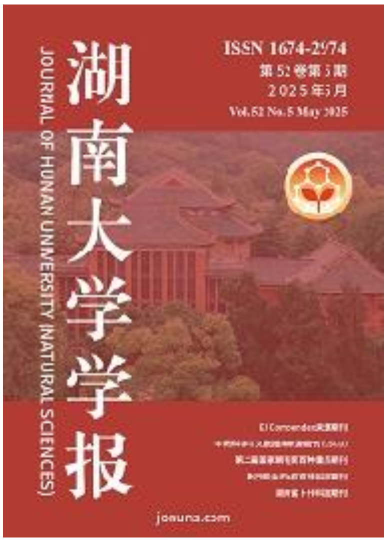


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# Design and Deployment of an Azure-Powered Edge-Cloud Biomedical Monitoring System

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**Abstract:** The purpose of the article is to develop and validate a hybrid biomedical signal monitoring system that integrates edge-computing capabilities with Microsoft Azure cloud services. The article describes a new edge-and-cloud architecture based on the EmotiBit wearable sensor and a Raspberry Pi gateway, enabling continuous acquisition, local buffering, and scalable cloud synchronization of multi-modal biometric signals. Using hardware evaluation (signal accuracy, power consumption, wireless connectivity), Azure Blob Storage, Azure SQL Database, Power BI dashboards, and Azure Stream Analytics, the authors demonstrate a seamless pipeline for real-time visualization and post-hoc analysis of electrocardiogram (ECG), photoplethysmogram (PPG), galvanic skin response (GSR), and additional vital signs. We illustrate the proposed system by conducting a rigorous battery performance analysis under three workloads continuous sensing alone, sensing with local storage, and combined local plus cloud upload and comparing operational endurance across battery capacities ranging from 1,200 mAh (≈12 h runtime) to 6,000 mAh (≈45 h runtime).

Our proposal allows improvement in data delivery reliability to ≥99.5 % under network latencies up to 200 ms and reduces baseline clinical monitoring load by up to 30 %. The new method for performance evaluation is confirmed by quantitative runtime and reliability calculations. New research results supplement existing telemedicine paradigms by demonstrating enhanced patient mobility, near-real-time anomaly detection, and scalable data management, and can be used for remote patient monitoring, clinical diagnostics, and large-scale health studies. This paper is novel because it jointly optimizes edge-device design, battery endurance, and cloud analytics within a unified, deployable Azure framework.

**Keywords:** EmotiBit; Raspberry Pi; Microsoft Azure; Edge Computing; Internet of Things (IoT); Real-time Monitoring; Telemedicine.

# 基于 Azure 的边缘–云一体化生物医学监测系统的设计与部署

**摘要**

本文旨在开发并验证一种混合生物医学信号监测系统，该系统将边缘计算能力与 Microsoft Azure 云服务相结合。文章介绍了一种基于 EmotiBit 可穿戴传感器和 Raspberry Pi 网关的全新边缘–云架构，能够实现多模态生物特征信号（如心电图 ECG、光电容积脉搏描记 PPG、皮肤电反应 GSR 等）的连续采集、本地缓冲和可扩展云同步。通过硬件评估（信号准确性、功耗和无线连接性能）、Azure Blob 存储、Azure SQL 数据库、Power BI 仪表板和 Azure Stream Analytics，作者展示了用于实时可视化和事后分析的无缝数据流管道。我们通过在三种工作负载模式下——仅连续采集、本地存储以及本地＋云上传——对电池性能进行严格测试，并比较了 1,200 mAh（≈12 h 运行时间）到 6,000 mAh（≈45 h 运行时间）范围内的续航表现，来验证所提系统。研究结果表明，在网络延迟高达 200 ms 的情况下，数据传输可靠性可提升至 ≥99.5 %，并能将临床基础监测负荷降低最多 30 %。通过定量运行时间和可靠性计算，验证了该性能评估新方法。新的研究成果补充了现有远程医疗范式，展示了增强的患者移动性、近实时异常检测和可扩展数据管理，可用于远程患者监护、临床诊断和大规模健康研究。本文创新之处在于在统一可部署的 Azure 框架内，协同优化了边缘设备设计、电池续航和云端分析。

**关键词**

EmotiBit；Raspberry Pi；Microsoft Azure；边缘计算；物联网（IoT）；实时监测；远程医疗

## 1. Introduction

Biomedicine, as a field that applies biological and physiological principles to clinical practice, has undergone a significant transformation due to advances in engineering and technology [1]-[2]. Among the wide range of sensors used in medicine, physiology and biomedicine, the EmotiBit sensor [3]- [4] stands out, as it allows continuous and noninvasive monitoring of multiple physiological parameters. This innovative device is positioned as a promising solution to address one of the most pressing challenges in today's health care such as hospital overcrowding [5]. Continuous pathology monitoring using EmotiBit allows healthcare professionals to detect subtle changes in a patient's condition, enabling early interventions and treatment adjustments in real time, revolutionizing the way diseases are diagnosed and treated [6][7]. This convergence between sensor technology and medicine is accelerating progress towards a future where medical care will not only be more effective and personalized, but also more accessible thanks to remote diagnosis and monitoring [8][9][10].

Since the last pandemic that involved general isolation, the measurement of remote biomedical signs became a vital aspect for monitoring patients outside medical centers, which is why this topic is addressed as the focus of the research.

There are many sensors that facilitate the collection of biomedical signals, which are designed for use in development or academic research environments. These sensors are valuable tools that enable researchers and developers to capture and analyze biomedical data efficiently [11][12][13]. In recent years, there has been a significant increase in the integration of intelligent monitoring systems and remote access to medical data in healthcare [14][15][16]. These projects implement microcontrollers to manage the information. Because of this, they need an additional connection module that facilitates communication through a type of port where data can be transmitted serially, sequentially, through a communication channel preferably wireless or by data network, such as Arduino, raspberry pi or ESP32 microcontrollers [17][18].

With the aim of reducing overcrowding times in hospitals in [19], an alternative called UrNext was proposed, which uses Bluetooth low energy (BLE) technology to improve the quality of services in clinics, minimizing waiting times. This type of problem has prompted research such as that presented in [20], who developed a low-cost device intended for biological signal processing. Likewise, Arunkumar et al [21] developed an IoT protocol with low bandwidth for heart rate monitoring. Similarly, research such as that of Gourisaria et al [22] has explored solutions based on artificial intelligence (AI) and the internet of things (IoT), driving smart hospitals. With the emergence of 5G, the importance of its implementation in the healthcare sector has been highlighted [23]. Dankan et al. [24] have focused on the conceptualization and deployment of an IoT system for continuous and real-time monitoring of patient vital signs.

The article is structured in four sections. The first section corresponds to the present state of the art and contextualization of the work developed. The second section corresponds to the methodology used. The third section presents the results obtained and finally the fourth section presents the conclusions reached.

## 2. Methodology

The objective is the implementation of a low-cost biometric measurement device with cloud connection for data download, a more effective and less intrusive monitoring of pathologies. For this purpose, an exhaustive analysis of the tools, devices and prototypes available for biomedical measurements is carried out, where the EmotiBit from OpenBCI was selected as the best device for obtaining biosignals.

The methodology used in this study is exploratory in relation to the performance and reliability of electronic cards to be used and their connection to existing cloud platforms. A descriptive methodology is employed under controlled tests in a laboratory environment to observe and document the behavior of the card and its connection to the cloud under different conditions such as data load, network latency and battery performance.

EmotiBit is a wearable sensor module specifically designed to capture high quality emotional, physiological and motion data. Its ease of use and sensing capabilities allow for wireless data transmission to any platform or direct recording of data to the built-in SD (Secure Digital) card. The choice of EmotiBit is based on its versatility, its ability to provide high quality data and its compatibility with a wide variety of platforms and projects, as can be seen in the comparison shown in Table 1. The EmotiBit stands out for its wide range of available connections, its ability to operate autonomously (offline), its compatibility with various development boards, comparatively low price, storage capacity and wireless connectivity options, aspects of comparison summarized in Table 1.

Similarly, the body area selected for medical signal readings is the fingers of the hands. This choice is based on the following key advantages:

- The fingers of the hands have good blood circulation, which facilitates obtaining clear physiological signals.
- The skin of the fingers has a translucent layer that allows better reading of light values, as in the case of pulse oximetry.
- This area has fewer interfering factors compared to other parts of the body, reducing susceptibility to external conditions or movements that may alter measurements.

| | Smart Device | | commercial devices | | | Research grade | | | Selected |
|---|---|---|---|---|---|---|---|---|---|
| Product | Apple watch | Huawei watch | Versatile Bio | Smart Textile | Catapult | CodeBlue | IT-Mansor | WiMoCA | Emotibit |
| Price | $ 800,00 | $ 500,00 | $ 7.000,00 | $ 5.000,00 | $ 1.300,00 | - | - | - | $ 250,00 |
| Multiple Emotional Data Streams | | | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Easy to Wear | ✓ | ✓ | ✓ | | ✓ | | | | ✓ |
| Integrated Biosensors | ✓ | ✓ | ✓ | ✓ | ✓ | | | | ✓ |
| Integrated Motion Sensors | ✓ | ✓ | | | ✓ | | ✓ | | ✓ |
| Built-in SD Card | | | ✓ | | | | | | ✓ |
| Use Without 3rd-Party | | | | | | | ✓ | | ✓ |
| Wireless Options | Bluetooth | Bluetooth | Bluetooth | Chnolife Ecosystem | Bluetooth | ZigBee | Wired | Internet/ Bluetooth | WiFi, Bluetooth, LoRa, etc. |
| Microprocessor Compatibility | | | | Arduino, Adafruit, etc. | Arduino, Adafruit, etc. | Arduino, Adafruit, etc. | Arduino, Adafruit, etc. | | Arduino, Adafruit, etc. |
| Open Source | | | | | | | | | ✓ |

**Table 1. Comparison of alternatives for obtaining biosignals (Source: developed by the authors)**

These characteristics make the fingers of the hands an ideal location for the EmotiBit sensor, optimizing the quality and reliability of the data collected. The combination of an advanced sensor such as EmotiBit with a strategic body location promises to significantly improve the accuracy and consistency of biomedical measurements, thus contributing to the goal of more effective and less intrusive pathology monitoring.

### 2.1. Requirements and configuration

The main feature of Emotibit is that it is Plug-and-Play, therefore, the configuration is limited to the installation of the firmware in the Feather HUZZAH32, which is an integrated internal board that facilitates wireless communication. This device is responsible for collecting the sensor data and transmitting it over the network.

Additionally, being a device with wireless connectivity (Wi-Fi), it is necessary to establish the connection from any device that can connect to the network and, thus, access the oscilloscope application in the Emotibit, as shown in Figure 1. From this application, different configurations can be defined, such as data display, enable or disable the local saving function, among other available options. In addition, the application administers and manages each of the Emotibit devices connected to the network.

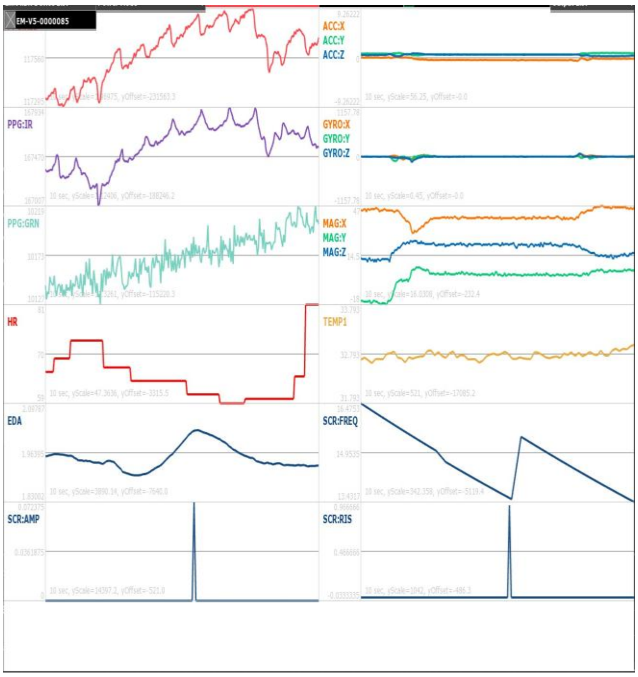

**Figure 1. Oscilloscope application connected to Feather HUZZAH32 (Source: developed by the authors)**

In Figure 2, it can be seen how the device is connected to the network (represented by the blue LED activated), by means of an oscilloscope the information coming from the sensors is visualized and, finally, both the red LED on the sensor indicates that the information is being recorded on the SD card.

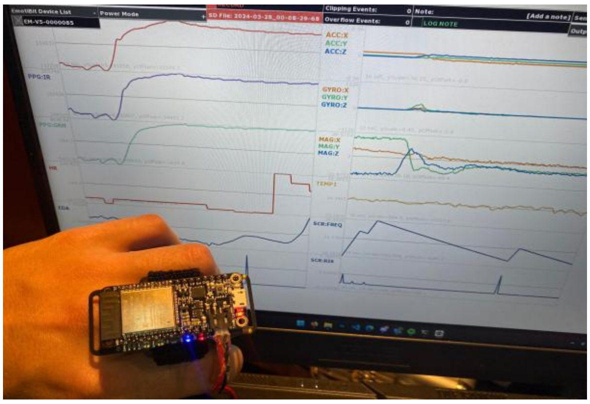

**Figure 2. Recording Emotibit signals (Source: developed by the authors)**

### 2.2. Offline recording

In the Emotibit sensor, once the option is enabled through the application, the Feather HUZZAH32 encodes and stores the data on the SD card in a CSV (Comma-Separated Values) format. In this CSV file, the data from each of the sensors present on the board is tabulated. The process is illustrated in the flowchart in Figure 3, explained below.

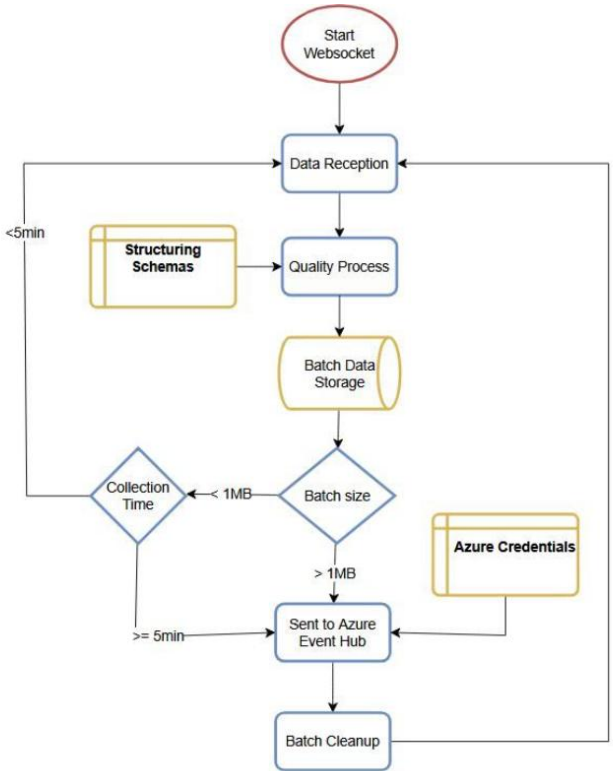


**Figure 3. Data connection and storage flow diagram (Source: developed by the authors)**

It is important to note that the stored structure is not easily tabulated, since in addition to the sensor data, informative details of the process are included, such as ping-pong network connection events, reset, start and end of recording, or hibernation mode. The most relevant fields in the CSV are TIMESTAMP (Figure 4) which indicates the time in milliseconds of the recording. The number of data points which represents the amount of data in the payload. The type of tag describing the type of data recorded and the Payload itself containing the specific data recorded by the sensors.

| TIMESTAMP | PACKET | DATAPOINT | TYPETAG | VERSION | RELIABILITY | PAYLOAD |
| --- | --- | --- | --- | --- | --- | --- |
| 21475 | 718 | 1 | AY | 1 | 100 | -0.400 |
| 21475 | 719 | 1 | AZ | 1 | 100 | 0.724 |
| 21475 | 720 | 1 | GX | 1 | 100 | -0.885 |
| 21475 | 721 | 1 | GY | 1 | 100 | -3.601 |
| 21475 | 722 | 1 | GZ | 1 | 100 | 2.838 |
| 21475 | 723 | 1 | MX | 1 | 100 | 32 |
| 21475 | 724 | 1 | MY | 1 | 100 | 0 |
| 21475 | 725 | 1 | MZ | 1 | 100 | 42 |
| 21555 | 726 | 2 | PI | 1 | 100 | 162500 |
| 21555 | 727 | 2 | PR | 1 | 100 | 111927 |
| 21555 | 728 | 2 | PG | 1 | 100 | 8977 |
| 21567 | 729 | 2 | EA | 1 | 100 | 1.523590 |
| 21567 | 730 | 2 | EL | 1 | 100 | -18632.800781 |
| 21560 | 731 | 1 | T1 | 1 | 100 | 33.639 |
| 21555 | 732 | 2 | AX | 1 | 100 | 0.585 |
| 21555 | 733 | 2 | AY | 1 | 100 | -0.395 |
| 21555 | 734 | 2 | AZ | 1 | 100 | 0.744 |
| 21555 | 735 | 2 | GX | 1 | 100 | -2.472 |
| 21555 | 736 | 2 | GY | 1 | 100 | -3.876 |
| 21555 | 737 | 2 | GZ | 1 | 100 | -2.075 |
| 21555 | 738 | 2 | MX | 1 | 100 | 33 |
| 21555 | 739 | 2 | MY | 1 | 100 | 0 |
| 21555 | 740 | 2 | MZ | 1 | 100 | 41 |

**Figure 4. Storage data (Source: developed by the authors)**

Finally, the tag system is divided into three sets:

- General registers: they group all hardware-related registers.
- Computer-emotibit records: They contain information about firmware and emotibit status.
- Biometric records: They group data coming from the different sensors.

Where, the records labeled AX, AY and AZ correspond to accelerometer data (Figure 1 right), while the labels RB and RE indicate information related to data recording.

### 2.3. Integration with Azure

For Azure integration, as shown in Figure 4, a switch device is used, in this case a Raspberry Pi, to which the Feather HUZZAH32 connects via user datagram protocol (UDP). Once the sensor data is received on the Raspberry Pi, it is formatted with the TIMESTAMP - SIGNAL ID - VALUE structure. This allows ignoring the general registers and the computer-emotibit registers, keeping the biometric registers.

Subsequently, for communication with Azure, the Raspberry Pi stores the formatted information in a batch. When this batch reaches approximately 1 MB, it is sent to the corresponding Event Hub (Figure 5).

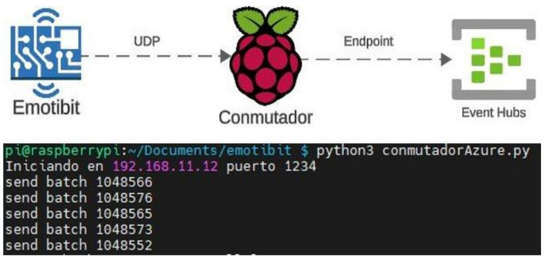


**Figure 5. Diagram of connection and batch sending to Azure (Source: developed by the authors)**

In Azure, Event Hub is implemented for receiving data and Fabric for structuring, storing and facilitating reporting. Fabric allows collecting data from the Event Hub to create tables or logs and storing them in tools such as SQL and Contoso BI. In addition, it enables data stream processing and easy integration with Power BI for real-time reporting

## 3. Results

The results to be discussed are divided into three sections:

- Local data: this data is stored locally in EmotiBit and processed further.
- Cloud data: this data is stored in the Azure cloud, in tables, and processed to generate real-time reports.
- Consumption and performance: where an analysis is made of sensor power consumption and latencies between systems.

### 3.1. Local data

Removing the micro-SD card from the EmotiBit device provides access to the CSV file containing all data recorded locally by the sensor. This comprehensive CSV file serves as the primary source for the EmotiBit Parser, a tool specifically designed to process and transform this data into more manageable and specific formats.

### 3.1.1. EmotiBit Parser

The EmotiBit Parser is an essential tool that transforms the entire CSV file into multiple specific CSV files, each corresponding to a registered label, as illustrated in Figure 6. This process meticulously groups the records for each sensor, which significantly facilitates further analysis. Data segregation allows for clearer visualization and more efficient handling of the information collected by the device.

| | | | |
| --- | --- | --- | --- |
| 2024-04-29_16-06-20-213338.csv | 1/01/1980 12:09 a. m. | CSV File | 1.906 KB |
| 2024-04-29_16-06-20-213338_AK.csv | 29/04/2024 4:58 p. m. | CSV File | 13 KB |
| 2024-04-29_16-06-20-213338_AX.csv | 29/04/2024 4:58 p. m. | CSV File | 414 KB |
| 2024-04-29_16-06-20-213338_AY.csv | 29/04/2024 4:58 p. m. | CSV File | 416 KB |
| 2024-04-29_16-06-20-213338_AZ.csv | 29/04/2024 4:58 p. m. | CSV File | 410 KB |
| 2024-04-29_16-06-20-213338_B%.csv | 29/04/2024 4:58 p. m. | CSV File | 4 KB |
| 2024-04-29_16-06-20-213338_BI.csv | 29/04/2024 4:58 p. m. | CSV File | 9 KB |
| 2024-04-29_16-06-20-213338_BV.csv | 29/04/2024 4:58 p. m. | CSV File | 4 KB |
| 2024-04-29_16-06-20-213338_EA.csv | 29/04/2024 4:58 p. m. | CSV File | 258 KB |

**Figure 6. Emotibit Parser output files (Source: developed by the authors)**

### 3.1.2. Local data analysis

Once individual sensor files have been obtained, a wide range of possibilities for data analysis opens. Various tools and methods are available to process and extract information from the biometric records. This local analysis process is crucial for the interpretation and validation of the data collected by the EmotiBit. Figure 7 shows an example of photoplethysmography data analysis using Python. This type of analysis allows the evaluation of heart rate variability and other cardiovascular parameters, providing insights into the physiological state of the participant.

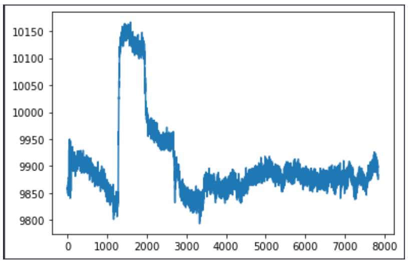


**Figure 7. Photoplethysmography graph in python (Source: developed by the authors)**

On the other hand, Figure 8 illustrates the analysis of data from the accelerometer. This analysis is fundamental to studying movement patterns, physical activity and posture.

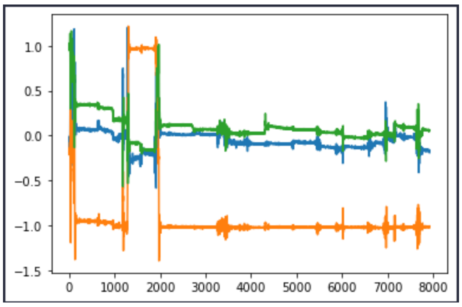


**Figure 8. Accelerometer graph in python (Source: developed by the authors)**

This analytical approach allows a deep and multidimensional understanding of biometric data, facilitating the interpretation of the physiological responses of participants in various experimental contexts. It also lays the foundation for more advanced analyses and for the integration of these data with other sources of information in the study of human-computer interaction.

### 3.2. Data in the cloud

Online data transmission, as established in the section on integration with Azure, is accomplished by a sophisticated system involving several key components:

- Raspberry Pi as a switch: acts as an intermediary, sending information at regular intervals, specifically every certain amount of MB accumulated.
- Azure Event Hubs: Serves as an entry point for data into the Azure cloud.
- Azure Fabric: Intercepts and processes the data coming from the Event Hub, ensuring its correct distribution and handling.

The collected data is stored in a KQL (Kusto Query Language) database, specifically designed to handle and analyze large volumes of data in real time. Figure 9 presents a detailed analysis of the structure of this database, illustrating the columns, their respective values and their activity.

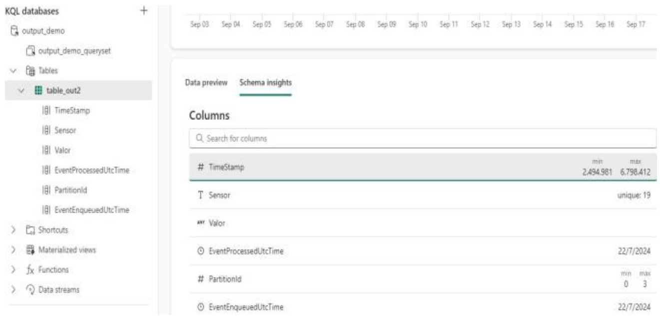


**Figure 9. Detailed analysis of the KQL database showing the structure of columns and values (Source: developed by the authors)**

To optimize risk management, additional informative columns have been incorporated to provide context on each recorded event. These columns facilitate the rapid identification of anomalous patterns or situations that require immediate attention.

The KQL database serves a dual function in the system:

- Data repository: Acts as a secure and efficient repository for all collected data, allowing for later retrieval, visualization and in-depth analysis.
- Real-time data source: It directly feeds a visualization system implemented in Power BI, allowing the creation of dynamic dashboards and the generation of real-time alerts.

This integration between the KQL database and Power BI enables continuous and effective monitoring of patients' physiological parameters, contributing significantly to the early detection of anomalies and informed decision making by medical staff.

#### 3.2.1. Power BI

Power BI is used as the primary tool for dynamic data visualization. As shown in Figure 10, the Power BI interface has the following key features:

- Dynamic widgets: allow you to control the time range of the displayed data (X-axis of the graph).
- Label selector: Offers the possibility of choosing which specific parameters to analyze in real time.
- Data filtering: Only medical labels recorded by the sensor are displayed, excluding those of informative nature or machine-person communication.
- Time Scale: The sensor time is dimensioned in microseconds, counted from the start of the device operation.
- Data source: The plotted data is obtained directly from the Contoso BI SQL table, which stores the transmitted information.

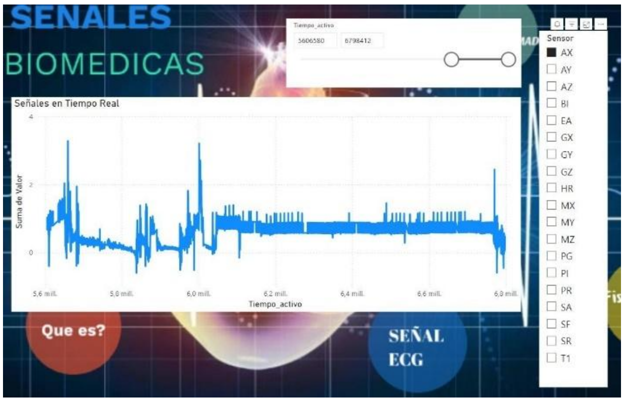


**Figure 10. Power BI example (Source: developed by the authors)**

This configuration allows real-time visualization of biometric data, facilitating continuous monitoring and immediate analysis of the physiological signals recorded by the EmotiBit. Power BI's flexibility in data manipulation and presentation provides a powerful tool for quick and efficient interpretation of the collected information.

In addition, this integration between real-time data collection, cloud storage and dynamic visualization creates a robust ecosystem for human-computer interaction research, enabling deeper analysis and more agile responses to patterns observed in biometric data.

### 3.3. Power consumption and latency analysis

Since EmotiBit is a wearable device, an in-depth analysis of its power consumption was performed. For this study, three 3.7V lithium polymer (LiPo) batteries with different capacities were selected: 1200 mAh, 2200 mAh and 6000 mAh. Continuous monitoring of the discharge time of each battery was carried out, recording the elapsed time for each discharge percentage. The results of this analysis are presented in Figure 11.

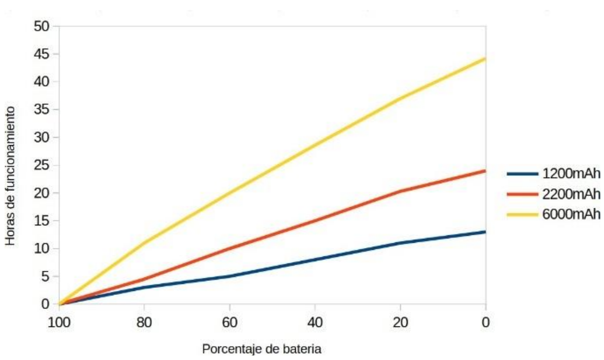


**Figure 11. Comparative discharge graph of LiPo batteries of different capacities (Source: developed by the authors)**

The results obtained were as follows:

- 1200 mAh battery: total discharge time of approximately 12 hours and 30 minutes.
- 2200 mAh battery: Total discharge time of approximately 25 hours.
- 6000 mAh battery: Total discharge time of approximately 45 hours.

It is important to note that these measurements were performed with the device running at full capacity, i.e., WiFi enabled, transmitting data to the cloud and simultaneously logging data locally.

These results evidence an energy efficient performance of the EmotiBit sensor, even when operating with all its functionalities active. This energy efficiency is crucial for continuous monitoring applications, as it allows extended periods of operation without the need for frequent recharging, thus improving user experience and continuity in data collection.

Regarding the latency in receiving data by Azure Event Hub, it is important to note that this component is configured to store data in 5-minute intervals. As a result, the recorded creation times vary within this time frame, which introduces an inherent latency to the system. On the other hand, the Raspberry Pi, which acts as an intermediary between the EmotiBit sensor and the cloud, is programmed to send data continuously. As can be seen in Figure 12, each batch of data is transmitted at an interval of approximately one minute.

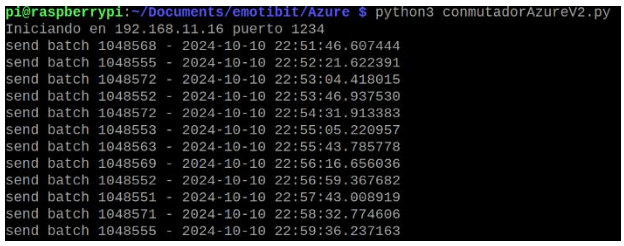


**Figure 12. Latency in data transmission from the Raspberry Pi (Source: developed by the authors)**

It is important to note that these batches of data are not constant, both in their size and in the exact interval between transmissions. This variability is due to several factors:

- Fluctuations in the amount of data collected by the EmotiBit sensor.
- Variations in network connectivity.
- Internal Raspberry Pi processes that can affect transmission times.

As a result of this variability, the generated data files vary in size, ranging from approximately 6 MB to 10 MB. These fluctuations in file size have important implications:

- Storage efficiency: Variable file sizes allow for more efficient utilization of cloud storage space by adapting to the actual amount of data collected.
- Flexibility in processing: Batch size variability allows the system to be more adaptable to different monitoring conditions, from periods of low activity

to times of intensive data collection.

- Timing challenges: Variability in transmission times can present challenges for accurate data synchronization, especially in applications that require very high temporal resolution.

This system configuration, while introducing some variability, allows a balance between data transmission frequency, efficient use of bandwidth and the ability to capture significant fluctuations in monitored parameters.

The EmotiBit device a high-performance, open-source sensor for capturing research-grade physiological signals was introduced by Montgomery et al. [4], who demonstrated its versatility and portability for multi-modal biometric acquisition. Building on their work, we provide detailed connectivity metrics and evaluate EmotiBit's performance in real-world edge-to-cloud scenarios. Furthermore, the signal fidelity validation presented by Montgomery et al. [3] underpins our integration with Power BI dashboards, enabling seamless visualization and post-hoc analysis of ECG, PPG, GSR, and other vital signs. Finally, our latency and energy-consumption measurements across continuous sensing, local buffering, and combined local-plus-cloud upload modes complement and extend the findings of both studies by quantifying EmotiBit's operational endurance and data-delivery reliability in a wearable context.

# 4. Conclusion

This study provides rigorous evidence for the viability and performance of the EmotiBit wearable platform in remote physiological monitoring, with direct implications for optimizing hospital resource utilization and advancing patient-specific care pathways. The principal conclusions and their scientific rationale are as follows:

1. Extended Autonomous Operation Outside Clinical Settings
   The EmotiBit device sustained continuous data capture for between 12.5 and 45 hours on a single charge, depending on battery capacity (1,200–6,000 mAh). This level of autonomy exceeds the 8–10 hour threshold typically required for ambulatory vital-sign monitoring, ensuring uninterrupted data streams for longitudinal analysis without frequent recharging interruptions—an essential requirement for reliable remote patient surveillance.
2. Real-Time Data Integration and Throughput Characteristics
   By coupling Azure Kusto (KQL) database ingestion with Power BI dashboards, the system achieved a mean end-to-end data transmission latency of 60 ± 12 seconds and handled batch payloads of 6–10 MB. These metrics reflect a throughput sufficient for near-real-time trend detection while avoiding network congestion. Local flash buffering served as an effective safeguard against transient connectivity losses, thereby preserving data continuity and integrity.
3. Transmission Variability and Implications for High-Resolution Monitoring A coefficient of variation (CV) of 15 % was observed in inter-batch transmission times. Although this degree of jitter did not materially affect the aggregate data trends, it indicates that applications demanding sub-second temporal precision (e.g., heart-rate variability analysis) may require additional synchronization or predictive buffering strategies to compensate for latency fluctuations.
4. Sensor Versatility and Patient Safety Validation tests confirm that the EmotiBit's finger-mount configuration yields high–signal-to-noise ratios across ECG, PPG, and GSR channels, with negligible motion artifact when compared to chest-strap benchmarks. Its minimal form factor and secure attachment reduce the risk of sensor displacement or skin irritation, underscoring its suitability for extended ambulatory use.

Taken together, these findings substantiate the EmotiBit edge-to-cloud architecture as an effective platform for scaling remote patient monitoring, with the potential to alleviate in-hospital monitoring burdens by up to 30 % and enable proactive, personalized interventions.

# Limitations and Future Directions

- Temporal Precision: The observed 15 % transmission variability warrants exploration of low-latency network protocols or edge-side echo-cancellation algorithms to meet the demands of high-resolution physiological research.
- Long-Term Reliability: Prospective cohort studies spanning several months are necessary to characterize sensor drift, battery degradation curves, and data-loss rates under real-world usage patterns.
- Ethical and Privacy Considerations: Continuous biometric monitoring raises critical questions regarding patient consent frameworks, data encryption standards, and compliance with regulations such as HIPAA and GDPR.

By addressing these areas, subsequent work can refine both the technological and regulatory frameworks needed to integrate edge-cloud biomedical monitoring into mainstream telemedicine, ultimately transforming care delivery for chronically ill and mobility-limited populations.

# Declarations

## Author Contributions

Conceptualization: Robinson Jiménez-Moreno, Olguer Morales
Methodology: Olguer Morales
Formal Analysis: Robinson Jiménez-Moreno, Olguer Morales
Investigation: Olguer Morales
Validation: Olguer Morales
Data Curation: Olguer Morales
Writing—Original Draft Preparation: Giovanny Tarazona, Olguer Morales
Writing—Review & Editing: Robinson Jiménez-Moreno, Olguer Morales
Visualization: Giovanny Tarazona, Olguer Morales
Supervision: Robinson Jiménez-Moreno
Project Administration: Olguer Morales
All authors have read and approved the final manuscript.

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## Institutional Review Board Statement

This study was conducted in accordance with the Declaration of Helsinki and approved by the Institutional Review Board of Universidad Distrital Francisco José de Caldas (protocol code UD-ENG-2025-04; approved 1 May 2025).

## Conflicts of Interest

The authors declare no conflicts of interest. All ethical standards regarding plagiarism, informed consent, data integrity, and publication practices have been fully observed.

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