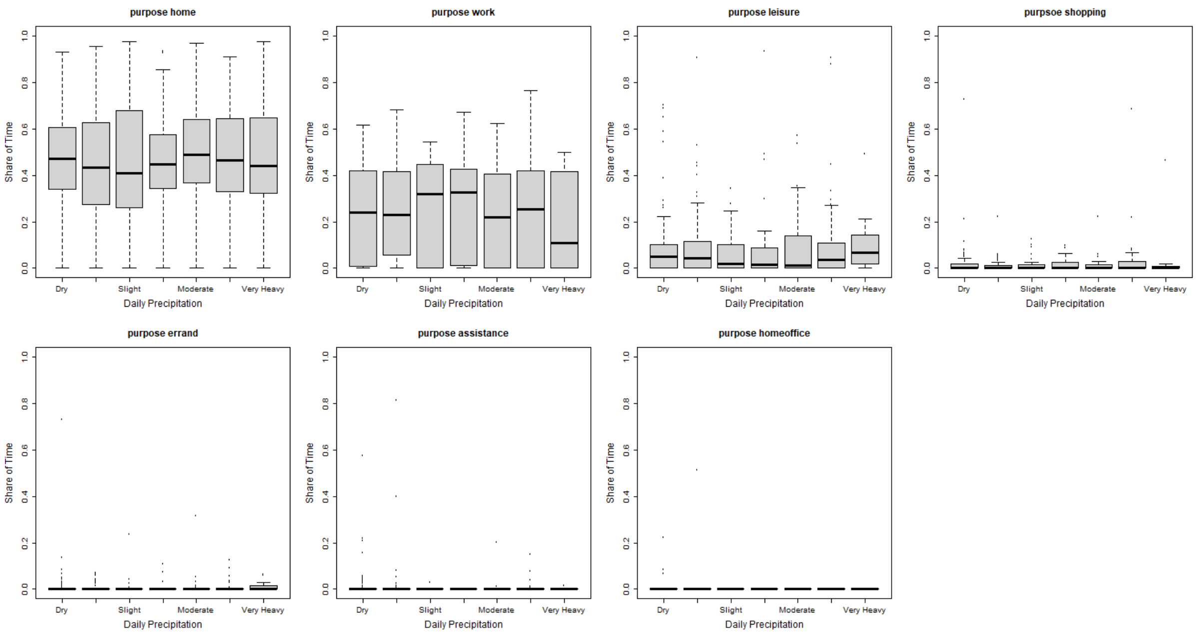


Figure 35: Box Plot of Purpose Share by Daily Precipitation, Phase 1, Stream 2



C Additional Results from Cluster Analysis

C.1 Detailed Result of Cluster Analysis for Each Mode and Purpose, Grouped by Phase

This section shows more detailed results for Table 14.

Table 23: P-Values from Cluster Analysis for Mode, Grouped by Phase, Stream 1, Detailed Version

Car							
Kruskal-Wallis Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.0345	0.0000	0.0002	0.9117	0.0000	0.0000
P2	0.0345	NA	0.0000	0.0000	0.0495	0.0000	0.0000
P4	0.0000	0.0000	NA	0.0000	0.0000	0.0000	0.0000
P5	0.0002	0.0000	0.0000	NA	0.0001	0.4862	0.0306
P6	0.9117	0.0495	0.0000	0.0001	NA	0.0000	0.0000
P7	0.0000	0.0000	0.0000	0.4862	0.0000	NA	0.1379
P8	0.0000	0.0000	0.0000	0.0306	0.0000	0.1379	NA
Levene's Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.0218	0.0000	0.1526	0.0703	0.0010	0.0000
P2	0.0218	NA	0.0000	0.0003	0.6958	0.0000	0.0000
P4	0.0000	0.0000	NA	0.0000	0.0000	0.0000	0.0003
P5	0.1526	0.0003	0.0000	NA	0.0019	0.0772	0.0005
P6	0.0703	0.6958	0.0000	0.0019	NA	0.0000	0.0000
P7	0.0010	0.0000	0.0000	0.0772	0.0000	NA	0.0826
P8	0.0000	0.0000	0.0003	0.0005	0.0000	0.0826	NA
Walk							
Kruskal-Wallis Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.0089	0.0000	0.0000	0.5860	0.6518	0.1712
P2	0.0089	NA	0.0000	0.0085	0.0517	0.0024	0.2499
P4	0.0000	0.0000	NA	0.0003	0.0000	0.0000	0.0000
P5	0.0000	0.0085	0.0003	NA	0.0000	0.0000	0.0006
P6	0.5860	0.0517	0.0000	0.0000	NA	0.3606	0.4091
P7	0.6518	0.0024	0.0000	0.0000	0.3606	NA	0.0813
P8	0.1712	0.2499	0.0000	0.0006	0.4091	0.0813	NA
Levene's Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.0198	0.0157	0.0625	0.4845	0.7233	0.4013
P2	0.0198	NA	0.8612	0.5223	0.0011	0.0186	0.0808
P4	0.0157	0.8612	NA	0.4255	0.0009	0.0149	0.0635
P5	0.0625	0.5223	0.4255	NA	0.0048	0.0686	0.2361
P6	0.4845	0.0011	0.0009	0.0048	NA	0.2262	0.0872
P7	0.7233	0.0186	0.0149	0.0686	0.2262	NA	0.5530
P8	0.4013	0.0808	0.0635	0.2361	0.0872	0.5530	NA

Table 24: P-Values from Cluster Analysis for Mode, Grouped by Phase, Stream 1, Detailed Version, Cont.1

Train							
Kruskal-Wallis Test							
P1	NA	0.0072	0.0000	0.0000	0.0000	0.0000	0.0000
P2	0.0072	NA	0.0000	0.0000	0.0001	0.0000	0.0000
P4	0.0000	0.0000	NA	0.0000	0.0000	0.0000	0.0000
P5	0.0000	0.0000	0.0000	NA	0.0000	0.0003	0.3743
P6	0.0000	0.0001	0.0000	0.0000	NA	0.5632	0.0010
P7	0.0000	0.0000	0.0000	0.0003	0.5632	NA	0.0061
P8	0.0000	0.0000	0.0000	0.3743	0.0010	0.0061	NA
Levene's Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.3805	0.0000	0.0000	0.0035	0.0000	0.0000
P2	0.3805	NA	0.0000	0.0000	0.0633	0.0001	0.0000
P4	0.0000	0.0000	NA	0.0003	0.0000	0.0000	0.0000
P5	0.0000	0.0000	0.0003	NA	0.0000	0.0071	0.2083
P6	0.0035	0.0633	0.0000	0.0000	NA	0.0429	0.0032
P7	0.0000	0.0001	0.0000	0.0071	0.0429	NA	0.2348
P8	0.0000	0.0000	0.0000	0.2083	0.0032	0.2348	NA
Bicycle							
Kruskal-Wallis Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.0015	0.8364	0.0003	0.0000	0.4465	0.8769
P2	0.0015	NA	0.0034	0.0000	0.0000	0.0001	0.0025
P4	0.8364	0.0034	NA	0.0002	0.0000	0.3362	0.9613
P5	0.0003	0.0000	0.0002	NA	0.0941	0.0043	0.0002
P6	0.0000	0.0000	0.0000	0.0941	NA	0.0000	0.0000
P7	0.4465	0.0001	0.3362	0.0043	0.0000	NA	0.3567
P8	0.8769	0.0025	0.9613	0.0002	0.0000	0.3567	NA
Levene's Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.0157	0.6186	0.0003	0.0000	0.3772	0.2934
P2	0.0157	NA	0.0029	0.0000	0.0000	0.0017	0.1094
P4	0.6186	0.0029	NA	0.0010	0.0000	0.6642	0.1041
P5	0.0003	0.0000	0.0010	NA	0.2098	0.0055	0.0000
P6	0.0000	0.0000	0.0000	0.2098	NA	0.0001	0.0000
P7	0.3772	0.0017	0.6642	0.0055	0.0001	NA	0.0546
P8	0.2934	0.1094	0.1041	0.0000	0.0000	0.0546	NA

Table 25: P-Values from Cluster Analysis for Mode, Grouped by Phase, Stream 1, Detailed Version, Cont.2

Bus							
Kruskal-Wallis Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.3187	0.0000	0.0000	0.0000	0.0000	0.0000
P2	0.3187	NA	0.0000	0.0000	0.0000	0.0000	0.0000
P4	0.0000	0.0000	NA	0.0208	0.0000	0.0000	0.0000
P5	0.0000	0.0000	0.0208	NA	0.0001	0.0000	0.0064
P6	0.0000	0.0000	0.0000	0.0001	NA	0.8361	0.1866
P7	0.0000	0.0000	0.0000	0.0000	0.8361	NA	0.1277
P8	0.0000	0.0000	0.0000	0.0064	0.1866	0.1277	NA
Levene's Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.2863	0.0000	0.0000	0.0000	0.0000	0.0000
P2	0.2863	NA	0.0000	0.0000	0.0000	0.0000	0.0000
P4	0.0000	0.0000	NA	0.0015	0.0000	0.0000	0.0000
P5	0.0000	0.0000	0.0015	NA	0.0028	0.0016	0.0700
P6	0.0000	0.0000	0.0000	0.0028	NA	0.9570	0.1710
P7	0.0000	0.0000	0.0000	0.0016	0.9570	NA	0.1595
P8	0.0000	0.0000	0.0000	0.0700	0.1710	0.1595	NA
Tram							
Kruskal-Wallis Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.5526	0.0000	0.0000	0.0000	0.0000	0.0000
P2	0.5526	NA	0.0000	0.0000	0.0000	0.0000	0.0000
P4	0.0000	0.0000	NA	0.0083	0.0001	0.0002	0.0000
P5	0.0000	0.0000	0.0083	NA	0.2308	0.2521	0.1017
P6	0.0000	0.0000	0.0001	0.2308	NA	0.9607	0.6575
P7	0.0000	0.0000	0.0002	0.2521	0.9607	NA	0.6243
P8	0.0000	0.0000	0.0000	0.1017	0.6575	0.6243	NA
Levene's Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.4639	0.0000	0.0000	0.0000	0.0000	0.0000
P2	0.4639	NA	0.0000	0.0000	0.0000	0.0000	0.0000
P4	0.0000	0.0000	NA	0.0129	0.0053	0.0007	0.0019
P5	0.0000	0.0000	0.0129	NA	0.8149	0.3485	0.6241
P6	0.0000	0.0000	0.0053	0.8149	NA	0.4695	0.7969
P7	0.0000	0.0000	0.0007	0.3485	0.4695	NA	0.6282
P8	0.0000	0.0000	0.0019	0.6241	0.7969	0.6282	NA

Table 26: P-Values from Cluster Analysis for Mode, Grouped by Phase, Stream 1, Detailed Version, Cont.3

Motorbike							
Kruskal-Wallis Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.6245	0.1537	0.6198	0.8666	0.0227	0.0119
P2	0.6245	NA	0.3462	0.9961	0.5122	0.0702	0.0401
P4	0.1537	0.3462	NA	0.3490	0.1124	0.3712	0.2501
P5	0.6198	0.9961	0.3490	NA	0.5068	0.0708	0.0403
P6	0.8666	0.5122	0.1124	0.5068	NA	0.0151	0.0077
P7	0.0227	0.0702	0.3712	0.0708	0.0151	NA	0.7948
P8	0.0119	0.0401	0.2501	0.0403	0.0077	0.7948	NA
Levene's Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.8262	0.0874	0.7872	0.3033	0.0552	0.0246
P2	0.8262	NA	0.0851	0.6448	0.4305	0.0570	0.0295
P4	0.0874	0.0851	NA	0.1730	0.0195	0.7507	0.4693
P5	0.7872	0.6448	0.1730	NA	0.2179	0.1157	0.0590
P6	0.3033	0.4305	0.0195	0.2179	NA	0.0130	0.0068
P7	0.0552	0.0570	0.7507	0.1157	0.0130	NA	0.7069
P8	0.0246	0.02947	0.4693	0.0590	0.0068	0.7069	NA
Airplane							
Kruskal-Wallis Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.1469	0.0000	0.0000	0.0006	0.0041	0.0000
P2	0.1469	NA	0.0009	0.0009	0.0319	0.1315	0.0009
P4	0.0000	0.0009	NA	NaN	0.0832	0.0252	NaN
P5	0.0000	0.0009	NaN	NA	0.0832	0.0252	NaN
P6	0.0006	0.0319	0.0832	0.0832	NA	0.4804	0.0832
P7	0.0041	0.1315	0.0252	0.0252	0.4804	NA	0.0252
P8	0.0000	0.0009	NaN	NaN	0.0832	0.0252	NA
Levene's Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.7251	0.0002	0.0002	0.0073	0.3338	0.0002
P2	0.7251	NA	0.0028	0.0028	0.0205	0.2606	0.0028
P4	0.0002	0.0028	NA	NaN	0.0857	0.1584	NaN
P5	0.0002	0.0028	NaN	NA	0.0857	0.1584	NaN
P6	0.0073	0.0205	0.0857	0.0857	NA	0.4162	0.0857
P7	0.3338	0.2606	0.1584	0.1584	0.4162	NA	0.1584
P8	0.0002	0.0028	NaN	NaN	0.0857	0.1584	NA

Table 27: P-Values from Cluster Analysis for Purpose, Grouped by Phase, Stream 1, Detailed Version

Home							
Kruskal-Wallis Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.0478	0.0000	0.0000	0.0011	0.0000	0.0000
P2	0.0478	NA	0.0000	0.0000	0.1644	0.0000	0.0000
P4	0.0000	0.0000	NA	0.0017	0.0000	0.0321	0.4161
P5	0.0000	0.0000	0.0017	NA	0.0000	0.2572	0.0121
P6	0.0011	0.1644	0.0000	0.0000	NA	0.0000	0.0000
P7	0.0000	0.0000	0.0321	0.2572	0.0000	NA	0.1687
P8	0.0000	0.0000	0.4161	0.0121	0.0000	0.1687	NA
Levene's Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.0272	0.0000	0.0000	0.0000	0.0000	0.0000
P2	0.0272	NA	0.0000	0.0000	0.0000	0.0000	0.0000
P4	0.0000	0.0000	NA	0.0001	0.0001	0.0103	0.0409
P5	0.0000	0.0000	0.0001	NA	0.8825	0.2061	0.0691
P6	0.0000	0.0000	0.0001	0.8825	NA	0.1647	0.0530
P7	0.0000	0.0000	0.0103	0.2061	0.1647	NA	0.5935
P8	0.0000	0.0000	0.0409	0.0691	0.0530	0.5935	NA
Work							
Kruskal-Wallis Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.1202	0.0000	0.0000	0.0000	0.0000	0.0000
P2	0.1202	NA	0.0000	0.0000	0.0000	0.0000	0.0001
P4	0.0000	0.0000	NA	0.0000	0.0000	0.0000	0.0000
P5	0.0000	0.0000	0.0000	NA	0.1441	0.0457	0.0002
P6	0.0000	0.0000	0.0000	0.1441	NA	0.5406	0.0179
P7	0.0000	0.0000	0.0000	0.0457	0.5406	NA	0.0830
P8	0.0000	0.0001	0.0000	0.0002	0.0179	0.0830	NA
Levene's Test							
P1	NA	0.1833	0.0000	0.0000	0.0010	0.0186	0.5940
P2	0.1833	NA	0.0000	0.0000	0.0001	0.0020	0.1671
P4	0.0000	0.0000	NA	0.0008	0.0000	0.0000	0.0000
P5	0.0000	0.0000	0.0008	NA	0.1649	0.0391	0.0004
P6	0.0010	0.0001	0.0000	0.1649	NA	0.4788	0.0258
P7	0.0186	0.0020	0.0000	0.0391	0.4788	NA	0.1362
P8	0.5940	0.1671	0.0000	0.0004	0.0258	0.1362	NA

Table 28: P-Values from Cluster Analysis for Purpose, Grouped by Phase, Stream 1, Detailed Version, Cont.1

Leisure							
Kruskal-Wallis Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.3073	0.0000	0.0000	0.6361	0.0000	0.0000
P2	0.3073	NA	0.0000	0.0000	0.5379	0.0000	0.0000
P4	0.0000	0.0000	NA	0.0000	0.0000	0.0000	0.0000
P5	0.0000	0.0000	0.0000	NA	0.0000	0.8620	0.0004
P6	0.6361	0.5379	0.0000	0.0000	NA	0.0000	0.0000
P7	0.0000	0.0000	0.0000	0.8620	0.0000	NA	0.0008
P8	0.0000	0.0000	0.0000	0.0004	0.0000	0.0008	NA
Levene's Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.4593	0.0000	0.0059	0.0616	0.0001	0.0000
P2	0.4593	NA	0.0000	0.0009	0.2646	0.0000	0.0000
P4	0.0000	0.0000	NA	0.0000	0.0000	0.0000	0.0550
P5	0.0059	0.0009	0.0000	NA	0.0000	0.3178	0.0001
P6	0.0616	0.2646	0.0000	0.0000	NA	0.0000	0.0000
P7	0.0001	0.0000	0.0000	0.3178	0.0000	NA	0.0013
P8	0.0000	0.0000	0.0550	0.0001	0.0000	0.0013	NA
Shopping							
Kruskal-Wallis Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.4938	0.0000	0.3940	0.8876	0.7538	0.7114
P2	0.4938	NA	0.0000	0.8994	0.4017	0.6894	0.7317
P4	0.0000	0.0000	NA	0.0000	0.0000	0.0000	0.0000
P5	0.3940	0.8994	0.0000	NA	0.3112	0.5757	0.6146
P6	0.8876	0.4017	0.0000	0.3112	NA	0.6388	0.6098
P7	0.7538	0.6894	0.0000	0.5757	0.6388	NA	0.9594
P8	0.7114	0.7317	0.0000	0.6146	0.6098	0.9594	NA
Levene's Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.0973	0.0000	0.8542	0.2650	0.2995	0.6546
P2	0.0973	NA	0.0000	0.1403	0.6026	0.0114	0.0500
P4	0.0000	0.0000	NA	0.0000	0.0000	0.0000	0.0000
P5	0.8542	0.1403	0.0000	NA	0.3511	0.2270	0.5354
P6	0.2650	0.6026	0.0000	0.3511	NA	0.0403	0.1398
P7	0.2995	0.0114	0.0000	0.2270	0.0403	NA	0.5688
P8	0.6546	0.0500	0.0000	0.5354	0.1398	0.5688	NA

Table 29: P-Values from Cluster Analysis for Purpose, Grouped by Phase, Stream 1, Detailed Version, Cont.2

Errand							
Kruskal-Wallis Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.6992	0.0000	0.0007	0.0003	0.2650	0.0206
P2	0.6992	NA	0.0000	0.0028	0.0013	0.4651	0.0542
P4	0.0000	0.0000	NA	0.0009	0.0022	0.0000	0.0000
P5	0.0007	0.0028	0.0009	NA	0.8083	0.0222	0.2787
P6	0.0003	0.0013	0.0022	0.8083	NA	0.0119	0.1853
P7	0.2650	0.4651	0.0000	0.0222	0.0119	NA	0.2250
P8	0.0206	0.0542	0.0000	0.2787	0.1853	0.2250	NA
Levene's Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.2198	0.0000	0.0006	0.0049	0.1059	0.0058
P2	0.2198	NA	0.0000	0.0009	0.0217	0.5191	0.0262
P4	0.0000	0.0000	NA	0.0277	0.0072	0.0008	0.0034
P5	0.0006	0.0009	0.0277	NA	0.4001	0.0487	0.2977
P6	0.0049	0.0217	0.0072	0.4001	NA	0.2089	0.8852
P7	0.1059	0.5191	0.0008	0.0487	0.2089	NA	0.2424
P8	0.0058	0.0262	0.0034	0.2977	0.8852	0.2424	NA
Assistance							
Kruskal-Wallis Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.1433	0.0000	0.2260	0.5879	0.0303	0.0792
P2	0.1433	NA	0.0000	0.0086	0.0478	0.0003	0.0014
P4	0.0000	0.0000	NA	0.0003	0.0000	0.0058	0.0016
P5	0.2260	0.0086	0.0003	NA	0.5083	0.3612	0.6023
P6	0.5879	0.0478	0.0000	0.5083	NA	0.1120	0.2320
P7	0.0303	0.0003	0.0058	0.3612	0.1120	NA	0.6817
P8	0.0792	0.0014	0.0016	0.6023	0.2320	0.6817	NA
Levene's Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.1322	0.6250	0.3008	0.3178	0.1480	0.0169
P2	0.1322	NA	0.0558	0.7024	0.6096	0.0032	0.0001
P4	0.6250	0.0558	NA	0.1500	0.1522	0.4006	0.0993
P5	0.3008	0.7024	0.1500	NA	0.9200	0.0184	0.0015
P6	0.3178	0.6096	0.1522	0.9200	NA	0.0143	0.0007
P7	0.1480	0.0032	0.4006	0.0184	0.0143	NA	0.3537
P8	0.0169	0.0001	0.0993	0.0015	0.0007	0.3537	NA

Table 30: P-Values from Cluster Analysis for Purpose, Grouped by Phase, Stream 1, Detailed Version, Cont.3

Homeoffice							
Kruskal-Wallis Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.1822	0.0054	0.2042	0.6066	0.0106	0.0006
P2	0.1822	NA	0.0001	0.0113	0.0689	0.0002	0.0000
P4	0.0054	0.0001	NA	0.1198	0.0219	0.7979	0.5111
P5	0.2042	0.0113	0.1198	NA	0.4487	0.1906	0.0271
P6	0.6066	0.0689	0.0219	0.4487	NA	0.0400	0.0033
P7	0.0106	0.0002	0.7979	0.1906	0.0400	NA	0.3637
P8	0.0006	0.0000	0.5111	0.0271	0.0033	0.3637	NA
Levene's Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.3007	0.0001	0.0112	0.0906	0.0002	0.0000
P2	0.3007	NA	0.0023	0.1729	0.6278	0.0080	0.0011
P4	0.0001	0.0023	NA	0.0549	0.0057	0.5254	0.9547
P5	0.0112	0.1729	0.0549	NA	0.3375	0.1662	0.0437
P6	0.0906	0.6278	0.0057	0.3375	NA	0.0200	0.0030
P7	0.0002	0.0080	0.5254	0.1662	0.0200	NA	0.5358
P8	0.0000	0.0011	0.9547	0.0437	0.0030	0.5358	NA

Table 31: P-Values from Cluster Analysis for Mode, Grouped by Phase, Stream 2, Detailed Version

Car							
Kruskal-Wallis Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.2782	0.0000	0.0000	0.3678	0.0023	0.0000
P2	0.2782	NA	0.0000	0.0000	0.0577	0.0001	0.0000
P4	0.0000	0.0000	NA	0.0000	0.0000	0.0000	0.0000
P5	0.0000	0.0000	0.0000	NA	0.0000	0.0485	0.4343
P6	0.3678	0.0577	0.0000	0.0000	NA	0.0294	0.0006
P7	0.0023	0.0001	0.0000	0.0485	0.0294	NA	0.2176
P8	0.0000	0.0000	0.0000	0.4343	0.0006	0.2176	NA
Levene's Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.1132	0.0000	0.1133	0.5330	0.4055	0.0019
P2	0.1132	NA	0.0000	0.0019	0.3695	0.0181	0.0000
P4	0.0000	0.0000	NA	0.0000	0.0000	0.0000	0.0000
P5	0.1133	0.0019	0.0000	NA	0.0343	0.4651	0.2101
P6	0.5330	0.3695	0.0000	0.0343	NA	0.1613	0.0003
P7	0.4055	0.0181	0.0000	0.4651	0.1613	NA	0.0376
P8	0.0019	0.0000	0.0000	0.2101	0.0003	0.0376	NA
Walk							
Kruskal-Wallis Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.3977	0.0003	0.1600	0.6367	0.0000	0.0033
P2	0.3977	NA	0.0064	0.6168	0.7496	0.0000	0.0000
P4	0.0003	0.0064	NA	0.0347	0.0031	0.0000	0.0000
P5	0.1600	0.6168	0.0347	NA	0.3598	0.0000	0.0001
P6	0.6367	0.7496	0.0031	0.3598	NA	0.0000	0.0021
P7	0.0000	0.0000	0.0000	0.0000	0.0000	NA	0.2621
P8	0.0033	0.0000	0.0000	0.0001	0.0021	0.2621	NA
Levene's Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.1478	0.3979	0.9683	0.0306	0.0776	0.0321
P2	0.1478	NA	0.4881	0.1394	0.0010	0.0020	0.0005
P4	0.3979	0.4881	NA	0.3937	0.0037	0.0080	0.0021
P5	0.9683	0.1394	0.3937	NA	0.0229	0.0573	0.0209
P6	0.0306	0.0010	0.0037	0.0229	NA	0.4914	0.6656
P7	0.0776	0.0020	0.0080	0.0573	0.4914	NA	0.7439
P8	0.0321	0.0005	0.0021	0.0209	0.6656	0.7439	NA

Table 32: P-Values from Cluster Analysis for Mode, Grouped by Phase, Stream 2, Detailed Version, Cont.1

Train							
Kruskal-Wallis Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.6214	0.0000	0.0000	0.0000	0.0000	0.0000
P2	0.6214	NA	0.0000	0.0000	0.0002	0.0001	0.0000
P4	0.0000	0.0000	NA	0.0011	0.0001	0.0001	0.0053
P5	0.0000	0.0000	0.0011	NA	0.4319	0.4699	0.6066
P6	0.0000	0.0002	0.0001	0.4319	NA	0.9404	0.1941
P7	0.0000	0.0001	0.0001	0.4699	0.9404	NA	0.2163
P8	0.0000	0.0000	0.0053	0.6066	0.1941	0.2163	NA
Levene's Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.6449	0.0000	0.0031	0.2523	0.0020	0.0008
P2	0.6449	NA	0.0001	0.0353	0.5545	0.0290	0.0153
P4	0.0000	0.0001	NA	0.0077	0.0002	0.0026	0.0154
P5	0.0031	0.0353	0.0077	NA	0.1114	0.9890	0.6976
P6	0.2523	0.5545	0.0002	0.1114	NA	0.0954	0.0522
P7	0.0020	0.0290	0.0026	0.9890	0.0954	NA	0.6854
P8	0.0008	0.0153	0.0154	0.6976	0.0522	0.6854	NA
Bicycle							
Kruskal-Wallis Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.1224	0.0050	0.1135	0.0001	0.9951	0.4428
P2	0.1224	NA	0.0000	0.0022	0.0000	0.1267	0.0227
P4	0.0050	0.0000	NA	0.2245	0.2647	0.0052	0.0403
P5	0.1135	0.0022	0.2245	NA	0.0192	0.1156	0.4077
P6	0.0001	0.0000	0.2647	0.0192	NA	0.0001	0.0013
P7	0.9951	0.1267	0.0052	0.1156	0.0001	NA	0.4514
P8	0.4428	0.0227	0.0403	0.4077	0.0013	0.4514	NA
Levene's Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.5604	0.0001	0.0051	0.0000	0.6549	0.2075
P2	0.5604	NA	0.0000	0.0009	0.0000	0.2873	0.0631
P4	0.0001	0.0000	NA	0.3307	0.5304	0.0003	0.0058
P5	0.0051	0.0009	0.3307	NA	0.1177	0.0129	0.0913
P6	0.0000	0.0000	0.5304	0.1177	NA	0.0000	0.0009
P7	0.6549	0.2873	0.0003	0.0129	0.0000	NA	0.3891
P8	0.2075	0.0631	0.0058	0.0913	0.0009	0.3891	NA

Table 33: P-Values from Cluster Analysis for Mode, Grouped by Phase, Stream 2, Detailed Version, Cont.2

Bus							
Kruskal-Wallis Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.7723	0.0000	0.0083	0.3216	0.0786	0.2170
P2	0.7723	NA	0.0000	0.0032	0.1959	0.0394	0.1256
P4	0.0000	0.0000	NA	0.0007	0.0000	0.0000	0.0000
P5	0.0083	0.0032	0.0007	NA	0.0915	0.3678	0.1509
P6	0.3216	0.1959	0.0000	0.0915	NA	0.4331	0.8040
P7	0.0786	0.0394	0.0000	0.3678	0.4331	NA	0.5922
P8	0.2170	0.1256	0.0000	0.1509	0.8040	0.5922	NA
Levene's Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.9503	0.0000	0.0005	0.0113	0.0062	0.0165
P2	0.9503	NA	0.0001	0.0043	0.0343	0.0223	0.0440
P4	0.0000	0.0001	NA	0.0051	0.0000	0.0003	0.0000
P5	0.0005	0.0043	0.0051	NA	0.1593	0.2993	0.1238
P6	0.0113	0.0343	0.0000	0.1593	NA	0.7403	0.8707
P7	0.0062	0.0223	0.0003	0.2993	0.7403	NA	0.6282
P8	0.0165	0.0440	0.0000	0.1238	0.8707	0.6282	NA
Tram							
Kruskal-Wallis Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.4014	0.0000	0.0413	0.0772	0.0533	0.1916
P2	0.4014	NA	0.0000	0.0043	0.0094	0.0058	0.0325
P4	0.0000	0.0000	NA	0.0041	0.0016	0.0026	0.0004
P5	0.0413	0.0043	0.0041	NA	0.7627	0.8931	0.4379
P6	0.0772	0.0094	0.0016	0.7627	NA	0.8659	0.6332
P7	0.0533	0.0058	0.0026	0.8931	0.8659	NA	0.5179
P8	0.1916	0.0325	0.0004	0.4379	0.6332	0.5179	NA
Levene's Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.5928	0.0001	0.8974	0.0480	0.0886	0.0432
P2	0.5928	NA	0.0001	0.8392	0.0209	0.0390	0.0189
P4	0.0001	0.0001	NA	0.0515	0.0098	0.0327	0.0018
P5	0.8974	0.8392	0.0515	NA	0.2578	0.2921	0.2628
P6	0.0480	0.0209	0.0098	0.2578	NA	0.9138	0.9452
P7	0.0886	0.0390	0.0327	0.2921	0.9138	NA	0.9543
P8	0.0432	0.0189	0.0018	0.2628	0.9452	0.9543	NA

Table 34: P-Values from Cluster Analysis for Mode, Grouped by Phase, Stream 2, Detailed Version, Cont.3

Motorbike							
Kruskal-Wallis Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.6098	0.8107	0.4374	0.5028	0.2844	0.0817
P2	0.6098	NA	0.7830	0.7864	0.2407	0.5677	0.2055
P4	0.8107	0.7830	NA	0.5869	0.3635	0.4026	0.1289
P5	0.4374	0.7864	0.5869	NA	0.1518	0.7636	0.3153
P6	0.5028	0.2407	0.3635	0.1518	NA	0.0861	0.0191
P7	0.2844	0.5677	0.4026	0.7636	0.0861	NA	0.4770
P8	0.0817	0.2055	0.1289	0.3153	0.0191	0.4770	NA
Levene's Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.2397	0.8410	0.4000	0.4413	0.3638	0.1251
P2	0.2397	NA	0.2132	0.6442	0.0387	0.7302	0.4958
P4	0.8410	0.2132	NA	0.4284	0.2884	0.3812	0.0811
P5	0.4000	0.6442	0.4284	NA	0.0856	0.9196	0.2950
P6	0.4413	0.0387	0.2884	0.0856	NA	0.0751	0.0157
P7	0.3638	0.7302	0.3812	0.9196	0.0751	NA	0.3586
P8	0.1251	0.4958	0.0811	0.2950	0.0157	0.3586	NA
Airplane							
Kruskal-Wallis Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.5543	0.0080	0.0080	0.0934	0.0331	0.0933
P2	0.5543	NA	0.0251	0.0251	0.2547	0.1019	0.2559
P4	0.0080	0.0251	NA	NaN	0.1571	0.3173	0.1571
P5	0.0080	0.0251	NaN	NA	0.1571	0.3173	0.1571
P6	0.0934	0.2547	0.1571	0.1571	NA	0.5634	1.0000
P7	0.0331	0.1019	0.3173	0.3173	0.5634	NA	0.5634
P8	0.0933	0.2559	0.1571	0.1571	1.0000	0.5634	NA
Levene's Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.1108	0.0171	0.0171	0.0409	0.0237	0.0322
P2	0.1108	NA	0.0829	0.0829	0.3897	0.1615	0.2756
P4	0.0171	0.0829	NA	NaN	0.2934	0.3175	0.1604
P5	0.0171	0.0829	NaN	NA	0.2934	0.3175	0.1604
P6	0.0409	0.3897	0.2934	0.2934	NA	0.5611	0.8569
P7	0.0237	0.1615	0.3175	0.3175	0.5611	NA	0.5656
P8	0.0322	0.2756	0.1604	0.1604	0.8569	0.5656	NA

Table 35: P-Values from Cluster Analysis for Purpose, Grouped by Phase, Stream 2, Detailed Version

Home							
Kruskal-Wallis Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.8982	0.0000	0.0374	0.4764	0.0000	0.0000
P2	0.8982	NA	0.0000	0.0432	0.4280	0.0000	0.0000
P4	0.0000	0.0000	NA	0.0006	0.0000	0.2798	0.9827
P5	0.0374	0.0432	0.0006	NA	0.0093	0.0045	0.0000
P6	0.4764	0.4280	0.0000	0.0093	NA	0.0000	0.0000
P7	0.0000	0.0000	0.2798	0.0045	0.0000	NA	0.1660
P8	0.0000	0.0000	0.9827	0.0000	0.0000	0.1660	NA
Levene's Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.7931	0.0007	0.0081	0.0173	0.9170	0.2158
P2	0.7931	NA	0.0003	0.0042	0.0092	0.9045	0.3137
P4	0.0007	0.0003	NA	0.3564	0.2140	0.0020	0.0000
P5	0.0081	0.0042	0.3564	NA	0.7448	0.0168	0.0006
P6	0.0173	0.0092	0.2140	0.7448	NA	0.0320	0.0013
P7	0.9170	0.9045	0.0020	0.0168	0.0320	NA	0.3142
P8	0.2158	0.3137	0.0000	0.0006	0.0013	0.3142	NA
Work							
Kruskal-Wallis Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.3799	0.1236	0.4857	0.7401	0.5545	0.2674
P2	0.3799	NA	0.0190	0.1267	0.2359	0.7793	0.8220
P4	0.1236	0.0190	NA	0.4165	0.2364	0.0369	0.0104
P5	0.4857	0.1267	0.4165	NA	0.7255	0.2083	0.0821
P6	0.7401	0.2359	0.2364	0.7255	NA	0.3610	0.1601
P7	0.5545	0.7793	0.0369	0.2083	0.3610	NA	0.6149
P8	0.2674	0.8220	0.0104	0.0821	0.1601	0.6149	NA
Levene's Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.2420	0.3766	0.2936	0.6355	0.2621	0.2196
P2	0.2420	NA	0.8411	0.9449	0.4915	0.9736	0.9173
P4	0.3766	0.8411	NA	0.8977	0.6592	0.8257	0.7706
P5	0.2936	0.9449	0.8977	NA	0.5544	0.9228	0.8674
P6	0.6355	0.4915	0.6592	0.5544	NA	0.4994	0.4440
P7	0.2621	0.9736	0.8257	0.9228	0.4994	NA	0.9476
P8	0.2196	0.9173	0.7706	0.8674	0.4440	0.9476	NA

Table 36: P-Values from Cluster Analysis for Purpose, Grouped by Phase, Stream 2, Detailed Version, Cont.1

Leisure							
Kruskal-Wallis Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.3122	0.0000	0.0000	0.0065	0.0000	0.0000
P2	0.3122	NA	0.0000	0.0000	0.0916	0.0000	0.0000
P4	0.0000	0.0000	NA	0.0000	0.0000	0.0000	0.0000
P5	0.0000	0.0000	0.0000	NA	0.0001	0.0927	0.3959
P6	0.0065	0.0916	0.0000	0.0001	NA	0.0125	0.0000
P7	0.0000	0.0000	0.0000	0.0927	0.0125	NA	0.0084
P8	0.0000	0.0000	0.0000	0.3959	0.0000	0.0084	NA
Levene's Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.8453	0.0000	0.0192	0.3274	0.0014	0.0000
P2	0.8453	NA	0.0000	0.0124	0.4241	0.0008	0.0000
P4	0.0000	0.0000	NA	0.0000	0.0000	0.0001	0.0155
P5	0.0192	0.0124	0.0000	NA	0.0025	0.5632	0.0561
P6	0.3274	0.4241	0.0000	0.0025	NA	0.0001	0.0000
P7	0.0014	0.0008	0.0001	0.5632	0.0001	NA	0.1452
P8	0.0000	0.0000	0.0155	0.0561	0.0000	0.1452	NA
Shopping							
Kruskal-Wallis Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.6321	0.0003	0.3669	0.4219	0.8770	0.4742
P2	0.6321	NA	0.0013	0.6908	0.7370	0.5171	0.8171
P4	0.0003	0.0013	NA	0.0048	0.0038	0.0001	0.0029
P5	0.3669	0.6908	0.0048	NA	0.9462	0.2940	0.8701
P6	0.4219	0.7370	0.0038	0.9462	NA	0.3325	0.9332
P7	0.8770	0.5171	0.0001	0.2940	0.3325	NA	0.3756
P8	0.4742	0.8171	0.0029	0.8701	0.9332	0.3756	NA
Levene's Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.1718	0.0000	0.2675	0.0581	0.7924	0.6487
P2	0.1718	NA	0.0002	0.8946	0.5860	0.3343	0.4655
P4	0.0000	0.0002	NA	0.0017	0.0006	0.0002	0.0007
P5	0.2675	0.8946	0.0017	NA	0.5452	0.4412	0.5759
P6	0.0581	0.5860	0.0006	0.5452	NA	0.1538	0.2418
P7	0.7924	0.3343	0.0002	0.4412	0.1538	NA	0.8528
P8	0.6487	0.4655	0.0007	0.5759	0.2418	0.8528	NA

Table 37: P-Values from Cluster Analysis for Purpose, Grouped by Phase, Stream 2, Detailed Version, Cont.2

Errand							
Kruskal-Wallis Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.4859	0.0039	0.0211	0.1487	0.1277	0.0884
P2	0.4859	NA	0.0003	0.0026	0.0305	0.0265	0.0153
P4	0.0039	0.0003	NA	0.5479	0.1385	0.1635	0.2181
P5	0.0211	0.0026	0.5479	NA	0.3752	0.4191	0.5312
P6	0.1487	0.0305	0.1385	0.3752	NA	0.9323	0.7971
P7	0.1277	0.0265	0.1635	0.4191	0.9323	NA	0.8571
P8	0.0884	0.0153	0.2181	0.5312	0.7971	0.8571	NA
Levene's Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.1103	0.0031	0.0045	0.0337	0.0182	0.0030
P2	0.1103	NA	0.0049	0.0102	0.3250	0.1484	0.0036
P4	0.0031	0.0049	NA	0.6543	0.1284	0.1580	0.8955
P5	0.0045	0.0102	0.6543	NA	0.2065	0.2719	0.6949
P6	0.0337	0.3250	0.1284	0.2065	NA	0.7435	0.1248
P7	0.0182	0.1484	0.1580	0.2719	0.7435	NA	0.1476
P8	0.0030	0.0036	0.8955	0.6949	0.1248	0.1476	NA

Assistance							
Kruskal-Wallis Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.3639	0.0014	0.1601	0.0841	0.0137	0.0001
P2	0.3639	NA	0.0228	0.6284	0.4111	0.1202	0.0026
P4	0.0014	0.0228	NA	0.0723	0.1449	0.4533	0.4392
P5	0.1601	0.6284	0.0723	NA	0.7337	0.2842	0.0110
P6	0.0841	0.4111	0.1449	0.7337	NA	0.4667	0.0280
P7	0.0137	0.1202	0.4533	0.2842	0.4667	NA	0.1282
P8	0.0001	0.0026	0.4392	0.0110	0.0280	0.1282	NA
Levene's Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.3432	0.9918	0.5633	0.4260	0.2146	0.0388
P2	0.3432	NA	0.4358	0.7506	0.9049	0.0481	0.0092
P4	0.9918	0.4358	NA	0.6321	0.5099	0.3849	0.1768
P5	0.5633	0.7506	0.6321	NA	0.8453	0.1145	0.0298
P6	0.4260	0.9049	0.5099	0.8453	NA	0.0725	0.0167
P7	0.2146	0.0481	0.3849	0.1145	0.0725	NA	0.4295
P8	0.0388	0.0092	0.1768	0.0298	0.0167	0.4295	NA

Table 38: P-Values from Cluster Analysis for Purpose, Grouped by Phase, Stream 2, Detailed Version, Cont.3

Homeoffice							
Kruskal-Wallis Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.0452	0.0141	0.0080	0.1571	0.0046	0.0141
P2	0.0452	NA	0.5240	0.3636	0.4124	0.2441	0.5225
P4	0.0141	0.5240	NA	0.7781	0.1549	0.5889	0.9959
P5	0.0080	0.3636	0.7781	NA	0.0935	0.7940	0.7823
P6	0.1571	0.4124	0.1549	0.0935	NA	0.0561	0.1546
P7	0.0046	0.2441	0.5889	0.7940	0.0561	NA	0.5928
P8	0.0141	0.5225	0.9959	0.7823	0.1546	0.5928	NA
Levene's Test							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.0964	0.0339	0.0189	0.2400	0.0123	0.0207
P2	0.0964	NA	0.4799	0.2462	0.2662	0.1746	0.2675
P4	0.0339	0.4799	NA	0.6158	0.0891	0.4786	0.6548
P5	0.0189	0.2462	0.6158	NA	0.0442	0.8384	0.9565
P6	0.2400	0.2662	0.0891	0.0442	NA	0.0289	0.0486
P7	0.0123	0.1746	0.4786	0.8384	0.0289	NA	0.7959
P8	0.0207	0.2675	0.6548	0.9565	0.0486	0.7959	NA

C.2 Result of Cluster Analysis for Inter- and Intra-Personal Distance, Grouped by Phase

This section shows more results for inter- and intra-personal distance grouped by phase.

Table 39: P-Values from Cluster Analysis for Intra-Personal Distance, Grouped by Phase, Stream 1

Stream 1							
Mean - Kruskal-Wallis							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.000	0.0000	0.0000	0.0000	0.0000	0.0000
P2	0.0000	NA	0.0000	0.0000	0.0000	0.0000	0.0000
P4	0.0000	0.0000	NA	0.0000	0.0000	0.0000	0.0000
P5	0.0000	0.0000	0.0000	NA	0.0000	0.0000	0.0000
P6	0.0000	0.0000	0.0000	0.0000	NA	0.0000	0.0000
P7	0.0000	0.0000	0.0000	0.0000	0.0000	NA	0.0000
P8	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	NA
Mean - Levene's							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.0011	0.0000	0.0000	0.4681	0.0000	0.0726
P2	0.0011	NA	0.0000	0.0000	0.0001	0.0000	0.1620
P4	0.0000	0.0000	NA	0.0000	0.0000	0.0000	0.0000
P5	0.0000	0.0000	0.0000	NA	0.0000	0.7914	0.0000
P6	0.4681	0.0001	0.0000	0.0000	NA	0.0000	0.0146
P7	0.0000	0.0000	0.0000	0.7914	0.0000	NA	0.0000
P8	0.0726	0.1620	0.0000	0.0000	0.0146	0.0000	NA
Variance - Kruskall-Wallis							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
P2	0.0000	NA	0.0000	0.0000	0.0000	0.0000	0.0000
P4	0.0000	0.0000	NA	0.0000	0.0000	0.0000	0.0000
P5	0.0000	0.0000	0.0000	NA	0.7610	0.0000	0.0000
P6	0.0000	0.0000	0.0000	0.7610	NA	0.0000	0.0000
P7	0.0000	0.0000	0.0000	0.0000	0.0000	NA	0.0000
P8	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	NA
Variance - Levene's							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.0005	0.0000	0.0000	0.0000	0.0000	0.0000
P2	0.0005	NA	0.0000	0.0000	0.0000	0.0000	0.0000
P4	0.0000	0.0000	NA	0.0000	0.0000	0.0000	0.0000
P5	0.0000	0.0000	0.0000	NA	0.0000	0.0000	0.0083
P6	0.0000	0.0000	0.0000	0.0000	NA	0.0000	0.0000
P7	0.0000	0.0000	0.0000	0.0000	0.0000	NA	0.0000
P8	0.0000	0.0000	0.0000	0.0083	0.0000	0.0000	NA

This section shows more cluster analysis results for KOF stringency index, daily increase, hospitalized and deceased.

Table 40: P-Values from Cluster Analysis for Intra-Personal Distance, Grouped by Phase, Stream 2

Stream 2							
Mean - Kruskal-Wallis							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
P2	0.0000	NA	0.0000	0.0000	0.0000	0.0010	0.0000
P4	0.0000	0.0000	NA	0.0000	0.0000	0.0000	0.0000
P5	0.0000	0.0000	0.0000	NA	0.0000	0.0000	0.0000
P6	0.0000	0.0000	0.0000	0.0000	NA	0.0000	0.0000
P7	0.0000	0.0010	0.0000	0.0000	0.0000	NA	0.0000
P8	0.0001	0.0000	0.0000	0.4613	0.4142	0.9061	NA
Mean - Levene's							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.0001	0.0000	0.0000	0.4613	0.4142	0.9061
P2	0.0001	NA	0.0000	0.0000	0.0034	0.0000	0.0003
P4	0.0000	0.0000	NA	0.7844	0.0000	0.0000	0.0000
P5	0.0000	0.0000	0.7844	NA	0.0000	0.0000	0.0000
P6	0.4613	0.0034	0.0000	0.0000	NA	0.1338	0.5505
P7	0.4142	0.0000	0.0000	0.0000	0.1338	NA	0.3675
P8	0.9061	0.0003	0.0000	0.0000	0.5505	0.3675	NA
Variance - Kruskall-Wallis							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
P2	0.0000	NA	0.0000	0.0000	0.0000	0.0000	0.0000
P4	0.0000	0.0000	NA	0.0000	0.0000	0.0000	0.0000
P5	0.0000	0.0000	0.0000	NA	0.0798	0.0000	0.0000
P6	0.0000	0.0000	0.0000	0.0798	NA	0.0000	0.0000
P7	0.0000	0.0000	0.0000	0.0000	0.0000	NA	0.0000
P8	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	NA
Variance - Levene's							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.5420	0.0000	0.0000	0.0000	0.0000	0.0000
P2	0.5420	NA	0.0000	0.0000	0.0000	0.0000	0.0000
P4	0.0000	0.0000	NA	0.7070	0.0000	0.6376	0.0000
P5	0.0000	0.0000	0.7070	NA	0.0000	0.4125	0.0000
P6	0.0000	0.0000	0.0000	0.0000	NA	0.0000	0.0005
P7	0.0000	0.0000	0.6376	0.4125	0.0000	NA	0.0000
P8	0.0000	0.0000	0.0000	0.0000	0.0005	0.0000	NA

Table 41: P-Values from Cluster Analysis for Inter-Personal Distance, Grouped by Phase, Stream 1

Stream 1							
Mean - Kruskal-Wallis							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
P2	0.0000	NA	0.0000	0.0000	0.0000	0.0000	0.0000
P4	0.0000	0.0000	NA	0.0000	0.0000	0.0000	0.0000
P5	0.0000	0.0000	0.0000	NA	0.1965	0.0000	0.0000
P6	0.0000	0.0000	0.0000	0.1965	NA	0.0000	0.0000
P7	0.0000	0.0000	0.0000	0.0000	0.0000	NA	0.0000
P8	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	NA
Mean - Levene's							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
P2	0.0000	NA	0.0000	0.0000	0.0000	0.0000	0.0000
P4	0.0000	0.0000	NA	0.0000	0.0000	0.0000	0.0000
P5	0.0000	0.0000	0.0000	NA	0.1850	0.0437	0.0000
P6	0.0000	0.0000	0.0000	0.1850	NA	0.3316	0.0000
P7	0.0000	0.0000	0.0000	0.0437	0.3316	NA	0.0000
P8	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	NA
Variance - Kruskall-Wallis							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
P2	0.0000	NA	0.0000	0.0000	0.0000	0.0000	0.0000
P4	0.0000	0.0000	NA	0.0000	0.0000	0.0000	0.0000
P5	0.0000	0.0000	0.0000	NA	0.0001	0.0000	0.0000
P6	0.0000	0.0000	0.0000	0.0001	NA	0.0000	0.0000
P7	0.0000	0.0000	0.0000	0.0000	0.0000	NA	0.0000
P8	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	NA
Variance - Levene's							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.0862	0.0000	0.0000	0.0000	0.0000	0.0000
P2	0.0862	NA	0.0000	0.0000	0.0000	0.0000	0.0000
P4	0.0000	0.0000	NA	0.0000	0.0000	0.0000	0.0000
P5	0.0000	0.0000	0.0000	NA	0.0000	0.0000	0.0000
P6	0.0000	0.0000	0.0000	0.0000	NA	0.0000	0.0000
P7	0.0000	0.0000	0.0000	0.0000	0.0000	NA	0.0000
P8	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	NA

Table 42: P-Values from Cluster Analysis for Inter-Personal Distance, Grouped by Phase, Stream 2

Stream 2							
Mean - Kruskal-Wallis							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.0000	0.0000	0.0000	0.0000	0.0063	0.0000
P2	0.0000	NA	0.0000	0.0000	0.0000	0.6560	0.0199
P4	0.0000	0.0000	NA	0.0000	0.0000	0.0000	0.0000
P5	0.0000	0.0000	0.0000	NA	0.0012	0.0000	0.0000
P6	0.0000	0.0000	0.0000	0.0012	NA	0.0000	0.0000
P7	0.0063	0.6560	0.0000	0.0000	0.0000	NA	0.1228
P8	0.0000	0.0199	0.0000	0.0000	0.0000	0.1228	NA
Mean - Levene's							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
P2	0.0000	NA	0.0000	0.0000	0.0000	0.0000	0.0000
P4	0.0000	0.0000	NA	0.0210	0.0061	0.0005	0.9971
P5	0.0000	0.0000	0.0210	NA	0.8725	0.5627	0.0305
P6	0.0000	0.0000	0.0061	0.8725	NA	0.6564	0.0111
P7	0.0000	0.0000	0.0005	0.5627	0.6564	NA	0.0014
P8	0.0000	0.0000	0.9971	0.0305	0.0111	0.0014	NA
Variance - Kruskall-Wallis							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.0047	0.0000	0.0000	0.0000	0.0000	0.0000
P2	0.0047	NA	0.0000	0.0000	0.0000	0.0000	0.0000
P4	0.0000	0.0000	NA	0.0000	0.0000	0.0000	0.0000
P5	0.0000	0.0000	0.0000	NA	0.0000	0.0000	0.0016
P6	0.0000	0.0000	0.0000	0.0000	NA	0.0000	0.0000
P7	0.0000	0.0000	0.0000	0.0000	0.0000	NA	0.0000
P8	0.0000	0.0000	0.0000	0.0016	0.0000	0.0000	NA
Variance - Levene's							
	P1	P2	P4	P5	P6	P7	P8
P1	NA	0.0028	0.0000	0.0000	0.0000	0.0000	0.0000
P2	0.0028	NA	0.0000	0.0000	0.1648	0.0000	0.0000
P4	0.0000	0.0000	NA	0.0000	0.0000	0.0000	0.0000
P5	0.0000	0.0000	0.0000	NA	0.0000	0.0000	0.0082
P6	0.0000	0.1648	0.0000	0.0000	NA	0.0000	0.0000
P7	0.0000	0.0000	0.0000	0.0000	0.0000	NA	0.0000
P8	0.0000	0.0000	0.0000	0.0082	0.0000	0.0000	NA

Table 43: P-Values from Cluster Analysis for Mode and Purpose, Grouped by KOF Stringency Index

	Stream 1		Stream 2	
Statistical Test	Kruskal-Wallis	Levene's	Kruskal-Wallis	Levene's
Car, Train, Bicycle, Bus	0.0000	0.0000	0.0000	0.0000
Walk	0.0000	0.0467	0.0000	0.0025
Tram	0.0000	0.0000	0.0000	0.0301
Motorbike	0.0146	0.0225	0.4645	0.3449
Airplane	0.0000	0.0000	0.0258	0.0380
Home, Leisure	0.0000	0.0000	0.0000	0.0000
Work	0.0000	0.0000	0.1847	0.9820
Shopping	0.0000	0.0000	0.0016	0.0000
Errand	0.0000	0.0000	0.0048	0.0018
Assistance	0.0000	0.0548	0.0015	0.2043
Homeoffice	0.0000	0.0000	0.0044	0.0006

Table 44: P-Values from Cluster Analysis for Mode and Purpose, Grouped by Daily Increase

	Stream 1		Stream 2	
Statistical Test	Kruskal-Wallis	Levene's	Kruskal-Wallis	Levene's
Car, Train, Bicycle, Bus	0.0000	0.0000	0.0000	0.0000
Walk	0.0000	0.6553	0.0000	0.0166
Tram	0.0000	0.0000	0.0000	0.1199
Motorbike	0.0024	0.0139	0.1946	0.2853
Airplane	0.0000	0.0007	0.0066	0.0068
Home, Leisure	0.0000	0.0000	0.0000	0.0000
Work	0.0000	0.0000	0.0476	0.3826
Shopping	0.0000	0.0000	0.0000	0.0021
Errand	0.0000	0.0000	0.0000	0.0001
Assistance	0.0000	0.0002	0.0013	0.0335
Homeoffice	0.0000	0.0000	0.0974	0.1153

Table 45: P-Values from Cluster Analysis for Mode and Purpose, Grouped by Daily Hospitalized

	Stream 1		Stream 2	
Statistical Test	Kruskal-Wallis	Levene's	Kruskal-Wallis	Levene's
Car, Bicycle	0.0000	0.0000	0.0000	0.0000
Walk	0.0001	0.1361	0.0000	0.0589
Train	0.0000	0.0000	0.0000	0.0001
Bus	0.0000	0.0000	0.0001	0.0001
Tram	0.0000	0.0000	0.0001	0.1084
Motorbike	0.0034	0.0279	0.0738	0.1241
Airplane	0.0000	0.0039	0.0564	0.0469
Home, Leisure	0.0000	0.0000	0.0000	0.0136
Work	0.0000	0.0000	0.0039	0.2208
Shopping	0.0006	0.0405	0.0000	0.0000
Errand	0.0000	0.0001	0.0024	0.0043
Assistance	0.0000	0.0010	0.0034	0.0065
Homeoffice	0.0000	0.0000	0.0701	0.1134

Table 46: P-Values from Cluster Analysis for Mode and Purpose, Grouped by Daily Deceased

	Stream 1		Stream 2	
Statistical Test	Kruskal-Wallis	Levene's	Kruskal-Wallis	Levene's
Car	0.0000	0.0000	0.0000	0.0000
Walk	0.0000	0.2336	0.0000	0.0225
Train	0.0000	0.0000	0.0000	0.0001
Bicycle	0.0101	0.0000	0.4562	0.0438
Bus	0.0000	0.0000	0.0001	0.0003
Tram	0.0000	0.0000	0.0044	0.2245
Motorbike	0.0501	0.0564	0.1571	0.3824
Airplane	0.0000	0.0020	0.2536	0.3586
Home, Leisure	0.0000	0.0000	0.0000	0.0000
Work	0.0000	0.0000	0.0135	0.1570
Shopping	0.0000	0.0441	0.0000	0.0684
Errand	0.0000	0.0001	0.0379	0.0465
Assistance	0.0000	0.0002	0.0147	0.0967
Homeoffice	0.0000	0.0000	0.2213	0.3260

C.3 Result of Cluster Analysis for KOF Stringency Index, Daily Increase, Hospitalized and Deceased

This section shows more cluster analysis results for KOF stringency index, daily increase, hospitalized and deceased.

Table 47: P-Values from Cluster Analysis for Mode and Purpose, Grouped by KOF Stringency Index

	Stream 1		Stream 2	
Statistical Test	Kruskal-Wallis	Levene's	Kruskal-Wallis	Levene's
Car, Train, Bicycle, Bus	0.0000	0.0000	0.0000	0.0000
Walk	0.0000	0.0467	0.0000	0.0025
Tram	0.0000	0.0000	0.0000	0.0301
Motorbike	0.0146	0.0225	0.4645	0.3449
Airplane	0.0000	0.0000	0.0258	0.0380
Home, Leisure	0.0000	0.0000	0.0000	0.0000
Work	0.0000	0.0000	0.1847	0.9820
Shopping	0.0000	0.0000	0.0016	0.0000
Errand	0.0000	0.0000	0.0048	0.0018
Assistance	0.0000	0.0548	0.0015	0.2043
Homeoffice	0.0000	0.0000	0.0044	0.0006

Table 48: P-Values from Cluster Analysis for Mode and Purpose, Grouped by Daily Increase

	Stream 1		Stream 2	
Statistical Test	Kruskal-Wallis	Levene's	Kruskal-Wallis	Levene's
Car, Train, Bicycle, Bus	0.0000	0.0000	0.0000	0.0000
Walk	0.0000	0.6553	0.0000	0.0166
Tram	0.0000	0.0000	0.0000	0.1199
Motorbike	0.0024	0.0139	0.1946	0.2853
Airplane	0.0000	0.0007	0.0066	0.0068
Home, Leisure	0.0000	0.0000	0.0000	0.0000
Work	0.0000	0.0000	0.0476	0.3826
Shopping	0.0000	0.0000	0.0000	0.0021
Errand	0.0000	0.0000	0.0000	0.0001
Assistance	0.0000	0.0002	0.0013	0.0335
Homeoffice	0.0000	0.0000	0.0974	0.1153

Table 49: P-Values from Cluster Analysis for Mode and Purpose, Grouped by Daily Hospitalized

	Stream 1		Stream 2	
Statistical Test	Kruskal-Wallis	Levene's	Kruskal-Wallis	Levene's
Car, Bicycle	0.0000	0.0000	0.0000	0.0000
Walk	0.0001	0.1361	0.0000	0.0589
Train	0.0000	0.0000	0.0000	0.0001
Bus	0.0000	0.0000	0.0001	0.0001
Tram	0.0000	0.0000	0.0001	0.1084
Motorbike	0.0034	0.0279	0.0738	0.1241
Airplane	0.0000	0.0039	0.0564	0.0469
Home, Leisure	0.0000	0.0000	0.0000	0.0136
Work	0.0000	0.0000	0.0039	0.2208
Shopping	0.0006	0.0405	0.0000	0.0000
Errand	0.0000	0.0001	0.0024	0.0043
Assistance	0.0000	0.0010	0.0034	0.0065
Homeoffice	0.0000	0.0000	0.0701	0.1134

Table 50: P-Values from Cluster Analysis for Mode and Purpose, Grouped by Daily Deceased

	Stream 1		Stream 2	
Statistical Test	Kruskal-Wallis	Levene's	Kruskal-Wallis	Levene's
Car	0.0000	0.0000	0.0000	0.0000
Walk	0.0000	0.2336	0.0000	0.0225
Train	0.0000	0.0000	0.0000	0.0001
Bicycle	0.0101	0.0000	0.4562	0.0438
Bus	0.0000	0.0000	0.0001	0.0003
Tram	0.0000	0.0000	0.0044	0.2245
Motorbike	0.0501	0.0564	0.1571	0.3824
Airplane	0.0000	0.0020	0.2536	0.3586
Home, Leisure	0.0000	0.0000	0.0000	0.0000
Work	0.0000	0.0000	0.0135	0.1570
Shopping	0.0000	0.0441	0.0000	0.0684
Errand	0.0000	0.0001	0.0379	0.0465
Assistance	0.0000	0.0002	0.0147	0.0967
Homeoffice	0.0000	0.0000	0.2213	0.3260

C.4 Additional Result of Cluster Analysis for Precipitation and Temperature

This section shows the stream 2 cluster analysis of Table 15 and Table 16, as well as the cluster analysis of inter-personal and intra-personal distance results for both precipitation and temperature.

Table 51: P-Values from Cluster Analysis for Mode and Purpose, Grouped by Precipitation, Stream 2

Term	Test	P1	P2	P4	P5	P6	P7	P8
Car	K-W	0.0970	0.5689	0.0185	0.4022	0.6950	0.2426	0.0116
	L	0.0418	0.3201	0.0017	0.4500	0.3204	0.4036	0.0280
Walk	K-W	0.4821	0.0044	0.0000	0.0180	0.5080	0.3543	0.0083
	L	0.3340	0.0894	0.0015	0.1682	0.1723	0.8017	0.7998
Train	K-W	0.8480	0.4077	0.8191	0.1916	0.6177	0.7251	0.3135
	L	0.3941	0.1645	0.9953	0.1318	0.9327	0.1785	0.4217
Bicycle	K-W	0.6946	0.4363	0.3881	0.0117	0.0117	0.0162	0.6651
	L	0.7225	0.7674	0.1718	0.0008	0.0553	0.0097	0.2451
Bus	K-W	0.1545	0.7993	0.5811	0.7487	0.2229	0.3211	0.5789
	L	0.2483	0.9248	0.7637	0.4520	0.0351	0.7653	0.8556
Tram	K-W	0.4694	0.4125	0.8672	0.8539	0.9486	0.7149	0.2090
	L	0.2029	0.7842	0.9891	0.9327	0.9968	0.8734	0.5294
Motorbike	K-W	0.9007	0.9225	0.7667	0.2312	0.4352	0.1501	0.6747
	L	0.8595	0.9335	0.9154	0.8974	0.8750	0.4206	0.7131
Airplane	K-W	0.3343	0.7392	NA	NA	0.9813	0.9962	0.8488
	L	0.6988	0.8642	NA	NA	0.9963	0.9962	0.8551
Home	K-W	0.5684	0.3224	0.0497	0.0278	0.0000	0.8602	0.0241
	L	0.3607	0.1244	0.6054	0.0052	0.0819	0.7041	0.0708
Work	K-W	0.0751	0.3513	0.3529	0.8027	0.1114	0.8240	0.4396
	L	0.1054	0.2574	0.1437	0.5998	0.0207	0.9121	0.4274
Leisure	K-W	0.2290	0.4087	0.4550	0.0031	0.0240	0.5699	0.0881
	L	0.6150	0.9295	0.8670	0.1485	0.1255	0.6321	0.0540
Shopping	K-W	0.0981	0.3125	0.0512	0.0000	0.0627	0.0000	0.0000
	L	0.3900	0.2088	0.3822	0.0708	0.9048	0.6132	0.3924
Errand	K-W	0.3677	0.9826	0.9478	0.2545	0.9672	0.1204	0.1460
	L	0.0277	0.8706	0.9108	0.6094	0.9835	0.7640	0.6501
Assistance	K-W	0.8326	0.2576	0.4515	0.6009	0.4795	0.8689	0.9066
	L	0.2243	0.2755	0.9741	0.9481	0.7910	0.3748	0.9205
Homeoffice	K-W	NA	0.0000	0.1200	0.8369	0.2985	0.6995	0.9037
	L	NA	0.5484	0.0006	0.6392	0.5455	0.8859	0.8341

Table 52: P-Values from Cluster Analysis for Intra- and Inter-Personal Distance, Grouped by Daily Precipitation

Stream 1							
Intra-Personal Distance Mean							
	P1	P2	P4	P5	P6	P7	P8
K-W	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
L	0.0043	0.0001	0.0000	0.0000	0.0496	0.0001	0.0000
Intra-Personal Distance Variance							
K-W	0.0000	0.1467	0.0000	0.0000	0.0119	0.0000	0.0000
L	0.0371	0.2162	0.0000	0.0000	0.0000	0.0096	0.0000
Inter-Personal Distance Mean							
K-W	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
L	0.0000	0.0001	0.0000	0.0000	0.0000	0.0000	0.3548
Inter-Personal Distance Variance							
K-W	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
L	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Stream 2							
Intra-Personal Distance Mean							
K-W	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
L	0.0043	0.0001	0.0000	0.0000	0.0496	0.0001	0.0000
Intra-Personal Distance Variance							
K-W	0.0000	0.1467	0.0000	0.0000	0.0119	0.0000	0.0000
L	0.0371	0.2162	0.0000	0.0000	0.0000	0.0096	0.0000
Inter-Personal Distance Mean							
K-W	0.0049	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
L	0.0651	0.4394	0.0211	0.0000	0.9204	0.0000	0.0000
Inter-Personal Distance Variance							
K-W	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
L	0.0000	0.0000	0.0000	0.0000	0.3696	0.0000	0.0008

*K-W represents Kruskal-Wallis test and L represents Levene's test
**P represents Phase

Table 53: P-Values from Cluster Analysis for Mode and Purpose, Grouped by Average Temperature, Stream 2

Term	Test	P1	P2	P4	P5	P6	P7	P8
Car	K-W	0.7850	0.7353	0.0671	0.1537	0.8339	0.7260	0.8281
	L	0.2501	0.4226	0.0200	0.5290	0.1401	0.5971	0.7856
Walk	K-W	0.0309	0.0070	0.1146	0.5766	0.0571	0.4419	0.5069
	L	0.0003	0.0000	0.0278	0.0583	0.0009	0.4270	0.9278
Train	K-W	0.1127	0.1579	0.2164	0.0019	0.1904	0.1751	0.1648
	L	0.9308	0.8651	0.0860	0.8657	0.1401	0.1767	0.3226
Bicycle	K-W	0.4603	0.5683	0.0037	0.0660	0.8184	0.0548	0.4923
	L	0.0000	0.7566	0.0001	0.7525	0.9120	0.0188	0.5750
Bus	K-W	0.7303	0.9229	0.8652	0.0718	0.0977	0.7631	0.1391
	L	0.7706	0.0001	0.9272	0.0656	0.0075	0.6727	0.0435
Tram	K-W	0.9503	0.2678	0.0668	0.1902	0.5438	0.2304	0.2944
	L	0.9741	0.0122	0.7281	0.9798	0.8000	0.8033	0.5265
Motorbike	K-W	0.2590	0.3493	0.1128	0.9760	0.0001	0.0172	0.1723
	L	0.4855	0.0480	0.3832	0.8955	0.8593	0.0344	0.0567
Airplane	K-W	0.6878	0.7568	NA	NA	0.2859	0.3463	0.8421
	L	0.7265	0.5816	NA	NA	0.9863	0.3467	0.8448
Home	K-W	0.0013	0.2782	0.1743	0.0732	0.0110	0.8728	0.2260
	L	0.0167	0.0211	0.2267	0.8258	0.0376	0.8396	0.4244
Work	K-W	0.2334	0.1088	0.0014	0.6365	0.0365	0.3282	0.8393
	L	0.0367	0.3141	0.0000	0.7810	0.0000	0.6930	0.0703
Leisure	K-W	0.0469	0.8151	0.3978	0.2559	0.0472	0.6931	0.7568
	L	0.2767	0.1034	0.1737	0.0056	0.2243	0.6206	0.9731
Shopping	K-W	0.7444	0.3990	0.4779	0.6146	0.1174	0.3393	0.0085
	L	0.7359	0.6971	0.9663	0.0003	0.4409	0.7470	0.5384
Errand	K-W	0.5352	0.8796	0.0041	0.7881	0.3369	0.7100	0.2410
	L	0.2344	0.7738	0.5190	0.7687	0.4652	0.3802	0.3292
Assistance	K-W	0.3852	0.9087	0.9804	0.7040	0.4730	0.4907	0.9358
	L	0.3648	0.5249	0.5205	0.6502	0.8964	0.2041	0.7604
Homeoffice	K-W	NA	0.0682	0.2345	0.6329	0.2859	0.2132	0.6018
	L	NA	0.1790	0.3400	0.7199	0.9767	0.6376	0.5017

Table 54: P-Values from Cluster Analysis for Intra- and Inter-Personal Distance, Grouped by Daily Average Temperature

Stream 1							
Intra-Personal Distance Mean							
	P1	P2	P4	P5	P6	P7	P8
K-W	0.0000	0.0000	0.0000	0.1054	0.0000	0.0000	0.0000
L	0.0258	0.2467	0.1343	0.1619	0.2462	0.0482	0.0859
Intra-Personal Distance Variance							
K-W	0.0000	0.0000	0.0000	0.1511	0.0019	0.0000	0.0000
L	0.0778	0.4809	0.6425	0.0024	0.1717	0.0008	0.0003
Inter-Personal Distance Mean							
K-W	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0012
L	0.0000	0.0002	0.0000	0.0000	0.0000	0.0000	0.1440
Inter-Personal Distance Variance							
K-W	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.2969
L	0.0000	0.0000	0.0006	0.0015	0.0000	0.6527	0.0000
Stream 2							
Intra-Personal Distance Mean							
K-W	0.0000	0.0000	0.0000	0.1054	0.0000	0.0000	0.0000
L	0.0258	0.2467	0.1343	0.1619	0.2462	0.0482	0.0859
Intra-Personal Distance Variance							
K-W	0.0000	0.0000	0.0000	0.1511	0.0019	0.0000	0.0000
L	0.0778	0.4809	0.6425	0.0024	0.1717	0.0008	0.0003
Inter-Personal Distance Mean							
K-W	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
L	0.0080	0.0205	0.0000	0.0000	0.0000	0.0432	0.0062
Inter-Personal Distance Variance							
K-W	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
L	0.0000	0.0000	0.0000	0.0000	0.3137	0.0000	0.1990

*K-W represents Kruskal-Wallis test and L represents Levene's test
**P represents Phase

D Additional Modeling Results

This section shows the modeling results for inter- and intra-personal distance, when considering each COVID-19 related parameters separately, instead of using phase.

Table 55: Additional Estimation Result for Intra-Personal Distance Using Panel Effects Regression Model

Term (Reference) Variable	Mean Coefficient (P value)	Standard Deviation Coefficient (P value)
Intercept	314.540*** (0.000)	179.786*** (0.000)
Days of the week (Monday)		
Tuesday	-5.059* (0.031)	-1.410 (0.223)
Wednesday	-6.404** (0.006)	-1.548 (0.173)
Thursday	-4.703* (0.043)	-1.216 (0.288)
Friday	1.270 (0.600)	-2.683* (0.024)
Saturday	24.047*** (0.000)	0.467 (0.694)
Sunday	22.012*** (0.000)	1.560 (0.209)
KOF Stringency Index (KOF Stringency Index = 0)		
1 - 40	6.197 (0.649)	-7.976 (0.234)
40 - 45	-26.403*** (0.000)	-13.542*** (0.000)
45 - 55	-36.042*** (0.000)	-10.314*** (0.000)
55 - 60	-40.072*** (0.000)	-12.548*** (0.000)
60 - 65	-44.917*** (0.000)	-11.733*** (0.000)
65 - 70	-10.969 (0.421)	-17.140* (0.011)
>70	-26.340. (0.056)	-10.612 (0.118)
Daily Increase (Daily Increase = 0)		
1 - 500	-18.410 (0.172)	10.717 (0.106)
500 - 1500	-13.400 (0.332)	13.207. (0.052)
1500 - 4500	-14.826** (0.003)	-5.369* (0.031)
4500 - 6000	-11.635* (0.011)	-5.097* (0.023)
6000 - 6500	-12.369* (0.010)	-3.437 (0.147)
Precipitation (No Rain)		
Very Slight	6.069*** (0.000)	3.871*** (0.000)
Slight to Low Moderate	7.163** (0.005)	2.304. (0.064)
Moderate	4.960. (0.089)	3.277* (0.022)
Heavy	-4.122 (0.113)	0.191 (0.881)
Very Heavy to Violent	-7.653* (0.037)	1.005 (0.577)
Daily Average Temperature (<10C)		
10 - 15C	1.011 (0.558)	-0.968 (0.254)
15 - 20C	4.943. (0.090)	-1.309 (0.362)
20 - 30C	1.825 (0.673)	-4.481* (0.036)
Gender (Male)		
Female	-10.192* (0.042)	-8.095** (0.003)
Age (Below 40)		
40 - 49	-27.511*** (0.000)	-11.780*** (0.001)
50 - 59	-19.917** (0.002)	-8.511* (0.015)
Above 60	-6.495 (0.443)	-2.497 (0.592)

Table 56: Additional Estimation Result for Intra-Personal Distance Using Panel Effects Regression Model, Cont.

Income (Below 8000CHF)		
8,001 - 12,000CHF	-12.585* (0.021)	-7.869** (0.009)
Above 12,000CHF	12.614* (0.030)	6.641* (0.038)
Household Size (Size 1)		
Size 2	-23.050. (0.050)	-11.260. (0.082)
Size 3	-8.381 (0.482)	-7.681 (0.242)
Size 4 or More	-13.624 (0.231)	-8.655 (0.167)
Education Level (Mandatory and Secondary)		
Higher	-12.060** (0.009)	-2.172 (0.395)
Employment Status (Unemployed)		
Employed	15.875* (0.013)	4.777 (0.177)
PT Pass (without PT pass)		
Subscription (exclude Half Fare)	7.252 (0.145)	4.796. (0.080)
Half Fare	1.234 (0.785)	1.252 (0.615)
Mobility Ownership		
Own a Car	-21.526* (0.024)	-6.487 (0.215)
Own a Bicycle	10.334 (0.238)	4.388 (0.363)
Own a Motorbike	-2.614 (0.675)	-3.748 (0.275)
Car Size (Medium)		
Small	-10.414 (0.110)	-4.065 (0.258)
Big	-6.525 (0.235)	-6.575* (0.030)
Car Year (2012)		
Before 2010	4.171 (0.515)	6.207. (0.079)
After 2015	-5.031 (0.386)	-4.006 (0.210)
Bike Type (E-Bike)		
Regular Bike	-8.556 (0.292)	-5.454 (0.222)
Overview		
Total Sum of Squares	78192000	17853000
Residual Sum of Squares	67928000	16442000
R-Squared	0.099	0.034
Adjusted R-Squared	0.096	0.031
P value	0.000	0.000
Effects		
	std.dev(share)	std.dev(share)
idiosyncratic	72.430(0.815)	35.860(0.775)
individual	34.560(0.185)	19.320(0.225)

Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Table 57: Additional Estimation Result for Inter-Personal Distance Using Panel Effects Regression Model

Term (Reference) Variable	Mean Coefficient (P value)	Standard Deviation Coefficient (P value)
Intercept	373.433*** (0.000)	107.272*** (0.000)
Days of the week (Monday)		
Tuesday	0.960 (0.648)	-2.855*** (0.000)
Wednesday	6.721** (0.001)	-2.131** (0.005)
Thursday	5.779** (0.006)	-1.332. (0.081)
Friday	16.188*** (0.000)	-3.612*** (0.000)
Saturday	4.660* (0.031)	3.596*** (0.000)
Sunday	-12.226*** (0.000)	15.628*** (0.000)
KOF Stringency Index (KOF Stringency Index = 0)		
1 - 40	8.617 (0.247)	14.216*** (0.000)
40 - 45	-33.920*** (0.000)	11.290*** (0.000)
45 - 55	-38.859*** (0.000)	11.893*** (0.000)
55 - 60	-55.084*** (0.000)	10.658*** (0.000)
60 - 65	-52.853*** (0.000)	14.498*** (0.000)
65 - 70	-43.508*** (0.000)	12.920*** (0.000)
>70	-62.050*** (0.000)	26.851*** (0.000)
Daily Increase (Daily Increase = 0)		
1 - 500	19.551** (0.007)	-3.897 (0.140)
500 - 1500	20.719** (0.009)	-10.925*** (0.000)
1500 - 4500	2.486 (0.510)	-1.057 (0.441)
4500 - 6000	9.547** (0.005)	-1.565 (0.201)
6000 - 6500	11.340** (0.006)	-3.332* (0.027)
Precipitation (No Rain)		
Very Slight	16.629*** (0.000)	-1.995*** (0.000)
Slight to Low Moderate	7.644*** (0.000)	-1.129 (0.152)
Moderate	6.607* (0.013)	0.018 (0.985)
Heavy	5.296* (0.033)	-0.531 (0.556)
Very Heavy to Violent	-0.478 (0.902)	-0.671 (0.635)
Daily Average Temperature (<10C)		
10 - 15C	5.345*** (0.001)	-1.820** (0.002)
15 - 20C	2.827 (0.230)	-4.262*** (0.000)
20 - 30C	-2.347 (0.526)	-6.104*** (0.000)
Gender (Male)		
Female	-15.658. (0.065)	1.311 (0.582)
Age (Below 40)		
40 - 49	-10.430 (0.338)	0.964 (0.753)
50 - 59	-8.280 (0.439)	1.971 (0.512)
Above 60	-28.575* (0.044)	7.729. (0.052)

Table 58: Additional Estimation Result for Inter-Personal Distance Using Panel Effects Regression Model, Cont.

Income (Below 8000CHF)		
8,001 - 12,000CHF	7.053 (0.421)	-1.836 (0.456)
Above 12,000CHF	5.886 (0.560)	-3.153 (0.266)
Household Size (Size 1)		
Size 2	-3.271 (0.861)	1.728 (0.742)
Size 3	-25.882 (0.167)	7.204 (0.171)
Size 4 or More	-21.779 (0.225)	5.046 (0.317)
Education Level (Mandatory and Secondary)		
Higher	-2.311 (0.764)	2.563 (0.237)
Employment Status (Unemployed)		
Employed	-6.766 (0.541)	-3.174 (0.307)
PT Pass (without PT pass)		
Subscription (exclude Half Fare)	24.058** (0.002)	-6.846** (0.002)
Half Fare	14.262. (0.085)	-2.503 (0.282)
Mobility Ownership		
Own a Car	-4.014 (0.790)	0.234 (0.956)
Own a Bicycle	4.560 (0.754)	-3.362 (0.411)
Own a Motorbike	-16.378. (0.083)	2.490 (0.347)
Car Size (Medium)		
Small	-8.548 (0.429)	2.054 (0.498)
Big	5.859 (0.517)	-0.505 (0.842)
Car Year (2012)		
Before 2010	1.316 (0.901)	0.698 (0.814)
After 2015	-9.923 (0.288)	3.276 (0.212)
Bike Type (E-Bike)		
Regular Bike	-9.004 (0.510)	3.053 (0.427)
Overview		
Total Sum of Squares	67711000	8696900
Residual Sum of Squares	59144000	7830400
R-Squared	0.120	0.107
Adjusted R-Squared	0.117	0.104
P value	0.000	0.000
Effects		
	std.dev(share)	std.dev(share)
idiosyncratic	65.700(0.738)	23.710(0.829)
individual	39.110(0.262)	10.780(0.171)

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1