Auscultawear: A Wearable Audio-Based Monitoring Platform for Heart and Respiratory Rates

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***Abstract*—Most commercial wearable health devices are unable to measure both heart and respiratory rate simultaneously as they rely on photoplethysmography (PPG). Audio-based approach is a promising development in wearable devices as they can detect and measure both heart and respiratory rate simultaneously. In this study, a platform using an nRF52840 MCU and MAX4466 electret microphone is used to record physiological signals. These signals are sent to a mobile device where a bandpass filter isolates the target frequency of physiological signals. The signal undergoes wavelet thresholding and decomposition using the db6 wavelet, which shows a similar structure to the S1 and S2 signals in heart sounds, to further isolate and denoise the targeted frequencies. A Hilbert transform is applied to get the envelope of the system, which will then pass through a customized peak detection algorithm. The overall device was tested against a pulse oximeter (PPG), a smart watch (EKG), and a KardiaMobile© EKG Monitor. Results show the device achieved the best heart rate accuracy at FS1 (upper right intercostal space auscultation point) and FS4 (bottom left intercostal space, apex of the heart), with MAE scores of *5.23±1.79 BPM* and *5.18±6.58 BPM*, respectively. Further validation at FS1 yielded an MAE of *4.58±2.54 BPM* on an individual with normal BMI, reinforcing FS1 as the optimal auscultation point for HR monitoring. The most accurate RR measurement was at BS1 with an MAE of *1.98±1.21 BPM*. Power profiling estimates a battery life of *68.979* hours. Auscultawear demonstrates potential as a reliable, low-cost wearable for real-time monitoring of HR and RR. However, these findings are preliminary, and additional refinements and large-scale validation across diverse demographic groups are necessary to establish the system's robustness and generalizability.**

I. Introduction

Health is a key indicator of a person's ability to perform daily tasks [1]. Vital signs like heart rate (HR) and respiratory rate (RR) help detect early signs of health decline, especially for medical professionals, chronic patients, and fitness enthusiasts. Globally, the WHO cites cardiovascular diseases, respiratory illnesses, and neonatal conditions as leading causes of death [2]. In the Philippines, heart and respiratory diseases are top causes of mortality [3], [4].

Conventional methods like ECG, plethysmography, and imaging (e.g., MRI, ultrasound) are accurate but costly and clinic-bound [5], [6]. Photoplethysmography (PPG), common in wearables, offers portability but suffers from limitations due to motion, skin tone, tattoos, and ambient light [7], [8]. Pulse oximeters using PPG can be uncomfortable for prolonged use. Ultrasonic techniques, while effective, are unsuitable for long-term monitoring due to tissue risks [9].

This study investigates wearable acoustic auscultation, which leverages body-generated sounds traditionally captured via stethoscope [10], [11]. Monasterial *et al.* showed audio-based HR and RR monitoring using digital signal processing on smartphone recordings [12]. While effective, their work remained offline and algorithm-focused. This study extends it by creating a wearable system with real-time signal acquisition, processing, and BLE-based mobile visualization. Audio-based wearables avoid the drawbacks of light-based systems and provide a direct, non-invasive way to track vital signs.

II. Methodology

A. System Overview

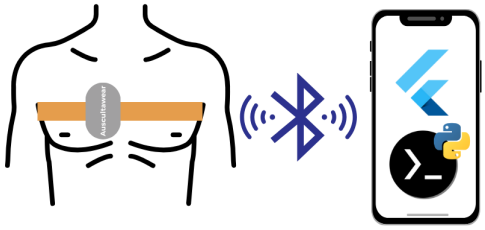

Fig. 1: System Overview Comprising of Auscultawear and Mobile Devices

The system is composed of three main components: the signal acquisition, signal presentation, and signal processing. The signal acquisition is done within the Auscultawear wearable device. Signal presentation is done with the use of a mobile device, which communicates with the Auscultawear wearable device via BLE. Underneath the mobile device is a mobile application designed to handle signal processing, which processes the received data to extract features and returns it back to the mobile application for display. The wearable device is designed for daily use, and with smartphones

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being an everyday item, a mobile application is developed to connect to the wearable device for monitoring their health. Smartphones typically have a much greater processing power than the development board, and by running the processing algorithm in the mobile device, it should not only process the data faster, but also reduce the power consumption within the wearable device, extending its operation time for long-term use. The overview of how the device works is shown in Fig. 1.

B. Device Prototype

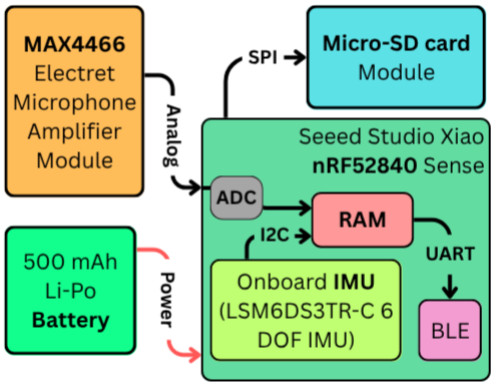

Fig. 2: Framework of Device Prototype

1) Hardware Architecture: This study used the Seeed Studio XIAO nRF52840 Sense development board, featuring a Nordic nRF52840 MCU and powered by a 3.7V 500mAh Li-Po battery. An electret microphone with a range of 20Hz to 20kHz with a MAX4466 amplifier provided directional sound capture via a diaphragm connector. The onboard LSM6DS3TR-C IMU enabled synchronized motion tracking. A micro-SD module ensured backup data logging in case of BLE communication loss. A summary of the framework is shown in Fig. 2 and the device prototype is shown in Fig. 4.

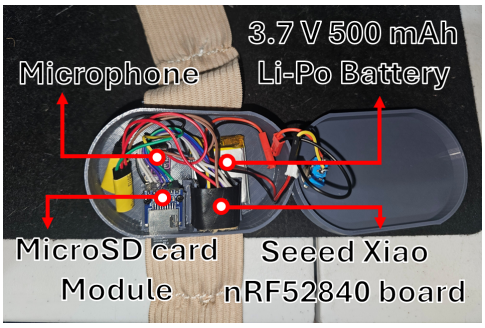

Fig. 3: Labeled Device Prototype

2) Code Architecture: The code architecture of how it communicates with the mobile device. The device begins with initialization, then starts advertising via BLE under the name Auscultawear. Upon connection, it enters Manual mode by default, awaiting commands from the mobile app. When instructed to record, it captures a 20-second audio sample, stores it in local RAM and the micro-SD card, then transmits it via BLE. In Auto mode, the device records and sends 20-second segments continuously until a stop command is issued through the app. The 20-second duration was selected as it provides a practical balance for the signal processing algorithm: it is long enough to reliably detect valid respiratory cycles, yet short enough to maintain accuracy in the rolling average computation for heart rate without distortion.

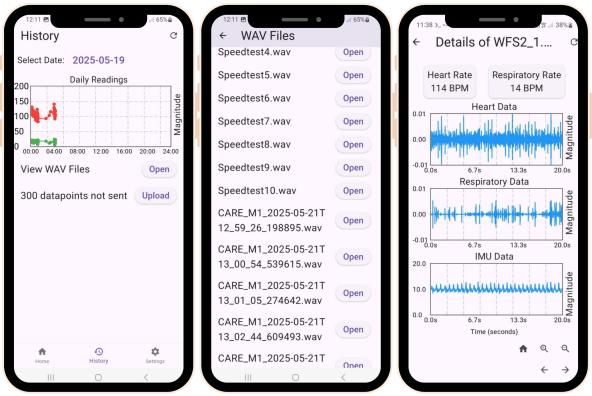

Fig. 4: Mobile Application (History Page and its subpages to view WAV files)

3) Mobile Application: The mobile application was designed using Flutter Development Kit. For the purpose of this study, the mobile application was mainly developed for Android, however given Flutter's multi-platform feature, it should be possible to easily replicate the current mobile application on other platforms like iOS, Windows, or Mac. There are two (2) main parts in the code, which is a recording page and a history page. In the recording page, the mobile application is able to connect to the MCU via the FlutterBluePlus package. The mobile application only connects to devices with a unique service UUID. Upon connecting to a device, it will immediately open up the device screen, which will show the beats per Minute of the heart rate and respiratory rate. This shows the current BPM over the 20-second audio data the MCU has recorded and transmitted via BLE. The processing is mainly done in termux, a terminal emulator, and it runs a python-based digital signal processing algorithm which will be discussed later on, the termux acts as a remote server for the python program to run and it directly communicates with the Flutter application using Flask-HTTP method, additionally in the python program, the audio data are also saved as a wave file, while the IMU data as a text file, both using consistent time-based filename convention for easier association. Upon receiving the processed data, the Flutter application updates the graphs and displays the BPM. Afterwards, there would be an attempt to transmit and save the data into a cloud database in the UP CARE platform and a local SQL database within the application. The history page is capable of loading the data recorded in the recording page, selecting a date will show the heart and respiratory rates in BPM for the selected date, and the 20-second recordings may also be viewed by opening the wave file of the audio data and the text file of the IMU data. A screenshot of the developed application is shown in Fig. 4.

4) Signal Processing: A summary of the data processing for the recorded auscultation sound is shown in Fig. 5. The

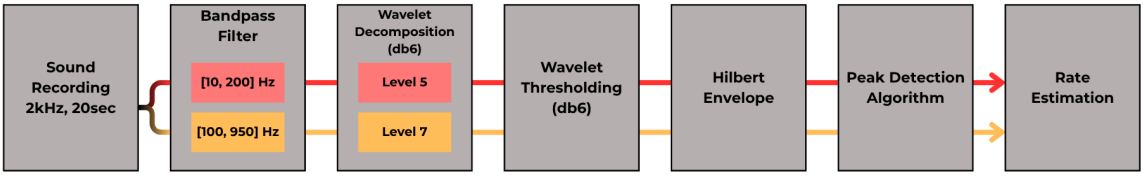

Fig. 5: Flowchart of the data processing for the recorded sound.

audio recorded from the device is converted into an array using the *read* method of the *soundfile* library. This sound is then passed through bandpass filters in the ranges 10-200 Hz for heart sound, and 100-950 Hz for respiratory sound using *SciPy*'s *butter* and *filtfilt* methods. These signals are then passed through wavelet decomposition using the *db6* wavelet–wavelet being used as it has a high time resolution and low-frequency resolution for high frequencies, low time resolution, and high-frequency resolution for low frequencies [13]; with heart sound at level 5 and respiratory sound at level 7. Both of these signals are passed through wavelet thresholding using the same wavelet to remove any small noises in their respective frequency signal. These signals are then passed through a Hilbert transform to obtain their envelope. Finally, the processed heart and respiratory sounds are passed through their respective peak detection algorithms.

a) Heart Sound Peak Detection: Every signal of the envelope is compared to a rolling mean window of 0.5 seconds. Only signals that are within 2 to 10 times the rolling mean will proceed with the analysis. The first 2 peaks will be automatically accepted to serve as the baseline of the rejection algorithm. The succeeding peaks will then undergo a Z-core test. If the peak occurred sooner than expected, which is represented by a Z-score greater than 3, then the peak is rejected. Otherwise, it would be accepted and any signals within a distance of 0.1 seconds would be ignored. All accepted peaks would be placed into two groups which would serve as the S1 and S2 groupings. The distance between the peaks of both groups would be calculated to obtain the average heart rate as shown in equation 2, where $t_{Si,n}$ is the time of the n-th peak of the i-th group. The average of both groups, BPM_{S1} and BPM_{S2}, would serve as the overall heart rate as shown in equation 1.

$$BPM = \frac{BPM_{S_1} + BPM_{S_2}}{2} \tag{1}$$

$$BPM_{S_i} = \frac{60}{\frac{\sum_1^{n-1}(t_{Si,n+1} - t_{Si,n})}{n}} \tag{2}$$

b) Respiratory Sound Peak Detection: The signal envelope of the respiratory sound is further processed by integrating the envelope over a window of 0.5 seconds. The window starts at 0 or the previous 0.5 seconds before the signal. This is done to ensure that long, prominent breathing sounds are prioritized over quick, transient heart beats. The local maxima are obtained using *SciPy*'s *find_peaks* method. If the signal between two peaks crosses below the mean of the integral of the 20 second signal, then the signal is accepted. Finally, if the number of peaks is more than four, then the same groupings from the heart sound peak detection is used as shown in equation 1 and 2. This approach, similar to the heart sound peak detection, ensures that a respiratory rate can be obtained even if only a few respiratory sounds were detected.

C. Performance Evaluation

1) Data Aggregation: To validate the device's accuracy, recordings were made alongside a medical-grade pulse oximeter and the ECG feature of a Samsung Galaxy Watch 6 for heart rate comparison. Respiratory rate was manually counted for each trial. Tests were conducted at six body sites (Fig. 6), with an additional walking test at FS2 to assess motion performance. For improved signal quality, participants wore the device directly on the skin [14].

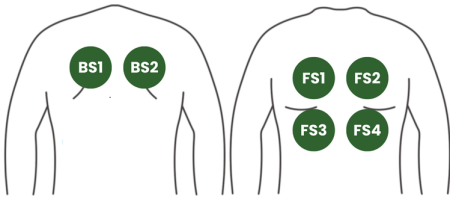

Fig. 6: Auscultation Points in the Study (on the left is the posterior side and on the right is the anterior side)

2) Device Data Quality: Ten recordings were collected per sector—half during regular breathing and half with slightly heavier breathing. For each trial, the absolute error was calculated against corresponding values from a pulse oximeter and ECG. The Mean Absolute Error (MAE), computed using equation 3, provided a quantitative measure of device performance, where y_i represents the reference value (ECG, pulse oximeter, or KardiaMobile®) and x_i is the Auscultawear output for the i-th trial over n trials.

$$MAE = \frac{\sum_{i=1}^{n} |y_i - x_i|}{n} \tag{3}$$

Building on these results, the sector with the best MAE was selected for further testing using KardiaMobile®This step served to benchmark Auscultawear's heart rate accuracy against a recognized gold standard.

3) Power Requirements: The power consumption of Auscultawear was evaluated using Nordic's Power Profiling Kit 2, which measured current draw during a single operation cycle for each mode. Battery life was then estimated using the measured power P, battery voltage V_{batt}, capacity Q_{batt}, and regulator efficiency η, as shown in:

$$t_{\text{batt}} = \frac{\eta Q_{\text{batt}} V_{\text{batt}}}{P} \tag{4}$$

III. Results and Discussion

As described in the methodology, 10 samples were collected per auscultation sector. The primary participant was a 23-year-old male, weighing 70 kg and measuring 1.65 m in height. Two additional participants were involved in device benchmarking: one weighing 84.2 kg and 1.64 m tall, and another weighing 81.15 kg and 1.69 m tall.

A. Data Collection and Display

The mobile application displays the collected data for each recorded session. The processing algorithms used to generate the graphs shown in Fig. 8 and 7 were executed on a laptop. Additionally, Table I presents the average processing time over ten trials for three different devices, each running the same audio samples. The specifications for the test devices are as follows: Laptop (Intel(R) Core(TM) i5-10300H CPU @ 2.50GHz), Phone 1 (Exynos 9611, Octa-core 4×2.3GHz Cortex), and Phone 2 (Exynos 1380, Octa-core 4×2.4GHz Cortex). Despite differences in runtime, all devices produced identical outputs, confirming the platform-independence of the signal processing pipeline.

Despite being a mid-range Android device, Phone 1 demonstrated an average processing time significantly shorter than the 20-second sampling interval of the Auscultawear device. This confirms that even low-to-mid tier mobile phones are capable of real-time data processing without falling behind. Offloading computation from the wearable to the smartphone not only ensures faster execution but also reduces the power consumption of the wearable, extending its battery life and enabling more efficient continuous monitoring.

TABLE I: Average Processing Time per 20-second Audio Sample

Device	Laptop	Phone 1	Phone 2
Average Time (s)	0.4713	3.3943	1.0025

B. Device Data Quality

To consider a heart rate measurement to be valid while a person is at rest, the MAE must be no greater than 5.21 BPM. In contrast, during walking activity, the MAE threshold increases and the values must remain at or below 9.33 BPM to be deemed acceptable. However for the respiratory rate, the measurements are considered acceptable when the mean absolute error is less than 5.20 breaths per minute [15].

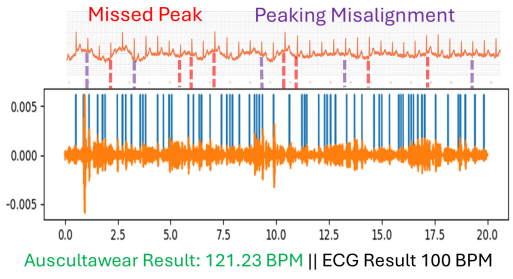

Fig. 7: Example of a bad performance of the device

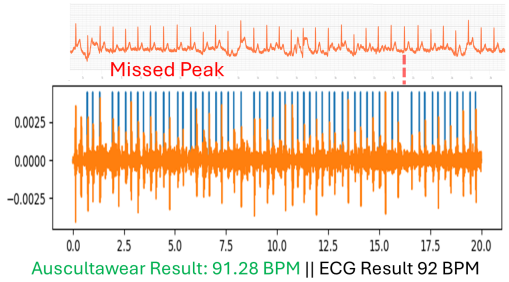

Fig. 8: Example of a good performance of the device

As described in the methodology, MAE values across sectors were compiled into a table for quantitative analysis. To visually assess performance, time-synchronized ECG signals were overlaid on post-processed audio with annotated peaks. Fig. 7 shows a case with poor alignment—ECG recorded 100 BPM, while the device computed 121.23 BPM, likely due to missed and false peaks. In contrast, Fig. 8 illustrates a well-aligned case, with ECG at 92 BPM and the device at 91.28 BPM. Most ECG peaks aligned with the S1 heart sounds, with a slight error due to one missed peak around the 16-second mark.

	POxi MAE		ECG MAE		RS MAE	
FS1	**5.75 ± 2.97**	5.91 ± 1.88	**5.23 ± 1.79**	5.44 ± 1.68	**3.81 ± 2.55**	3.53 ± 3.12
		5.56 ± 4.03		5.02 ± 2.09		4.01 ± 2.22
FS2	**6.70 ± 4.79**	10.12 ± 5.91	**7.32 ± 3.92**	9.03 ± 5.00	**6.03 ± 3.40**	5.98 ± 3.25
		3.28 ± 4.08		5.60 ± 3.11		6.08 ± 3.93
FS3	**8.88 ± 6.69**	7.16 ± 5.74	**7.94 ± 5.78**	6.35 ± 5.30	**7.95 ± 5.18**	6.72 ± 4.06
		10.60 ± 8.23		9.52 ± 6.86		9.19 ± 6.63
FS4	**5.54 ± 4.81**	7.00 ± 6.81	**5.18 ± 6.58**	7.66 ± 8.76	**5.86 ± 2.63**	4.58 ± 3.25
		4.08 ± 2.39		2.70 ± 4.53		7.14 ± 2.23
BS1	**13.89 ± 19.71**	7.96 ± 8.94	**13.98 ± 20.45**	6.40 ± 9.79	**3.71 ± 4.52**	4.06 ± 3.47
		19.81 ± 28.18		21.55 ± 29.07		3.37 ± 5.83
BS2	**8.34 ± 7.03**	5.90 ± 6.36	**6.54 ± 6.52**	7.20 ± 7.01	**1.98 ± 1.21**	2.24 ± 1.71
		10.78 ± 8.40		5.88 ± 6.82		1.71 ± 0.60
WFS2	**4.76 ± 3.93**		**6.48 ± 4.12**		**5.67 ± 2.06**	

Fig. 9: Mean average error of Auscultawear. The frequency range of the heart sound of FS1, FS3, and WFS2 are from 10-200 Hz, while the heart sound of the other sectors are from 50-200 Hz.

Fig. 9 shows the mean average error of Auscultawear when compared to a pulse oximeter, ECG from a smart watch, and manual respiratory rate counting. The MAE highlighted in green is during light breathing, while the one in orange is during heavy breathing. The performance of Auscultawear on heart rate barely passed the threshold of 5.21 BPM at sector FS4 against ECG, but its performance on respiratory rate is acceptable being well under the 9.33 BPM threshold on all sectors. It is important to note that the heart rate performance of the device on sector FS4 is the most accurate, especially during light breathing, but sector FS1 is the most precise while still being accurate.

The heart rate MAE of sectors FS2, FS4, BS1, and BS2 were considerably worse when compared to the heart rate MAE of sectors FS1 and FS3 when using 10-200 Hz, but improves when the frequency range is 50-200 Hz. Notably, sectors FS1 and FS3 are the same sectors where the heart is closer and the heartbeats are more audible. This is why

including the sub-50 Hz frequency on its range improves the heart rate MAE. Meanwhile, the other sectors benefit from clipping the sub-50 Hz frequency as these sectors are mostly noise since the heart beats are barely audible.

In general, FS1 and FS4 are the best for monitoring heart rate, while BS2 is optimal for measuring respiratory rate.

It was also found that the bandpass frequency for heart rate affects the performance according to the sector. When changing the bandpass frequency from 10-200 Hz to 50-200Hz, sectors FS1, FS3, BS1, and BS2 increased its accuracy by 57%, 8%, 43%, and 71% respectively. Only sectors FS2 and FS4 were degraded, with a decrease of 99% and 88% in accuracy respectively. It can be seen that FS2 and FS4 are located where the bass of the heartbeats is heard prominently. By filtering out the sub-50 Hz signals in these sectors, the heart sounds could have been reduced significantly, causing a considerably decrease in accuracy. Meanwhile, other sectors that benefited from filtering out the sub-50 Hz signals are located far from the heart, where the heart sound is just as loud as the respiratory sounds. This suggests that the sub-50 Hz signal barely includes heart sounds.

C. Device Benchmarking

As discussed in the previous section, the device performed best in heart sound detection at sectors FS1 and FS4. For focused evaluation against a clinical-grade gold standard, Sector FS1 was selected due to its higher measurement precision. Benchmarking was conducted using the *KardiaMobile EKG*, yielding an MAE of 4.58 ± 2.54 BPM for a participant with a near-normal BMI.

In contrast, two additional participants with higher BMI classifications—overweight and obese class I—showed significantly elevated MAEs of 32.34 ± 8.69 BPM and 31.37 ± 8.01 BPM, respectively. This variation may be due to increased subcutaneous fat attenuating the acoustic signals, reducing microphone sensitivity to heart sounds.

TABLE II: Heart Rate Benchmarking Results Using KardiaMobile EKG at Sector FS1

Participant	BMI Category	BMI	MAE (BPM)
Participant 1	Near Normal	25.7	4.58 ± 2.54
Participant 2	Obese Class I	31.3	31.37 ± 8.01
Participant 3	Overweight	28.4	32.34 ± 8.69

D. Power Requirements

TABLE III: Average Power Consumption in Different Modes

	Measuring	Transmission	Idle	Ratio
Ave Power (mW)	26.418	34.854	24.050	26.820

Table III shows the average power consumption across three modes of operation. In Measure mode, the device simultaneously records data from the IMU and MIC for 20 seconds. Transmission mode involves sending the recorded data via BLE and consumes the most power. However, this only occurs once every 20 seconds, limiting its impact on overall power usage. Idle mode represents the device running without active tasks, consuming the least power. The fourth column in the figure shows the combined effect of the measurement and transmission ratio. Although actual data transmission takes approximately 0.785 seconds, we conservatively round this to 1 second for estimation, reflecting the higher power usage shown.

In summary, the battery life was evaluated based on the measurement mode as shown in Table IV. Using Formula 4, the computed battery life is 68.979h. This exhibits that the device can last for more than two days before needing to be recharged.

TABLE IV: Battery Life Evaluation of the Device

Regulator Efficiency	Capacity (mAh)	Battery Voltage (V)	Power (mW)	Battery Life (h)
$\sim$1	500	3.7	26.82	68.979

IV. Conclusion and Recommendations

This study successfully developed a compact, wearable audio acquisition system that captures 20-second physiological sound recordings and transmits them to a mobile application via Bluetooth Low Energy (BLE). The system also synchronizes motion magnitude data using an onboard IMU, enabling future implementation of noise reduction techniques such as adaptive filtering.

From the statistical analyses of the experiments across different auscultation sectors, heart rate (HR) calculations performed best at FS1 and FS4, with ECG MAE scores of 5.23 ± 1.79 BPM and 5.18 ± 6.58 BPM, respectively. While these values slightly exceed the target MAE threshold of ≤ 5.21 BPM for resting-state measurements, they remain close enough to suggest the system's viability with further refinement in signal processing and hardware. Benchmarking against the KardiaMobile EKG confirmed the device's accuracy for individuals with near-normal BMI (MAE = $4.58, \pm, 2.54$ BPM), but showed significant degradation in accuracy for overweight and obese participants. This suggests that body composition may influence acoustic signal transmission and should be considered in future algorithm development and hardware calibration.

For respiratory rate (RR), the most accurate results were observed at BS1, with an MAE of 1.98 ± 1.21 BPM, well within the acceptable error range of ≤ 5.20 breaths per minute. This highlights the reliability of the acoustic-based RR measurements in static conditions.

Additionally, the walking experiment conducted at sector WFS2 produced comparable results to FS2, with an ECG MAE score of 6.48 ± 4.12 BPM. Although this falls within the relaxed threshold of ≤ 9.33 BPM for motion scenarios, it also underscores the importance of accounting for potential inaccuracies caused by motion artifacts—both in the test device and in the control measurement.

Compared to the earlier work of Monasterial *et al.*, which focused on software-based algorithm validation using a smartphone microphone and an available online dataset, this study was able to improve upon their approach by embedding the processing pipeline into a wearable hardware prototype [12].

For future researchers, it is recommended to look into signal acquisition, particularly with the directionality of the mic and soundproofing from ambient noise. A more sophisticated signal processing algorithm could be made with the

help of the IMU data, to which we could apply adaptive noise cancelling to that data. An improvement on the mobile application backend implementation for it to be truly embedded within the application could also improve the system. Furthermore, the range of frequency and auscultation placement should be further studied to be able to identify the most optimal frequency range for each sector. Lastly, it is recommended to have a larger quantity of patients to verify the device's performance in a wide variety of demographics to be able to observe changes due to patient characteristics.

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