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Title: **Remote monitoring of vital signs: pulse, temperature, and oxygen saturation using cloud computing**

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Remote monitoring of vital signs: pulse, temperature, and oxygen saturation using cloud computing

Monitoreo remoto de signos vitales: pulso, temperatura y saturación de oxígeno empleando cloud computing

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Telemedicine; VDI methodology; statistical analysis; sample surveys; internet of things.

Telemedicina; metodología VDI; análisis estadístico; encuestas de muestra; internet de las cosas.

ABSTRACT: Telemedicine has gained significant relevance by allowing patients to be attended to at any time and place, reducing the cost and time of medical care. Therefore, this research aimed at the development of a remote monitoring system for vital signs using cloud computing. Through surveys and expert input, specific system requirements were identified. The chosen sensors, MAX30102 and MLX90614, accurately captured pulse, oxygen saturation, and body temperature. The Arduino Mega-Embedded board facilitated data acquisition, while the Raspberry Pi Zero W enabled remote data transmission. The ThingSpeak platform was used for communication, and the system architecture was established through hardware and software tests. The system's functionality was verified through expert judgment and statistical tests, showing no significant differences compared to commercial equipment. The remote sampling time for vital sign data was approximately 117 seconds. Overall, this study successfully implemented a robust and efficient remote monitoring system for patients undergoing home treatment.

RESUMEN: La telemedicina ha ganado gran relevancia al permitir que los pacientes sean atendidos en cualquier momento y lugar, lo que a su vez reduce el costo y el tiempo de atención médica. De este modo, la presente investigación logró el desarrollo de un sistema de monitoreo remoto de signos vitales utilizando la computación en la nube. A través de encuestas y aportes de expertos, se identificaron requisitos específicos del sistema. Los sensores elegidos, MAX30102 y MLX90614, capturaron de manera precisa el pulso, la saturación de oxígeno y la temperatura corporal. La placa Arduino Mega-Embedded facilitó la adquisición de datos, mientras que la Raspberry Pi Zero W permitió la transmisión remota de los datos. Se utilizó la plataforma ThingSpeak para la comunicación, y la arquitectura del sistema se estableció mediante pruebas de hardware y software. La funcionalidad del sistema se verificó a través del juicio de expertos y pruebas estadísticas, mostrando que no existían diferencias significativas en comparación con un equipo comercial. El tiempo de muestreo remoto de los datos de signos vitales fue de aproximadamente 117 segundos. En general, este estudio implementó con éxito un sistema de monitoreo remoto sólido y eficiente para pacientes que reciben tratamiento en el hogar.

1. Introduction

Vital signs monitoring is an important tool in the health field. These measurements provide basic information about our body's functioning, which is very useful to determine a person's medical condition [1]. They are also indicators that help identify changes or abnormalities in our bodies that may require treatment or immediate attention from a physician [2][3]. Thus, the constant monitoring of vital signs can help prevent, detect, and diagnose serious diseases that could be terminal if they're not treated in time [4][5].

There are five main vital signs that healthcare professionals monitor: body temperature, heart rate or pulse, respiratory rate, blood pressure, and oxygen saturation. These five measures are essential for assessing a person's physical condition [2][3]. Hence, there are many systems that allow the monitoring of these signs through sensors for their subsequent collection, processing, and analysis [6].

Correspondingly, remote healthcare emerges as a solution to the needs and deficiencies in the medical field [7], which in turn leads to the development of wearable medical devices for patient health monitoring [8]. For this reason, a standard application in the Internet of Medical Things (IoMT) is telemedicine, which uses information and communication technologies (ICT) together with medical technologies to provide remote medical care [9].

Telemedicine practice is increasingly being used in the medical field due to the great benefits it brings to the patient, reducing distance, time, and cost of treatment, as well as detection and prevention of diseases, and constant monitoring, among other benefits [8][10]. It is mainly aimed at patients with chronic diseases, mobility problems, disabilities, post-operative patients, newborns, and the elderly, since all of them have the necessary conditions to constantly monitor their state of health [10]. Henceforth, the utilization of telemedicine is anticipated to further ascend in the forthcoming period. This escalation is chiefly attributed to the advent of the 2019 coronavirus pandemic, which notably underscored its significance and efficacy; in addition, this requires the development of devices or equipment that allow the collection and exchange of information obtained from patients [11].

Telemedicine has become more implemented in some Latin American countries. For example, the Cardiovascular Foundation of Colombia, where a remote vital signs monitoring system was implemented to evaluate patients with heart diseases constantly [12]. Similarly, in 2016 in Peru, a telemonitoring system was implemented, processing the biometric and vital signs information obtained from the person in a database platform for clinical follow-up [13].

A more recent event occurred in 2019, due to the pandemic caused by the COVID-19 virus. In these circumstances, a report was issued in Peru on the feasibility of applying a telemedicine system, including the use of a finger pulse oximeter to monitor patients receiving home treatment for COVID-19. It was concluded that oxygen saturation was a determining factor in the mortality rate due to this disease [14]. Chile has also applied this practice by issuing recommendations to carry out teleconsultations between patients and doctors [15].

Another work using vital sign sensors can be found in [16], where a system was created that allows controlling the risks presented in hospital environments, by using an IoT platform and a microcontroller. Then, in [17], a wireless sensor network was developed for the acquisition of electrocardiographic signals, temperature and pulse with the implementation of nodes, consisting of a microcontroller and a biomedical sensor for each vital sign. In addition, in [18], experimental research was carried out to identify the different areas of the body where it is possible to measure the pulse and oxygen saturation.

Nonetheless, these remote monitoring systems require a large capacity for the continuous management of the information received from the sensors, creating requirements for security, storage, computing power, analysis and data information wherever the user is connected. All these factors can be addressed by using Cloud Computing (CC), since this tool allows us to perform all these tasks efficiently, in addition to being low-cost [19]. The cloud-based platform to be developed must be robust and highly accessible because a network or system disconnection with the server could have fatal consequences for the patient [20][21].

In this way, the evolution of IoT solutions in healthcare has resulted in more advanced and intelligent systems that are capable of performing analysis, detecting activities, and making decisions, rather than just collecting, transmitting, and visualizing data from sensors. However, this is closely associated with implementing artificial intelligence and machine learning techniques, which often require significant computing power that is often only available through cloud services [19].

Although IoMT technology is a current trend in telemedicine solutions, there remain certain challenges to overcome for telemonitoring systems, such as sensor accuracy and limitations in battery life [22], protection of shared personal information, absence of eye-to-eye intercommunication or even lack of adequate legislation [23].

Therefore, this research aims to further the development of telemonitoring systems, implementing a remote monitoring system of vital signs, including pulse, temperature, and oxygen saturation, using cloud computing technology. The selection of these variables stems from the conclusions drawn in [2] and [3], as well as from an appropriate survey detailed later in the methodology. The system will provide patients with home treatment the ability to have their vital signs remotely monitored, allowing for early detection and timely intervention in case of any abnormalities. By applying cloud computing, the system will offer scalability, flexibility, and accessibility, enabling healthcare providers to deliver efficient and effective care to their patients.

2. Statistical Analysis

To ensure accurate validation, meticulous statistical analysis is essential. For example, [24] and [25] advocate for the Kolmogorov-Smirnov test to characterize and analyze vital signs, respectively. Conversely, [26] and [27] employ the Wilcoxon Rank Sum Test for their variable analysis of vital signs. Subsequent subsections elaborate on these methods, categorizing them based on their application in the current research.

2.1 Normal Distributions

Normal distribution (also named Gaussian distribution) holds a rightful position as the primary distribution in the field of statistics. It is considered normal because it is frequently a highly accurate model for the frequency distribution observed in numerous naturally happening events [28].
Normal distributions offer a practical approximation for the distribution of diverse variables. It has a bell-shaped and symmetric form and is occasionally referred to as a normal curve. The areas under the curve correspond to probabilities, enabling researchers to make probabilistic inferences [28][29][30].
Numerous variables of interest exhibit frequency distributions with a mound-shaped pattern, which can be effectively approximated by a normal curve. Thus, the normal random variable and its associated distribution play a crucial role in statistical inference [29][30]. Numerous variations of normal distributions exist, and they are differentiated by their mean (μ) and standard deviation (σ) [29].

Standard normal distribution

The standard normal distribution is a specific normal distribution with a mean (μ) of 0 and a standard deviation (σ) of 1. It is a common practice to use the letter "z" to denote a variable whose distribution is described by the standard normal curve. The term "z curve" is frequently employed instead of "standard normal curve" [29].

2.2 Normality Test

Parametric statistical testing relies on several underlying assumptions, one of which is multivariate normality. This assumption states that the variables in our data are distributed according to a normal distribution [30]. To assess normality, we can employ various methods, which can be broadly categorized as graphical (histograms and Q-Q probability plots) or analytical (involving tests such as the Shapiro-Wilk test and the Kolmogorov-Smirnov test) [31].
Normality tests are conducted on individual variables, with the Kolmogorov-Smirnov test used for sample sizes larger than 50, and the Shapiro-Wilk test for smaller sample sizes [31].

2.2.1 Kolmogorov-Smirnov Test

The Kolmogorov-Smirnov (KS) tests were developed to compare either an observed frequency distribution, *f(x)*, with a theoretical distribution, *g(x)*, or two observed distributions. In these two scenarios, the test involves constructing the cumulative frequency distributions, *F(x)* and *G(x)*, and determining the maximum difference between them [28].
The assumption underlying this test is that the distribution is normal. Therefore, if the test yields a significant result, it indicates that the data deviates from the normal model and should be considered non-normal [31].

2.3 Inferences about Population Central Values

The goal of statistics is to draw conclusions about a population using information obtained from a sample. Populations are described by numerical summary measures known as parameters [30].
There are two main methods for making inferences about parameters. The first one involves estimating or predicting the value of the population parameter of interest. The second method involves testing a hypothesis about the value of the parameter [30].

2.3.1 Estimation of μ

The initial stage of statistical inference involves point estimation, calculating a single value (statistic) using the sample data to estimate a population parameter. By employing appropriate point estimators (a formula) for specific parameters, we can generate confidence intervals (interval estimates) for these parameters [30]. In this particular context, we focus on point and interval estimation for a population mean μ.
In most cases, the sample mean (y-axis) serves as a point estimate for μ. We also employ them to construct an interval estimate for the population mean. We assess the effectiveness of an interval estimation procedure by examining the proportion of times, in repeated sampling, that interval estimates would encompass the parameter being estimated. This proportion, known as the confidence coefficient, is typically 0.95 [30].

2.3.2 A Statistical Test

The second category of the inference-making procedure is statistical testing, also known as hypothesis testing. Similar to estimation procedures, we aim to draw inferences about a population parameter, but the nature of the inference differs. In hypothesis testing, we utilize sample data from the population to determine the value of the parameter. It involves having a predetermined notion about the population parameter [28][30].
A statistical study involves two competing theories or hypotheses. The first is the research hypothesis proposed by the researcher, while the second theory is the negation of this hypothesis (null hypothesis). The objective of the study is to decide whether the data support the research hypothesis [30].

Statistical testing follows a proof-by-contradiction approach and consists of five components [30]:

1. Research hypothesis, denoted as H_a
2. Null hypothesis, denoted as H_O
3. Test statistic, denoted as T.S.
4. Rejection region, denoted as R.R.
5. Checking assumptions and drawing conclusions

The decision regarding whether the data supports the research hypothesis is based on a quantity computed from the sample data, known as the test statistic. Similar to any decision-making process, errors can occur by mistakenly rejecting or falsely accepting the null hypothesis [30].

2.3.3 Level of significance: p-value

The p-value is a numeric representation typically ranging from 0 to 1.00, which indicates the likelihood of obtaining a result (based on a specific test statistic) due to a genuine effect rather than random chance. The significance of a p-value is assessed by comparing it to a critical value, often set at 0.05 [31].
Formally, the p-value can be defined as the probability of obtaining a value that is equally or more extreme than the observed value of the test statistic, assuming that the null hypothesis is true. Consequently, if the level of significance is small, the sample data do not support the null hypothesis, leading to the rejection of *Ho*. Besides, if the level of significance is large, we fail to reject the null hypothesis [30].

2.3.4 Parametric Test: Z test

Z-tests typically involve random samples with a size of 30 or more and focus on assessing whether the sample mean, as an estimate of the population mean, significantly differs from a specific value, or if the difference appears to be insignificant. In all cases, the process involves transforming the data into z-scores, where the denominator represents the estimated standard error (since the focus is on mean values and proportions rather than individual data items). It is common practice to test for Normality before conducting such tests to ensure the validity of the results [28][30][31].

2.3.5 A Non-parametric Alternative: The Wilcoxon Rank Sum Test

When a continuous variable deviates from a normal distribution, there are alternative approaches to consider. Non-parametric tests are used when certain assumptions for regular tests are not met. These tests involve similar comparisons but rely on different assumptions, and can be applied to unpaired or paired datasets [28][31].

For analyzing differences within groups, the Wilcoxon Signed Ranks Test is recommended. This test examines both the magnitude and direction of the differences in scores. It assesses whether two independent samples come from the same continuous distributions with equal medians, or if their medians differ [28].

This test assumes independent random samples taken from two populations. It also considers that distributions are identical except for a possible shift in one distribution relative to the other [30].

3. Methodology

This research is rooted in the methodology of an engineering project, with the aim to address a specific problem: the development of a remote monitoring system for vital signs tailored for patients undergoing home treatment. The design methodology draws from the "Design methodology for mechatronic systems" outlined by the German Association of Engineers (VDI, Verein Deutscher Ingenieure), which underwent revisions in 2016 based on the outcomes of the VDI Guideline 2206:2004. The validation of the V-model within this context, along with its enhancements and comparisons, is documented [32]. A flowchart illustrating the methodology is presented in Figure 1 to provide a succinct overview.

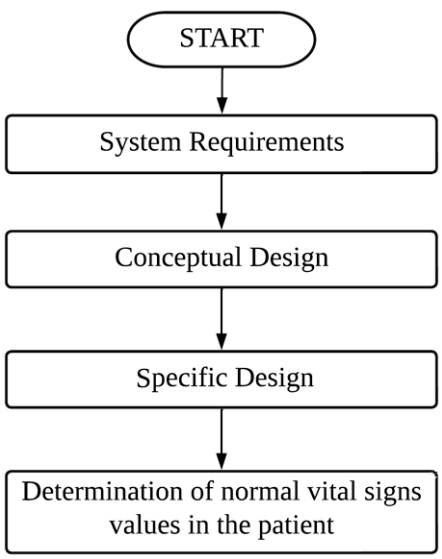

Figure 1 Methodology flowchart.

3.1 System Requirements

Based on the documentation provided by the Ministry of Health of Peru (MINSA), a survey of healthcare workers, and a literature review, certain guidelines have been formulated for the development of the system requirements.

In this section, the survey was essential in identifying specific characteristics that the system should possess. The results are presented below:

- 100% of the participants measure vital signs (pulse, blood oxygen saturation, and body temperature) as part of their professional duties.
- Regarding functional characteristics, 100% prefer to use a web page accessible from any device, and 75% prefer to use a physical screen on the device or a mobile phone application.
- Regarding physical characteristics, 75% prefer the equipment to be drop-resistant (robust) and intuitively assembled and disassembled.
- Regarding materials for the construction of supports and containers, there is a 100% preference for rubber and a 75% preference for plastic or similar materials.

The aforementioned results served as input, primarily for the equipment construction.

Another equally important aspect considered in the survey was determining the most suitable areas of the body for measuring vital signs. The results were as follows:

- 100% of the participants prefer to take the pulse at the wrist, while 75% prefer to do it at the finger (Figure 2).
- 100% of the participants believe it is ideal to measure oxygen saturation at the finger (Figure 3).
- 100% of the participants believe it is ideal to measure temperature, using contact sensors, in the axillary area (Figure 4).
- 100% of the participants believe it is ideal to measure temperature, using non-contact sensors, in the forehead area (Figure 5).

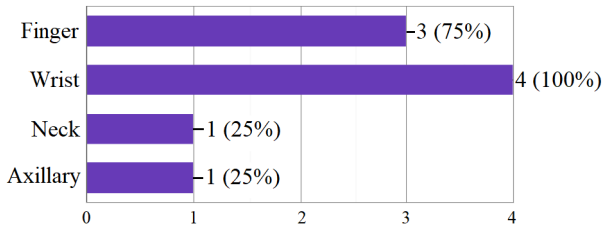

Figure 2 Bar chart of the ideal zones for pulse measurement. Source: Google Forms.

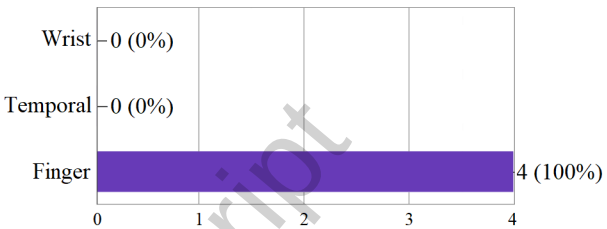

Figure 3 Bar chart of the ideal zones for measuring blood oxygen saturation. Source: Google Forms.

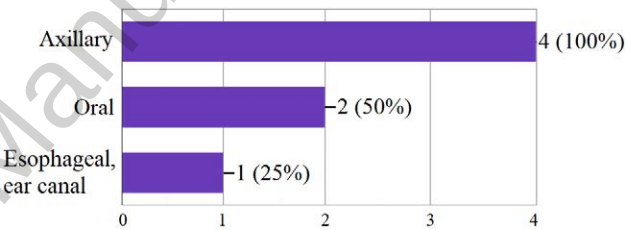

Figure 4 Bar chart of the ideal zones for measuring body temperature with contact sensors. Source: Google Forms.

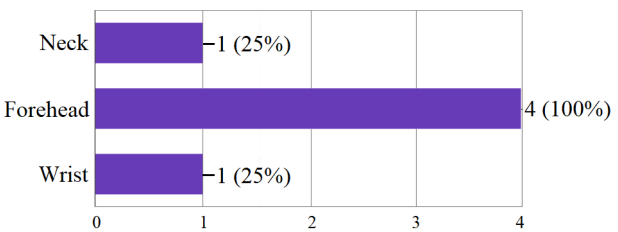

Figure 5 Bar chart of the ideal zones for measuring body temperature with non-contact sensors. Source: Google Forms.

In addition, a list of requirements or demands for the system is presented below, which should be taken into consideration together with the previous results for the design of the solution.

- The power source must be compatible with the electrical grid.
- The construction materials must be resistant to environmental chemicals and non-toxic to the patient.

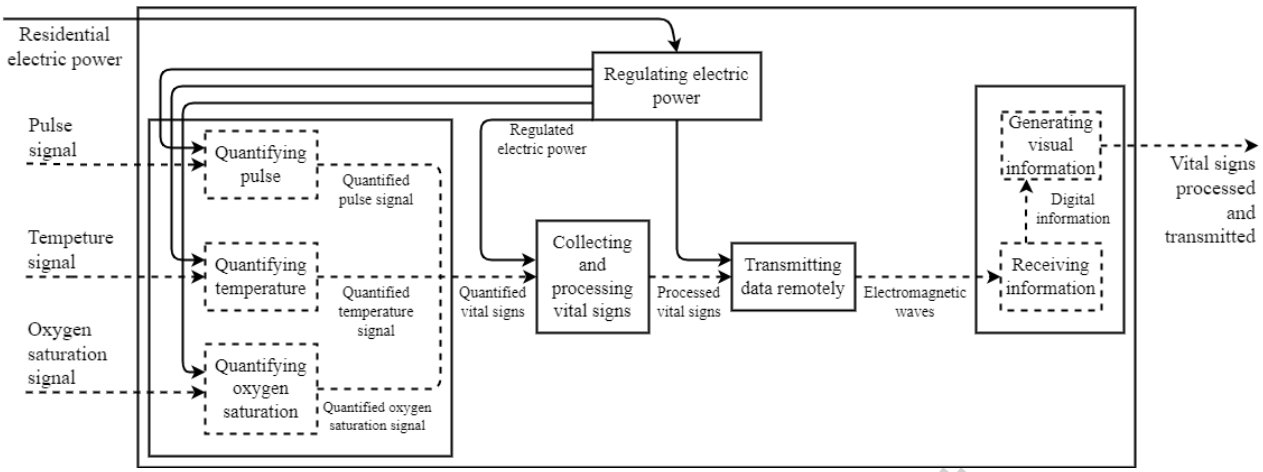

Figure 6 Functional structure of the remote monitoring system of vital signs.

- Sensor limit values: for temperature, they should be within the range of 30°C to 45°C; for blood oxygen saturation, from 0 to 100%; and for heart rate, the range is from 0 to 100.
- The communication between the sensors and the controller must be implemented using a secure protocol suitable for the constant transmission of information.
- The circuits and/or components must be properly isolated.
- Encryption tools must be employed to ensure wireless connection security against potential vulnerabilities, as required by the Technical Health Standard of the MINSA.
- Vital signs should be measured according to the MINSA guidelines and the patient's normal values.
- The container and supports must be robust against falls.
- The system should have components that are easy to replace and program.
- The price of the system should not exceed 10 thousand nuevos soles.

As we aim to develop a practical remote monitoring system for vital signs, a key challenge is designing a compact system that can be easily installed without disrupting the patient's activities. In addition to this, the system must provide accurate vital sign values based on each patient's normal readings and offer an interface for remote monitoring. Lastly, the system components should be easily replaceable to ensure its maintenance.

3.2 Conceptual Design

In order to select and implement the necessary hardware and software, the system functions were defined, and their operating principles were identified following the VDI2206 design methodology, using the results obtained in the survey and the list of requirements.

3.2.1 Functional Structure

The function structure of the system is then created, starting from the general function, that is, monitoring patients with home treatment using domestic electrical power and recording the patient's vital signs (pulse, temperature, and blood oxygen saturation) while displaying the process information remotely. Then, this general function can be separated into sub-functions in order to achieve it. The structure is illustrated in Figure 6.

3.2.2 Morphological Matrix

Once the function structure was defined, different alternatives of devices and platforms that fulfilled each sub-function, as shown in Figure 6, were identified. All of these elements are presented in Table 1.

A comparison was made among the devices using their technical specifications and performing some tests, as well as between the interfaces and communication protocols. A morphological matrix was then created using Table 1, compatibility matrices were developed, and three combinations were extracted as solution concepts.

To evaluate these solutions, certain criteria based on the previously mentioned list of requirements were used together with a score-based evaluation to determine the alternative with the highest technical value and

suitable economic worth. The subsequent parts enumerate all the criteria assessed for each function.

Table 1 Devices and platforms alternatives for the operating principles of the system functions.

Functions	Principles of Operation		
Regulating electrical power	AC - DC voltage transformer		
	Source for Protoboard 3.3V/5V (micro-USB)	DC-DC Voltage converter Step-Down 5A XL4005	
Quantifying pulse	SEN-PULSE-FE Sensor	Pulse Oximeter MAX30102	
Quantifying temperature	MLX90614 Sensor	DS18B20 Sensor	TMP36 Sensor
Quantifying oxygen saturation	Pulse Oximeter MAX30100	Pulse Oximeter MAX30102	
Collecting and processing vital signs	Arduino Nano	Arduino Mega 2560 - Embedded	Node MCU
Transmitting data remotely	Raspberry Pi Zero W	Shield Module SIM900	Node MCU
Receiving information	Thingspeak	Beebotte	
Generating visual information	PC	Mobile phone	

1. **Regulating electrical power:** Output voltage, input voltage, output current, channels, price.
2. **Quantifying pulse:** Current consumption, communication interface, supply, documentation, price.
3. **Quantifying temperature:** Signal type, communication interface, physical contact, current consumption, operation voltage, accuracy, temperature range, resolution, price.
4. **Quantifying oxygen:** Interface communication, operation voltage, current consumption, resolution, operation temperature, and price.
5. **Collecting and processing vital signs:** Digital input/outputs, analog input/outputs, CPU speed, processor, SRAM, flash, supply voltage, current consumption, I/O maximum current, I/O voltage logic level, serial communication, I2C communication, programming language, and price.
6. **Transmitting data remotely:** GPIO's pines, clock speed, processor, SRAM, flash, operation voltage, programming language, UART interface, wireless connectivity, audio/video, price.
7. **Receiving information:** Hardware, scope, communication protocols, advantages and disadvantages.
8. **Generating visual information:** Compatibility analysis.

3.2.3 Solution Concept

The winning solution concept consisted of using an AC-DC voltage transformer and two DC-DC voltage converter XL4005 to regulate the electrical energy. For vital signs quantification, an MLX90614 sensor is used for temperature, and a MAX30102 pulse oximeter is used for both oxygen saturation and pulse. An Arduino Mega 2560 - Embedded is chosen for data collection and processing, and a Raspberry Pi Zero W for data transmission. The Thingspeak platform is used to receive information in the cloud, and the information is visually generated using a PC.

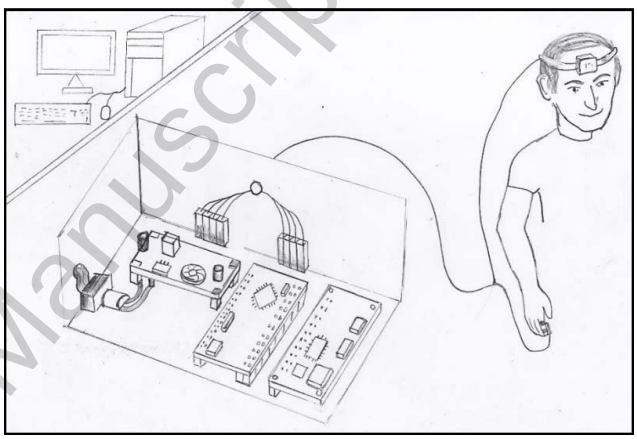

Figure 7 Winner solution concept sketch.

Finally, the forehead is chosen for temperature measurement, and the finger is chosen for both oxygen saturation and pulse measurement.

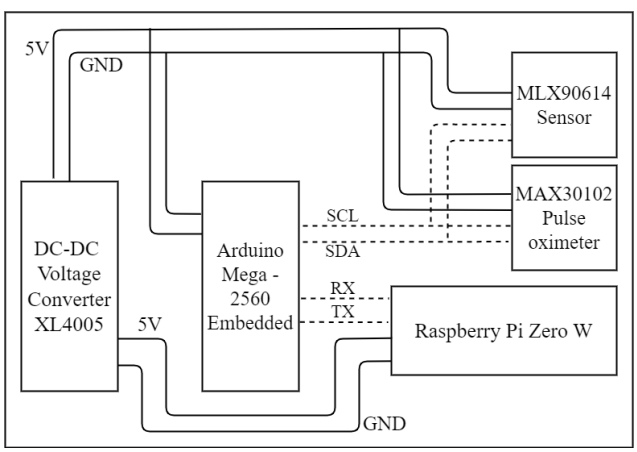

Figure 8 Block diagram of the winning solution concept.

This solution and all its components were outlined and presented in Figure 7. Then, the block

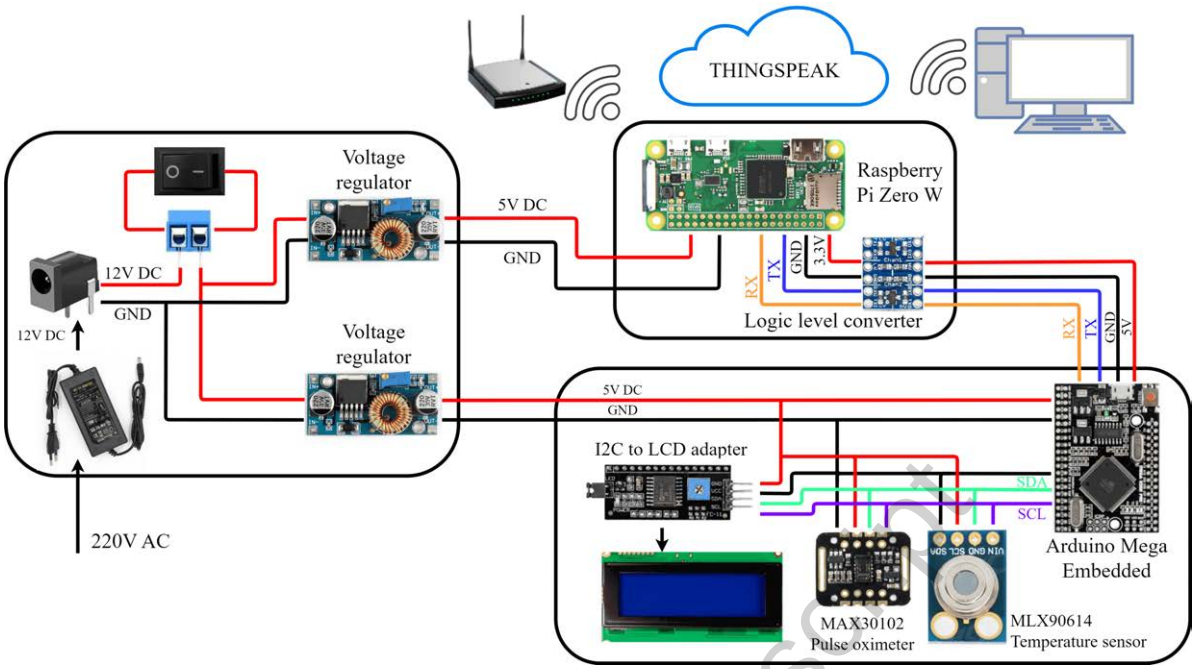

Figure 9 Detailed system architecture diagram.

diagram showing the connection between each of the aforementioned elements in the winning solution is depicted in Figure 8.

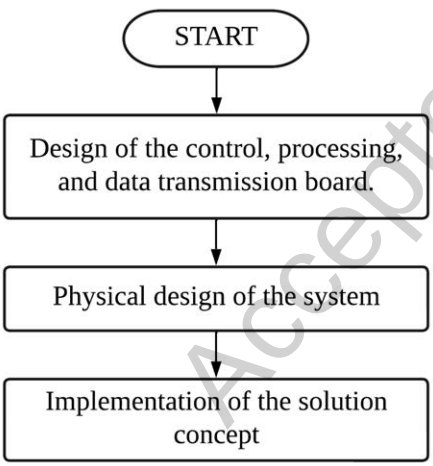

Figure 10 Methodology flowchart for the specific design.

On the other hand, to model the system, hardware, and software configuration, different tests were first run for each sensor and control card selected, according to their technical characteristics and configuration tests of the Thingspeak platform. Then, a study was conducted to determine the power consumption of the system. Finally, a detailed schematic diagram of the system was drawn to show how the components would be connected.

3.3 Specific Design

This section addressed the design of the schematic diagram and PCB of the circuit board and the physical design of the necessary supports and enclosure for the system. The flowchart in Figure 10 illustrates the procedure followed in this section. Then, Figure 11 presents how the control board was designed and Figure 9 shows the detailed schematic diagram mentioned above, illustrating how all the components of the winning solution would be interconnected.

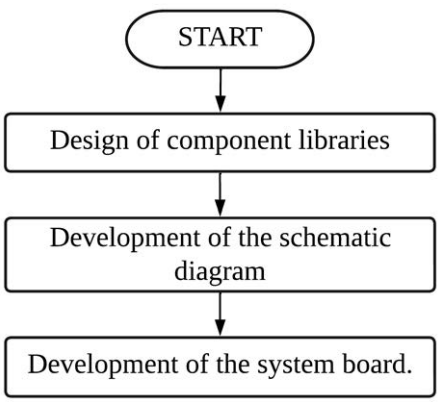

Figure 11 Methodology flowchart for the design of the circuit board.

3.3.1 Design of the Control, Processing, and Data Transmission Board

Using the student license of Autodesk's Eagle software, the board was designed. Based on the system modeling, the following diagram in Figure 11 was developed, which shows this process and is detailed below.

1. **Design of component libraries.**

   Due to the lack of libraries for certain components in the Eagle software program, each one was specifically designed using the environment provided by the software. Each library consists of three parts: the device, its package, and the symbol.

   First, the physical dimensions of each component had to be determined, followed by the package (based on the Association Connecting Electronics Industries standard), and finally the symbols of each one were developed to enable the corresponding connections. The results of this process are shown in Figure 12.

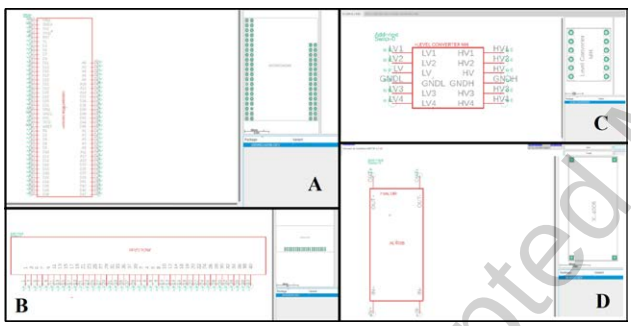

Figure 12 Design of the control, processing, and data transmission board. (A) Package and symbol of the Arduino Mega-Embedded, (B) Package and symbol of the Raspberry Pi Zero W, (C) Package and symbol of the Level Converter, and (D) Package and symbol of the Voltage Regulator.

2. **Development of the schematic diagram.**

   The development of the system circuit was based on the architecture diagram detailed in Figure 9 and hardware and software configuration tests.

3. **Development of the system board.**

   The AUTO WIRE tool in Eagle software was used, and some modifications were implemented manually according to the PCB theory formulated in 2001 by the University of Granada for this type of design. Some of the modifications included the use of angles not less than 45°, a hole diameter of 0.6mm with a pad diameter of 1.2mm, and a track width between pads of 0.4mm (this last one was determined through the study of power consumption for the circuit with all components).

3.3.2 Physical Design of the System

For the physical design of the system, the diagram shown in Figure 13 was determined, and each part of it is subsequently detailed.

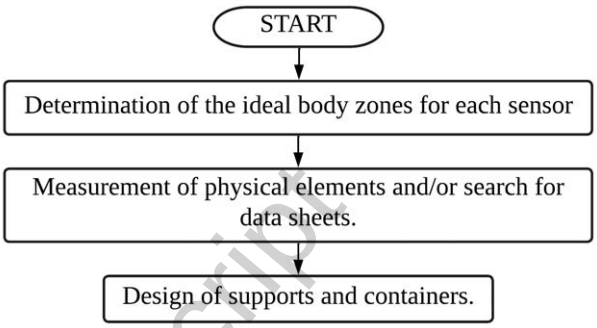

Figure 13 Methodology flowchart for the physic design.

1. **Determination of the ideal body zones for each sensor.**

   The ideal body parts for measuring the vital signs included in this research were determined based on a background review and on the results of the survey conducted among medical personnel mentioned in section 3.1, according to the selected sensors. Thus, the finger was chosen for measuring pulse and oxygen saturation, and the forehead was chosen for measuring temperature.

2. **Measurement of physical elements and/or search for datasheets.**

   Measurements were taken of the sensors and of the PCB designed in Eagle CAD software, as well as a review of the datasheets of the components to determine the precise measurements and correct openings for the relevant connections of each device.

3. **Design of supports and containers.**

   Structural Supports were designed for the sensors in contact with the patient and the container for the main system board. Solidworks software was used under a student license for the 3D design of the parts. These designs are presented in Figure 14.

   A holder was developed for the MAX30102 sensor, taking the design of the CONTEC CMS50D pulse oximeter as a reference. It consists of three pieces and returns to its initial position after external force is applied. It has a cavity in the lower piece

designed to contain the sensor and an ergonomic cover for finger positioning.

For the MLX90614 temperature sensor, a holder consisting of two parts was created. It was considered that the sensor should be close to the person's body at a distance of (0.5 cm).

A container was designed for the board, which consists of two parts, a lower and an upper piece that have openings for connection to the AC-DC power supply, the ON/OFF button, the LCD, and the sensor wiring.

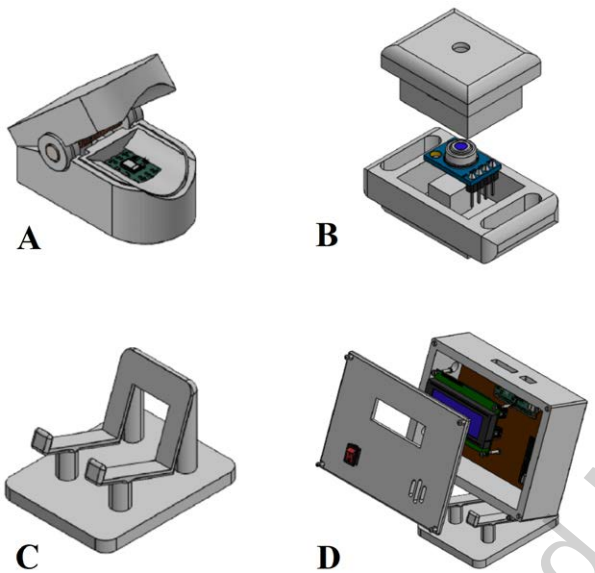

Figure 14 Isometric views of the designed parts. (A) Isometric view of the support for the MAX30102 sensor, (B) Isometric view of the support for the MLX90614 sensor, (C) Isometric view of the support for the container and (D) Isometric view of the system container.

3.3.3 Implementation of the Solution Concept

In order to implement the previously shown designs, the procedure illustrated in Figure 15 was followed.

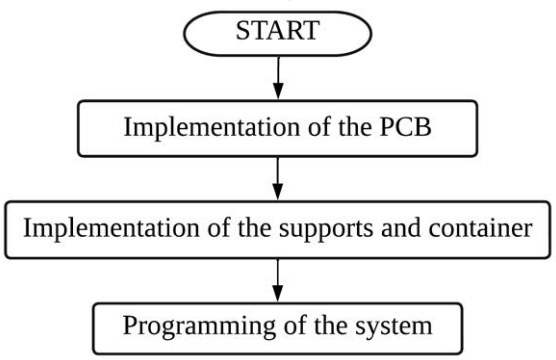

Figure 15 Methodology flowchart for the implementation of the system.

1. **Implementation of the PCB.**

   The serigraphy method was used to implement the PCB. For this, a bakelite board with a copper layer thickness of 35 microns (with the dimensions according to the board designed in Eagle), ferric acid, Thinner, plate, clear lacquer, 96% ethyl alcohol, steel mesh, soldering iron, solder roll, solder paste, and coated paper were used. As an additional step, a layer of lacquer was applied to the circuit ridges as an additional step to protect them. Figure 16 shows on the left the tracks already printed on the PCB and on the right its components.

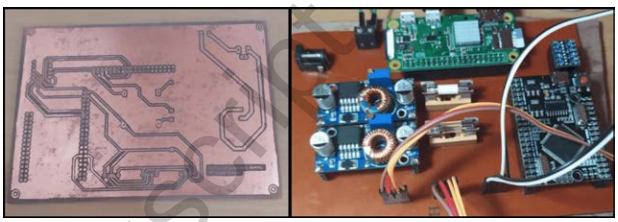

Figure 16 Implementation of the PCB

2. **Implementation of the supports and container.**

   A Tronxy XY-2 3D printer was used for the printing. PLA was used as the printing material, which was selected based on expert judgment and for having greater moldability than other materials. In addition, Velcro straps were used for the pieces that attach to the body, as well as micro-porous material and rubber for the areas in contact with the skin. Figure 17 shows the printed and assembled parts corresponding to the supports where the vital signs will be measured.

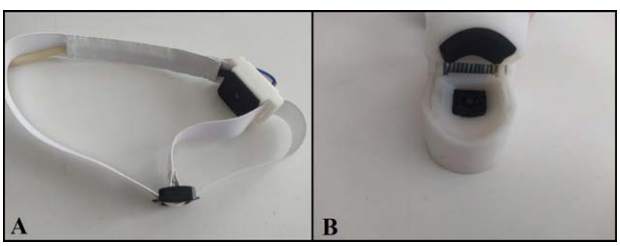

Figure 17 Finger and forehead supports printed in 3D.

The cable used for the sensors had a mesh interference protection composed of 6 threads for the sensors and 9 threads for the main bus that goes to the main board; in addition, 4-pin MOLEX connectors were used for the interconnection of 9 to 6 threads. These connections are best illustrated in Figures 18 and 19.

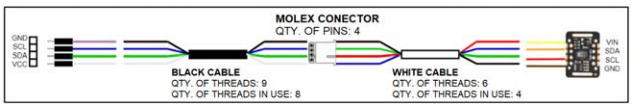

Figure 18 Connection threads for the pulse oximeter.

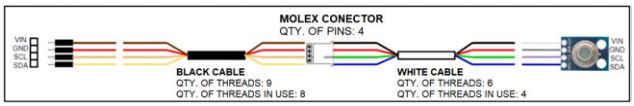

Figure 19 Connection threads for the temperature sensor.

Finally, the fully implemented system, with the connections and wiring between the sensors, the control components and the printed parts are presented in Figure 20.

Figure 20 System completely implemented.

3. **Programming of the system.**

To program the system, the necessary software libraries were first determined for certain components, such as the sensors. Then, the necessary code functions were created for data collection (where an algorithm was experimentally implemented to remove unwanted values), followed by establishing communication between the data acquisition and transmission systems. Finally, communication was established between the backend and frontend.

The data collection subsystem was programmed first, where the SparkFun Max3010x library was used for pulse and oxygen saturation vital signs, and the Adafruit-MLX90614 library was used for body temperature. Additionally, the Liquid Crystal I2C master library was implemented to control the LCD-2004 screen, which was determined to be necessary for the modeling.

Then, for the programming of the data transmission subsystem, the Pyserial, time, and requests libraries were implemented. The serial library helps with communication between the Arduino Mega board and the Raspberry Pi Zero W. Additionally, the requests library is used to implement remote communication as it allows the use of the HTTP communication protocol, and the time library allows for the creation of a delay to control the wait time for opening the serial port.

For the information reception and visual information generation subsystems, the ThingSpeak platform is used to create a new channel to store all the data the system collects. The Private View tab of this platform is used for information generation, where the visualization of the three Fields corresponding to each vital sign can be added, and widgets were created for each of these. This cloud-based platform is presented in Figure 21.

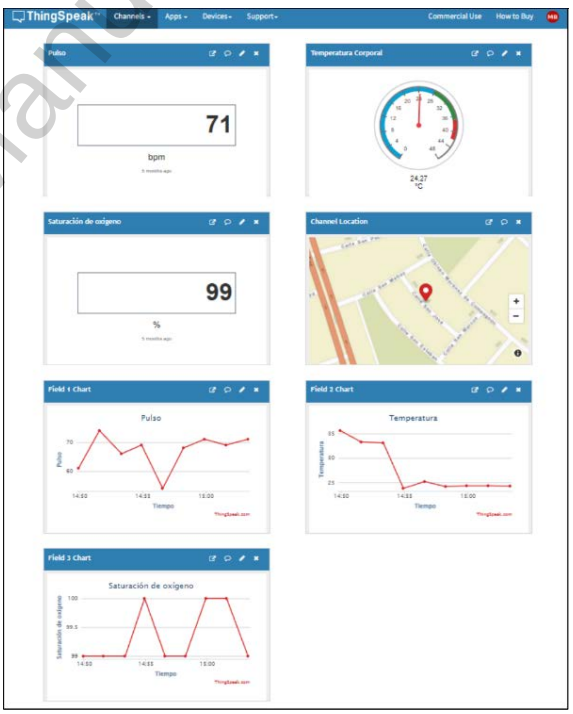

Figure 21 ThingSpeak plataform implemented.

3.4 Determination of Normal Vital Signs Values in the Patients

As already known, these values are different for each person and even for certain times of the day, so it is necessary to determine which are normal values for each patient in order to obtain a range in which the signs obtained by our system can be validated.

Based on expert judgment, it was determined that measurements of heart rate, blood oxygen saturation, and body temperature should be taken every 7 hours for 4 days.
These measurements were performed for comparison purposes on 10 individuals using the system developed in the present research, as well as commercial devices, specifically the CONTEC CMS50D pulse oximeter (pulse and oxygen saturation) and the KANGJI KY-111 infrared thermometer (temperature). In this way, the range of normal vital sign values for these individuals was obtained. Figure 22 shows the ranges of normal vital signs of 3 of them.

N°	Individual	Vital Sign	Normal range Values
1	Mauricio Bejarano	Pulse	[57 – 72] BPM
		Temperature	[35 – 37.1] °C
		Oxygen saturation	[96 – 100] %
2	Hugo Bejarano	Pulse	[66 – 76] BPM
		Temperature	[35.0 – 37.1] °C
		Oxygen saturation	[96 – 99] %
3	Rocío Reyes	Pulse	[66 – 69] BPM
		Temperature	[35.1 – 36.9] °C
		Oxygen saturation	[97 – 100] %

Figure 22 Normal range values for vital signs in 3 individuals.

4. System Validation

Verification of Proper Data Acquisition Compared to Commercial Devices.
As mentioned in the previous section, a sampling of the proposed vital signs was conducted on 10 individuals, which is of great utility in validating the system. This sampling is then evaluated statistically by grouping the data based on each measured sign and using two paired samples as the data type is the same under two different conditions, specifically two different systems: the commercial system and our own system.
First, an analysis of the variable's distribution is performed by conducting a normality test for the sampled data using the developed and commercial systems for each proposed vital sign in the research. For this purpose, the null hypothesis is defined as the average measurement of each vital sign using the commercial equipment being equal to that of the proprietary equipment (Equation 1), while the alternative hypothesis states that the average measurement with the commercial equipment is not equal to that of the proprietary equipment (Equation 2).
Then, the corresponding equations for these hypotheses are:

$$H_O \text{ (Normality)} : \mu_{commercial} = \mu_{own} \quad (1)$$

$$H_A \text{ (Non-Normality)} : \mu_{commercial} \neq \mu_{own} \quad (2)$$

Where:
H_O : The vital sign measure is the same in both devices.
H_A : The vital sign measure is different in both devices.

The obtained p-value is then compared in the respective tests, under the conditions that if $p < 0.05$, the null hypothesis is rejected, and if $p \geq 0.05$, the null hypothesis is accepted. For this purpose, the IBM SPSS Statistics program is used, considering the Kolmogorov-Smirnov test due to the 120 sampled data points from 10 individuals, according to the parameters obtained from the mentioned survey in section 3. Based on this, the results of the normality test for the sampled data were obtained, generating Tables 2, 3, and 4.

Table 2 Normality test of sampled pulse data.

	Kolmogorov-Smirnova		
	Statistical	gl	Sig.
PULSE_COMMERCIAL-SYSTEM	0.080	120	0.059
PULSE_OWN-SYSTEM	0.079	120	0.062

Table 3 Normality test of sampled temperature data.

	Kolmogorov-Smirnova		
	Statistical	gl	Sig.
TEMP_COMMERCIAL-SYSTEM	0.077	120	0.081
TEMP_OWN-SYSTEM	0.073	120	0.182

Table 4 Normality test of sampled oxygen saturation data.

	Kolmogorov-Smirnova		
	Statistical	gl	Sig.
PULSOXI_COMMERCIAL-SYSTEM	0.195	120	0.000
PULSOXI_OWN-SYSTEM	0.210	120	0.000

Analyzing Tables 2 and 3, it can be observed that the variables follow a normal distribution, accepting the null hypothesis with a 95% level of confidence, as the p-value (shown as "Sig." in the tables) is greater than 0.05. Therefore, the paired samples z-test is employed since we have samples with more than 30 data points. On the other hand, analyzing Table 4, it is not observed that the variables follow a normal distribution, thus rejecting the null hypothesis with a 95% level of

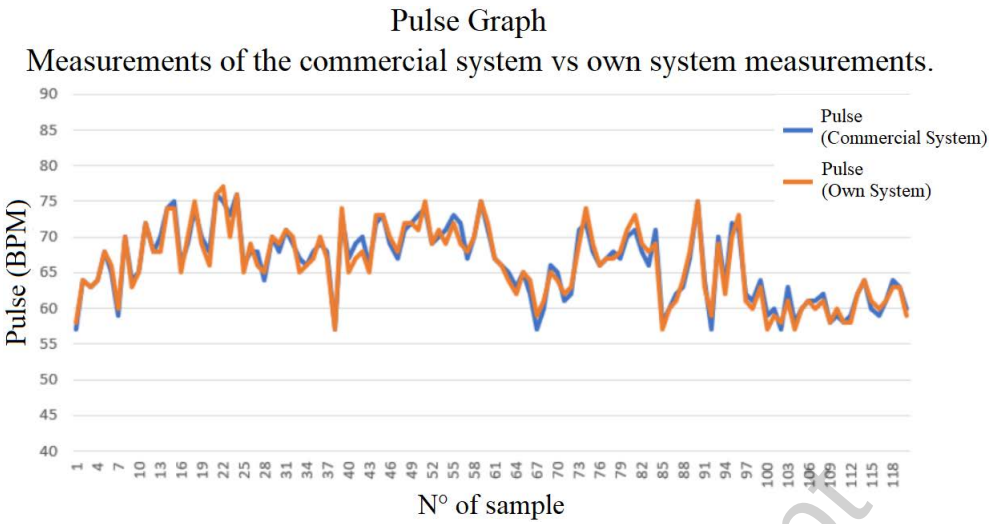

Figure 23 Comparative graph for Pulse

confidence, as the p-value (Sig.) is less than 0.05. Therefore, the Wilcoxon test for paired samples was employed.

Then, a comparative graph is presented, illustrating the sampled values obtained with both devices (commercial and proposed) regarding the pulse, as shown in Figure 23.

From the application of the two-sample z-test conducted using Excel software on the sampled pulse data with the two systems, Table 5 was obtained.

Table 5 Parameters obtained from the two-sample z-test for means for the vital sign "pulse"

	Variable 1	Variable 2
Mean	66.325	66.2
Variance	25.616	26.161
Observations	120	120
Hypothetical difference of means	0	
z	0.19029711	
P(Z ≤ z) one tail	0.42453816	
Critical value of z (one tail)	1.64485363	
Critical value of z (two tails)	0.84907632	
Critical value of z (two tails)	1.95996398	

Since a p-value of 0.425, greater than 0.05, was obtained, the null hypothesis was not rejected. Furthermore, the value of z remained within the critical range for a two-tailed test (-1.959 ≤ z ≤ 1.959). Thus, it can be confidently stated with 95% certainty that there is no significant difference between the average pulse data obtained with the commercial and the own system.

Now, the comparative graph of the sampled temperature values obtained with both devices is presented in Figure 24.

Thus, Table 6 is obtained, which is generated by Excel when performing the two-sample z-test for temperature data with both systems.

The null hypothesis was not rejected as the obtained p-value of 0.37 is greater than 0.05, and furthermore, the value of z is once again within the range of the critical value for a two-tailed test. Therefore, it can be confidently stated with 95% certainty that there is no significant difference between the average temperature data sampled with the commercial and own equipment.

Table 6 Parameters obtained from the two-sample z-test for means for the vital sign "temperature"

	Variable 1	Variable 2
Mean	35.93	35.9033333
Variance	0.392	0.387
Observations	120	120
Hypothetical difference of means	0	
z	0.33097152	
P(Z ≤ z) one tail	0.370333	
Critical value of z (one tail)	1.64485363	
Critical value of z (two tails)	0.740666	
Critical value of z (two tails)	1.95996398	

Similarly, we have Figure 25, which shows the comparative graph of the sampled oxygen saturation values obtained with both devices.

In this case, the non-parametric Wilcoxon test, mentioned earlier, is performed using IBM SPSS Statistics software for the sampled oxygen saturation data with both systems. Table 7 is obtained.

Table 7 Parameters obtained from the Wilcoxon test for paired samples for the vital sign "oxygen saturation".

	SAT.OXY_OWNSYSTEM - SAT.OXY_COMMERCIALSYST.
Z	-,757[b]
Sig. asin. (bilateral)	0.449

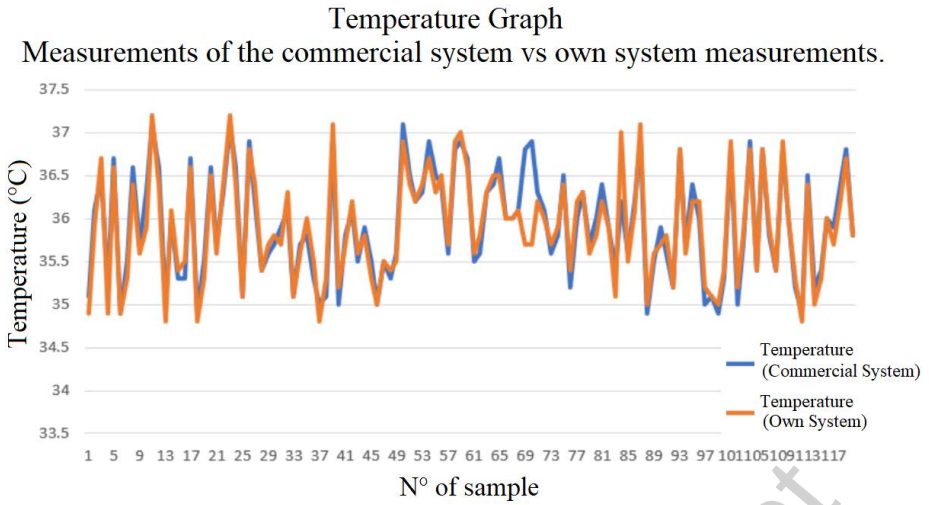

Figure 24 Comparative graph for Temperature

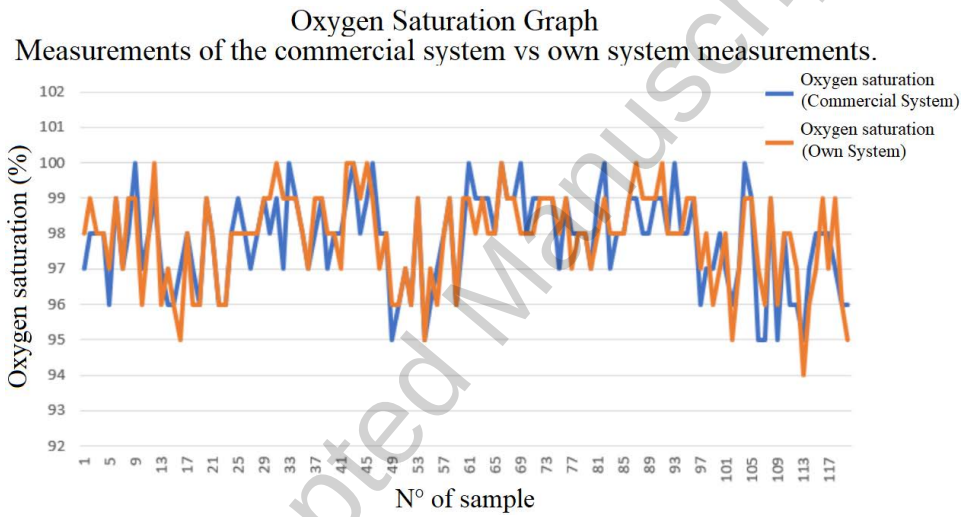

Figure 25 Comparative graph for Oxygen Saturation

The null hypothesis was not rejected since the p-value was 0.449, which is greater than 0.05. Therefore, it can be stated with 95% confidence that the null hypothesis is accepted (the measurement of the vital signs is equal in both devices).

Furthermore, it was ensured that the majority of the collected data falls within or close to the limits of the normal value ranges for the vital signs of the patients considered in the research. However, it should be noted that commercial devices also have a margin of error.

Analysis of the delay time in remote monitoring of vital signs.

The boot-up time of the Raspberry Pi board, including the initiation of the operating system (with the installation of Raspbian OS Lite), establishment of a local network connection, and automatic execution of the program, was approximately 47 seconds. During this time, the board remained in a standby mode through serial communication.

On the other hand, the time from the startup of the main board to the display of the first vital signs sample on the LCD screen was approximately 101 seconds when using the power button. Monitoring the processes on the Raspberry Pi board through a monitor confirmed that the transmission time through the serial communication protocol was nearly imperceptible.

Finally, the time interval between the first and second data samples was approximately 99 seconds, allowing us to approximate the sampling time of the Arduino board to 100 seconds. For the visualization of the sampled data on the graphical interface developed on the ThingSpeak platform, the transmission time through the HTTP protocol was nearly imperceptible, but a minimum update rate of 15 seconds was established within the platform.

5. Discussion

Throughout the investigation, it has been noted that vital sign values vary from individual to individual due to diverse factors as elucidated within the theoretical framework. . Nonetheless, [18] research concludes that no significant discrepancy exists among the values sampled in three subjects. Furthermore, the sampling of normal values for the individuals in this study is delineated within the following ranges: [57 – 77 BPM], [34.9 – 37.2 °C], and [94 – 100 %], juxtaposed with the values sampled for pulse and oxygen saturation by [18], averaging 55 BPM and 98%, respectively, and the mean temperature sampled by [33] at 37 °C. This underscores the absence of a markedly significant difference. Nonetheless, as expounded upon in the theoretical framework, it remains imperative to establish fundamental patient data upon their admission to a healthcare institution, forming a crucial component of their medical history.

For the development of the prototype in this study, the sampling of vital signs data—pulse, blood oxygen saturation, and body temperature—was considered. This data was collected at intervals of 7 hours per day, over 4 days, based on expert judgment gathered from the applied survey. From this, 12 data points were obtained for each vital sign, following a similar approach to [33], who sampled 15 data points per vital sign for the development of their prototype.

The correct acquisition of vital signs compared to commercial devices was validated through the application of the two-sample Z-test and the Wilcoxon signed-rank test. This methodology mirrors that employed by [34], who utilized the Student's t-test with a two-tailed critical t-value and a 95% confidence interval. Similarly, in prior research such as that conducted by [35], a comparable approach was employed. However, their focus was on pain intensity as the principal variable, rather than device assessment as in our study. [35] conducted a comparative analysis of vital signs among patients based on pain intensity, categorized into three distinct levels. Prior to this analysis, a normality test of the samples was performed to determine the feasibility of applying a parametric test or the necessity of resorting to a non-parametric test.

6. Conclusions

Using cloud computing, the development of a remote monitoring system for vital signs (pulse, temperature, and oxygen saturation) was successfully achieved for patients undergoing home treatment.

A specific set of system requirements was elaborated, based on the information gathered from a survey conducted with healthcare professionals, the theoretical framework, and relevant research references.

The Raspberry Pi Zero W single-board computer (SBC) was chosen for the remote transmission of the acquired vital signs, due to its capability to operate with the 802.11 standard in the 2.4GHz band. Additionally, the Raspberry Pi Zero W offers a variety of libraries and frameworks that facilitate the development of a REST API interface or the application of a client-server model and cloud computing through HTTP requests, as demonstrated throughout the research. Moreover, it allows for audio and video integration to collect subjective parameters provided by the patients to healthcare personnel.

The proper acquisition of vital signs was verified by sampling the data according to expert judgment and validating them through the implementation of relevant statistical tests. The results concluded that with a 95% level of confidence, no significant difference was observed for each considered vital sign

A sampling time of approximately 117 seconds was achieved for the remote data sampling of vital signs, with the Arduino board's process being the most determining factor in the overall time.

For future research, it is recommended to expand the investigation by integrating audio and video capabilities for capturing subjective values provided by the patient. This approach would enhance the depth of data collection and provide a more comprehensive understanding of the patient's condition.

In addition, it's beneficial to consider implementing multiple microcontrollers for vital signs data collection. This approach allows for parallel processing of vital sign acquisition processes, enhancing efficiency and potentially reducing latency in data collection and analysis.

7. Declaration of competing interest

We declare that we have no significant competing interests including financial or non-financial, professional, or personal interests interfering with the full and objective presentation of the work described in this manuscript.

8. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

9. Author contributions

M. A. B. conceived, designed and implemented the system. J. N. R. validated the system and wrote the paper. E. A. M. validated the design and supervise the writing of the paper.

10. Data availability statement

The authors confirm that the data supporting the findings of this study are available within the article and its supplementary materials.

References

[1] Y. Khan, A. E. Ostfeld, C. M. Lochner, A. Pierre, and A. C. Arias, "Monitoring of vital signs with flexible and wearable medical devices," *Advanced Materials*, vol. 28, no. 22, p. 4373 – 4395, 2016.

[2] D. Dias and J. P. S. Cunha, "Wearable health devices—vital sign monitoring, systems and technologies," *Sensors (Switzerland)*, vol. 18, no. 8, 2018.

[3] Y. Eddahchouri, M. Koeneman, M. Plokker, E. Brouwer, T. H. van de Belt, H. van Goor, and S. J. Bredie, "Low compliance to a vital sign safety protocol on general hospital wards: A retrospective cohort study," *International Journal of Nursing Studies*, vol. 115, p. 103849, 2021.

[4] M. J. Deen, "Information and communications technologies for elderly ubiquitous healthcare in a smart home," *Personal and Ubiquitous Computing*, vol. 19, no. 3, p. 573 – 599, 2015.

[5] S. Majumder, T. Mondal, and M. J. Deen, "Wearable sensors for remote health monitoring," *Sensors (Switzerland)*, vol. 17, no. 1, 2017.

[6] F. Jamil, S. Ahmad, N. Iqbal, and D.-H. Kim, "Towards a remote monitoring of patient vital signs based on iot-based blockchain integrity management platforms in smart hospitals," *Sensors (Switzerland)*, vol. 20, no. 8, 2020.

[7] K. Mohammed, A. Zaidan, B. Zaidan, O. Albahri, M. Alsalem, A. Albahri, A. Hadi, and M. Hashim, "Real-time remote-health monitoring systems: a review on patients prioritisation for multiple-chronic diseases, taxonomy analysis, concerns and solution procedure," *Journal of Medical Systems*, vol. 43, no. 7, 2019.

[8] Y. Yuan, B. Liu, H. Li, M. Li, Y. Song, R. Wang, T. Wang, and H. Zhang, "Flexible wearable sensors in medical monitoring," *Biosensors*, vol. 12, no. 12, 2022.

[9] P. S. Mendoza, K. . Hernández, C. V. Núñez, and D. J. Molinares, "Internet of things and home-centered health; (internet de las cosas y la salud centrada en el hogar)," *Salud Uninorte*, vol. 32, no. 2, p. 337 – 351, 2016.

[10] L. P. Malasinghe, N. Ramzan, and K. Dahal, "Remote patient monitoring: a comprehensive study," *Journal of Ambient Intelligence and Humanized Computing*, vol. 10, no. 1, p. 57 – 76, 2019.

[11] S. Omboni, R. J. McManus, H. B. Bosworth, L. C. Chappell, B. B. Green, K. Kario, A. G. Logan, D. J. Magid, B. McKinstry, K. L. Margolis, G. Parati, and B. J. Wakefield, "Evidence and recommendations on the use of telemedicine for the management of arterial hypertension: An international expert position paper," *Hypertension*, vol. 76, no. 5, p. 1368 – 1383, 2020.

[12] J. C. Monsalve, "Programa innovador desarrollado por la fcv y la upb, muestra resultados significativos en niños con cardiopatías congénitas," January 2022. [Online]. Available: https://www.fcv.org/co/prensa/noticias/

[13] ESSALUD, *Cuidado integral del paciente con Hipertensión arterial en el Seguro Social de Salud - ESSALUD*, Gerencia Central de Prestaciones de Salud, Lima-Perú, 2016. [Online]. Available: https://ww1.essalud.gob.pe/compendio/pdf/0000003396_pdf.pdf

[14] Seguro Social de Salud (EsSalud) and Instituto de Evaluación de Tecnologías en Salud e Investigación (IETSI), "Pulsioxímetro para uso domiciliario en pacientes con covid-19 catalogados inicialmente como casos leves y con factores de riesgo," Seguro Social de Salud de Perú, Reporte breve 33, 2020. [Online]. Available: https://repositorio.essalud.gob.pe/handle/20.500.12959/1778

[15] C. N. en Sistemas de Información en Salud (CENS), *Telemedicina durante la epidemia de COVID-19 en Chile: guía de buenas prácticas y recomendaciones; [Telemedicine during the COVID-19 epidemic in Chile: guide of good practices and recommendations]*, Ministerio de Salud de Chile, 2020. [Online]. Available: https://pesquisa.bvsalud.org/portal/resource/en/biblio-1140282

[16] J. D. Esquicha, "Implementación de un prototipo de seguridad física, para monitorear gases, agua, temperatura y humedad en ambientes hospitalarios por medio de raspberry pi y beebotte," Ph.D. dissertation, UCSM, Apr 2019. [Online]. Available: https://repositorio.ucsm.edu.pe/handle/20.500.12920/8823

[17] R. Yauri, "Implementación de una red inalámbrica de sensores para el monitoreo remoto de variables fisiológicas en pacientes ambulatorios," Ph.D. dissertation, Universidad Nacional del Callao, 2018. [Online]. Available: http://hdl.handle.net/20.500.12952/2816

[18] F. Gónzales and L. Reina, "Diseño e implementación de un pulsioxímetro reflexivo y estudio de su funcionamiento en diferentes zonas del cuerpo," Ph.D. dissertation, Universidad de Sevilla, 2019. [Online]. Available: https://hdl.handle.net/11441/94193

[19] G. Aceto, V. Persico, and A. Pescapé, "Industry 4.0 and health: Internet of things, big data, and cloud computing for healthcare 4.0," *Journal of Industrial Information Integration*, vol. 18, 2020.

[20] L. Greco, G. Percannella, P. Ritrovato, F. Tortorella, and M. Vento, "Trends in iot based solutions for health care: Moving ai to the edge," *Pattern Recognition Letters*, vol. 135, p. 346 – 353, 2020.

[21] A. Albahri, J. K. Alwan, Z. K. Taha, S. F. Ismail, R. A. Hamid, A. Zaidan, O. Albahri, B. Zaidan, A. Alamoodi, and M. Alsalem, "Iot-based telemedicine for disease prevention and health promotion: State-of-the-art," *Journal of Network and Computer Applications*, vol. 173, 2021.

[22] A. Ghubaish, T. Salman, M. Zolanvari, D. Unal, A. Al-Ali, and R. Jain, "Recent advances in the internet-of-medical-things (iomt) systems security," *IEEE Internet of Things Journal*, vol. 8, no. 11, pp. 8707–8718, 2020.

[23] I. Kehayov, P. Uchikov, T. Kitova, and B. Kitov, "Limitations of telemedicine in low-and middle-income countries," *Neurosurgical Focus*, vol. 53, no. 3, p. E20, 2022.

[24] A. Taoum, M. Sabbagh, H. Amoud, and F. Mourad-Chehade, "Features extraction from vital signs to characterize acute respiratory distress syndrome," in *2018 IEEE 4th Middle East Conference on Biomedical Engineering (MECBME)*. IEEE, 2018, pp. 62–66.

[25] K. Kalpakis, S. Yang, P. F. Hu, C. F. Mackenzie, L. G. Stansbury, D. M. Stein, and T. M. Scalea, "Permutation entropy analysis of vital signs data for outcome prediction of patients with severe traumatic brain injury," *Computers in biology and medicine*, vol. 56, pp. 167–174, 2015.

[26] N. E. Hammond, A. J. Spooner, A. G. Barnett, A. Corley, P. Brown, and J. F. Fraser, "The effect of implementing a modified early warning scoring (mews) system on the adequacy of vital sign documentation," *Australian Critical Care*, vol. 26, no. 1, pp. 18–22, 2013.

[27] H. Abu-Naim, O. Ahmad, D. Akelah, Y. Salem, E. Midoun *et al.*, "Vital signs changes during different dental procedures: A prospective longitudinal cross-over clinical trial," *Oral Surgery, Oral Medicine, Oral Pathology and Oral Radiology*, vol. 127, no. 1, pp. 30–39, 2019.

[28] D. S. M. John, *Statistical Analysis Handbook A Comprehensive Handbook of Statistical Concepts, techniques and software tools.* Drumlin Publications, 2018.

[29] R. Peck, C. Olsen, and J. L. Devore, *Introduction to statistics and data analysis*, 3rd ed. Thomson Brooks/Cole, 2005.

[30] R. Ott Lyman and M. Longnecker, *An Introduction to Statistical Methods and Data Analysis*, 5th ed. Duxbury, 2001.

[31] E. C. Fein, J. Gilmour, T. Machin, and L. Hendry, *Statistics for Research Students "An Open Access Resource with Self-Tests and Illustrative Examples".* y University of Southern Queensland, 2021.

[32] I. Graessler and J. Hentze, "The new v-model of vdi 2206 and its validation," *at-Automatisierungstechnik*, vol. 68, no. 5, pp. 312–324, 2020.

[33] J. P. Gutierrez Segales, "Implementación de un prototipo de una red inalámbrica de sensores biomédicos, para la adquisición y almacenamiento de datos, usando cloud computing, para pacientes en casa," 2019.

[34] B. E. Y. Reyes Rengifo, "Diseño de sistema de monitoreo de signos vitales de pacientes en emergencias de la cía. de bomberos salvadora trujillo n 26," 2018.

[35] L. Suso-Martí, F. Cuenca-Martínez, A. Arredondo-López, and A. Gil-Martínez, "Análisis comparativo de las constantes vitales en pacientes agudos hospitalizados en función de la intensidad de dolor," *Revista de la Sociedad Española del Dolor*, vol. 26, no. 4, pp. 215–220, 2019.

[36] P. Mao, H. Li, and Z. Yu, "A review of skin-wearable sensors for non-invasive health monitoring applications," *Sensors*, vol. 23, no. 7, p. 3673, 2023.

[37] A. Haleem, M. Javaid, R. P. Singh, and R. Suman, "Telemedicine for healthcare: Capabilities, features, barriers, and applications," *Sensors international*, vol. 2, p. 100117, 2021.

[38] G. Nittari, R. Khuman, S. Baldoni, G. Pallotta, G. Battineni, A. Sirignano, F. Amenta, and G. Ricci, "Telemedicine practice: review of the current ethical and legal challenges," *Telemedicine and e-Health*, vol. 26, no. 12, pp. 1427–1437, 2020.

[39] Z. Ali and S. B. Bhaskar, "Basic statistical tools in research and data analysis," *Indian journal of anaesthesia*, vol. 60, no. 9, pp. 662–669, 2016.