RESEARCH ARTICLE

VOL. 46 |NO 3.|**SEPTEMBER- DECEMBER 2025** | PP 1-22

Revista Mexicana de Ingeniería Biomédica

https://dx.doi.org/10.17488/RMIB.46.3.1502

E-LOCATION ID: e1502

Portable and non-invasive system for gas exchange dynamics estimation and energy expenditure as an indicator of metabolic state

Sistema portátil y no invasivo para la estimación de la dinámica del intercambio gaseoso y el gasto energético como indicador del estado metabólico.

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ABSTRACT

Accurate estimation of energy expenditure and gas exchange dynamics is essential for health monitoring and performance optimization. This study addresses the limitations of traditional systems by developing a portable, non-invasive, and real-time solution that correlates physiological signals with energy metabolism. The proposed system estimates energy expenditure and metabolic state using oxygen and carbon dioxide flows derived from non-invasive variables such as respiratory ventilation and heart rate. It utilizes Bluetooth Low Energy (BLE) for wireless communication and includes user-friendly interfaces for smartphones and computers to facilitate data visualization and recording. Calibration is performed using a calorimeter, resulting in an average estimation error of 14.83%. The system demonstrates reliable performance under various conditions, providing real-time estimations of energy expenditure and gas exchange. Its portability and ergonomic design improve usability; however, precise calibration remains essential, and broader testing is required to validate robustness. A key advantage of the system is its ability to operate entirely offline, relying solely on BLE for data transmission, making it suitable for real-time monitoring in diverse environments.

KEYWORDS: **dynamic modeling, energy expenditure, gas exchange estimation, non-invasive monitoring, wearable device.**

RESUMEN

La estimación precisa del gasto energético y de la dinámica del intercambio gaseoso resulta fundamental para el monitoreo de la salud y la optimización del rendimiento deportivo. El presente estudio aborda las limitaciones de los sistemas tradicionales mediante el desarrollo de una solución portátil, no invasiva y en tiempo real, que correlaciona señales fisiológicas con el metabolismo energético. El sistema propuesto estima el gasto energético y el estado metabólico a partir de los flujos de oxígeno y dióxido de carbono, derivados de variables no invasivas como la ventilación respiratoria y la frecuencia cardíaca. Utiliza Bluetooth de baja energía (BLE) para la comunicación inalámbrica e incorpora interfaces intuitivas para teléfonos inteligentes y computadoras, facilitando la visualización y el registro de datos. La calibración se realiza mediante un calorímetro, obteniéndose un error promedio de estimación del 14,72%. El sistema demuestra un rendimiento confiable en diversas condiciones, proporcionando estimaciones precisas del gasto energético y del intercambio gaseoso en tiempo real. Su portabilidad y diseño ergonómico mejoran la usabilidad; sin embargo, se requiere una calibración precisa y una validación más amplia para confirmar su robustez. Una ventaja clave del sistema radica en su capacidad para operar completamente sin conexión a internet, utilizando únicamente BLE para la transmisión de datos, lo que lo hace ideal para el monitoreo en línea en diferentes entornos.

PALABRAS CLAVE: dispositivo portátil, estimación del intercambio gaseoso, gasto energético, modelado dinámico, monitoreo no invasivo.

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Received:

07 January 2025

Accepted:

13 August 2025

Published:

19 December 2025

INTRODUCTION

The increasing focus on health, physical performance, and personalized monitoring has led to significant advancements in portable devices designed to measure physiological variables and estimate energy expenditure (EE). Over the past few years, wearable technologies such as smartwatches, smartphones, and specialized devices have integrated multiple physiological measurements, offering actionable insights. For instance, Polar devices provide accurate data on heart rate, while Garmin's Body Battery® interprets energy levels and expenditure based on stress and heart rate variability, incorporating other factors like nutrition and hydration to assess overall well-being and performance[1][2].

However, despite their widespread adoption, these systems rely on heart rate-based estimations rather than direct physiological measurements, limiting their accuracy under varying effort conditions. They do not integrate real-time gas exchange dynamics, which are essential for precise metabolic monitoring. As a result, their estimations can be affected by individual variability in cardiorespiratory responses, leading to inaccuracies in EE assessment. This study addresses these limitations by developing a portable system that estimates metabolic state and EE based on real-time respiratory dynamics, offering a physiologically grounded alternative to existing wearable devices.

In the domain of respiratory gas measurements, COSMED® has emerged as a leading device, offering detailed analyses of energy expenditure during both rest and exercise by examining oxygen and carbon dioxide flows. This technology allows for precise estimations of substrate utilization and energy dynamics, essential for understanding metabolic behavior in diverse conditions[3]. Similarly, BioHarness® measures heart rate, respiratory rate, and heart rate variability to estimate physiological stress levels, making it valuable for monitoring exercise intensity and recovery[4].

While COSMED and similar devices offer high accuracy, they require face masks and bulky equipment, restricting their usability in real-world applications. In contrast, wearable devices like Garmin and Polar are compact and convenient but lack direct gas exchange measurements. This study proposes a portable, mask-free system that estimates EE using a mathematical model based on respiratory dynamics, providing a balance between accuracy and usability.

Parallel to these technological advancements, bioenergetic modeling has enhanced the understanding EE. In 2017, Rosero, Martínez, and Corno developed a cyclist bioenergetic model that optimizes endurance performance by analyzing the human-machine interaction during cycling[5]. In 2018, the same authors employed gas exchange models through cycle ergometry, improving the accuracy of anaerobic performance estimations[6]. In 2021, Realpe *et al.* proposed a system for estimating metabolic status during bicycle use, leveraging wireless microcontroller technology and gas exchange models to monitor everyday activities[7]. In 2022, Sanz-Morère *et al.* analyzed the energetic cost of locomotion in transfemoral amputees, providing insights into energy dynamics in rehabilitation contexts[8].

Despite these advances, many gas exchange measurement systems continue to rely on cumbersome respiratory masks, which not only hinder user comfort but may also affect natural ventilation patterns. This work aims to develop a compact, portable, and non-invasive system capable of estimating EE without requiring face masks or laboratory-grade equipment.

In a comparative assessment with the Calibre Bio device, our system demonstrated an average estimation error of 14.83%, highlighting both its feasibility and the need for further calibration improvements. This error aligns with findings from[9], who evaluated the accuracy of 15 CPET systems and reported substantial variability across devices, with errors ranging from 1.10% to 13.3% for VO_2 and 1.07% to 18.3% for VCO_2. These results emphasize the challenges of achieving high precision in gas exchange measurements, particularly with portable and non-invasive alternatives.

One of the main advantages of the proposed system is its portability, as it does not require large laboratory equipment and can be used in various environments, including clinics, sports facilities, and home settings. Additionally, the usability of the system is enhanced by its wireless data transmission via Bluetooth, allowing real-time monitoring on both mobile and desktop applications. Unlike traditional systems that rely on complex calibration and restrictive respiratory masks, this system employs a non-invasive measurement approach, making it more comfortable for users while maintaining a competitive accuracy level.

This paper presents a device capable of obtaining respiratory gases non-invasively, focusing on oxygen (VO_2) and carbon dioxide (VCO_2) as key metabolic indicators. These values, combined with heart rate and ventilation data, provide a comprehensive view of the body's energy dynamics. The system is designed for portability and ease of use, featuring Bluetooth communication for real-time monitoring and analysis. The integration of this technology aims to improve health monitoring, sports performance, and rehabilitation, providing an innovative and practical tool for metabolic assessment.

MATERIALS AND METHODS

During physical activity, oxygen (O_2) and carbon dioxide (CO_2) are fundamental to understanding metabolic processes, as they provide critical indicators of energy production and substrate utilization. O_2 is essential for oxidative metabolism, where it combines with substrates such as carbohydrates (CHO) and fats (FAT) to generate ATP. Meanwhile, CO_2 is a byproduct of these metabolic reactions and serves as a key indicator of energy expenditure and substrate oxidation rates[10][11].

The ratio of CO_2 produced to O_2 consumed, known as the respiratory quotient (RQ) or the respiratory exchange ratio (RER), offers insights into the balance between carbohydrate and fat oxidation. RQ values near 1.0 indicate predominant carbohydrate metabolism, while lower values (~0.7) reflect fat utilization. These metrics are invaluable for assessing metabolic state, estimating energy expenditure, and tailoring interventions for both health monitoring and athletic performance optimization[11][12].

Given the importance of these variables, this research focuses on the precise estimation of O_2 and CO_2 flows, along with derived indicators such as respiratory quotient (RQ), respiratory exchange ratio (RER), fat, and carbohydrate (CHO) oxidation rates. This approach enables a comprehensive analysis of energy metabolism during exercise, providing a robust framework for monitoring and understanding physiological responses in real-time.

These measurements form the foundation for dynamic models that accurately estimate energy expenditure and substrate utilization, offering practical applications in sports and healthcare[11][12].

System architecture

The developed system consists of a compact, portable unit designed for real-time physiological monitoring. The device is securely fastened to the participant's back using adjustable straps and operates autonomously with an integrated battery system as shown in Figure 2. It features a microcontroller that processes sensor data, transmitting information via Bluetooth Low Energy (BLE) to an Android-based user interface. The system does not require an internet connection, ensuring functionality in various environments, including outdoor and laboratory settings. The schematic representation of the system's architecture is shown in Figure 1.

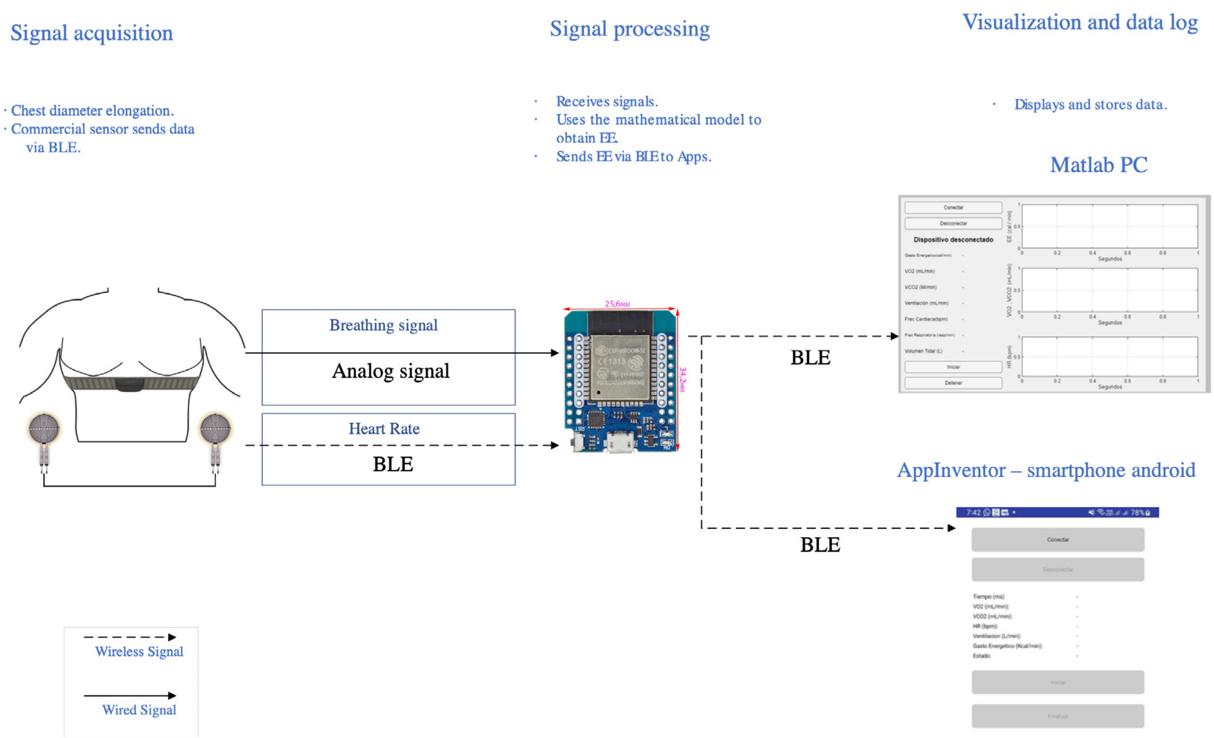

FIGURE 1. Schematic diagram of the operation of the developed system.

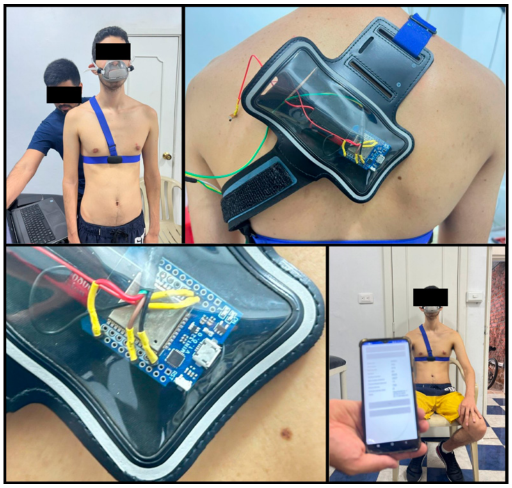

FIGURE 2. Placement of the portable sensor on the body.

Oxygen flow rate from heart rate

Oxygen flow rate (VO_2) measures the oxygen consumed by the body during physical activity. It can be expressed in two forms: absolute VO_2, which indicates total oxygen consumption in liters per minute (L/min), independent of individual characteristics, and relative VO_2, which normalizes oxygen consumption to body weight (mL/kg/min), allowing comparisons across individuals of varying sizes. A linear relationship between heart rate (HR) and VO_2 is assumed within a certain range. Incremental and decremental models are developed to account for the changes in oxygen dynamics during incremental or decremental exercise.

The data used to generate Figure 3 was obtained during a stationary test using the instruments described in section 4.3. These tests allowed the correlation of respiratory gas values with heart rate (HR) to illustrate the relationship. As shown in Figure 3, linear relationship between VO_2 and HR is illustrated. This relationship holds for most of the working zone, but deviations from linearity may occur as the workload approaches VO_2MAX. These deviations are often observed as either an incremental peak or a valley, and this phenomenon remains an area of ongoing research in the field of physiology. For the development of the system, a linear model is applied for both incremental and decremental load steps.

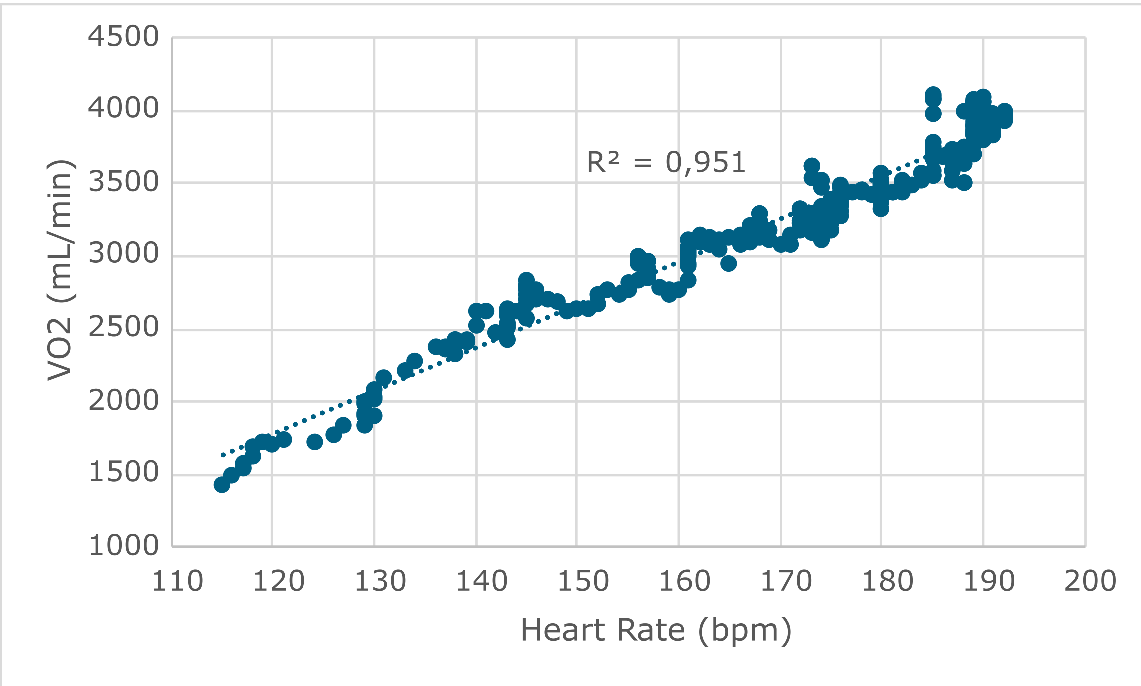

FIGURE 3. Relationship between oxygen flow VO_2 and heart rate HR.

Carbon dioxide flow rate from respiratory ventilation

Obtaining the carbon dioxide flow (VCO_2) is a challenging task, as it typically requires the use of oxygen masks or invasive implements. Compared to other variables, such as heart rate, VCO_2 exhibits non-linearities, which complicates the parameterization of pre-established models. Future work aims to use the alveolar ventilation rate (BR) to estimate VCO_2[13], where a relationship between alveolar ventilation and carbon dioxide production is established. This relationship is then scaled to validate the connection between total respiratory ventilation and VCO_2.

The data used for Figure 4 was obtained under stationary conditions using the same instruments presented in section 4.3. These measurements correlated respiratory ventilation (Ve) with carbon dioxide flow (VCO_2), enabling the illustration of the relationship. As with the oxygen flow obtained from heart rate, non-linearity is observed in the system during a decremental or reduced intensity physical activity step. To address this, the model is modified, resulting in improved system performance.

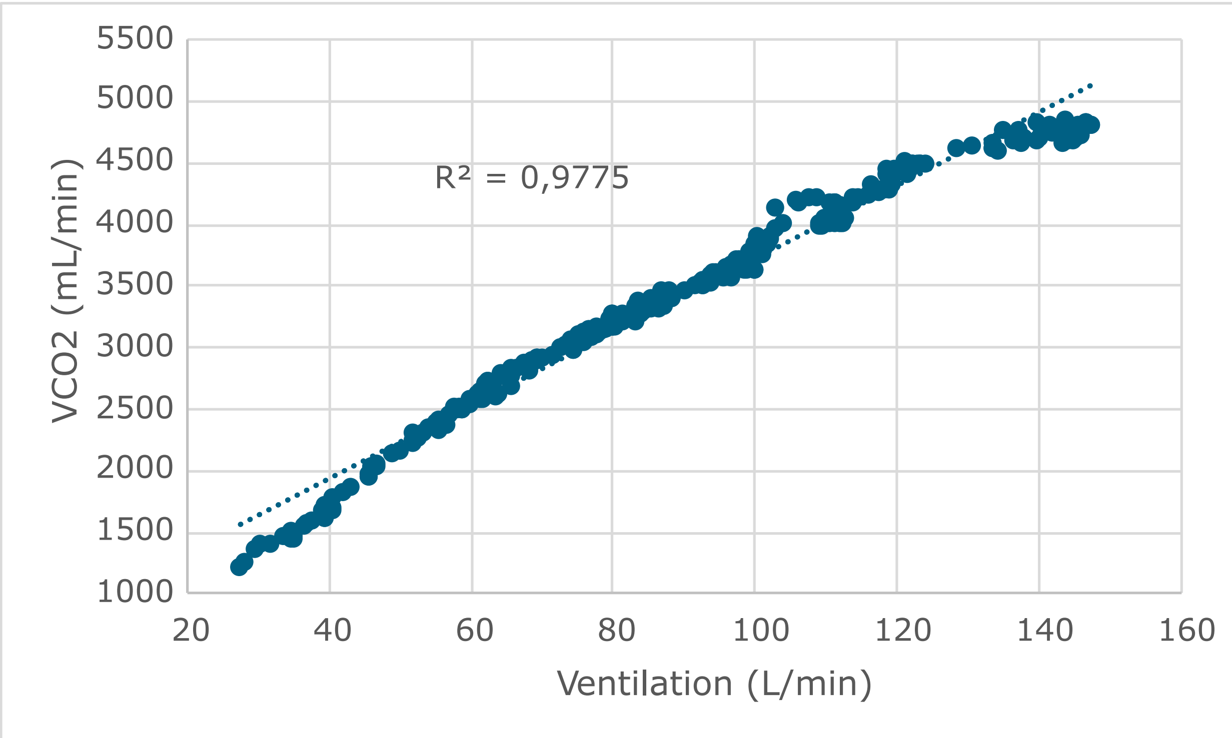

FIGURE 4. **Relationship between carbon dioxide flow VCO_2 and heart rate Ve.**

Energy expenditure estimation algorithm

Energy expenditure (EE) is the system's output variable and the primary parameter to be estimated. It reflects the total amount of energy the body requires to support both vital functions and physical activity, typically expressed in calories per minute (cal/min)[14]. In this study, EE is determined based on macronutrient metabolism—specifically the consumption of carbohydrates, proteins, and fats—via glycolytic and oxidative pathways, which are assessed through respiratory gas exchange.

To estimate EE, the study employs the Weir equation, a widely recognized method in indirect calorimetry. This equation enables the calculation of energy expenditure by integrating oxygen consumption (VO_2) and carbon dioxide production (VCO_2), and is mathematically defined as follows

$$EE = 3.94\, VO_2 + 1.11\, VCO_2, \tag{1}$$

where VO_2 represents the oxygen consumption (mL/min), VCO_2 represents the carbon dioxide production (mL/min) and the coefficients 3.94 and 1.11 are derived from the caloric equivalents of oxygen and carbon dioxide under standard physiological conditions[11]. Thus, the Weir equation serves as the foundation for EE estimation in this research.

Discretized system modeling

The discretized system evolves according to the state spaces discrete is defined as shown in (2)

$$x[k+1] = A_d\, x[k] + B_d\, u\,[k] + K_d$$
$$y[k] = C_d\, x[k], \tag{2}$$

where A_d , B_d, C_d, and K_d are the discrete-time system matrices, and k is the discrete-time index.

The output of the developed system is $EE[k]$, measured in kcal/min. The system consists of four states, the first state, $x_1\,[k]$, represents the $VO_2\,[k]$, while $x_2\,[k]$ corresponds to the $VCO_2\,[k]$. The third state, $x_3\,[k]$, allows for a low-pass filter on the output $EE[k]$, based on the equation where alpha (α=0.001) is a fixed parameter necessary for filtering, is given by

$$x_3\,[k+1] = \alpha\, EE[k] + (1-\alpha)\, x_3\,[k]. \tag{3}$$

The fourth state, $x_4\,[k]$, defined in equation (4) is used to determine the trend (either incremental or decremental) of the filtered $EE[k]$ obtained from state $x_3\,[k]$. This state is represented as

$$x_4[k+1] = \alpha\, EE[k] - \alpha\, x_3[k]. \tag{4}$$

The system inputs $u[k]$ are the heart rate (HR) and ventilation (Ve) variables, measured in beats per minute and breaths per minute, respectively.

Since there is a change in linearity in the system's gain relationship, the inputs are related to the system's dynamics using the matrix B_d depending on the sign of $x_4\,[k]$ defined in equation (5), it means, the system gain changes depending on whether the physical activity is incremental or decremental. B_d is shown as

$$B_d(x_4[k]) = \frac{1}{2}\begin{bmatrix} b_{1_{incr}} + b_{1_{decr}} & 0 \\ 0 & b_{4_{incr}} + b_{4_{decr}} \\ 0 & 0 \\ 0 & 0 \end{bmatrix} + \frac{1}{2} Sig(x_4[k]) \begin{bmatrix} b_{1_{incr}} - b_{1_{decr}} & 0 \\ 0 & b_{4_{incr}} - b_{4_{decr}} \\ 0 & 0 \\ 0 & 0 \end{bmatrix}, \tag{5}$$

where the parameters b_{1incr}, b_{1decr} ,b_{4incr} and b_{4decr} are obtained from posterior system parameterization.

The output matrix C_d is defined as

$$C_d = [C_1 \quad C_2 \quad 0 \quad 0], \tag{6}$$

where the constants C_1 and C_2 are derived from Weir equation (1), which relates VO_2 and VCO_2 to energy expenditure.

There is also an offset matrix K_d, which represents the values of the baseline respiratory gas flows, necessary for the correct coupling of the system to the actual values

$$K_d = \begin{bmatrix} K_1 \\ K_2 \\ 0 \\ 0 \end{bmatrix}. \tag{7}$$

Once the matrices A_d , B_d, C_d, and K_d are calculated. It has also been used the Weir equation shown in equation (1) to build the output matrix and finally the fully discretized system is expressed as

$$\begin{gathered}\begin{bmatrix} VO_2[k+1] \\ VCO_2[k+1] \\ x_3[k+1] \\ x_4[k+1] \end{bmatrix} = \begin{bmatrix} a_{d1} & 0 & 0 & 0 \\ 0 & a_{d4} & 0 & 0 \\ \alpha\ 3.94 & \alpha\ 1.11 & 1-\alpha & 0 \\ \alpha\ 3.94 & \alpha\ 1.11 & -\alpha & 0 \end{bmatrix} \begin{bmatrix} VO_2[k] \\ VCO_2[k] \\ x_3[k] \\ x_4[k] \end{bmatrix} + B_d(x_4[k]) \begin{bmatrix} HR[k] \\ Ve[k] \end{bmatrix} + K_d \\ EE[k] = [3.94 \quad 1.11 \quad 0 \quad 0] \begin{bmatrix} VO_2[k] \\ VCO_2[k] \\ x_3[k] \\ x_4[k] \end{bmatrix}. \end{gathered} \tag{8}$$

Model parameterization

The model parameterization is carried out using MATLAB®'s *fminunc* tool from the Optimization Toolbox, which is designed to find the minimum values of a multivariable function. This tool is particularly suited for nonlinear systems, such as the one being analyzed. The system's parameters are identified by comparing the model's predicted values of VO_2 and VCO_2, as expressed in equation (8), with experimental data from a previously conducted exercise test. The objective function is defined as

$$J = \sum_{i=1}^{n} ((\dot{V}O_2[k] - \dot{V}O_{2Experimental}[k])^2 + (\dot{V}CO_2[k] - \dot{V}CO_{2Experimental}[k])^2). \tag{9}$$

Heart rate measurement

Heart Rate (*HR*) is measured non-invasively using electrocardiographic devices, reflecting the electrical activity of the heart influenced by the autonomic nervous system[15][16]. HR has a proportional relationship with VO_2, making it a reliable input variable for estimating oxygen consumption[17].

An electrocardiography-based HR sensor measures HR, with data retrieved via ANT+ or Bluetooth Low-Energy (BLE)[18]. BLE was chosen for compatibility and technological availability, here, the MAGENE H64 (Figure 5) sensor was selected, but any BLE-compatible HR sensor is suitable. Sensor data was tested using Nordic Semiconductor’s nRF Connect App, identifying the service UUID 0000180d-0000-1000-8000-00805f9b34fb and characteristic UUID 00002a37-0000-1000-8000-00805f9b34fb.

FIGURE 5. **H64 Heart rate sensor by electrocardiogram**.

Ventilation measurement

Ventilation (*Ve*) refers to the respiratory airflow, measured in milliliters per minute (*mL/min*), determined by the product of tidal volume (*VC*) and breathing rate (*BR*) [19]. *VC* increases during physical activity, allowing higher ventilation within the inspiratory capacity range[20], and *Ve* is directly proportional to VCO_2, enabling straightforward and computationally efficient modeling.

Ventilation (*Ve*) is measured indirectly using a signal obtained from chest elongation during breathing, as illustrated in the schematic blocks in Figure 6.

The ventilation equation(10) is given by

$$Ve = VC * BF, \qquad 10)$$

where *VC* is tidal volume (L), and *BF* is breathing rate (breaths per minute). The RP-C18.3 ST pressure sensor, with a resistance range of $4k$ to $20k$ ohms, is placed under the HR band on the back for optimal signal variability during respiration.

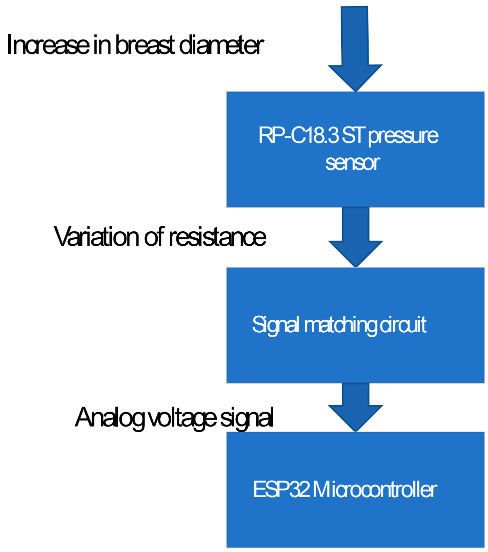

FIGURE 6. **Data acquisition scheme for respiratory ventilation.**

Development board: ESP32 D1 Mini

The ESP32-based D1 Mini development board, selected for its BLE capabilities, external power input, and dual-core processor, fulfils portability and wireless communication requirements[21]. The respiratory signal is read the IO34 port (ANALOG_0), while BLE retrieves HR data, with processed data written to UUID service 4fafc201-1fb5-459e-8fcc-c5c9c331914b and characteristic UUID beb5483e-36e1-4688-b7f5-ea07361b26a8.

Signals are sampled every 200 *ms*, filtered with a moving average (period 5), and parameterized using a commercial gas sensor as a reference. Peak detection identifies *BF* per respiratory cycle, allowing ventilation to be calculated through equation (10). The processed signal is shown in Figure 7.

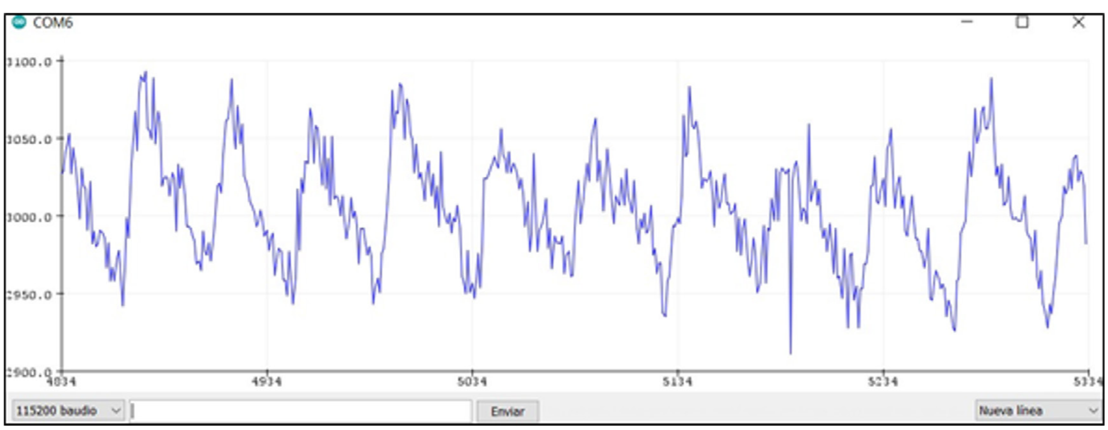

FIGURE 7. **Signal obtained from the pressure sensor.**

User interface

The interfaces must connect and disconnect from the BLE device responsible for measurements and mathematical model calculations. They periodically read the defined BLE characteristic, display the obtained data, and store it in a comma-separated values (CSV) file. The system uses the service UUID: 4fafc201-1fb5-459e-8fcc-c5c9c331914b and characteristic UUID: beb5483e-36e1-4688-b7f5-ea07361b26a8. The computer and smartphone clients periodically read these published objects, display the data via graphical user interfaces, and save it in CSV format.

The system exclusively relies on Bluetooth Low Energy (BLE) for communication, eliminating the need for an internet connection. This architecture ensures continuous operation in any environment, making the system suitable for real-time monitoring in outdoor and remote settings where connectivity may be limited.

The system's functionality was tested across multiple software versions to ensure stability and reliability. Specifically, it was validated using MATLAB versions 2023b, 2024a, and 2024b, as well as on Android operating systems version 13 and 14. These tests confirmed consistent performance, demonstrating that software updates do not negatively impact the system's operation.

The BLE device is identified as "UV-EE." Once connected, the device characteristic, containing seventeen bytes of data representing the variables listed in Table 1.

TABLE 1. **Variables published via BLE.**

Variable	Bytes
HR (beats/min)	0-1
Ventilation (L/min)	2-3
VO2 (mL/min)	4-5
VCO2 (mL/min)	6-7
Energy expenditure (cal/min)	8-9
BR (breaths/min)	10-11
Tidal volume (L)	12-13

MATLAB interface

The computer desktop interface, developed with MATLAB AppDesigner[22][23], combines signal analysis and digital processing capabilities, leveraging its built-in BLE communication tools for this research. The interface integrates modules for value control and visualization, alongside graphical representation of energy expenditure, as shown in Figure 8. The *ble*() library in MATLAB was used to simplify BLE protocol integration. This library provides predefined instructions to connect to a BLE server and read specific characteristics.

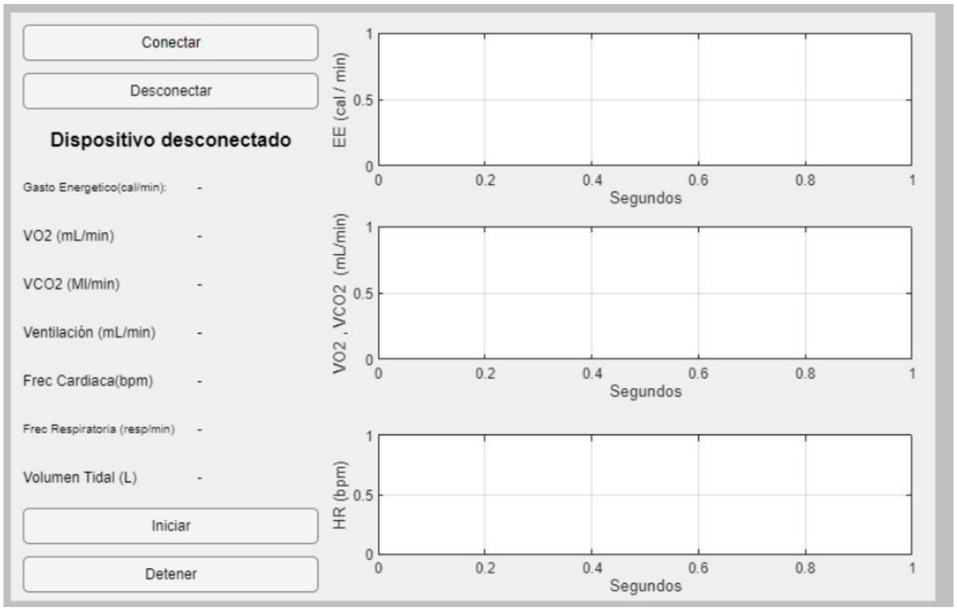

FIGURE 8. **MATLAB® desktop user interface.**

Android interface

The Android interface was developed using MIT App Inventor II, a software environment designed for rapid and functional deployment on Android platforms. This interface enables real-time data visualization with updates every 0.5 seconds. To use the application, the measurement device must be placed on the user, powered on, and its pilot LED activated. After enabling Bluetooth on the smartphone, the application is launched, and the "Connect" button is pressed to display a list of available devices. The device named "EE-UV" is selected, establishing the connection, and displaying the status as "Connected." Once connected, the "Start" button allows data to be visualized and saved in CSV format. The process ends by pressing the "Stop" button to finalize data storage, followed by "Disconnect" to complete the session. Figure 9 illustrates the Android interface used for this purpose.

In App Inventor, the BluetoothLE library was used for BLE communication. After initializing the necessary variables and permissions, the application searches for the "UV-EE" device. Once connected, the app enables periodic (every 0.5 seconds) data reads from the BLE characteristic. The received 14-byte data array is parsed and reorganized using the format in Table 1. Data is saved as a CSV file in the app's installation directory, with the filename containing the creation timestamp.

FIGURE 9. **Android user interface.**

Type of study

The study adopts a proof-of-concept approach to validate the functionality of the developed system, employing quantitative, correlational, and exploratory research design. It is situated at the intersection of biomedical engineering, dynamic systems modeling, and exercise physiology, with particular emphasis on parameter identification and model validation. The methodology follows a case-study format, enabling the integration of these disciplines to assess and refine the system's performance and applicability[24].

Volunteer selection

Three volunteers participate in this study, all of whom meet the established inclusion criteria and provide informed consent. The participants are deliberately selected based on strict health parameters to minimize variability in physiological responses and to validate the system's technical performance. Specifically, none present a history of metabolic or cardiovascular disease and all exhibit normal motor functions. The inclusion criteria ensure that only healthy individuals—without conditions that may interfere with exercise—are selected, while the exclusion criteria eliminate confounding factors such as cardiovascular symptoms (e.g., chest pain or dizziness during physical activity), joint disorders potentially aggravated by exercise, or the use of medications for blood pressure or heart conditions.

Prior to testing, each volunteer completes a health questionnaire to assess suitability for participation, and a baseline electrocardiogram (ECG) is performed to identify any underlying cardiovascular risk. This study is conducted as proof of concept with three participants, aiming to validate the feasibility and performance of the system during its initial development phase. Although the limited sample size restricts the generalizability of the results, it allows for a controlled assessment without interference from pre-existing health conditions. Future studies will include a broader range of individuals with varying metabolic and physiological profiles, enabling a more comprehensive evaluation of the system's robustness and applicability across diverse exercise conditions.

Equipment

The CALIBRE BIO® Ergo Spirometer[25], calibrated according to the manufacturer's manual, was used to measure respiratory gases. The QHR V Clinical Stress Electrocardiogram, Polar Pedometer, and Welch Allyn Sphygmomanometer, along with a Welch Allyn Stethoscope, were employed for cardiovascular monitoring. The Monark® 828E Ergometer Bicycle was utilized to conduct stress tests, while standardized instruments, including Kenwell scales and standard stadiometers, were used for clinical and anthropometric evaluations.

Methodology for model parameter estimation

The following outlines the protocol for system parameterization and performance testing. To ensure safety, continuous monitoring of heart rate (HR), blood pressure, and cardiac activity is conducted during all tests. An emergency vehicle, equipped with a defibrillator and staffed by trained personnel, remains on standby throughout the process. The study protocol was approved by the Ethics Committee of the Faculty of Engineering of the Universidad del Valle.

Two days system test

The test begins with a basal metabolic measurement, where the participant rests for 20 minutes to allow for respiratory gas measurement. This is followed by an incremental stress test that starts at 50 Watts, with increases of 30 Watts every 3 minutes, until the maximum effort is reached. The first and second ventilatory thresholds (VT1 and VT2) are determined during this test.

On the second day, a series of load tests are conducted: first, a sub-VT1 load test (5 minutes), then a load test between VT1 and VT2 (5 minutes), and finally a load test above VT2 (5 minutes). There is a 24-hour gap between each test, with no additional exertion during this period.

Calibration Procedure

To ensure the accuracy of gas exchange estimations, the system underwent a calibration process using the Calibre Bio device as a reference calorimeter. The calibration process consisted of two main stages: tidal volume adjustment and dynamic model parameterization, ensuring that both respiratory measurements and energy expenditure estimation were accurately mapped to a validated reference.

The first calibration step aimed to correlate the system's ADC signal amplitude with actual tidal volume measurements obtained from the Calibre Bio device. This step was necessary to establish a direct relationship between the raw sensor output and physiologically meaningful respiratory parameters. The procedure was as follows:

1. The participant wore both the developed system and the Calibre Bio device simultaneously.
2. The participant performed five shallow breaths (low tidal volume). The ADC signal amplitude from the developed system was recorded and correlated with the average tidal volume measured by the Calibre Bio.
3. The participant then performed five deep breaths (high tidal volume). Again, the ADC signal amplitude was recorded and correlated with the average tidal volume measured by the Calibre Bio.
4. These two sets of data points were used to establish a linear mapping function that converts ADC values into tidal volume estimates, ensuring that subsequent respiratory measurements were physiologically accurate.

After tidal volume calibration, the participant performed a graded exercise test on a Monark ergometer while data from both the system and the calorimeter were collected. These experimental values were used to parameterize the mathematical model via MATLAB's *fmincon* optimization tool, refining the accuracy of respiratory and energy expenditure estimations. This phase involved:

1. Performing an incremental exercise test using the Calibre Bio as a reference.
2. Recording experimental data for EE, VO_2, VCO_2 , and ventilation throughout the test.
3. Using the collected data to parametrize the mathematical model of respiratory gas exchange and EE estimation.
4. Applying MATLAB's *fmincon* optimization tool to determine the optimal coefficients for the dynamic model, minimizing estimation errors between the developed system and the reference calorimeter.

Data processing

Data obtained during the tests is stored in an Excel database, used to parameterize the model and estimate energy expenditure. The measured variables are detailed in Table 2.

TABLE 2. **Definition of variables used in the system.**

Variable	Operational Definition	Variable Type	Possible Values
Date of Birth	Date of birth (DD/MM/YY)	Nominal category	
Sex	Patient's sex	Nominal category	Female, Male
Age	Age in years	Continuous quantitative	Between 18 and 60 years
HR (Heart Rate)	Number of heart beats per minute	Quantitative category	Between 50 and 200 beats per minute
BR (Breathing Rate)	Number of breaths per minute	Quantitative category	Between 6 and 60 breaths per minute
Respiratory Ventilation	Volume in liters per minute of air breathed	Continuous numerical	Between 5 and 150 liters per minute
Oxygen Consumption	Amount of oxygen consumed by the user in milliliters per minute	Continuous numerical	Between 400 and 5000 milliliters per minute
Carbon Dioxide Production	Amount of carbon dioxide produced by the user in milliliters per minute	Continuous numerical	Between 200 and 5000 milliliters per minute
Energy Expenditure	Number of calories consumed per minute	Quantitative category	Between 1 and 25 calories per minute

RESULTS AND DISCUSSION

Table 3 below summarizes the key physiological characteristics and results from the system parameterization tests for three participants. These include demographic data (age and sex), as well as measurements such as maximum heart rate (HR), maximum ventilation (Ve), maximum oxygen consumption (VO_2MAX), and maximum carbon dioxide production (VCO_2MAX). Additionally, the table details the heart rate and ventilation levels at the first and second ventilatory thresholds (VT1 and VT2), which are critical for understanding individual metabolic responses during exercise.

Environmental factors such as ambient temperature and humidity were monitored throughout the tests, as they can affect sensor performance and calibration. Although the controlled laboratory environment minimized these effects, future studies will explore the system's robustness under varying environmental conditions. Overall, the observed precision across different exercise intensities demonstrates that while the system performs adequately under a range of metabolic conditions, further optimization and calibration may enhance its accuracy, particularly during high-intensity exercise

TABLE 3. **Physiological characteristics.**

Characteristic	Individual one	Individual two	Individual three
Age (years)	27	28	55
Sex	Female	Male	Male
Max HR (bpm)	200	181	160
Max Ve (L/min)	79.3	136.6	120.6
VO_2MAX (mL/min)	2920	3253	2612
VCO_2MAX (mL/min)	3232	3991	3039
VT1 HR (bpm)	140	147	130
VT1 Ve (L/min)	37	68	68
VT2 HR (bpm)	180	167	150
VT2 Ve (L/min)	67	96	112

Figure 10 presents the results of the incremental test conducted with the parameterized model for individual two. The Figure compares the performance of the identified model with the experimental data obtained during the test.

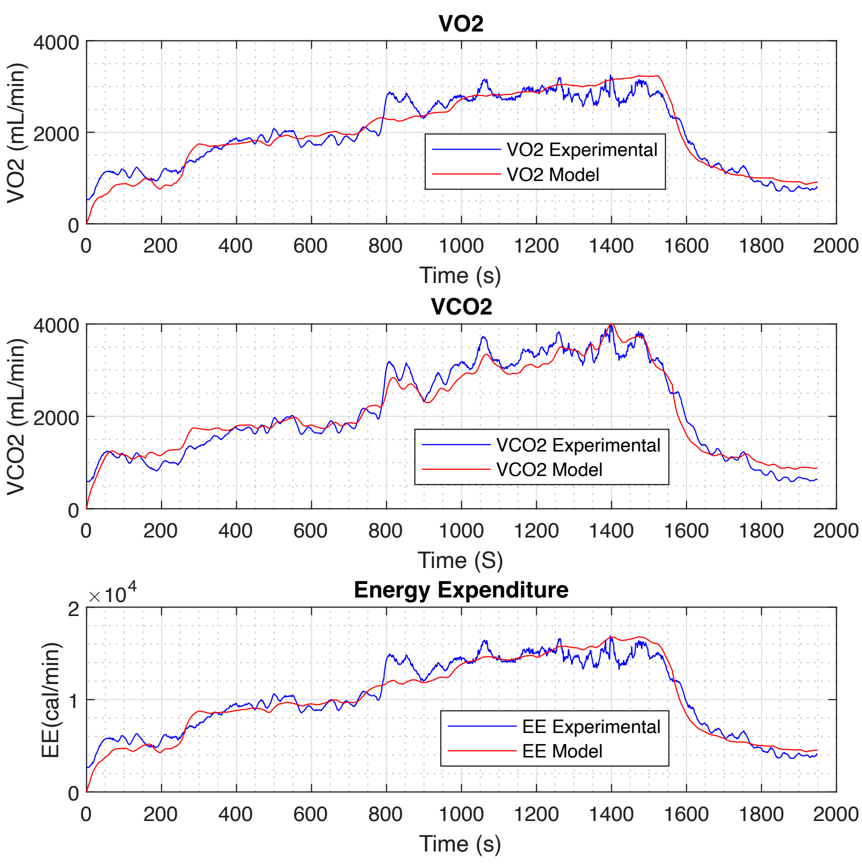

FIGURE 10. **Performance of the identified model compared to experimental data.**

Table 4 presents the parameters identified for the dynamic models corresponding to each participant. These parameters include coefficients related to system dynamics, gains, and model components for increasing and decreasing behaviors. These parameters reflect individual physiological responses and are essential for accurately simulating the relationship between input variables and metabolic outputs.

TABLE 4. **Model parameters for each participant.**

Parameter	Individual one	Individual two	Individual three
a_{d1}	0.9772	0.9672	0.9802
a_{d4}	0.9551	0.9561	0.9512
K_1	-52.51	-71.35	-49.93
K_2	4.39	7.47	6.29
$b_{1_{incr}}$	0.91357	0.6469	0.8723
$b_{1_{decr}}$	0.56278	0.4343	0.5236
$b_{4_{incr}}$	0.89256	0.6231	0.8412
$b_{4_{decr}}$	0.56203	0.4152	0.5174

Figure 11 and Figure 12 illustrate a comparison between the experimental measurements and the signals predicted by the dynamic models for Participant 2. This example highlights the system's capability to replicate the observed physiological variables, such as VO_2 and VCO_2, using the identified parameters. The alignment between the experimental data and model outputs demonstrates the model's accuracy and reliability in capturing individual metabolic dynamics.

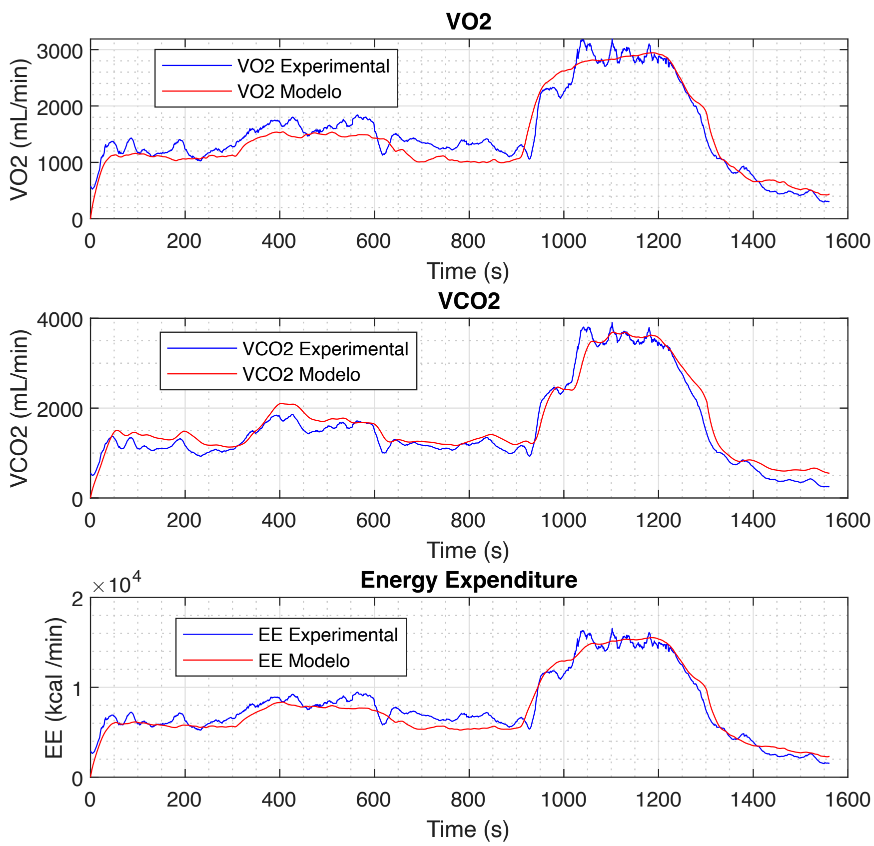

FIGURE 11. **System validation result for individual two.**

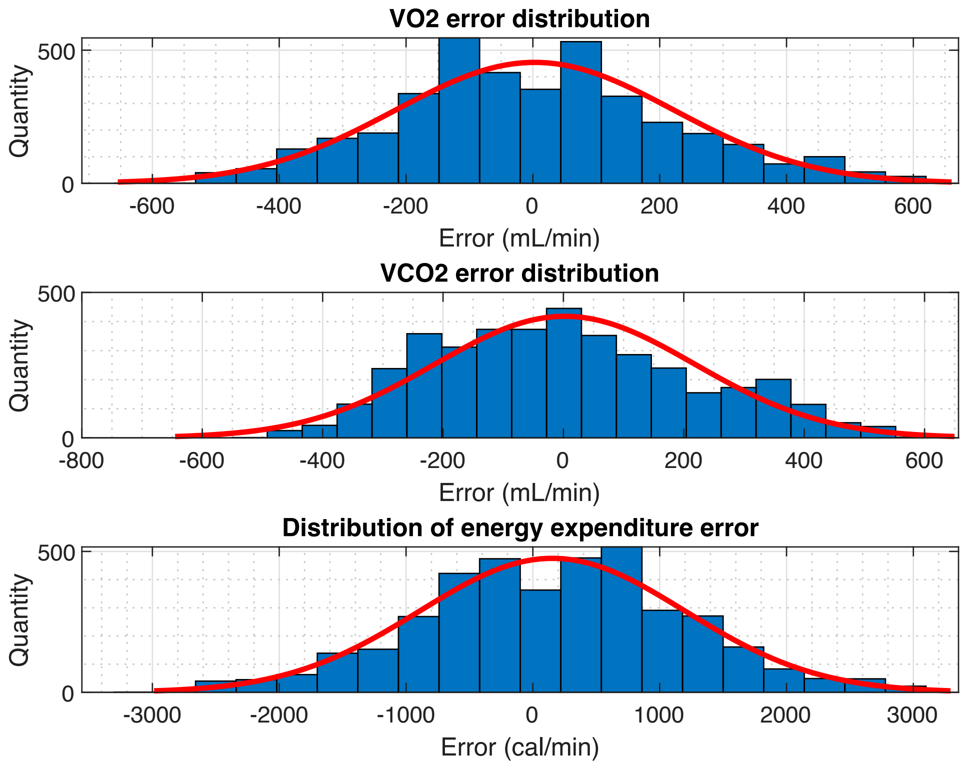

FIGURE 12. **Error distribution in parameter estimation for individual two.**

During the validation tests, a constant bias error was observed, due to environmental factors like temperature and humidity, which affected the calibration of the reference measurement device. Despite this, the system's dynamic behavior remained consistent, with both experimental and model signals showing similar response times and stabilization patterns. Overfitting was addressed through heuristic adjustments to the parameters. Additionally, a stronger linearity between VCO_2 and Ve compared to the VCO_2 and HR relationship was noted, confirmed through error and standard deviation analysis. The results, as shown in Table 5, demonstrate satisfactory outcomes, though expected errors remain due to sensor quality issues, particularly with the ventilation and gas sensors.

TABLE 5. **Summary of results.**

ID	Test	VO_2 error (%)	VCO_2 error (%)	EE error (%)
1	Param	18.5	15.5	13.8
1	Valid	20.2	26.9	16.2
2	Param	10.8	11.4	9.8
2	Valid	13.4	18.0	12.1
3	Param	11.0	12.0	12.2
3	Valid	16.1	10.9	16.2

Table 4 shows that model parameters vary among participants, suggesting the need for individualized calibration. Additionally, the estimation errors in Table 5 indicate that system accuracy largely depends on the quality of the sensors used for ventilation and gas exchange measurement

A broader comparison with existing bioenergetic models highlights the proposed system's performance in terms of estimation error and robustness. Validation tests indicate that the system achieves an average estimation error of 14.83% across different exercise intensities and individuals. In comparison, the Garmin Forerunner 55 exhibits a higher error of 25.8% for Subject 1, aligning with the 25.16% error reported by L. Roose *et al.*[27] for similar devices. Additionally, the model proposed by Chiza *et al.*[28] reported error rates of 26%, 19%, 4.7%, and 1.7% across different subjects, illustrating significant variability in estimation precision depending on individual metabolic responses.

In contrast, the proposed system maintains a relatively stable error across subjects and exercise intensities, reinforcing its robustness as a viable alternative for non-invasive metabolic monitoring. Although absolute accuracy remains a challenge, consistent performance under varying physiological and environmental conditions supports the system's applicability in real-world scenarios. Future work will address the integration of additional physiological parameters and refinement of the calibration process to further improve estimation accuracy and generalizability across diverse populations.

The results indicate that the system can estimate energy expenditure with acceptable accuracy under laboratory conditions. However, outdoor testing under varying temperature and humidity conditions could impact system calibration, suggesting the need for additional adjustments to ensure robustness.

CONCLUSIONS

This study presents a novel portable device for the real-time estimation of energy expenditure and gas exchange dynamics, addressing the limitations of traditional systems using non-invasive variables and dynamic modeling. By eliminating the need for masks or intrusive equipment, the system offers a user-friendly and versatile alternative suitable for diverse environments and physical activities.

The system estimates energy expenditure and gas exchange based on oxygen and carbon dioxide flows derived from respiratory ventilation and heart rate. Dynamic models are validated, achieving an average estimation error of 14.83%, which supports the system's reliability across different users. This level of accuracy highlights the importance of proper calibration of the calorimeter during the parameterization process to ensure optimal performance.

Intuitive interfaces for Android (AppInventor 2) and desktop computers (Matlab AppDesigner) are developed to facilitate data visualization, real-time monitoring, and efficient data recording. These features enhance the system's applicability for health monitoring, performance analysis in sports, and personalized tracking.

One of the main advantages over commercial devices such as Polar and Garmin lies in the system's ability to estimate metabolic parameters through a more comprehensive physiological approach. While commercial wearables typically rely on heart rate-based estimations, this system integrates ventilation and respiratory gas data, resulting in a more accurate assessment of energy expenditure. However, unlike laboratory-grade solutions such as COSMED®, which provide high-precision data through direct gas analysis, the proposed system requires periodic calibration to maintain accuracy. Additionally, COSMED® systems involve high costs and laboratory conditions, limiting their practical use in real-world settings. The present system offers a cost-effective, portable, and contact-free alternative, increasing accessibility in field applications for sports and health monitoring.

Moreover, unlike other commercial solutions that depend on internet connectivity for data transmission and cloud-based processing, this device operates independently using Bluetooth Low Energy (BLE). This feature ensures reliable real-time data collection and analysis even in environments with limited or no network access, thereby enhancing its utility in a wide range of contexts.

Ethical statement

This project has been approved by the Research Ethics Committee of the Faculty of Engineering at the University of Valle (Approval Act No. 007-2023). According to Resolution No. 8430 of 1993 from the Ministry of Health (Colombia), the study is classified as minimal risk. The exercise tests focus on measuring physiological and mechanical variables under moderate exertion, with the expected risks being muscle pain in the legs, discomfort in the perineum, and arms due to the use of the ergometer bicycle; discomfort from the mask used in the CALIBRE BIO Ergo Spirometer, which does not interfere with breathing volumes; potential ischemias or abnormal electrocardiographic patterns, with referral to a specialist if necessary; and possible hypotension after exertion, for which emergency procedures are available. The benefit of the study includes providing valuable information on metabolism and cardiovascular behavior at rest and during exercise. The protocol for COVID-19 is followed according to the guidelines established in Colombia[26].

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