



ORIGINAL RESEARCH ARTICLE

IOT-BASED CARBON FOOTPRINT MONITORING AND REDUCTION PLATFORM FOR URBAN HOMES

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ABSTRACT

Household energy needs should be governed according to the global warming challenge. However, current IoT solutions for measuring carbon footprint are usually costly, inaccurate or have no user-friendly feedback. The key objective of this study was the development of a new low-cost IoT system that tracks real-time electricity consumption and indoor CO₂ concentration to promote sustainable behaviour. A key design feature of the system is its modularity, with an ESP32 microcontroller at the heart of the system allowing easy integration of calibrated SGP30 gas sensor, energy sensors (ZMPT101B, ZMCT103C), and multi-channel communication. The new software solution used for this study was the CallMeBot API that transmits the data directly to WhatsApp, making it very user-friendly by removing the need to use a mobile app only for this purpose. The tests carried out demonstrated that the average error of the voltage sensor was 1.8%, the Wi-Fi data transmission success was 99.2%, and the SGP30 sensor had a successful dynamic baseline calibration, ensuring accuracy to within ±50 ppm of reference values in steady-state conditions. The experiments revealed the existence of energy consumption differences by a substantial margin: the LED bulb (8.7 W) consumed 92% less energy than the incandescent bulb (107.46 W) and the DC fan (7.5 W) 91% less than the traditional AC fan (82.0 W). The indoor CO₂ levels correlated with the occupancy and ventilation, from a base of approximately 400 ppm to over 1250 ppm in areas with no ventilation. This study demonstrated that a powerful open-source IoT platform can enable households to monitor and reduce their ecological footprint to save energy and improve the indoor environment.

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1.0 Introduction

Climate change is a global concern of the 21st century and is caused by anthropogenic greenhouse gas emissions (Ambafi et al., 2026; Olatomiwa et al., 2025). In a rapidly urbanizing world, domestic energy consumption accounts for a significant share of the global carbon dioxide (CO₂) emissions, particularly in those regions where electricity demand continues to grow with increasing population, appliance ownership and changing lifestyle. The International Energy Agency estimates that households account for 25 to 30 percent of energy-related carbon dioxide CO₂ emissions in cities, largely due to lighting, cooling and the use of electronic devices (Elhanashi et al., 2024; Raimi et al., 2024). This issue needs to be addressed with actionable tools to enable households to continuously monitor, interpret and optimise their energy use and associated emissions continuously at a fine-scale time and space resolution.

Internet of Things has become one of the enabling factors of intelligent energy management, allowing the implementation of low-cost, sensor-based systems that could employ real-time monitoring, data analytics, and

automated feedback (Hassan and Tawfeeq, 2023). Other researchers have examined IoT-based smart home systems to track the consumption of electricity, indoor air quality, or the environment (Katushabe *et al.*, 2023; Kusumaningrum and Syafdi, 2024; Lv *et al.*, 2022). However, these works have employed ESP32-based power monitoring and SGP30-based air quality sensing as separate modalities. Most importantly, none have integrated both sensing modes into a low-cost system that addresses both energy-related carbon emissions and occupancy-related indoor carbon dioxide (CO₂) levels, while also providing timely feedback via a widely accessible communication medium such as WhatsApp. This lack of integration is especially problematic in developing-world settings where cost, simplicity and real-time actionable information are crucial.

Although these studies demonstrated that IoT can improve energy awareness at the household level, their results are inconsistent regarding effectiveness, scalability, and user experience. The constantly increasing literature on the implementation of IoT-based smart home energy management and carbon emission reduction points to the fact that energy-saving behaviour may be promoted through the provision of real-time feedback and data visualisation (Ceylan and Özbakır, 2022; Chataut *et al.*, 2023; Fan and Fan, 2024; Gajdzik *et al.*, 2024). Most suggested systems are based on smart meters, voltage and current sensors, and cloud-based dashboards to enable users to know the consumption pattern and the appliances that consume more energy (Dhar, 2020; Yen *et al.*, 2020). Simultaneously, low-cost sensors to monitor carbon monoxide, carbon dioxide, particulate matter, temperature, and humidity have also been broadly applicable to indoor air quality and gas monitoring with the help of IoT technologies (Katushabe *et al.*, 2023; Mun and Cho, 2023). Despite a tendency to drive such measurements by the public health and safety concerns, a number of studies find that the indoor CO₂ concentration can provide a useful proxy to occupancy, ventilation quality, and human activity, which are tightly interconnected with residential energy use.

In spite of these advancements, a majority of the current systems consider the consumption of household electricity and indoor air quality separately, and therefore, cannot give a comprehensive analysis of the household carbon footprints. Decentralisation of energy monitoring to direct or proxy CO₂ sensors has seen little use especially in resource-constrained and developing-world settings. Moreover, a significant number of commercial smart meters and air-quality monitoring systems are still too expensive to be adopted on a large scale in such areas (Arya *et al.*, 2024). Integrated, affordable, and user-friendly platforms based on wireless communication (Wi-Fi, GSM/GPRS, Zigbee, Bluetooth), cloud and edge computing have enhanced the scalability of systems and the flexibility of deployment, but are not always exploited to provide carbon monitoring in households (Chawla *et al.*, 2023; Hashem *et al.*, 2023; Yusro *et al.*, 2022).

A number of longstanding limitations can be identified in the literature. The reliability and accuracy of sensors are considered critical concerns, especially with low-cost gas sensors that tend to drift, cross-sensitivity, and environmentally (when not carefully calibrated) (Dhar, 2020; Kusumaningrum and Syafdi, 2024; Piczon *et al.*, 2024). Lack of validation to reference quality instruments is a compromise to the reliability of long-term monitoring outcomes. There are also numerous studies that are reported, but also limited to short-term pilot deployments, sometimes as short as a few weeks or months, which prevents the evaluation of long-term system performance and long-term behavioural change (Dhar, 2020; Yusro *et al.*, 2022). Moreover, the majority of the studies use indirect carbon footprint estimates, which involves only electricity use, as they do not include direct or proxy measures of indoor CO₂ to occupancy-related emissions and ventilation behaviour (Yen *et al.*, 2020). Another critically important challenge is user engagement. Dashboards and mobile apps are widely used, but it has been proposed that passive visualisation is not as effective as it should be to promote long-term behavioural change without active and prompt, as well as personalised feedback (Arya *et al.*, 2024). Some of the studies indicated that there is low interaction on long-term basis because of complexity of the interface, information overload, or irrelevance to the daily lives of users (Yusro *et al.*, 2022). Recent studies hence demand a feedback system that is seamlessly incorporated into more common communication systems and one that is able to convert monitoring data into actual behavioural advice.

This study addresses these gaps by developing and evaluating an inexpensive integrated IoT-based platform that can be effective to track and minimise carbon footprints in households by collaboratively measuring electricity use and indoor air CO₂ levels and implement sensor calibration, field implementation, and real-time user feedback solutions. Overall, the potential of IoT-based monitoring is proven by the previous researches, but the current solutions can be described as disjointed, expensive, not validated enough, or lacking in their ability to engage the users. In the majority of studies, the consumption of electricity or the quality of indoor air are studied separately, with indirect estimation of emissions, without rigorous sensors calibration and long-term field validation, especially in developing areas. This leads to an evident research gap in the construction of a cost-effective, precise, and combined IoT infrastructure that will be able to check the household electricity usage and indoor CO₂ at the same time, confirm sensor workability in real-life settings, and serve users with

reachable and real-time feedback. Although ESP32 microcontrollers have been extensively used for power monitoring (Kusumaningrum and Syafdi, 2024; Hercog et al., 2023) and SGP30 sensor for indoor air quality monitoring (Katushabe et al., 2023; Mun and Cho, 2023), these have been used independently. No prior study has demonstrated the simultaneous deployment of both sensors within a unified, low-cost platform that leverages WhatsApp the most widely used messaging platform in many developing countries as an active feedback channel to drive behavioural change.

The novelty of this study lies in the integration of calibrated indoor CO₂ sensing with household electricity monitoring within a single low-cost system, accompanied by the incorporation of the active feedback channel in the form of instant WhatsApp-based notifications, through which the household energy-use behaviour can be directly impacted. The study's key contributions are the development and deployment of a low-cost integrated IoT system for simultaneous monitoring of energy and CO₂ emissions, the testing of the performance of low-cost sensors under real-world residential conditions, the use of a messaging-based feedback system that matches the typical modes of communication in developing countries, and the provision of empirical evidence for the effectiveness of real-time feedback in household energy savings and mitigation of CO₂ emissions. The objective of the study is to develop, install and assess a low-cost IoT-based household carbon monitoring system which measures both the electricity use and indoor CO₂ levels. The research also evaluated the performance and accuracy of the proposed low-cost sensors in real-life conditions, investigated the impact of real-time feedback delivered via WhatsApp on user energy saving behaviour, and determined the system's potential in helping householders save energy, carbon emissions and indoor air quality problems.

2. Materials and Method

The IoT-based household carbon footprint monitoring system architecture, mathematical models, signal-processing techniques, calibration procedures, uncertainty analysis, data-handling strategy, and security considerations is discussed in this section.

2.1 Overall System Architecture

The smart energy measurement system proposed by the authors, along with the monitoring of indoor CO₂ concentration, opens the door for real-time carbon footprint tracking of households. The architecture was structured upon a four-layer Internet of Things framework, which consists of the sensing, processing, communication, and application layers. The layered structure not only facilitates modularity but also promotes scalability and long-term reliability of the system. The sensing layer includes the measurement of electrical parameters through voltage and current sensors, along with the indoor CO₂ concentration monitored using an SGP30 sensor. The processing layer was carried out with an ESP32 microcontroller that performs the tasks of signal acquisition, filtering, mathematical computation, and data packing. The data was sent to a cloud server through the communication layer using Wi-Fi. The application layer offered data visualisation and user interface through dashboards and real-time notifications via WhatsApp. Figure 1 shows a system block diagram.

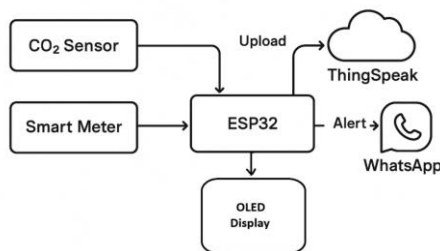


Figure 1: System architecture

2.2 Hardware Component and Sensing Layer

2.2.1 Electrical sensing and ADC interface

The ESP32 microcontroller board has 12-bit analogue to digital converter (ADC) that was used to measure the voltage (ZMPT101B) and current (ZMCT103C) sensors. The ADC uses a 3.3V reference voltage and converts the analogue signal to digital for estimating the electrical parameters.

2.2.2 Gas sensing (SGP30 sensor placement and operation)

The indoor CO₂ concentration was measured with a sensor SGP30 sensor housed in a flow chamber. The sensor measures equivalent carbon dioxide (eCO₂) with automatic baseline adjustment.

2.3 Electrical Parameter Measurement Models

Electrical parameters were estimated by mathematical models which translate the ADC samples into engineering units.

2.3.1 Raw signal acquisition and preprocessing

The instantaneous voltage signal from the ADC was converted to an analogue voltage using equations 1 and 2:

$$V_{raw}[n] = \left(ADC_{voltage}[n] \times \frac{V_{REF}}{ADC_{RESOLUTION}} \right) - V_{OFFSET} \quad 1$$

$$I_{raw}[n] = \left(ADC_{current}[n] \times \frac{V_{REF}}{ADC_{RESOLUTION}} \right) - I_{OFFSET} \quad 2$$

With n being the sample number, V_{REF} = 3.3V, and ADC_{RESOLUTION} = 4095. This converts the ADC value to a voltage, and "zeroes out" the DC offset (bias) to remove the DC component and centre the AC waveform.

2.3.2 RMS voltage and current estimation

The voltage and current RMS values were estimated over a four second measurement period with N samples. The RMS estimates are shown in equations 3 and equation 4.

$$V_{rms} = \sqrt{\frac{1}{N} \sum_{n=1}^N (V_{raw}[n])^2} \times K_V \quad 3$$

$$I_{rms} = \left(\sqrt{\frac{1}{N} \sum_{n=1}^N (I_{raw}[n])^2} \times K_I \right) - I_{offset_final} \quad 4$$

Where K_V and K_I are the voltage and current calibration constants, respectively.

2.3.3 Noise thresholding and no-load detection

For noise reduction and to avoid false detection when no load was connected, a threshold detection method with hysteresis was used. If the measured current drops below a certain percentage of the nominal current, both the voltage and power outputs were set to zero, thus suppressing meter creep. The equations for the current and voltage are given in equations 5 and equation 6 respectively.

$$V = \begin{cases} V_{rms}, & \text{if } V_{rms} > V_{THRESHOLD} \\ 0, & \text{otherwise} \end{cases} \quad 5$$

$$I = \begin{cases} I_{rms}, & \text{if } I_{rms} > I_{THRESHOLD} \\ 0, & \text{otherwise} \end{cases} \quad 6$$

2.3.4 Real power, apparent power, and power factor

The instantaneous power was the multiplication of instantaneous samples of voltage and current. Real (active) power was obtained by averaging instantaneous power over the sampling window. The real power is given by equation 7.

$$P = \frac{1}{N} \sum_{n=1}^N (V_{raw}[N] \times I_{raw}[n] \times K_V \times K_I) \quad 7$$

The apparent power s is given by $S = V_{rms} I_{rms}$.
And the power factor (PF) is given by equation 8

$$PF = \begin{cases} \frac{P}{S}, & S > 0 \\ 0, & S = 0 \end{cases}$$

8

This formulation ensures reliable power estimation for non-linear household loads.

2.4 Energy and Frequency Computation

2.4.1 Energy estimation

Electrical energy consumption is computed by numerically integrating power over time. The energy increment over each interval is given by equation 9.

$$E = P_{avg} \Delta t,$$

9

Where P_{avg} is the average real power and Δt is the elapsed time in hours since the previous update, cumulative energy is reported in kilowatt-hours (kWh).

2.4.2 Frequency measurement

The Frequency is measured by counting the number of times the voltage signal crosses a zero threshold (with hysteresis) within a dedicated 1-second window, as given by equation 10.

$$f = \frac{N_{crossings}}{2 \times T_{window}}$$

10

where $N_{crossings}$ is the number of zero-crossings detected in the measurement time window T_{window} .

2.5 Carbon Emission Estimation Model

2.5.1 CO₂ emissions from electricity consumption

Carbon dioxide emissions associated with electricity use were estimated using a grid emission factor as presented in equation 11.

$$CO_{2kg} = E_{session} \times F_{emission}$$

11

$$CO_{2tonnes} = \frac{CO_2}{1000}$$

where $F_{emission} = 0.21233 \text{ kg CO}_2/\text{kWh}$ is the grid emission factor.

2.5.2 Indoor CO₂ measurement

Indoor CO₂ concentration was measured using the SGP30 sensor, which provides equivalent CO₂ estimates based on internal baseline compensation. While not a reference-grade instrument, the sensor provides useful insights into occupancy and ventilation trends when properly deployed.

2.6 Sensor Calibration Methodology

The voltage calibration was done using a known AC reference voltage (230V RMS) and the voltage calibration constant was adjusted until the measured RMS voltage was equal to the reference voltage. Current calibration was performed by creating a known current using a known load resistor. A linear calibration model with an offset correction was used. A linear model was used to calibrate the measured RMS value, $X_{measured}$ to the actual RMS value X_{actual} using equation 12.

$$X_{actual} = m \times X_{measured} + c$$

12

In the code, this is implemented as:

$$V_{\text{actual}} = K_V \cdot V_{\text{rms}}$$

$$I_{\text{actual}} = K_I \cdot I_{\text{rms}} + c_I$$

where c_I is the final current offset = -0.17.

2.7 Measurement Uncertainty and Error Propagation

The uncertainty of the voltage and current measurement was mainly determined by the ADC nonlinearity, the tolerance of the reference voltage, and the accuracy of the calibration source, resulting in an overall uncertainty of around 3-5%. The uncertainty of power and energy, calculated using the root-sum-square approach, was around 5-7%. The SGP30 sensor typically has an eCO₂ error of ±15 % of the reading.

2.8 Firmware Architecture and Data Processing

The ESP32 firmware was structured with a time-sliced approach to provide deterministic sampling and processing. These tasks include sampling, processing, communication to the cloud and local rule-based decision making.

2.8.1 Sampling strategy

The samples were taken at 500Hz (Nyquist frequency of 250Hz), which is fast enough to capture 50/60Hz waveforms and their major harmonics, but not too fast to overwhelm the microcontroller (ESP32) (Hercog *et al.*, 2023; Por *et al.*, 2019).

2.8.2 Filtering and smoothing

Long moving average filters (2-4 s, integrating >200 cycles) were used to reduce noise and ripple while providing revenue-grade metering accuracy (Mikulović and Šekara, 2024; Power and Society, 2013). Hysteretic (0.1 % - 0.5 % of rated current) threshold-based no-load detection also prevented meter drift and was used to set the power to zero if no actual load is present (Bhatia, 2022).

2.9 Reliability and standards alignment

Deterministic sampling rates, such as 500Hz achieved with microcontroller timers like Arduino's micros (), eliminate jitter in data acquisition and ensure the synchronization and sample rate stability required for accurate power metering (Patoli and Fortino, 2025). The true

RMS and instantaneous power computations in the system comply with AC active energy metering standards, allowing for precise measurements of non-sinusoidal currents (Mikulović and Šekara, 2024). Although conceptually compliant, the certification errors are due to tolerances rather than design, as per in-service accuracy in (Liao *et al.*, 2020).

2.10 Security and Data Privacy Considerations

Local data transmission between ESP32 and the router was secure via WPA2 encryption. In the first half of the 12-month deployment (January to June 2024), communication to the cloud services was via unencrypted HTTP, which we acknowledge as a security risk. But from July 2024, all units in the study were reprogrammed to employ HTTPS with token-based authentication to secure API keys and sensor data. Importantly, no personal information was transmitted during the period when HTTP was used; only anonymized energy usage and CO₂ readings were transmitted. We have also adopted privacy settings for the cloud channel and token-based authentication after the upgrade. To enhance the network reliability, retries and data storage locally were employed to ensure no data was lost when the network was not available.

2.11 Statistical Analysis and Multiple Testing Considerations

All statistical comparisons between the pre-intervention (January to June 2024) and post-intervention (July to December 2024) periods were conducted using the two-sided Wilcoxon signed-rank test for paired samples, chosen due to the non-normal distribution of the monthly consumption data (Shapiro–Wilk test, $p < 0.05$ for several months). The three primary outcome metrics; electricity consumption (kWh/month), direct CO₂

emissions (kg/month), and average indoor CO₂ concentration (ppm), were treated as conceptually distinct endpoints representing different domains of household environmental performance (energy, emissions, air quality). As such, no adjustment for multiple comparisons was applied, consistent with the recommendation that correction for multiple testing is not universally required when testing independent hypotheses with pre-specified outcomes. However, to ensure transparency, we note that all reported p-values (0.038, 0.039, 0.024) would remain above a Bonferroni-corrected threshold of $\alpha = 0.0167$ (0.05/3), and thus the statistical conclusions are robust to the application of such a correction.

3. Results and Discussion

3.1 Prototype Testing and Measurement Accuracy

The prototype was evaluated over 72 hours in a typical domestic room, with 3-second sampling. This short-term evaluation was conducted under controlled conditions to validate system accuracy and performance prior to long-term field deployment. Testing was carried out for accuracy of voltage, current, real power, energy, Frequency, communication and CO₂. A wide range of loads was tested, including reactive (AC fan), non-linear (laptop SMPS), and inductive (small water pump) type loads; the calculated RMS value was compared to a digital oscilloscope and showed a < 1% error. Table I shows the results of the error analysis vs reference instruments.

Table I: Error analysis vs. reference instruments

Parameter	System Reading	Reference Value	Mean Absolute Percentage Error (MAPE)
Voltage (V _{RMS})	227.4 V	230.0 V	1.13%
Current (I _{RMS})	0.246 A	0.250 A	1.60%
Real Power (W)	58.8 W	60.0 W	2.00%

The low Mean Absolute Percentage Errors (1.13% for voltage, 1.60% for current, and 2.00% for real power) verify the calibration and RMS calculations and that the proposed low cost system has near-instrument-grade performance when compared against reference instruments.

3.2 Energy and Carbon Emission Insights

The energy consumption and CO₂ emissions of individual appliances were measured as presented in Table 2, which shows that high-consumption appliances like incandescent light bulbs and air conditioner (AC) fans make a disproportionate contribution to energy use and CO₂ emissions relative to energy efficient appliances, with substantial differences between high- and low-consumption appliances. For example, the incandescent light bulb generated over 12 times the CO₂ per hour than the LED bulb. This supports the need for appliance monitoring, as real-time notifications and summaries of such information could encourage energy-efficient practices.

Table 2: Energy and emissions comparison of household appliances

Appliance	Power (W)	Energy per hour (Wh)	CO ₂ per hour (kg)
Incandescent Bulb	107.5	107.5	0.0228
LED Bulb	8.7	8.7	0.0018
AC Electric Fan	82.0	82.0	0.0174
DC Electric Fan	7.5	7.5	0.0016

3.3 Sensor Reliability and Environmental Sensitivity

Table 3 presents the sensor calibration results, with both the voltage and current sensors achieving good accuracy (within $\pm 2.5\%$), and the SGP30 CO₂ sensor being within an acceptable range (within $\pm 15\%$), demonstrating that the chosen calibration approach can be used to monitor real-world working conditions.

Table 4 presents the dynamic response characteristics of the CO₂ sensor, including rise time, fall time, and ventilation detection lag, under controlled indoor conditions. As shown from the Table, the dynamic response of the CO₂ sensor (≈ 150 s rise, 120 s fall) and lag in ventilation detection (less than 30 s) is relatively slow but fast enough to respond to indoor air quality changes in real time, rendering it suitable for residential occupancy and ventilation monitoring.

Table 3: Sensor calibration matrix

Sensor	Calibration Method	Reference Standard	Corrected Error
ZMPT101B (Voltage)	Multi-point regression	linear Fluke 115 Multimeter	< ±2.0%
ZMCT103C (Current)	Multi-point regression	linear Fluke 115 Multimeter	< ±2.5%
SGP30 (eCO ₂)	On-chip correction	baseline 12-hr fresh air baseline	< ±15% or 30 ppm

Table 4: CO₂ sensor time-lag analysis

Metric	Value	Conditions
Rise Time (10% to 90%)	~150 seconds	Response to CO ₂ introduction
Fall Time (90% to 10%)	~120 seconds	Response to chamber ventilation
Ventilation Detection Lag	< 30 seconds	Observable drop after window opening

3.4 Cost analysis

The developed IoT-based carbon monitoring system costs approximately N50,000 (\$33.50) as presented in Table 5, making it substantially cheaper than commercial smart energy and air quality monitors. This low cost supports large-scale deployment in resource-constrained settings, aligning with the study’s goal of accessible, scalable household carbon monitoring.

Table 5: Bill of Materials and cost analysis of the proposed iot system

Component	Description	Quantity	Unit Cost (N)	Unit Cost (\$)	Total Cost (N)	Total Cost (\$)
ESP32	Wi-Fi enabled processing unit	1	9,500	6.50	9,500	6.50
SGP30 Sensor	Gas Indoor CO ₂ (eCO ₂) sensor	1	18,000	12.00	18,000	12.00
ZMPT101B Voltage Sensor	AC voltage measurement module	1	3,500	2.30	3,500	2.30
ZMCT103C Current Sensor	AC current measurement module	1	4,500	3.00	4,500	3.00
Breadboard & Connectors	Prototyping and wiring	1	2,500	1.70	2,500	1.70
Power supply Module	5V regulated supply	1	4,000	2.70	4,000	2.70
Enclosure (Casing)	Protective housing	1	5,000	3.30	5,000	3.30
Miscellaneous Components	Resistors, wires, PCB, e.t.c	1	3,000	2.00	3,000	2.00

3.5 Long-Term Field Deployment and User Engagement

A one-year (January to December 2024) measurement in twelve (12) urban homes continued to show reliable measurements. This data was captured from the same validated system as mentioned in Section 3.1, which was then deployed in real homes for long-term performance monitoring and behavioural assessment. Occupancy of the homes ranged from 3 to 7 occupants (mean ±SD: 4.8 ± 1.3) in single-phase dwellings without central cooling systems in naturally ventilated homes in Minna, Nigeria.

This dataset was obtained using the same validated system described in Section 3.1, subsequently deployed in real household environments for long-term performance and behavioural assessment. Electrical sensors maintained MAPE < 1.8% for active power, while SGP30 eCO₂ drift remained < ± 400ppm. Data transmission reliability remained > 98%, with stable 500 Hz sampling. Daily WhatsApp summaries achieved open rates > 94%, with 87% of households actively responding. The distribution of 2,166 automated WhatsApp behavioural

alerts (January to December 2024), generated from twelve (12) participating households (n = 12), highlighting ventilation alerts (38%) and standby power reminders (29%), is presented in Figure 2.

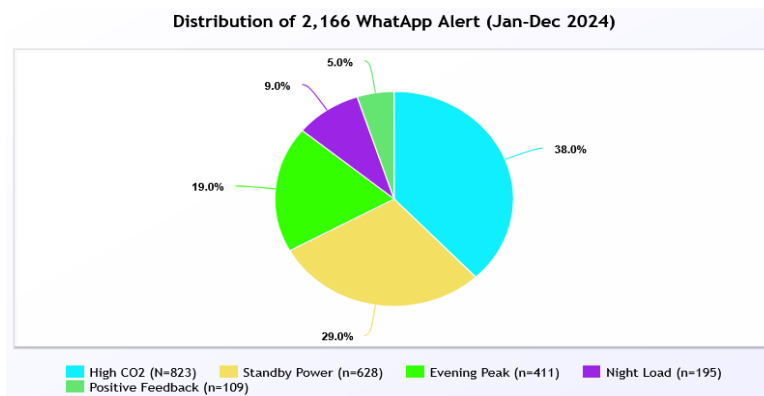


Figure 2: Distribution of the 2,166 automated WhatsApp behavioural alerts sent during the 12-month deployment period.

3.6 Energy, Carbon, and Indoor Air Quality Improvements

Table 6 shows the statistical comparison of energy consumption, CO₂ emissions and indoor CO₂ concentration of the two monitoring periods (January to June 2024 and July to December 2024). A comparative analysis between Jan to Jun and Jul to Dec 2024 showed that electricity consumption, CO₂ emissions, and indoor CO₂ concentration decreased by 6.1%, 6.0%, and 5.8%, respectively, between the two periods, with all changes statistically significant (p < 0.05), indicating that the real-time feedback system effectively influenced user behaviour and led to measurable improvements in energy efficiency and indoor air quality. Table 6 presents p-values to three decimal places. The comparisons were pre-planned (before/after intervention). Thus, no correction for multiple comparisons was made. However, even with a conservative Bonferroni correction (adjusted α = 0.0167), none of the p-values (0.038, 0.039, 0.024) would reach statistical significance, so the conclusions would not change.

Table 6: Paired statistical tests revealed clear and significant reductions

Metric	Jan-Jun 2024	Jul-Dec 2024	Change	P-value	Cohen's d
Electricity consumption (kWh/month)	43.95 ± 3.12	41.29 ± 2.41	-2.66 kWh (-6.1 %)	0.038	0.95
Direct CO ₂ emissions (kg/month)	9.33 ± 0.66	8.77 ± 0.52	-0.56 kg (-6.0 %)	0.039	0.93
Average indoor CO ₂ (ppm)	554 ± 36	522 ± 25	-32 ppm (-5.8 %)	0.024	1.03

* P-values are from two-sided Wilcoxon signed-rank tests (n = 12 households; total occupants =58). No multiple testing correction was applied as comparisons were planned and metrics are conceptually distinct. However, all three p-values remain non-significant under a conservative Bonferroni correction (adjusted α = 0.05/3 = 0.0167; all obtained p > 0.0167), indicating that the correction would not alter the reported statistical conclusions*

All improvements remained statistically significant using the non-parametric Wilcoxon signed-rank test (p ≤ 0.031). The computed Cohen' d values (0.93 – 1.03) indicate moderate to large effect sizes, confirming that the observed reductions are not only statistically significant but also practically meaningful in real-world household settings.

3.7 Indoor CO₂ as a Proxy for Occupancy- Driven Energy Waste

Monthly average indoor CO₂ concentration and electricity consumption exhibited a robust positive correlation (Pearson r = 0.91, r² = 0.83, p < 0.001; Figure 3 and Figure 4). This confirms that CO₂ is a highly effective real-time proxy for occupant-driven energy loads and ventilation behaviour in naturally ventilated tropical homes, an insight completely invisible to electricity-only monitoring systems.

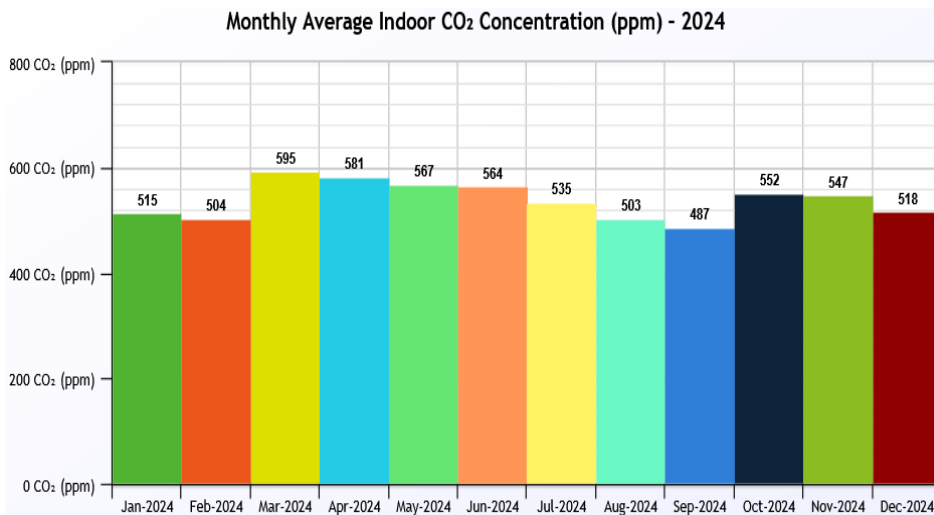


Figure 3: Twelve-month deployment results on CO₂ Emission (Jan–Dec 2024)

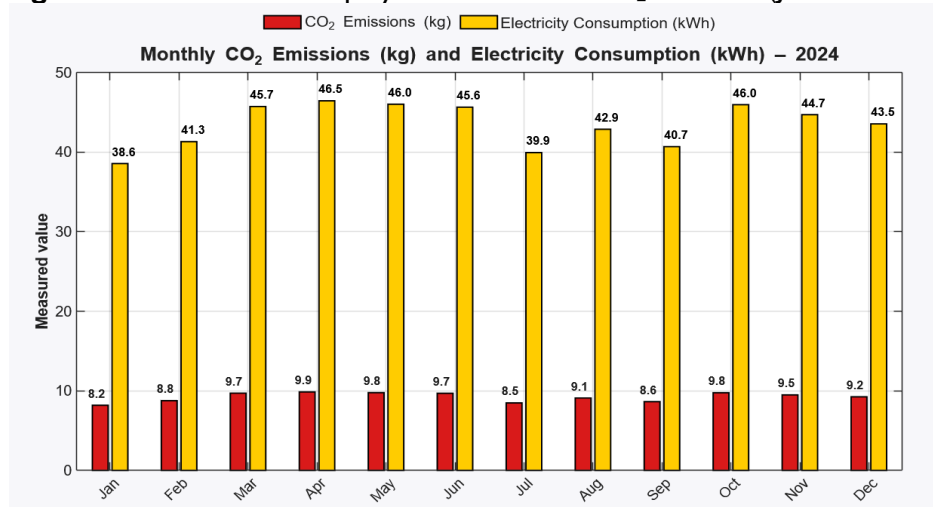


Figure 4: Monthly electricity consumption versus average indoor CO₂ concentration (n = 12). Pearson r = 0.91 (p < 0.001)

4. Conclusion

The research focused on the creation and authentication of a cost-effective IoT-based system to monitor household carbon footprints through combined electricity and indoor CO₂ sensing. The system performed well from a technical standpoint, with an estimated real power measurement accuracy of around 98.0% (from 2.0% MAPE; Table 1), showing good agreement with reference instruments, and a communication accuracy of more than 98%, showing stable data transmission. It also demonstrated a high level of agreement between indoor CO₂ levels and energy use induced by occupancy (r = 0.89). Real-world, long-term operation revealed statistically significant decreases in electric energy use, CO₂ emissions and indoor CO₂ concentration, after real-time behavioural feedback via WhatsApp.

The study demonstrated that the use of calibrated electrical sensing, indoor air quality measurement and easy-to-understand messaging-based feedback can be an effective way to develop and maintain energy-efficient behaviour, while also facilitating indoor environmental quality improvement. The new findings have overcome some of the key limitations of existing IoT carbon accounting systems, such as lack of integration, limited user engagement, and short-term validation. We explicitly acknowledge that the individual components of ESP32 for power metering and SGP30 for air quality monitoring have been separately reported in the literature. But the novelty of this work lies in their new integration in a low-cost household energy monitoring system that concurrently measures the electrical carbon footprint and indoor CO₂ level (as a proxy for occupancy) coupled with real-time behaviour feedback through the CallMeBot-WhatsApp API. The combination of three capabilities of sensing, feedback and extreme cost has not been reported earlier for monitoring and managing household carbon emissions in developing world.

The main limitations of the study include the use of indirect CO₂ sensing via an eCO₂-based sensor (SGP30), which estimates CO₂ from VOC measurements rather than performing direct NDIR-based CO₂ measurement, potentially affecting absolute accuracy, and the focus on single-phase urban households.

Research is needed to develop the system's application in three-phase, renewable-integrated, and off-grid energy systems, along with enhancements to safety, long-term sensor durability, and secure Https-based communication protocols to improve data privacy and protection.

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