
LONGITUDINAL ANALYSIS OF HEART RATE AND PHYSICAL ACTIVITY COLLECTED FROM SMARTWATCHES

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November 17, 2022

ABSTRACT

Smartwatches (SWs) can continuously and autonomously monitor vital signs, including heart rates and physical activities involving wrist movement. The monitoring capability of SWs has several key health benefits arising from their role in preventive and diagnostic medicine. Current research, however, has not explored many of these opportunities, including longitudinal studies. In our work, we gathered longitudinal data points, e.g., heart rate and physical activity, from various brands of SWs worn by 1,014 users. Our analysis shows three common heart rate patterns during sleep but two common patterns during the day. We find that heart rate and physical activities are higher in summer and the first month of the new year compared to other months. Moreover, physical activities are reduced on weekends compared with weekdays. Interestingly, the highest peak of physical activity is during the evening.

Keywords Smartwatch · Physical Activity · Heart Rate · Digital Health

1 Introduction

Digital medicine is gaining popularity and utility through the advent of wearable technologies as these devices are socially accepted throughout the globe, e.g., SWs and fitness trackers. These devices are becoming a highly ubiquitous type of technology, and have revolutionized the use of Holter devices. Wearable technologies are used to collect physiological parameters, such as heart rate, fitness activities, Galvanic Skin Resistance (GSR), and temperature, which are also helpful for monitoring users' vital signs [1]. They can be used long-term, even by healthy individuals, constantly sensing, gathering, and reflecting on physiological data.

Interestingly, smart everyday wearable technologies are the most popular devices as ranked by the consumers [2, 3, 4]. SWs and fitness trackers (the most popular wearable devices) have constant contact with the skin [5]. This feature

makes them valuable tools for tracking and improving users' health. The positive impact of SW is realized by assessing users' health through collecting biological, environmental, and behavioral information and quick access to them [6].

Covid-19 pandemic [7] that limited one-one contact with healthcare professionals boosted the popularity of SWs and fitness trackers for health monitoring increased among end-users. In parallel, the cost of manufacturing SWs has dropped tremendously, increasing global access to these multi-functional devices [8]. With a smartwatch, users can measure heart rate with their Photo-Plethysmo-Graphy (PPG) sensor and check their heart rate without expert monitoring or carrying extra devices [9]. Additionally, accelerometers and gyroscope sensors function as a pedometer and count the number of steps to compute the consumed calories, allowing individual users to gain awareness of their dietary habits and the consequent physical health.

Altogether, more than 350,000 mobile health (mHealth) applications on the market [10]. A large group of existing mHealth applications focuses on automatically tracking the physical activities of users, which are known as fitness trackers. However, healthcare costs are increasing worldwide, especially in the U.S. [11], which has a very high smartwatch penetration rate and is the largest consumer market for the wearable. This issue implies that there are still unexplored potentials in mHealth technologies.

We believe long-term studies on users' heart rate and physical activity can tap into new behavioral patterns to mitigate health-related risks.

Our study aims to identify users' new behavioral patterns and behavioral dynamics of physical activity along with heart rate changes. Different stakeholders in this field could benefit from our results, including general health practitioners, application designers, device producers, and smartwatch end-users.

In this research, we used SWs with a pedometer to measure physical activity and PPG to measure heart rate in many users. We studied the dataset containing about 660,000 physical activity data points for 1,014 users and selected 322 users who chose to share their continuous heart rate variability data and 363 users who shared their physical activities; in total, we analyzed 685 users' data.

In particular, our contributions to the field of digital medicine are listed as follows.

- We study heart rate variability during sleep time and the day to identify common patterns in heart rate variability at different times.
- We study different temporal patterns of physical activities, including changes in physical activities during the time of day, weekdays versus weekends, and different seasons.
- we experiment with different clustering and grouping methods and identify the most accurate clustering algorithm (Rand index and Purity) to group heart rate variability.

2 Related Works

In this section, we highlight recent advancements in research that focus on leveraging SWs or fitness trackers for remote health monitoring and promoting well-being [12]. Since our work focuses on large-scale analysis of smartwatch data for health purposes, we also benefit from previous works that analyze smartwatch data.

The first section focuses on smartphone and smartwatch approaches to analyze longitudinal health data. The second section highlights methodologies to analyze heart rate data collected from SWs, and the third section lists modalities that analyze physical activity data from SWs. We divided our related works into three sections based on the contributions of our research.

Given that other studies, [13, 8, 14] relevant to longitudinal data of SWs are not collecting health data (heart rate and physical activity in our case); we did not include them in the discussion of our related work.

2.1 Longitudinal health studies on smartphones and SWs

Mobile Health (mHealth) applications currently use battery-powered devices such as smartphones for personalized health monitoring [15, 16].

Many researchers investigated the impact of smartphones on health and the utility of smartphone features for wellness and wellbeing [17, 18, 19, 20, 21, 22]. There are apps focused on a single use case, such as managing relapses after quitting smoking [23], tracking and managing diabetes [24], such as monitoring nutrition, dietary behaviors, and food consumption [25], sleep disorders [26], psychological distress [27], and etc. Sensors and characteristics of existing smartphones enable developers to build healthcare apps and allow caregivers to have continuous access to users'

personal information, such as allergies, that can be checked daily by the smartphone application. Therefore, there is a social shift in the use of smartphones. Since the smartphone’s computing power supports other apps[28], these devices cannot provide sufficient power of computing for sensors that require a constant connection to the skin, such as heart rate and galvanic skin resistance (GSR) and body temperatures [29]. However, wearable devices such as SWs or fitness trackers bridge this gap and enable continuous sensing data collection. This capability of SWs and fitness trackers makes them an ideal device for the continued collection of heart rate variability data and physical activity. These two sensors have many other practical applications in healthcare [30]. The exponential use of SWs and fitness trackers in healthcare [31] and its rapid growth is other evidence of the efficiency of such wearable technology in improving the population’s health. In general remote monitoring enables non-invasive monitoring of various types of physiological data and activities, such as stress[32], sleep quality [33], or physical activities and fitness status of users [15].

2.2 Analysis of heart rate

Jovan on [34] work is among the early research work that leverages physiological monitoring performance of existing SWs to analyze users’ health. While valuable, these findings have limitations due to the shortcomings of SWs at the time. The author employed SWs for longitudinal and continuous health monitoring for four months. Later there were other works [35, 36, 37] that explored SWs for health purposes. On the broader scale some [38, 39] analyze datasets of heart rate variability and some analysis physical activity [40, 41, 42]. However, they were analyzed independently, and no study has been done to identify the correlation between the two approaches.

Identifying cardiac arrhythmia enables caregivers to recognize pulse irregularity and variability. An example is the Apple Heart [43] that studies atrial fibrillation and applies an algorithm that uses pulse rate data to identify and evaluate "atrial fibrillation" in a large group of Apple Watch users. Another example is the apps that investigate the smartwatch for monitoring fluctuations in Parkinson’s disease [44, 45, 46, 47]. Using the device has proven to be efficacious in patient-clinician communication, allowing for monitoring motor symptoms in Parkinson’s disease. Another group of studies [48, 49, 50] focused on rehabilitating elderly users or individuals with chronic conditions that may lack the requisite ability to monitor health. Altogether, wearable devices maintain access to patient data enabling better monitoring and consequent medical interventions.

2.3 Analysis of physical activity

Physical activity monitoring using SWs [51, 52] can overcome the limitations of fitness trackers and incorporate individual feedback. Using [53] smartphone data analysis for the distribution of physical activity demonstrated a correlation between exercise, obesity prevalence, and geographical location. This report highlighted the significance of smartwatch use in improving physical activity. Another study [54] combined data from SWs and social media sharing to help users lose weight and effectively increase their motivation to perform physical activity.

While these results are encouraging but they share a significant limitation. Despite the diversity of SWs in the market, previous studies relied on data collected with uniform devices. Analysis of specific brands does not account for heterogeneity while biasing toward device limitations and configurations. In our work, we used a wide range of smartwatch datasets, including heart rate, and physical activity, for a long time (almost five years).

3 Method

In this section, first, we describe the dataset we use for our analysis. Then, we describe our approaches to analyzing heart rate and physical activities as separate modalities.

3.1 Dataset

We analyze a unique dataset collected using an Android SW application ¹. The data collection process is IRB approved, and the privacy of a user who has agreed to participate and share their data is preserved. Besides, to respect users’ privacy we do not collect any demographic information, which is a limitation of our work. This study complies with the Guidelines for Accurate and Transparent Health Estimates Reporting (GATHER) [55]. Our dataset includes eight different sensors [56]. Still, we benefit from two of them in this study, “activity” that The Google Fit (<https://developers.google.com/fit>) API was used to gather this data and “heart rate” that was performed using native libraries of the Wear OS platform. More detail about the characteristics of each sensor with implementation and data collection principles are accessible in another work [56].

¹<https://play.google.com/store/apps/details?id=com.insight.insight>

Table 1: The geographical distribution of users by longitude and region. As seen from here, the number of users in the southern hemisphere is insignificant. Therefore, winter and summer weather is not contracting each other for different users.

Region	Users(in Percentage)
Europe	47.92
North America	41.11
Asia	10.21
Australia& Ocean	0.63
South America	0.13
North Africa	0.601

If users consent to share their data, when a WiFi connection is available on the smartphone, data is uploaded to the smartphone from the SW, via Bluetooth, every three hours. Then the compressed data is uploaded to the privacy-protected cloud (AWS S3 instance). To retain SW storage data, data only retains on the device for ten days and afterward discarded automatically. The bi-modal data storage mechanism is advantageous as reduces the uploading of large data packets to the network. [14].

We benefited from covering 1,014 users worldwide distribution of the participants is represented in 1. Users can choose to share or not share what types of information. This results in having a limited number of users sharing both their heart rate and physical activities, in total, we have 314 users who share both information, 322 users share only physical activities and 363 users share only heart rate variability.

The default option in monitoring is to log heart rate once every 30 minutes. Such a data recording results in 8,847 recordings in a week. Among these reports 3,328 records belong to the morning (between 6:00 a.m. and 12:00 p.m.); 3,314 recordings to the evening (between 12:00 p.m. and 6 p.m.), and 2,357 recordings at night (between 6 p.m. and 12 p.m) 3,702 on weekends, and 5,175 on the weekdays. Users can also configure how often the device records their heart rate (e.g.,10 minutes, 30 minutes, or one hour).

3.2 Grouping Common Patterns

The objective of this study is to identify common patterns of heart rate changes, and temporal dynamics of human activities using smartwatch sensors. The smartwatch sensor data comes from the smartwatch’s pedometer (accelerometer, gyroscope), and heart rate (PPG) sensors. The heart rate data is considered as a daily time series from the beginning of the day (00:00) to the end of the day (23:59). To identify these patterns, we apply time-series clustering to find common patterns in heart rate.

We investigate various methods of clustering, including partition-based clustering (k-mean [57] and k-shape [58] and kernel k-means [59]), density-based clustering (DBSCAN[60] and OPTICS [61]), and agglomerative hierarchical clustering, Ward [62]. Besides, we employ Self-Organized-Maps (SOM) for projecting data into lower dimensions and then applying SOM clustering, based on distances between data points.

3.2.1 Rational of Clustering Algorithm Selection

Since the clusters may have a non-elliptical shape, we used DBSCAN and OPTICS density-based clustering methods[63]. DBSCAN and OPTICS account for the adjacent areas of high appearance density that are separated from other clusters by low density and also noise or outliers.

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Agglomerative hierarchical clustering [64] is a type of hierarchical clustering algorithm that builds a cluster structure using the bottom-up approach and each cluster can have several sub-clusters. Since we suspect some behavioral patterns could have hierarchical characteristics, we also used agglomerative for clustering.

To implement partition-based clustering we use k-mean and k-shape algorithms. The k-means clustering algorithm is one of the most popular unsupervised clustering algorithms. Another partition-based clustering is the k-shape algorithm. It measures distances based on the shape defined[58] during the time series clustering. Since it uses cross-correlation it is not sensitive to shift and scale. Another algorithm in this category is Kernel k-means[59] is considered a version

Table 2: Silhouette scores for k-means, k-shape, and kernel k-means to identify the optimal number of clusters.

Silhouette Index			
num. of clusters	k-means	k-shape	kernel k-means
2	0.136	0.11	0.13
3	0.056	0.11	0.14
4	0.058	0.055	0.14
5	0.394	0.052	0.12
6	0.051	0.012	0.14
7	0.040	0.028	0.12
8	0.064	0.014	0.11
9	0.044	0.010	0.10
10	0.027	-0.093	0.10
11	0.021	-0.045	0.096
12	0.019	-0.057	0.095
13	0.018	-0.022	0.095
14	0.022	-0.021	0.084
15	0.023	-0.091	0.088
16	0.005	-0.020	0.075
17	0.010	-0.0027	0.070
18	0.063	-0.091	0.084
19	0.0017	-0.0201	0.084
20	0.0018	-0.0027	0.082

of the k-means algorithm that transforms the input space to a high-dimensional feature space where the nonlinear separators apply in this space.

The Self-Organizing-Map uses a one-layer neural network to extract features from time series[65], and project the result into a lower-dimensional space. Due to its superior accuracy, we use it for clustering heart rate time series. We train a SOM neural network with heart rate variability data.

3.3 Statistical Analysis

We examined the correlation between heart rate and physical activity, by using Pearson, Kendal Tau, and Spearman correlation metrics. We do not get a high correlation score. This is due to the fact that heart rate changes depends on many factors, such as age [66], cardiovascular disease [67], high cholesterol [68], diabetes [69], emotional state (e.g. stress) [70]. Many contributing factors lead to complex heart rate patterns that are not necessarily correlated with fitness activities. Therefore, fitness and physical activity level are one of them and can not establishes a direct correlation with the data.

4 Result

All results reported in this section and a comparison between two or more a group of data have been verified with a statistical significance test. In other words, we achieve $p - value < 0.05$, by using KS-Test for all reported results and we do not report results that are not statistically significant. We compare all of the time series clustering algorithms that we have listed in the method section and evaluate the quality of clusters to obtain the best result that leads to identifying behavioral patterns.

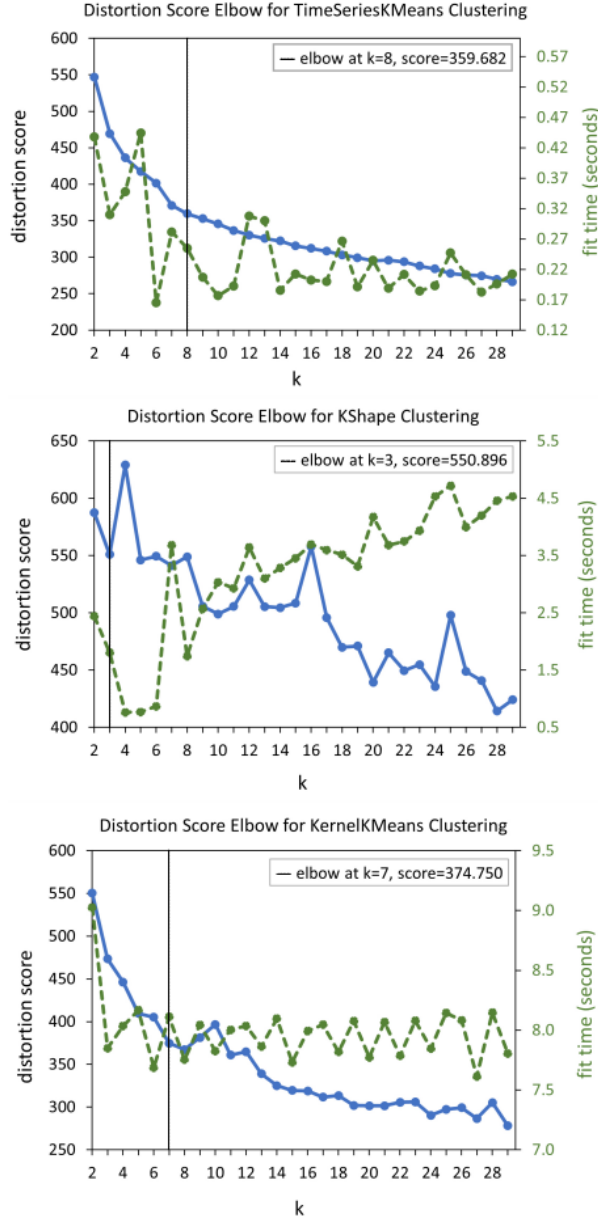


Figure 1: The elbow method, based on distortion score, for identifying the optimal number of clusters in three methods: k-means, k-shape, and kernel k-means.

We experiment with different clustering configurations and evaluate the result. This enables us to select the best clustering algorithm with the best parameter settings.

4.1 Intrinsic Evaluation

A fundamental stage for any clustering approach is to determine the number of clusters. First, we analyze partitioning methods using the Silhouette Index and Elbow method, common approaches to calculating the intrinsic measurement. Afterward, we find the optimal node for SOM.

4.1.1 Silhouette Index

To identify the optimal number of clusters while using partitioning-based clustering, we use the Silhouette Coefficient [71] that provides a quantitative score using the mean intra-cluster distance and the mean nearest-cluster distance

ranging from -1 to +1. In particular, it performs a similarity comparison between clusters that separate clusters from each other. Table 2 shows the average silhouette score for the k-means, kernel k-means, and k-shape algorithms.

4.1.2 Elbow Method

Another common method in cluster analysis is the elbow method [72] which determines the optimal number of clusters into which the data may be clustered. The method consists of plotting that considers variation as a relation between the number of clusters and a cost function. By observing the plot, we can pick the elbow of the curve as the optimal number of clusters.

As shown in Figure 1 the elbow in k-means is eight, in kernel k-means is seven and in k-shape is three. Nevertheless, due to high fluctuations of k-shape clustering, we can not rely on the elbow method for this algorithm.

4.1.3 Evaluating SOM

To our knowledge, there is no ultimate solution exists for identifying an optimal number of clustering in SOM. There are promising studies [73, 74] that determine the number of clusters, but they are very dataset dependent. We experimented to evaluate the quality of SOM clustering and finally apply this equation: $num - clusters = \left\lceil \sqrt{\sqrt{num - users}} \right\rceil^2$, that this formula has the better result for our dataset and can get it direct from this link [kaggle²](https://www.kaggle.com/code/izzettunc/introduction-to-time-series-clustering/notebook) that analyzes time-series clustering.

4.2 Extrinsic Evaluation

In addition to intrinsic evaluation, we employ human subject to measure the quality of clustering and compares cluster labels with the expert annotated label. To conduct this experiment, two human experts annotate cluster content, with Cohen's kappa of 0.97, which is almost perfect agreement.

4.2.1 Purity

A common approach to determine the quality of a clustering is cluster purity [75] which is a transparent validation measure. It compares the output of the clustering algorithm with the ground truth dataset, which is labeled manually by human subjects.

To conduct this evaluation a confusion matrix of size 2×2 which computes the similarity between two of its inputs is constructed. After that utilizing the Purity, a score between 0 and 1 is provided, one indicates a high purity score (good clustering result), and zero indicates a low purity score (weak clustering result). Table 3 presents results, SOM achieves the highest score and density-based clustering methods (DBSCAN and OPTICS) get the lowest score among other clustering methods.

4.2.2 Rand Index

Another common method for qualitative evaluation is the Rand Index [76], which also relies on the ground truth dataset. Rand Index is a measure that evaluates the match between clustering and ground truth. It provides a score between zero and one, when the score is close to one, is more consistent with ground truth, while a score close to zero is a sign of randomness.

Density-based clustering methods receive the lowest Rand Index score and the SOM achieves the highest score (similar to Purity measurement). Also, partition-based methods have high Rand Index values close to each other.

Based on the result acquired from qualitative evaluations (Purity and Rand Index) and quantitative ones (Silhouette Index and Elbow Method), we select the SOM as the clustering approach and apply it to the dataset after 10000 iterations. The result achieved strongly separated clusters of data, and it divides the dataset into 16 result groups, see Figure 5.

In this Figure, each cluster is summarized with a red curve as an average of all its time series in the cluster. The horizontal axis shows the time from "00:00" in the morning to "23:59" at night. The vertical axis shows the heart rate, mapped from the interval (31-245) to the interval (0-1).

²<https://www.kaggle.com/code/izzettunc/introduction-to-time-series-clustering/notebook>

Table 3: Results of extrinsic evaluation methods (Rand index and Purity).

Algorithm	Rand Index	Purity
SOM	0.903	0.24
Kmeans	0.894	0.22
Kshape	0.879	0.20
kernelKmeans	0.885	0.22
OPTICS	0.451	0.14
BDSCAN	0.691	0.14
Agglomerative	0.832	0.16

5 Discussions and Findings

5.1 Heart rate Analysis

Our analysis shows that 62% of users have a heart rate between 60 and 100, which means their average heart rate is normal, 21% have above average upper bound or 100 (fast heart rate) and the rest of the users are below 60 or average lower bound (slow heart rate).

Through using statistical analysis and time series clustering, We have analyzed the heart rate variation of users in the different time scopes. In particular, we investigate the heart rate at different times, (i) during the day, (ii) during a month, and (iii) months a year.

All findings we report are statistically significant ($p - value < 0.05$), otherwise we mention them explicitly. Our analysis reveals the average heart rate of users is 73 bpm at night (6 p.m. to 12 p.m.) and slower than at other times, such as in the morning time (6 a.m. to 12 noon) and in the afternoon time (12 noon to 6 p.m.). In other words, the average heart rate of most users is decreasing during the day that heart rate in the morning is 80 bpm and in the afternoon is 77 bpm.

Analysis of users' heart rate during the days of a month shows the average heart rate in the middle of the month is at the lowest (Figure2). We did not identify any proper justification for this phenomenon and we leave it for future investigation.

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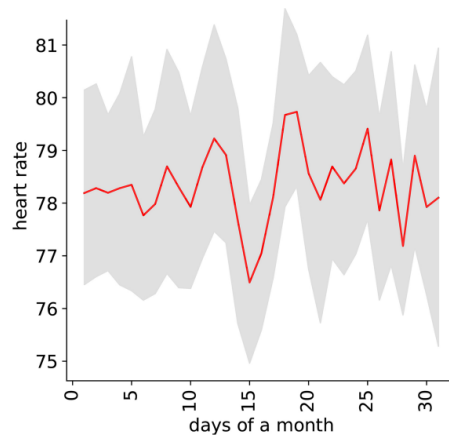


Figure 2: The average heart rate variability of all users, based on the day of a month.

Analysis of users' heart rate during the days of a month shows the average heart rate in the middle of the month is at the lowest (Figure2). We did not identify any proper justification for this phenomenon and we leave it for future investigation.

Studying heart rate variability patterns based on the month of the year shows that the average heart is highest in summer, and at the beginning of the year, which could be related to vacation times, when users have less work and more time for physical activities. As it is shown in Figure 4, August has the highest heart rate, and March has the lowest one. The lowest value is in the fall (see Figure 4).

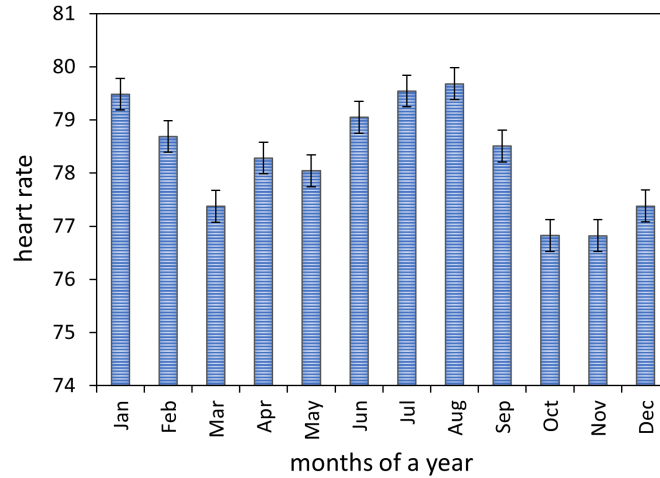


Figure 3: The average heart rate variability of all users, based on the months of the year.

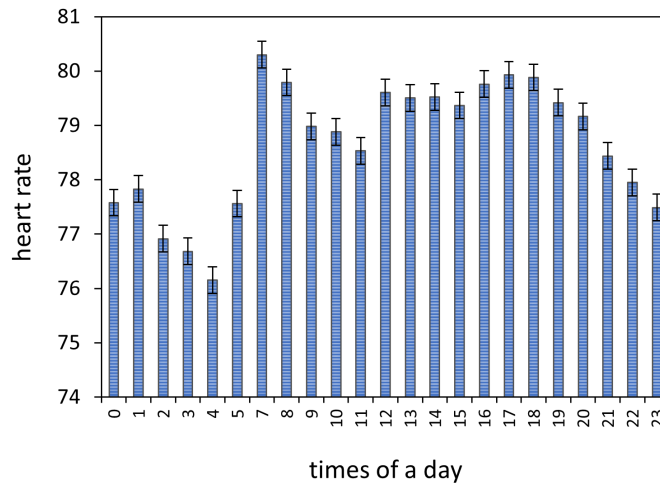


Figure 4: The average heart rate variability of all users, based on the time of the day.

Our examination of the heart rate during the day shows that the heart rate decreases during sleep time and reaches its lowest value at around 4:00 a.m. and its highest value around 7:00 am in the morning. Furthermore, the heart rate decreases during the day from 7 a.m. to 11 a.m. and is almost constant until 6 p.m. in the evening. Afterward, it decreases until the end of the day.

In the next sections, by examining the time series clustering, we investigate the reason for these peaks. Next, we experiment with time series clustering of heart rate data at various times (sleep time, daytime, different seasons, weekends vs weekdays) and examine the findings in each part. The normal range of individual heart rate is between 60 and 100 which varies from person to person [77], but different factors such as physical activity [78], hydration level [79], and body temperature [80] affect heart rate and our dataset is unable to capture all those details. Therefore, we describe our results without considering these factors.

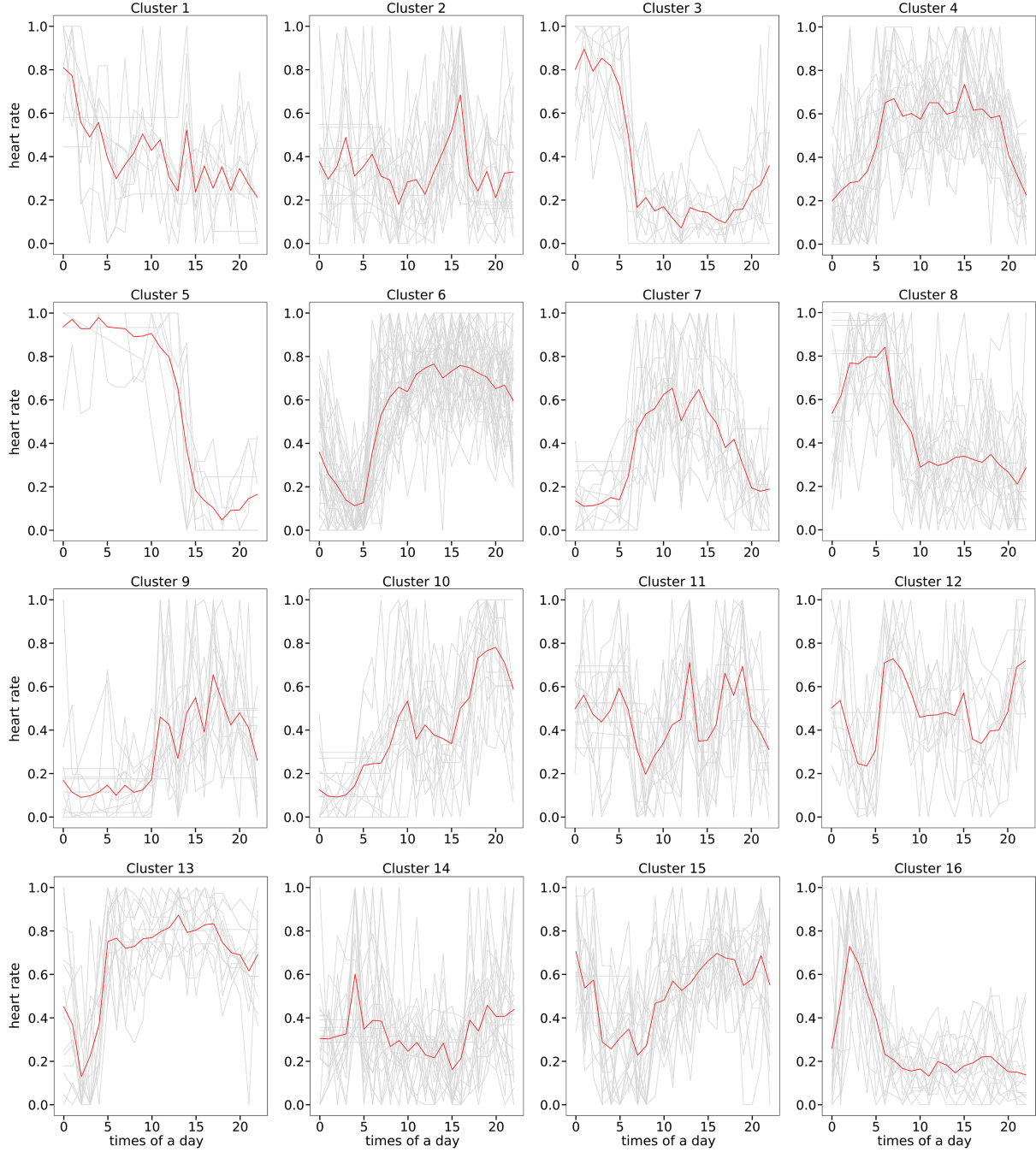


Figure 5: Results of heart rate clustering by using SOM algorithm.

5.1.1 Heart Rate Patterns During the Sleep Time

We study the heart rate variability, as a time series, during sleep time (from 12 a.m. to 8 a.m. which the timing is recommended by another work [81]), which is an important factor to check the heart health status and its functions [82]. Furthermore, blood pressure is directly correlated with heart rate variability [83], and thus investigating heart rate variability have several applications in users' health [84].

There are 29 users who are physically active during their sleep time and we do not include them in the study. We suspect that their job has night shifts, and thus they are not sleeping during the night time.

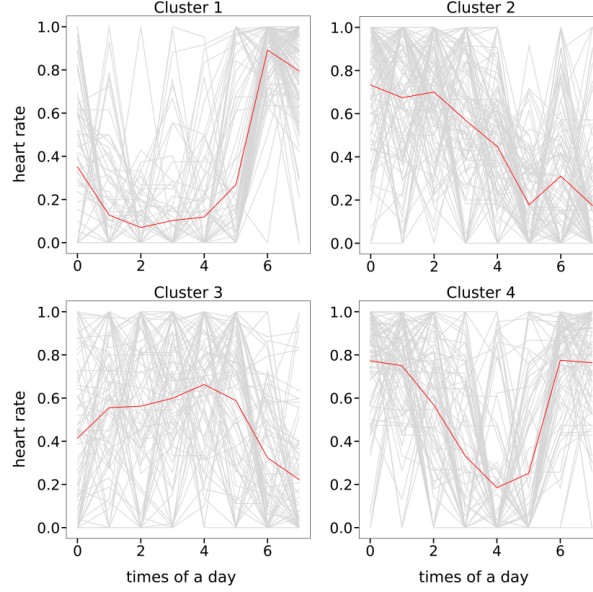


Figure 6: Results of the SOM clustering of heart rate during sleep time. Note that Cluster 2 and Cluster 3 present fairly similar patterns, and thus we summarize them in three patterns.

To identify patterns of heart rate variability during sleep time, we study the sloping trend of the heart rate curve, the highest, and lowest point in the curve. As a result, we identify three significant heart rate patterns during sleep time; (i) **valley pattern**, (ii) **downward pattern**, and (iii) **peak pattern**, these patterns are visualized in Figure 6. The heart rate patterns we have obtained via time series clustering from our dataset, are similar to findings that were measured with accurate Holter devices used for medical purposes [85, 86, 87]. This evidence could verify that even SWs that are not accurate can be used instead of expensive Holter devices used for health tracking, with a reasonable performance. Note that a user might have different patterns during different nights, but we report the most frequent pattern for each user.

valley pattern: indicates that the body organs relax in the early stages of sleep, and thus heart rate and blood pressure begin to decrease. The heart rate curve reaches the lowest heart rate in the middle of sleep when the melatonin levels peak [88]. The valley pattern is known as the ideal progression of heart rate during sleep [89]. When the body is synchronized with the patterns of the sun, the body temperature gradually decreases[90]. When waking up in the morning, the heart rate starts to increase due to the stress hormone cortisol[91], and at the end of sleep, the heart rate increases and peaks after waking up[92]. As a result, the valley pattern shows a high-quality sleep that the body has relaxed during the night [89] and the lower resting heart rate that we observe in this pattern is a symptom of healthy sleep[67]. 44% of users have a valley pattern, which means that they have a normal sleep rhythm, which is an important part of a healthy lifestyle [93].

downward pattern: This pattern shows a high heart rate at the beginning of sleep and reaches its lowest point just before waking up. This phenomenon indicates that the metabolism is visibly at work [94] and therefore the body feels weak [95] at the beginning of the day and blood pressure drops [83]. Late dinner time [96], and drinking alcohol before bed [97] are some of the important factors causing this sleep pattern. 29.5% users' data show a downward pattern in their sleep time.

peak pattern: This pattern shows an increase in heart rate just after falling asleep, and once reaching its peak, then it decreases. This pattern is known to cause some problems in physical or mental health [98, 99]. A common reason is related to late sleeping and exhaustion during the day [100]. If the subject sleeps on time and still this pattern persists, the heart rate may increase during sleep due to high stress or anxiety [101], or a nightmare occurs during the sleep time [102]. 26.3% of users show a peak pattern.

5.1.2 Heart Rate Patterns During the Day time

The result of clustering revealed, two main patterns for heart rate variability during the day (6 a.m. to 12 a.m.), i.e., (i) **downward trend** and (ii) **upward trend**, These two patterns are presented in Figure 7. The downward trend shows heart rate decreases at the end of the day when the body is relaxed during the rest period [103] and the quality of night sleep affects heart rate during the day. In 78% clusters, during the daytime, where the sleep pattern is the peak, the

downward pattern occurs. These two sleep patterns are known as not of good quality [104] and affect the body system during the day.

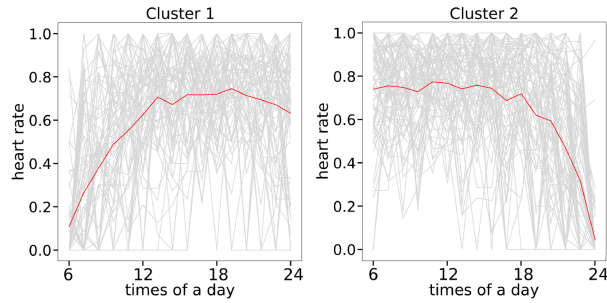


Figure 7: Results of heart rate clustering, during the daytime, by using the SOM algorithm.

In particular, as the heart rate drops, so does the blood pressure, the weakness of the body continues [105] and causes a lack of energy [106] and low stamina [107]. There are various reasons for reduced heart rate including changes in cardiac-vagal tone, representing mechanical, physiological, and pathological alteration in the parasympathetic nervous system that regulates cardiac function. Another is hypothyroidism [108], in which the thyroid gland does not produce enough thyroid hormones [109].

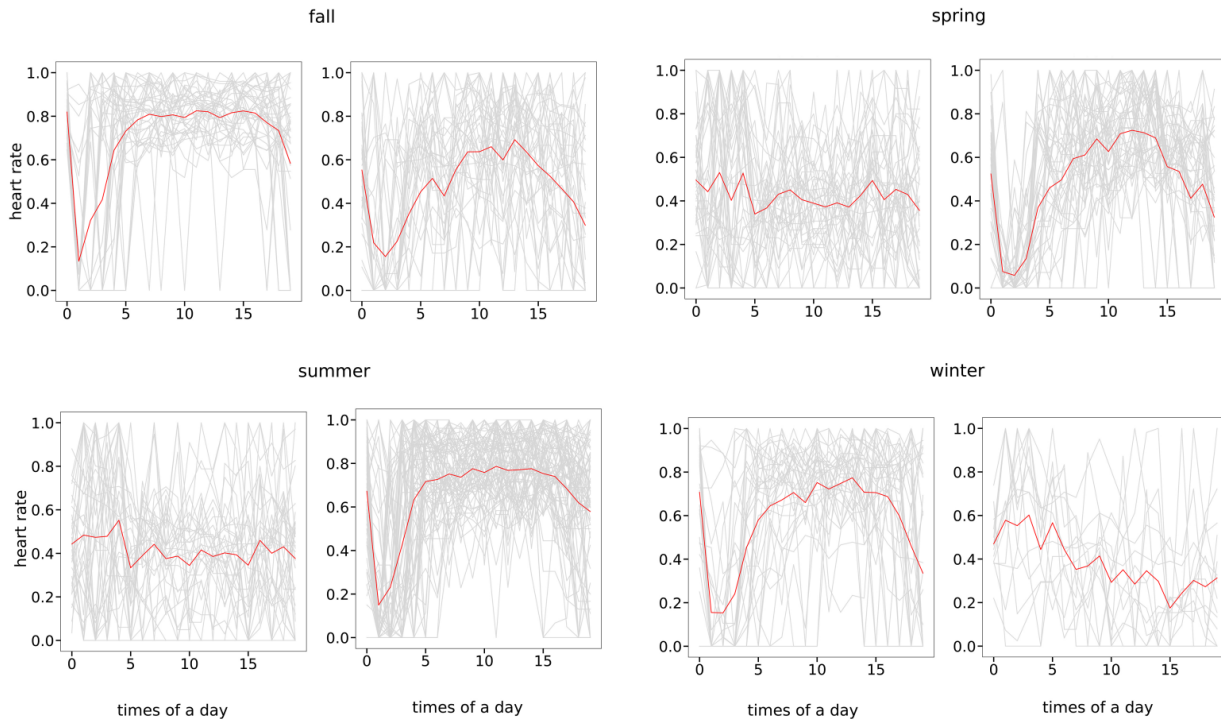


Figure 8: Results of SOM clustering based on seasons, i.e. common seasonal patterns.

Hypothyroidism can affect the health of blood vessels [110], which in turn can cause a slow heart rate [111]. The other potential reason is hypoxia [110] which happens when the body does not receive enough oxygen [112].

41% of users show a downward trend during the daytime. Given that we had no access to health records, and because the regulation of heart rate is multifactorial, we only provided examples of potential causes.

The upward trend of heart rate can originate from the increase in physical activity(11), exercises significantly increase heart rate[113]. Moreover, when there is no physical activity, there are other reasons such as warm temperature, [114, 115], smoking and tobacco consumption [116, 117] that make the heart beat faster. Stress is another major factor contributing to the increase of heart rate, the higher the stress level, the faster the heart beats [118], 37% of users show an upward trend during the daytime.

5.1.3 Seasonal Patterns

The sleep time patterns that we examined in the previous section occur in different seasons according to the conditions of each season.

We study the heart rate during sleep time (from 12 a.m. to 8 a.m.) in four seasons of the year. Our analysis revealed, *during the fall, the valley pattern. which is a sign of a healthy sleep routine is at its highest, $p - value < 0.5$.* A reason we speculate is the mild climate that regulates the heart rate.

In winter and summer, the heart rate variability during sleep time is not significantly different and includes two main patterns; valley (62%) and peak (31%) happens. In spring in addition to the valley pattern (51%), we observe the downward pattern (47%) as well, and the heart rate decreases during sleep time.

5.1.4 Weekend versus Weekday patterns

We examine the heart rate on weekdays and weekends. Given that most of our users were localized in countries with Saturday and/or Sunday as weekends, we considered Sunday as the unifying weekend.

First, we found that heart rate on Sunday nights includes three patterns(figure 9); the valley pattern that 63% users have the valley sleep behavior and which is a sign of proper sleep, the peak pattern (cluster 6) that occurs when users sleep late, 14%, and the last pattern is downward (cluster 2), i.e. 11%. It might be either exhaustion during the week that affects sleep on weekends [119], or users' nightlife, as it is shown in Figure 9.

Moreover, we study the heart rate on weekdays which is shown in Figure 10. The valley pattern also exists during this time period, and the peak pattern (cluster 6) i.e. 17%, happens on weekdays.

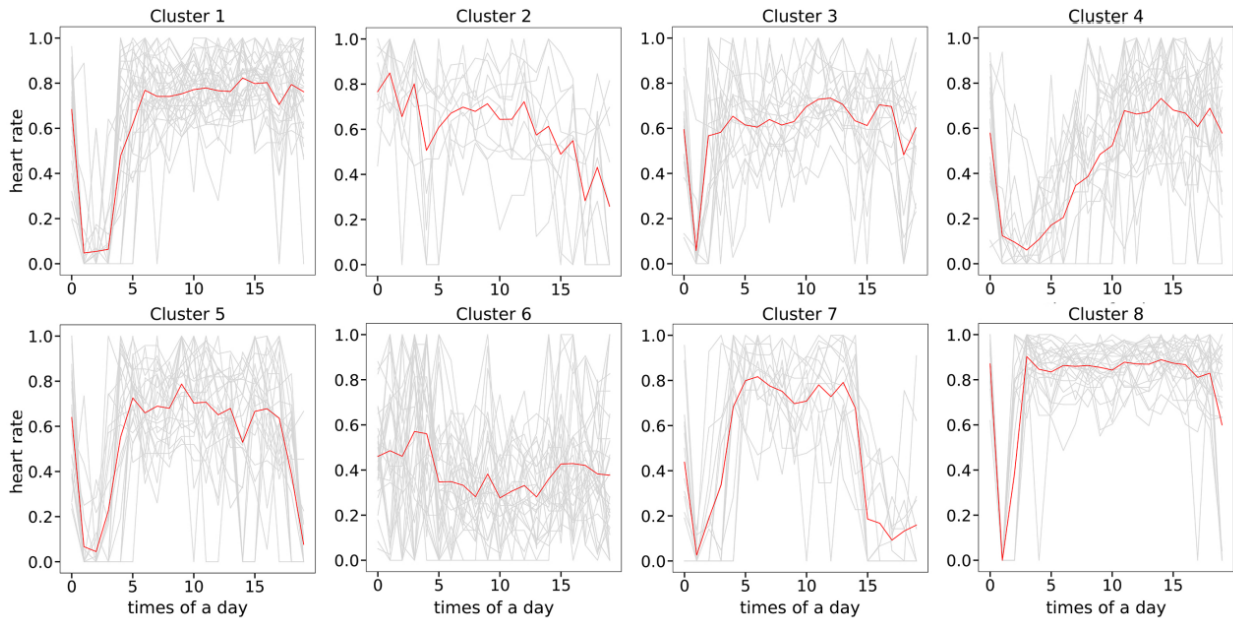


Figure 9: Results of heart rate clustering for weekends, by using SOM algorithm.

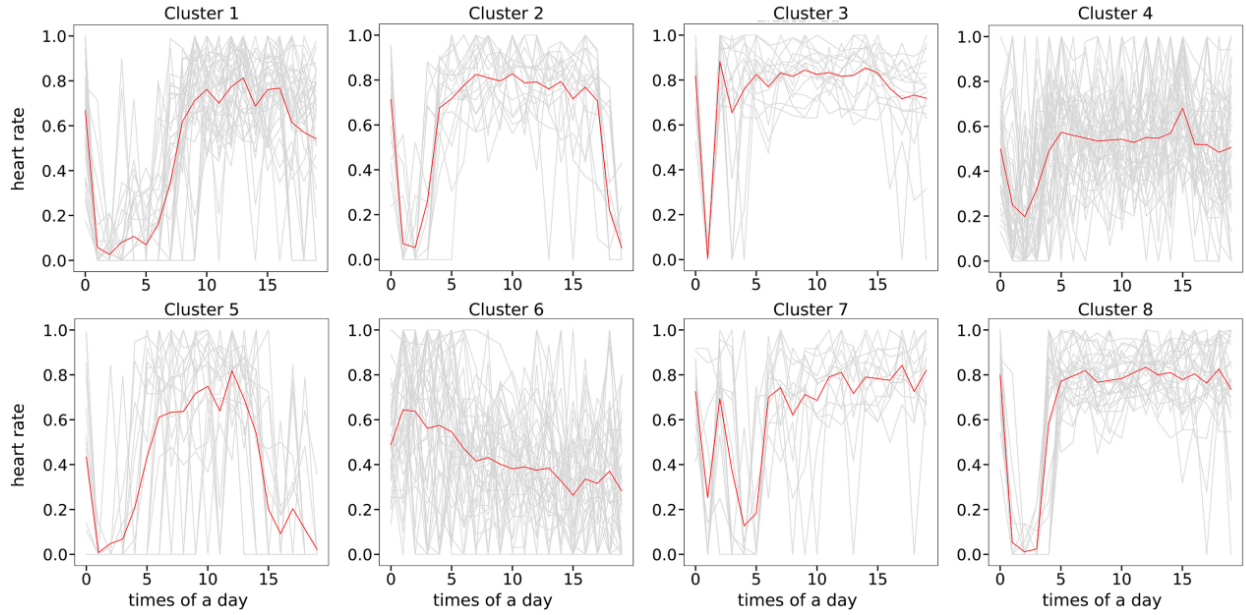


Figure 10: Results of heart rate clustering for weekdays, by using SOM algorithm.

5.1.5 Physical activity Analysis

To analyze the physical activity of users we use statistical methods. This is due to the fact that clustering algorithms with different parameters and settings do not provide consistent results and patterns. Unless specifically noted, all results reported in this section are statistically significant ($p - value < 0.5$).

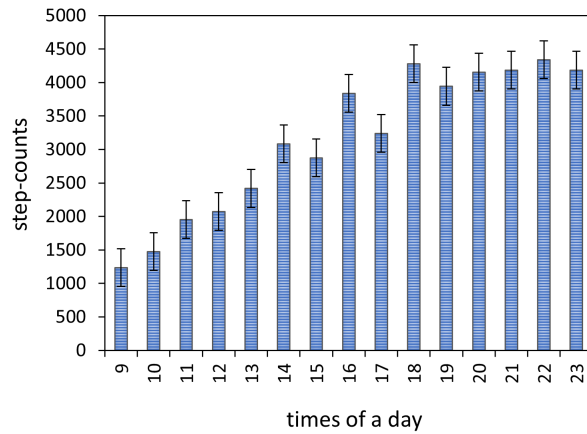


Figure 11: The average amount of physical activity, in terms of steps taken, during a day.

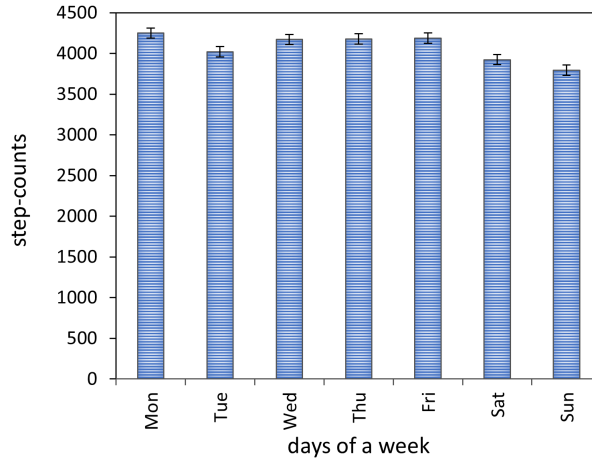


Figure 12: The average number of steps taken, during the day of the week. On weekdays, the number of steps is higher than on weekends.

As shown in Figure 11, our statistical analysis reveals that physical activity is increasing during the day, and the highest activity time is at 6:00 p.m. and at the end of the day. We speculate that this pattern is the routine exercise time that users usually perform after working hours. We found that users significantly increase physical activities in the afternoon, and after that, step counts in the morning are higher than at night. Figure 12 presents the number of weekday physical activities. We can conclude physical activity on the weekend are less than on weekdays. By investigating physical activity in different months, we found that p -value in August, September, October, and November were not significant. Based on the result presented in Figure 13 statistical analysis the rest of the months show physical activity is the most at the beginning of the new year.

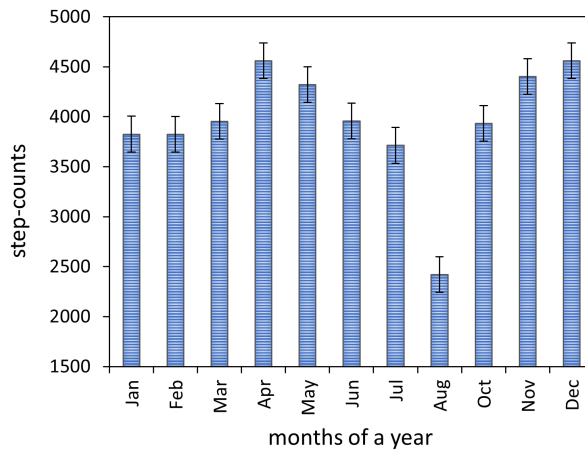


Figure 13: Distribution of physical activities (number of steps taken) by months of a year.

5.2 Limitations

Although we analyzed a large dataset of smartwatch users, our research has several limitations. To fully respect users' privacy, the application does not enforce or motivate them to provide any demographic information. Therefore, our dataset lacks information about users' gender, age, and medical conditions.

Our dataset can only estimate for the user's region and is not equipped with a precise geographical location. There, we would not be able to evaluate the climate and community (urban versus rural) and their impact on heart rate and physical activities.

Our existing data and clustering algorithm did not specify a common pattern of physical activity among the group who participated in our study. In our analysis, if statistical significance has not been reached we did not show any trend.

6 Conclusion

We analyzed the SW dataset of 1,014 users. Our dataset was collected in the real world from heterogeneous devices; thus the accuracy of the data can not be compared with Holter devices. Excitingly, however, the heart rate variability patterns we identified strongly resemble Holter devices. We identify several temporal patterns in heart rate variability and physical activities using clustering and statistical analysis. We believe our findings can be desirable for general health practitioners, application designers, device producers, and smartwatch users. In the future, we intend to focus on clinical settings and identify temporal dynamics of heart-rate variability and physical activity associated with disease and therapeutic modalities such as pharmacotherapy, radiotherapy, and others.

References

- [1] Blaine Reeder and Alexandria David. Health at hand: A systematic review of smart watch uses for health and wellness. *Journal of biomedical informatics*, 63:269–276, 2016.
- [2] Yanglei Gan, Tianyi Wang, Alireza Javaheri, Elaheh Momeni-Ortner, Milad Dehghani, Mehdi Hosseinzadeh, and Reza Rawassizadeh. 11 years with wearables: Quantitative analysis of social media, academia, news agencies, and lead user community from 2009-2020 on wearable technologies. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, 5(1):1–26, 2021.
- [3] Sumit Majumder, Tapas Mondal, and M Jamal Deen. Wearable sensors for remote health monitoring. *Sensors*, 17(1):130, 2017.
- [4] Lin Lu, Jiayao Zhang, Yi Xie, Fei Gao, Song Xu, Xinghuo Wu, Zhewei Ye, et al. Wearable health devices in health care: narrative systematic review. *JMIR mHealth and uHealth*, 8(11):e18907, 2020.
- [5] Reza Rawassizadeh, Blaine A Price, and Marian Petre. Wearables: Has the age of smartwatches finally arrived? *Communications of the ACM*, 58(1):45–47, 2014.
- [6] Tianyi Wang, Yanglei Gan, Scott D Arena, Lubomir T Chitkushev, Guanglan Zhang, and Reza Rawassizadeh. Advances for indoor fitness tracking, coaching, and motivation: A review of existing technological advances. *IEEE Systems, Man, and Cybernetics Magazine*, 7(1):4–14, 2021.
- [7] Asma Channa, Nirvana Popescu, Justyna Skibinska, and Radim Burget. The rise of wearable devices during the COVID-19 pandemic: A systematic review. *Sensors*, 21(17):5787, 2021.
- [8] Aku Visuri, Zhanna Sarsenbayeva, Niels van Berkel, Jorge Goncalves, Reza Rawassizadeh, Vassilis Kostakos, and Denzil Ferreira. Quantifying sources and types of smartwatch usage sessions. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, pages 3569–3581, 2017.
- [9] Reza Rawassizadeh, Taylan Sen, Sunny Jung Kim, Christian Meurisch, Hamidreza Keshavarz, Max Mühlhäuser, and Michael Pazzani. Manifestation of virtual assistants and robots into daily life: Vision and challenges. *CCF Transactions on Pervasive Computing and Interaction*, 1(3):163–174, 2019.
- [10] A Murray and D Nass. Digital health trends 2021: Innovation, evidence, regulation, and adoption. iqvia institute; 2021, 2022.
- [11] John A Poisal, Andrea M Sisko, Gigi A Cuckler, Sheila D Smith, Sean P Keehan, Jacqueline A Fiore, Andrew J Madison, and Kathryn E Rennie. National Health Expenditure Projections, 2021–30: Growth To Moderate As COVID-19 Impacts Wane: Study examines National Health Expenditure Projections, 2021-30 and the impact of declining federal supplemental spending related to the COVID-19 pandemic. *Health Affairs*, 41(4):474–486, 2022.
- [12] Phaik Khee Beh, Yuvaraj Ganesan, Mohammad Iranmanesh, and Behzad Foroughi. Using smartwatches for fitness and health monitoring: the utaut2 combined with threat appraisal as moderators. *Behaviour & Information Technology*, 40(3):282–299, 2021.
- [13] Hayeon Jeong, Hee-pyung Kim, Rihun Kim, Uichin Lee, and Yong Jeong. Smartwatch wearing behavior analysis: a longitudinal study. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, 1(3):1–31, 2017.
- [14] Morteza Homayounfar, Amirhossein Malekijoo, Aku Visuri, Chelsea Dobbins, Ella Peltonen, Eugene Pinsky, Kia Teymourian, and Reza Rawassizadeh. Understanding smartwatch battery utilization in the wild. *Sensors*, 20(13):3784, 2020.
- [15] Thyra De Jongh, Ipek Gurol-Urganci, Vlasta Vodopivec-Jamsek, Josip Car, and Rifat Atun. Mobile phone messaging for facilitating self-management of long-term illnesses. *Cochrane Database of Systematic Reviews*, (12), 2012.

- [16] Chris Smith, Judy Gold, Thoai D Ngo, Colin Sumpter, and Caroline Free. Mobile phone-based interventions for improving contraception use. *Cochrane Database of Systematic Reviews*, (6), 2015.
- [17] Mahmood Ahmad, Muhammad Bilal Amin, Shujaat Hussain, Byeong Ho Kang, Taechoong Cheong, and Sungyong Lee. Health fog: a novel framework for health and wellness applications. *The Journal of Supercomputing*, 72(10):3677–3695, 2016.
- [18] Nicholas D Lane, Mashfiqui Mohammad, Mu Lin, Xiaochao Yang, Hong Lu, Shahid Ali, Afsaneh Doryab, Ethan Berke, Tanzeem Choudhury, and Andrew Campbell. Bewell: A smartphone application to monitor, model and promote wellbeing. In *5th international ICST conference on pervasive computing technologies for healthcare*, volume 10, 2011.
- [19] Sharon Horwood and Jeromy Anglim. Problematic smartphone usage and subjective and psychological wellbeing. *Computers in Human Behavior*, 97:44–50, 2019.
- [20] Jaehee Cho. Roles of smartphone app use in improving social capital and reducing social isolation. *Cyberpsychology, behavior, and social networking*, 18(6):350–355, 2015.
- [21] Ioannis Bakolis, Ryan Hammoud, Michael Smythe, Johanna Gibbons, Neil Davidson, Stefania Tognin, and Andrea Mechelli. Urban mind: Using smartphone technologies to investigate the impact of nature on mental well-being in real time. *BioScience*, 68(2):134–145, 2018.
- [22] Fiona H McKay, Annemarie Wright, Jane Shill, Hugh Stephens, and Mary Uccellini. Using health and well-being apps for behavior change: a systematic search and rating of apps. *JMIR mHealth and uHealth*, 7(7):e11926, 2019.
- [23] Jonathan B Bricker, Noreen L Watson, Kristin E Mull, Brianna M Sullivan, and Jaimee L Heffner. Efficacy of smartphone applications for smoking cessation: a randomized clinical trial. *JAMA internal medicine*, 180(11):1472–1480, 2020.
- [24] Morwenna Kirwan, Corneel Vandelanotte, Andrew Fenning, Mitch J Duncan, et al. Diabetes self-management smartphone application for adults with type 1 diabetes: randomized controlled trial. *Journal of medical Internet research*, 15(11):e2588, 2013.
- [25] Steven S Coughlin, Mary Whitehead, Joyce Q Sheats, Jeff Mastromonico, Dale Hardy, and Selina A Smith. Smartphone applications for promoting healthy diet and nutrition: a literature review. *Jacobs journal of food and nutrition*, 2(3):021, 2015.
- [26] Guanhua Ye, Hongzhi Yin, Tong Chen, Hongxu Chen, Lizhen Cui, and Xiangliang Zhang. Fenet: a frequency extraction network for obstructive sleep apnea detection. *IEEE Journal of Biomedical and Health Informatics*, 25(8):2848–2856, 2021.
- [27] Davide Maria Cammisuli, Giada Pietrabissa, and Gianluca Castelnuovo. Improving wellbeing of community-dwelling people with mild cognitive impairment: the senior (system of nudge theory based ict applications for older citizens) project. *Neural Regeneration Research*, 16(5):963, 2021.
- [28] Caroline Free, Gemma Phillips, Lambert Felix, Leandro Galli, Vikram Patel, and Philip Edwards. The effectiveness of m-health technologies for improving health and health services: a systematic review protocol. *BMC research notes*, 3(1):1–7, 2010.
- [29] Genevieve F Dunton, Yue Liao, Stephen S Intille, Donna Spruijt-Metz, and Maryann Pentz. Investigating children’s physical activity and sedentary behavior using ecological momentary assessment with mobile phones. *Obesity*, 19(6):1205–1212, 2011.
- [30] Frederic Ehrler and Christian Lovis. Supporting elderly homecare with smartwatches: advantages and drawbacks. *Studies in health technology and informatics*, 205:667–71, 2014.
- [31] Magnus T Jensen, Roderick W Treskes, Enrico G Caiani, Ruben Casado-Arroyo, Martin R Cowie, Polychronis Dilaveris, David Duncker, Marco Di Rienzo, Ines Frederix, Natasja De Groot, et al. Esc working group on e-cardiology position paper: Use of commercially available wearable technology for heart rate and activity tracking in primary and secondary cardiovascular prevention—in collaboration with the european heart rhythm association, european association of preventive cardiology, association of cardiovascular nursing and allied professionals, patient forum, and the digital health committee. *European Heart Journal-Digital Health*, 2(1):49–59, 2021.
- [32] Delores CS James and Cedric Harville. Barriers and motivators to participating in mhealth research among african american men. *American journal of men’s health*, 11(6):1605–1613, 2017.
- [33] Dimitrios E Iakovakis, Fotini A Papadopoulou, and Leontios J Hadjileontiadis. Fuzzy logic-based risk of fall estimation using smartwatch data as a means to form an assistive feedback mechanism in everyday living activities. *Healthcare technology letters*, 3(4):263–268, 2016.

- [34] Emil Jovanov. Preliminary analysis of the use of smartwatches for longitudinal health monitoring. In *2015 37th annual international conference of the IEEE engineering in medicine and biology society (EMBC)*, pages 865–868. IEEE, 2015.
- [35] Roxanne Gal, Anne M May, Elon J van Overmeeren, Monique Simons, and Evelyn M Monninkhof. The effect of physical activity interventions comprising wearables and smartphone applications on physical activity: a systematic review and meta-analysis. *Sports medicine-open*, 4(1):1–15, 2018.
- [36] Amelia Romeo, Sarah Edney, Ronald Plotnikoff, Rachel Curtis, Jillian Ryan, Ilea Sanders, Alyson Crozier, Carol Maher, et al. Can smartphone apps increase physical activity? systematic review and meta-analysis. *Journal of medical Internet research*, 21(3):e12053, 2019.
- [37] Darius A Rohani, Maria Faurholt-Jepsen, Lars Vedel Kessing, and Jakob E Bardram. Correlations between objective behavioral features collected from mobile and wearable devices and depressive mood symptoms in patients with affective disorders: systematic review. *JMIR mHealth and uHealth*, 6(8):e9691, 2018.
- [38] Geoffrey H Tison, José M Sanchez, Brandon Ballinger, Avesh Singh, Jeffrey E Olgin, Mark J Pletcher, Eric Vittinghoff, Emily S Lee, Shannon M Fan, Rachel A Gladstone, et al. Passive detection of atrial fibrillation using a commercially available smartwatch. *JAMA cardiology*, 3(5):409–416, 2018.
- [39] Jennifer L Hicks, Tim Althoff, Rok Susic, Peter Kuhar, Bojan Bostjancic, Abby C King, Jure Leskovec, and Scott L Delp. Best practices for analyzing large-scale health data from wearables and smartphone apps. *NPJ digital medicine*, 2(1):1–12, 2019.
- [40] Michelle Holko, Tamara R Litwin, Fatima Munoz, Katrina I Theisz, Linda Salgin, Nancy Piper Jenks, Beverly W Holmes, Pamela Watson-McGee, Eboni Winford, and Yashoda Sharma. Wearable fitness tracker use in federally qualified health center patients: strategies to improve the health of all of us using digital health devices. *NPJ Digital Medicine*, 5(1):1–6, 2022.
- [41] Geoffrey H Tison, Robert Avram, Peter Kuhar, Sean Abreau, Greg M Marcus, Mark J Pletcher, and Jeffrey E Olgin. Worldwide effect of covid-19 on physical activity: a descriptive study. *Annals of internal medicine*, 173(9):767–770, 2020.
- [42] Hugo Barbosa, Marc Barthelemy, Gourab Ghoshal, Charlotte R James, Maxime Lenormand, Thomas Louail, Ronaldo Menezes, José J Ramasco, Filippo Simini, and Marcello Tomasini. Human mobility: Models and applications. *Physics Reports*, 734:1–74, 2018.
- [43] Marco V Perez, Kenneth W Mahaffey, Haley Hedlin, John S Rumsfeld, Ariadna Garcia, Todd Ferris, Vidhya Balasubramanian, Andrea M Russo, Amol Rajmane, Lauren Cheung, et al. Large-scale assessment of a smartwatch to identify atrial fibrillation. *New England Journal of Medicine*, 381(20):1909–1917, 2019.
- [44] Rob Powers, Maryam Etezadi-Amoli, Edith M Arnold, Sara Kianian, Irida Mance, Maxim Gibiansky, Dan Trietsch, Alexander Singh Alvarado, James D Kretlow, Todd M Herrington, et al. Smartwatch inertial sensors continuously monitor real-world motor fluctuations in parkinson’s disease. *Science translational medicine*, 13(579):eabd7865, 2021.
- [45] Luis Sigcha, Ignacio Pavón, Néelson Costa, Susana Costa, Miguel Gago, Pedro Arezes, Juan Manuel López, and Guillermo De Arcas. Automatic resting tremor assessment in parkinson’s disease using smartwatches and multitask convolutional neural networks. *Sensors*, 21(1):291, 2021.
- [46] Harishchandra Dubey, Jon C Goldberg, Mohammadreza Abtahi, Leslie Mahler, and Kunal Mankodiya. Echowear: smartwatch technology for voice and speech treatments of patients with parkinson’s disease. In *Proceedings of the conference on Wireless Health*, pages 1–8, 2015.
- [47] Vinod Sharma, Kunal Mankodiya, Fernando De La Torre, Ada Zhang, Neal Ryan, Thanh GN Ton, Rajeev Gandhi, and Samay Jain. Spark: personalized parkinson disease interventions through synergy between a smartphone and a smartwatch. In *International Conference of Design, User Experience, and Usability*, pages 103–114. Springer, 2014.
- [48] Shyamal Patel, Hyung Park, Paolo Bonato, Leighton Chan, and Mary Rodgers. A review of wearable sensors and systems with application in rehabilitation. *Journal of neuroengineering and rehabilitation*, 9(1):1–17, 2012.
- [49] Sang Hoon Chae, Yushin Kim, Kyoung-Soub Lee, and Hyung-Soon Park. Development and clinical evaluation of a web-based upper limb home rehabilitation system using a smartwatch and machine learning model for chronic stroke survivors: prospective comparative study. *JMIR mHealth and uHealth*, 8(7):e17216, 2020.
- [50] Julia Thorpe, Birgitte Hysse Forchhammer, Anja M Maier, et al. Adapting mobile and wearable technology to provide support and monitoring in rehabilitation for dementia: feasibility case series. *JMIR formative research*, 3(4):e12346, 2019.

- [51] Wayne CW Giang, Liberty Hoekstra-Atwood, and Birsen Donmez. Driver engagement in notifications: A comparison of visual-manual interaction between smartwatches and smartphones. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, volume 58, pages 2161–2165. Sage Publications Sage CA: Los Angeles, CA, 2014.
- [52] Rúben Gouveia, Evangelos Karapanos, and Marc Hassenzähl. How do we engage with activity trackers? a longitudinal study of habito. In *Proceedings of the 2015 ACM international joint conference on pervasive and ubiquitous computing*, pages 1305–1316, 2015.
- [53] Tim Althoff, Rok Sosič, Jennifer L Hicks, Abby C King, Scott L Delp, and Jure Leskovec. Large-scale physical activity data reveal worldwide activity inequality. *Nature*, 547(7663):336–339, 2017.
- [54] Zachary C Pope, Daheia J Barr-Anderson, Beth A Lewis, Mark A Pereira, and Zan Gao. Use of wearable technology and social media to improve physical activity and dietary behaviors among college students: A 12-week randomized pilot study. *International Journal of Environmental Research and Public Health*, 16(19):3579, 2019.
- [55] Gretchen A Stevens, Leontine Alkema, Robert E Black, J Ties Boerma, Gary S Collins, Majid Ezzati, John T Grove, Daniel R Hogan, Margaret C Hogan, Richard Horton, et al. Guidelines for accurate and transparent health estimates reporting: the gather statement. *PLoS medicine*, 13(6):e1002056, 2016.
- [56] Reza Rawassizadeh, Martin Tomitsch, Manouchehr Nourizadeh, Elaheh Momeni, Aaron Peery, Liudmila Ulanova, and Michael Pazzani. Energy-efficient integration of continuous context sensing and prediction into smartwatches. *Sensors*, 15(9):22616–22645, 2015.
- [57] William HE Day and Herbert Edelsbrunner. Efficient algorithms for agglomerative hierarchical clustering methods. *Journal of classification*, 1(1):7–24, 1984.
- [58] John Paparrizos and Luis Gravano. k-shape: Efficient and accurate clustering of time series. In *Proceedings of the 2015 ACM SIGMOD international conference on management of data*, pages 1855–1870, 2015.
- [59] Inderjit S Dhillon, Yuqiang Guan, and Brian Kulis. Kernel k-means: spectral clustering and normalized cuts. In *Proceedings of the tenth ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 551–556, 2004.
- [60] Martin Ester, Hans-Peter Kriegel, Jörg Sander, Xiaowei Xu, et al. A density-based algorithm for discovering clusters in large spatial databases with noise. In *kdd*, volume 96, pages 226–231, 1996.
- [61] Mihael Ankerst, Markus M Breunig, Hans-Peter Kriegel, and Jörg Sander. Optics: Ordering points to identify the clustering structure. *ACM Sigmod record*, 28(2):49–60, 1999.
- [62] Fionn Murtagh and Pierre Legendre. Ward’s hierarchical clustering method: clustering criterion and agglomerative algorithm. *arXiv preprint arXiv:1111.6285*, 2011.
- [63] Karl-Jürgen Bär, Michael Karl Boettger, Mandy Koschke, Steffen Schulz, Pratap Chokka, Vikram K Yeragani, and Andreas Voss. Non-linear complexity measures of heart rate variability in acute schizophrenia. *Clinical neurophysiology*, 118(9):2009–2015, 2007.
- [64] J MacQueen. Classification and analysis of multivariate observations. In *5th Berkeley Symp. Math. Statist. Probability*, pages 281–297, 1967.
- [65] Juha Vesanto and Esa Alhoniemi. Clustering of the self-organizing map. *IEEE Transactions on neural networks*, 11(3):586–600, 2000.
- [66] Conny MA van Ravenswaaij-Arts, Louis AA Kollee, Jeroen CW Hopman, Gerard BA Stoeltinga, and Herman P van Geijn. Heart rate variability. *Annals of internal medicine*, 118(6):436–447, 1993.
- [67] Kim Fox, Jeffrey S Borer, A John Camm, Nicolas Danchin, Roberto Ferrari, Jose L Lopez Sendon, Philippe Gabriel Steg, Jean-Claude Tardif, Luigi Tavazzi, Michal Tendera, et al. Resting heart rate in cardiovascular disease. *Journal of the American College of Cardiology*, 50(9):823–830, 2007.
- [68] Julian F Thayer, Shelby S Yamamoto, and Jos F Brosschot. The relationship of autonomic imbalance, heart rate variability and cardiovascular disease risk factors. *International journal of cardiology*, 141(2):122–131, 2010.
- [69] Yiling J Cheng, Michael S Lauer, Conrad P Earnest, Timothy S Church, James B Kampert, Larry W Gibbons, and Steven N Blair. Heart rate recovery following maximal exercise testing as a predictor of cardiovascular disease and all-cause mortality in men with diabetes. *Diabetes care*, 26(7):2052–2057, 2003.
- [70] Jenni Anttonen and Veikko Surakka. Emotions and heart rate while sitting on a chair. In *Proceedings of the SIGCHI conference on Human factors in computing systems*, pages 491–499, 2005.
- [71] Anja Struyf, Mia Hubert, and Peter Rousseeuw. Clustering in an object-oriented environment. *Journal of Statistical Software*, 1:1–30, 1997.

- [72] Robert L Thorndike. Who belongs in the family. 1953.
- [73] Jing Tian, Michael H Azarian, and Michael Pecht. Anomaly detection using self-organizing maps-based k-nearest neighbor algorithm. In *PHM Society European Conference*, volume 2, 2014.
- [74] Gökhan Akçapınar, Arif Altun, and Erdal Cosgun. Investigating students’ interaction profile in an online learning environment with clustering. In *2014 IEEE 14th International Conference on Advanced Learning Technologies*, pages 109–111. IEEE, 2014.
- [75] Ying Zhao and George Karypis. Criterion functions for document clustering: Experiments and analysis. 2001.
- [76] William M Rand. Objective criteria for the evaluation of clustering methods. *Journal of the American Statistical association*, 66(336):846–850, 1971.
- [77] David H Spodick, Padma Raju, Richard L Bishop, and Robert D Rifkin. Operational definition of normal sinus heart rate. *The American journal of cardiology*, 69(14):1245–1246, 1992.
- [78] Scott J Strath, Ann M Swartz, DAVID R Bassett Jr, WILLIAM L O’Brien, George A King, and Barbara E Ainsworth. Evaluation of heart rate as a method for assessing moderate intensity physical activity. *Medicine and science in sports and exercise*, 32(9 Suppl):S465–70, 2000.
- [79] Robert Carter III, Samuel N Cheuvront, D Walter Wray, Margaret A Kolka, Lou A Stephenson, and Michael N Sawka. The influence of hydration status on heart rate variability after exercise heat stress. *Journal of Thermal Biology*, 30(7):495–502, 2005.
- [80] G Berggren and E Hohwü Christensen. Heart rate and body temperature as indices of metabolic rate during work. *Arbeitsphysiologie*, 14(3):255–260, 1950.
- [81] Reza Rawassizadeh, Elaheh Momeni, Chelsea Dobbins, Joobin Gharibshah, and Michael Pazzani. Scalable Daily Human Behavioral Pattern Mining from Multivariate Temporal Data. *IEEE Transactions on Knowledge and Data Engineering*, 28(11):3098–3112, 2016.
- [82] Altug Cincin, Ibrahim Sari, Mustafa Oğuz, Sena Sert, Mehmet Bozbay, Halil Ataş, Beste Ozben, Kursat Tigen, and Yelda Basaran. Effect of acute sleep deprivation on heart rate recovery in healthy young adults. *Sleep and Breathing*, 19(2):631–636, 2015.
- [83] Charles F George and Meir H Kryger. Sleep and control of heart rate. *Clinics in chest medicine*, 6(4):595–601, 1985.
- [84] Raj Padwal, Norm RC Campbell, Michael A Weber, Daniel Lackland, Daichi Shimbo, Xin-Hua Zhang, Aletta E Schutte, Michael Rakotz, Gregory Wozniak, Raymond Townsend, et al. The accuracy in measurement of blood pressure (aim-bp) collaborative: background and rationale. *The Journal of Clinical Hypertension*, 21(12):1780–1783, 2019.
- [85] Phyllis K Stein, Stephen P Duntley, Peter P Domitrovich, Pallavi Nishith, and Robert M Carney. A simple method to identify sleep apnea using holter recordings. *Journal of cardiovascular electrophysiology*, 14(5):467–473, 2003.
- [86] C Maier, H Wenz, and H Dickhaus. Robust detection of sleep apnea from holter ecgs. *Methods of information in medicine*, 53(04):303–307, 2014.
- [87] Phyllis K Stein and Yachuan Pu. Heart rate variability, sleep and sleep disorders. *Sleep medicine reviews*, 16(1):47–66, 2012.
- [88] Barbara Griefahn. The validity of the temporal parameters of the daily rhythm of melatonin levels as an indicator of morningness. *Chronobiology international*, 19(3):561–577, 2002.
- [89] Michael G Smith, Ilona Croy, Mikael Ögren, and Kerstin Persson Waye. On the influence of freight trains on humans: a laboratory investigation of the impact of nocturnal low frequency vibration and noise on sleep and heart rate. *PloS one*, 8(2):e55829, 2013.
- [90] Ronald Szymusiak. Body temperature and sleep. *Handbook of clinical neurology*, 156:341–351, 2018.
- [91] Esa Hynynen, Niilo Konttinen, Ulla Kinnunen, Heikki Kyröläinen, and Heikki Rusko. The incidence of stress symptoms and heart rate variability during sleep and orthostatic test. *European journal of applied physiology*, 111(5):733–741, 2011.
- [92] Esa Hynynen, Niilo Konttinen, and Heikki Rusko. Heart rate variability and stress hormones in novice and experienced parachutists anticipating a jump. *Aviation, space, and environmental medicine*, 80(11):976–980, 2009.
- [93] Hideki Tanaka and Shuichiro Shirakawa. Sleep health, lifestyle and mental health in the japanese elderly: ensuring sleep to promote a healthy brain and mind. *Journal of psychosomatic research*, 56(5):465–477, 2004.

- [94] Akira Bannai and Akiko Tamakoshi. The association between long working hours and health: a systematic review of epidemiological evidence. *Scandinavian journal of work, environment & health*, pages 5–18, 2014.
- [95] K Nakamura, S Shimai, S Kikuchi, H Takahashi, M Tanaka, S Nakano, Y Motohashi, H Nakadaira, and M Yamamoto. Increases in body mass index and waist circumference as outcomes of working overtime. *Occupational Medicine*, 48(3):169–173, 1998.
- [96] Yasushi Azami, Mitsuhiko Funakoshi, Hisashi Matsumoto, Akemi Ikota, Koichi Ito, Hisashi Okimoto, Nobuaki Shimizu, Fumihiko Tsujimura, Hiroshi Fukuda, Chozi Miyagi, et al. Long working hours and skipping breakfast concomitant with late evening meals are associated with suboptimal glycemic control among young male Japanese patients with type 2 diabetes. *Journal of diabetes investigation*, 10(1):73–83, 2019.
- [97] Michael R Irwin, Edwin M Valladares, Sarosh Motivala, Julian F Thayer, and Cindy L Ehlers. Association between nocturnal vagal tone and sleep depth, sleep quality, and fatigue in alcohol dependence. *Psychosomatic Medicine*, 68(1):159–166, 2006.
- [98] Yasmine Azza, Marcus Grueschow, Walter Karlen, Erich Seifritz, and Birgit Kleim. How stress affects sleep and mental health: Nocturnal heart rate increases during prolonged stress and interacts with childhood trauma exposure to predict anxiety. *Sleep*, 43(6):zsz310, 2020.
- [99] Zvi Shinar, Solange Akselrod, Yaron Dagan, and Armanda Baharav. Autonomic changes during wake–sleep transition: A heart rate variability based approach. *Autonomic Neuroscience*, 130(1-2):17–27, 2006.
- [100] ESA Hynynen, Arja Uusitalo, Niilo Kontinen, and Heikki Rusko. Heart rate variability during night sleep and after awakening in overtrained athletes. *Medicine and science in sports and exercise*, 38(2):313, 2006.
- [101] Jos F Brosschot, Eduard Van Dijk, and Julian F Thayer. Daily worry is related to low heart rate variability during waking and the subsequent nocturnal sleep period. *International journal of psychophysiology*, 63(1):39–47, 2007.
- [102] Lampros Perogamvros, Hyeong-Dong Park, Laurence Bayer, Aurore A Perrault, Olaf Blanke, and Sophie Schwartz. Increased heartbeat-evoked potential during rem sleep in nightmare disorder. *NeuroImage: Clinical*, 22:101701, 2019.
- [103] Seung Rok Kang, Jin-Young Min, Changho Yu, and Tae-Kyu Kwon. Effect of whole body vibration on lactate level recovery and heart rate recovery in rest after intense exercise. *Technology and Health Care*, 25(S1):115–123, 2017.
- [104] Hannah G Lund, Brian D Reider, Annie B Whiting, and J Roxanne Prichard. Sleep patterns and predictors of disturbed sleep in a large population of college students. *Journal of adolescent health*, 46(2):124–132, 2010.
- [105] Patrick John Butler, Jonathan Andrew Green, IL Boyd, and JR Speakman. Measuring metabolic rate in the field: the pros and cons of the doubly labelled water and heart rate methods. *Functional ecology*, 18(2):168–183, 2004.
- [106] Urban Wiklund, Marcus Karlsson, Mats Öström, and Torbjörn Messner. Influence of energy drinks and alcohol on post-exercise heart rate recovery and heart rate variability. *Clinical physiology and functional imaging*, 29(1):74–80, 2009.
- [107] Maja Udovicic, Raul Herrera Pena, Bhargavi Patham, Laila Tabatabai, and Abhishek Kansara. Hypothyroidism and the heart. *Methodist DeBakey cardiovascular journal*, 13(2):55, 2017.
- [108] Ching-Chi Lin, Kun-Wu Tsan, and Pei-Jan Chen. The relationship between sleep apnea syndrome and hypothyroidism. *Chest*, 102(6):1663–1667, 1992.
- [109] Milena Cojić and Ljiljana Cvejanov-Kezunović. Subclinical hypothyroidism—whether and when to start treatment? *Open access Macedonian journal of medical sciences*, 5(7):1042, 2017.
- [110] Irwin Klein and Sara Danzi. Thyroid disease and the heart. *Circulation*, 116(15):1725–1735, 2007.
- [111] M Buchheit, R Richard, S Doutreleau, E Lonsdorfer-Wolf, G Brandenberger, and C Simon. Effect of acute hypoxia on heart rate variability at rest and during exercise. *International journal of sports medicine*, 25(04):264–269, 2004.
- [112] WR Barrionuevo and WW Burggren. O₂ consumption and heart rate in developing zebrafish (danio rerio): influence of temperature and ambient O₂. *American Journal of Physiology-Regulatory, Integrative and Comparative Physiology*, 276(2):R505–R513, 1999.
- [113] Luciano Bernardi, Felice Valle, Michel Coco, Alessandro Calciati, and Peter Sleight. Physical activity influences heart rate variability and very-low-frequency components in holter electrocardiograms. *Cardiovascular research*, 32(2):234–237, 1996.
- [114] AP Farrell. Effects of temperature on cardiovascular performance. In *SEMINAR SERIES-SOCIETY FOR EXPERIMENTAL BIOLOGY*, volume 61, pages 135–158. Cambridge University Press, 1997.

- [115] Charles P Lyman. Oxygen consumption, body temperature and heart rate of woodchucks entering hibernation. *American Journal of Physiology-Legacy Content*, 194(1):83–91, 1958.
- [116] Steven W Edwards, Elbert D Glover, and Kathleen L Schroeder. The effects of smokeless tobacco on heart rate and neuromuscular reactivity in athletes and nonathletes. *The Physician and Sportsmedicine*, 15(7):141–147, 1987.
- [117] Ziad M El-Zaatari, Hassan A Chami, and Ghazi S Zaatari. Health effects associated with waterpipe smoking. *Tobacco control*, 24(Suppl 1):i31–i43, 2015.
- [118] Veronika Engert, Anna M Koester, Antje Riepenhausen, and Tania Singer. Boosting recovery rather than buffering reactivity: higher stress-induced oxytocin secretion is associated with increased cortisol reactivity and faster vagal recovery after acute psychosocial stress. *Psychoneuroendocrinology*, 74:111–120, 2016.
- [119] Heather Noland, James H Price, Joseph Dake, and Susan K Telljohann. Adolescents’ sleep behaviors and perceptions of sleep. *Journal of school health*, 79(5):224–230, 2009.