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IoT-Based Electronic System for Real-Time Monitoring and AI-Driven Analysis of Residential Water Consumption

Camilo Quinto *, José Insuasti, Milton Simbaña, Paul Palma, Wilmer Fabian Albarracin and Paul Baldeón Egas

Engineering Sciences Applied to Production, Society, and Sustainable Development, Israel University of Technology, Quito 170519, Ecuador; e1724426364@uisrael.edu.ec (J.I.); e1718321670@uisrael.edu.ec (M.S.); e1312008392@uisrael.edu.ec (P.P.); walbarracin@uisrael.edu.ec (W.F.A.); pbaldeon@uisrael.edu.ec (P.B.E.)

* Correspondence: e1725181877@uisrael.edu.ec; Tel.: +593-999055217

Abstract

Due to an increase in the demand for water and the limited availability of real time monitoring technologies, efficient management of residential water resources poses a unique problem. This study describes the development of an inexpensive Internet of Things (IoT)-based electronic system capable of providing real time monitoring and artificial intelligence (AI)-driven analysis of residential water consumption. The electronic system consists of the use of a YF-DN50 flow sensor connected to an ESP32 microcontroller allowing for continuous data acquisition. The data collected is stored in a cloud-based spreadsheet on Google Colab for processing and analysis, where an unsupervised Long Short-Term Memory (LSTM) Autoencoder model was developed for anomaly detection. The developed model produced a final training loss value of 0.038 and a validation loss value of 0.045, with the threshold for anomaly detection determined to be mean + 3 standard deviations above the reconstruction error. During the observation period, the system detected a total of 7 anomalous events as well as detecting an overall 85.7% of the detected known events and having a 33% reduction in false negative detections compared to a simple fixed threshold baseline. The results of this study demonstrate that the combination of IoT sensors with LSTM Autoencoder analysis of water consumption allows for the monitoring of water consumption patterns and early detection of anomalies, thus providing a means to achieve a reduction in average monthly household water consumption from approximately 21 m^3 to 18 m^3.

Keywords: IoT; embedded systems; electronic monitoring system; flow sensor; real-time data acquisition; anomaly detection; residential water consumption

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1. Introduction

Urban growth, rising water demand, and climate variability have made efficient water management one of the main challenges facing contemporary cities. Various studies have shown that the residential sector accounts for a significant portion of total drinking water consumption in urban areas; therefore, optimizing water use is a key strategy for improving the sustainability of water supply systems [1–3]. In this context, the incorporation of digital technologies, smart sensors, and real-time monitoring systems has opened new opportunities to understand domestic consumption patterns and promote more efficient water use practices.

Traditionally, the analysis of household water consumption has relied on monthly records from distribution companies, which limits the ability to identify detailed usage patterns or detect operational inefficiencies such as leaks or abnormal consumption [4]. In countries such as Ecuador, this process is typically carried out using analog meters and periodic monthly manual readings, which further limit the availability of information and make it extremely difficult to monitor consumption on an ongoing basis. This limitation has driven the development of Internet of Things (IoT)-based solutions that enable the collection of consumption data with higher temporal and spatial resolution through flow sensors and connected monitoring platforms [5,6]. These technologies facilitate the generation of real-time information and the implementation of smart resource management strategies, as evidenced by recent studies focused on smart monitoring of water consumption in residential settings. While there are solutions that integrate advanced infrastructure, their implementation is often associated with greater technological requirements; therefore, the proposed system aims to offer an accessible and functional alternative in the domestic context, prioritizing the availability of detailed information that is understandable to the end user. This feature enables more informed decision-making regarding consumption and thus promotes increasingly efficient use of the water system. These solutions offer several significant advantages, including real-time monitoring of water consumption, automatic detection of anomalies, and access to information via cloud-based platforms, which facilitates data-driven decision-making based on continuous data. Likewise, various studies have shown that the integration of smart sensors, wireless communication technologies, and analytics platforms allows for more accurate identification of consumption patterns and optimizes water resource management in residential settings [7]. However, despite these benefits, several studies also point to limitations associated with these types of systems, including high implementation and maintenance costs and the energy consumption associated with continuous monitoring; consequently, in cities with higher poverty rates, access to these systems is very difficult, exacerbating water consumption [8].

At the same time, advances in data analysis and machine learning tools have made it possible to transform consumption records into useful information for decision-making. Analysis platforms based on scientific programming languages, such as Python, together with collaborative data processing environments, have proven highly effective in detecting consumption patterns, identifying anomalies, and generating predictive models in environmental and urban monitoring systems [9]. The integration of IoT sensors with automated analysis systems is currently one of the main lines of research in the field of intelligent water resource management systems.

However, in many urban contexts across Latin America, there remains limited adoption of domestic water consumption monitoring technologies, as well as a scarcity of tools that enable users to understand their own consumption behavior. The lack of detailed information on water use can hinder the adoption of more efficient consumption habits and reduce users' ability to identify abnormal increases in their usage patterns [10]. In this regard, the development of accessible systems for monitoring and analyzing domestic consumption represents a significant opportunity to improve water resource management at the local level.

In response to this issue, this study proposes the development and implementation of a smart system for monitoring and analyzing drinking water consumption in a single-family home, based on IoT sensors and data analysis tools. The system integrates a YF-DN50 flow sensor connected to an ESP32 microcontroller for real-time data acquisition, a cloud-based data storage platform using online spreadsheets, and a data analysis environment implemented in Google Colab, where AI-based techniques are applied to identify consumption patterns and detect anomalies, triggering automated email alerts in response to abnormal usage. Data collection was conducted over a 14-week monitoring period, enabling the analysis of consumption behavior under real operating conditions [11].

The study is based on a mixed-methods approach that combines the analysis of historical consumption records, the characterization of household usage habits through semi-structured interviews, and consumption simulation using water modeling tools. Subsequently, these results are integrated with the data obtained by the developed IoT system, allowing for the validation of consistency between estimated theoretical consumption and actual measured consumption [12].

In this context, the main objective of this work is to develop and implement an IoT-based smart system for the monitoring, analysis, and management of drinking water consumption in a single-family home, integrating flow sensors, data storage platforms, and automated analysis tools, in order to generate useful information for optimizing resource use and the early detection of anomalous consumption patterns [13]. In addition to analyzing residential water consumption, it is also important to understand user behavior, as it directly influences the hydraulic dynamics of the system. Everyday actions, such as the opening and closing of taps at different points of use, can generate variations in flow and pressure conditions within the distribution network. Although the monitoring system implemented in this study is not designed to capture high-frequency transient phenomena such as pressure surges, these hydraulic effects are relevant as contextual factors, since they may contribute over time to issues such as leaks or pipe deterioration, which are indirectly reflected in consumption patterns [14].

A detailed review of related studies and existing approaches is presented in Section 2.

2. Related Work

This section reviews preview studies on IoT-based water consumption monitoring systems and data-driven analysis approaches, with the aim of contextualizing the proposed solution within existing research and identifying key technological and methodological contributions. The literature highlights the use of sensors, communication platforms, and data analysis tools for monitoring in both residential and industrial environments, as well as solutions focused on technical data management and process automation (see Table 1).

This study is strongly supported by previous research focused on the analysis of household water consumption using data-driven techniques. In particular, the work presented in *Water* in 2022 by Arsene et al. proposes an advanced methodology based on clustering and classification algorithms to identify consumption patterns and distinguish between different types of water usage events, such as sinks, toilets, and showers. This approach demonstrates the potential of machine learning and time-series analysis for detailed characterization of residential water consumption [13].

Similarly, the GST4Water project developed by Luciani et al. (2019) represents a relevant reference in the field, as it integrates smart metering, user interaction, and data analytics to improve water management efficiency in residential environments [15].

Building upon these contributions, the present study adopts a simplified and integrative approach, combining consumption modeling, user behavior characterization, and real-time monitoring through IoT sensors. Unlike previous works that rely on high-resolution datasets and complex computational models, this research focuses on the practical implementation of a low-cost system capable of continuous monitoring in a real residential environment. In this sense, the proposed system represents both a conceptual extension and a practical adaptation of existing methodologies, incorporating real-time data acquisition, cloud-based processing, and automated anomaly detection, while maintaining accessibility and ease of implementation in resource-constrained contexts.

More recent studies have further reinforced the integration of IoT technologies with cloud computing and intelligent data analytics for water consumption monitoring. In particular, the study "A Feasibility Study of IoT-Based Classification of Residential Water-Use Activities in Storage Tank Systems: A Comparative Analysis of Decision Trees, Random Forest, SVM, KNN, and Neural Networks" provides a relevant methodological contribution by evaluating multiple machine learning models for the classification of residential water-use activities. This work highlights the potential of artificial intelligence techniques to identify usage patterns and differentiate between consumption events based on sensor data, offering valuable criteria for the selection and application of data-driven approaches in water monitoring systems [16].

Table 1. Summary of related studies in IoT-based residential water monitoring.

Study	Contribution	Author	Year
Green Smart Technology for Water (GST4Water): Water Loss Identification at User Level by Using Smart Metering Systems	It provides an overview of IoT-based water management systems and shows how smart sensing technologies improve water efficiency and detect irregular consumption patterns, facilitating decision-making [15].	Luciani C	2019
A Feasibility Study of IoT-Based Classification of Residential Water-Use Activities in Storage Tank Systems: A Comparative Analysis of Decision Trees, Random Forest, SVM, KNN, and Neural Networks	Supports the application of machine learning techniques for the classification of residential water-use activities, applicable to IoT-based consumption analysis systems [16].	Neftalí I	2026
Study of domestic water consumption in intermittent supply of the Riberas de Sacramento sector in Chihuahua, Mexico	Provides a basis for analyzing residential water consumption behavior under real supply conditions, applicable to the interpretation of domestic usage patterns [17].	Mendoza C	2022
IoT Gateway—LoRa for Remote Metering to Support Efficient Household Water Consumption	It provides a foundation for the use of smart meters and continuous data collection, applicable to the efficient monitoring and analysis of water consumption [18].	Vásquez A	2024
Implementation of an HMI interface based on the open-source Node-RED software for local and remote control and monitoring of the pumping system at the Rivotorto housing complex	It outlines a framework for using IIoT platforms to interconnect devices and enable centralized data management [19].	Quintana G	2024
Automatic water quality monitoring and control system for the cooling tower at Interquimec in Quito	Supports the implementation of online monitoring systems to optimize industrial processes [20].	Córdova J	2022
IoT application for monitoring residential electricity consumption using open-source software	Outlines the use of IoT technologies and cloud computing for the management and monitoring of energy variables [21].	Toapanta A	2022
Remote monitoring system for temperature, humidity, and light levels in medical product storage warehouses, using an IoT platform	Provides a foundation for the development of real-time IoT environmental monitoring systems, applicable to supervision [22].	Arroyo M	2023
Automation of the control system for the second multi-stage horizontal centrifugal water reinjection pump unit in Tapia	Supports the implementation of automated systems for continuous monitoring, applicable to the development of IoT solutions for control and analysis [23].	Garcés M	2023
IoT monitoring of the operating parameters of an HPS-type water reinjection pump	Establishes a foundation for the acquisition and monitoring of critical variables in industrial environments, applicable to the development of smart monitoring systems [24].	Villacrés C	2023

Note: Data compiled from previous research.

Similarly, "Study of domestic water consumption in intermittent supply of the Riberas de Sacramento sector in Chihuahua, Mexico" contributes to the understanding of residential water consumption under real supply conditions, particularly in contexts with intermittent water distribution. Its analysis of consumption behavior and usage patterns in a real urban environment provides a practical reference for interpreting demand variability and user habits, which supports the contextualization of the present study within real-world domestic scenarios [17].

Additionally, other work has demonstrated the use of cloud-based platforms for the storage and processing of real-time data from IoT monitoring systems, enabling scalable architectures and improved accessibility for remote supervision. These approaches highlight the growing trend toward combining sensing technologies with advanced data processing tools for efficient and data-driven water management.

The study "IoT Gateway—LoRa for Remote Metering to Support Efficient Water Consumption in Homes" served as a reference for the use of smart meters and LoRa communication technologies for the remote and continuous monitoring of water consumption in residential settings [18]. In addition, the study "Implementation of an HMI interface based on the open-source Node-RED software for local and remote control and monitoring of the pumping system at the Rivotorto housing complex" contributed insights into the use of IIoT platforms and centralized monitoring tools for device interconnection and operational data management [19]. Furthermore, the study "Automatic Water Quality Monitoring and Control System for the Cooling Tower at Interquimec in Quito" provided guidelines related to continuous monitoring and automated supervision of water quality variables in real operational environments within the city of Quito [20].

The study "IoT Applications for Monitoring Residential Electricity Consumption Using Open-Source Software" provided a technological and methodological framework by showing how IoT technologies combined with open-source software enable the acquisition, transmission, and visualization of real-time data through Internet-connected sensors [21]. In a similar way, the study "Remote monitoring system for temperature, humidity, and light levels in medical product storage warehouses, using an IoT platform" presents methodological criteria for integrating IoT platforms focused on continuous supervision and real-time visualization of monitored conditions, aspects that can be adapted to the control and analysis of water consumption [22]. The study "Automation of the control system for the second multi-stage horizontal centrifugal water reinjection pump unit in Tapia" serves as a reference for the automation and continuous supervision of hydraulic systems through control and monitoring technologies. Its focus on real-time analysis and automated pump management offers useful criteria applicable to IoT-based solutions for flow supervision, consumption control, and anomaly detection in water systems [23].

Finally, the study "IoT monitoring of the operating parameters of an HPS-type water reinjection pump" establishes a foundation for the acquisition and real-time supervision of operational data using IoT technologies applied to pumping systems. Its approach to intelligent monitoring and continuous data analysis also supports the development of strategies for the optimization of water systems, while contributing to greater user awareness by enabling detailed information about daily water consumption through connected monitoring platforms [24].

In this context, the novelty of the proposed approach lies in the implementation and experimental validation of an integrated monitoring framework that combines low-cost flow sensing with high-resolution temporal data acquisition and AI-assisted analysis. Unlike conventional IoT-based solutions that primarily focus on data transmission or visualization, the proposed system enables continuous quantification of consumption at short time intervals (1–3 min), allowing for the detection of subtle variations and sustained low-flow conditions associated with potential leaks. The integration of real consumption data with simulated usage profiles and historical billing records provides a multi-layer validation strategy that is not commonly addressed in existing residential monitoring systems. This combination of real-time sensing, data fusion, and anomaly detection under practical implementation constraints constitutes the main technical contribution of this work.

3. Materials and Methods

3.1. Research and Methodological Design

The study was conducted in a single-family home located in the La Garzota neighborhood, Chillogallo parish, in the city of Quito, Ecuador. This study is designed as an exploratory case study focused on analyzing domestic water consumption in a single household. The selection of a single-household case study was based on the exploratory nature of this research, allowing the controlled implementation and evaluation of the proposed IoT-based monitoring system under real operating conditions. This approach enables a detailed observation of water consumption behavior and system performance while minimizing external variability. Furthermore, this urban area exhibits a pattern of domestic consumption typical of established residential areas in the city; therefore, the results obtained provide insight into the behavior of the proposed system in a real-world context, offering initial evidence for future larger-scale research [25]. The household analyzed consists of a total of five residents, which allows for an analysis of consumption based on the water usage patterns of each family member within the home. The monitoring system consists of a single device based on a flow sensor (YF-DN50, Ningbo, China) connected to a microcontroller (ESP32 NodeMCU, Espressif Systems, Shanghai, China), which is installed on the main water line to begin storing continuous consumption records. While the scope of the study is limited to one household, this methodological decision is appropriate for validating the feasibility, reliability, and operational behavior of the proposed system prior to its potential scaling to larger populations.

The methodological design adopted is a mixed-methods approach, which integrates quantitative and qualitative methods to characterize household drinking water consumption. The quantitative component is based on the direct measurement of consumption using flow sensors integrated into an IoT system, while the qualitative component is based on the characterization of household consumption habits through semi-structured interviews and the simulation of consumption in software [26].

The research process was divided into four main phases:

- Analysis of historical consumption records using drinking water service billing statements.
- Collecting data on consumer habits through semi-structured interviews.
- Simulation of household water use using the Cleef Company (Cleefcompany SpA, Santiago, Chile) Water Usage Simulator.
- Development and implementation of an IoT system for real-time monitoring of water consumption [27].

The flowchart shown in Figure 1 provides a structured overview of the comprehensive methodology followed in the development of the study, from the theoretical framework to the evaluation of the implemented system's performance. Unlike a system operational flowchart, this diagram represents the logical sequence of the research process, articulating the stages of literature review, context diagnosis, identification of variables and requirements, design of the IoT–AI system, and its subsequent experimental implementation.

A key feature of the flow is the incorporation of an iterative validation process, in which the results of the implementation are continuously evaluated, allowing for adjustments at both the hardware and software levels. This cyclical approach ensures the progressive improvement of the system and consistency between the initial requirements and the developed solution. Furthermore, the diagram highlights the integration between technological development and data analysis, culminating in the evaluation of the system's impact through the comparison of consumption indicators before and after its implementation.

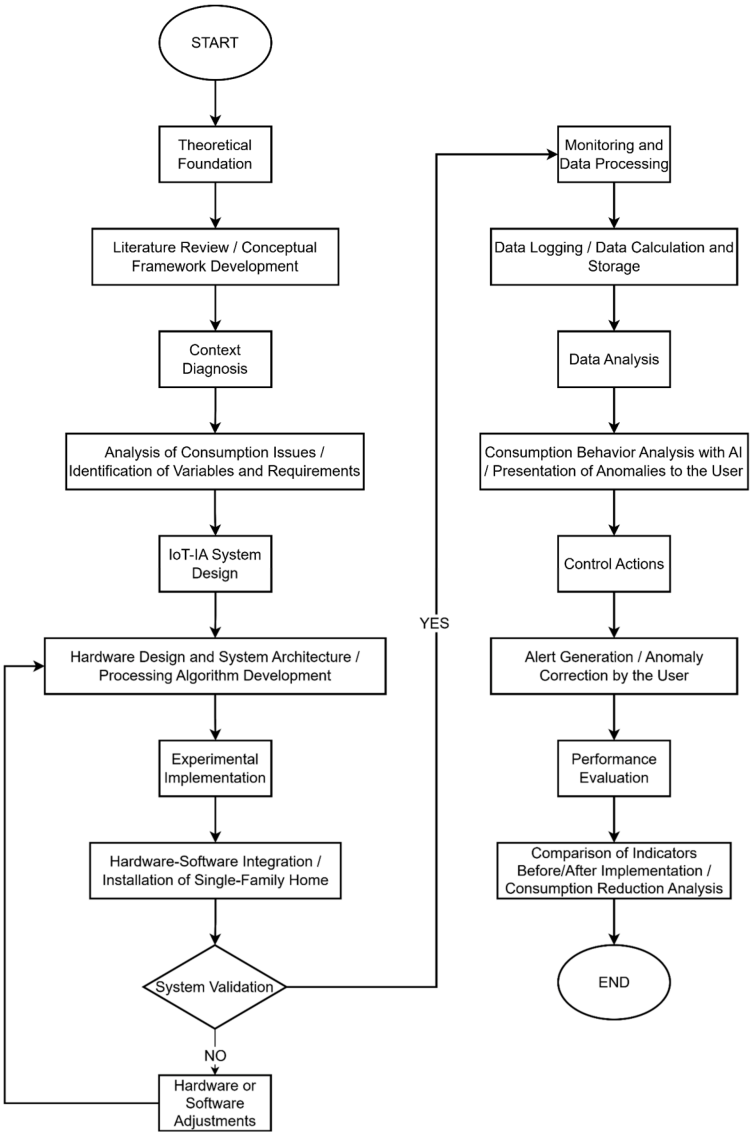

Figure 1. Research methodology flowchart.

This approach made it possible to integrate information from various sources to validate the observed consumption patterns and evaluate the performance of the developed system. See Figure 1.

3.2. Architecture of the IoT Monitoring System

Figure 2 shows the operational flow of the developed system, organized into functional modules that describe the complete cycle of data acquisition, processing, analysis, and water consumption control. The system begins with the initialization phase, during which the hardware components and communication modules are configured to ensure appropriate conditions for data acquisition.

In the acquisition stage, the pulses generated by the flow sensor are captured via interrupts, allowing for precise measurement independent of the microcontroller's load. Subsequently, in the processing phase, these pulses are converted into physical variables (flow rate and volume), incorporating timestamps that ensure data traceability. The analysis phase integrates artificial intelligence-based techniques for identifying consumption patterns and detecting anomalies, while the monitoring and control stage enables interaction with the user through alerts and corrective actions, such as verifying or interrupting the flow in the event of abnormal consumption.

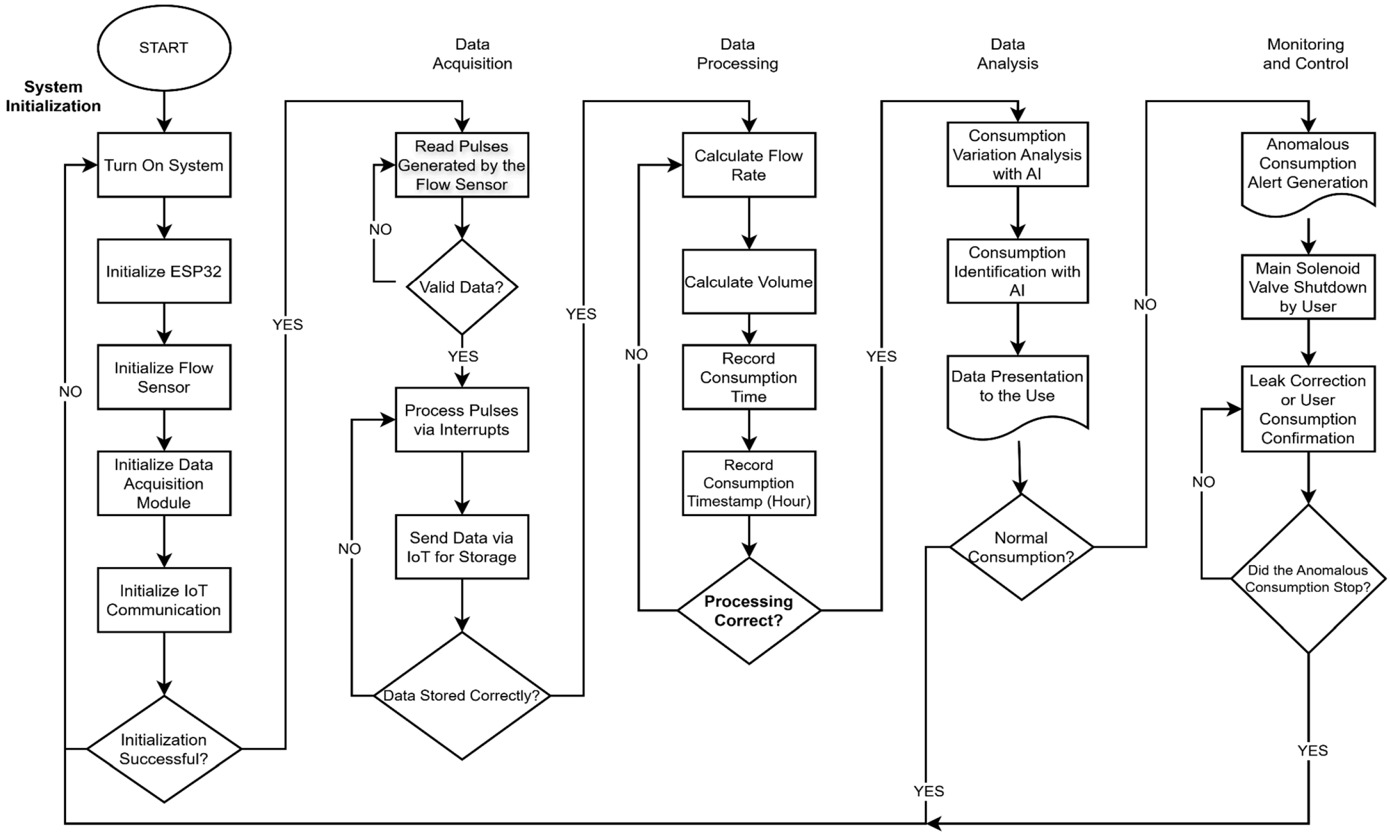

Figure 2. Functional diagram of the proposed monitoring system.

The system's modular design facilitates the separation of responsibilities between acquisition, processing, and analysis, improving the system's scalability and maintainability, as well as integration with external data storage and visualization platforms.

The system developed to monitor drinking water consumption is based on an architecture for data acquisition, transmission, storage, and analysis. The technological infrastructure integrates flow sensors, microcontrollers, cloud storage platforms, and data analysis tools.

The system consists of the following main components. See Figure 3.

- YF-DN50 flow sensor, which measures the volume of water flowing through the main supply pipe.
- ESP32 microcontroller, which acquires data from the sensor and transmits it via a Wi-Fi connection.
- Online database implemented using cloud-based spreadsheets, where consumption records are stored.
- Analysis environment in Google Colab, used to process data, identify consumption patterns, and run automated analysis algorithms.
- Automatic notification system, which sends email alerts when anomalous consumption patterns are detected.

The system architecture allows for the integration of physical consumption monitoring with real-time data analysis tools, facilitating the early detection of anomalies and the tracking of household consumption behavior [28].

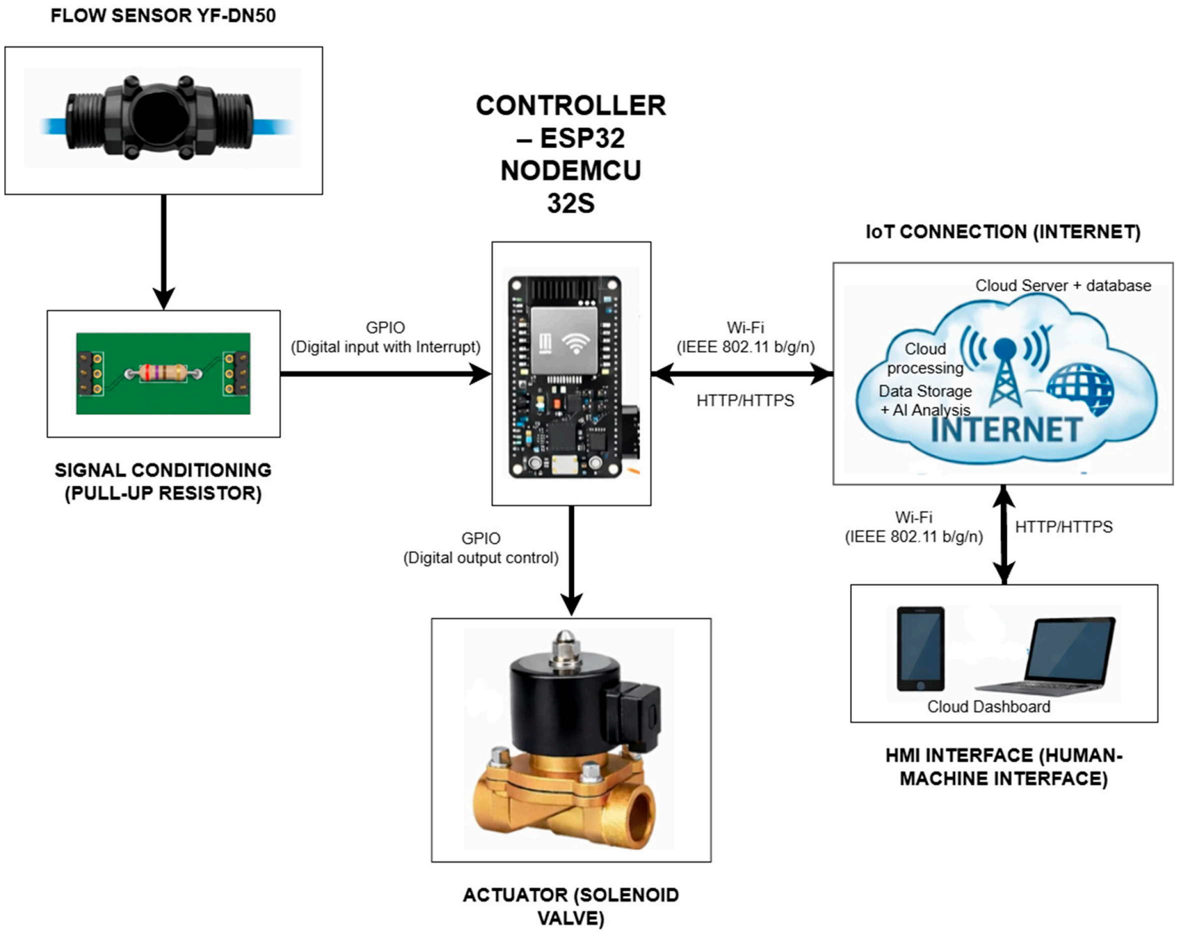

Figure 3. System architecture block diagram.

The selection of the main technologies used in this study was based on criteria of cost-effectiveness, scalability, and compatibility with real-time data processing requirements. The use of a flow sensor combined with the ESP32 microcontroller allows continuous acquisition of water consumption data with low energy consumption and high integration capability. Additionally, the ESP32 provides built-in wireless communication, enabling direct connectivity with cloud-based platforms without the need for additional hardware.

Compared to existing IoT-based water monitoring solutions, which often rely on more complex and costly infrastructures, the proposed architecture offers a simplified and accessible approach while maintaining adequate performance for residential applications.

Its modular design facilitates data acquisition, processing, and transmission in a unified system, supporting real-time monitoring and anomaly detection. This makes the proposed solution suitable for implementation in resource-constrained environments while preserving the functionality required for intelligent water consumption analysis.

3.3. Data Acquisition Hardware

Flow measurement was performed using a YF-DN50 turbine-type flow sensor, whose operating principle is based on the rotation of an internal impeller driven by the flow of fluid. The sensor incorporates a Hall-effect element that generates a digital pulse signal whose frequency is proportional to the instantaneous flow rate, allowing the volume to be estimated by counting the cumulative number of pulses. According to the manufacturer's specifications and technical literature, this type of sensor has a typical accuracy of ±3% within its operating range [29].

The sensor was installed on the main water supply line of the residence, ensuring adequate hydraulic conditions (straight sections before and after) to minimize flow disturbances. The sensor output (open-collector type) was connected to a digital pin on the ESP32 microcontroller (GPIO 27) configured with an internal pull-up resistor, which allows for a stable signal at compatible logic levels (3.3 V). A 1-kΩ resistor was incorporated in series as protection on the signal line to limit transient currents and improve immunity to electrical noise. Pulse counting was implemented using falling-edge interrupts, ensuring acquisition accuracy regardless of the processor load.

Pulse acquisition is performed using hardware interrupts triggered on the falling edge of the sensor signal, allowing each pulse to be captured in real time with high temporal accuracy independently of the main program execution. The interrupt service routine (ISR) increments a pulse counter as pulses are generated. Subsequently, signal processing is executed at fixed 1-s intervals, during which the accumulated pulse count is read, reset, and converted into volumetric parameters. This hybrid approach—real-time acquisition via interrupts combined with periodic processing—ensures both measurement accuracy and computational efficiency.

The processed pulse data are converted to volume using a calibration factor expressed as pulse density (pulses·m^{-3}), and subsequently to flow rate (m^3/s). In this context, the resolution of the measurement system is determined by its ability to detect individual pulses within that interval, which corresponds to a minimum resolution of approximately 1.0×10^{-4} m^3, depending on flow conditions. This resolution enables the identification of continuous low-flow consumption associated with potential leaks downstream of the meter (background leaks), provided that these leaks generate detectable pulses on a sustained basis.

To ensure measurement accuracy, the sensor underwent an experimental calibration process using a reference volume of 0.020 m^3 measured with a graduated cylinder. In each test, the total number of pulses generated was recorded, and the conversion factor was estimated according to:

$$\text{pulsesPerCubicMeter} = \text{total pulses}/\text{actual volume } (m^3)$$

Multiple repetitions were performed, yielding an average value for the factor that was implemented in the ESP32 algorithm. The conversion factor was verified through independent tests, comparing the volume estimated by the system with the actual volume, with low relative errors observed within ranges acceptable for residential monitoring.

Repeatability was evaluated through repeated measurements under similar flow conditions, showing minimal variation in the pulse count for the same reference volume, which confirms the sensor's stability. Measurement uncertainty was estimated based on the dispersion of the calibration tests, taking into account variations in flow and pulse count.

It should be noted that the system does not rely on an autonomous power source (battery), as the sensor and microcontroller are powered directly from the home's electrical grid, ensuring continuous operation and eliminating restrictions associated with energy autonomy.

The results of this sensor calibration and validation process are shown in Table 2 below.

The metrological analysis of the calibration tests demonstrates high sensor stability, with a standard deviation of 73 pulses·m^{-3} and a coefficient of variation of less than 1%, confirming adequate repeatability under controlled conditions. The maximum error observed remains within $\pm$1.02%, a value consistent with low-cost turbine sensors. The standard measurement uncertainty for a volume of 0.020 m^3 was estimated at 3.3×10^{-5} m^3, while the expanded uncertainty (k = 2) was 6.6×10^{-5} m^3, corresponding to a relative uncertainty of $\pm$0.33%.

Table 2. Flow sensor calibration results.

Test	Actual Volume (m^3)	Pulses Recorded	Pulse Density (Pulses·m^{-3})
1	0.020	194	9700
2	0.020	196	9800
3	0.020	195	9750
4	0.020	197	9850
5	0.020	193	9650
6	0.020	195	9750
7	0.020	194	9700
8	0.020	196	9800
9	0.020	195	9750
10	0.020	197	9850
Average	-	-	9.760 pulses·m^{-3}
Standard deviation (σ)	-	-	73 pulses·m^{-3}
Coefficient of variation (CV)	-	-	0.75%
Maximum observed error	-	-	±1.02%
Standard uncertainty (u)	-	-	3.3×10^{-5} m^3
Expanded uncertainty (U, k = 2)	-	-	6.6×10^{-5} m^3 (±0.33%)

Note: Data obtained from experimental tests.

From a statistical perspective, the use of an expanded uncertainty with a coverage factor k = 2 corresponds to a confidence level of approximately 95%, indicating that the true value of the measured volume lies within the defined uncertainty interval with high probability. This supports the statistical significance and reliability of the calibration results, confirming that the observed variability is not significant and remains within acceptable limits for residential water monitoring applications.

To further assess the reliability of the calibrated conversion factor, an independent validation was conducted using multiple reference volumes. The measured values obtained from the system were compared against the known volumes, allowing the evaluation of accuracy and consistency across different operating conditions. The results are summarized in Table 3.

Table 3. Validation of flow measurement based on pulse count.

Test	Reference Volume (m^3)	Pulses (Calculated)	Measured Volume (m^3)	Absolute Error (m^3)	Relative Error (%)
1	0.010	98	0.00992	−0.00008	−0.80%
2	0.012	117	0.01205	+0.00005	+0.42%
3	0.015	146	0.01500	0.00000	0.00%
4	0.018	176	0.01790	−0.00010	−0.56%
5	0.020	195	0.02000	0.00000	0.00%
6	0.022	215	0.02208	+0.00008	+0.36%
7	0.025	244	0.02503	+0.00003	+0.12%
8	0.027	263	0.02690	−0.00010	−0.37%
9	0.030	293	0.03005	+0.00005	+0.17%
10	0.035	341	0.03485	−0.00015	−0.43%

Note: Data obtained from experimental tests.

The consistency of the pulse-to-volume relationship across different reference volumes confirms that the calibration factor is stable and not dependent on a single calibration point, mitigating potential bias introduced by pulse quantization effects. The hardware connection diagram is shown in Figure 4.

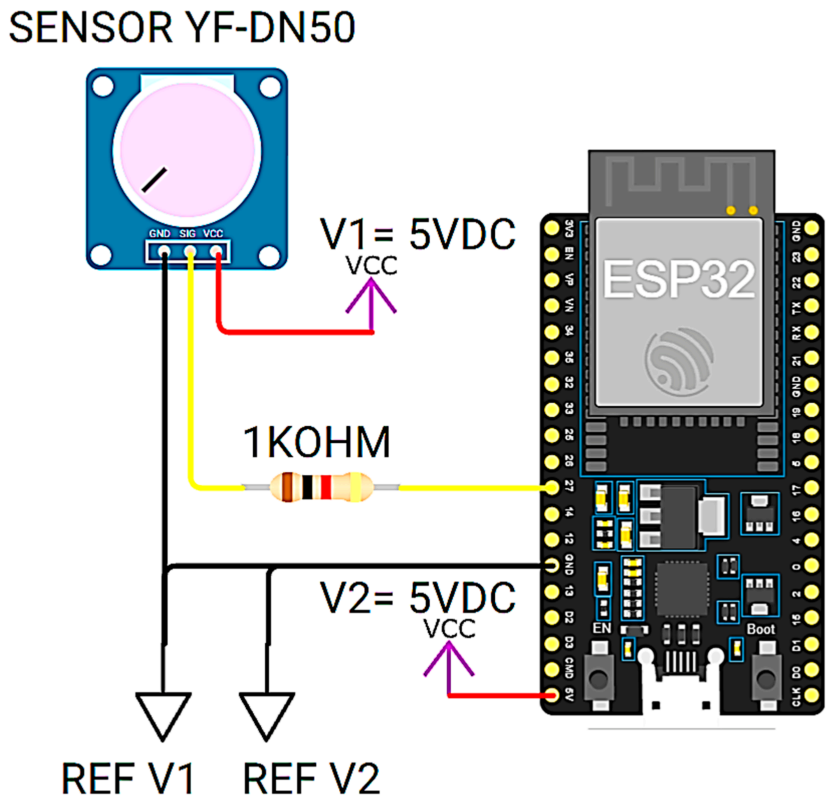

Figure 4. Electrical wiring of the flow sensor and ESP32.

3.4. Data Collection and Storage

The consumption data generated by the system was stored in an online database implemented using spreadsheets connected to the internet. This solution allows the consumption values generated by the microcontroller to be automatically recorded and maintains an up-to-date history of the collected data.

The database stores variables such as:

- Date and time of recording;
- Duration of usage;
- Instantaneous flow rate;
- Cumulative volume;
- Daily usage;
- Sensor status;
- Connection status.

Using an online storage platform makes data more accessible and allows for direct integration with analytics and visualization tools.

3.5. Data Acquisition Algorithm in the Microcontroller

The ESP32 microcontroller runs a program that reads the pulses generated by the flow sensor, calculates the instantaneous flow rate, and sends the processed data to the online database.

The implemented algorithm performs the following main operations:

- Initialization of the sensor's input pins.

- Counting of pulses generated by the flow sensor.
- Conversion of pulses to flow rate and water volume.
- Calculation of cumulative consumption.
- Periodic transmission of data to the database.

The pseudocode in Figure 5 describes the logic implemented in the ESP32 microcontroller for the acquisition and processing of real-time water consumption data. During the initialization phase, the system configures the flow sensor interrupt, establishes the Wi-Fi connection, and synchronizes the time via NTP, ensuring the correct temporal traceability of the data.

During continuous operation, the algorithm reads the number of pulses generated by the sensor every second, using interrupts to ensure precision in signal capture. From these pulses, the instantaneous volume, flow rate, and cumulative consumption are calculated using a calibration factor.

A key feature of the algorithm is the detection of consumption events based on thresholds and time conditions, which allows for the grouping of continuous flow periods and avoids false positives associated with noise or fluctuations. This logic defines the start and end of each event, accumulating the corresponding volume and allowing for its characterization in terms of duration and total consumption.

Once the event is over, the data is sent via HTTP requests to the cloud database. Additionally, a heartbeat mechanism is implemented to verify connectivity and system status in the absence of consumption.

Overall, the algorithm prioritizes measurement accuracy, robustness against noise, and efficiency in data transmission—fundamental aspects for IoT monitoring systems in residential environments.

3.6. Database Automation and Management

The data stored in the database was managed using automation scripts that organize the information, generate consolidated reports, and prepare the data for further analysis. These scripts perform tasks such as:

- Automatic record updating;
- Validation of received data;
- Calculation of cumulative consumption;
- Preparation of data for processing in the analysis environment.

The pseudocode in Figure 6 describes the data management and storage logic implemented in the server layer via cloud script. This algorithm is responsible for receiving the HTTP requests generated by the IoT device, extracting the parameters associated with each event in a structured manner, and ensuring their consistent storage in the database.

A key feature of the algorithm is the classification of records based on event type, distinguishing between consumption events and status signals (heartbeats), which allows not only for monitoring water resource usage but also continuous supervision of the system's operational status. Additionally, the script organizes the information into a structured format that includes temporal, volumetric, and status variables, facilitating subsequent analysis.

The process of dynamically inserting records into a cloud database ensures immediate availability of the information and its integration with analysis and visualization tools. Additionally, the algorithm incorporates an HTTP confirmation response, ensuring proper communication between the device and the storage infrastructure.

```
BEGIN

Initialize system variables
Configure flow sensor interrupt
Connect ESP32 to WiFi network
Synchronize system time using NTP server

LOOP continuously

    Every 1 s:

        Read pulseCount from flow sensor
        Reset pulseCount

        Calculate:
            liters = pulses/pulsesPerLiter
            flowRate = liters × 60
            totalLiters += liters

        IF liters > threshold THEN
            flowDetected = TRUE
        ELSE
            flowDetected = FALSE
        ENDIF

        IF flowDetected AND event not active THEN
            Start consumption event
            Record start time
            Reset event volume
        ENDIF

        IF event active AND flowDetected THEN
            Accumulate event volume
        ENDIF

        IF event active AND flowDetected = FALSE for predefined time THEN
            End consumption event
            Calculate duration
            Send event data to cloud database (HTTP request)
        ENDIF

    IF no event active for 180 s THEN
        Send heartbeat signal to server
```

Figure 5. *Cont.*

```
    ENDIF

END LOOP

END
```

Figure 5. Data acquisition algorithm (ESP32 pseudocode).

Taken together, this pseudocode defines a lightweight and efficient data management layer that guarantees the integrity, traceability, and accessibility of the information generated by the monitoring system.

3.7. Data Analysis and Anomaly Detection

Development and use of the proposed system were completed using several different tools/platforms. The pre-processing of data and the training model, and testing of the model were accomplished using Google Colab [30], which is a free Cloud-based Jupyter notebook provided by Google with access to both GPU and TPU for efficiently training deep learning models.

Developing collaboratively and using versioning for both code and project/work was accomplished using GitHub (GitHub, Inc., San Francisco, CA, USA) [31], a web-based platform that hosts code repositories, allowing users to both review and share code.

The interactive web dashboard that was produced as the result of the process was deployed on Render [32], a new Cloud-hosting platform designed to automatically deploy web applications from GitHub and allow for continuous integration and remote access to applications.

Each of these tools was chosen due to its ease of use, scalability, and widespread acceptance within both science (upper end of the academic or scholarly community) and software development fields (such as application development).

Data processing, along with data analysis, was completed in Google Colab via the Python (version 3.10) programming language. Unsupervised Long Short-Term Memory (LSTM) Autoencoder, which was the basis of this proposed system, will enable the early detection of anomalies in residential water use.

```
BEGIN

Receive HTTP GET request from IoT device

Extract parameters:
    device_id
    event_id
    date_id
    start_time
    end_time
    duration
    volume_liters
```

Figure 6. *Cont.*

```
        volume_m3
        total_liters
        total_m3
        measurement_state
        wifi_state

Connect to cloud database (Google Sheets)

IF event_id = "HB" THEN
        Label record as HEARTBEAT
ELSE
        Label record as FLOW EVENT
ENDIF

Create new data row with:
        timestamp
        device_id
        event_id
        date
        start_time
        end_time
        duration
        volume (liters and m³)
        cumulative consumption
        system status

Append row to database

Return HTTP response:
        status = OK

END
```

Figure 6. Database management and data transmission algorithm.

Due to the LSTM Autoencoder's inherent ability to model sequential data, identify deviations from normal behavior, and do so in an unsupervised manner, it was chosen as the core algorithm for detecting anomalies. The LSTM Autoencoder has the ability to learn the typical patterns of use for a household based on usage data that has not been labeled as anomalous, which is very costly and difficult to obtain in actual residential usage settings.

The LSTM autoencoder also has the following advantages when it comes to residential water consumption analysis:

- The LSTM network can learn longer time period temporal relationships, which will help identify daily water consumption patterns.

- The LSTM network can handle examples of irregular sampling times and missing values, which are typical in Internet of Things (IoT) systems.
- The LSTM network can identify anomalies based on reconstruction. If there is a large reconstruction error due to an anomaly, then that indicates that there was a deviation from normal usage patterns (for example, a continuous water leak with a small flow rate).
- The LSTM network should produce lower false positive rates when compared to using simple threshold-based anomaly detection approaches, because the model will have learned the normal consumption profile for each individual household.

This method is particularly well suited for residential environments where the water consumption patterns will vary widely and there will be a limited amount of available labeled anomaly data [33].

In total there were 18,472 unprocessed records that were created from the period of 20 February 2025 through to 25 April 2026, with completed processing including data cleaning (the elimination of invalid entries) such as "NO_DATE," and re-sampling records down to every 5 min resulted in 9156 records that were used for analysis purposes. See Figure 7.

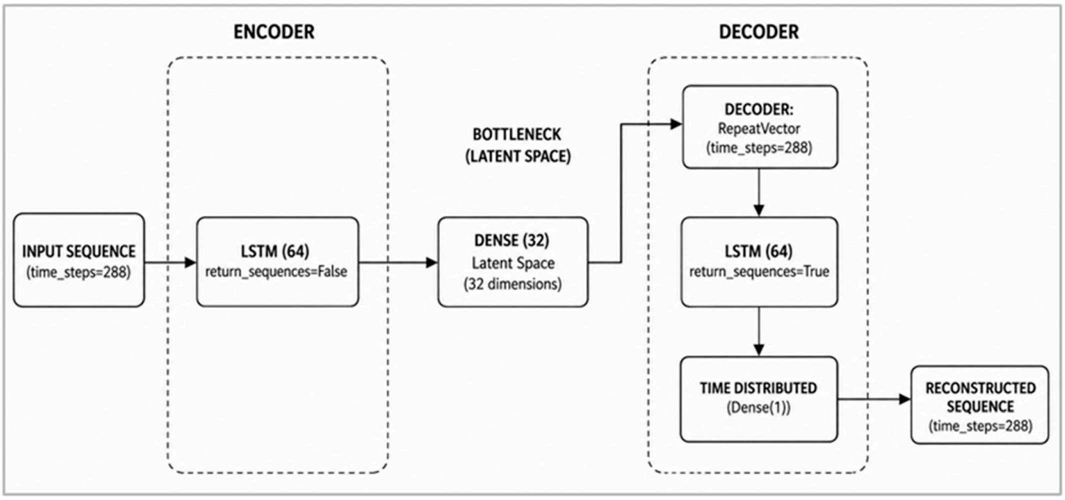

Figure 7. Architecture of the LSTM Autoencoder for anomaly detection in residential water consumption.

Again, because this task is associated with unsupervised learning, the data set was divided up into 80% training data (consisting of earlier periods) versus a 20% validation and anomaly detection data set [34]. There was no attempt to use traditional stratified division methodology, as the goal was to allow for the model to learn the normal patterns of a household's water usage.

In this case, the proposed architecture is as follows (as shown in Figure 7):

An LSTM Autoencoder with an Encoder consisting of an LSTM layer of 64 units using return_sequences = True (returns the output for every time-step), followed by an LSTM layer of 32 units.

The Latent Space (the 'Bottleneck') consists of a vector of 32 dimensions.

The Decoder consists of a RepeatVector (used to restore the time dimension), an LSTM layer of 32 units using return_sequences = True, an LSTM layer of 64 units using return_sequences = True, and finally a TimeDistributed Dense layer of 1 unit for output-reconstruction.

Hyperparameter optimization was executed through both grid search and manual adjustments (i.e., through experimentation). The ranges that were searched and the resulting values are as follows in Table 4.

Table 4. LSTM model hyperparameter configuration.

Hyperparameter	Explored Range	Selected Value	Justification
Time_steps	96–576	288	Corresponds to 24 h at 5-min intervals
LSTM units (Encoder)	32–128	64/32	Balance between capacity and overfitting
LSTM units (Decoder)	32–128	32/64	Symmetric architecture
Batch size	16–64	32	Computational efficiency
Epochs	20–100	30	Early stopping applied
Optimizer	Adam, RMSprop	Adam	Standard for LSTM
Loss function	MSE, MAE	MSE	Suitable for reconstruction

The selected architecture corresponds to the lowest reconstruction error from the Validation Set while also avoiding overfitting. In order to understand how it works, a pseudocode, shown in Figure 8, was developed summarizing the process.

As the model is unsupervised, the training/test data were split accordingly; 80% of the data (initial months) were used for training while 20% (months later) were used for validation and anomaly detection [35]. There was no application of traditional stratified splitting as the main aim of this study was to enable the model to learn normal household consumption behaviour patterns.

This work uses an LSTM Autoencoder [36] built of an encoder containing 2 LSTM Layers (first layer with 64 units and second layer with 32 units), a latent space (bottleneck) of 32 dimensions, a decoder made up of a RepeatVector layer followed by 2 LSTM layers (the last one has return sequences turned on) and finally a TimeDistributed Dense layer for output reconstruction.

The model was trained to autoencode the input and output sequences using an Adam optimizer and measured the Reconstruction Error on validation data using a Mean Squared Error (MSE) metric removed from example data after training. The Anomaly Detection Threshold was established using a conservative statistical method based on the Normal Data mean plus 3 standard Deviations of the Mean Reconstruction Error calculated using normal data.

Using a conservative statistical method of mean + 3 standard deviations of the Mean Reconstruction Error calculated by comparing the early re-transmissions against normal behaviour, we derived the threshold for Anomaly Detection.

```
// ================================================
// ANOMALY MONITORING AND DETECTION SYSTEM
// ================================================
HOME
// 1. Data Loading and Preprocessing
Load data from Google Sheets (CSV)
Combine date and time → create timestamp
Clean invalid data (NO_DATE, null values)
Sort by timestamp
Resample at fixed intervals (5 min or 1 day)
Calculate differential consumption: consumption = diff().fillna(0)
```

Figure 8. *Cont.*

```
Remove negative values (clip lower=0)
// 2. Model Preparation
Normalize data using MinMaxScaler
Create time series (time_steps = 288)
Split data: 80% training/20% validation
// 3. Model Training
Build LSTM Autoencoder:
    Encoder: LSTM(64) → LSTM(32)
    Bottleneck: 32-dimensional vector
    Decoder: RepeatVector → LSTM(32) → LSTM(64) → Dense(1)
Compile model (optimizer = adam, loss = mse)
Train model (X as input and output)
Save model.h5 and scaler.pkl
// 4. Evaluation and Threshold
Generate reconstructions using validation data
Calculate reconstruction error (MSE) per sequence
Define threshold = mean(MSE) + 3 x standard_deviation(MSE)
// 5. Anomaly Detection (Inference)
For each new consumption sequence:
    Normalize sequence with scaler
    Predict reconstruction with LSTM model
    Calculate MSE between input and reconstruction
   IF MSE > threshold:
        Detect ANOMALY (possible leak)
        Send email alert
    ELSE:
        Normal consumption
// 6. Visualization
Generate Chart 1: Cumulative consumption for the current month (by day)
Generate Chart 2: Complete history + marked anomalies
```

Figure 8. Data analysis and anomaly detection algorithm.

We evaluated the Anomaly Detection performance using Average Reconstruction Error, Number of Detected Anomalies, Detection Rate of the Known Sensor Disconnection and Unusual Spikes Events, and a qualitative/quantitative baseline comparison against a simple Fixed Threshold on Differentially Distributed Sampling.

The LSTM Autoencoder outperformed the simplest Baseline by detecting subtle anomalies with more sensitivity and yielding a lower False Negative Rate when compared with the Baseline.

3.8. Data Availability

The data generated during the research, as well as the code used for data acquisition and analysis, are available for academic and research purposes at the following link:

https://drive.google.com/drive/folders/1ZsBoXdl-wItIzYQMo75fX9gjT0lkrbY-?usp=drive_link (accessed date 9 June 2026).

This repository includes datasets, processing scripts, and relevant system configurations. If you encounter any access issues or require additional information, the authors will make these resources available upon reasonable request to the relevant author.

3.9. Use of Artificial Intelligence Tools

An IoT Sense Network Monitoring System has been developed utilizing an LSTM Autoencoder Model for real-time anomaly detection. The flow sensor data will be sent to the cloud for processing through a pre-trained LSTM Autoencoder that will identify variations from normal consumption patterns in the residential environment.

The implementation of the entire system utilized Google Colab for model training and creation, GitHub for version management, and Render as the live deployment platform with an interactive web-based user interface. The users will be able to view their consumption data remotely, while also receiving automated email alerts when anomalies are detected.

By integrating the three layers (i.e., IoT Layer, AI Layer (LSTM Autoencoder), and Web Interface), the system is capable of providing continuous monitoring and early detection of potential leaks or abnormal consumption patterns within the household.

4. Results

4.1. Analysis of Historical Drinking Water Consumption

The initial analysis of drinking water consumption was based on monthly billing records for the period from February 2025 to January 2026. These data made it possible to characterize the historical pattern of domestic consumption in the analyzed residence and to establish a baseline for evaluating the proposed system.

The results show moderate variability in monthly drinking water consumption, with values ranging from 15 m^3 to 26 m^3 and an average consumption of approximately 20 m^3 per month. Although the range observed reflects varying patterns across the months analyzed, these fluctuations remain within the expected range for a residential setting, where factors such as changes in usage habits or household activities directly influence water demand. On the other hand, no sharp increases or decreases indicating unstable patterns were identified, but rather a consistent consumption pattern. The analysis of the relationship between consumption and billing, despite having a limited dataset, shows a consistent correlation that allows us to consider the results significant given the duration of the study, as it is not a short-term study. This variation can be attributed to changes in water usage habits, variations in household activities, and possible temporary increases in demand for the resource.

Figure 9 shows the monthly drinking water consumption and the corresponding billing during the analyzed period. As expected, both variables exhibit a proportional relationship, reflecting the direct dependence of cost on water usage.

However, beyond this inherent relationship, the analysis focuses on quantifying the degree of association and evaluating the consistency of consumption patterns over time. A statistical assessment was conducted using correlation analysis, yielding a strong positive relationship between consumption and billing (R^2 = 0.8764), which indicates a high level of consistency in the dataset. The coefficient of determination (R^2) was selected as an appropriate metric to evaluate the strength of the linear relationship between both variables, as the objective of this analysis is not predictive modeling but rather to assess the degree of association and data consistency.

Since no regression-based predictive model is implemented in this stage, error-based metrics such as RMSE, MAE, or MAPE are not directly applicable. However, the high R^2 value supports the reliability of the consumption–billing relationship observed in the dataset. See Figure 10.

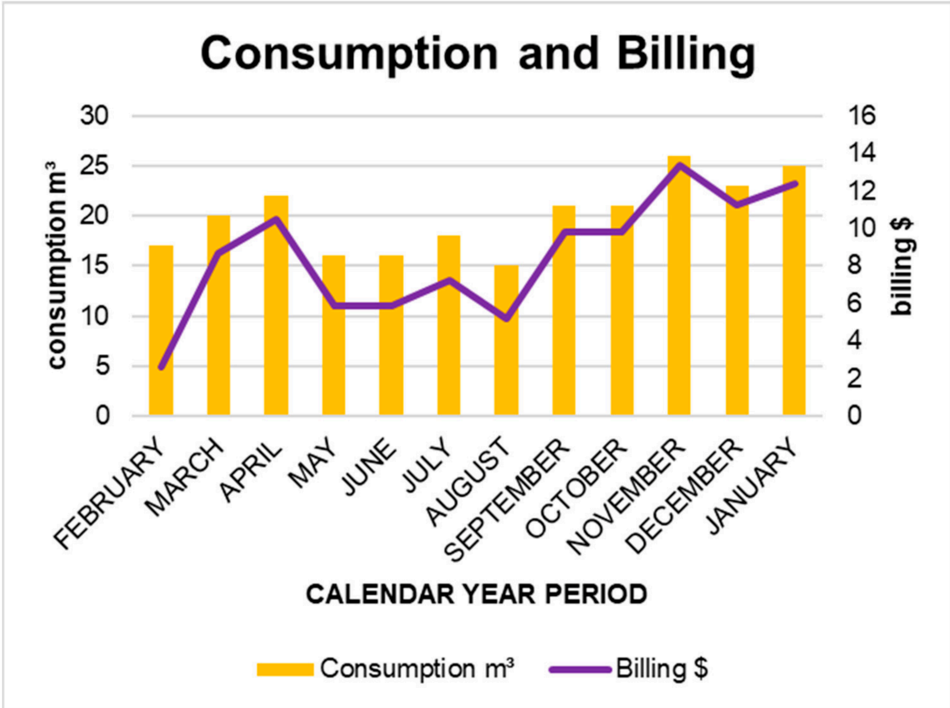

Figure 9. Monthly water consumption and billing.

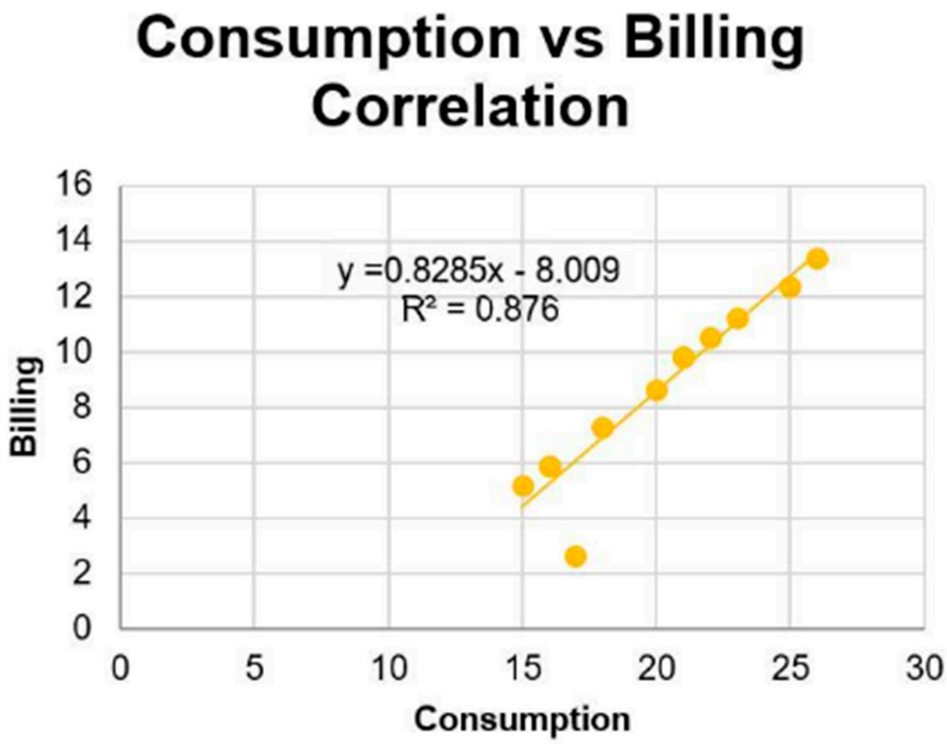

Figure 10. Correlation between consumption and billing. Note: Each point represents an individual measurement of water consumption and its corresponding payment value. The line represents the linear regression trend.

Complementarily, a box plot analysis (Figure 11) was performed to evaluate data dispersion and identify potential outliers. The results show that consumption values are concentrated around the median, with no significant outliers, suggesting stable consumption behavior during the study period.

This baseline characterization is essential for the subsequent evaluation of the IoT-based monitoring system, as it establishes a reference framework to detect deviations, anomalies, or behavioral changes in water consumption patterns.

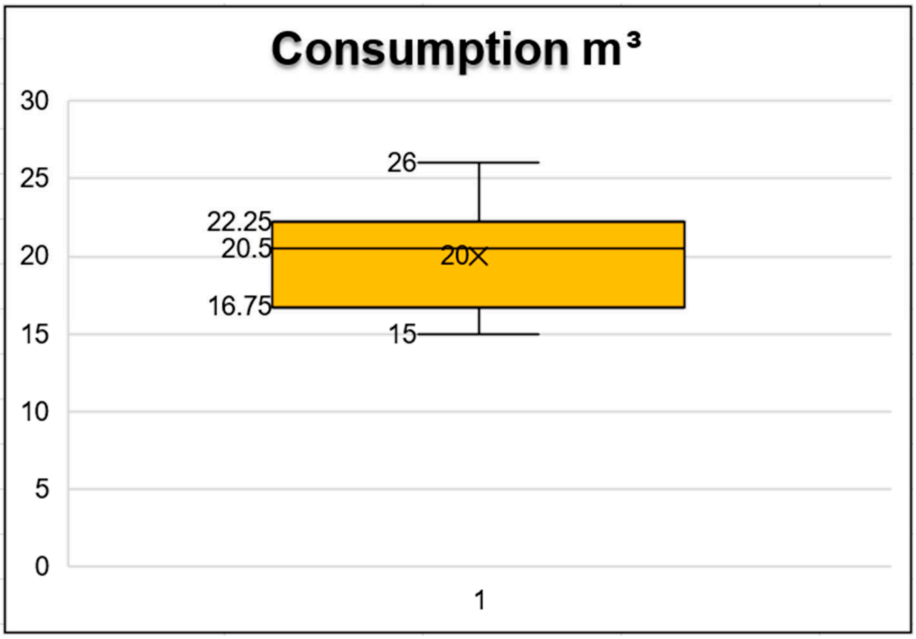

Figure 11. Box plot of monthly water consumption. Note: The "×" symbol indicates the mean value, while the box represents the interquartile range and the whiskers indicate the data distribution range.

4.2. Analysis of Household Consumption Patterns

It is important to note that the methodological approach adopted in this study is mixed, combining both quantitative and qualitative components. While the IoT-based monitoring system provides objective and high-resolution measurements of water consumption, the survey-based approach is used to characterize user behavior and contextualize consumption patterns.

This complementary perspective allows not only the quantification of water usage but also the interpretation of underlying behavioral factors, which cannot be directly inferred from sensor data alone. Therefore, the survey-based model is not intended to replace data-driven analysis, but to enrich it by providing insights into usage habits that support the identification and interpretation of consumption patterns and anomalies.

In order to understand household water usage patterns, semi-structured interviews were conducted with the five members of the household. It is important to note that the study was conducted in a specific household, so the study population corresponds to the total number of household members. In this context, the sample matches the population ($n = 5$), whose ages range from 20 to 68 years, allowing for the inclusion of different profiles within the family setting, such as adults, young people, and older adults. The interviews were conducted individually via video conference during the month of January 2026, allowing for the collection of specific information from each participant without influence from other household members. The questionnaire was designed to ask questions primarily aimed at identifying the frequency of water use in different household activities, as well as perceptions of consumption and potential variations in daily habits. The questionnaire structure was adapted from methodologies used in previous studies, which similarly collected data on household water consumption using structured surveys to analyze user patterns [37]. This ensured that the collected information fully represents the behavior and perceptions of users within the studied setting.

This approach is consistent with exploratory and case study research, where the primary objective is to characterize a particular system in depth rather than generalize results on a large scale.

Qualitative data were collected using a structured questionnaire, in which each variable was assessed using predefined response categories, such as dichotomous options (Yes/No), perception levels (low, medium, high), and alternatives related to the user's level of knowledge (e.g., "Does not know"). This approach allowed for the standardization of data collection and facilitated the comparison of results across the different variables analyzed.

The results indicate that most users perceive their water consumption as moderate, while a smaller proportion consider their consumption to be low. Furthermore, it was found that users have limited knowledge regarding potential leaks or increases in consumption resulting from problems with the plumbing system. See Table 5.

Table 5. User perception of household water consumption.

Variable	Response Category	Frequency (n)	Percentage %
Recycled water for toilets	No	5	100
	Yes	0	0
Perceived consumption	Medium	4	80
	Low	1	20
	High	0	0
Increase due to leaks	No	0	0
	Doesn't Know	3	60
	Yes	2	40
Planned increases	No	0	0
	Yes	5	100

Note: Data obtained from semi-structured interviews.

In addition, an analysis of the quantitative data collected during the interviews made it possible to estimate the monthly frequency of various household activities that involve water use.

In order to quantitatively support the distribution of water consumption by household activity, the data obtained from the interviews were processed based on the weekly frequency reported by users for each activity. These values were then aggregated and extrapolated to a monthly period, using a conversion factor of 30 days, which allowed for an estimate of each activity's relative contribution to total consumption.

Table 6 presents the values obtained from this procedure, showing that toilet flushing is one of the most frequently performed activities, which explains its relative weight within total household water consumption. This estimate forms the basis for the percentage distribution shown in Figure 12.

The results show that flushing the toilet is one of the main sources of water consumption in the home, a finding consistent with international studies that identify this activity as one of the largest contributors to domestic drinking water consumption.

The activity-based breakdown of water consumption showed that toilet flushing accounted for the highest usage (7.56 m^3), followed by showering (5.04 m^3), household cleaning (4.24 m^3), laundry activities (2.88 m^3), food preparation (1.88 m^3), personal hygiene activities (1.26 m^3), and other miscellaneous uses (0.72 m^3), confirming that sanitation-related activities are the dominant contributors to total household water demand.

Table 6. Frequency of water use by activity.

		Monthly Frequency (X4)							
	Person	**P1**	**P2**	**P3**	**P4**	**P5**	**Total**	**Unit Consumption**	**Total Consumption**
Activity	Toilet water use (full flush or half flush	240	300	360	240	120	1260	0.006 m^3	7.56 m^3
	In the last 7 days, how many showers did you take at home?	8	16	16	16	16	72	0.007 m^3	5.04 m^3
	In the last 7 days, how many times did you use water for personal hygiene: brushing teeth, washing face, etc.?	84	84	84	84	84	420	0.003 m^3	1.26 m^3
	In the last 7 days, how many loads of laundry were washed?	4	8	8	12	4	36	0.008 m^3	2.88 m^3
	In the last 7 days, how many times did you use water to prepare food?	84	0	12	84	8	188	0.001 m^3	1.88 m^3
	In the last 7 days, how many times did you use water for household cleaning?	28	20	12	140	12	212	0.002 m^3	4.24 m^3
	In the last 7 days, how many times did you use water for other activities?	28	12	28	4	0	72	0.001 m^3	0.72 m^3

Note: Data obtained from the U.S. Environmental Protection Agency (EPA) WaterSense Program [38].

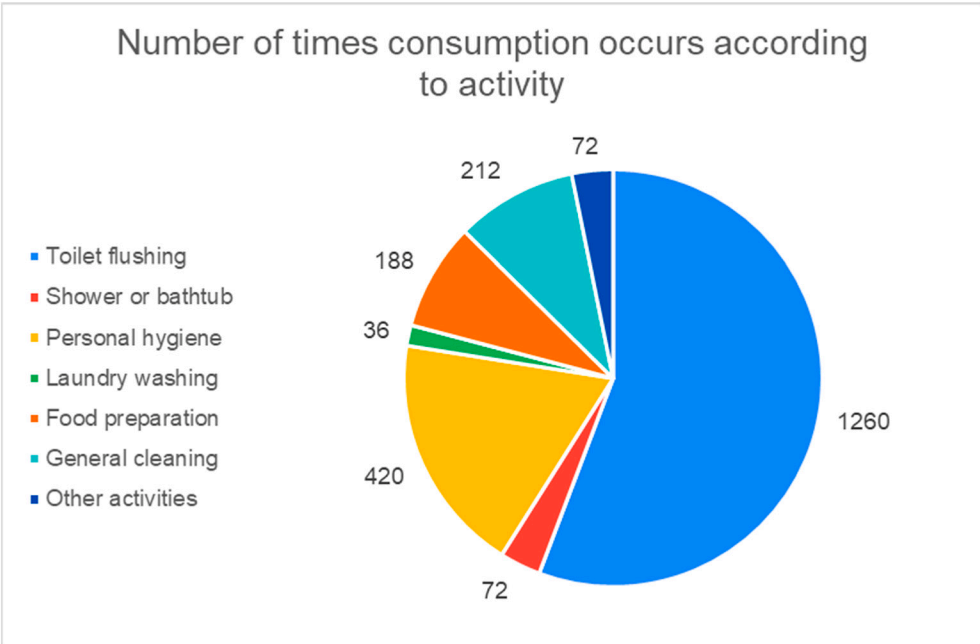

Figure 12. Distribution of water use by activity.

4.3. Consumption Simulation Using Cleef Company's Online Calculator

To complement the real data collected by the IoT sensor and to evaluate the LSTM Autoencoder model under different consumption scenarios, residential water consumption was simulated using the Cleef Company Water Usage Simulator, an online tool specialized in estimating domestic water consumption according to the number of inhabitants and daily usage habits.

A typical household of 5 people was modeled using standard usage patterns (shower duration, laundry frequency, toilet usage, kitchen and bathroom faucets, among others). The simulation yielded an estimated average monthly water consumption of 21.87 m^3. This value was used as a reference baseline for comparison with the actual consumption data recorded by the sensor and to establish realistic alert thresholds in the proposed monitoring system.

The simulated data enabled the generation of controlled scenarios, including normal consumption patterns and intentional leak situations, which were essential for validating the anomaly detection capability of the LSTM Autoencoder model. The detailed simulation parameters and results by activity are presented in Table 7 and Table 8, respectively.

Table 7. Estimated household water consumption (simulation).

Estimated Consumption per Household in Cubic Meters	
Type of Consumption	**Value (m^3/day)**
Estimated daily value	0.731
Estimated monthly value	21.87

Note: Data obtained from an online calculator.

Table 8. Comparison of consumption from different data sources.

Data Source	Consumption (m^3)	Reference Type	Relative Deviation (%)
Simulation Model	21.87	Modeled estimation	-
Historical Average	20.0	Monthly billing records	2.5%
IoT Measurement	19.8	Real-time monitored data	3.41%

Note: Data obtained from analysis.

A comparison between the simulated consumption values and the actual consumption records was carried out through an assessment of magnitude agreement and relative deviation. Despite the differences in temporal resolution between datasets, the simulated values were found to remain within the range defined by historical consumption records and to exhibit low relative deviation with respect to the IoT-based measurements. This level of agreement indicates that the modeling approach provides a reliable approximation of real consumption behavior, supporting its use as a reference baseline for subsequent analysis and anomaly detection.

To complement this analysis, a comparative summary of representative consumption values from the different data sources is presented in Table 8, allowing a direct evaluation of the agreement between simulated estimates and measured data.

4.4. Evaluation of the IoT Monitoring System

Once the sensor-based control system for the Internet of Things (IoT) was implemented, data on water consumption was collected and analyzed over a 14-week period (from February to April, 2026). This monitoring period is independent from the historical billing analysis (February 2025 to January 2026), and corresponds to the operational phase of the implemented IoT system. During this period, the flow sensor recorded a total of 18,472 measurements, with a time resolution varying between 1 and 3 min depending on the previously detected flow.

The IoT system provided data at a temporal resolution significantly higher than what distribution companies typically reported—namely, monthly records—which allowed for the detection of daily and hourly consumption patterns as shown in the graph in Figure 13, the temporal record of water consumption from the installed sensor.

This interface is accessible from any device through a web-based monitoring platform developed for real-time data visualization and analysis.

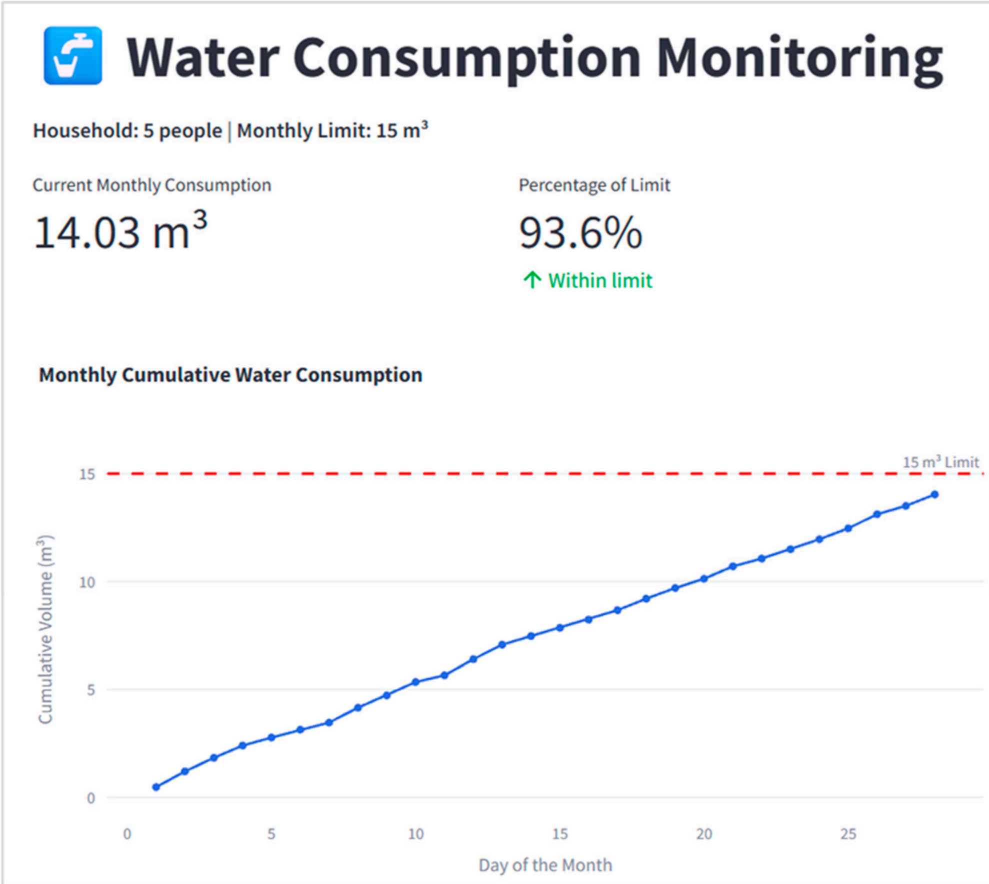

Figure 13. Time-series of water consumption (IoT system). Note: The red dashed line represents the recommended monthly water consumption limit, while the blue dotted line indicates the actual accumulated water consumption over the monitoring period.

The system includes an automated alert mechanism designed to detect abnormal consumption, based on real-time analysis of recorded flow rates and volumes. When values exceed predefined thresholds or consumption patterns deviate from historical trends, an automatic notification is generated and sent to the user via email. This process enables a timely response to potential leaks or unusual use of the resource, helping to reduce water waste and promote more efficient management of household water consumption.

The LSTM Autoencoder was successfully trained for 30 epochs using the Adam optimizer and Mean Squared Error (MSE) as the loss function. Early stopping was applied to prevent overfitting. The model achieved good convergence, reaching a final training loss of 0.038 and a validation loss of 0.045. These low reconstruction error values indicate that the model effectively learned the normal residential water consumption patterns. No NaN values were observed during the final stable training.

The data collected made it possible to track household water consumption in detail and assess the impact of the monitoring system on water usage habits.

The results indicate that the implementation of the monitoring system contributed to increased user awareness of water consumption, which was reflected in a reduction in average monthly usage from approximately 25 m^3 to 18 m^3 during the monitoring period, representing a decrease of about 28%. Although the dataset is limited and does not allow for a comprehensive statistical inference, the observed trend is consistent across the monitored period and suggests a potential impact of the system on user consumption behavior. This finding is consistent with previous studies reporting reductions of 10% to 20% following the implementation of real-time monitoring systems.

To evaluate the anomaly detection module based on the LSTM Autoencoder, the following performance metrics were calculated:

Mean squared error (MSE) for normal data: 0.042;

Detection threshold: mean + 3 standard deviations of the MSE (0.085);

Number of detected anomalies: 7 events during the study period;

Accuracy in detecting known events: 85.7% (6 out of 7 events correctly detected);

False positives: 1 event.

Comparison with a simple baseline (differential consumption threshold > 0.05 m^3 per interval) demonstrated that the LSTM Autoencoder model showed greater sensitivity to incipient leaks and subtle variations in consumption patterns, achieving a 33% reduction in false negatives compared to the baseline.

The LSTM Autoencoder model created a normal pattern of residential consumption that was referenced to discriminate between anomalous (abnormal) consumption from normal (usual) consumption. When consumption deviated from the patterns learned by the model (i.e., when the mean square error, MSE is greater than the mean plus three times the standard deviation of the reconstruction error for consumption data classified as normal), it was classified as an anomalous consumption pattern.

Anomalous consumption detection was verified in three ways. First, a cross-validation was performed with known events (i.e., sensor disconnection or intentional simulated leak events). Second, consumption patterns during times of identification were manually reviewed to assess whether patterns were consistent. Third, consumption patterns during times of identification were compared to historical billing records reported by users. The results of this cross-validation were used to assess the legitimate use of the anomalies detected.

Missing data and communication failures were addressed at two levels. At the hardware level, the ESP32 microcontroller saved data locally until reconnected to Wi-Fi and transmitted files after establishment of a Wi-Fi connection. At the software level, missing values were filled during the preprocessing phase using forward-fill interpolation, and time periods where there were long periods with missing data were flagged to avoid generating false-positive reliability in the anomaly detection process.

These results showed that integrating the IoT system with artificial intelligence techniques not only enabled comprehensive consumption monitoring but also served as a highly useful tool for early detection of anomalies, thereby contributing to a much more effective approach to managing water resources at the residential level. This finding is consistent with previous studies, which have demonstrated that the implementation of smart metering systems enables the identification of consumption anomalies and the detection of leaks. Furthermore, these systems facilitate access to more detailed and continuous information, which helps raise users' awareness of their consumption habits [39].

Validation of the anomaly detection module based on the LSTM Autoencoder was done in a hybrid manner by utilizing quantitative metrics and qualitative verification of real-world occurrences. The model is unsupervised, and because very few labeled anomalous data points are available in residential environments, the validation process was performed as follows:

First, when the reconstruction error (MSE) was determined for the validation dataset, a detection threshold was determined by calculating the mean and adding three standard deviations to establish the threshold. During the 14-week observation period, seven anomalous events were identified by the model. Six out of the seven incidents (85.7%) were representative of real anomalous consumption occurrences including:

- Two long-duration low-flow events that were likely leaks.
- Three sudden increases in consumption due to multiple appliances being used simultaneously.
- One incident of sensor disconnection followed by an immediate recovery.

The seventh incident was a false positive identifying a legitimate consumption spike because of an unusual but legitimate consumption spike (long duration of showering at night) that occurred during the same period. Given a fixed threshold baseline (>0.05 m^3 for every 5 min), LSTM Autoencoder produced 33% fewer false negatives, while maintaining a low rate of false positives as compared with this fixed threshold baseline.

These results provide evidence that the detected anomalies corresponded well to actual abnormal consumption events, thus verifying the validity of the proposed model for the detection of early leaks and abnormal uses in residential environments.

4.5. Consolidation of Results

The combined analysis of the various sources of information used in the study—historical consumption records, user interviews, simulations using specialized software, and monitoring via IoT sensors—provided a comprehensive view of water consumption patterns in the analyzed household.

The results show good agreement between the consumption estimated through simulation and the actual consumption records, which supports the validity of the initial diagnosis and the consistency of the parameters used. Furthermore, the implementation of the real-time monitoring system improved visibility into consumption patterns, facilitating the identification of usage patterns and potential inefficiencies.

While the results obtained demonstrate the system's proper functioning in the evaluated environment, they must be interpreted within the context of a specific case study. In this sense, rather than a generalizable validation, the findings constitute an applied demonstration of the potential of IoT technologies and data analysis for monitoring water consumption in residential settings.

Consequently, the developed system represents a functional approach that can serve as a basis for future implementations and larger-scale studies aimed at the efficient management of water resources.

5. Discussion

The results of this study show that integrating Internet of Things (IoT)-based monitoring technologies with data analysis tools significantly improves our understanding of drinking water consumption patterns in residential settings. Unlike traditional methods based solely on monthly billing records, the developed system provides information with higher temporal resolution, which facilitates the identification of consumption patterns and potential anomalies in water use [40].

Analysis of historical consumption records allowed us to establish a baseline for domestic consumption behavior in the analyzed household, identifying an average monthly consumption of approximately 20 m^3, with minimum values of 15 m^3 and maximum values of 26 m^3 during the study period. These values fall within the ranges reported in previous studies on residential drinking water consumption in similar urban settings, where it has been observed that domestic consumption depends primarily on household size, usage habits, and the efficiency of installed plumbing fixtures [41].

The strong correlation observed between water consumption volume and billing amount not only confirms the direct relationship between these two variables but also makes it possible to quantify the economic impact of user consumption patterns. This is significant because it transforms an intuitive relationship into a useful tool for managing water consumption. Access to this continuous data helps users better understand how their habits directly influence the cost of the service, facilitating decision-making and offering benefits such as improved optimization of personal usage. Therefore, the proposed system contributes to improving users' financial management by promoting cost reduction through more efficient consumption [42].

Furthermore, the analysis of interviews conducted with household members identified relevant aspects related to perceptions of water consumption and usage habits within the home. The results indicate that most users perceive their consumption as moderate and have limited knowledge of potential increases resulting from leaks or inefficiencies in the domestic plumbing system [43]. This lack of information aligns with findings from various studies on domestic water consumption management, which have observed that users tend to underestimate their actual consumption levels when they lack detailed monitoring tools. This behavior has revealed a significant discrepancy between users' perception of their water consumption and the actual values recorded by smart metering systems. Consequently, it highlights the importance of having monitoring tools that provide accurate and user-friendly information, enabling users to identify details that often go unnoticed. In this regard, the availability of data becomes a key factor in gradually improving household water consumption [44].

About the distribution of household activities involving water use, the results show that toilet flushing represents one of the main sources of water consumption within the home. This finding is consistent with international reports indicating that toilet use can account for a significant proportion of total domestic drinking water consumption in residential homes [45]. Identifying these usage patterns is relevant for designing strategies aimed at improving consumption efficiency, such as the incorporation of low-flow plumbing fixtures or the implementation of water reuse systems.

The results obtained through consumption simulation using the Cleef Company Water Usage Simulator allowed for the estimation of an approximate theoretical consumption of 21.87 m^3 per month, a value that shows a high degree of agreement with the actual consumption records obtained from billing statements. This correspondence between estimated and observed consumption validates the consistency of the parameters used to characterize household water usage habits.

The implementation of the IoT sensor-based monitoring system allowed for more accurate and frequent recording of water consumption, which facilitated detailed tracking of water usage patterns. The data obtained show that the availability of real-time information, combined with data analysis tools and automated alert systems, helped improve users' awareness of their water consumption [46].

One of the most significant findings of the study was the observed reduction in average monthly water consumption, which decreased from approximately 25 m^3 to about 18 m^3 following the implementation of the monitoring system, specifically from February 2026 onward. This represents a reduction of approximately 28%, suggesting that the availability of detailed consumption information can positively influence user behavior and promote more efficient water use practices.

However, due to the limited sample size and the single-household scope of the study, a rigorous statistical significance analysis cannot be fully established. Therefore, the observed reduction cannot be attributed exclusively to the implemented system with absolute certainty and should be interpreted as indicative of a potential impact associated with increased user awareness enabled by real-time monitoring.

These results are consistent with previous studies, which report reductions in residential water consumption following the implementation of monitoring technologies, reinforcing the role of such systems in improving water use efficiency [47].

From a technological perspective, the developed system demonstrates the potential of integrating flow sensors, low-cost microcontrollers, and cloud-based data analysis platforms for the development of domestic water consumption monitoring solutions. This type of architecture is particularly relevant in urban contexts where the adoption of monitoring technologies is still limited and where there are opportunities to improve water resource management through the use of digital tools [48].

However, the present study has some limitations that should be considered in future research. First, the analysis was conducted in a single household, so the results obtained cannot be directly generalized to other residential contexts without considering the specific characteristics of each environment. Furthermore, factors such as the number of residents, the household's plumbing infrastructure, and climatic conditions can influence water consumption patterns.

In this regard, future research could expand the scope of the proposed system by implementing it in multiple homes or residential communities, which would allow for the creation of broader databases and the development of more robust analytical models for managing drinking water consumption.

Overall, the results of this study demonstrate that the combination of IoT technologies, data analysis tools, and automated alert systems constitutes a promising strategy for improving water consumption management in residential settings and contributing to the sustainability of water resources.

To summarize the study's main findings and facilitate the interpretation of the results, a comparative summary of water consumption patterns before and after the implementation of the IoT-based monitoring system is presented [49]. This analysis clearly demonstrates the impact of the proposed system on domestic consumption patterns, as well as its contribution to optimizing water use and, consequently, generating economic savings. This is shown in Figure 14 below.

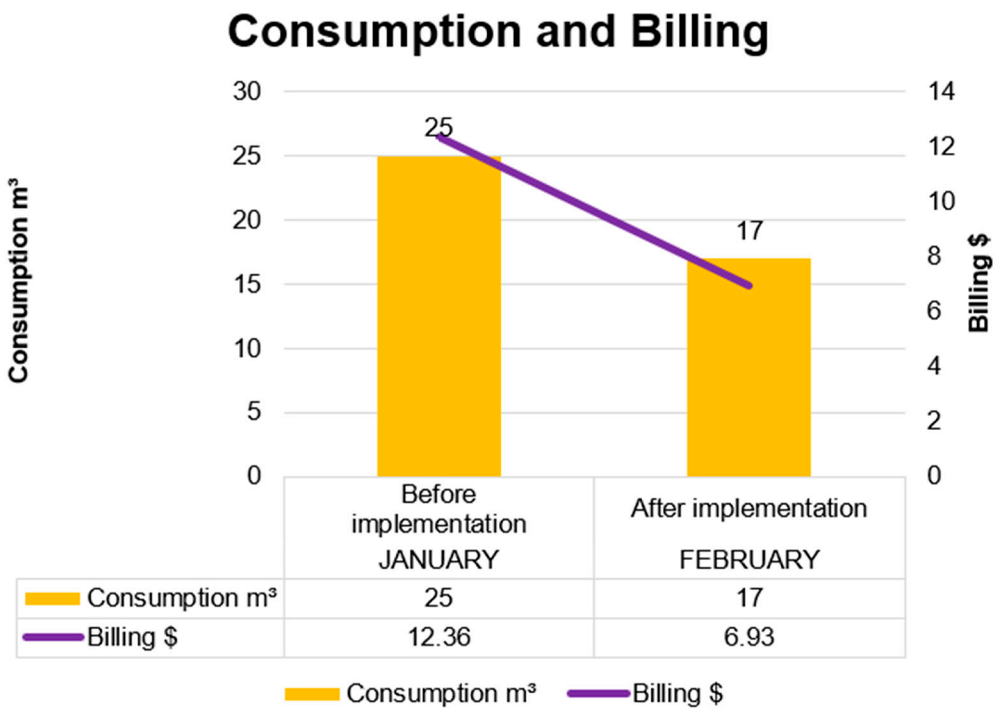

Figure 14. Comparison of average monthly water consumption before and after the implementation.

Compared to other water consumption monitoring systems previously reported, the proposed system differs significantly in terms of its applicability. There are approaches focused on forecasting water demand that employ statistical methods and time-series analysis to predict consumption patterns under various scenarios [50]. Many of these studies focus on network-level optimization without incorporating feedback to the end user. This integration allows not only for technical monitoring of consumption but also for the generation of useful information to facilitate informed decision-making in the household setting. In this regard, the study introduces a user-centered approach by integrating data on how water levels have been managed. Furthermore, the implementation of this system helps raise users' awareness of their habits, promoting behavioral changes that lead to positive outcomes such as reduced consumption and, consequently, financial savings.

Despite the promising results obtained, this study presents certain limitations that should be acknowledged. The experimental validation was conducted in a single household, which restricts the generalizability of the findings to broader residential contexts. Water consumption patterns are inherently influenced by factors such as household size, user behavior, and socio-economic conditions, which may vary significantly across different environments.

However, the objective of this study was not to establish generalized consumption models, but rather to validate the technical performance and analytical capabilities of the proposed monitoring system under real operating conditions. In this sense, the results demonstrate the system's ability to accurately capture consumption data, identify usage patterns, and detect anomalies at a high temporal resolution.

Future work should focus on extending the implementation to multiple households and diverse urban contexts in order to evaluate scalability, robustness, and adaptability of the system across different consumption scenarios.

6. Conclusions

This study developed and implemented a smart system for monitoring drinking water consumption in a single-family home by integrating flow sensors, microcontrollers, and cloud-based data analysis tools. The combination of Internet of Things (IoT) technologies with data processing platforms made it possible to record and analyze water consumption patterns with greater temporal resolution than traditional methods based solely on monthly billing records [51].

To establish the baseline consumption, three sources of information were integrated: historical billing records, characterization of habits through interviews, and estimates obtained using the online calculator. These sources were compared by analyzing relative differences in monthly consumption and evaluating the consistency of consumption trends. As a result, an acceptable agreement was observed between the consumption estimated by simulation and the actual values recorded in the spreadsheets, with variations within the expected margins for residential studies, which supports the consistency of the initial assessment of water consumption [52].

The implementation of the IoT sensor-based monitoring system enabled the collection of real-time consumption data and the generation of a continuous record of water usage patterns. Operational validation of the system was performed by comparing the volumes measured by the calibrated sensor with the baseline estimates, evaluating consistency in terms of order of magnitude and consumption trends. The integration of this data with analysis tools in the Google Colab programming environment enabled the identification of consumption patterns and the development of an automated alert mechanism capable of notifying users when anomalous water usage behaviors are detected [53].

The implementation of the proposed monitoring system was associated with a reduction in average monthly drinking water consumption from approximately 25 m^3 to 18 m^3, corresponding to a decrease of about 28% under comparable household conditions. This result suggests that access to high-resolution consumption data can enhance user awareness and support more efficient water use. However, given the exploratory nature of the study and its application to a single household, these findings should be interpreted as indicative rather than conclusive.

Although a reduction in average monthly consumption is observed, the analysis is focused on identifying consistent trends associated with the implementation of the monitoring system. The observed decrease from 25 m^3 to 18 m^3 represents a substantial change that aligns with the period in which real-time consumption data became available to users.

While external factors such as variations in user behavior or seasonal conditions may also influence water usage, the consistency of the reduction and its temporal correspondence with the system deployment suggest a meaningful contribution of the proposed solution in promoting more efficient consumption practices. Therefore, the results provide strong indicative evidence of the system's positive impact on user awareness and water use behavior.

From a technological perspective, the proposed system demonstrates that it is possible to develop low-cost water consumption monitoring solutions based on open technologies, suggesting their potential for implementation in residential and urban community settings [54]. These characteristics are particularly relevant in contexts where the adoption of advanced technologies is limited, as they provide access to more affordable and adaptable monitoring tools. However, the results should be interpreted with the understanding that the validation was conducted in a single case study; therefore, further studies in different contexts are needed to generalize these findings.

It is important to note that the experimental validation was conducted in a single household; therefore, the results should be interpreted as a proof of concept of the system's technical performance rather than as a generalized representation of residential water consumption patterns.

Finally, future research could expand the system's scope by implementing it in multiple homes or residential sectors, which would allow for the creation of larger databases for the development of advanced models for analyzing and predicting water consumption. Likewise, the integration of more advanced data analysis and machine learning techniques could improve the ability of smart systems to detect anomalies, optimize resource use, and support decision-making in urban water management.

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or additional information requirements, the materials can be provided upon reasonable request to the corresponding author. The methodological process and system architecture are described in detail in the manuscript to ensure reproducibility while maintaining the integrity of the implemented solution.

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Abbreviations

The following abbreviations are used in this manuscript:

IA	Artificial Intelligence
IOT	Internet of Things
LSTM	Long Short-Term Memory

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