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List of Abbreviations

ANS	Autonomic Nervous System
ECG	Electrocardiogram
HRV	Heart Rate Variability
MAP	Maximum A Posteriori
MCMC	Markov Chain Monte Carlo
SNS	Sympatnetic Nervous System

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Abstract

The main goal of the study was to assess the relationship between meteorological factors and Heart Rate Variability (HRV) parameters which were derived from daily Electrocardiogram (ECG) measurement taken while bathing. This research utilized a unique quantitative long-term dataset of HRV parameters to investigate what meteorological factors influence them. By adapting state space model, the study accounted for time-dependent patterns in the data to estimate the impacts of meteorological data such as temperature, relative humidity, sea-level atmospheric pressure, precipitation, snowfall, sunshine duration, and wind speed on multiple HRV parameters. Key findings indicated that some of temperature-related and precipitation-related factors, including mean, maximum, and minimum temperatures, were estimated as the most influence on HRV parameters, exhibiting relatively large Maximum A Posteriori (MAP) estimation values or consistently positive/negative credible intervals. Additionally, humidity, sea-level atmospheric pressure, and wind speed also demonstrated consistent credible intervals and moderate MAP estimation values for certain HRV parameters. In contrast, meteorological factors such as snowfall and sunshine duration showed more limited association with fewer HRV parameters. These findings suggest that specific meteorological factors may fluctuate certain HRV parameters, some of which are related to Autonomic Nervous System (ANS) activities, providing valuable insights into environmental influences on health regulation and supporting the results and proposals of previous studies.

Chapter 1

Introduction

1.1 Background

In recent years, various symptoms, such as headache, which are widely believed to be caused by meteorological changes, have been attracting attention and are referred to as meteoropathy. Meteoropathy is considered as a new disease or syndrome [2] that represents any pathological reactions in some way related to weather conditions, and it could occur to people who have diseases which are sensitive to weather changes and even healthy people. Some people troubling in meteoropathy do not notice they have symptoms related to meteorological factors, hence the symptoms or intensity in individuals are different from person to person, and it is difficult to be diagnosed as meteoropathy.

Indeed, according to a survey conducted by a Japanese company Weathernews.inc in 2020 and 2023, considerable number of people reported they are suffering from meteoropathy [1, 3]. For example, more than half of the participants in the survey have experienced headache on days with bad weather. Besides this, dizziness, joint pain, and stiff neck are also symptoms which are mainly mentioned by them as shown in Figure 1.1. The number of people who perceived suffering from meteoropathy has been increasing according to the survey. Additionally, a study showed that nearly 30% of people in the world have experienced symptoms associated with meteoropathy [4]. A few services have launched to provide prediction of the onset of meteoropathy over the past several years [5, 6] to deal with the symptoms in advance in Japan. Consequently, numerous people are interested in why the symptoms appear and how we can address them in order to maintain a healthy condition.

1.2 Prior Studies

There have been several studies that examined relationship between specific diseases and meteorological factors. L. Ma et al. [7] and Costilla-Esquivel A et al. [8] mentioned that the number of patients of respiratory diseases are influenced by meteorological factors. The former reported that the factors having a greater impact on the number of patients with respiratory diseases are daily minimum temperature, minimum atmospheric pressure, and minimum wind speed. In contrast, the latter insisted that weekly minimum temperature, median relative humidity, and total precipitation were effective factors on the number of weekly patients of respiratory diseases. Although

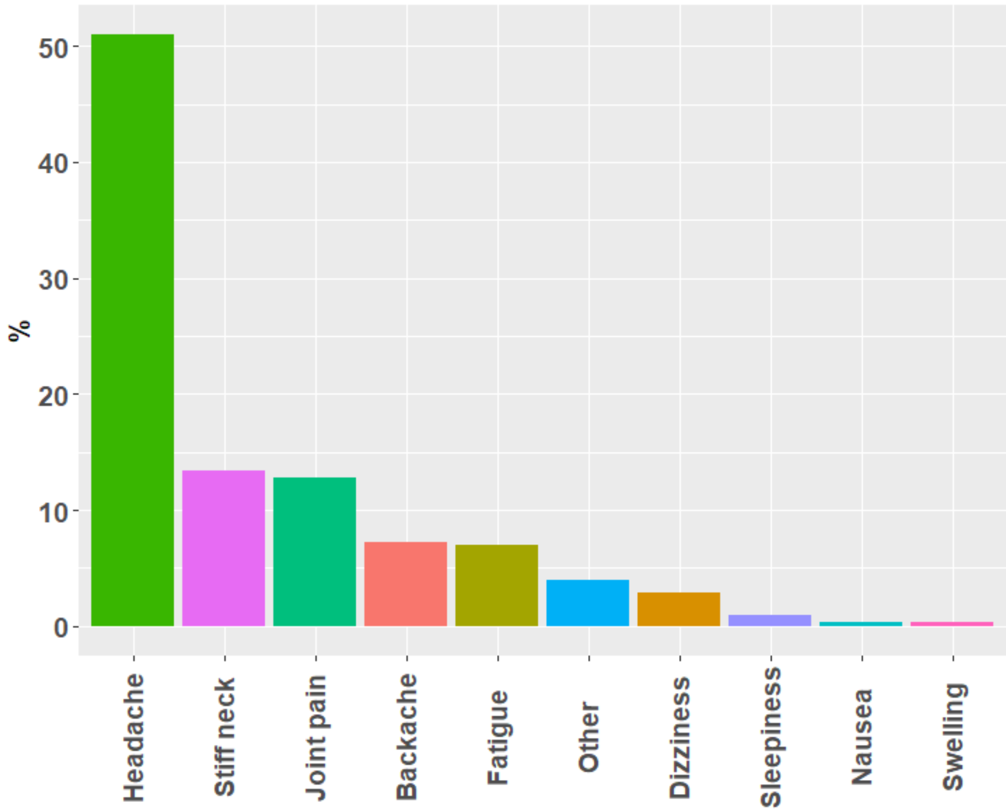

Figure 1.1: Percentage of the survey ”What is your biggest symptom?” conducted in 2020 [1]

minimum temperature is one of common factors in both studies, the latter concluded it could have a reducing effect on the target variable, conflicting the former study's conclusion.

Hamida Azzouzi and Linda Ichchou [9] and Fagerlund AJ et al. [10] evaluated pain intensity level associating with meteorological factors. Hamida Azzouzi and Linda Ichchou examined pain caused by rheumatoid arthritis using patients' pain assessment from computerized medical record. They stated that minimum temperature and atmospheric pressure were negatively correlated to pain intensity. Besides, Fagerlund AJ et al. focused on pain intensity with fibromyalgia, using questionnaire form data. They reported low atmospheric pressure and high relative humidity induced stronger pain intensity. There is a common factor between the two previous studies, however, few meteorological factors overlapped.

In addition to effects on physical body, mental health could be changed by weather. For example, Lee M et al. [11] described maximum temperature and relative humidity caused fatigue, utilizing diary form questionnaire. They also suggested that women's health condition were more sensitive than men to weather change. Additionally, Lickiewicz J et al. [12] also investigated mental health aggravation with psychiatric setting. They pointed that decrease of atmospheric pressure and increase of temperature worsened mental health condition. They suggested weather change in macro scale, such as air mass and weather fronts also could have an effect on our health condition.

Although the previous studies mentioned above focused on certain diseases, there are some previous studies with healthy individuals who perceived weather-related change in their condition. Mazza M et al. [2] proposed a concept Meteorosensitivity defined as "biological susceptibility to feel the effect of particular atmospherical events on [the] mind and body" and a questionnaire METEO-Q to detect meteoropathy. Besides, Oniszczenko W [13] assessed the relationship between meteoropathy and meteorosensitivity with questionnaire METEO-Q [2], and showed that a large correlation was found between them among women. Therefore, the more sensitive they are to changes in weather, the more possibly they are to experience meteoropathy symptoms.

Furthermore, other than the study carried out by Lee M et al [11], several studies also described that women were easier to perceive weather changes and more severe symptoms, and it is related to onset of meteoropathy [13, 14]. However, Bellini S et al [15] conducted a survey about meteoropathy using METEO-Q with adult outpatients, and they reported that men showed higher level of meteoropathy than women.

In many previous papers, the researchers have stated results that patients are affected by weather, but some of those results are not consistent. For example, focusing on atmospheric pressure, some concluded that it had a positive effect, while others suggested it was either not effective or had a negative effect. That would be because of differences in methodology such as data collection conditions. For instance, there are studies that utilized questionnaire-based experiments, however, the details of the questionnaires were different. Summary of the previous studies are shown in Table 1.1, highlighting these inconsistent findings.

Moreover, a few previous studies suggested that meteoropathy may be linked to the ANS. For instance, Sato J et al. [16] examined a behavior of mice which had pain and were exposed to low atmospheric pressure in controlled room. They observed that lowering atmospheric pressure induced more severe pain-related behaviors. On the other hand, when the mice with a surgically removed Sympatnetic Nervous System (SNS) were exposed to the same conditions, and the pain-related behaviors were no longer

Table 1.1: Summary of previous studies introduced the section

Author, Year	**Symptom**	**Effective factor(s)**	**Data format**
L. Ma et al., 2021 [6]	Respiratory diseases	Temperature, atmospheric pressure, wind speed	Medical record
Costilla-Esquivel A et al., 2013 [7]	Respiratory diseases	Temperature, humidity, precipitation	Public database
Azzouzi H & Ichchou L, 2020 [8]	Rheumatoid Arthritis	Temperature, atmospheric pressure	Medical record
Fagerlund AJ et al., 2019 [9]	Fibromyalgia	Relative humidity, atmospheric pressure	Questionnaire
Lee M et al., 2018 [10]	Fatigue	Temperature, relative humidity	Daily diary
Lickiewicz J et al., 2020 [11]	Aggressive emotion	Temperature, atmospheric pressure	Medical record
Mazza M et al. 2012	Meteoropathy	Sex (Women)	Questionnaire (METEO-Q)
Oniszczenko W, 2020 [12]	Affective temperaments	Sex (Women)	Questionnaire (METEO-Q)
Rzeszutek M et al., 2020 [13]	Meteoropathy	Sex (Women)	Questionnaire (METEO-Q)
Bellini S et al., 2015 [14]	Meteoropathy	Sex (Men)	Qestionnaire (METEO-Q)

observed. This finding suggests that the ANS, particularly the SNS, plays a significant role in the onset of meteoropathy. Also, Oniszczenko W et al. [13] claimed that the mechanism of emotion could be affected by weather, if weather impacted on ANS functions, because ANS would link to the mechanism of emotion, and many organs.

1.3 Aim of the Study

Although various studies have sought to understand the causes of meteoropathy, they are still not fully clarified. To our knowledge, few previous studies have conducted an analysis of long-term quantitative data related to HRV parameters. Some of HRV parameters closely associated with changes in our health condition are related to the dynamics of the ANS, which has been suggested to be affected by meteorological factors in several studies. In the current study, we examined the association between HRV parameters and meteorological factors in order to assess which meteorological factors have impacts on them, based on ECG data as quantitative measures. Additionally, we discussed how we manage the symptoms and explored the future developments in order to contribute to maintaining health.

Achieving these aims would provide valuable insights into which meteorological factors influence HRV parameters' dynamics.

Chapter 2

Methods

2.1 Data Collection

2.1.1 ECG Data

The ECG data utilized in this study was collected in a bathtub environment for special experiment of ECG measurement in the University of Aizu [17]. The purpose of this setup was to integrate the experiment into regular daily activities without interfering with them. Daily data collection started from July 2017 to July 2024, covering approximately 7 years in total, though with some missing days. The subject was a healthy adult man whose height is 172 cm, and body weight ranged between 60 and 64 kg, which depends on seasonal condition. In the bathtub environment, bathing condition was typically kept nearly identical conditions, specifically, amount of bath water was about 180 liters, and the temperature was set between 37 and 40 degrees Celsius depending on the season or health condition [17].

For ECG measurement, a self made equipment of biosignal measurement unit was adopted to record ECG data by Lead-II by sampling rate of 500 Hz while the subject was taking a bath. There were three electrodes on the bathtub wall, one was located on the bathtub wall close to subject's left leg, and the others were placed on it close to subject's right arm and leg respectively as shown in Figure 2.1. As mentioned earlier in this section, this measurement method aimed to minimally interferes with normal daily life.

2.1.2 Meteorological Factors

Daily meteorological data corresponding to the ECG data were gathered from the Japan Meteorological Agency's database [18]. The location of monitoring point by the Japan Meteorological Agency was Aizu-Wakamatsu city, Fukushima, Japan [19]. Aizu-Wakamatsu city is surrounded by mountain, and that yields many heavy snowy and cold days in winter, which similar to Japan Sea area. Besides, a large number of high temperature and humid days happen in summer, lasting high temperature until late night because of the location. In spring and autumn, a difference of temperature between daytime and nighttime is relatively considerable caused by inland climate feature.

In this study, 12 meteorological factors were collected, and which include maximum, minimum, or mean representative values for each meteorological factor as shown below Table 2.1. According to the statistical guideline of the Japan Meteorological

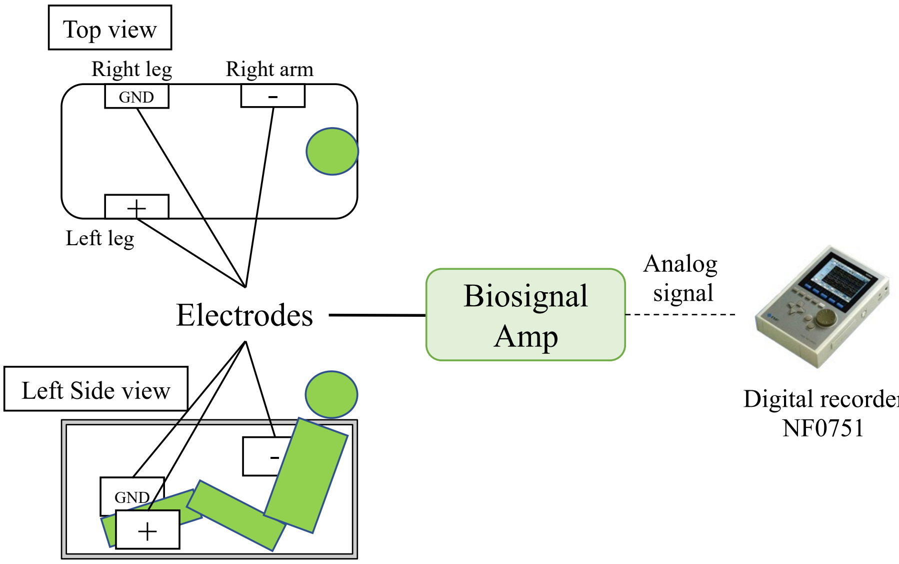

Figure 2.1: Experiment environment for ECG measurement in bathtub

Agency's database, calculation protocols for the representative values are defined as follows [20]. The daily mean values of temperature, relative humidity, and sea-level atmospheric pressure are recorded every hour on the hour. Similarly, total precipitation, total snowfall, and sunshine duration values are collected following the same protocol. In addition to that, the daily maximum or minimum representative values of temperature, relative humidity, sea-level atmospheric pressure, and hourly precipitation are gathered every 10 minutes, as well as the mean wind speed.

Table 2.1: Collected daily 12 meteorological factors' types

Factor	**Statistics**
Temperature ($^\circ C$)	Mean
	Maximum
	Minimum
Relative humidity ($\%$)	Mean
	Minimum
Sea-level atmospheric pressure (hPa)	Mean
	Minimum
Precipitation (mm)	Total
	Hourly maximum
Snowfall (cm)	Total
Sunshine duration (hour)	Total
Wind speed (m/s)	Mean

2.2 Pre-processing

2.2.1 HRV Calculation

HRV parameters derived from ECG data were calculated using software MATLAB R2023a and a library HRV tool [21]. The adopted HRV parameters in this study are presented in Table 2.2 and Table 2.3, separating into time domain parameters and frequency domain parameters [22]. Before calculating HRV parameters, the ECG data were handled to convert raw ECG data into R-R interval data for HRV tool. Firstly, first one minute of the ECG data and last one minute of the ECG data were eliminated, because those parts had much noise due to movement for getting in and out. Secondly, the ECG data were filtered to suppress noise, such as hum noise and myoelectricity. Finally, R-R interval sequences were calculated after detecting each R peak and computing difference following formula 2.1. An example of the HRV calculation flow and R-R interval sequence results are shown in Figure 2.2 and Figure 2.3.

Table 2.2: Calculated HRV parameters in time domain

Parameter	**Unit**	**Note**
Heart rate	beat/min	The number of heart beats in a minute
SDNN	ms	Standard deviation of NN intervals
RMSSD	ms	Root mean square of successive RR interval differences
pNN50	%	Ratio of successive RR intervals that differ by more than 50 ms
TINN	ms	Baseline width of the RR interval histogram

Table 2.3: Calculated HRV parameters in frequency domain

Parameter	**Unit**	**Note**
VLF	ms^2	Absolute power of the very-low-frequency band (0.0033 - 0.04 Hz)
LF	ms^2	Absolute power of the low-frequency band (0.04 - 0.15 Hz)
HF	ms^2	Absolute power of the high-frequency band (0.15 - 0.4 Hz)
LF/HF	%	Ratio of LF and HF

$$RR_i = (R\,peak)_{i+1} - (R\,peak)_i \tag{2.1}$$

Many of HRV parameters have practical meaning to diagnose diseases and monitor health condition change [22]. For example, RMSSD, one of time domain HRV parameters, can be considered as an indicator of parasympathetic nervous system's fluctuation. LF/HF, one of frequency domain HRV parameters, could be interpreted as balance between sympathetic and parasympathetic nervous systems. Furthermore, SDNN is applied to predict mortality in medical situation, classifying the value of SDNN based on its size [22]. In those manner, HRV parameters are utilized in various ways to evaluate our health condition by using ECG data or any other biosignal.

2.2.2 Imputation of Missing Values in Meteorological Factors

The meteorological data contained several missing values because of replacement or malfunction of the measurement equipment [23]. In total, there were 14 days which included missing values in some meteorological factors data as shown in Table 2.4.

Missing values in explanatory variable were not acceptable to the model used in this study. Therefore, the missing values were processed before the meteorological data were utilized in the model. The missing values were imputed by the seven-year average value for the same dates with missing data as presented in Formula 2.2, and

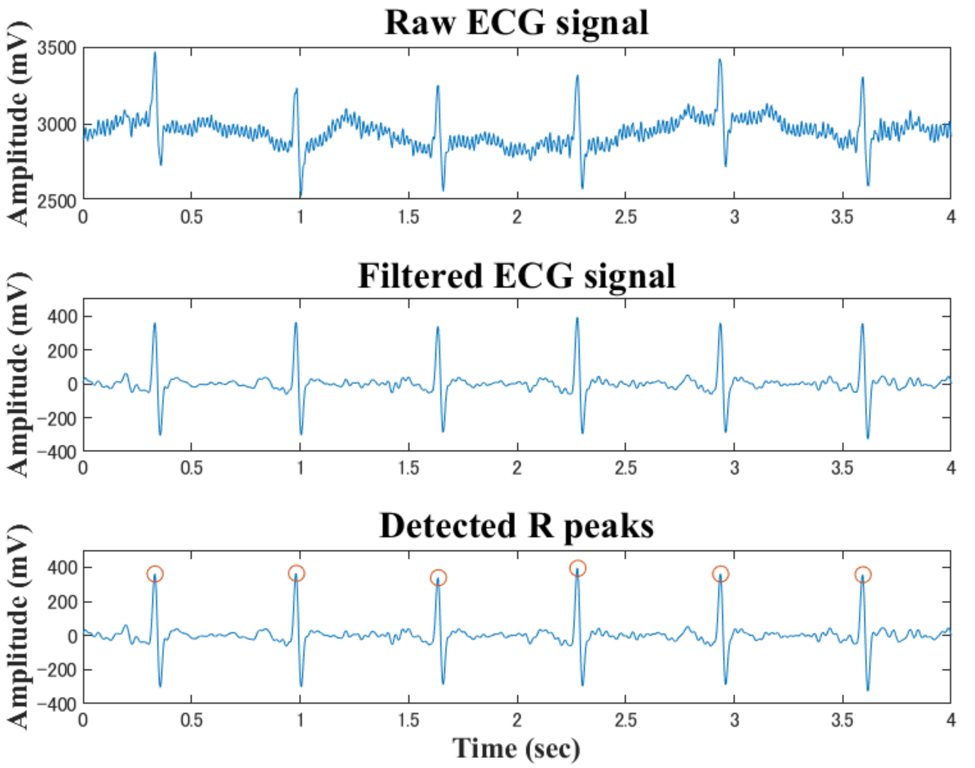

Figure 2.2: Flow of R peaks detection for R-R interval calculation

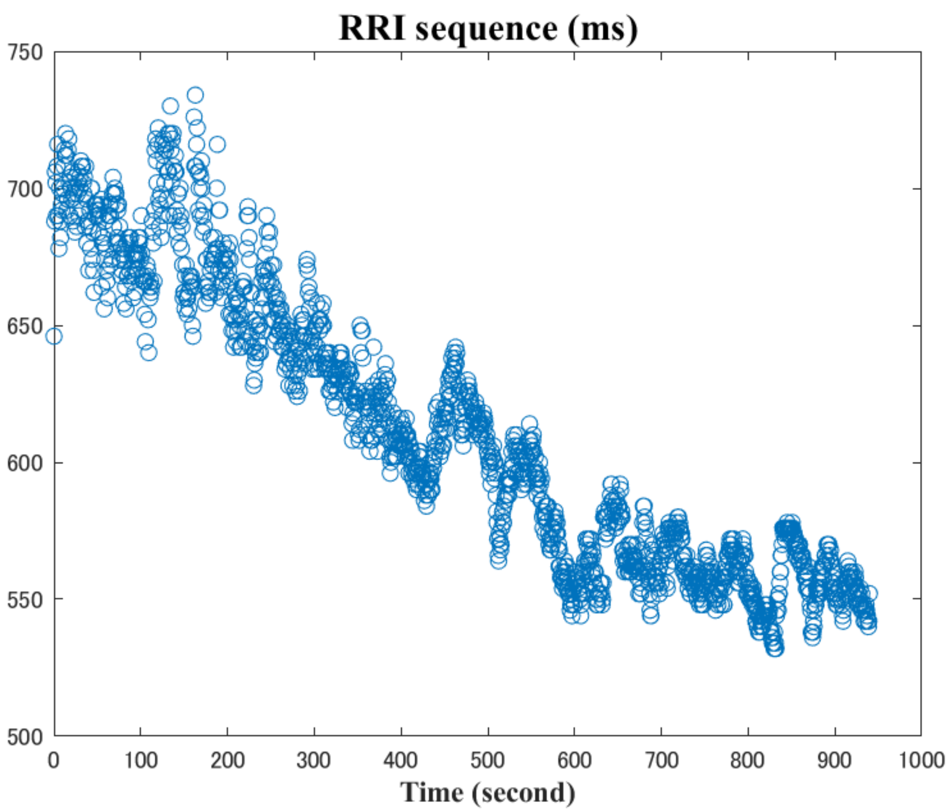

Figure 2.3: An example of R-R interval sequence

Table 2.4: List of dates included missing values in meteorological data

Factor	Missing dates (YYYY-MM-DD)
Temperature	No missing dates
Relative humidity	2017-10-22, 2017-10-23, 2017-10-24
Sea-level atmospheric pressure	No missing dates
Precipitation	2019-10-15, 2020-06-02, 2020-06-03, 2020-06-04, 2020-06-05, 2022-10-02
Snowfall	No missing dates
Sunshine duration	2020-02-13
Wind speed	2020-03-29, 2021-01-05, 2022-02-11, 2024-02-06

*Mean, maximum, or minimum for each meteorological factor had same missing dates

the imputed results are shown in Figure 2.4. This pre-processing was conducted with software Python 3.11.8 and one of its libraries, Polars 0.20.19.

$$Average_{date,factor} = \sum_{i \in Year} X_{i,date,factor} \tag{2.2}$$

(where $Year$ is the set of years excluding those with missing values, and date and factor refer to the same date and meteorological factor)

2.3 Model

2.3.1 Analysis Model

The HRV parameters data were time-dependent sequence, therefore, time series approach was adopted in this study. State space model, one of time series analysis approaches, was utilized to estimate the size of each meteorological factor's effect. In this study, standardized ($mean = 0, std = 0$) meteorological data which were mentioned earlier was input data as explanatory variables to the model, and each HRV parameter was target variable. State space model comprises two equations, state equation and observation equation, which are described as follow Formula 2.3 [24].

$$\begin{aligned} x_t &= T_t x_{t-1} + v_t \\ y_t &= Z_t x_t + \epsilon_t \end{aligned} \tag{2.3}$$

Using a state space model allows us to derive estimation results in a more interpretable form, as the model separates the estimation into states values and observations values, with explanatory variables considered as influences on the observation values. Additionally, a pre-processing to remove stationary, such as data transformation by computing differences seen in estimation using AR and ARIMA model, is not essential process in a state space model, which could avoid compromising the information contained in the data. Furthermore, even if there are missing values in the target variables, model estimation remains possible, and missing data imputation for target variables is

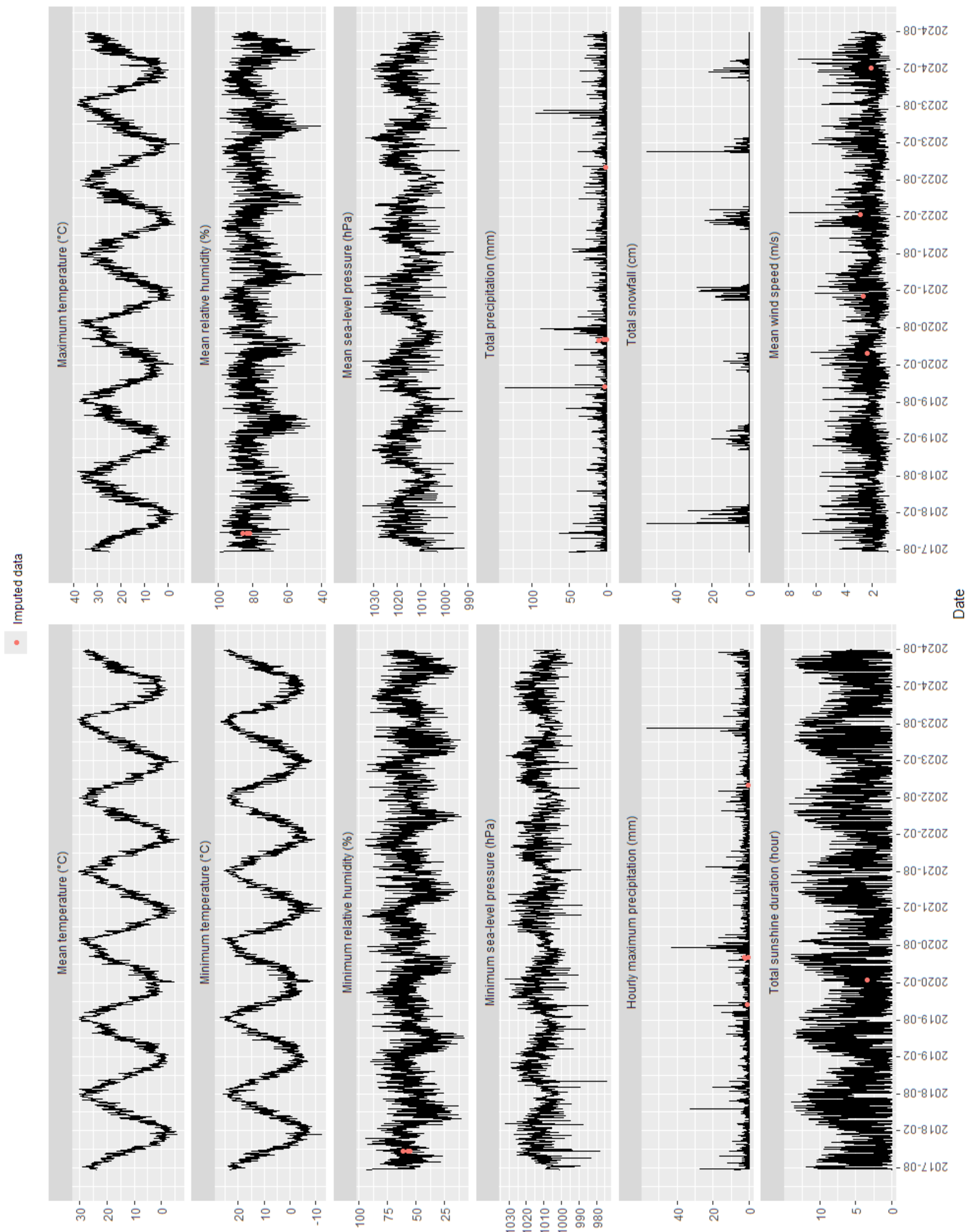

Figure 2.4: 12 meteorological data for 7 years after imputing missing values

feasible as well, since the estimation of states and observations are handled separately.

The regression model adopted in this study is shown below. Formula 2.4 is state equation μ containing second-order difference term μ_{t-2}, which could capture trend of the data [25]. The trend component may be comprehended as reflecting long-term tendencies by unobserved factors other than the meteorological factors. Formula 2.5 is observation equation, which included regression term for estimating the effect of meteorological factors [26].

$$\mu_t = 2\mu_{t-1} - \mu_{t-2} + v_t, v_t \sim Normal(0, \sigma_v^2) \tag{2.4}$$

$$y_t = \mu_t + \boldsymbol{X}_t\boldsymbol{b} + \epsilon_t, \epsilon_t \sim Normal(0, \sigma_\epsilon^2) \tag{2.5}$$

where $\boldsymbol{X}$ indicates explanatory variable, that is, meteorological data, $\boldsymbol{b}$ is regression coefficients vector with 12 dimensions for each variable, and v_t and ϵ_t are error term which follow normal distribution with mean 0 and standard deviation σ_v, σ respectively.

The space state model mentioned above is also written in state space expression in the manner of Formula 2.3 [27]. State vector x_t was defined as 2.6 with 14 dimensions, where μ_t and μ_{t-1} are trend components, and $b_1, \cdots, b_{12}$ are regression components.

$$x_t = \begin{pmatrix} \mu_t & \mu_{t-1} & b_1 & \cdots & b_{12} \end{pmatrix}^t \tag{2.6}$$

State transition matrix T_t was described as 2.7 with 14 $\times$ 14 dimensions.

$$T_t = T = \begin{pmatrix} T_\mu & 0 \\ 0 & T_w \end{pmatrix} \tag{2.7}$$

Here, T_μ and T_w are submatrix corresponding to trend component and coefficients component respectively as shown below.

$$T_\mu = \begin{pmatrix} 2 & -1 \\ 1 & 0 \end{pmatrix} \tag{2.8}$$

$$T_w = \begin{pmatrix} 1 & & 0 \\ & \ddots & \\ 0 & & 1 \end{pmatrix} \tag{2.9}$$

Observation vector Z_t with 14 dimensions was constructed with below 2.10, which includes each meteorological factor's data at time t $X_{1,t}, \cdots, X_{12,t}$.

$$Z_t = \begin{pmatrix} 1 & 0 & X_{1,t} & \cdots & X_{12,t} \end{pmatrix} \tag{2.10}$$

Estimation of state space model was realized using R 4.2.3 and RStan 2.32.2.

2.3.2 Bayesian Approach

Recently, data analysis with bayesian approach is becoming more popular, because the estimated results are easier to interpret than conventional statistical methods such as p-value [28]. For example, conventional statistical methods including maximum likelihood estimation output a point as estimated result, which might be difficult to understand uncertainty of the results. Additionally, indicators such as p-value are claimed that several problems could be happened without precisely proper usage of p-value and knowledge to understand.

In this study, model estimation was conducted using Bayesian approach to obtain credible interval of the estimated values. Particularly, Markov Chain Monte Carlo (MCMC), one of sampling methods from posterior (estimated) distribution, was adopted to obtain estimation results. In Bayesian estimation process, multiple dimensional integration is necessary to normalize the posterior distribution which has multiple estimation parameters. According to Bayes' theorem, the posterior distribution of the estimation parameter θ given the observed data y, is expressed in Formula 2.11.

$$\begin{aligned} p(\theta|y) &= \frac{p(y|\theta)p(\theta)}{p(y)} \\ &= \frac{p(y|\theta)p(\theta)}{\int_\theta p(y|\theta)p(\theta)d\theta} \\ &\propto p(y|\theta)p(\theta) \end{aligned} \tag{2.11}$$

where $p(y|\theta)$ denotes the likelihood, describing the probability of the data y under a specific parameter θ; $p(\theta)$ represents the prior distribution, which holds prior knowledge or assumption about θ; and $p(y)$ is the marginal likelihood which is constant value as normalization term. To obtain the posterior distribution, it is necessary to compute $p(y)$ by integrating over all possible values of θ. This integration would span a high dimensional parameter space, leading to a multiple dimension integral which is computationally impassible to solve analytically.

MCMC is one of computing methods of high dimensional integral in Bayesian estimation, providing a solution by approximating the posterior distribution. Rather than directly computing the integral, MCMC methods generate a large number of random samples from the posterior distribution by utilizing Markov chain. This sampling approach enables us to estimate representative values from the posterior distribution, such as mean, median, and credible intervals.

$$\begin{aligned} \hat{\theta}_{map} &= argmax_\theta p(\theta|y) \\ &= argmax_\theta \frac{p(y|\theta)p(\theta)}{p(y)} \end{aligned} \tag{2.12}$$

The prior distribution of the regression coefficients was specified as a Laplace distribution to encourage sparsity in the coefficients and feature selection. This approach helped to identify the most relevant features by shrinking less impactful coefficients toward zero, enhancing model interpretability [29].

In recent years, analysis methods focusing on interpretability and explanability have been attracting attention. These analysis methods, state space model with bayesian approach, would be advanced as the point of view of interpretable model construction compared to deep neural network which has millions of parameters.

2.4 Method flow

The analysis part consisted of 7 components for several purposes which were explained above; meteorological data collection, ECG measurement, missing values imputation of meteorological data, HRV parameters calculation, model construction, model estimation, and results evaluation. The flow of them are shown in Figure 2.5.

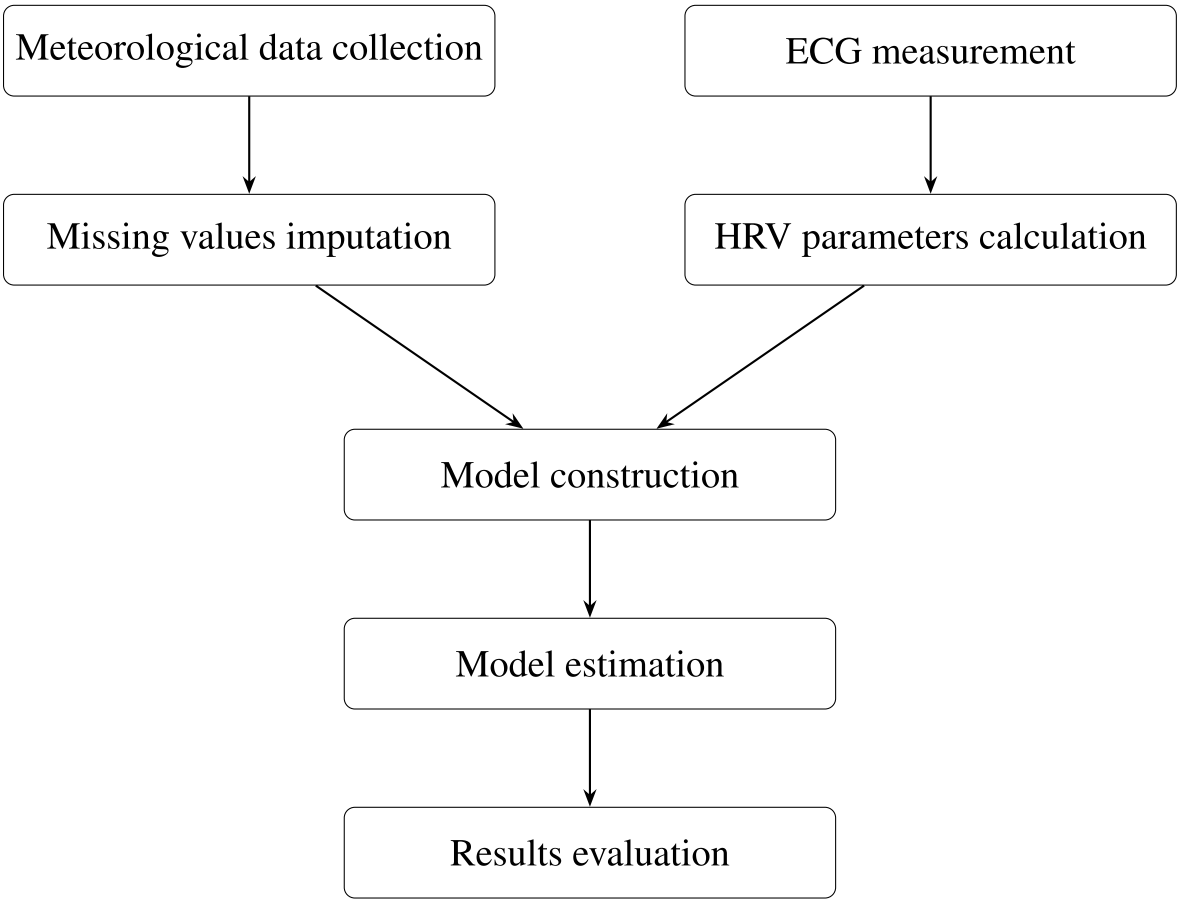

Figure 2.5: Analysis flowchart

Chapter 3

Results

In this chapter, we present the estimated coefficients for each HRV parameter. Results are organized by parameter to highlight. Each section provides a detailed analysis of the effects of meteorological factors on HRV parameters based on the estimated coefficients. Tables in each section include MAP estimation values and 50% credible intervals of estimated distribution.

3.1 Heart Rate

The estimation results for HRV parameter heart rate are summarized below Table 3.1. The MAP estimation values for heart rate in various meteorological factors suggests notable influences of minimum relative humidity, total precipitation, mean temperature, maximum temperature, and mean wind speed. For instance, the credible intervals of those factors indicate consistent positive/negative impacts, with higher estimation values than the others. This findings would suggest that fluctuations in heart rate may be especially sensitive to changes in those factors.

Meteorological factor	**MAP (50% CI)**
Mean temperature	1.3433 (0.7591, 2.3247)
Maximum temperature	1.5229 (0.8492, 2.0623)
Minimum temperature	0.0247 (-0.2712, 0.2773)
Mean relative humidity	0.0083 (-0.0804, 0.2348)
Minimum relative humidity	0.1110 (0.0256, 0.3884)
Mean sea-level atmospheric pressure	-0.0281 (-0.2252, 0.1198)
Minimum sea-level atmospheric pressure	-0.0663 (-0.3290, 0.0102)
Total precipitation	-0.2301 (-0.3322, -0.0690)
Hourly maximum precipitation	-0.0010 (-0.0899, 0.1317)
Total snowfall	0.0025 (-0.0861, 0.0956)
Total sunshine duration	0.0427 (-0.0317, 0.2210)
Mean wind speed	-0.4270 (-0.5290, -0.3247)

Table 3.1: MAP of estimated coefficients distribution for Heart rate

3.2 SDNN

For HRV parameter SDNN, we detail the estimated coefficients and their implications here. As shown in Table 3.2, the MAP estimation values and its credible intervals for SDNN provide insights into the quantitative effects of meteorological factors. For example, factors such as mean relative humidity, minimum relative humidity, total snowfall, mean, minimum, maximum temperature, and mean wind speed showed consistent positive/negative credible intervals. Particularly, mean temperature and mean wind speed could have stronger effects in SDNN compared to the other factors.

Meteorological factor	**MAP (50% CI)**
Mean temperature	-2.2893 (-3.4115, -1.1023)
Minimum temperature	-0.3573 (-1.4098, -0.0772)
Maximum temperature	-0.2095 (-1.7819, -0.2078)
Mean relative humidity	0.6991 (0.4753, 1.2762)
Minimum relative humidity	-0.1914 (-0.9066, -0.1360)
Mean sea-level atmospheric pressure	0.1232 (-0.0090, 0.6275)
Minimum sea-level atmospheric pressure	0.0191 (-0.3291, 0.2365)
Total precipitation	0.0876 (-0.0323, 0.4400)
Hourly maximum precipitation	-0.0453 (-0.3265, 0.0922)
Total snowfall	-0.3084 (-0.5110, -0.1341)
Total sunshine duration	0.0198 (-0.1969, 0.2245)
Mean wind speed	0.5629 (0.3540, 0.7542)

Table 3.2: MAP of estimated coefficients distribution for SDNN

3.3 RMSSD

The outcomes of HRV parameter RMSSD estimations provide insights to meteorological changes. Table 3.3 shows the MAP estimation values and credible intervals for RMSSD, and the MAP estimation values were generally small in all meteorological factors, with all credible intervals spanning zero, indicating a lack of enough evidence for clear associations. To some extent, minimum sea-level atmospheric pressure, total precipitation, and mean temperature were estimated relatively larger compared to the others.

3.4 pNN50

For pNN50, the MAP estimation values were consistently very low, and the credible intervals included zero for all meteorological factors as shown in Table 3.4. These results imply that any association between pNN50 and meteorological factors is close to zero or remains uncertain for some reason. However, it might be argued that total precipitation have relatively stronger influence on pNN50, as it had the largest MAP estimation value among the factors.

Meteorological factor	MAP (50% CI)
Mean temperature	0.0037 (-0.0394, 0.0757)
Minimum temperature	0.0011 (-0.0265, 0.1042)
Maximum temperature	0.0002 (-0.0367, 0.0808)
Mean relative humidity	-0.0011 (-0.0487, 0.0547)
Minimum relative humidity	0.0004 (-0.0778, 0.0332)
Mean sea-level atmospheric pressure	-0.0003 (-0.0534, 0.0483)
Minimum sea-level atmospheric pressure	-0.0025 (-0.0857, 0.0295)
Total precipitation	0.0047 (-0.0084, 0.1340)
Hourly maximum precipitation	0.0014 (-0.0098, 0.1259)
Total snowfall	-0.0005 (-0.0943, 0.0239)
Total sunshine duration	-0.0004 (-0.0590, 0.0476)
Mean wind speed	-0.0004 (-0.0403, 0.0642)

Table 3.3: MAP of estimated coefficients distribution for RMSSD

Meteorological factor	MAP (50% CI)
Mean temperature	0.00049 (-0.0060, 0.0164)
Minimum temperature	0.00042 (-0.0051, 0.0153)
Maximum temperature	0.00010 (-0.0079, 0.0137)
Mean relative humidity	0.00014 (-0.0061, 0.0136)
Minimum relative humidity	0.00001 (-0.0221, 0.0035)
Mean sea-level atmospheric pressure	-0.00007 (-0.0091, 0.0114)
Minimum sea-level atmospheric pressure	0.00009 (-0.0164, 0.0047)
Total precipitation	0.00075 (-0.0003, 0.0347)
Hourly maximum precipitation	0.00022 (-0.0067, 0.0122)
Total snowfall	-0.00022 (-0.0105, 0.0065)
Total sunshine duration	0.00008 (-0.0147, 0.0063)
Mean wind speed	0.00028 (-0.0123, 0.0052)

Table 3.4: MAP of estimated coefficients distribution for pNN50

3.5 TINN

Table 3.5 presents the MAP estimation values and credible intervals for TINN. Similar to pNN50, the MAP estimation values were small, and the credible intervals included zero for all meteorological factors. Whereas, some meteorological factors had relatively larger MAP values and credible intervals, such as minimum sea-level atmospheric pressure, minimum relative humidity, and mean, minimum, maximum temperature. These findings for specific factors may suggest potential associations with TINN, though the credible intervals still spanning zero indicate uncertain results.

Meteorological factor	**MAP (50% CI)**
Mean temperature	-0.0317 (-1.8174, 0.0108)
Minimum temperature	-0.0160 (-1.2393, 0.0739)
Maximum temperature	-0.0567 (-1.6995, 0.0061)
Mean relative humidity	0.0062 (-0.2241, 0.6734)
Minimum relative humidity	0.0207 (-0.0427, 1.1243)
Mean sea-level atmospheric pressure	0.0031 (-0.2207, 0.7075)
Minimum sea-level atmospheric pressure	0.0244 (-0.0281, 1.0944)
Total precipitation	0.0090 (-0.1583, 0.6857)
Hourly maximum precipitation	0.0131 (-0.1619, 0.6554)
Total snowfall	-0.0092 (-0.8098, 0.1381)
Total sunshine duration	-0.0062 (-0.5683, 0.2083)
Mean wind speed	0.0009 (-0.2482, 0.4976)

Table 3.5: MAP of estimated coefficients distribution for TINN

3.6 VLF

For HRV parameter VLF, we describe the estimated coefficients and their relationship in this section. Table 3.6 provides the MAP estimation values and credible intervals for VLF, including possibly effective factors with higher MAP estimation values. The credible intervals for VLF in several meteorological factors had constant positive/negative impacts including mean sea-level atmospheric pressure, mean relative humidity, hourly maximum precipitation, mean, minimum, maximum temperature, and mean wind speed.

3.7 LF

In this section, the estimated values for HRV parameter LF are shown. The MAP estimation values and credible intervals are summarized in Table 3.7 for LF. The MAP estimation values were small in general, however, the credible intervals were spanning wide range. Additionally, the credible interval of total precipitation was constantly estimated as positive, which could suggest that it had a positive effect on LF.

Meteorological factor	MAP (50% CI)
Mean temperature	-3.19877 (-41.3828, -3.0369)
Minimum temperature	-2.02846 (-18.9517, -1.3188)
Maximum temperature	-1.78833 (-17.6527, -0.7156)
Mean relative humidity	3.40616 (1.6849, 11.4811)
Minimum relative humidity	-0.05980 (-6.4729, 3.3482)
Mean sea-level atmospheric pressure	2.86103 (2.4916, 19.4262)
Minimum sea-level atmospheric pressure	0.18124 (-7.0335, 3.2416)
Total precipitation	0.39241 (-2.1729, 5.9141)
Hourly maximum precipitation	2.60146 (0.9209, 11.0100)
Total snowfall	1.03373 (-0.5560, 6.7514)
Total sunshine duration	-0.54539 (-8.9971, 0.8158)
Mean wind speed	0.89891 (0.5911, 8.5995)

Table 3.6: MAP of estimated coefficients distribution for VLF

Meteorological factor	MAP (50% CI)
Mean temperature	-0.0147 (-4.8709, 0.0900)
Minimum temperature	-0.0023 (-2.0605, 0.1997)
Maximum temperature	-0.0363 (-0.8752, 0.7408)
Mean relative humidity	0.0084 (-0.3693, 1.1165)
Minimum relative humidity	-0.0148 (-1.1588, 0.2999)
Mean sea-level atmospheric pressure	0.0780 (-0.0142, 3.1469)
Minimum sea-level atmospheric pressure	0.0207 (-1.3165, 0.2792)
Total precipitation	0.0938 (0.0770, 3.4360)
Hourly maximum precipitation	0.0177 (-0.4172, 0.9148)
Total snowfall	-0.0048 (-1.0847, 0.2458)
Total sunshine duration	-0.0774 (-2.3933, 0.0046)
Mean wind speed	0.0206 (-0.1305, 1.3662)

Table 3.7: MAP of estimated coefficients distribution for LF

3.8 HF

Table 3.8 outlines the MAP estimation values and credible intervals for HF. Similar to LF, the MAP estimation values were generally low, and the credible interval of total precipitation was constantly positive. However, in contrast to LF, the credible intervals of most meteorological factors were narrower than the results for LF. It could imply that uncertainty of the estimation for HF was relatively less than LF, suggesting the effects of meteorological factors on HF might be lower compared to the their effects on LF.

Meteorological factor	**MAP (50% CI)**
Mean temperature	0.0136 (-1.2754, 0.8652)
Minimum temperature	-0.0040 (-0.8072, 1.3170)
Maximum temperature	0.0283 (-0.7777, 1.2450)
Mean relative humidity	0.0235 (-0.1006, 2.4250)
Minimum relative humidity	0.0373 (-0.5740, 1.4737)
Mean sea-level atmospheric pressure	0.0059 (-0.2580, 1.9597)
Minimum sea-level atmospheric pressure	-0.0198 (-0.8515, 0.9038)
Total precipitation	0.0878 (0.0670, 3.9918)
Hourly maximum precipitation	-0.0050 (-0.4923, 1.4054)
Total snowfall	-0.0030 (-1.2025, 0.5656)
Total sunshine duration	-0.0282 (-1.8295, 0.2735)
Mean wind speed	0.0047 (-0.9862, 0.5763)

Table 3.8: MAP of estimated coefficients distribution for HF

3.9 LF/HF

For HRV parameter LF/HF, the MAP estimation values and credible intervals are shown in Table 3.9. The MAP estimation values were derived as very low values in all meteorological factors, with the credible intervals including zero, implicitly expressing a insufficient evidence for distinct link between them. Focusing on the credible intervals, some meteorological factors had relatively larger values, such as various temperature measures and mean relative humidity, although the results remain still uncertain.

Meteorological factor	**MAP (50% CI)**
Mean temperature	-0.0335 (-1.6065, 0.1106)
Minimum temperature	-0.0445 (-2.4983, 0.0355)
Maximum temperature	-0.0598 (-1.6215, 0.0532)
Mean relative humidity	-0.0183 (-1.4413, 0.0953)
Minimum relative humidity	-0.0100 (-0.2573, 0.7489)
Mean sea-level atmospheric pressure	0.0051 (-0.9012, 0.1911)
Minimum sea-level atmospheric pressure	0.0112 (-0.8861, 0.2494)
Total precipitation	-0.0147 (-1.0588, 0.1044)
Hourly maximum precipitation	-0.0120 (-0.6232, 0.2451)
Total snowfall	-0.0090 (-0.9979, 0.1895)
Total sunshine duration	-0.0062 (-0.9182, 0.2065)
Mean wind speed	0.0009 (-0.1115, 0.9800)

Table 3.9: MAP of estimated coefficients distribution for LF/HF

Chapter 4

Discussion

The purpose of the study was to analyze the relationship between meteorological factors and HRV parameters. We collected daily ECG data under the specified conditions and meteorological data from the database. Our analysis aimed to identify which factors have an influence on HRV. By identifying meteorological factors that could have an effect on HRV parameters, the authors considered that these findings might provide insights supporting future research on physiological responses to environmental conditions.

Many researchers have investigated the effects of meteorological factors on certain diseases such as papers mentioned in the introduction, generally utilizing qualitative data sources, including questionnaires and diaries. Few researchers have examined the impact of various meteorological factors on quantitative biological indicators like HRV parameters fluctuations. The effects of weather elements could be analyzed by using SSM, which is capable to account for time-dependent patterns.

Building on these key findings, we interpret the significance of each meteorological factor by exploring how variations correspond to changes in HRV parameters, as indicated by the MAP estimation values. Specifically, a 1-sigma increase in each meteorological factor corresponds to a MAP estimation values change in HRV, providing a basis for assessing the relative influence of each weather element. Below, we discuss the results and their physical implications, focusing on the key meteorological factors and their potential impacts on HRV parameters.

Temperature, including mean, maximum, and minimum values, emerge as a significant factor influencing HRV parameters. For example, for heart rate, a 1-sigma increase in mean and maximum temperature was associated with an increase of MAP estimation value of 1.3-1.5 bpm in heart rate. Additionally, also for several HRV parameters, some statistics of temperature tended to be estimated that the MAP estimation values were larger than the other meteorological factors,implying its impacts for our body condition change were relatively considerable. This suggests that ambient temperature may induce reactions in body thermal regulation such as SNS. In general, temperature shows more substantial effects on our body than other meteorological factors, which might be explained by homeostasis. Keeping our body temperature constantly is essential in human survival, including sweating in human for heat-defense response [30]. In many cases, the ambient temperature works as an element which could stress our human body, especially people suffering from certain diseases [31]. T. Haritini et al. have examined an association between extreme temperatures and public health in Cyprus, concluding the mortality was strongly associated with high temperature weather [32]. Based on those previous studies, this study's results were consistent with them and reasonable.

Relative humidity, including mean and minimum, showed relatively larger estimation values. For instance, a 1-sigma increase in mean relative humidity would be related to an increase 0.6 ms for SDNN. Although the MAP estimation values for all HRV parameters were not prominent, they were relatively larger compared to the other meteorological factors, and the credible intervals were calculated as constantly positive/negative for heart rate, SDNN, and VLF. These findings may indicate relative humidity have larger impacts on our health condition. Jane W et al. stated that exposure to higher levels of relative humidity would worse heat stress by decreasing sweat regulation function [33]. Additionally, William G et al. examined the relationship between chronic pain and weather, concluding one of associated weather elements was humidity [34]. Based on those previous studies, our discussion is reasonable and consistent with those, making sure the relationship between them is clear.

Sea-level atmospheric pressure, including mean and minimum, was estimated that it had a constantly positive credible interval for only VLF, indicating a 1-sigma increase in mean sea-level atmospheric pressure is could be related to an increase about $2.8m^2$. For some HRV parameters, the credible intervals were slightly skewed toward positive/negative range, however, it cannot be said that there were pronounced effects by sea-level pressure from the results. Nevertheless, even though the effects were estimated small, it should not be neglected. Indeed, numerous of people think atmospheric pressure is the most related factor which could cause their weather-related symptoms [1]. In addition, Sato J et al. showed lowering atmospheric pressure could cause aggravation of pain-related behavior in mice [35]. Therefore, study designs such as model structures and data collection methods should be considered to take into account that facts in further studies.

Precipitation, including total and hourly maximum, showed consistently positive/negative credible intervals and relatively larger MAP estimation values for several HRV parameters. For example, a 1-sigma decrease in total precipitation could be related to an increase 0.2 bpm for heart rate. Especially, precipitation was only one meteorological factor that was estimated constant positive/negative credible interval for LF and HF, suggesting it was more important weather element for those HRV parameters. Generally, rainfall affects on various health condition changes. Nassikas NJ et al. examined relationship between precipitation and respiratory health, arguing that greater precipitation might cause airway inflammation among patients with asthma [36]. Additionally, Deng X et al. investigated what weather condition could trigger mental disorders, concluding one of those was rainfall [37]. From these previous studies, rainfall is one of meteorological factors which has an impact on our health condition, and our results were partially consistent with those previous studies.

Total snowfall was analyzed that it had a consistently negative credible interval for only SDNN, indicating snowfall may cause a decrease of SDNN. Perhaps, the effect of snowfall was relatively small on our health condition, because it showed clear relation with only SDNN. There are few previous studies that focused on a relationship between snow and health, which makes it challenging to compare our findings with existing results. However, these findings could be valuable for future studies to examine differences of the results. Generally speaking, snowfall appears on colder temperature days, suggesting that temperature partially carried the effect of snowfall, which made it smaller. Additionally, it is possible that the estimations were challenging to derive accurately because the values were close to zero outside of winter season. Therefore, the reliability of these results may be limited.

Total sunshine duration showed no remarkable effects on any HRV parameters on contrast to previous studies. For example, according to some previous studies, exposure to sunshine was a important factor which considerably influence body health and even mental health [38–40]. This conflict between our results and previous studies could be a limitation of this study, highlighting room for further improvement.

Mean wind speed was calculated as influential factor for several HRV parameters, taking consistently positive/negative credible intervals for them. For instance, the MAP estimation value for heart rate was about -0.4, suggesting a 1-sigma increase in mean wind speed may cause a decrease 0.4 bpm in heart rate. William G et al. stated that wind speed had an effect on deterioration of chronic pain, which is consistent with our study. Although there are not many previous studies that investigate the relationship between health and wind speed, these consistent findings would be valuable information.

Especially, some meteorological factors showed they may have effects on HRV parameters which are related to ANS activities such as heart rate, SDNN, and HF. Some previous studies suggested that ANS activities were related to meteorological factors' changes, causing various symptoms [13, 41]. Additionally, a prior study mentioned at the beginning found that mice which were removed SNS showed no pain aggravation in low atmospheric pressure environment, but mice without the treatment had worse pain, indicating SNS is one of mechanisms that induces various symptoms affected by environment [16]. Moreover, Sato J discussed that what mechanisms underlie the influence of weather changes on chronic pains, and they pointed to importance of ANS activities [42,43]. For example, the author stated that lowering atmospheric pressure increase SNS activities, which stimulates an activity of pain perception and induce aggravation of chronic pain. Based on those previous studies, our results were consistent with the suggestion of relationship between ANS and weather changes, supporting opinions of previous studies.

Chapter 5

Conclusion

This study aimed to analyze the relationship between meteorological factors and HRV parameters to identify which factors influence fluctuation in HRV parameters. To the best of our knowledge, this is a unique study which investigated the association between them with such a long-term biosignal data. Despite some limitations, our study's results may provide new perspective on the association between them.

As notable results, some statistics of meteorological factors except for sunshine duration were estimated as relatively more influential factors on certain HRV parameters, exhibiting consistent credible intervals and relatively large MAP estimation values, which may indicate they are related to related to them compared to the other meteorological factors. Particularly, temperature, humidity, precipitation, and wind speed may have effects on more HRV parameters than the other meteorological factors. Among the meteorological factors considered in this study, the results suggested some of them might have an effect on HRV parameters that are related to ANS activities, which could support several previous studies proposals.

Chapter 6

Limitations

In this study, only one subject participated in the ECG data measurement, which may introduce some limitations due to the study condition. One of possible limitations is the difficulty in generalizing the results to other individuals, as the degree of health condition variability can depend on individual characteristics. For instance, as introduced at the beginning, sensitivity to meteorological factors' fluctuation would be different between male and female [11].

Besides, the ECG data were measured while the subject was taking bath in a bathtub. Although the method had various advantages for measuring biosignals in daily life, the ECG data were possibly influenced by the bathing effect. Some studies have evaluated the effect of bathing on HRV parameters' fluctuation, concluding that it had a significant impact on HRV parameters change such as an increase in heart rate.

Chapter 7

Future Works

In order to eliminate the limitation mentioned above, pulse wave measurement with multiple subjects might provide more suitable data for evaluating HRV parameters compared to the bathing ECG data. Pulse wave can be continuously recorded using wearable devices throughout the day, preventing subjects from interfering their daily activities, similar to the data collection methods employed in this study. Additionally, multiple subjects' data enable us to analyze individual differences, such as gender and age, using hierarchical models [44].

Climate difference would be critical factor in the study area, for instance, the conflicts among previous studies described earlier might be because of variations in climate. Charlson F et al. [45] investigated the effects of climate change on mental health condition, concluding that several climate exposures, including heat and rainfall could affect badly on mental health, leading to increases in suicide rates and psychiatric hospitalizations. Based on these findings, long-term climate change should be considered to evaluate both short-term weather changes and long-term climate changes across various regions of world. Perhaps, the global warming or an increase of abnormal weather is possibly one of significant factors influencing our health conditions. One of possible problems here is the difficulty in measuring biosignal data over a sufficiently long period to effectively assess long-term climate change.

Weather-related changes in health condition could be induced by not only weather but also the living environment, highlighting the importance of detailed environmental data. For instance, temperature conditions can vary between indoors and outdoors, and whether air conditioning is used can also affect health. Moreover, changes in atmospheric pressure can occur in various situations, such as mid-flight or during mountain climbing, potentially inducing changes in health. Indeed, room temperature has been shown to affect sleep quality and blood pressure [46], making it essential to consider the living environment for a more accurate analysis.

In recent weather forecasts, they not only provide basic weather information but also include ”real feel” weather [47, 48]. Lee M et al. [11] suggested that such data may have an impact on the risk of various symptoms, using dew point as an alternative measure of relative humidity. ”Real feel” weather could enhance model development to analyze even subtle fluctuations in health conditions, as individual sensitivities to weather vary. From the point of view of ”real feel”, the database from the Japan Meteorological Agency distribute data with a restriction where values below the threshold are recorded as 0 for some meteorological factors such as rainfall. This constraint may leave room for improvements in analysis, therefore using exact data values would be one of options.

With the results of this study and the late deep neural network techniques such as large language models, a prediction regarding the onset of weather-related symptoms could become more accurate and valuable. Particularly, individual differences can be addressed through fine-tuned networks, which can provide better outputs obtained by adapting to the characteristics of individuals.

By achieving further developments from this study, we may gain insights into the mechanisms of the onset of weather-related symptoms. This could enable proactive support for patients, including medication and other strategies.

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