

# Predicting Positive Distance Running Experiences

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## Introduction

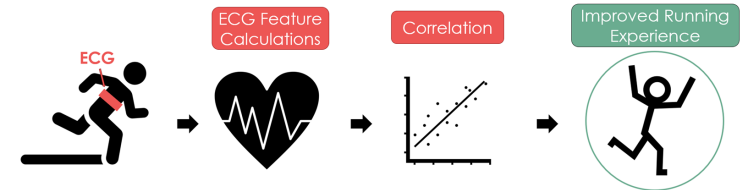
- < 1/4 adults reach fitness guidelines<sup>1</sup>
- Running is a simple and accessible form of exercise
- Better Feeling Runs = More Running<sup>2</sup>

### Can we make running more enjoyable?

- ECG (heart rate) data could indicate running enjoyment
- Heart Rate Variability (a metric calculated from ECG) shows promise due to its relationships to general health (stress<sup>3</sup>, sleep<sup>4</sup>, and diet<sup>5</sup>), **exercise**<sup>6</sup> and **emotion**<sup>7</sup>

## Project Goal

Assess the promise of utilizing ECG (heart rate) data in a wearable biofeedback system to improve running experiences



## Exemplar Results: Heart Rate Variability

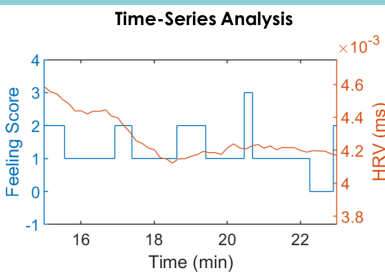


Figure 2: An exemplar 8-minute section of Feeling Score and HRV overlaid.  
➤ No obvious trends in time-series data

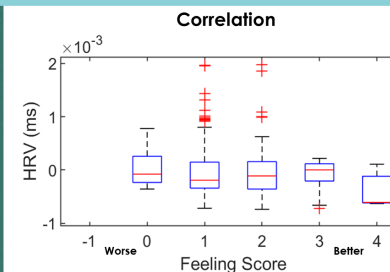


Figure 3: HRV vs Feeling Score box plots.  
➤ No obvious trends across Feeling Score

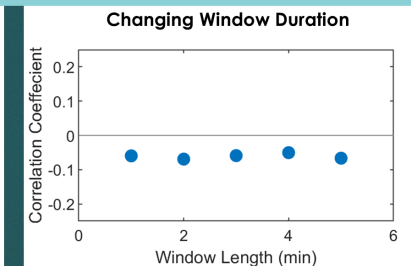


Figure 4: Correlation Coefficient vs Window Length.  
➤ Consistently low correlation coefficient across all window durations

## Methods

### 1. Experimental Protocol

- Pilot data from three trial runs on the same course
- ~50 min of steady-state overground running
- Subject Details
  - Female
  - Mid-20's
  - Experienced Distance Runner and Racer

### 2. Instrumentation

- Polar H10 Chest Strap Heart Rate Monitor sampling at 130 Hz
- Recorded enjoyment (via Feeling Scale ratings) throughout run



Fig. 1: Polar H10<sup>10</sup>

### 3. Data Pre-Processing

- Raw ECG data imported into Kubios HRV software<sup>8</sup>
- Upsampled data through 4Hz cubic spline interpolation<sup>9</sup>
- Performed automatic heartbeat correction algorithm identifying erroneous beats
- Calculated 8 different time-varying HRV features using a sliding window of varying lengths

### 4. Data Analysis

- Imported HRV features and Feeling Score time-series into MATLAB
- Overlaid the Feeling Score with each HRV feature to determine optimal data representations to assess correlation
- Performed correlation tests over all features over a range of window interval durations

## Conclusions

No obvious correlation or relationships existed between any of our calculated ECG features and Feeling Score. If ECG data is to be implemented in a wearable biofeedback system, **more complex analysis** will likely be needed to produce useful results.

## Limitations

- Only used data from a single subject
- Reliability of subjective Feeling Score
- ECG signal/HRV feature quality during exercise

## Next Steps

- Collect more data (more subjects and more runs with each)
- Integrate data into more complex predictive model (machine learning)

## References

- [1] Whitfield 2019 (MMWR)
- [2] Rhodes 2015 (Ann. Behav. Med.)
- [3] Kim 2018 (Psychiatry Investig.)
- [4] Sajjadi 2020 (Tanaffuz)
- [5] Young 2018 (Behav. Pharmacol.)
- [6] Silva 2017 (J. Strength, Cond. Res.)
- [7] Chapleau 2011 (Heart Fail. Rev.)
- [8] Kubios HRV Premium (v. 3.50, Kuopio, Finland)
- [9] Ellis 2015 (Physiol.)
- [10] Polar H10 (Polar Electro, Kempele, Finland)