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Design and application of a controlled-environment calibration system for low-cost CO_2 sensing devices

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A B S T R A C T

This study presents the design, development, and experimental validation of a portable CO_2 calibration system capable of generating reproducible concentration profiles under actively controlled air temperature and relative humidity. The platform integrates a modified environmental chamber, an automated gas injection system, and a centralized control and data acquisition architecture, enabling both fixed set-point and dynamic concentration profiles representative of real indoor environments. The performance of the calibration system was first evaluated independently to assess its stability, repeatability, and linearity. Repeatability tests conducted under fixed and dynamic operating conditions demonstrated a good level of reproducibility, with expanded uncertainties in the range of ±14–17 ppm and linear behavior across the 400–2000 ppm concentration range, confirming the suitability of the system for multi-point sensor calibration. Following chamber validation, the platform was applied to the calibration of a commercial low-cost CO_2 sensor as a case study. The sensor response was characterized against a reference instrument using a stepwise multi-point exposure protocol. Results revealed a systematic bias of 154 ppm and a sensitivity coefficient of 1.2 ($R^2 = 0.99$). After applying a linear correction derived from the calibration procedure, the sensor achieved an expanded uncertainty of ±26 ppm under the tested conditions. A subsequent 48-h in-situ deployment confirmed its practical applicability, as the chamber-calibrated sensor reliably tracked real-world dynamic ambient fluctuations ($R^2 = 0.96$) with a RMSE equal to 66 ppm. Compared with conventional laboratory-grade calibration facilities, the proposed system offers a portable, cost-effective, and reproducible alternative that bridges the gap between high-cost laboratory systems and in-situ calibration approaches and supports the deployment of dense low-cost sensor networks.

1. Introduction

The measurement and evaluation of air quality have become a central component of environmental and human well-being, influencing conditions in both outdoor and indoor environments. While CO_2 is extensively monitored globally as a primary anthropogenic greenhouse gas [1,2], it also plays a key role in indoor environments, where it serves as a widely adopted proxy for indoor air quality (IAQ), occupancy, and ventilation performance [3,4], particularly given the large proportion of time people spend indoors. While outdoor baselines are approximately 400 ppm, indoor levels can rise substantially in enclosed spaces, making effective measurement essential to prevent occupant discomfort [4,5]. To achieve high-resolution spatial and temporal monitoring, modern strategies increasingly rely on dense networks of Low-Cost Sensors (LCS). However, to ensure data reliability, these networks require robust evaluation using controlled experimental setups, such as calibration chambers [6]. Such calibration is particularly important given the growing evidence that elevated indoor CO_2 impacts human health and productivity [7,8]. Indoor CO_2 concentrations often exceed outdoor levels due to human respiration and insufficient ventilation, leading to both physiological and cognitive effects. At moderate levels, typically above 1000 ppm, occupants often report symptoms associated with Sick Building Syndrome (SBS), including headaches, fatigue, dizziness, and irritation of the eyes, nose, and throat [8,9]. Epidemiological studies have demonstrated a statistically significant dose–response relationship between indoor CO_2 differentials and symptom prevalence, indicating that even moderate ventilation deficiencies can compromise well-being [8]. More recent research has highlighted the impact of CO_2 on cognitive performance, with concentrations between 1000 and 2500 ppm, commonly observed in classrooms, offices, and meeting rooms, linked to declines in decision-making ability, information usage, and strategic thinking [10,11]. These findings highlight CO_2 as not only a comfort indicator but also a factor affecting human performance. Regulatory frameworks reflect the dual role of CO_2 as both a health hazard and an IAQ indicator. While occupational safety agencies (e.g., OSHA, EU Commission) set long-term exposure limits at 5000 ppm to prevent acute

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physiological effects [12,13], building and IAQ standards adopt much stricter guidelines to preserve occupant comfort and cognition. Consequently, frameworks such as ASHRAE 62.1, EN 16798-1, and various national regulations generally target indoor concentrations below 1000–1200 ppm [11,14–16], with some actively mandating continuous CO_2 monitoring in high-density spaces to ensure adequate ventilation [17]. Ensuring compliance with these standards has traditionally relied on reference-grade monitoring stations, which form the backbone of regulatory air quality networks [18]. For CO_2, reference measurement techniques like high-precision Non-Dispersive Infrared (NDIR) spectroscopy and Gas Chromatography offer high accuracy, stability, and traceability [1,18]. However, their substantial cost, size, power demands, and need for strictly controlled operating conditions severely restrict their widespread spatial deployment [6]. As a result, monitoring networks are sparse, limiting the detection of localized pollution patterns and short-term variability, particularly in indoor or highly dynamic environments [19]. To address these limitations, LCS have emerged as a complementary approach, enabling dense monitoring networks with enhanced spatial resolution [6,19]. For CO_2 monitoring, miniaturized NDIR sensors dominate due to their direct selectivity and relatively low susceptibility to chemical interference compared to metal-oxide-based alternatives [1,19]. LCS networks support applications ranging from indoor air quality assessment to urban micro-scale monitoring and citizen science initiatives, such as the EU-funded SOCIO-BEE project [20]. However, LCS are affected by significant metrological challenges, including sensitivity to air temperature and relative humidity, spectral interference, cross-sensitivity, and long-term drift caused by component aging and contamination [19,21–24]. These limitations highlight the need for accessible and reliable calibration infrastructures for large-scale deployments. Consequently, this work presents the development and characterization of a controlled CO_2 calibration system tailored specifically for the evaluation of LCS. The proposed platform provides a controlled and reproducible testing environment by regulating CO_2 concentration, air temperature, and relative humidity within a sealed chamber. The experimental campaign is structured in two stages: first, the metrological performance of the calibration bench itself is characterized in terms of repeatability, stability, and linearity of the generated concentration profiles; subsequently, the LCS is collocated with a reference-grade instrument under identical environmental conditions to quantify bias, sensitivity, linearity, and measurement uncertainty. This approach addresses the need for intermediate calibration solutions that balance experimental rigor with portability and operational simplicity. The remainder of the paper is structured as follows. Chapter 2 reviews the state of the art, covering laboratory-grade environmental chambers, in-situ calibration and co-location strategies, and portable calibration systems. Chapter 3 describes the materials, experimental setup, and methods used to design and validate the calibration chamber, the sensor calibration case study conducted using a low-cost CO_2 sensor, and the protocol for the real-world in-situ deployment. Subsequent chapters present experimental results, discussion, and conclusions.

2. State of the art

To structure this study, existing CO_2 sensor calibration methodologies were reviewed and classified by authors into three main categories: laboratory-grade environmental chambers, in-situ calibration and co-location strategies, and portable or compact calibration systems. This framework enables a systematic comparison of their advantages, limitations, and suitability for low-cost CO_2 monitoring. Laboratory climatic chambers represent the highest level of metrological rigor for sensor characterization. These systems provide tightly controlled environmental conditions, allowing individual variables to be isolated and confounding effects minimized. Early studies demonstrated advanced chambers capable of operating over wide temperature ranges (-32 °C to $+177$ °C) with precisely regulated humidity, enabling detailed assessments of sensor accuracy, detection limits, and environmental sensitivity under reproducible conditions [25]. Subsequent work emphasized spatial homogeneity, which is essential for calibrating multiple sensors simultaneously. In particulate matter studies, dedicated chambers achieved uniform pollutant distributions and high inter-sensor agreement (Intra Class Correlation, ICC $>$0.771) through controlled aerosol generation [26]. Further refinements were achieved using computational fluid dynamics (CFD) to optimize internal airflow and fan configurations, ensuring equivalent exposure across sensor locations and reducing calibration uncertainty [27]. Despite their accuracy and reproducibility, laboratory-grade chambers have major practical drawbacks. They are typically bulky, energy-intensive, and costly, restricting their use to specialized laboratories or certification facilities. Consequently, they are unsuitable for the frequent, decentralized recalibration required to maintain data quality in dense sensor networks. To address these constraints, in-situ calibration methodologies have gained prominence. The most common approach is sensor co-location, in which LCS are temporarily deployed alongside regulatory-grade reference stations to derive correction factors under real-world conditions. Studies have shown that this strategy can mitigate cross-sensitivities and environmental effects, for instance, recent research demonstrated that using multipollutant calibration models can achieve good correlations ($R^2 > 0.8$) and significantly reduce measurement error (e.g., lowering RMSE, Root Mean Squared Error for NO_2 to 5 parts per billion), although performance strongly depends on the representativeness of ambient conditions during the calibration period [28]. Long-term field campaigns indicate that periodic co-location can reduce sensor drift and improve agreement with reference measurements, particularly for particulate matter sensors [29]. However, scalability is limited by the sparse distribution of reference stations, leaving large portions of sensor networks unverified, especially in locations distant from regulatory infrastructure [30]. Moreover, in-situ calibration is inherently passive, as it cannot actively impose controlled variations in temperature, humidity, or pollutant concentration. Recent approaches based on proxy calibration and machine-learning techniques attempt to address these limitations but still rely on robust ground-truth reference data [31]. A third category seeks to bridge the gap between laboratory accuracy and field applicability through portable and compact calibration systems. These solutions, often described as DIY or ad-hoc platforms, aim to provide accessible calibration tools for citizen science and decentralized monitoring. Some systems have been developed for specialized applications, such as calibrating CO_2 sensors for drone-based monitoring, enabling characterization of response time and cross-sensitivity with a concentration uncertainty of less than 3%, yet often relying on complex auxiliary equipment that limits true portability [32]. Other low-cost approaches employ simple enclosures, such as small plastic boxes, to test sensor behavior under varying environmental conditions. While these setups demonstrate that factory calibration can be improved with minimal resources, they generally lack active environmental control and cannot reproduce dynamic or extreme conditions [33]. More recent developments include portable calibration chambers with wireless connectivity and software-based control interfaces, representing a step toward automated, field-deployable calibration [34]. Nevertheless, most compact systems still struggle to simultaneously regulate pollutant concentration, temperature, and relative humidity over a sufficiently wide range. Overall, the literature highlights a clear gap between highly accurate but immobile laboratory chambers and flexible yet metrologically limited field-based solutions. To bridge this gap, the present study proposes a novel calibration bench based on a modified environmental chamber, integrating controlled regulation of air temperature and relative humidity with automated gas injection. By combining portability with active environmental control, the proposed system aims to enable reliable and frequent calibration of low-cost CO_2 sensors directly in the field, improving data quality for indoor air quality monitoring and citizen science applications.

3. Materials and methods

This section describes the measurement system and experimental procedures adopted for the development and evaluation of the CO_2 calibration platform. The configuration of the portable calibration system is detailed, including the environmental test chamber, the automated gas injection unit, and the centralized control and data acquisition system. The instrumentation employed consists of a reference CO_2 sensor and a LCS. A standardized experimental protocol is defined for the generation of controlled CO_2 concentration profiles and for the evaluation of system repeatability and sensor calibration performance. Finally, the data acquisition architecture and post-processing methods adopted for regression analysis and uncertainty estimation are described.

3.1. Experimental set-up

Overall, the calibration platform was designed as a portable, modular system capable of generating controlled CO_2 profiles while regulating environmental parameters. Fig. 1 illustrates the conceptual workflow of the calibration process implemented in this study. Certified gas serves as the pollutant source and is introduced into a controlled calibration environment, where air temperature (t_a) and relative humidity (RH) are actively regulated. Within this environment, the sensors are exposed to predefined CO_2 concentration profiles. The resulting measurements are collected through the data acquisition system and subsequently processed during the data analysis phase, leading to sensor validation and calibration outputs. The architecture consists of four primary subsystems: the CO_2 source (A), the calibration environment (B), the sensors (C) and the control system (D) as displayed in Fig. 2. The core of the system is a modified environmental chamber (FIEM, Italy) with internal dimensions of 29.9 x 36.3 × 48 cm, providing a total volume of approximately 52 l. Unlike passive testing boxes used in previous low-cost studies, this chamber features an integrated PID thermal control system capable of regulating air temperature (t_a) from 0 °C to 45 °C and relative humidity (RH) from 0% to 75%. This forced convection mechanism minimizes vertical stratification, maintaining a thermal gradient of less than 0.5 °C between the upper and lower sections of the sensing volume. The chamber is sealed during operation to isolate the internal environment from ambient fluctuations, with dedicated ports used for gas injection tubing and sensor cabling. The generation of CO_2 concentration profiles is managed by a precise injection line. A certified CO_2 gas cylinder (SOL S.p.A.) serves as the source, fitted with a pressure reducer to step down the output pressure to safe operating levels. Flow control is achieved via a solenoid valve (U.S. Solid, 12V DC, 3/8″ orifice), installed in series between the pressure reducer and the chamber inlet. The valve is actuated by the central control unit via a relay module, powered by a dedicated 12V Power Supply. By modulating the valve's opening time (pulse duration), the system can inject discrete “packets” of CO_2 to achieve precise target set-points (e.g., 700 ppm) or execute continuous ramp profiles (e.g., increasing concentration by 100 ppm every 2 min). The entire platform is governed by a Raspberry Pi 5 single-board computer running custom Python scripts that coordinate all hardware components. The control architecture simultaneously manages the actuation logic, opening the solenoid valve for precisely calculated intervals to reach the target concentration steps, and the data-logging routines, which continuously query the connected sensors via I^2C or USB and store timestamped measurements at 10-s intervals. Inside the chamber, the LCS is positioned close to the reference instrument so that both sample the same air mass under identical environmental conditions. The experimental setup employs two sensing devices whose key specifications, summarized in Table 1, highlight differences in measurement principle, accuracy, and operational range. The reference instrument is the Sensirion SCD40, a photoacoustic NDIR module that achieves a compact form factor without sacrificing metrological performance. It provides CO_2 readings between 400 and 2000 ppm with an accuracy of ± (50 ppm +5% of reading) [35]. For validation, the Extech CO240 handheld CO_2 meter was used as the device under test, namely the LCS. It relies on conventional NDIR spectroscopy, covering a wider range (0–9999 ppm) with a declared accuracy of ± (75 ppm +5% of reading) [36].

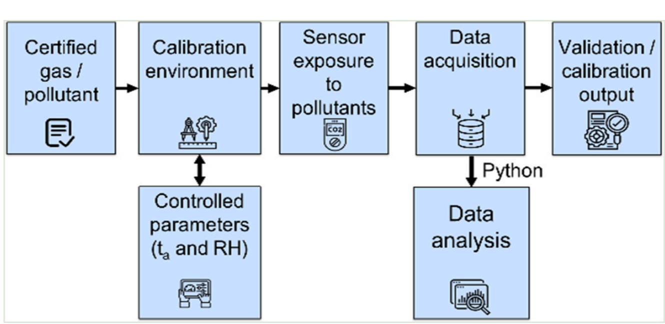

Fig. 1. A conceptual map of the calibration process.

To mitigate safety risks associated with high CO_2 concentrations, the experimental protocol includes a ventilation phase. Upon completion of a calibration cycle, the chamber is opened adjacent to a laboratory fume hood or forced ventilation source. This ensures the rapid purging of residual gas, restoring the internal atmosphere to ambient baseline levels (≈400 ppm) before the subsequent test run begins. A standardized experimental protocol was defined based on a stepwise injection logic. The procedure was iteratively refined to minimize transient instabilities and ensure that the sensors under test were exposed to homogeneous gas concentrations.

3.2. Experimental protocol

3.2.1. Calibration bench validation

The repeatability of the calibration bench was evaluated to assess its capability to reproducibly generate predefined CO_2 concentration levels under controlled environmental conditions. Two complementary tests were conducted to investigate both fixed set-point stability and the repeatability of dynamic concentration profiles. In the first test, the ability of the system to reproduce a fixed concentration level was assessed. Starting from ambient conditions (approximately 400–500 ppm), the CO_2 concentration inside the chamber was increased to a target set-point of 700 ppm, representative of typical indoor occupancy conditions. CO_2 injection was performed using a certified gas cylinder with a regulated pressure of approximately 3 bar and a solenoid valve opening time of 1 s. After injection, the internal circulation fan ensured homogeneous mixing of the gas before data acquisition. Once steady-state conditions were reached, measurements were recorded, and the chamber was subsequently ventilated to restore ambient CO_2 levels. This fixed set-point procedure was repeated ten consecutive times under constant environmental conditions (ta = 21 °C, RH = 50%) to quantify the repeatability of the generation system. In the second test, the repeatability of the calibration bench in generating dynamic concentration profiles was evaluated. Beginning from an initial concentration of approximately 500 ppm, the CO_2 level inside the chamber was incrementally increased in steps of 100 ppm every 2 min until a maximum concentration of approximately 2000 ppm was reached. Fig. 3a) shows visually the experimental procedure. Throughout the test, air temperature and relative humidity were maintained constant to isolate the effects of the gas generation process. The complete incremental concentration profile was repeated ten times to assess the consistency of the system response under dynamic operating conditions. The results of these repeatability tests were used to characterize the stability and reproducibility of the calibration bench and to verify its suitability for subsequent sensor calibration experiments.

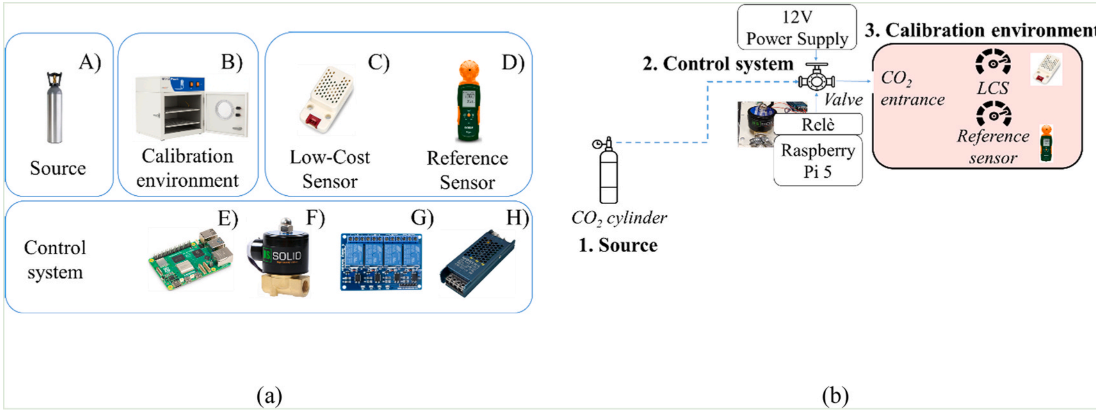

Fig. 2. (a). The experimental set-up. A) CO_2 cylinder, B) The experimental chamber, C) LCS (Extech CO240), D) The reference sensor (Sensirion SCD40), E) Raspberry Pi 5, F) Solenoid Valve, G) Relay Module, H) 12V Power Supply.
(b). Diagram showing the interconnections among the components of the experimental setup.

Table 1
Datasheet for the reference sensor (Sensirion SCD40) and the LCS (Extech CO240).

Sensor	Parameter	Value
Reference Instrument (Sensirion SCD40)	CO_2 Range	400 – 2000 ppm
	Accuracy	± (50 ppm +5% of reading)
LCS (Extech CO240)	CO_2 Range	0 – 9999 ppm
	Accuracy	± (75 ppm +5% of reading)

3.2.2. Sensor calibration case study

Following the validation of the calibration bench, a commercial low-cost CO_2 sensor (Extech CO240) was selected as a case study to demonstrate the application of the proposed calibration platform under controlled conditions. The short-term repeatability of the sensor response was evaluated at a fixed CO_2 concentration level. The sensor was exposed to a target concentration of 700 ppm using the calibration bench in fixed set-point mode, with a cylinder pressure of approximately 3 bar and a solenoid valve opening time of 1 s, consistent with the bench validation procedure. After stabilization, steady-state measurements were recorded and the chamber was ventilated to restore ambient conditions before the subsequent cycle. This single-point exposure was repeated ten consecutive times to assess the repeatability of the sensor under identical environmental and operational conditions. Sensor calibration was performed using a stepwise multi-point exposure methodology covering the indoor air quality concentration range of interest. The sensor was sequentially exposed to four nominal CO_2 concentration levels, approximately 600, 1000, 1500, and 2000 ppm, starting from ambient conditions. For each concentration step, CO_2 was injected into the chamber to reach the target level by adjusting the cylinder pressure and the solenoid valve opening time according to the parameters reported in Table 2. Each step was maintained for approximately 2 min to ensure steady-state conditions, during which synchronous measurements were acquired from both the LCS and the reference instrument. The complete multi-point calibration sequence was repeated five times to account for sensor hysteresis and short-term drift. An example of the stepwise CO_2 concentration profile adopted during the calibration procedure is reported in Fig. 3b).

Table 2
Calibration protocol.

Concentration	Cylinder Pressure	Opening time of the valve
600 ppm	3 bar	0.5 s
1000 ppm	5 bar	10 s
1500 ppm	8 bar	10 s
2000 ppm	8 bar	20 s

3.3. Data acquisition and post-processing

Data acquisition and system control were implemented through a centralized architecture in which a Raspberry Pi 5 single-board computer acted as the master unit for both sensor interrogation and gas injection control. Custom Python scripts were developed to ensure synchronous operation of all hardware components, including the solenoid valve actuation, environmental chamber operation, and sensor data logging. This centralized approach guaranteed temporal alignment between the imposed CO_2 concentration profiles and the recorded sensor responses. The reference instrument (Sensirion SCD40) communicated with the control unit via the I^2C interface, providing digital measurements of CO_2 concentration, air temperature, and relative humidity. In parallel, the LCS (Extech CO240) was interfaced to the same logging system, allowing both devices to sample the chamber atmosphere simultaneously under identical environmental conditions. All measurements were timestamped and stored locally for subsequent analysis. A uniform sampling interval of 10 s (0.1 Hz) was adopted for all experiments. This value was selected as a compromise between sufficient temporal resolution to capture concentration step transitions and stabilization dynamics, and a manageable data volume for repeated and long-duration test sequences. Data acquisition was continuously active throughout each experimental run, including baseline stabilization, gas injection, mixing, and steady-state exposure phases. Raw datasets were post-processed to ensure consistency and comparability between sensors. Timestamp alignment was first verified to correct for any minor communication delays between data streams. Data points acquired during the gas injection phase and the initial mixing period were excluded from further analysis, as these intervals are characterized by transient and non-uniform concentration conditions. Only measurements corresponding to steady-state conditions at each target concentration level were retained. For each concentration step, the remaining steady-state data were averaged to obtain a single representative value for both the reference instrument and the LCS. These averaged values formed the basis for subsequent performance evaluation and calibration analysis. Sensor behavior was assessed through linear regression between the LCS output and the reference measurements across the investigated concentration range. Key performance indicators derived from the calibration curves included the coefficient of determination (R^2), used to quantify linearity; the sensitivity coefficient, defined as the slope of the regression line and representing the sensor response relative to the reference; and the bias, expressed as the intercept of the regression model [37]. The non-linearity (NL) of the generated gas concentration

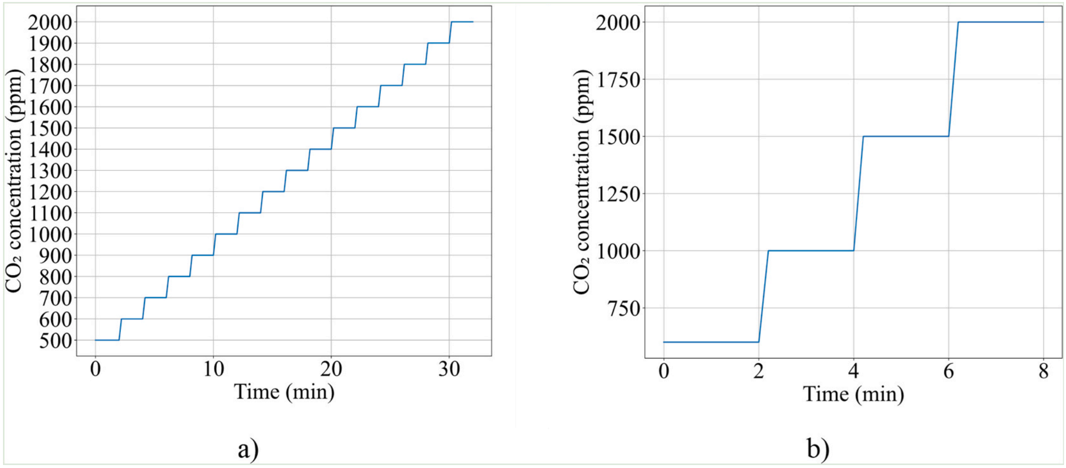

Fig. 3. a). Example of the stepwise CO_2 concentration profile adopted for multi-point sensor calibration. Starting from 500 ppm, the concentration is incrementally increased (100 ppm per step) to 2000 ppm, with each level maintained for approximately 2 min to ensure steady-state conditions.
b). Example of the stepwise CO_2 concentration profile adopted for multi-point sensor calibration. Starting from ambient conditions, the concentration is incrementally increased to 600, 1000, 1500, and 2000 ppm, with each level maintained for approximately 2 min to ensure steady-state conditions.

gradients was evaluated using a terminal-based linearity assessment. This metric quantifies the maximum absolute deviation between the empirically measured steady-state concentrations ($C_{measured}$) and an ideal theoretical response line (C_{ideal}) drawn linearly between the minimum and maximum experimental calibration points. To express this worst-case deviation as a standard percentage of the tested Full Scale (% FS), which is standard practice in sensor characterization in accordance with IEC 61298-2 guidelines [38], the maximum residual is normalized by the highest measured concentration in the ramp (C_{max}):

$$NL = \max\left(\frac{|C_{measured} - C_{ideal}|}{C_{max}}\right)\cdot 100$$

The combined standard uncertainty (u_c) of the reference CO_2 concentration inside the chamber was evaluated according to the GUM framework [39]. It was calculated using the root-sum-square (RSS) method by combining two primary, uncorrelated uncertainty components: the reference sensor uncertainty (u_{ref} , evaluated as a Type B contribution from manufacturer specifications using a rectangular distribution) and the calibration bench repeatability (u_{rep}, evaluated as a Type A contribution from the standard deviation of repeated experimental trials). The combined standard uncertainty is thus expressed as:

$$u_c = \sqrt{{u_{ref}}^2 + {u_{rep}}^2}$$

Measurement uncertainty was evaluated by combining the relevant uncertainty contributions and expressed as expanded uncertainty using a coverage factor of $k = 2$, corresponding to a confidence level of approximately 95%.

3.4. *Real-world in-situ deployment protocol*

Following the controlled chamber characterization, a comprehensive in-situ validation campaign was designed to evaluate the practical applicability of the chamber-derived calibration models under real-world conditions. A 48-h continuous co-location test was conducted in an occupied, actively utilized office space subject to standard mechanical HVAC ventilation dynamics. To ensure strict metrological continuity, the identical physical sensor nodes (the Sensirion SCD40 reference and the Extech CO240 LCS) previously characterized inside the chamber were deployed for this field test. Both devices were co-located in close proximity to ensure they sampled the same ambient air mass. During the deployment, raw concentration data was logged continuously. To ensure robust statistical analysis, the raw dataset was subsequently aggregated into 1-h temporal averages. The performance of the chamber-calibrated LCS was then quantitatively evaluated against the reference instrument using standard statistical indicators, including the coefficient of determination (R^2), Pearson correlation coefficient (r), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE). Furthermore, to rigorously characterize the absolute measurement error, the standard uncertainty of the input (s_{qi}) was calculated, it was used to derive the final expanded uncertainty (U) of the field deployment, applying a coverage factor of $k = 2$ for an approximate 95% confidence interval.

4. Results and discussion

This section presents and discusses the experimental results obtained using the calibration system described in Section 3. Results are organized to first evaluate the performance and repeatability of the calibration bench, and subsequently to analyze the metrological behavior of a representative low-cost CO_2 sensor under controlled conditions. Finally, the implications of the findings for sensor calibration and indoor air quality monitoring are discussed.

4.1. *Calibration system performance and repeatability*

The performance of the calibration system was first evaluated in terms of stability, repeatability, and linearity of the generated CO_2 concentration profiles. Repeatability was initially investigated under constant environmental conditions ($t_a \approx 21$ °C and RH ≈ 50 %) by performing ten identical CO_2 injection cycles. Each cycle consisted of a stepwise increase from ambient background concentrations (~400 ppm) to a target level of 700 ppm, representative of typical indoor occupancy conditions. As shown in Fig. 4a) and 4b), the reference instrument exhibited highly consistent peak concentrations across all repetitions. The standard deviation of the measured steady-state values corresponded to an expanded uncertainty (coverage factor $k = 2$) of ±14 ppm. This low dispersion demonstrates the good repeatability of the gas injection protocol and confirms that the solenoid valve actuation and mixing strategy are capable of producing stable and reproducible concentration set-points.

A second repeatability test was performed using a continuous concentration ramp from 500 ppm to 2000 ppm (visible in Fig. 5, the procedure was explained in Table 2 and Fig. 3b), intended to emulate gradual CO_2 accumulation in poorly ventilated indoor environments. The complete ramp profile was repeated ten consecutive times under identical environmental conditions. Under these dynamic conditions,

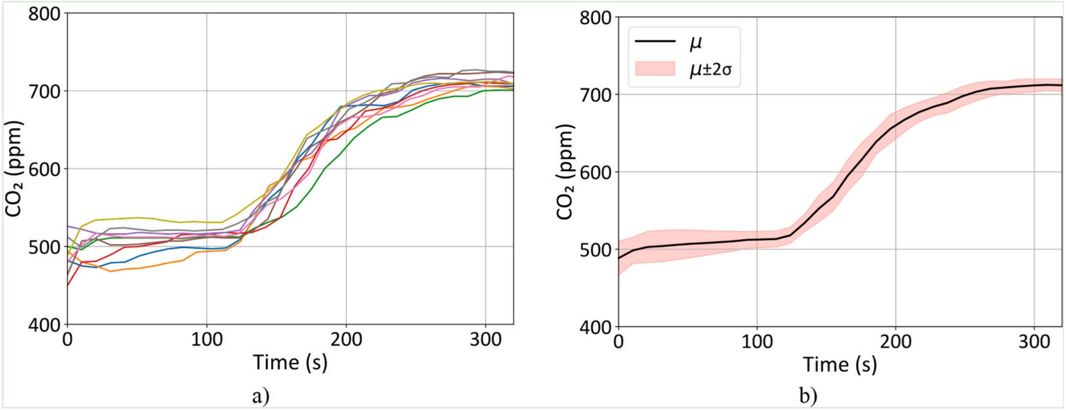

Fig. 4. a). The repeatability test (with 700 ppm as the target concentration). b). The mean curve with the expanded uncertainty as red bands.

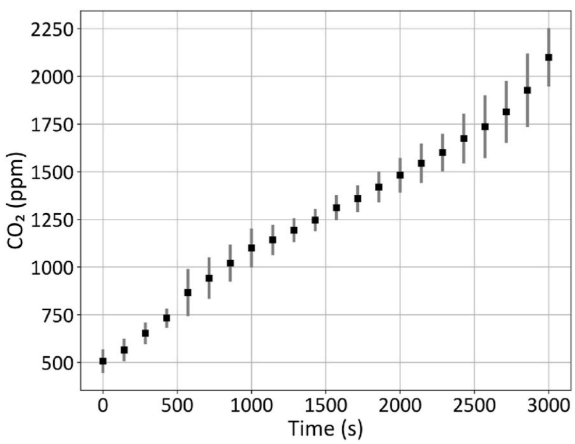

Fig. 5. The continuous concentration ramp.

the repeatability uncertainty increased slightly to ±17 ppm (k = 2), reflecting the added influence of transient effects during continuous injection. Nevertheless, the observed variability remained small relative to the overall concentration range, indicating that the chamber maintains adequate control even during non-steady-state operation. To illustrate the uncertainty budget, an explicit calculation was performed at the 700 ppm concentration level. The reference sensor (Sensirion SCD40) introduces a Type B standard uncertainty of 49 ppm (derived from the ±85 ppm accuracy specification divided by $\sqrt{3}$ for a rectangular distribution). The chamber's Type A repeatability standard uncertainty at this level was experimentally determined to be 7 ppm. Combining these factors yields a combined standard uncertainty of 49.6 ppm. Applying a coverage factor of k = 2, for a 95% confidence interval results in an expanded total uncertainty of ±99 ppm. This demonstrates that the uncertainty budget is heavily dominated by the systematic specifications of the reference instrument rather than the random variations of the calibration bench. Applying the terminal-based linearity assessment to the dynamic concentration ramp, the system exhibited a maximum non-linearity (NL) of 7.5% relative to the full scale tested. This worst-case deviation confirms that the chamber maintains a highly proportional and predictable gas mixing capability across the entire target dynamic range. This confirms that the injected concentrations scale predictably with valve opening time and validates the suitability of the platform for multi-point calibration procedures.

4.2. Low-cost sensor calibration results

Following the validation of the calibration bench, the metrological performance of the Extech CO240 low-cost CO_2 sensor was evaluated using the multi-point calibration protocol described in Section 3.2.2. The response of the Extech CO240 sensor was analyzed by comparing its steady-state readings against those of the reference instrument at four concentration levels (approximately 600, 1000, 1500, and 2000 ppm). Fig. 6 illustrates the resulting calibration curve and corresponding linear regression. The regression analysis yielded a sensitivity coefficient (slope) of 1.2, indicating that the sensor systematically overestimates changes in CO_2 concentration relative to the reference. Additionally, a positive bias of 154 ppm was observed, revealing a consistent offset across the tested range. Despite the presence of this bias, the coefficient of determination (R^2 = 0.99) demonstrates a good linear relationship between the sensor output and the reference concentrations. This high degree of linearity suggests that the sensor response is highly predictable and that the observed systematic errors can be effectively corrected through calibration. Following the application of a linear correction derived from the regression parameters, a substantial reduction in systematic error was achieved, confirming the effectiveness of the multi-point exposure method implemented in the calibration chamber. However, a residual calibration uncertainty remains, primarily associated with the dispersion of the data points around the regression line. This calibration uncertainty was estimated to be approximately ±93 ppm (expanded uncertainty, k = 2). This confidence interval represents the expected residual error in the sensor measurements after linear calibration and indicates that, despite the high R^2 value, variations on the order of several tens of ppm persist due to sensor noise and intrinsic performance limitations.

The intrinsic performance of the Extech CO240 was evaluated through a dedicated repeatability test at a fixed concentration of

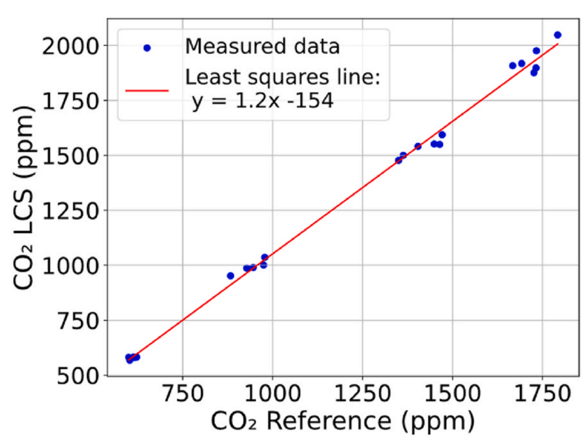

Fig. 6. The calibration curve for the multi-point test.

700 ppm under stable environmental conditions. The histogram of the residuals, visible in Fig. 7, shows a mean value of 66 ppm, this indicates that, at this specific concentration, the sensor exhibits a systematic offset. This deterministic error suggests that the sensor consistently deviates from the reference value in a predictable manner, which is a characteristic that can be effectively corrected through calibration. The sensor exhibited an expanded uncertainty of ±26 ppm (k = 2), which is well within the range required for indoor air quality monitoring applications. This result confirms that, once calibrated, the device can provide stable and repeatable measurements over short timescales. Overall, the results demonstrate that the proposed calibration platform is capable of generating reproducible CO_2 concentration profiles with sufficient stability and linearity to support the characterization and calibration of LCS across the indoor air quality range of interest.

4.3. Real-world deployment verification

To contextualize the chamber-derived calibration models within a practical scenario, a comprehensive 48-h continuous in-situ validation campaign was executed in an occupied, actively utilized office environment. The space was characterized by modern HVAC ventilation dynamics. During this deployment, the previously characterized Extech LCS was co-located with the Sensirion reference instrument to evaluate the real-world performance of the applied correction model. To ensure robust statistical analysis, the raw dataset was aggregated into 1-h temporal averages. The comparison between the reference instrument and the chamber-calibrated LCS is illustrated in Fig. 8. To quantitatively assess the performance of the calibrated sensor during this field deployment, standard statistical indicators were employed. The degree of linear agreement and correlation between the LCS and the reference instrument was evaluated using the coefficient of determination (R^2) and the Pearson correlation coefficient (r). Furthermore, the absolute magnitude of the residual measurement error was quantified using the Root Mean Square Error (RMSE), the Mean Absolute Error (MAE), the standard uncertainty of the input (s_{qi}) and the final expanded uncertainty (U).

The statistical performance of the chamber-calibrated sensor during this real-world deployment is summarized in Table 3.

As expected for an adequately ventilated real-world indoor space, the ambient CO_2 concentration during the 48-h deployment remained within a typical baseline range of 400–600 ppm. Despite operating exclusively at the absolute lower extremity of its calibrated operational range, the chamber-calibrated sensor exhibited a high linear correlation with the reference instrument ($R^2 = 0.96$, Pearson r = 0.98). This confirms that the sensor successfully captured the macroscopic, dynamic trends of the room's CO_2 concentration. The absolute error metrics yielded a RMSE of 66 ppm and a MAE of 65 ppm. To rigorously quantify the absolute measurement error during the field deployment, the

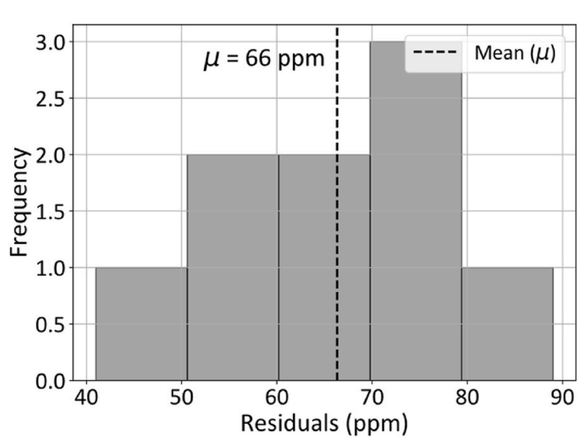

Fig. 7. The histogram of the residuals.

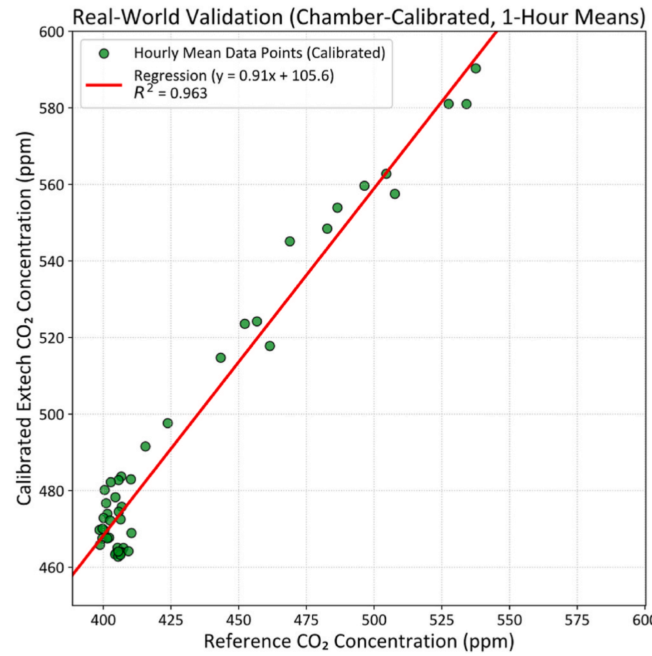

Fig. 8. Comparison between calibrated LCS and reference sensors.

Table 3
Statistical performance of the chamber-calibrated LCS.

Parameter	Chamber-Calibrated LCS
RMSE	66 ppm
MAE	65 ppm
Pearson	0.98
R^2	0.96
s_{qi}	8 ppm
U	±16 ppm

variance of the regression residuals was evaluated according to standard metrological practices. For the chamber-calibrated sensor, this analysis yielded an input standard uncertainty (s_{qi}) of 8 ppm. Applying a coverage factor of k = 2, corresponding to an approximate 95% confidence interval, results in a final expanded uncertainty (U) of ±16 ppm under real-world dynamic conditions. This statistically stable baseline offset is an inherent and expected mathematical consequence of the proposed calibration architecture. The portable chamber is explicitly engineered to derive a robust, full-scale linear regression across a wide dynamic occupancy range (400–2000 ppm). This global model is mathematically optimized to guarantee accuracy and structural stability at higher concentrations (>1000 ppm), which represents the critical operational threshold where IAQ monitoring becomes vital for health assessments and HVAC interventions. Consequently, evaluating this wide-range global regression exclusively at its lowest boundary (the 400–600 ppm field conditions) naturally highlights this minor offset. This behavior represents a necessary metrological trade-off: accepting a predictable, minor deviation in empty or highly ventilated rooms to effectively neutralize severe slope non-linearities and prevent massive extrapolation errors when the room reaches full capacity. Ultimately, these findings underscore a fundamental limitation of relying exclusively on passive ambient field validation. Natural building ventilation often prevents passive field testing from reaching the high-concentration thresholds required to rigorously stress-test NDIR sensors. The high correlation demonstrates that the dynamic calibration is sound, while simultaneously reinforcing that an active, controlled, and modular calibration chamber is strictly necessary to safely characterize these sensors for their entire operational lifecycle. Table 4 summarizes the different sources of uncertainty discussed throughout Sections 4.1–4.3,

Table 4
Summary of Expanded Uncertainties (U, k = 2) across validation stages.

Category	Expanded Uncertainty (U)	Description
Bench Uncertainty	±99 ppm	Combined uncertainty at 700 ppm, dominated by reference instrument (Type B).
Calibration Uncertainty	±93 ppm	Residual error after linear calibration.
Sensor Repeatability	±26 ppm	Repeatability at 700 ppm under controlled conditions.
Field Measurement Uncertainty	±16 ppm	Uncertainty during 48 h real-world deployment (1 h averages).

distinguishing between bench, calibration, and field measurement contributions.

4.4. Discussion

The experimental results provide a comprehensive assessment of both the proposed calibration platform and the behavior of a representative low-cost CO_2 sensor under controlled conditions. The discussion is organized to highlight the implications of these findings in relation to existing calibration strategies, indoor air quality requirements, and the practical deployment of LCS networks. A first key outcome concerns the performance of the calibration chamber itself. The observed repeatability of ±14 – 17 ppm demonstrates that the gas generation and mixing strategy is highly stable and reproducible, even when operating in a compact and portable configuration. While this level of uncertainty is higher than that achievable with large, laboratory-grade climatic chambers, it is nevertheless well suited to the calibration of LCS, whose declared accuracies are typically one order of magnitude larger. Importantly, the uncertainty analysis indicates that the dominant contribution arises from the reference instrument rather than from the chamber dynamics. This confirms that the proposed platform does not introduce significant additional variability. The linearity of the generated concentration profiles across the 400–2000 ppm range further validates the robustness of the injection approach based on time-controlled solenoid valve actuation. The ability to reliably produce both discrete steps and gradual ramps is particularly relevant for sensor characterization, as it enables the investigation of steady-state accuracy as well as sensor behavior under slowly varying concentrations, which are representative of real indoor environments. Compared to passive calibration boxes or uncontrolled in-situ exposure, the active regulation of temperature and relative humidity significantly reduces confounding factors, allowing sensor deviations to be attributed primarily to concentration effects. The calibration results obtained for the Extech CO240 are consistent with behaviors widely reported in the literature for low-cost NDIR-based CO_2 sensors. The high coefficient of determination ($R^2 = 0.99$) confirms that the sensing principle provides a robust and highly linear response to CO_2 concentration. At the same time, the sensitivity greater than unity and the positive bias of 154 ppm reveal systematic errors associated with factory calibration. From a practical standpoint, such a bias is non-negligible in indoor air quality applications, where guideline thresholds (e.g. 800–1000 ppm) are close to background levels. An uncorrected offset of this magnitude could therefore lead to systematic misclassification of ventilation adequacy or delayed mitigation actions in occupied spaces. Crucially, the strong linearity observed across the entire tested range indicates that these systematic errors can be effectively corrected using a simple linear calibration model derived under controlled conditions. This finding underscores the value of multi-point chamber-based calibration compared to single-point adjustment or short-term co-location, as it enables both slope and offset errors to be quantified and corrected in a reproducible manner. Once calibrated, the sensor exhibited an expanded uncertainty of ±26 ppm at 700 ppm, a level of repeatability that is fully compatible with continuous indoor monitoring and comparable to values reported for similar low-cost devices. From a broader perspective, the results highlight the relevance of an intermediate calibration approach that balances metrological rigor with operational flexibility. In contrast to co-location strategies, which are constrained by the availability and representativeness of reference stations, the proposed platform enables systematic and repeatable exposure to predefined concentration levels under controlled environmental conditions. At the same time, it avoids the cost, size, and infrastructure requirements of full-scale laboratory chambers, making it suitable for decentralized use in research laboratories, institutional buildings, or maintenance workflows for dense sensor networks. Some limitations of the current study should nevertheless be acknowledged. A primary metrological limitation of the current prototype is the absolute accuracy of the integrated reference instrument (Sensirion SCD40). As demonstrated in the uncertainty budget, the reference sensor's declared accuracy (e.g., ±85 ppm at 700 ppm) dominates the overall system uncertainty, significantly overshadowing the highly stable intrinsic repeatability of the calibration bench itself (±14 ppm). Consequently, the absolute accuracy of the calibration is inherently constrained by the specifications of this reference node. This selection was a necessary design compromise to prioritize the ultra-portable, low-cost, and modular nature of the platform for field deployments. Nevertheless, the system's relative stability proved more than sufficient to successfully isolate and mathematically correct the much larger systematic baseline and sensitivity errors typical of commercial low-cost monitors (e.g., the >150 ppm deviations observed in the Extech CO240). Future iterations of the bench architecture will aim to integrate higher-precision, miniaturized dual-channel NDIR or photoacoustic spectroscopy (PAS) reference modules to tighten the traceability chain and further reduce baseline uncertainty without compromising portability. While this study focused on concentration-dependent performance under fixed temperature and humidity conditions, the platform is inherently capable of supporting more advanced test protocols. The system is also compatible to perform tests with other pollutants like Particulate Matter (PM). Systematic investigations of temperature and humidity cross-sensitivity, response time, long-term drift, and sensor aging would further strengthen the applicability of the system for long-term field deployments. Overall, the discussion confirms that the developed calibration chamber represents a practical and effective tool for improving the reliability of low-cost CO_2 sensors. By enabling controlled, reproducible, and portable calibration across the indoor air quality range of interest, the proposed system contributes to closing the gap between laboratory-grade calibration and real-world sensor deployment, supporting more accurate and trustworthy indoor air quality monitoring.

5. Conclusion

This study presents the design, development, and comprehensive characterization of a portable CO_2 calibration system specifically aimed at supporting the evaluation of LCS. The system combines control of air temperature and relative humidity with a gas injection mechanism, enabling the generation of reproducible CO_2 concentration profiles across the indoor air quality range of interest (400–2000 ppm). This integrated approach allows for both stepwise and gradually ramped concentration changes, mimicking realistic indoor occupancy scenarios and providing a versatile testing environment. Experimental results demonstrated that the calibration chamber produces stable and repeatable concentration profiles, with expanded uncertainties of ±14 – 17 ppm for both discrete and ramped injections. The high linearity of the generated profiles confirms the reliability of the valve-based injection protocol and the effectiveness of the internal mixing system in maintaining uniform gas distribution throughout the chamber volume. The repeatability and predictability of the generated CO_2 levels confirm that the platform can serve as a calibration tool for low-cost CO_2 sensors. The performance of the Extech CO240 low-cost CO_2 sensor was systematically assessed using the chamber. Linear regression analysis revealed a systematic positive bias of 154 ppm and a sensitivity coefficient of 1.2, with a coefficient of determination $R^2 = 0.99$. These results indicate that, although factory calibration introduces systematic errors, the sensor response remains highly predictable and can be effectively corrected through a multi-point calibration procedure. Once corrected, the sensor exhibited an expanded uncertainty of ± 26 ppm ($k = 2$), demonstrating its reliability and suitability for continuous indoor air quality monitoring. Beyond the immediate sensor characterization, the study highlights the broader implications of the chamber as a practical calibration platform. It provides an intermediate solution that balances the accuracy and environmental control of laboratory-grade systems with the portability and cost-effectiveness required for field deployments. This enables not only the validation of individual sensors but also the maintenance of dense LCS networks, enhancing the spatial and temporal resolution of indoor air quality measurements for research, institutional applications, and citizen science initiatives. Looking forward, the platform offers the potential for further enhancements. Future work could include systematic evaluation of long-term sensor drift, and aging effects. Additionally, the system could be adapted to calibrate a wider range of environmental sensors beyond CO_2, supporting the broader development of reliable, low-cost monitoring networks. In conclusion, the developed calibration chamber represents a robust, flexible, and accessible tool that bridges the gap between expensive laboratory facilities and uncontrolled in-situ methods. By providing controlled, reproducible, and portable calibration capabilities, it significantly contributes to improving the performances of low-cost CO_2 sensors, thereby supporting more trustworthy indoor air quality monitoring and advancing the deployment of high-resolution sensor networks.

CRediT author statement

•Gianluca Sartini: Conceptualization, Methodology, Software, Investigation, Formal analysis, Data curation, Visualization, Validation, Writing – original draft.

•Nicole Morresi: Conceptualization, Methodology, Software, Investigation, Formal analysis, Data curation, Visualization, Validation, Writing – review & editing.

•Sara Casaccia: Supervision, Project administration, Resources, Funding acquisition, Writing – review & editing.

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Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Given Nicole Morresi's role as Associate Editor, had no involvement in the peer review of this article and had no access to information regarding its peer review. Full responsibility for the editorial process for this article was delegated to another journal editor. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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