Abstract

Background: Physical exercise affects the autonomic nervous system and causes rapid modifications in the functioning of the cardiovascular system. These modifications are observed through variations in the signals recorded by the ECG

Materials and Methods: In our ECG without Arduino project, an ECG was recorded at rest using an ECG machine for a duration of one minute. A three-electrode configuration was used, with electrodes placed on the right hand, left hand, and a reference electrode on the left leg.

First, an ECG at rest was recorded for one minute. Then, the subject performed a light aerobic exercise consisting of jogging for 20 minutes. Immediately after the exercise, the subject returned to the laboratory, and a stress ECG was recorded for one minute using the same electrode configuration.

The signal was recorded and stored at a sampling frequency of 1 kHz. The data was provided in TST file format and processed using Python. Since the data was stored using a European numerical format with commas as decimal separators, the commas were converted into decimal points before processing.

After this step, temporal vector reconstruction and signal filtering were performed. A band-pass filter between 0.5 Hz and 40 Hz was applied to remove unwanted noise such as motion artifacts, respiration effects, and sweat-related interference. Additionally, a notch filter at 50 Hz was used to remove power-line interference.

Finally, the R peaks were detected, and the RR intervals and heart rate were calculated.

Statistical Analysis: Based on our results, the mean heart rate increased from 19.98 BPM at rest to 125.88 BPM after exercise, showing that the heart was beating faster following 20 minutes of jogging. This increase was accompanied by a decrease in the RR interval from 660.6 ms to 477.81 ms.

In addition, a slight reduction in heart rate variability was observed, as indicated by the decrease in SDNN. SDNN represents the standard deviation of the RR intervals and reflects how much the beat-to-beat timing of the heart varies. At rest, the RR intervals showed greater fluctuation, meaning the time between heartbeats was more irregular. This resulted in a higher SDNN value of 27.6 ms, indicating higher heart rate variability and a more relaxed cardiac state.

After exercise, the RR intervals became more uniform, with less variation between consecutive heartbeats. As a result, the SDNN decreased to 23.74 ms, reflecting a reduction in heart rate variability and a more stable cardiac rhythm due to increased sympathetic activation.

Results: Post-exercise ECG showed higher HR and shorter RR intervals compared with rest, consistent with an acute exercise response.

Conclusion: A short bout of aerobic exercise produced measurable changes in ECG derived timing parameters in this subject, supporting the use of ECG analysis for assessing acute cardiovascular responses.

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symbols	Meaning
ECG	Electrocardiogram
HR	Heart rate
RR interval	The time between two consecutive R peaks in the ECG, representing the time between heartbeats.
SDNN	Standard Deviation of NN (RR) intervals
bpm	Beats per minute
ms	Miliseconds
Hz	Hertz
P wave	Represents atrial depolarization (electrical activation of the atria).
PR interval	Time from the onset of the P wave to the onset of the QRS complex.
QRS complex	Represents ventricular depolarization.
QTc	Corrected QT interval
TXT / CSV	File formats used to store ECG data and summary tables
Δ (Delta)	Absolute change between post-exercise and rest values (post − rest).
Python	Programming language used for data processing and analysis.
Min / Max	Minimum and maximum values observed during the recording.
Standard deviation (SD)	A measure of how much values vary around the mean.

1.1 Introduction

During physical activity, the nervous system increases the heart rate by sending signals more frequently, which reduces the time between each heartbeat. This effect was observed in our ECG recordings. Exercise-induced ECG changes, especially in wave morphology and timing intervals, are well known and mainly reflect cardiovascular adaptation to increased metabolic demand.

These changes are particularly visible in temporal parameters such as heart rate and RR intervals. Under proper measurement conditions, morphological parameters such as the P, QRS, QT, and corrected QT (QTc) intervals can also be analyzed.

During ECG recording, the signal quality was affected by muscle noise, respiratory activity, and electrical interference from the power line (50 Hz) power-line noise. To address this signal processing techniques were applied to remove noise and improve signal accuracy, allowing better interpretation and reliable extraction of ECG characteristics.

This study involved the analysis of ECG signals recorded at rest and immediately after a 20-minute jogging exercise, providing the opportunity to examine the effects induced by physical activity. The work also demonstrates a complete processing pipeline, including data acquisition, preprocessing, feature extraction, and presentation of results using figures and tables.

2.1 Aim and Objectives

2.1.2 Aim

The aim of this project is to investigate the effect of a continuous 20-minute jogging exercise on ECG parameters by comparing ECG recordings acquired at rest and immediately after exercise in a healthy adult subject..

2.1.3 Objectives

- First, record a one minute resting ECG using a three lead limb configuration.
- Second record a one minute post exercise ECG immediately after 20 minutes of jogging.
- Third Preprocess of ECG signals (data cleaning, bandpass, filtering, and notch filtering).
- Fourth find the Rpeaks and extract RR intervals and heart rate measures.
- Compare resting vs post-exercise values using descriptive statistics and tabulated

results.

- Finaly, compare the resting and post-exercise numbers using basic stats and put them in a table.

3.1 Hypothesis Formulation and Testing

3.1.1 Research Hypothesis H1

Acute aerobic exercise produces measurable changes in ECG parameters, particularly an in- crease in heart rate and a shortening of RR intervals in the post-exercise ECG compared with rest.

When you do a quick burst of cardio, your ECG shows clear changes. Your heart rate goes up, and the time between heartbeats gets shorter right after you finish compared to when you're resting.

3.1.2 Null Hypothesis H0

Any ECG variations observed immediately after exercise are **transient** and do not represent meaningful physiological change beyond short-term fluctuations or measurement noise.

3.2 How the hypotheses are tested in this study

a) **Primary test variables:** mean HR (bpm) and mean RR (ms), derived from detected R-peaks.

b) **Decision logic:**

- If post-exercise HR systematically increases and RR systematically decreases relative to rest in the expected physiological direction, that supports **H1**.
- If differences are inconsistent or comparable to random variability/noise, that sup- ports **H0**.

4.1 MATERIALS AND METHODS

4.1.1 Study design and setting

This pre-experimental, within subject study was conducted in a physiology laboratory environment.\at Anhalt University The experiment used a repeated measures design in which ECG recordings obtained under resting conditions were compared with ECG recordings obtained immediately after acute aerobic exercise. Because the study was conducted as a course laboratory project, the dataset represents a single participant (n=1) and is intended for the demonstration of ECG acquisition and signal processing.

4.1.2 Subject

The subject was a healthy adult volunteer (the investigator) with no known history of cardiovascular, respiratory, or metabolic disease. The subject was asymptomatic during the experiment and reported no acute illness at the time of recording. As this was a class based practical project.

4.1.3 ECG recording equipment and electrode placement

ECG signals were acquired using an ECG device configured with a three-electrode limb lead setup. Electrodes were placed on the right arm (RA), left arm (LA), and leg reference electrode to obtain a single lead limb ECG signal (Lead I equivalent).
Good electrode contact is essential in ECG recording because high impedance increases noise susceptibility and can reduce the clarity of low amplitude waveform components (P and T waves).

4.1.4 Baseline ECG recording (rest condition)

For the resting condition, the subject sat comfortably in a relaxed posture and was instructed to minimize movement and talking during recording. A 60-second ECG was recorded under quiet conditions. The sampling frequency was 1 kHz (1000 Hz). The signal was saved as a TXT time-series file containing ECG amplitude samples.

4.1.5 Exercise protocol

After baseline recording, the subject performed approximately 20 minutes of continuous jogging at moderate intensity (sufficient to elevate heart rate). The exercise protocol was chosen to produce an acute cardiovascular response through increased metabolic demand and autonomic (sympathetic) activation.

4.1.6 Post-exercise ECG recording

Immediately after completion of jogging, the subject returned to the recording position and a second ECG was recorded for 60 seconds, using the same electrode configuration and same sampling rate (1 kHz) to ensure comparability between conditions. The post-exercise ECG was saved as a TXT file in the same format as the resting ECG.

4.2 Data acquisition and signal processing

4.2.1 Data format handling and import

ECG recordings were stored as TXT files containing ECG amplitude values. Because some files used a comma as a decimal separator, the raw text was converted to a standard floating point format by replacing commas with decimal points prior to loading. The cleaned numeric values were imported into Python as a NumPy array, and a time vector was generated using the known sampling frequency (1 kHz) for time domain plotting.

4.2.2 Preprocessing and noise reduction

Initial visual inspection of the raw ECG showed baseline drift and high frequency noise consistent with common laboratory artefacts (motion, muscle activity, and mains interference). To improve signal interpretability and support reliable feature extraction, the following filtering was applied to both resting and post-exercise recordings using iden- tical settings:

After obersvation of the raw ECG signal of both rest and stress state it have been reliazed that biseline drift

a) **Band-pass filtering (0.5–40 Hz):**

A 4th-order Butterworth band-pass filter with cut-off frequencies 0.5 Hz (low)and 40 Hz (high) was applied.
The 0.5 Hz cut-off reduces baseline wander from respiration and slow movements.

The 40 Hz cut-off attenuates high-frequency noise (including electromy- ographic interference).

b) **Notch filtering (50 Hz):**

A 50 Hz notch filter was applied to suppress power-line interference where present.

To avoid phase distortion and preserve ECG morphology, filtering was implemented using zero-phase forward backward filtering (filtfilt).

4.2.3 Signal visualization

Both raw and filtered signals were plotted in the time domain. Short windows (e.g., first 10 seconds) were used to clearly visualize individual cardiac cycles and compare sig- nal quality before vs after filtering. Filtering typically improved QRS visibility and reduced baseline drift, although P and T waves may remain less distinct depending on noise level and electrode contact.

4.2.4 Feature extraction (HR, RR, variability)

A) R-peak detection

Rpeaks were detected automatically from the filtered ECG. A QRS enhancement pipeline was used to emphasize QRS activity and reduce false detections from noise and T waves. The detection approach consisted of:

Bandpass filtering in a QRS dominant range, differentiation and squaring to enhance sharp QRS slopes,

Moving window integration to identify candidate QRS events,

followed by refinement of each candidate by searching for the **local maximum**

in the filtered ECG within a short window around that candidate event.

B) RR interval and heart rate computation

From detected R-peak locations, the RR interval series was computed as the time difference between consecutive Rpeaks and reported in milliseconds (ms). Instantaneous heart rate (HR) was computed beat-to-beat as:

$$HR = 60/RR(s)$$

4.2.5 Morphological ECG intervals

Where waveform definition allowed, the following intervals can be assessed:

PR interval: Pwave onset to QRS onset QRS

duration: QRS onset to QRS end QT interval:

QRS onset to T-wave end

QTc: heart rate corrected QT interval (e.g., Bazett or Fridericia)

QT/QTc was assessed qualitatively due to limited Twave definition in some segments.

4.2.6 Statistical analysis

Because this was a single-subject repeated-measures dataset (n = 1), analysis focused on descriptive statistics rather than inferential population testing. For each condition (rest and post-exercise), ECG derived parameters (HR and RR) were summarized as mean ± standard deviation and as minimum–maximum values across the 60-s recordings. The primary comparison was the change from rest to post exercise (Δ = post − rest) and the percent change. All signal processing and calculations were performed in Python using NumPy/SciPy/Matplotlib.

5.1 RESULTS

5.1.1 Signal quality and filtering

The ECG recordings were successfully obtained for 60 s at rest and 60 s immediately after exercise, sampled at 1 kHz. Visual inspection of the raw signals showed baseline drift and high-frequency noise, likely from motion, muscle activity, and mains interference. To improve interpretability, the ECG signals were preprocessed using a 0.5–40 Hz band-pass filter and a 50 Hz notch filter, which reduced baseline wander and enhanced the visibility of the QRS complexes.

The resting ECG is first presented to show how filtering improves signal clarity under baseline condition

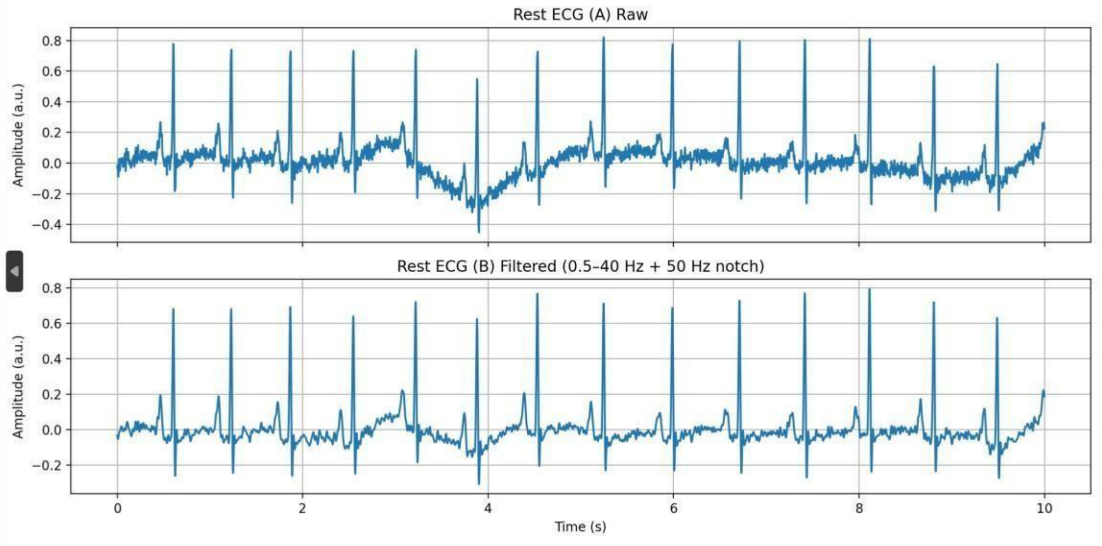

Figure 1. Resting ECG (first 10 s). (A) Raw signal. (B) Filtered signal (0.5–40 Hz band- pass + 50 Hz notch).

The same preprocessing is shown for the post-exercise ECG to demonstrate the higher noise level expected after movement and elevated respiration.

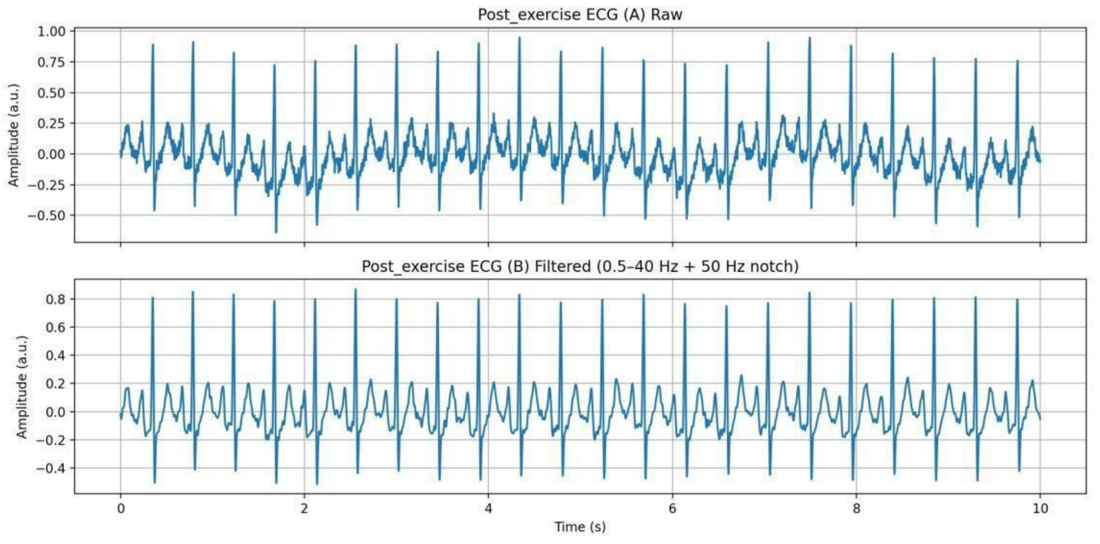

Figure 2. Post-exercise ECG (first 10 s). (A) Raw signal. (B) Filtered signal (0.5–40 Hz band-pass + 50 Hz notch).

5.1.2 Rpeak detection and RR interval computation

Rpeaks were detected from the filtered ECG using a QRS enhancement approach. Each heartbeat produces a candidate QRS event in the enhanced signal, and each candidate was refined to the true R-peak location by searching for the local maximum

in a short window around it. Using the final Rpeak locations, RR intervals were computed as the time difference between consecutive R peaks, and heart rate (HR) was computed beat to beat as HR = 60/RR (seconds).

The detected Rpeaks are displayed on the resting ECG to confirm that beats were identified correctly.

Rest ECG filtered with R-peak labels.

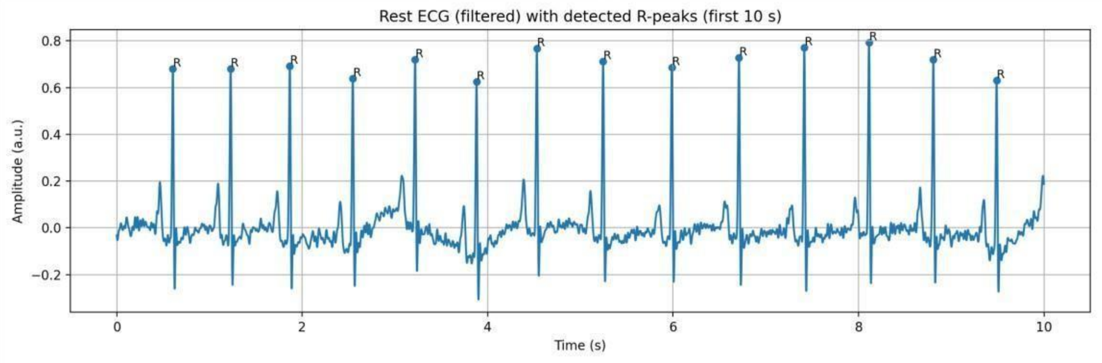

Figure 3. Resting ECG (filtered, first 10 s) with detected R-peaks overlaid.

The same R-peak detection is shown post-exercise to confirm robust detection under higher-noise conditions.

Post exercise ECG filtered with Rpeak labels.

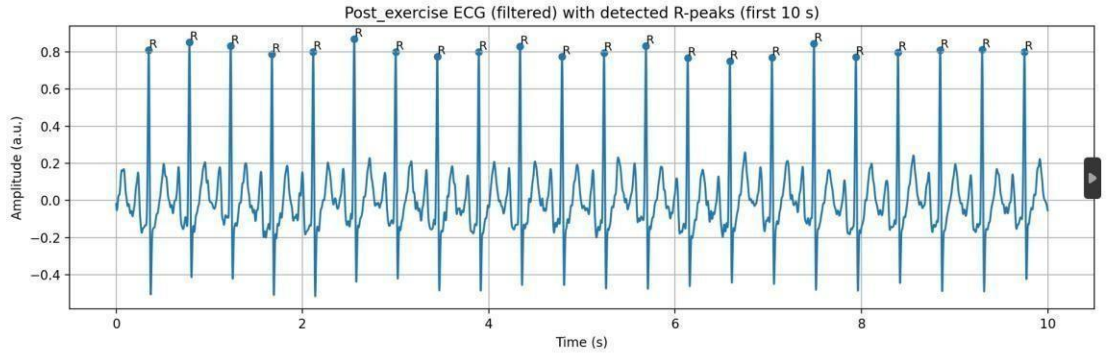

Figure 4. Post exercise ECG (filtered, first 10 s) with detected Rpeaks overlaid.

5.1.3 Identification of ECG components and RR interval illustration

To support physiological interpretation and demonstrate waveform morphology, representative cycles were annotated to show the approximate locations of P, Q, R, S, and T waves and an example RR interval between two consecutive R peaks. These annotations provide a visual explanation of how RR based features were derived from the ECG.

this representative resting cycle is labeled to demonstrate waveform identification under baseline conditions.

Rest ECG annotated (PQRST + RR).

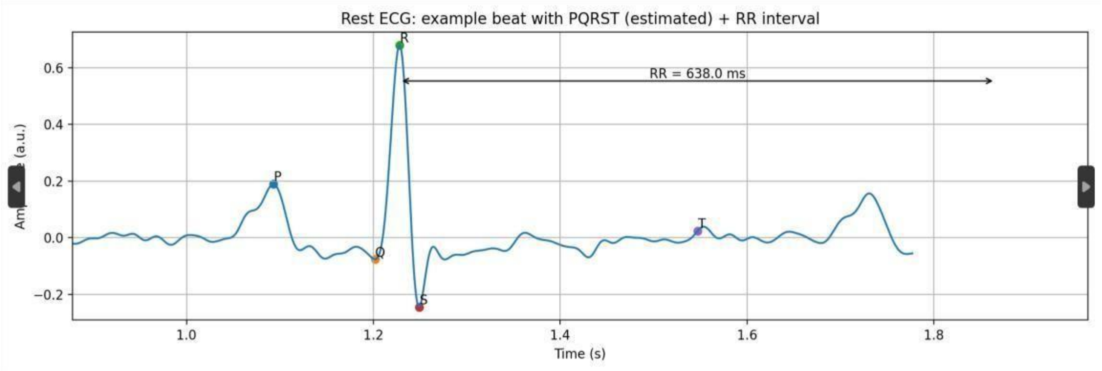

Figure 5. Resting ECG segment showing labeled P-QRS-T components and an example RR interval.

The same way the labeling was done in Rest condiction is repeated in the post exercise to illustrate how morphology visibility changes with exercise and noise.

Post-exercise ECG annotated (PQRST + RR intervale).

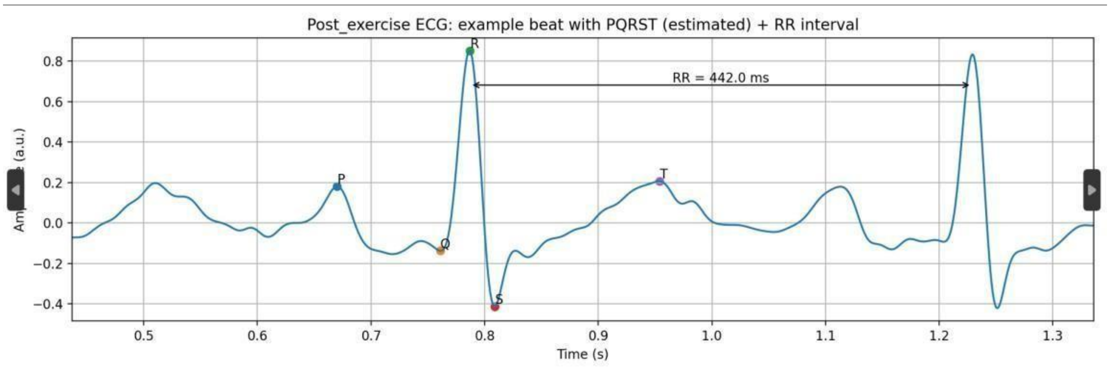

Figure 6. Post-exercise ECG segment showing labeled P-QRS-T components and an example RR interval.

5.1.4 Summary metrics at rest vs post-exercise

The time domain features derived from RR intervals were summarized for both conditions. These included mean HR, minimum/maximum HR, mean RR, minimum/maximum RR, and RR variability (SDNN). The post-exercise recording illustrate an increased HR and shortened RR intervals compared with rest, consistent with a temporal physiological response to exercise.

This table show a summary of resting vs post-exercise metrics which compare the two main dataset(rest and sress)

Rest vs post-exercise summary table.

Condition	File	Sampling rate (Hz)	Samples	Duration (s)	Detected beats (n)	Mean HR (bpm)	Min HR (bpm)	Min HR (bpm)	Mean RR (ms)	Min RR (ms)	Max RR (ms)	SDNN (ms)
Rest	01_ECG_1min_1kHz-Rest.txt	1000.0	60000	60.0	90	90.98	80.86	97.88	660.6	613.0	742.0	27.6
Post-exercise	02_ECG_1min_1kHz-Stress.txt	1000.0	60000	60.0	125	125.88	115.16	137.3	477.81	437.0	521.0	23.74

Table 1. Summary of ECG-derived HR and RR features at rest and post-exercise (60- s recordings).

To highlight the magnitude of exercise effect, the absolute change (Δ = post − rest) is shown for key parameters.

Parameter	Rest	Post-exercices	Delta(post-rest)
Mean HR (bpm)	90.98	125.88	34.89
Mean RR (ms)	660.6	477.81	-182.78
SDNN(ms)	27.6	23.74	-3.86

Table 2. Rest to post-exercise changes (Δ) in HR and RR derived features.

6.1 DISCUSSION

This practical report evaluated the acute influence of aerobic exercise on ECG derived parameters by comparing a 60s resting ECG recording with a 60s recording obtained immediately after approximately 20 minutes of jogging. Signal processing was applied to improve waveform quality, and time-domain features were extracted from detected Rpeaks to quantify changes in heart rate (HR), RR interval, and RR variability (SDNN).

6.1.1 Interpretation of heart rate and RR interval changes

The most consistent findings throughout this dataset were an increase in Heart Rate (HR) with a corresponding decrease in RR Interval (Table 1) following exercise. As one would expect during the immediate recovery from aerobic exercise, sympathetic activation and vagal withdrawal result in an increased firing rate of the sinoatrial node resulting in shorter beat to beat intervals (RR) and thus an elevated HR. Because HR is mathematically inversely proportional to RR by the equation HR = 60 / RR (seconds), a decrease in RR will lead to an increase in HR. Therefore, the post-exercise recording is indicative of a normal physiological response to exercise rather than an abnormal ECG finding.Showing in table 1 (rest vs post-exercise summary) and table 2(delta table)illustrate how the magnitude of change between condiction and helps present the ‘effect size’ clearly

6.1.2 RR variability (SDNN) after exercise

SDNN is an indicator of the amount of variation (spread) of RR intervals during the length of the recording. Post-exercise, SDNN values were lower than at rest (Table 1). Lower short-term RR variability may occur immediately after exercise due to the greater sympathetic control over the heart, and subsequent uniformity of RR intervals. However, caution must be used when interpreting these data because the recordings were only 60 seconds long, and only a single subject participated; therefore, SDNN values are generally more reliable when calculated based on longer recordings.

6.1.3 Signal quality, noise sources, and why filtering mattered

Atfer inspection of the raw ECG data showed baseline drift and high frequency noise, which can overshadow low amplitude components such as the P wave and T wave. All thos artefacts are common in laboratory ECG acquisition, especially in immediate post exercise recordings due to increased muscle activity, respiration, and motion. After applying the band-pass filter (0.5 to 40 Hz) and notch filter (50 Hz), the ECG baseline became more stable and QRS complexes became easier to detect.this were seen in this 2 figures

rest raw vs filtered figure here: rest_FIG_raw_vs_filtered.png

post-exercise raw vs filtered figure post_exercise_FIG_raw_vs_filtered.png

The signals with Rpeak markings show that the detected peaks wihch match the main QRS waves. This confirms that the RR intervals and heart rate calculations used in the results are reliable showing in R-label figure (rest): rest_FIG_filtered_with_Rlabels.png

Insert R-label figure (post): post_exercise_FIG_filtered_with_Rlabels.png

6.1.4 PQRST visibility and annotation figure

A dedicated annotated figure was produced to illustrate the approximate P, Q, R, S, and T components and the definition of the RR interval. This figure is useful for explaining the ECG physiology and the feature-extraction concept, but quantitative measurement of PR/QRS/QT intervals may be limited when T-wave definition is affected by noise, filtering, or lead configuration.

I PQRST + RR figure here (rest): rest_FIG_PQRST_and_RR.png

PQRST + RR figure here (post): post_exercise_FIG_PQRST_and_RR.png

6.1.5 Link to hypotheses

Hypothesis H1 states that acute exercise elicits detectable changes in ECG parameters such as HR and RR interval. The increases in HR and decreases in RR after exercise provide evidence to support H1 for time-based parameters. Hypothesis H0 states that any changes produced are temporary and reflect no real physiological changes. Since the changes observed occurred in a predictable and physiologically correct direction between rest and post-exercise, the results of this study do not provide evidence to support H0 regarding HR/RR changes in this dataset. However, the small sample size (n=1) and limited number of time points (2) limit the ability to generalize results from this study to other populations.

7.1 CONCLUSION

This single subject laboratory experiment demonstrated that acute aerobic exercise (approximately 20 minutes of jogging) produces measurable changes in ECG derived timing parameters. Compared with rest, the post exercise ECG showed an increased heart rate and shortened RR intervals, consistent with normal autonomic cardiovascular adaptation. Signal preprocessing using band-pass and notch filtering improved waveform clarity and supported robust R-peak detection, enabling reliable extraction of HR and RR based metrics. Although the results support the study hypothesis for HR/RR changes, broader conclusions about ECG morphology require improved noise control, additional recovery recordings, and a larger sample size

8.1 LIMITATIONS

Im our research we discorved some limitation due to:

1.number of participant(Sample size ,n=1): The dataset represents a single participant, so this research can not be generalized to a population and inferential statistics are not appropriate.

9.1 REFERENCES

https://pubmed.ncbi.nlm.nih.gov/6239355/

https://link.springer.com/article/10.1007/s00246-025-03945-y|(https://link.springer.com/article/10.1007/s00246-025-03945-y)

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https://pubmed.ncbi.nlm.nih.gov/19734501/

https://pubmed.ncbi.nlm.nih.gov/23303759/

10.1 APPENDIX

10.1.1 Appendix A: Python analysis workflow

In this report we used Python(NumPy, SciPy, Matplotlib, Pandas) to import ECG text files, apply preprocessing steps such as filtering,detection of Rpeaks, and compute HR/RR features. The preprocessing included:

1. Decimal conversion (comma to dot)
2. Band-pass filtering (0.5–40 Hz) to reduce baseline wander and high frequency noise
3. Notch filtering (50 Hz) to reduce mains interference
4. R-peak detection using a QRS-enhancement pipeline and peak refinement
5. Feature extraction: RR intervals, HR, SDNN

10.1.2 Appendix B: Data files and recording parameters

In this section it is the summarize processing of the data recording parameters.

Sampling frequency at **1000 Hz**

Duration per recording was **60 seconds**

Rest file_name: 01_ECG_1min_1kHz-Rest.txt

Post-exercise file_name: 02_ECG_1min_1kHz-Stress.txt

We used 3 electrode : right arm, left arm, left leg reference (single lead ECG equivalent to Lead I)

10.1.3 Appendix C: figures and tables Figures

Figures were in png format:

rest_FIG_raw_vs_filtered.png post_exercise_FIG_raw_vs_filtered.png

rest_FIG_filtered_with_Rlabels.png

post_exercise_FIG_filtered_with_Rlabels.png

rest_FIG_PQRST_and_RR.png

post_exercise_FIG_PQRST_and_RR.png

Tables (CSV format):

rest_summary.csv post_exercise_summary.csv

TABLE1_rest_vs_postexercise.csv

TABLE2_delta.csv

Declaration of independence

I hereby declare that this project was written independently and has not been submitted as an examination in the same or similar version in another course of study.

The experimental work, data acquisition, data analysis, figures, and results presented in this project are entirely my own.

Language-support tools (including AI-based tools) were used exclusively to improve clarity, grammar, and formulation of the text. No data, or scientific conclusions were generated by these tools.

Köthen, 12/20/2025	Samson komlan Agbadi
Location, Date	Student's signature

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