Using ECG Data to Predict Positive Distance Running Experiences

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Abstract

The feeling of going on a run can vary dramatically from person to person and even from day to day, with some runs feeling like flying and others like an uphill battle. But what causes these drastic differences in running experience, and, more importantly, is there something we can do to change this? Biomechanical parameters have been correlated with positive running experiences, while the potential relationship between ECG (heart rate) parameters and running experiences provides a promising avenue for additional discovery, due to the heart rate's link to exercise and emotion. In this study, we investigated the relationship between ECG data and good feelings on a run in order to assess the promise of ECG data for use in a wearable biofeedback system for improving distance running experiences. Specifically, we used preliminary pilot ECG and feeling data from three runs and performed a visual time series analysis inspecting for any obvious relationships, as well as correlation testing. We found no evident relationship from visual inspection of the time series data as well as no significant correlations (maximum across all features tested had $R = 0.09$, $p = 0.01$). However, there were a variety of limiting factors in this analysis that may have inhibited our ability to discover a relationship, including novel application of preprocessing techniques and a limited data set, suggesting that additional data collection and perhaps more complex analysis methods may be needed to uncover a potential relationship.

Introduction

Although there are significant health benefits to regular exercise, less than a quarter of adults in the US reach the aerobic and muscle-strengthening guidelines (Whitfield 2019). Distance running is a common form of exercise as it is relatively inexpensive and quick to start (Eime 2015). While there are numerous contributors to why people do or do not run (such as metamotivational state or mental toughness), many can be interpreted as affecting the balance between how hard the run is versus how good it feels. Affective valence offers a holistic measure of how good a run feels, thereby directly describing one side of this balance. Runs with a positive affective valence (i.e. positive running experiences) often lead to sustained participation in running (Rhodes 2015) and corresponding health benefits (Pedisic 2020). However, the running experience can vary dramatically from person to person and from day to day. This widespread inconsistency in running experience begs the question: what causes a run to feel "good", and is there anything we can do to make all runs feel good? In order to increase the consistency of positive running experiences, we first need to gain a better understanding of which biomechanical and physiological parameters impact the feel of a run.

To date, two studies have examined the relationship between specific running biomechanical parameters and affective valence during distance running. Lussiana and Gindre (2016) investigated the relationship between lower-body biomechanics (contact time, aerial time, and leg stiffness) on the affective valence of different types of runners on a track. Van der bie and Kröse (2015) investigated the relationship between wrist kinematics and affective valence during treadmill runs. Both studies reported significant correlations between affective valence and biomechanics, indicating promise in the use of biomechanical parameters to predict running experience. We aim to expand upon these works by examining an expanded set of biomechanical and physiological parameters to aid in the prediction of running experience, a comprehensive tool which may ultimately be used in a wearable biofeedback system to improve runs.

One promising physiological parameter that may be associated with affective valence is heart activity. Using an electrocardiogram (ECG), which measures the electrical signal of the heart, one can compute a variety of heart activity measurements, such as heart rate and heart rate variability. Heart rate is commonly used in the exercise and fitness community as ways to monitor aerobic intensity (Esposito 2004). Heart rate variability (HRV) is a measure of the amount of variation in the time between successive heartbeats and has been linked to a variety of factors such as stress (Kim 2018), sleep (Sajjadieh 2020), and diet (Young 2018). In general, a higher HRV is seen to indicate better overall health (Jarczok 2015). HRV has even been used as a training tool to adjust the intensity of a workout based on the individual's rest and readiness state (da Silva 2017). Measuring HRV during exercise is more challenging due to a variety of signal quality issues that arise (Namazi 2021), but HRV has been shown to exhibit an inverse relationship with exercise intensity (Michael 2017). HRV is also tied to the parasympathetic nervous system (Chapleau 2011), perhaps indicating a relationship with one's emotional state.

Therefore, we investigated the relationship between ECG data and affective valence during long-distance overground runs. In this preliminary, pilot analysis, we examined the relationship between a variety of ECG metrics and affective valence by visually inspecting for trends and correlating the metrics to affective valence.

Methods

Experimental Procedure and Data Collection

The data for this investigation consisted of three pilot runs collected from one subject (Female, age 23 years, with 9 years of competitive running including Division 1 racing, no current injuries). The subject proceeded on the approximately 50 minute run (on an outdoor, fairly flat, and paved course) while equipped with a full-body IMU (Inertial Measurement Unit) set and an ECG heart rate monitor. The subject was instructed to run at a moderate pace, such that if they were running with a friend they could carry on a conversation but with frequent pauses for breath. Throughout the duration of the run, the subject recorded her affective valence scores (using the Feeling Scale (Hardy 1989), ranging from +5 (Very Good) to -5 (Very Bad)) through buttons on a handheld APDM Opal (APDM, Portland, OR, US) IMU every time she perceived a change in affective valence. The ECG data was collected through the commercially available and widely-used Polar H10 chest strap heart monitor (Polar Electro, Kempele, Finland) (Caminal 2018). The ECG data was transmitted at 130 Hz from the Polar H10 via ECG Logger (ECG Logger for Polar H10, Matti Mononen) and logged on the runner's smartphone.

ECG Preprocessing

After the raw ECG data was collected, two preprocessing measures were applied to prepare the data for HRV feature calculation. To perform the preprocessing, we utilized Kubios HRV Premium (ver. 3.50, Kuopio, Finland), an ECG processing software tool that has been widely utilized and validated throughout the literature (Laborde 2017) (Tarvainen 2014). Within Kubios HRV, specific preprocessing measures can be applied, customized to the needs of one's specific dataset. The first preprocessing technique performed was upsampling through interpolation. Although the Polar H10's sampling rate of 130 Hz is high for wearable ECG's, when compared to hospital grade stationary ECG's that sample upwards of 1000 Hz the 130 Hz sampling rate is actually relatively low. This lower sampling rate challenges the validity of the HRV features calculated from the ECG data, and a variety of studies have investigated the effect of sampling rate on the reliability of HRV features in an attempt to establish recommendations for sufficient sampling and processing methods to give accurate HRV results (Ellis 2015). A common method to increase the effective sampling rate of a signal is to utilize upsampling through interpolation techniques. Although a variety of interpolation algorithms exist (Mahdiani 2015) (Choi 2018) (Morelli 2019), the 4 Hz cubic spline interpolation is the most common interpolation technique utilized with wearable ECG devices (Ellis 2015). Therefore, we applied a 4 Hz cubic spline interpolation to the raw ECG signal to obtain a 2000 Hz signal. After interpolation of the raw ECG data, we executed the Kubios beat detection algorithm to determine the RR intervals based on the Pan-Tompkins algorithm (Pan 1985). An RR interval is defined as the time between successive heartbeats (Figure 1), and is the data stream used to compute all other heart rate metrics.

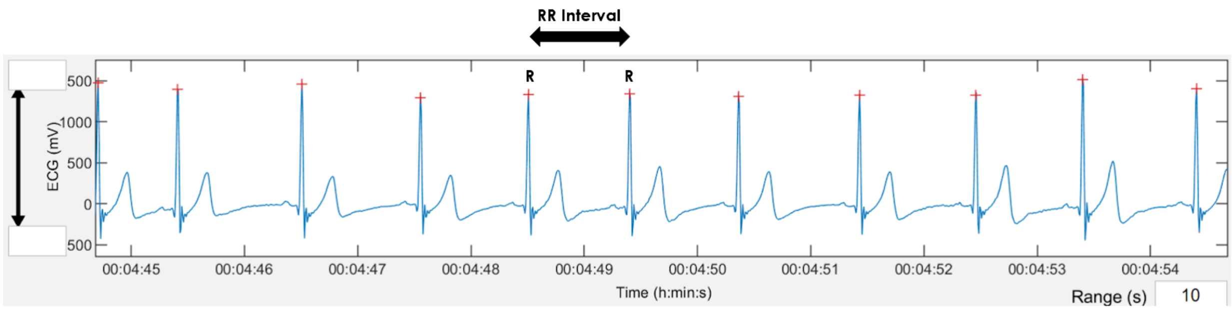

Figure 1: Example ECG signal with an RR interval called out.

After computing the RR intervals, we verified accurate RR interval detection using a two-pronged approach to both detect and fix erroneous measurements. First, we performed the Kubios automatic beat correction algorithm (Lipponen 2019), which identifies errors from a time series consisting of differences between successive RR intervals. Lastly, we applied the Kubios noise detection algorithm, which isolated particularly noisy sections of data, and we withheld these sections from subsequent feature calculations.

HRV Feature Calculation

After preprocessing the data, we calculated the six different ECG features shown below in Table 1. These six features were the most widely used ECG features throughout the literature (Laborde 2017) (Caminal 2018) and were chosen to envelop the broad range of possible types of ECG features.

Table 1: The six ECG features analyzed in the study.

Feature Name	Description (Tarvainen 2021)	Domain
Mean HR	Average Heart Rate	Heart Rate
RMSSD	Root Mean Square of Successive Differences Between Heartbeats	HRV - Time Domain
SDNN	Standard Deviation of RR Intervals	HRV - Time Domain

HF Power	High Frequency Band Power	HRV - Frequency Domain
LF Power	Low Frequency Band Power	HRV - Frequency Domain
LF/HF Power	Ratio between LF and HF Powers	HRV - Frequency Domain

After selecting the features to calculate, we then specified the time window over which to calculate each feature. As these features do not occur at an instant in time, one must choose a certain window length, or duration of time, over which to calculate an ECG feature. After a calculation is made for a specific time point, this window is then slid forward in time across the data, creating a time series output of the ECG feature. Therefore, determining an optimal window interval duration is an important engineering decision to make during data processing. Historically, five minute window intervals were thought to be the minimum amount of time necessary for accurate HRV feature calculations (Malik 1996). More recently, studies have shown that it may be feasible to obtain accurate results from even shorter durations, especially during rest, but even during exercising (specifically stationary cycling) (Kim 2021). However, these results have not been tested during running (which may be subject to more noise from external motion) nor with wearable and portable ECG devices such as the Polar H10. We therefore began with the aforementioned five minute window interval duration, as a conservative minimum window duration for feature calculation, and then iteratively reduced the duration down to one minute in an attempt to detect changes occurring on a smaller timescale.

The final processing step of the ECG data was excluding portions of the run where the subject was stationary. Although the goal of the run was a consistent, steady-state effort, due to the nature of running in a real-world, outdoor environment, our subject had multiple times throughout each run where she was stopped either at a stoplight or to take a quick break. These timestamps of stoppage were identified via visual inspection of IMU data from the feet, and after completing feature calculation, we isolated and removed all portions of the run where the ECG feature output was impacted by these pauses (i.e., time while actually stopped and time while within the 5-minute feature calculation window).

Data Analysis

After completing the ECG feature calculations, the Kubios data file containing the ECG metrics, as well as the IMU Feeling Score data was imported in MATLAB (R2019a) to prepare for analysis.

Time Series Analysis

The two data sets were overlaid on each other in a preliminary investigation of potential relationships between any HRV feature and the associated feeling scores. During this analysis, graphical relationships such as corresponding values, changes in values, or rate of changes were compared between the feeling score data and each HRV feature to see if any potential relationship was visible.

Correlation Testing

To test for potential correlations between the ECG metrics and the Feeling Score data, we performed a correlation test by pairing each ECG metric with the Feeling Score at the corresponding timestep. We first plotted grouped box and whiskers plots of each of the runs to determine how best to pool the data.

Aftering pooling the data, we plotted another set of box and whiskers plots to check for nonlinearities and determine whether any transformations were necessary prior to the linear Spearman correlation test.

After completing this analysis, we repeated the correlation testing with repeatedly shorter interval durations, from five minutes all the way down to one minute, to see if reducing the window interval size would allow us to detect relationships occurring on a shorter timescale.

Results and Discussion

Time Series Analysis

Figure 2 below shows an exemplar 8-minute section of Feeling Score and RMSSD (the exemplar ECG feature) overlaid. In the visual inspection, no obvious trends in values, changes of values, or rate of changes were seen. Additionally, there did not seem to be any apparent phase shift between the two datasets. A lack of obvious relationship was observed across all six features, and we therefore proceeded to correlation testing.

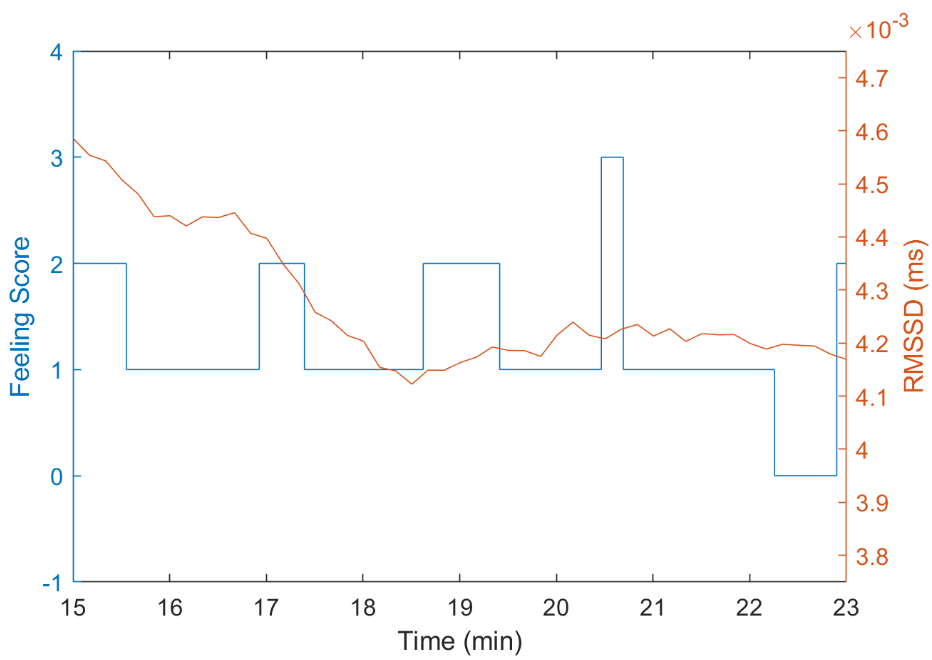

Figure 2: Exemplar 8-minute section of Feeling Score and RMSSD vs Time.

Correlation Testing

In order to include the data from all three runs in a correlation test, we inspected the values of each run individually to determine whether normalization was necessary prior to grouping. Figure 3 shows the Feeling Score and RMSSD for each of the three individual runs. The standard deviation of the RMSSD is similar across each run; however, the means of each are different, with run 1 having a higher mean RMSSD at all Feeling Scores. Therefore, prior to grouping all three runs together, the means of each were subtracted. The resulting grouped box and whiskers plot is shown below in Figure 4. No nonlinear relationships were evident, so we applied no further transformation prior to performing the correlation test. The correlation test revealed that Feeling Score and RMSSD were insignificantly correlated (R = -0.07, 95% CI = [-0.14, 0.01], p = 0.08). The low correlation was seen across all six ECG features, and because of this, we again varied the window interval duration.

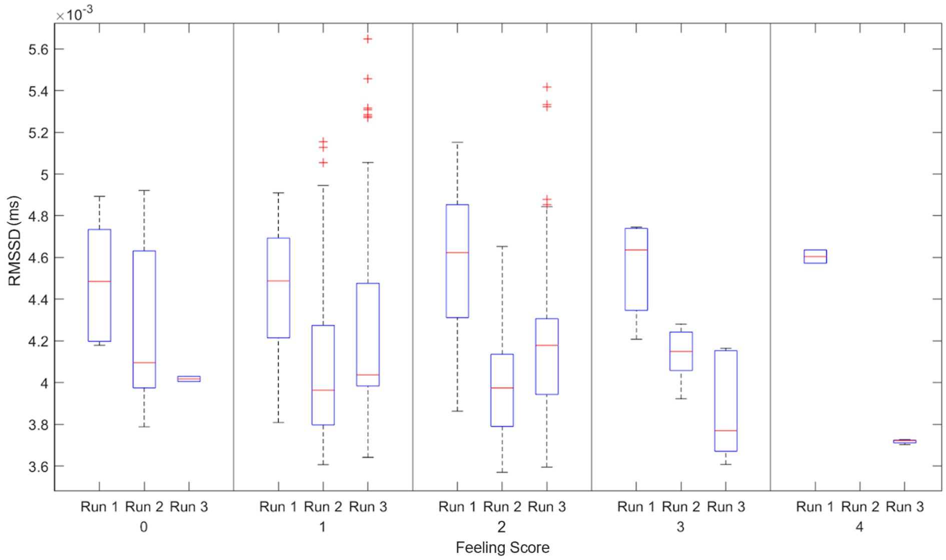

Figure 3: RMSSD vs Feeling Score box and whiskers plots for each of the three runs.

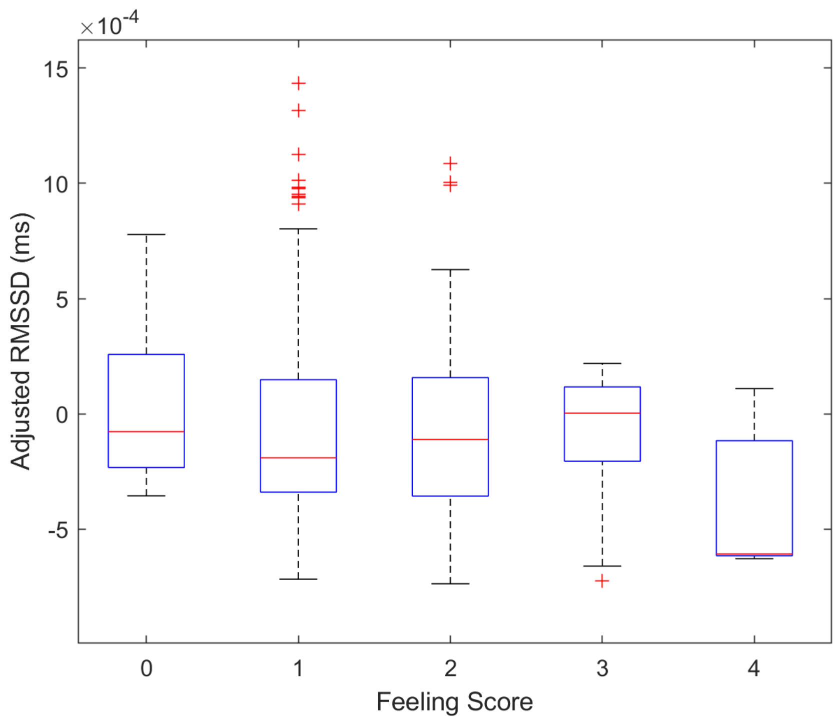

Figure 4: Adjusted RMSSD vs Feeling Score box and whiskers plot for all data.

Because changes in feeling occurred on shorter time scales than five minutes (the initial window interval length; see Figure 2), we incrementally reduced the window interval from the initial conservative length of five minutes down to one minute. Figure 5 below shows the Spearman correlation coefficients across window interval length. Lowering the window length appeared to have little to no effect on the correlation coefficient, which was consistently low ($|R| < 0.1$ and $p > 0.08$, indicating no significant correlation). This consistently low correlation coefficient was seen across all five other ECG features, where the largest magnitude correlation ($R = -0.09$, 95% CI = [-0.17, -0.02], $p = 0.01$) occurred with HF Power and two minute window duration. Ultimately, no obvious relationships existed between any of the ECG Features and the Feeling Score.

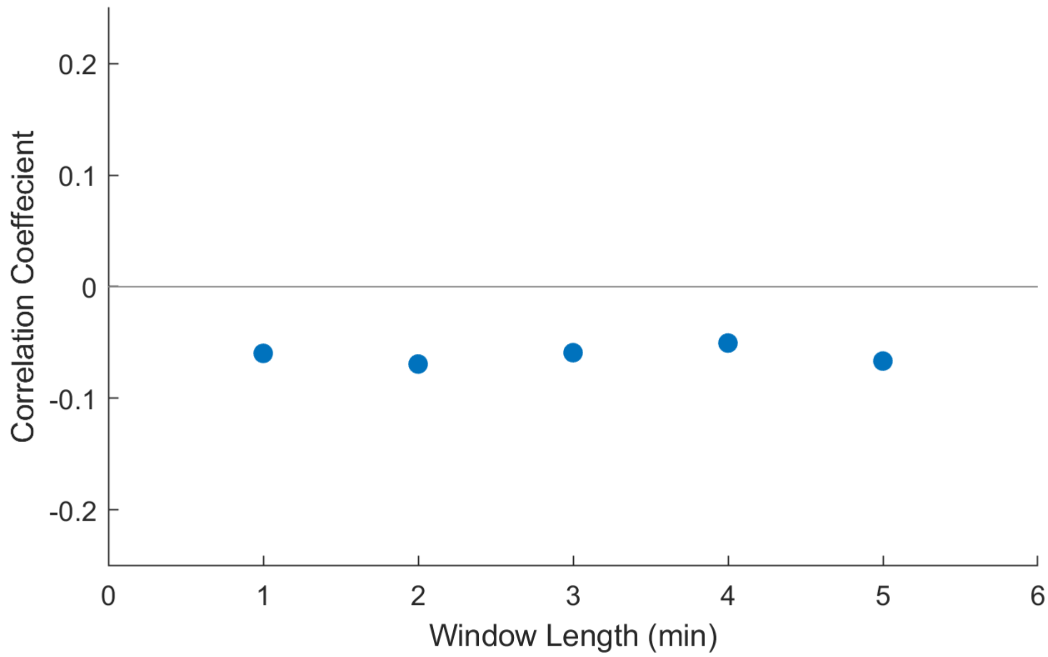

Figure 5: Correlation Coefficient vs Window Length for RMSSD.

Limitations

While this analysis did not uncover any relationship between ECG features and affective valence, this does not mean that no relationship exists. There are a variety of potential reasons our analysis did not uncover a possible relationship between ECG and Feeling Score.

While we followed the most pertinent processing recommendations for analyzing ECG data from wearable devices (including upsampling techniques and window interval durations), these recommendations were often developed for other activities which might have fewer motion artifacts (Ellis 2015) (Kim 2021) (Namazi 2021). Therefore, limitations of this analysis include the presence of motion-induced noise and low ECG sampling rate.

Next, although the Feeling Scale quantifies affective valence, feeling is inherently subjective and may be difficult to self-report. Therefore, reporting a feeling score holds an uncertain, and likely non-negligible, amount of error. It is likely that different individuals have different aptitude for self-reporting affective valence, and they may use different cues or interpretations of what feeling “good” means on a run.

Third, this study used preliminary pilot data consisting of just three runs from a single subject. This limited quantity of data is by no means comprehensive, and does not account for the possibility that a relationship between ECG and affective valence is simply not present for this subject or these individual runs. Substantially more data would be necessary to draw conclusions about broader relationships, or the lack thereof.

Lastly, the breadth of our analysis was very preliminary and it is possible that a more complex analysis would uncover a relationship.

Next Work

Future work may systematically expand the dataset, both by increasing the number of subjects and the number of runs with each subject. By collecting a large amount of additional data, we can perform more conclusive statistical analyses that are more robust to anomalies of any one individual and also explore more complex analysis methods. One such analysis method is machine learning, which may be able to uncover relationships in time series ECG data that are not captured by HRV features.

Although this study did not find evidence of a relationship between ECG data and affective valence during a run, this research has helped to establish future ECG processing and feature calculation protocols and pipelines. As we move forward with the research project, we will continue to assess the promise of ECG data in a wearable biofeedback system to improve the running experience, focusing on expanding the dataset and integrating a more complex analysis.

References

Bie, J.V., & Kröse, B.J. (2015). Happy Running? - Using an Accelerometer to Predict the Affective State of a Runner. *AmI*.

Caminal, P., Sola, F., Gomis, P., Guasch, E., Perera, A., Soriano, N., & Mont, L. (2018). Validity of the Polar V800 monitor for measuring heart rate variability in mountain running route conditions. *European journal of applied physiology*, *118*(3), 669–677. https://doi.org/10.1007/s00421-018-3808-0

Chapleau, M. W., & Sabharwal, R. (2011). Methods of assessing vagus nerve activity and reflexes. *Heart Failure Reviews*, *16*(2), 109–127. https://doi.org/10.1007/s10741-010-9174-6

Choi, A., & Shin, H. (2018). Quantitative Analysis of the Effect of an Ectopic Beat on the Heart Rate Variability in the Resting Condition. *Frontiers in physiology*, *9*, 922. https://doi.org/10.3389/fphys.2018.00922

da Silva, D. F., Ferraro, Z. M., Adamo, K. B., & Machado, F. A. (2019). Endurance Running Training Individually Guided by HRV in Untrained Women. *Journal of strength and conditioning research*, *33*(3), 736–746. https://doi.org/10.1519/JSC.0000000000002001

Eime, R., Sawyer, N.A., Harvey, J.T., Casey, M.M., Westerbeek, H., & Payne, W.R. (2015). Integrating public health and sport management: Sport participation trends 2001–2010. *Sport Management Review, 18*, 207-217.

Ellis, R. J., Zhu, B., Koenig, J., Thayer, J. F., & Wang, Y. (2015). A careful look at ECG sampling frequency and R-peak interpolation on short-term measures of heart rate variability. *Physiological Measurement*, *36*(9), 1827–1852. https://doi.org/10.1088/0967-3334/36/9/1827

Esposito, F., Impellizzeri, F. M., Margonato, V., Vanni, R., Pizzini, G., & Veicsteinas, A. (2004). Validity of heart rate as an indicator of aerobic demand during soccer activities in amateur soccer players. *European journal of applied physiology*, *93*(1-2), 167–172. https://doi.org/10.1007/s00421-004-1192-4

Hardy, C. J., & Rejeski, W. J. (1989). Not what, but how one feels: The measurement of affect during exercise. Journal of Sport & Exercise Psychology, 11(3), 304–317.

Jarczok, M. N., Kleber, M. E., Koenig, J., Loerbroks, A., Herr, R. M., Hoffmann, K., Fischer, J. E., Benyamini, Y., & Thayer, J. F. (2015). Investigating the associations of self-rated health: heart rate variability is more strongly associated than inflammatory and other frequently used biomarkers in a cross sectional occupational sample. *PloS one*, *10*(2), e0117196. https://doi.org/10.1371/journal.pone.0117196

Kim, H.-G., Cheon, E.-J., Bai, D.-S., Lee, Y. H., & Koo, B.-H. (2018). Stress and heart rate variability: A meta-analysis and review of the literature. *Psychiatry Investigation*, *15*(3), 235–245. https://doi.org/10.30773/pi.2017.08.17

Kim, J. W., Seok, H. S., & Shin, H. (2021). Is Ultra-Short-Term Heart Rate Variability Valid in Non-static Conditions?. *Frontiers in physiology*, *12*, 596060. https://doi.org/10.3389/fphys.2021.596060

Laborde, S., Mosley, E., & Thayer, J. F. (2017). Heart Rate Variability and Cardiac Vagal Tone in Psychophysiological Research - Recommendations for Experiment Planning, Data Analysis, and Data Reporting. *Frontiers in psychology*, *8*, 213. https://doi.org/10.3389/fpsyg.2017.00213

Lipponen, J. A., & Tarvainen, M. P. (2019). A robust algorithm for heart rate variability time series artefact correction using novel beat classification. *Journal of medical engineering & technology*, *43*(3), 173–181. https://doi.org/10.1080/03091902.2019.1640306

Lussiana, T., & Gindre, C. (2016). Feel your stride and find your preferred running speed. *Biology Open*, *5*(1), 45–48. https://doi.org/10.1242/bio.014886

Mahdiani, S., Jeyhani, V., Peltokangas, M., & Vehkaoja, A. (2015). Is 50 Hz high enough ECG sampling frequency for accurate HRV analysis?. *Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual International Conference*, *2015*, 5948–5951. https://doi.org/10.1109/EMBC.2015.7319746

Malik, M., Bigger, J. T., Camm, A. J., Kleiger, R. E., Malliani, A., Moss, A. J (1996). Heart rate variability: standards of measurement, physiological interpretation and clinical use. Task Force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology. *Circulation*, *93*(5), 1043–1065.

Michael, S., Graham, K. S., & Davis, G. M. (2017). Cardiac autonomic responses during exercise and post-exercise recovery using heart rate variability and systolic time intervals—A review. *Frontiers in Physiology*, *8*, 301. https://doi.org/10.3389/fphys.2017.00301

Morelli, D., Rossi, A., Cairo, M., & Clifton, D. A. (2019). Analysis of the Impact of Interpolation Methods of Missing RR-intervals Caused by Motion Artifacts on HRV Features Estimations. *Sensors (Basel, Switzerland)*, *19*(14), 3163. https://doi.org/10.3390/s19143163

Namazi, H. (2021). Complexity and information-based analysis of the heart rate variability (Hrv) while sitting, hand biking, walking, and running. *Fractals*, *29*(05), 2150201. https://doi.org/10.1142/S0218348X21502017

Pan, J., & Tompkins, W. J. (1985). A real-time QRS detection algorithm. *IEEE transactions on bio-medical engineering*, *32*(3), 230–236. https://doi.org/10.1109/TBME.1985.325532

Pedisic, Z., Shrestha, N., Kovalchik, S., Stamatakis, E., Liangruenrom, N., Grgic, J., Titze, S., Biddle, S. J., Bauman, A. E., & Oja, P. (2020). Is running associated with a lower risk of all-cause, cardiovascular and cancer mortality, and is the more the better? A systematic review and meta-analysis. *British journal of sports medicine*, *54*(15), 898–905. https://doi.org/10.1136/bjsports-2018-100493

Rhodes, R. E., & Kates, A. (2015). Can the affective response to exercise predict future motives and physical activity behavior? A systematic review of published evidence. *Annals of Behavioral Medicine*, *49*(5), 715–731. https://doi.org/10.1007/s12160-015-9704-5

Sajjadieh, A., Shahsavari, A., Safaei, A., Penzel, T., Schoebel, C., Fietze, I., Mozafarian, N., Amra, B., & Kelishadi, R. (2020). The Association of Sleep Duration and Quality with Heart Rate Variability and Blood Pressure. *Tanaffos*, *19*(2), 135–143.

Tarvainen, M. P., Niskanen, J. P., Lipponen, J. A., Ranta-Aho, P. O., & Karjalainen, P. A. (2014). Kubios HRV--heart rate variability analysis software. *Computer methods and programs in biomedicine*, *113*(1), 210–220. https://doi.org/10.1016/j.cmpb.2013.07.024

Tarvainen, M., Lipponen, J., Niskanen, J.-P., & Ranta-aho, P. O. (2021). *Kubios HRV Users Guide* [User Guide]. https://www.kubios.com/downloads/Kubios_HRV_Users_Guide.pdf

Whitfield, G. P., Carlson, S. A., Ussery, E. N., Fulton, J. E., Galuska, D. A., & Petersen, R. (2019). Trends in meeting physical activity guidelines among urban and rural dwelling adults—United states, 2008–2017. *MMWR. Morbidity and Mortality Weekly Report*, *68*(23), 513–518. https://doi.org/10.15585/mmwr.mm6823a1

Young, H. A., & Benton, D. (2018). Heart-rate variability: A biomarker to study the influence of nutrition on physiological and psychological health? *Behavioural Pharmacology*, *29*(2 and 3), 140–151. https://doi.org/10.1097/FBP.0000000000000383