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RESEARCH ARTICLE

Assessment of Respiratory Dynamics from ECG during Physical Exertion

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Abstract

Background: Monitoring respiratory dynamics during physical exertion is crucial for assessing cardiopulmonary performance, particularly in fields like exercise physiology, sports science, and clinical rehabilitation. Traditional methods of monitoring respiration typically depend on specialized sensors, which can be inconvenient during active movement. ECG-Derived Respiration (EDR) provides a non-invasive option by obtaining respiratory data from electrocardiogram signals.

Purpose/Objective: This study intends to evaluate respiratory dynamics at the onset of physical activity through the use of EDR. Important respiratory metrics, including respiration rate, variations in signal amplitude, and rhythm, are evaluated from ECG recordings.

Methods: ECG signals were collected from healthy subjects during the first grade of treadmill exercise. A hybrid signal processing approach was applied, combining wavelet transform for decomposing the ECG into relevant frequency bands and central moment analysis for capturing respiratory-induced morphological variations. The derived respiratory signals were used to estimate key parameters and were validated against reference data from a thermistor based respiratory sensor.

Results: The derived respiratory signals exhibit a steady increase in respiratory rate and noticeable ECG waveform modulation while active. The central moment method is superior to the wavelet approach at capturing fine-grained respiratory signal changes, especially during low-intensity stress. We have shown that the proposed method works well, based on the strong correlation of predicted parameters with reference measurements.

Conclusion: This study presents evidence for the application of ECG-derived respiration for non-invasive monitoring of respiration during strenuous activity. The central moment method performed the best in the evaluation process and is likely the best method for real-time processing situations where accuracy and clarity of the signal will benefit from the additional frequency of the signal. This technique will be applicable to wearable health monitoring devices, sports and exercise physiology settings, early detection of cardiopulmonary stress, and all requiring minimal sensor hardware.

Keywords: ECG Derived Respiration (EDR), Respiratory Dynamics, Physical Exertion, Central Moment Analysis, Wavelet Transform, Cardiorespiratory Assessment.

Introduction

Respiration rate is an essential physiological parameter that reflects the metabolic demand of the body, and the ventilatory response. It can be sensitive to early detection of changes in cardiorespiratory function, particularly while performing activity. It represents metabolic activity, metabolic oxygen demand and homeostasis. Monitored less than other vital signs such as heart rate or blood pressure, respiratory rate is often underutilized as an important indicator (Subbe et al., 2003).

The normal respiratory rate of a healthy adult at rest is between 12 and 20 breaths per minute. However, in times of exertion the respiratory rate rises through the body's demands for increased oxygen and more efficient removal of carbon dioxide. Respiration rate is thus an important measure of cardiorespiratory fitness and the body's ability to respond to stress.

There are many situations, such as exercise physiology, sports science, rehabilitation, and clinical diagnostics where continuous monitoring of Respiration rate is required. While traditional respirational activity capturing techniques (e.g., nasal thermistors, sensors that monitor chest expansion

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or spirometry) can be very accurate, they are often accompanied by various limitations in practice (i.e., motion artifacts, discomfort during activity, having to make direct contact with the patient, or having to calibrate) (Nicolò et al., 2023). When exercise intensity increases, these conventional methods might reduce performance or affect data quality (Hussain T. et al., 2023).

To overcome these limitations ECG-Derived Respiration (EDR) has emerged as a non-invasive and simple method of monitoring breathing. EDR uses crown moldable changes in the electrocardiogram (ECG) waveform associated with movement due to breathing (e.g. changes in electrode placement, thoracic resistance changes, and changes in cardiac autonomic tone) to quantify breath based variables (Folke et al., 2003). These small but meaningful changes enable researchers to derive respiration rate, rhythm, and amplitude dynamics from ECG reports without additional sensors (Moody et al., 1985).

Exercise is a vital contributor to the development of cardiovascular endurance, pulmonary function, and health, in general. Engagement in regular physical activity enhances oxygen uptake, increases cardiac output, and strengthens the respiratory muscles—enhancing cardiorespiratory efficiency (Plowman et al., 2013). Assessing these physiological adaptations necessitates extensive observation during exercise, and assessment via Cardiopulmonary Exercise Testing is the most ideal method. It is considered the gold standard in assessing the integrative modulation of the respiratory, muscular, and cardiovascular systems to graded workloads (Balady et al., 2010).

The previous studies (Moody et al., 1985, Dela Cruz et al.. 2021, and Varon et al. 2020) examined EDR extraction methods focused on EDR extraction at resting, or normal conditions. These studies employed signal processing tools to obtain respiratory patterns from ECG in resting conditions. However, limited work has been done to validate these techniques under dynamic conditions such as exercise, where motion artifacts and rapid physiological changes complicate signal processing.

In this context, selecting an appropriate exercise modality for data acquisition is critical. The treadmill emerges as a superior platform for evaluating respiratory dynamics during exertion. It allows for natural gait movement (walking or running), engages larger muscle groups, and results in a more representative cardiopulmonary response compared to other devices like cycle ergometers or step tests (Kenney et al., 2022). Treadmill protocols—especially graded ones like the Bruce protocol—enable controlled, progressive increases in workload, facilitating the detection of subtle respiratory changes at early exertion stages. Additionally, treadmill testing elicits higher peak oxygen consumption (VO_2 max) than other modalities and is widely accepted in clinical cardiopulmonary exercise testing (CPET) due to its reproducibility and integrability with physiological monitoring systems (Qi, W et al., 2019).

This study aims to assess respiratory dynamics during the onset of treadmill exercise using ECG-derived signals. A total dataset of 15 subjects—both male and female—was taken into consideration for this investigation. Simultaneous acquisition of the original ECG and respiration signals occurred during treadmill exercise. A hybrid signal processing framework is implemented, combining wavelet transform for signal decomposition and central moment analysis to extract respiration-induced morphological features from the ECG. The EDR-derived respiratory parameters are validated against thermistor-based respiration sensors, and the efficacy of the methods is evaluated based on correlation and signal clarity (Khambhati, V. et al., 2019).

Methodology

As explained below, the study was conducted using subject data collection, original signal pre-processing, EDR signal extraction, and statistical analysis of the estimated respiratory information.

In the present study, the Allengers Gemini A-DX treadmill was used for three minutes of exercise at a 10% inclination and 2.7 km/h. The experimental setup's schematic diagram is displayed in Figure 1. Using varying levels of physical stress, exercise-based research aims to assess cardiopulmonary response. Treadmills and cycle ergometers are typically utilized as exercise equipment.

Equipment selection for Physical stress

Cycle Ergometer

A cycle ergometer applies variable resistance to pedaling, controlled manually or electrically. By reducing upper-body movement, it facilitates the collection of physiological measures like blood pressure, respiration, and heart rate.

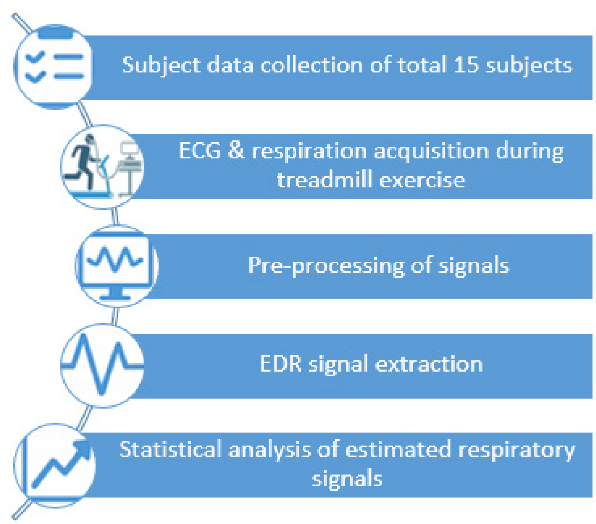

Figure 1: Experimental setup schematic illustration

It induces lower overall physiological stress than treadmill exercise, resulting in a lower peak VO_2. It is cost-effective and suitable for patients with mobility limitations; arm ergometers can be used for lower-limb disabilities.

Treadmill

Treadmill exercise engages larger muscle groups, simulating natural walking or running. The workload is controlled by speed and incline, and intensity can be accurately controlled. It produces a higher peak VO_2, making it ideal for determining maximal cardiorespiratory fitness. There may still be some residual motion artifacts when acquiring the signal, but it is a better demonstration of endurance, cardiovascular performance, and functional capacity than cycling.

The treadmill was chosen for data collection for this study. It has the potential to use more muscle groups, provides greater physiological stress, and measures cardiorespiratory parameters with greater accuracy. The treadmill has other advantages, like better imitation of natural movement and the generation of a higher peak VO_2, which is preferable when considering the timing and recovery of respiration dynamics, including EDR signals for a more realistic training scenario.

Exercise Protocol and Subject Selection

The methods of workload application helps determine how exercise protocols for treadmill or cycle ergometer testing are typically classified:

- Continuous Ramp Protocol: It allows for a precise evaluation of VO_2 kinetics by increasing exercise intensity gradually. However, standardizing across subjects could be challenging.
- Multistage Exercise Protocol: Typically every 2-3 minutes the exercise intensity is increased. This allows evaluation of physiological responses under controlled conditions at each step and for rehearsed protocols it is often employed in research and therapeutic settings.
- Constant Work Rate Protocol: The participant maintains a constant workload for a constant period of time. Though simple, it does not allow for the assessment of peak physiological responses or maximal aerobic capacity as well.

Due to reliability and clinical relevance the Bruce protocol, a proven multistage treadmill exercise protocol, was employed for this study (Bruce, R.A. et al., 1971). The Bruce protocol increases the effort by accelerating the ramp incline and speed of the treadmill every three minutes. Some of the key advantages include:

- Higher peak VO_2, allowing for measurement of maximal cardiorespiratory capabilities.
- Large muscle groups are engaged, mimicking normal gait and running patterns, which is necessary for precise electrodermal responses (EDR) and respiratory dynamics measurements.
- Standardized phases that guarantee consistency and equivalency throughout all courses.

The Bruce protocol was selected because it does an excellent job of monitoring heart rate, blood pressure, ECG, respiration, and EDR, while providing a gradual, safe, and systematic increase in exercise intensity.

For the purposes of evaluating all physiological and haemodynamic parameters, a total of 15 participants (8 male, 7 female, aged 20 to 40) participated in the current study. All subjects agreed to participate in a study after being fully informed of all research procedures and signing a consent form approved by the ethics committee of the Institute. A summary of the physical and haemodynamic characteristics for each subject is presented in Table 1.

ECG & respiration measurement system

Physiological signals were recorded continuously during stage-I of the treadmill exercise protocol in order to represent baseline responses at an exercise condition.

ECG data were obtained from electrodes placed on the right arm, left arm, and right foot as ground in a Lead-I configuration (Rahman et al., 2024). Stage-I exercise provided a minimal workload so that early cardiac responses were visible (the first few changes in heart rate and rhythms) without major fatigue. The ECG signal was sampled at 1 kHz, filtered to eliminate power-line interference and motion artifacts, and recorded for later analysis.

Respiration was tracked using a thermistor sensor placed at the participant's nostrils to measure airflow (Fei J. et al., 2009). In Stage-I, the thermistor was able to detect slight temperature changes during inhalation and exhalation that were indicative of both respiratory rate and amplitude. The received analog respiration signal was amplified, digitized, and synchronized with the ECG to allow for integrated analysis of cardiopulmonary interactions.The ECG and respiratory signals which were obtained, were pre-processed to remove baseline drift and noise. The respiratory rate and amplitude were then calculated from the respiration signals while feature information was extracted from the ECG data. This allowed for an examination of the relationship between

Table 1: Anthropometric profile of the Participants (n=15)

Variables	Mean ± SD
No of Subjects	15
Gender (M/F)	8M, 7F
Age (years)	29.5 ± 5.4
Weight (Kg)	63.20 ± 10.86
Height (cm)	161.93 ± 8.86
BMI (kg/m^2)	24.17 ± 4.11

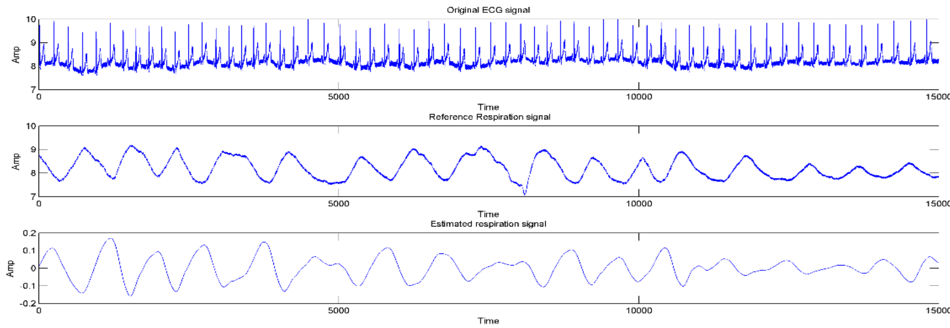

Figure 2: Wavelet-Based EDR Signal Implementation: A db9 Approach

cardiac and respiratory function at the beginning of exercise as the ECG and respiration signals were synchronized.

Extraction of EDR signal

The Exercised ECG signal was separated into several frequency sub-bands through wavelet decomposition to separate the respiratory components. The wavelet transform is ideal for the ECG analysis since the time and frequency localization are optimal in the algorithm. The ECG signal was decomposed at the various levels with wavelets known as Daubechies (db9), a wavelet often used in ECG processing due to its similarity to the QRS complex.

The detail coefficients preserved the higher frequency portions of the QRS, whereas the low frequency approximation coefficients took baseline changes associated with breathing into account. By reconstructing particular sub-bands we enhanced the respiratory modulation and extracted the EDR waveform. This method worked particularly well in limiting noise and movement artifacts' interference with respiratory oscillations in the ECG (Singh et al., 2006). Figure 2 illustrates an example of the EDR signal reconstruction using wavelet transform (db9) method.

For a second method of EDR extraction, nth-order central moment algorithm was applied. Due to thoracic impedance and variations in electrode placement as the chest expands, the overall amount of RS- and QR-slopes change in amplitude with respiration. This method is built on the concept of analyzing the slopes (Schmidt et al., 2015). The nth central moment for a given QRS complex is defined as:

$$m_n = \frac{1}{N}\sum_{i=1}^{N}(x(i) - \bar{x})^n$$

Where the ECG sample is denoted by x(i), the mean value by $\bar{x}$, and the order of the instant by n. More precise respiratory estimations are obtained using the approach for higher-order moments ($n \geq 4$). The advantage of this slope-based method is that R-peaks stay constant, whereas QR- and RS-slopes exhibit regular breathing-related modulation, which makes them ideal for EDR extraction under exercise conditions in which motion artifacts are frequent.

The methodical process for obtaining the breathing signal from an ECG recording is depicted in the figure 3. The initial ECG signal, which includes the faint respiratory-induced modulations as well as the cardiac electrical activity, is acquired. Concurrently, the real respiration signal—usually obtained from a direct respiratory sensor—is captured as a reference, demonstrating the regular rhythm of inhaling and exhalation. Using a bandpass filter of 0.1-0.3 Hz, which eliminates baseline drift and high-frequency noise while maintaining the frequency components linked to respiratory activity, the ECG's respiration-related fluctuations are separated.

Filtering reduces other ECG patterns while enhancing sensitivity to respiration-related changes by calculating the fourth-order central moment of the ECG signal. Next, in order to make the derivation of respiratory events easier, this continuous signal is transformed into a discrete form (Khambhati, V. et al., 2025). These places associated to breathing are indicated by red markers in the discrete signal. The discrete points undergo a spline interpolation to recreate a continuous and smooth breathing waveform. Even without direct respiratory measurement, the resultant waveform serves as a reliable method of inferring breathing patterns from ECG data since it closely resembles the real respiration signal.

Results and Discussion

The present study evaluated respiration rate (RR) responses during Stage 1 exercise at a 10% grade in a cohort of 15 participants, comprising 7 females and 8 males. The actual respiration rate (ARR) and estimated respiration rates using wavelet transform (ERR-WT) and central moment (ERR-CM) methods were recorded for three consecutive minutes of exercise (Table 2).

In the female participants (n = 7), the actual respiration rate (ARR) showed a progressive increase from 25.60 ± 1.24 breaths per minute (bpm) during the first minute to 27.07

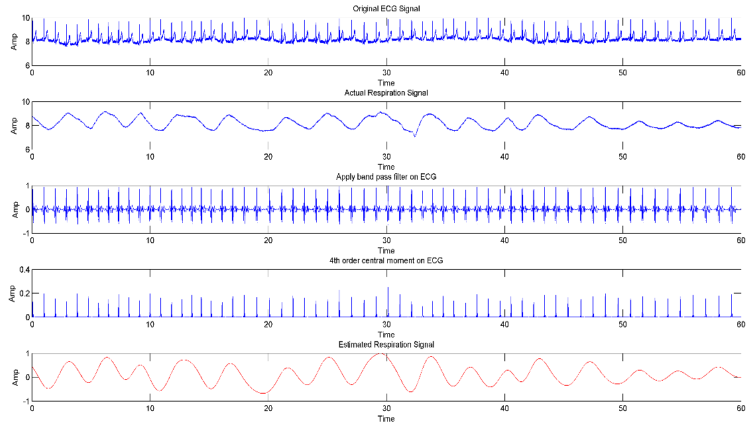

Figure 3: Central Moment-Based Implementation and Analysis of EDR Signal

Table 2: Agreement analysis between measured and predicted respiration rates in Stage 1 exercise

				STAGE 1 EXERCISE (10% GRADE)								
				1st Minute of Exercise			2nd Minute of Exercise			3rd Minute of Exercise		
Subjects	Gender	Age	BMI	ARR	ERR-WT	ERR-CM	ARR	ERR-WT	ERR-CM	ARR	ERR-WT	ERR- CM
Subject 1	Female	20	19.6	26	29	28	27	28	27	27	29	29
Subject 2	Male	24	16.3	28	26	29	28	26	25	29	27	28
Subject 3	Female	25	18.9	24	29	25	25	27	26	25	28	26
Subject 4	Female	26	19.6	25	27	26	26	29	27	26	28	28
Subject 5	Male	27	25.4	24	30	26	25	29	28	26	29	28
Subject 6	Male	27	23.5	26	29	27	27	29	28	28	30	29
Subject 7	Female	28	22.5	26	28	27	27	28	27	27	27	28
Subject 8	Male	28	23.8	26	29	28	27	30	29	28	30	29
Subject 9	Female	29	24.6	26	30	28	27	28	27	27	28	28
Subject 10	Female	30	26.5	27	31	29	27	30	28	28	30	29
Subject 11	Male	32	26.8	25	29	29	26	29	28	26	28	27
Subject 12	Male	34	28.5	24	30	26	25	29	28	26	28	27
Subject 13	Male	35	29.1	24	32	27	25	30	29	26	29	28
Subject 14	Female	38	27.3	27	29	28	28	30	29	29	31	30
Subject 15	Male	40	30.1	26	29	26	27	32	29	28	31	29
MEAN				25.60	29.13	27.27	26.47	28.93	27.67	27.07	28.87	28.20
STD				1.24	1.46	1.28	1.06	1.44	1.18	1.22	1.30	1.01

± 1.22 bpm in the third minute. The increase is expected as typically physiological adaptation occurs when engaging in low intensity exercise. The estimated respiration rate based on the central moment method (ERR-CM) closely followed those of the ARR across the minutes (27.27 ± 1.28 bpm to 28.20 ± 1.01 bpm) which suggested solid accuracy of estimation. The wavelet-based respiration rate estimation (ERR-WT) observed slight overestimations of RR (29.13 ± 1.46 bpm to 28.87 ± 1.30 bpm). The lower standard deviations observed with ERR-CM suggest consistency and reliability.

Similar trends were observed in the eight male participants, as ARR values increased from 25.29 ± 2.85 bpm in the first min to 27.20 ± 2.37 bpm in the third min. ERR-CM once again yielded the closest RR approximation to ARR (between 26.43 ± 1.46 bpm and 28.20 ± 1.01 bpm). ERR-WT overestimated RR values (29.13 ±1.46 bpm to 28.87 ± 1.30 bpm) more than ERR-CM. The larger SDs for males can be explained by the wider age (24-40 years) and BMI (16.3 - 30.1 kg/m^2) distributions yielding greater inter-subject variability compared to females.

The values for ARR, ERR-WT, and ERR-CM given in Table 3, mean ± standard deviation showed that ARR increased five times from 25.60 ± 1.24 bpm to 27.07 ± 1.22 bpm, mainly with low variability for each measure. Values for ERR-WT were consistently the largest values (from 29.13 ± 1.46 to 28.87 ± 1.30 bpm), meaning that RR was more often systematically overestimated. Values for ERR-CM showed predictable intermediary values (from 27.27 ± 1.28 bpm to 28.20 ± 1.01 bpm), maintained closer alignment to ARR, but only slightly less variability than ERR-WT. ERR-CM provided less variability with more accuracy for overall estimates than ERR-WT.

Graphical Analysis

The comparative performance of the three estimation methods is illustrated in Fig. 4 using a grouped bar chart with error bars. The bar heights represent mean values, while the black lines denote the corresponding standard deviations. As shown in Fig. 4, ARR consistently remained lower than ERR-WT, whereas ERR-CM closely followed ARR values across all minutes. The shorter error bars associated with ERR-CM highlight its reduced variability and improved stability relative to ARR and ERR-WT.

Overall, both male and female participants demonstrated progressive increases in ARR across three minutes of stage 1 exercise, consistent with physiological adaptation. ERR-CM consistently showed closer agreement with ARR compared to ERR-WT, which tended to overestimate RR. Gender-wise comparison indicated slightly higher variability in males due to a broader age and BMI distribution, whereas females exhibited more consistent respiratory responses.

Table 3: Comparative values of ARR, ERR-WT, and ERR-CM in terms of mean ± standard deviation

Minute	ARR (Mean ± STD)	ERR-WT) (Mean ± STD)	ERR-CM (Mean ± STD)
1	25.60 ± 1.24	29.13 ± 1.46	27.27 ± 1.28
2	26.47 ± 1.06	28.93 ± 1.44	27.67 ± 1.18
3	27.07 ± 1.22	28.87 ± 1.30	28.20 ± 1.01

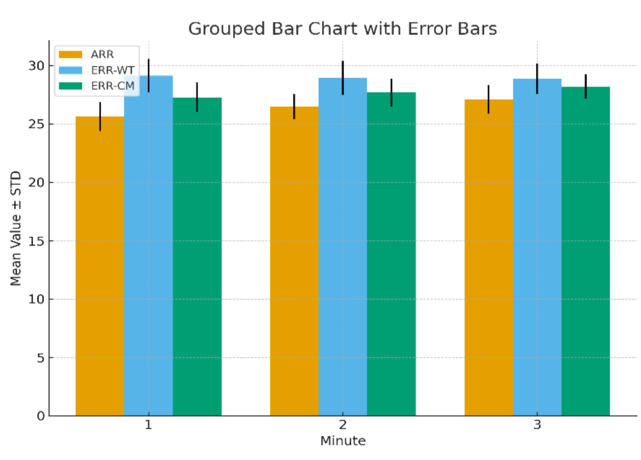

Figure 4: Grouped bar chart illustrating the mean ± standard deviation (STD) of ARR, ERR-WT, and ERR-CM across minutes

These results demonstrate that ERR-CM is a reliable technique for precise and consistent RR monitoring during low-intensity exercise and establish the credibility of ECG-derived respiration estimation.

In the present study, we evaluated the performance of ECG-derived respiration (EDR) estimation methods during stage 1 treadmill exercise at 10% grade. Both male and female subjects showed substantial increases in actual respiration rate (ARR) over the three-minute exercise period, which would be expected cardiorespiratory adjustment to sustained submaximal exercise intensity. This trend followed the established physiological descriptions detailed in the exercise physiology literature that progressive increases in ventilation during exercise occur with the increase of workload to meet metabolic demand (Hellsten, Y. et al., 2016).

The consistent overestimation of respiration rate with the wavelet-based, ERR-WT, was noteworthy; which corroborates with previous studies indicating that wavelet decomposition can overstate respiratory components and yield also greater skewed estimates while also making a modest contribution to the reduction of noise (Maghfiroh, A.M. et al., 2019). In contrast, the central moment based estimation, ERR-CM, demonstrated greater proximity to the overall ARR, based on both mean averages as well as standard deviation reductions. The lower variability inn ERR-CM indicates greater robustness to inter-subject differences, something that is beneficial for real-time monitoring.

The gender-wise analysis indicated that demographic factors played a role in the variability seen in the respiratory outcomes. In this study, the female subjects showed more consistent responses, possibly due to their relatively narrow ranges in BMI and age. Males showed slightly higher variability, likely due to the broader spread in the demographic groups - the BMI for males was (16.3-30.1 kg/m^2) and age had a range of (24-40 years). However, these findings are similar to previous findings in which estimates of respiratory dynamics and their stability were influenced by diversity in demographics (Bhatti, et al., 2019).

Conclusion

This investigation applied ECG-derived respiration (EDR) methods for analysis of respiratory dynamics during treadmill level 1 exercise. Consistent with anticipated physiological adaptation, the data indicated a progressive increase in actual respiration rate (ARR) across the entire three-minute protocol. All estimating methods were able to suggest relatively reliable responses, though the wavelet-based estimating technique (ERR-WT) tended to overestimate respiration rate, and the central moment technique (ERR-CM) demonstrated consistent lower variability and tighter association to ARR. Males demonstrated slightly more variability according to within-gender analysis likely contributed by the wider sampling of both age and BMI while the females demonstrated more stable and consistent respiratory responses.

In conclusion, the results highlight the reliability and accuracy of the central moment method for real-time tracking of breathing dynamics throughout low-intensity exercise. The central moment technique has great potential for sports physiology applications, wearable health systems, and earlier detection of cardiopulmonary stress, as this technique allows for accurate estimates of breathing patterns without actually having to wear additional sensors. Future studies are needed to test the scalability and generalizability of the proposed method, specific to testing a larger participant population, higher intensity exercise, and gold-standard measurements of respiration.

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Authors' Contributions

Vishakha Khambhati had formulated and executed the problem and prepared the draft of the manuscript. Dr. Rajan Kumar Singh had reviewed the manuscript.

Consent for Publication

All Authors will give their full consent to the journal for the publication.

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