
# An Independent Study on the Performance, Accuracy and Reliability of uHoo Smart Air Monitor in a Laboratory and Real Indoor Environment

SUMMARY

An independent study to evaluate the performance of low-cost monitors for real-time measurement of indoor air quality was conducted by Dr. Alberto Baldelli, a scientist from the Mechanical Engineering Department at the University of British Columbia in Vancouver, Canada. He evaluated the performance of the sensors of the uHoo Smart Air Monitor, which are:

- Temperature
- Relative Humidity
- Air Pressure
- Dust (PM2.5)
- Carbon dioxide (CO2)
- Carbon monoxide (CO)
- Nitrogen dioxide (NO2)
- Total Volatile Organic Chemicals (TVOCs)
- Ozone (O3)

These pollutants are important to monitor and measure because concentration levels beyond thresholds lead to health conditions such as asthma, allergies, and even increased risk of virus transmission.

The study sought to validate the correlation and cross-sensitivity of each uHoo sensor compared to reference methods in both a stable laboratory platform and a real indoor environment. It is noteworthy that this is the first study to show the full process of developing a laboratory platform that can validate the effectiveness of indoor air quality sensors and measurements of IAQ of low cost monitors in real environment.

The independent study was published in the scientific journal Measurement: Sensors on July 26, 2021 and made available digitally by Science Direct.

uHoo

## FINDINGS

The findings confirmed good correlation between the uHoo sensors and reference methods for readings of the 9 air quality factors in both the laboratory setting and the real indoor environment. It revealed how the uHoo Smart Air Monitor is capable of detecting common household pollutants - parameters that aren't only suitable for gauging virus transmission risks, but also asthma and allergen triggers.

Study results also show that uHoo's sensors were capable of detecting changes in indoor levels of these pollutants with a small margin of error.

uHoo Smart Air Monitor's high correlation with reference methods, low cost, and ease of use make it a compelling choice for measuring pollutants indoors to improve indoor air quality and create healthier living environments.

Measurement: Sensors 17 (2021) 100059

Contents lists available at ScienceDirect

Measurement: Sensors

journal homepage: www.sciencedirect.com/journal/measurement-sensors

# Evaluation of a low-cost multi-channel monitor for indoor air quality through a novel, low-cost, and reproducible platform

Alberto Baldelli

*Department of Mechanical Engineering, University of British Columbia, Canada*

A B S T R A C T

Short-term exposures to indoor air contaminants can cause adverse health impacts and warrant a need for real-time measurements. The most common indoor pollutants are carbon dioxide ($CO_2$), carbon monoxide (CO), ozone ($O_3$), nitrogen dioxide ($NO_2$), total volatile organic compounds (TVOCs), and particulate matter with a diameter of less than 2.5 μm ($PM_{2.5}$). Several low-cost monitors for indoor air quality are commercially available; however, few of them are accurately tested. A stable, easy to use, and reproducible platform was developed in this paper. In these laboratory conditions, the comparison between the low-cost sensors and calculated concentration was shown to be linear ($R^2$ of 0.980, 0.972, 0.990, 0.958, 0.987, and 0.816 and $r_s$ of 0.982, 0.985, 0.900, 0.924, 0.982, and 0.571 for $PM_{2.5}$, $CO_2$, CO, $NO_2$, TVOC (ethylene), and $O_3$ respectively). Laboratory conditions were used to test possible cross-interferences to the TVOC sensor; an increase of $CO_2$, CO, and $NO_2$ of 2500 ppm, 100 ppb, and 100 ppb respectively generated a change in the curve fit from linear to quadratic. A complete validation of a low-cost sensor was achieved by its application in a real indoor place. Good correlation between the reference methods and uHoo measurements of $PM_{2.5}$, $CO_2$, and $O_3$ was achieved ($r_s$ = 0.765 to 0.894, 0.721 to 0.863, and 0.523 to 0.622 respectively).

## 1. Introduction

Human beings spend about 87% of their time indoors, in buildings which are filled with pollutants of different types that, even in short-term exposure times, affect human health [1]. The most common indoor air pollutants measured are particulate matter smaller than 2.5 μm in diameter ($PM_{2.5}$), carbon monoxide (CO), carbon dioxide (CO2), nitrogen dioxide (NO2), volatile organic compounds (VOCs), and ozone (O3). The most common size of particulate matter (PM) measured is $PM_{2.5}$ since it has been linked with cardiovascular and respiratory diseases [2,3].

Humans are bad at perceiving the indoor pollutants listed above [4]. Consequently, measurements of indoor pollutants are needed to mitigate the risks to the health of building occupants. The United States Environmental Protection Agency (EPA) has established federal reference methods to accurately test each pollutant. Examples are filter-based gravimetric sensors for PM and chemo-adsorption for certain volatile organic compounds [1,5,6]. Even though these methods provide high accuracy and temporal resolution, the techniques are impractical for many studies [7]. Major issues include the need for quality control checks, frequent calibration, high cost, and requirement of an operator with specialized skills. Furthermore, these reference methods provide a level of accuracy that is unnecessary for many applications. However, the raise of interest in low-cost sensors and monitors is due, besides their affordability and easy accessibility, to some of the disadvantages in reference methods. For example, reference methods are very limited to one pollutant and in order to validate the IAQ, multiple reference methods would be needed [8]. In this cases, low-cost sensors are usually used even though their data might be less accurate but potentially still actionable [9].

Several sensors are available for the detection of $PM_{2.5}$ [10–14]. All of these low-cost sensors use optical light scattering. They are compact, low weight, energy efficient, and have a high sampling frequency [15]. Gaseous pollutants such as carbon monoxide (CO), nitrogen dioxide ($NO_2$), ozone ($O_3$), and volatile organic compounds (VOCs) can be detected using miniature photoionization detectors (PIDs), electrochemical (EC) sensors, or metal-oxide semiconductor (MOx) sensors. Of these sensors, PIDs have a major disadvantage: the inability to ionize different VOCs equally. As a result, EC and MOx sensors have been used in recent studies on the development of low-cost sensors for pollutant gases [16]. To detect $CO_2$, low-cost sensors use non-dispersive infrared absorption (NDIR) [17]. A few research studies demonstrated that low-cost NDIR sensors provide an accuracy that is sufficient for indoor applications [18–20].

Using standalone sensors to evaluate the quality of indoor air can be inconvenient. To remedy this issue, a vast number of low-cost sensors for indoor air quality (IAQ) have been developed in the last few decades to measure many types of pollutants simultaneously. These devices can easily collect large datasets that can be used to generate information on the variation of pollutant levels throughout the day. Real-time monitors

*E-mail address:* baldelli.alberto@yahoo.com.

https://doi.org/10.1016/j.measen.2021.100059
Received 13 March 2021; Received in revised form 10 July 2021; Accepted 24 July 2021
Available online 26 July 2021

can also alarm when the acceptable limits are exceeded, allowing quick action to minimize the pollutant.

Few commercially available low-cost, multi-channel monitors have been accurately calibrated [8,16,21–23]. Laboratory tests are fundamental to determine response time, limit of detection, and the linearity of response [1]. For PM, laboratory tests are necessary to determine additional properties of the sensors, such as the influence of the particulate type and size on readings [12,24,25]. In most previous studies, laboratory tests use a reference method as a comparison to the readings of each sensor [26]. As noted above, these reference methods can be expensive and require a skilled operator to accurately function. As well, current laboratory platforms have trouble with validating the cross-interference between two sensors contained in a low-cost monitor [27]. Furthermore, one of main drawback of low-cost monitors, including a variety of sensors, is the possible cross-sensitivity. Laboratory tests show a higher accuracy in validating the cross-sensitivity between several low-cost sensors [16,28].

Validating a low-cost monitor also requires testing in a real environment where pollutant concentrations can be highly variable. The response of a low-cost indoor air monitor to the variability of a real indoor environment needs to be validated against reference methods to determine the monitor correlation [8,12,16].

The objects of this study were 1) to generate a user-friendly, low-cost, reproducible, and stable platform to validate a low-cost monitor, 2) to validate the correlation and cross-sensitivity of each sensor contained in a low-cost monitor compared to reference methods in stable conditions, and 3) to confirm the correlation of some of the sensors included in a low-cost monitor compared to reference methods in a real indoor environment. As far as the authors know, this study is the first to show the full process of generating a laboratory platform, applying that platform to validate the efficacy of low-cost sensors, and measurements of IAQ of low-cost monitors in real environments. This study aims to be a guideline for future investigations focused on a deep and accurate validation of low-cost IAQ monitors.

## 2. Low-cost multi-channel monitor

### 2.1. Low-cost multi-channel monitor used in this study

The selected low-cost multi-channel monitor was produced by uHoo, Limited, Hong Kong, China, Table 1. The information reported in Table 1 was kindly provided by uHoo; detectable range, resolution, and estimated accuracy were provided by the manufacturers of the single sensors included in uHoo monitors [29,30].

A series of algorithms have been developed by uHoo to transform the raw data from each sensor into user-friendly data showing measurements of each indoor pollutant. The device generates readings each minute and auto-calibrates the $CO_2$ sensor every 168 h (7 days) and the TVOC, O3 and NO2 sensors every 24 h. This auto-calibration estimates exposure levels that the sensor is subject to during operation; then the software updates and becomes more accurate to the specific operating conditions. Due to this auto-calibration, a 48-h “warm up” period is needed for the uHoo monitor to provide better measurements. If the warm up is interrupted, it will restart from the beginning the next time it is powered on and connected to the network. The warm up is only necessary to be completed during first time use under a given operating condition. For example, if the monitor is moved between locations in a single facility, a second warm up is not necessary. Auto-calibration is important because chemical sensors age faster in polluted environments and their baselines need to be recalibrated frequently [31].

## 3. Methods

### 3.1. Development of a low-cost, stable laboratory platform

#### 3.1.1. Enclosure

For all laboratory tests, three uHoo monitors were placed in a 40 L enclosure (NBA-10172, Bud Industries, Cleveland, USA), Fig. 1 a). Experimental atmospheres were introduced into the enclosure at a flow rate close to 10 L/min. Changes in pressure inside the enclosure were not recorded. A mini fan (SmartDevil mini fan, SmartDevil, Technology) (12 × 4.3 mm) was placed close to the exit to decrease the pollutant mixing time in the 40 L enclosure. For more details, please see the SI.

#### 3.1.2. Particulate matter 2.5 ($PM_{2.5}$)

An atomizer was used to produce PM [32–34]. Solutions were inserted into the atomizer feeding system, Fig. 1 b. A drier (Aerosol Diffusion Dryer, Cambustion, USA) removed the remaining water droplets allowing only solid particulates to access the enclosure. An Optical Particle Sizer (OPS) (3330, TSI, Shoreview, Minnesota, USA) was the selected reference device for a few reasons. It shows a maximum difference of 10% with respect to other reference methods [35]. Moreover, the accuracy of OPS measurements was confirmed through comparison to gravimetric samples (see SI). The OPS had the added benefit of providing information on the particulate size distribution.

Refractive index, density, and shape factor are some of the aerosol properties influencing light scattering, according to the Mie theory [36]. The three main properties that impact the quantity of light scattered by a single particle are the particle diameter, refractive index, and shape factor. The three main properties that impact the quantity of light scattered by multiple particles composed of the same material are the particulate size distribution, refractive index, and shape factor. Ultimately, particle density influences the association between the particle mass ad the quantity of light scattered. Three solutes with different density, refractive index, and shape factor were selected. Sodium chloride, sucrose, and potassium iodide aerosols have a density of 2.16, 1.59, and 3.12 g/cm3, a refractive index of 1.58, 1.33, and 1.67, and a shape factor of 1.08, 1.9, and 1.08 [37], respectively. These parameters can be programed into the OPS, while the uHoo refractive index and shape factor are fixed at 1.58 and 1, respectively.

#### 3.1.3. Gas sensor

A similar experimental system was created to validate the CO2, CO, NO2, and TVOC sensors, Fig. 1 c). The TVOC MOx sensor was tested by

**Table 1**
Detectable range, resolution, and estimated accuracy of the tested low-cost multi-channel monitors.

| Sensor | Type | Model | Detectable range | Resolution | Estimated accuracy |
|---|---|---|---|---|---|
| PM2.5 | Optical scattering | Shinyei Kaisha PPD42-60 | 0–200 μg/m3 | 0.1 μg/m3 | ±20 μg/m3 or 10% of reading |
| CO2 | NDIR | ELT Sensor T-110-3V | 400 to 10,000 ppm | 1 ppm | ±50 ppm or 3% of reading |
| CO | Electrochemical | Figaro Engineering TGS5342 | 0–1000 ppb | 0.1 ppb | ±10 ppm |
| TVOC | Metal oxide | Cambridge CMOS CC881B | 0 to 1000 ppb | 1 ppb | ±10 ppb or 5% of reading, based on the types of VOC |
| O3 | Metal oxide | SGX Sensortech MICS-2714 | 0–1000 ppb | 1 ppb | ±10 ppb or 5% of reading |
| NO2 | Metal oxide | SGX Sensortech MICS-2714 | 0–1000 ppb | 1 ppb | ±10 ppb or 5% of reading |

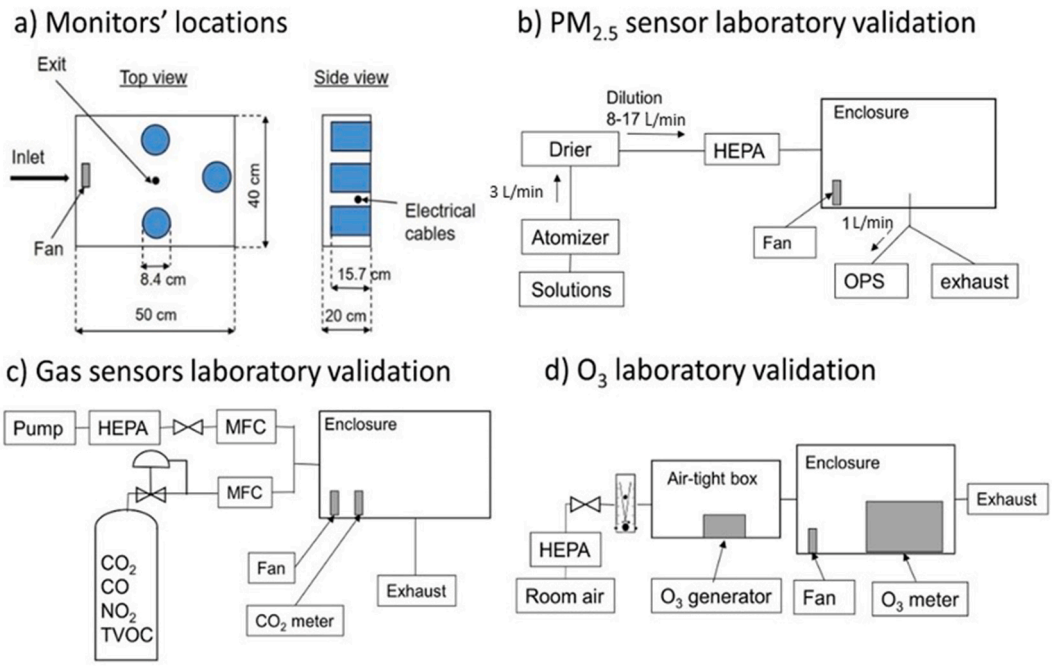


**Fig. 1.** Illustration of the dimensions of the enclosure selected, of the dimensions of uHoo monitors, and of the locations at which uHoo monitors were placed in the enclosure for each laboratory experiment.

using three different gases: ethylene (EY 3.0 PL-Q, Praxair, Guildford, UK), methane (ME 2.0, Praxair, Guildford, UK), and propane (NI PR30C-AS, Praxair, Guildford, UK). TVOC sensors are most commonly calibrated using isobutylene, although ethylene and propane are also used as calibration gases. In addition, low-cost MOx sensors are shown to react to methane [16,38]. Thus, by using methane, the response of the uHoo TVOC sensor to multiple gases was verified. Furthermore, methane and propane are both alkanes; however, methane has different bond strengths, which probably plays a role in its oxidation potential and therefore it is valuable to test the sensor to methane.

Two mass flow controllers (MFCs) were used to control the flow of both the selected gas and the filtered room air. The MFC used to control the filtered room air had a flow range of 0.1–10 L/min (Alicat MC-10SLPM, Tucson, Arizona, USA) while the MFC for the gases had a range of 0.02–0.2 L/min (Alicat, MC-200SCCM, Tucson, Arizona, USA). Since the MFC could only be set for pure gases, a gilibrator (Gilibrator-2 Calibrator, Sensidyne, St. Petersburg, Florida, USA) was used to calibrate the MFC.

The reference method used for $CO_2$ was a Vaisala $CO_2$ meter (Vaisala GMP222, Vantaa, Finland). This CO2 meter has a range of 0–2000 ppm with an accuracy of 2%. Details on its calibration are reported in the SI. For CO, NO2, and TVOC, theoretical calculations were used as a reference method. The Continuously Stirred Tank Reactor (CSTR) theory [39] was used to calculate the mass concentration of the selected gas injected in the enclosure at a certain time, Equation (1).

$$c(t) = \frac{\dot{Q}_{air}C_0 + \dot{Q}_{gas}c_{gas}}{\dot{Q}_{tot}} + \left(c_{in} - \frac{\dot{Q}_{air}C_0 + \dot{Q}_{gas}c_{gas}}{\dot{Q}_{tot}}\right)e^{-\frac{\dot{Q}_{tot}\,t}{V_{en}}} \qquad \text{Equation 1}$$

Where c(t) is the mass concentration in ppm of the selected gas in the enclosure at a certain time t, $C_0$ is the ambient concentration estimated in L/min converted from $c_0$ that is the ambient concentration estimated to 500 ppm for $CO_2$, 2.5 ppb for CO, 0.1 ppm for TVOC, 7 ppb for $NO_2$, and 1 ppb for $O_3$ (2) for indoor environments, $Q_{tot}$ is the total flow rate found as a sum of the gas flow rate $\dot{Q}_{gas}$ and the air flow rates $\dot{Q}_{air}$ in L/min, Ven is the volume of the enclosure, and $c_{in}$ is the initial concentration in ppm. Equation (1) was applied also to $CO_2$ and $O_3$ in order to validate its applicability.

Fig. 1 d) shows the experimental system used to validate the O3 sensor in uHoo monitors. An O3 generator (Villa 3000, OdorFree Machines, Tallahassee, Florida, USA) was placed in an airtight box. Filtered air was used to draw a portion of the ozone into the enclosure containing the uHoo monitors. Diluted O3 was then directed to a second enclosure where the three uHoo monitors were located. The ozone generator produced other gases, such as $NO_2$ and $CO_2$, which could potentially affect the uHoo $O_3$ sensor readings. However, an $O_3$ meter was used as a reference method (UV106L, Oxidation Technologies, Inwood, Iowa, USA); this $O_3$ meter works for a range of 1–100 ppm with a resolution of 0.1 ppb. More details on its validation can be found in the SI.

### 3.1.4. *Stability of the developed low-cost and stable laboratory platform*

The homogeneity of the distribution of particulate matter and one of the gas pollutants in the enclosure was validate. $PM_{2.5}$ (obtained using sodium chloride) and $CO_2$ were the pollutants selected. One of these pollutants was introduced in the enclosure at difference concentrations ($PM_{2.5}$ varying from 0 to 300 μg/m$^3$ and $CO_2$ varying from 500 to 3000 ppm). In case of $PM_{2.5}$, the inlet of the OPS was placed at different locations inside the enclosure. In case of $CO_2$, the inlet of the Vaisala meter was positioned at different locations. For both cases, measurements were recorded between the 40th to the 50th minutes from the injection time. This time window was selected since both $PM_{2.5}$ and $CO_2$ were injected at 1 L/min and by having a 40 L enclosure, the chamber was expected to be saturated after the 40th minute from each experiment starting point. The highest difference between two location was reported as an estimation of the homogeneity of the distribution of the pollutant tested. Particle and gas mass concentration (μg/m$^3$ and ppm) of minute-by-minute data was used. Standard deviations per each location was derived by considering a time window of 10 min.

### 3.1.5. *Validation of the correlation of the low-cost monitors with reference methods*

The detectable levels of $PM_{2.5}$, $CO_2$, CO, TVOC, and $NO_2$ were tested in order to evaluate uHoo performance in a controlled environment, Table 1. Laboratory tests were repeated five times at each concentration of pollutant. $PM_{2.5}$, $CO_2$, and $O_3$ levels were also measured with a

reference device, maintaining the low-cost sensors as the independent variable. For these measurements, a sample was considered stable if the recorded values differed by less than 2% after 5 min. Data was then collected for 20–40 min. Each sample was repeated five times generating a total of 100–200 data points. Note that $O_3$ was only tested between 0 and 20 ppb due to limitations in the laboratory platform. The limit of detection of $PM_{2.5}$ sensors was calculated, as shown in the SI.

Since the relation between the low-cost sensor readings and the reference meter readings or calculated concentrations appeared monotonic, a Spearman's rank-order correlation ($r_s$) was applied [40] to evaluate the correlation between the two measuring methods. To further compare uHoo monitors and reference methods, a regression analysis was performed. Linear, quadratic, and cubic models were fitted, using Origin Pro, to the data to find the most accurate equation (highest adjusted $R^2$ and Chi-squared) [41]. Moreover, linear increase was calculated over each minute and differences in the increase rates between low-cost sensors and reference methods were obtained by considering the time period of the whole experiment.

The interference of CO, CO2, and NO2, on the TVOC sensor was validated testing varying concentrations of interfering pollutants and repeating each test 5 times. Previous studies showed that CO and $CO_2$ can cause interferences [9] so investigating potential interferences of these gases in uHoo monitors was necessary. The interference of $NO_2$ on the TVOC sensor was tested since both $NO_2$ and TVOC sensors contained in uHoo monitors are of the same type, MOx. To study the cross-interference between CO, $CO_2$, $NO_2$, and TVOC, the system shown in Fig. 1 c) was slightly modified by adding an extra line that feeds one more gas in the enclosure (see SI). $CO_2$ levels of 0, 2500, 5000, 7500, and 9000 ppm, $NO_2$ levels of 0, 200, 400, 700, and 1000 ppb, and CO levels of 0, 100, 200, 300, and 400 ppb, were used to study the impact to the response of the TVOC sensor. Other cross-interferences are shown in the SI.

### 3.2. Verifying the low-cost monitor response to a real indoor environment

Three uHoo units were placed in a residential building located in central Vancouver, Canada, shown in the SI. The study was undertaken following the guidelines of the ASTM D72974-14 Standard Practice for Evaluating Residential Indoor Air Quality [42]. The low-cost monitors and the reference instruments were located at an approximate height of 1 m over the top of a drawer and at the center of a room [41]. The recording period was seven days, from March 31st, 2019 to April 6th, 2019 (period A) and from October 14th, 2019 to October 20th, 2019 (period B). $PM_{2.5}$ and $CO_2$ were measured during period B, while $O_3$ was measured during both periods.

During period A, the building was inhabited, however, major activities were not recorded. During period B, the building was inhabited by anywhere from 0 to 5 people. Common indoor activities occurred, such as cooking and cleaning [43]. In addition, two windows in the room were opened to introduce more variability to the measurements. More details on the building and room in which the sensors were placed are reported in the SI. The uHoo readings were obtained as an average between three sensors placed close to three windows.

Readings of $PM_{2.5}$, $CO_2$, and $O_3$ were also measured using the reference methods mentioned in the previous section. The period length was limited, but was sufficient to compare different measurement methods [41]. The OPS and the Vaisala $CO_2$ meter readings were continuously operating and 1-min averages were recorded. The $O_3$ meter was operating for 12 h a day. However, hour-by-hour data reported by the website AirMap (https://gis.metrovancouver.org/maps/air/) were used as further validation of uHoo $O_3$ sensors, see SI. Indoor ozone levels were estimated to be 20–70% of the outdoor levels [44].

### 3.3. Statistical analysis

In order to validate the correlation between the readings of uHoo low-cost sensors and reference methods or concentrations calculated using theoretical methods, a few parameters were used, such as a regression curve, the $R^2$ coefficient of determination, and the Spearman's coefficient ($r_s$). These parameters were calculated using the minute-by-minute data, averaged over 30 min for the laboratory tests, achieved using both low-cost sensors and reference methods. Standard errors and differences between low-cost sensors and reference methods data were similarly derived considering the minute-by-minute data over the time window of 30 min. Three low-cost sensors were used for the statistical analysis. In case of field tests, a Blandt- Altmann plot was generated in order to verify the comparison between the low-cost sensors and reference methods. The same statistical approach was used for both laboratory and field tests. However, the regression identified in the laboratory tests were not applied on the data achieved in a real indoor environment. In addition, the standard deviations between the measurements of the three low-cost monitors are reported using minute-by-minute data. In some cases, to examine the correlation between data generated by the analyzed low-cost monitor, and by reference methods, a Bland–Altman analysis was performed over minute-by-minute data [45]. An upper and lower bound of 1.96 standard deviations (SD) of the difference was applied. Moreno et al. showed that the 1.96 SD limits are appropriate to assess the impact of pollution on human health [41].

## 4. Results and discussion

### 4.1. Stability of the developed low-cost and stable laboratory platform

In $PM_{2.5}$ tests, the difference between the readings of the OPS at points A-F was 10.5% (Fig. 2a). Measurements of PM between 1 and 2.5 μm, the measurable range of uHoo monitor, showed a variability of 14.8%. The greatest difference in PM counts (17.4%) was found in the location farthest from the injection point (Side E in Fig. 2 a), which is still considered in agreement with previous literature data [21]. In CO2 tests, the largest difference between two locations was $17.8 \pm 1.3\%$. This high homogeneity ensures that the three uHoo monitors were exposed to similar levels of pollutants. Furthermore, the results shown in Fig. 2 emphasize the stability of the developed laboratory platform to both test PM and gas sensors.

### 4.2. Validation of the correlation of low-cost monitors with reference methods

Fig. 3a) and b) shows the experiments conducted to determine the response of the PM and $CO_2$ sensors, respectively. For the other gases, measurements have been recorded only when stable conditions were reached in the enclosure (difference of less of 2% in the average of the data of reference methods).

Fig. 3 shows another important parameter of the validation of low-cost monitors. uHoo monitors show a close response time compared to the reference methods. When a change in conditions is induced, such as for times 25–30 min in a) and 0–10 min in b), the average difference in increase rates between uHoo monitors and the reference methods is 7 and 2% for PM and $CO_2$ measurements respectively. In addition, in Fig. 3 b), the comparison between the reference method ($CO_2$ meter) and the calculated concentration is introduced. An average difference between the readings achieved using a $CO_2$ meter and the derivations achieved using a calculated concentration is 5%; a higher difference (11%) is achieved at low levels of $CO_2$ ($<200$ ppm) possibly due to a difference in the assumption in the initial concentration selected in the calculated concentration and the actual ppm contained in the enclosure.

Table 2 and Fig. 5 show the regressions and the box charts obtained for each sensor contained in the tested low-cost monitors. Plots of the raw data are shown in the SI. PM sensors typically showed a linear

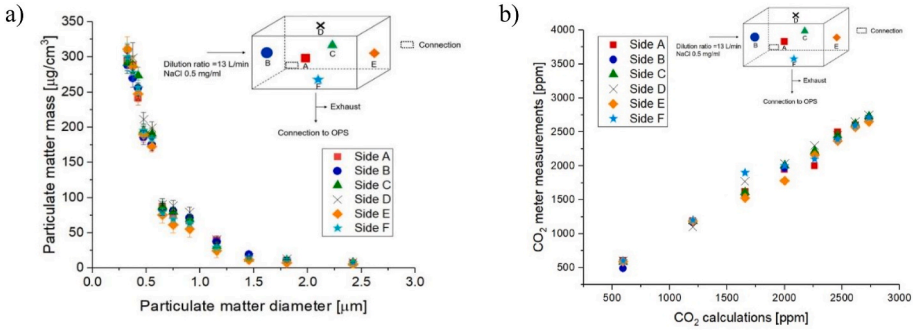


**Fig. 2.** Homogeneity of the distribution of the PM a) and of CO2 b) in the enclosure. Measurements obtained with OPS a) and with the CO2 meter b) and at six different locations in the enclosure were compared.

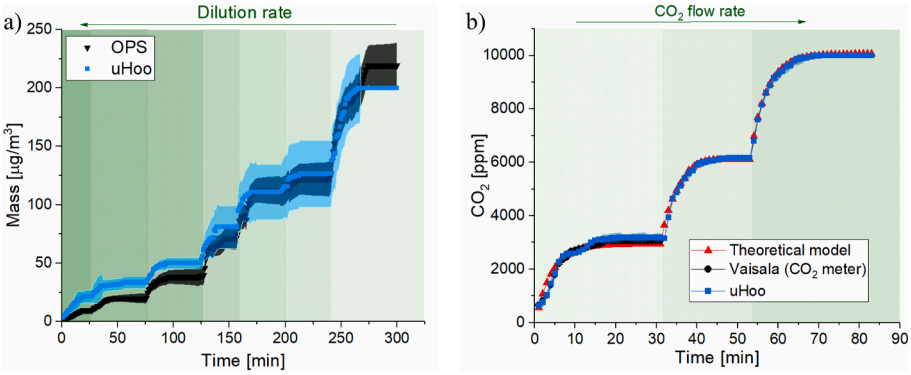


**Fig. 3.** Comparison between the measurements of uHoo monitors and the OPS. OPS data between the bin of 1–2.5 µm were used (same for uHoo sensors). Sodium chloride was used. Darker background tones indicate a higher dilution rate as shown in a) and comparison between the measurements of uHoo monitors and Vaisala $CO_2$ meter is shown in b). The error bars are indicated by the lighter done areas surrounding the data set. Error bars represent standard errors derived the experiment repetitions.

**Table 2**
Source, linearity coefficient R-squared, regression type, equation, R2 obtained per each sensor included in uHoo monitors. Comparison with both theoretical methods and reference methods are shown. In addition, in the case of PM2.5 and TVOC, different sources are used to verify the response of uHoo sensors. The Spearman's rank-order correlation is calculated to verify the association from one device to another. The last column n stays for the amount of data per each pollutant. The term theoretical model identifies the calculated concentrations performed. The variables x and y relate to the data obtained using the reference methods and the low-cost sensors, respectively.

| Pollutant | Source | Corresponding method | $R^2$ (Linear) | Regression | Equation | $R^2$ | $r_s$ |
|---|---|---|---|---|---|---|---|
| $PM_{2.5}$ | Sodium chloride | OPS[a] | 0.980 | Linear | $y = 18.127 + 0.871^{a}x$ | 0.987 | 0.982 |
| | Potassium iodide | OPS[a] | 0.971 | Quadratic | $y = 14.8 + 1{,}5\,x - 1 \times 10^{-3}\,x^2$ | 0.991 | 0.971 |
| | Sucrose | OPS[a] | 0.966 | Quadratic | $y = 15.5 + 2.6\,x - 0.01\,x^2$ | 0.983 | 0.735 |
| $CO_2$ | $CO_2$ | Vaisala meter | 0.972 | Quadratic | $y = -462 + 1.8\,x - 1.98\,x^2$ | 0.992 | 0.985 |
| | $CO_2$ | Theoretical model | 0.991 | Linear | $y = -69 + 0.97\,x$ | 0.991 | 0.896 |
| TVOC | Propane | Theoretical model | 0.997 | Linear | $y = 19.5 + 0.93\,x$ | 0.996 | 0.982 |
| | Ethylene | Theoretical model | 0.987 | Quadratic | $y = 13.7 + 1.1\,x - 1.27\,x^2$ | 0.993 | 0.924 |
| | Methane[b] | Theoretical model | 0.997 | Cubic | $y = -0.84 + 0.97\,x + 2.34 \times 10^{-4}\,x^2 - 3.76 \times 10^{-7}\,x^3$ | 0.993 | 0.711 |
| CO | CO | Theoretical model | 0.990 | Linear | $y = 9.74 + 1.11\,x$ | 0.990 | 0.909 |
| $NO_2$ | $NO_2$ | Theoretical model | 0.958 | Quadratic | $y = 18.2 + 0.81\,x - 1.65\,x^2$ | 0.997 | 0.924 |
| $O_3$ | $O_3$ [c] | UV606-L | 0.816 | Cubic | $y = 1.34 + 0.42\,x - 0.09\,x^2 + 1.6 \times 10^{-5}\,x^3$ | 0.994 | 0.671 |

[a] OPS parameers are set for the solute used as the source.
[b] Methane is considered a VOC and is used to verify the response of the TVOC sensor.
[c] Emissions from the $O_3$ generator might contain some $CO_2$ and TVOC.

regression when compared to reference methods [11,12,25]. However, other studies observed nonlinear responses for low-cost sensors [46,47], particularly for particles with small diameters and with different optical properties (i.e. ammonium nitrate particles [11,21]). For uHoo $PM_{2.5}$ sensor, a quadratic regression is chosen when particulates matter made of potassium iodide and sucrose are used. Furthermore, the Spearman coefficient was lower for sucrose tests and slightly higher for potassium iodide tests. More details are shown in the SI, Figure S2.

The OPS has the advantage of being adjustable for a specific aerosol with known optical properties. A sensor's performance depends on particle composition since light scattering is influenced by the refractive index. A higher proportion of light can be absorbed by organic compounds such as sucrose, due to similar vibrational energy levels of carbon bonds. Thus, the phototransistor receives less light in the test of sucrose particles, and so reports a lower mass concentration [21,48]. Therefore, the uHoo $PM_{2.5}$ sensor was highly affected by the particle type.

Particle size is also known to affect the particulates measurements [11,13,23,49]. Here, we noticed a larger standard error (an average 20%) for PM concentrations between 50 and 200 µg/m$^3$ compared to lower mass concentrations. Moreover, the standard errors increase with expected particle mass concentration, Fig. 5. The comparison of uHoo $PM_{2.5}$ with a particle counter that is not based on light scattering would deepen the investigation of the impact of the particle type.

The limit of detection (LOD) was measured for the PM sensor and was 3.3 ± 1.7 μg/m3; as similar studies [11,21]. The offset of uHoo reading at 0 p.m. was about 4.9 ± 1.9 μg/m3, details in the SI.

Based on the coefficients of $R^2$ (0.972) and Spearman (0.985), along with the slope and the intercept of the regression equation, introduced in Table 2, uHoo $CO_2$ sensors accurately predict the indoor levels compared to a reference device, such as the Vaisala meter. However, the Spearman coefficient $r_s$ decreases to 0.89 when theoretical methods were used as reference methods. Furthermore, the regression type was quadratic for a $CO_2$ meter and linear when calculated concentration was used. A possible overestimation of the levels of $CO_2$ obtained using theoretical methods can occur for levels higher than 1000 ppm. In addition, a quadratic regression between readings of low-cost $CO_2$ sensors and a Vaisala meter or a NDIR was defined in previous studies [50–52]. In this case, a moderate slope indicates a good correlation between low-cost sensors and reference methods. Even though calculated concentration appears less accurate than the reference method, their maximum difference is about 30%. In addition, the main difference between the calculated concentration and the $CO_2$ meter can be seen in the level between 1300 and 1700 ppm, Fig. 4. By overestimating this range, calculated concentration derives a linear regression of the data respect to uHoo readings, Table 2. Furthermore, fairly low values of intercept and slope validate the good correlation between the two methods.

More detailed investigations on the comparison between calculated concentrations and reference methods for pollutants such as TVOC, $O_3$, $NO_2$, and CO, would validate the use of calculated concentrations to verify readings of low-cost sensors. In any case, as far as the results shown in Table 2 and Fig. 4, the suggested calculated concentration can be used to validate the trend of low-cost sensor readings by considering their possible overestimation. In the case of $CO_2$, a close correlation between the calculated concentration and uHoo sensor readings was found ($r_s$ = 0.99). As in the case of the $PM_{2.5}$ sensor, the $CO_2$ sensor shows standard errors of about 4% for expected levels lower than 1260 ppm and 26% for expected levels between 1260 and 3500 ppm. These differences are considered acceptable for an indoor application since indoor levels of $CO_2$ typically vary between 600 and 1000 ppm. In any case, uHoo low-cost sensors seem to overestimate the $CO_2$ levels for expected concentrations of 1260 ppm, compared to the reference method, that could happen in case of an indoor source of pollutant. In this case, the intercept of the regression is the highest among all cases shown in Table 2. However, indoor concentrations above 1000 ppm (even up to 3000 ppm) are also common due to several reasons [53–55].

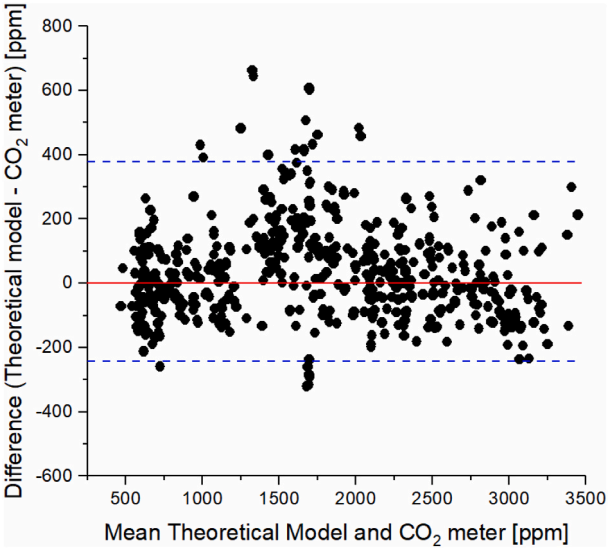


**Fig. 4.** A Blandt-Altmann plot between the calculated concentration and the $CO_2$ meter readings.

TVOC sensors have high uncertainties compared to other sensors [56–59]. Spearman's coefficient $r_s$ was found to be 0.98 and 0.92 when comparing calculated concentrations and uHoo readings of propane and ethylene respectively. A quadratic regression curve was selected for ethylene emissions. While exposed to different levels of propane and ethylene, uHoo TVOC sensors readings had standard errors, with an average of 35%, Fig. 5. A more detailed study on the selectivity of uHoo TVOC sensor would be beneficial to determine which gases generate a positive response. Furthermore, a TVOC meter, such as Graywolf [41], would be necessary. One drawback in the case of TVOC validation is estimating the emissions of one gas (propane or ethylene) and not a mix of multiple VOCs, which is a more realistic scenario.

In general, MOx gas sensors like the uHoo TVOC sensor respond to a large variety of gases [60,61]. Even though MOx sensors are highly sensitive, they are known to lack selectivity [62]. $NO_2$ and CO are shown to interfere with TVOC MOx sensors [62]. The influence of NO2 and CO to the TVOC sensor is shown in Table 3 where ethylene is the source gas. The regression type changes from quadratic to cubic after the smallest interference from $NO_2$ and CO. In addition, the $R^2$ coefficient decreases by 0.011 and 0.014 with an increase of 800 ppb of $NO_2$ and 300 ppm of CO respectively. These high concentrations of CO, and NO2 can be found in places with combustion sources and uncommonly in common households. However, when considering small increases of NO2 and CO mass levels (200 and 100 ppb respectively) the regression type changes from quadratic to cubic, further decreasing the linearity in the relationship. MOx sensors commonly show a response to practically all relevant targets and interfering gases except carbon dioxide ($CO_2$) [62,63]. Here, an addition of 2500 ppm of $CO_2$ generates a change in regression type from quadratic to cubic and a slight decrease in $R^2$. However, indoor environments with 2500 ppm in $CO_2$ are considered highly polluted (even though not uncommon [57]) and a lower $CO_2$ content might generate a much smaller interference to uHoo MOx TVOC sensors. Therefore, it could be suggested to consider uHoo TVOC sensor behavior at lower $NO_2$ and CO concentrations.

uHoo CO sensors showed strong correlation with the calculated concentration, having a Spearman's coefficient of 0.90, as well as a small value of intercept and slope of the linear regression equation. Electrochemical sensors tailored to the detection of CO have been shown to yield a linear response to CO levels [16,64–67]. Standard errors increased greatly (up to 27%) for CO levels above 400 ppm, Fig. 5; however, indoor levels of CO are commonly below 1 ppm and for this range [68], uHoo monitors showed good correlation with the calculated concentration (maximum difference of 2%).

Good correlation was also found for the $NO_2$ sensor with Spearman's coefficient of 0.97 as well as an intercept of 18.2, Table 2. Good correlation between MOx $NO_2$ low-cost sensors and reference methods was observed in a previous study [1,69]. Here, however, uHoo $NO_2$ sensors showed a quadratic regression curve indicating a possible underestimation of $NO_2$ ppm at levels of $NO_2$ above 800 ppb. At these levels, a higher number of outliers in the readings were seen, Fig. 5. However, most indoor environments do not exceed 200 ppb [68].

Lastly, $O_3$ uHoo sensors show poor correlation with the $O_3$ meter ($r_s$ = 0.57 and a cubic regression). Moreover, a cubic regression curve is generating the highest $R^2$; poor linearity of $O_3$ MOx sensors is a known property [8]. This trend might be due to the presence of $NO_2$, $CO_2$, and CO from the $O_3$ generator; these emissions might interfere with the $O_3$ uHoo sensor.

### 4.3. Verifying the low-cost monitor response to a real indoor environment

Parameters such as interferences, limits of detection, and impact of pollutant mass levels were estimated in laboratory tests. However, field tests are the ultimate test for the validation of an indoor low-cost monitor. In this project, the response of the uHoo sensors of $PM_{2.5}$, $CO_2$, and $O_3$ are tested in a real indoor environment.

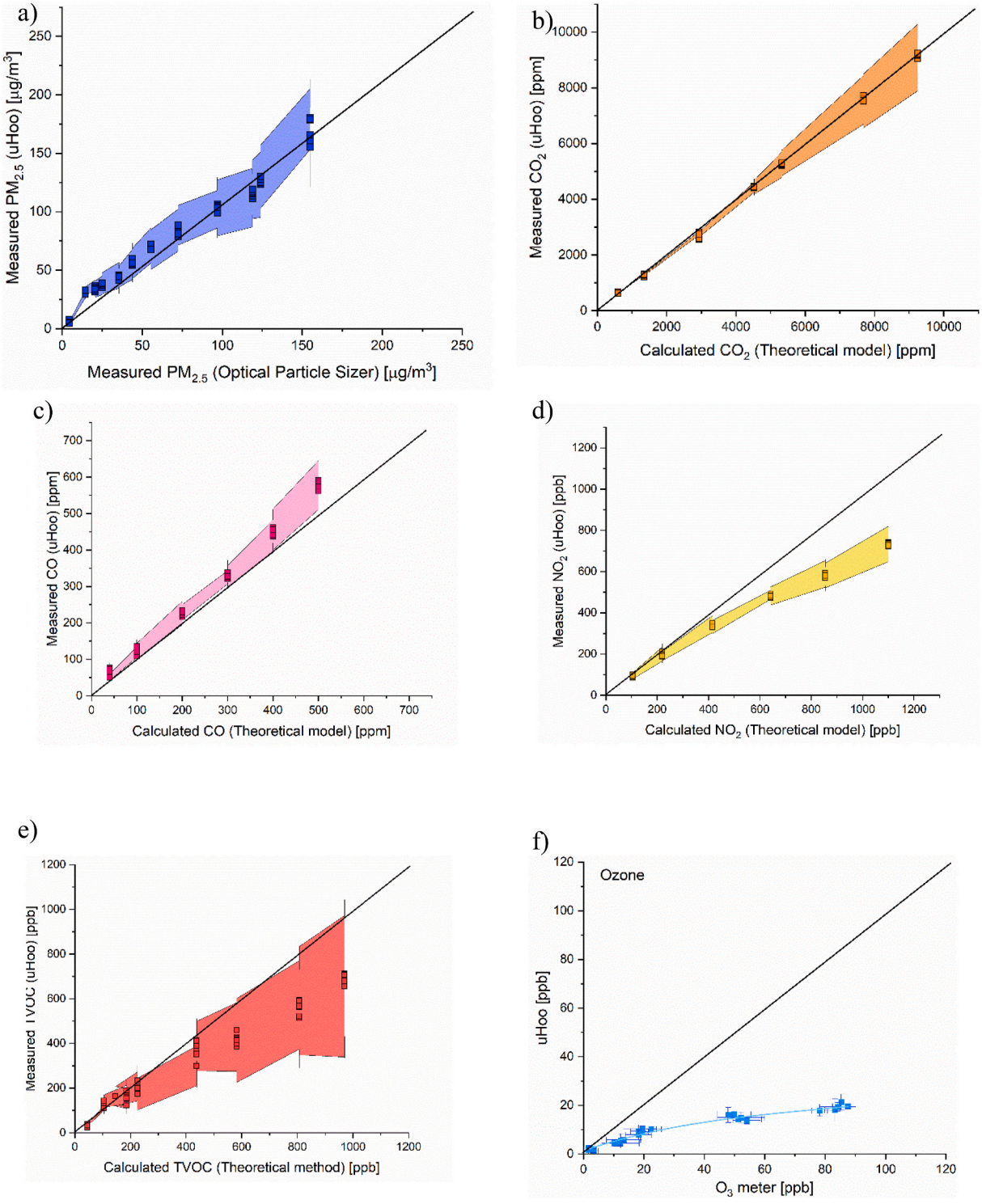


**Fig. 5.** In a), precision of the measurements of PM of uHoo monitors. Readings of PM mass readings achieved using the uHoo monitors and the OPS are compared for different PM mass concentrations. Measurements were achieved using sodium chloride and each data point indicate one data set (minute-by-minute data), while the area behind the data point indicates the standard errors obtained by comparing the three different low-cost sensors used. Linearity of response and precision of measurements for the following gas sensors in uHoo monitors: $CO_2$ b), CO c), $NO_2$ d), and TVOC e). Propane is used as TVOC source. Theoretical calculations and uHoo monitors readings were compared. Each data point indicates one data set (minute-by-minute data), while the area behind the data point indicates the standard errors obtained by comparing the three different low-cost sensors used. In f), linearity of response and precision of measurements for the $O_3$ sensor in uHoo monitors. An $O_3$ meter was used as a reference. Each data point indicates one data set (minute-by-minute data), while the area behind the data point indicates the standard errors obtained by comparing the three different low-cost sensors used.

**Table 3**
Impact of $CO_2$, $NO_2$, and CO to the TVOC sensor. Ethylene is used for TVOC measurements. The theoretical method is used to estimate the input masses.

| Gas | Masses | $R^2$ (Linear) | Regression type | Equation | $R^2$ | $r_s$ |
|---|---|---|---|---|---|---|
| $CO_2$ | 0 ppm | 0.968 | Quadratic | $y = 30.5 + 1.46\ x - 4.25\ 10^{-4}\ x^2$ | 0.991 | 0.998 |
| | 2500 ppm | 0.961 | Cubic | $y = -64.5 + 2.83\ x + 3.87\ 10^{-3}\ x^2 - 2.15\ 10^{-6}\ x^3$ | 0.995 | 0.997 |
| | 5000 ppm | 0.933 | Cubic | $y = 16.32 + 2.81\ x + 3.37\ 10^{-3}\ x^2 - 1.83\ 10^{-6}\ x^3$ | 0.979 | 0.995 |
| | 7500 ppm | 0.891 | Cubic | $y = 75.1 + 2.57\ x + 2.44\ 10^{-3}\ x^2 + 9.19\ 10^{-6}\ x^3$ | 0.964 | 0.990 |
| | 9000 ppm | 0.779 | Cubic | $y = 2.34 + 3.91\ x + 4.72\ 10^{-3}\ x^2 + 1.95\ 10^{-6}\ x^3$ | 0.959 | 0.987 |
| $NO_2$ | 0 ppb | 0.962 | Quadratic | $y = -16.5 + 1.91\ x - 1.02\ 10^{-3}\ x^2$ | 0.990 | 0.996 |
| | 200 ppb | 0.960 | Cubic | $y = 40.2 + 0.51\ x - 2.12\ 10^{-3}\ x^2 - 1.98\ 10^{-6}\ x^3$ | 0.993 | 0.987 |
| | 400 ppb | 0.955 | Cubic | $y = 26.5 + 0.68\ x - 1.12\ 10^{-3}\ x^2 - 9.82\ 10^{-6}\ x^3$ | 0.988 | 0.986 |
| | 700 ppb | 0.950 | Cubic | $y = 5.17 + 0.74\ x - 7.07\ 10^{-4}\ x^2 - 6.78\ 10^{-7}\ x^3$ | 0.996 | 0.994 |
| | 1000 ppb | 0.941 | Cubic | $y = 10.7 + 0.53\ x - 1.23\ 10^{-3}\ x^2 - 1.13\ 10^{-6}\ x^3$ | 0.986 | 0.998 |
| CO | 0 ppb | 0.971 | Quadratic | $y = = 16.4 + 1.91\ x + 1.12\ 10^{-3}\ x^2$ | 0.983 | 0.998 |
| | 100 ppb | 0.962 | Cubic | $y = -68.1 + 4.25\ x - 7.9\ 10^{-3}\ x^2 + 5.21\ 10^{-6}\ x^3$ | 0.979 | 0.994 |
| | 200 ppb | 0.923 | Cubic | $y = -67.8 + 4.78\ x - 9.2\ 10^{-3}\ x^2 + 6.25\ 10^{-6}\ x^3$ | 0.972 | 0.991 |
| | 300 ppb | 0.901 | Cubic | $y = -62.4 + 4.98\ x - 9.3\ 10^{-3}\ x^2 + 6.11\ 10^{-6}\ x^3$ | 0.977 | 0.983 |
| | 400 ppb | 0.816 | Cubic | $y = -56.7 + 5.64\ x - 1.3\ 10^{-2}\ x^2 + 6.87\ 10^{-6}\ x^3$ | 0.960 | 0.979 |

Fig. 6, Fig. 7, and Fig. 8 compare the reference methods with uHoo sensors for $PM_{2.5}$, $CO_2$, and $O_3$ respectively. As seen in Fig. 6, the uHoo $PM_{2.5}$ sensors and the reference method showed strong correlation ($r_s$ = 0.765 to 0.894). Furthermore, real-time variations of $PM_{2.5}$ measured by different uHoo sensors showed strong correlation ($r_s$ = 0.875 to 0.954). The uHoo $PM_{2.5}$ sensors appear to have a zeroing level of 4.5 μg/m$^3$, Fig. 6 a). Another effect worth noting is the underestimation by uHoo $PM_{2.5}$ sensors during activity peaks. Activities of cooking, floor cleaning, carpet cleaning, and frying generated peak PM levels that varied between 15 and 45 μg/m$^3$ as measured by OPS. However, when analyzed with uHoo $PM_{2.5}$ sensors the range was 12–35 μg/m$^3$. The difference between uHoo $PM_{2.5}$ sensors and the OPS is clarified by using a Bland-Altmann plot, Fig. 6 b). For PM levels below 10 μg/m$^3$, uHoo $PM_{2.5}$ sensors are overestimating the indoor level of $PM_{2.5}$ since they cannot detect levels below 4.5 μg/m$^3$. For PM levels above 10 μg/m$^3$, uHoo $PM_{2.5}$ sensors are underestimating $PM_{2.5}$. This is possibly due to the different methods of particle collection. While uHoo $PM_{2.5}$ sensors collect the particles passively, OPS collects particles by drawing air into the device at 1 L/min. Only 1.3% of the data exceeded the upper or the lower limits of correlation indicating strong correlation between uHoo sensors and the reference method.

Fairly good correlation was also identified between uHoo sensors and the reference method for $CO_2$ readings ($r_s$ = 0.721 to 0.863). Moreover, the difference, averaged over the minute-by-minute data and for the whole experiment length, between the readings of the three uHoo monitors was about 3.7%, confirming the results shown in Fig. 5. When no occupants were present, Fig. 7 a), uHoo $CO_2$ sensors showed higher levels compared to the Vaisala $CO_2$ meter (about 35% of difference). However, the uHoo CO2 sensors and the Vaisala $CO_2$ meter were strongly correlated in the presence of occupants and during activities (such as heating and cooking). ($r_s$ = 0.863). Furthermore, only 0.4% of the data exceeded the upper and the lower limits of correlations, emphasizing the close correlation between the two methods, Fig. 7 b).

For $O_3$ measurements, every peak reported by AirMap, uHoo monitors show a similar trend, Fig. 8 a). However, since the monitors were placed indoors, they showed 40–70% lower levels of ozone. The ozone values recorded by the ozone meter showed a difference of about 5% with respect to the ozone values recorded by uHoo monitors. Fig. 8 b) compares readings from the uHoo $O_3$ sensors and the reference method $O_3$ meter. The $O_3$ uHoo sensors underestimated indoor $O_3$ levels; in addition, 9% of the data exceeded the upper and the lower limits of correlation. As expected from laboratory test, uHoo $O_3$ sensors do not show strong correlation with respect to a calibrated $O_3$ sensor ($r_s$ = 0.423 to 0.622). Fig. 8 shows the importance of using a real-time monitor to verify the influence of the outdoor air on indoor air quality. Even for the $O_3$ tests, the three uHoo sensors used show an average difference, calculated as the average different between the highest and

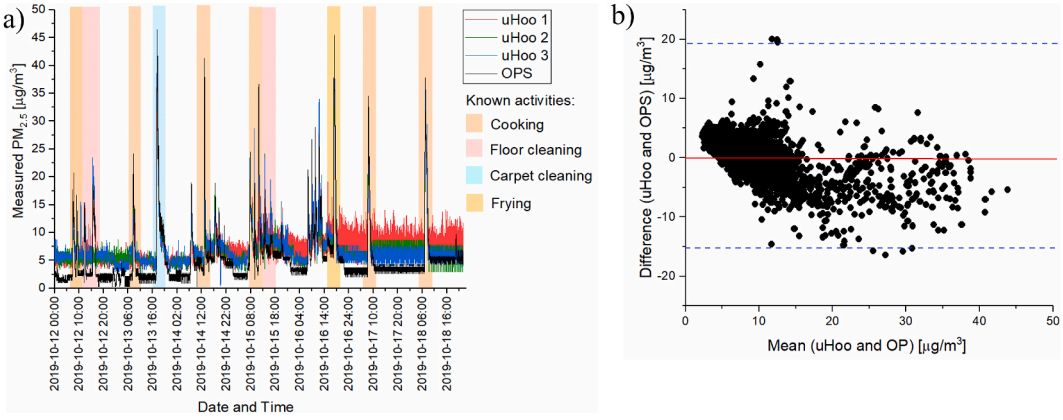


**Fig. 6.** p.m.$_{2.5}$ levels between October 12, 2019 and October 18, 2019 measured using three uHoo monitors and an Optical Particle Sizer (OPS) a). Bland–Altman plot of the correlation between the uHoo monitors and the OPS, b).

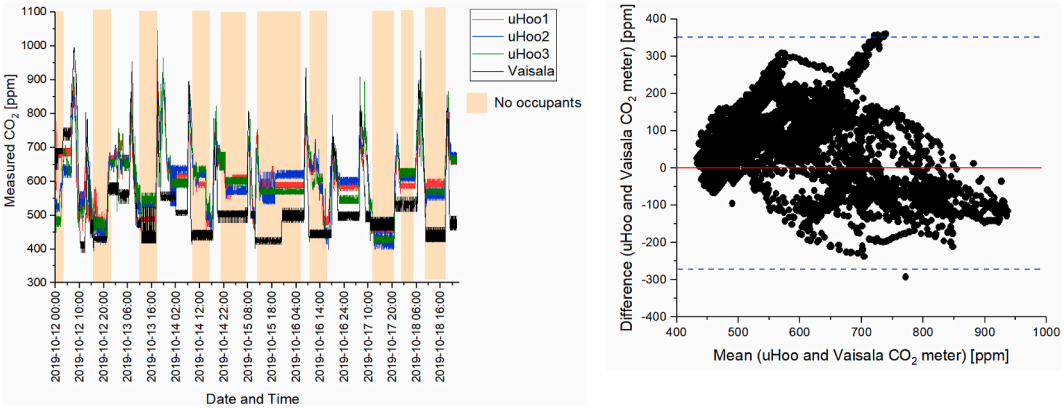


**Fig. 7.** $CO_2$ levels between October 12, 2019 and October 18, 2019 measured using three uHoo monitors and a Vaisala $CO_2$ meter a). Bland–Altman plot of the correlation between the uHoo monitors and the Vaisala $CO_2$ meter, b).

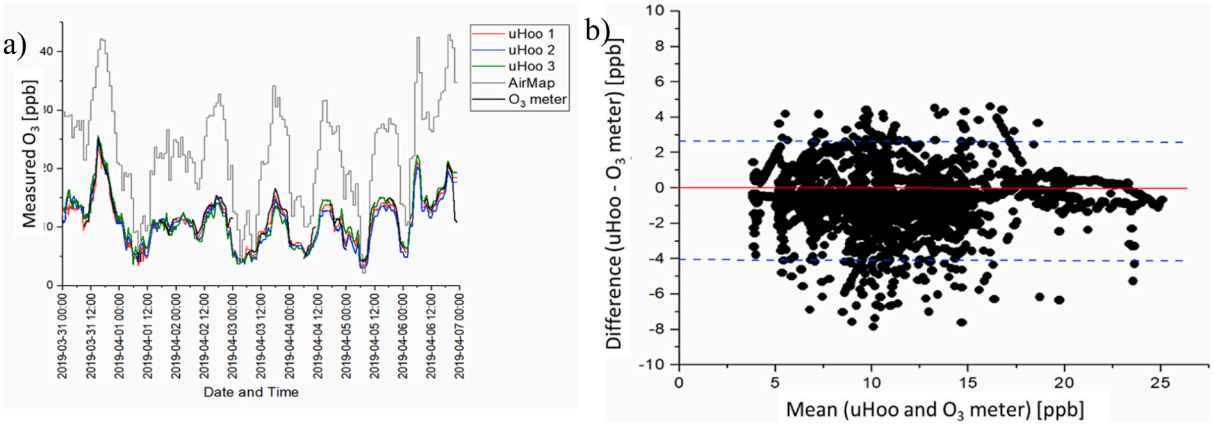


**Fig. 8.** In a), comparison between the hour-by-hour ozone readings of uHoo monitors (red, blue, and green lines) and ozone meter (black line) is shown. In b), a Blandt- Altmann plot represents the comparison between uHoo and O3 meter readings. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

lowest $O_3$ concentration measured at each timestamp, of 2.6%, emphasizing the precision between different sensors. Placing more sensors in the same space provided a more robust measurement; the redundancy of the acquired data from several monitors provided higher confidence and robustness to the dataset.

In general, field tests showed that uHoo sensors could identify the trend and sudden rises in indoor levels of $PM_{2.5}$, $CO_2$, and $O_3$, within a small margin of error. High correlation with reference methods, low-cost efforts, and ease of use make uHoo monitors an appealing alternative to measure indoor levels of pollutants. Further work will examine the comparison between the other sensors included in uHoo monitors and the relative reference methods.

## 5. Conclusion

A laboratory platform was implemented to validate the performance of uHoo low-cost multi-channel monitors. High homogeneity, low costs, and ease of use make this platform applicable to a broad range of low-cost monitors. In addition, the use of theoretical calculations can decrease the costs involved in the rental or purchase of rather expensive reference methods; for $CO_2$, theoretical calculations agreed with the reference method, a $CO_2$ meter, with a maximum difference of 5%. The main limitation of the laboratory platform related to ozone tests. The selected ozone generator did not produce more than 100 ppb of ozone; however, this level is expected to represent a maximum for indoor environments. Furthermore, the homogeneity of ozone measurements was about 25%. Another limitation was the lack of collecting real data as a comparison to theoretical calculations for CO, TVOC, and $NO_2$.

The tested low-cost monitors are estimated to generate reliable results when tested in laboratory conditions; the R-squared and the Spearman's Rank Correlation Coefficient ($r_s$) are above 0.8 and 0.6 for all the tested sensors. Even though the $r_s$ is above 0.98, $PM_{2.5}$ sensors were limited by a minimum reading of about 4.8 μg/m3. $PM_{2.5}$ sensors also showed a difference in their response when exposed to particulates with different refractive indexes. Furthermore, low levels of CO, NO2, and CO2 showed a change in the linearity response of uHoo TVOC sensors. Based on these limitations, future improvements of uHoo monitors should involve the $PM_{2.5}$ limit of detection, TVOC selectivity, and cross-interference to the TVOC sensor.

A good level of correlation was found between the uHoo monitor readings and reference methods when recording levels of common indoor pollutants in a residential building; the Spearman's coefficients varied between 0.765 and 0.894 for $PM_{2.5}$, 0.721 to 0.863 for $CO_2$, and 0.423 to 0.622 for $O_3$. Differences in the readings of sensors placed in the same location did not exceed 5%. However, the use of more than one unit to record the indoor pollutants in one space might be recommended since more robust results can be generated. The high correlation with reference methods, low cost, and ease of use make uHoo monitors applicable for the detection of common indoor pollutants in residential households. The other sensors included in the uHoo monitors were not considered and future studies on their validation are forthcoming.

## Funding

No funding was received for this work.

## Intellectual property

We confirm that we have given due consideration to the protection of intellectual property associated with this work and that there are no impediments to publication, including the timing of publication, with respect to intellectual property. In so doing we confirm that we have followed the regulations of our institutions concerning intellectual property.

## Authorship

The International Committee of Medical Journal Editors (ICMJE) recommends that authorship be based on the following four criteria:

1. Substantial contributions to the conception or design of the work; or the acquisition, analysis, or interpretation of data for the work; AND.

2. Drafting the work or revising it critically for important intellectual content; AND.

3. Final approval of the version to be published; AND.

4. Agreement to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

All those designated as authors should meet all four criteria for authorship, and all who meet the four criteria should be identified as authors. For more information on authorship, please see http://www.icmje.org/recommendations/browse/roles-and-responsibilities/defining-the-role-of-authors-and-contributors.html#two.

All listed authors meet the ICMJE criteria.

We attest that all authors contributed significantly to the creation of this manuscript, each having fulfilled criteria as established by the ICMJE.

We confirm that the manuscript has been read and approved by all named authors.

We confirm that the order of authors listed in the manuscript has been approved by all named authors.

## Contact with the editorial office

We confirm that the email address shown below is accessible by the Corresponding Author, is the address to which Corresponding Author's EVISE account is linked, and has been configured to accept email from the editorial office of American Journal of Ophthalmology Case Reports:

We understand that this author is the sole contact for the Editorial process (including EVISE and direct communications with the office). He/she is responsible for communicating with the other authors, including the Corresponding Author, about progress, submissions of revisions and final approval of proofs.

## Declaration of competing interest

No conflict of interest exists.

## Acknowledgements

The author would like to thank Professor Steven Rogak that allows the use of his well-equipped Aerosol Laboratory, which was used to develop the low-cost laboratory platform. In addition, the company uHoo should be thanked for providing their low-cost sensors. Furthermore, the author is thankful also to the funding source of Mitacs Accelerate for supporting this study.

## References

[1] R. Piedrahita, Y. Xiang, N. Masson, J. Ortega, A. Collier, Y. Jiang, K. Li, R.P. Dick, Q. Lv, M. Hannigan, The next generation of low-cost personal air quality sensors for quantitative exposure monitoring, Atmospheric Measurement Techniques 7 (2014) 3325–3336.

[2] T. Li, S. Cao, D. Fan, Y. Zhang, B. Wang, X. Zhao, B.P. Leaderer, G. Shen, Y. Zhang, X. Duan, Household concentrations and personal exposure of PM2. 5 among urban residents using different cooking fuels, Sci. Total Environ. 548 (2016) 6–12.

[3] Y.-F. Xing, Y.-H. Xu, M.-H. Shi, Y.-X. Lian, The impact of PM2. 5 on the human respiratory system, J. Thorac. Dis. 8 (2016) E69.

[4] I.L. Gee, S. Semple, A. Watson, A. Crossfield, Nearly 85% of tobacco smoke is invisible—a confirmation of previous claims, Tobac. Contr. 22 (2013) 429, 429.

[5] E.P. Felix, J. Passaretti Filho, G. Garcia, A.A. Cardoso, A new fluorescence method for determination of ozone in ambient air, Microchem. J. 99 (2011) 530–534.

[6] D. Gibson, C. MacGregor, A novel solid state non-dispersive infrared CO2 gas sensor compatible with wireless and portable deployment, Sensors 13 (2013) 7079–7103.

[7] U.S.E.P. Agency, Ambient Air Monitoring Ref- Erence and Equivalent Methods, vol. 40, CFR, 1999, p. 53.

[8] L. Spinelle, M. Gerboles, M.G. Villani, M. Aleixandre, F. Bonavitacola, Field calibration of a cluster of low-cost available sensors for air quality monitoring. Part A: ozone and nitrogen dioxide, Sensor. Actuator. B Chem. 215 (2015) 249–257.

[9] N. Castell, F.R. Dauge, P. Schneider, M. Vogt, U. Lerner, B. Fishbain, D. Broday, A. Bartonova, Can commercial low-cost sensor platforms contribute to air quality monitoring and exposure estimates? Environ. Int. 99 (2017) 293–302.

[10] M. Budde, M. Busse, M. Beigl, Investigating the use of commodity dust sensors for the embedded measurement of particulate matter, in: 2012 Ninth International Conference on Networked Sensing (INSS), IEEE, 2012, pp. 1–4.

[11] E. Austin, I. Novosselov, E. Seto, M.G. Yost, Laboratory evaluation of the Shinyei PPD42NS low-cost particulate matter sensor, PloS One 10 (2015), e0137789.

[12] K. Kelly, J. Whitaker, A. Petty, C. Widmer, A. Dybwad, D. Sleeth, R. Martin, A. Butterfield, Ambient and laboratory evaluation of a low-cost particulate matter sensor, Environ. Pollut. 221 (2017) 491–500.

[13] M. Budde, T. Müller, B. Laquai, N. Streibl, A. Schwarz, G. Schindler, T. Riedel, M. Beigl, A. Dittler, Suitability of the low-cost SDS011 particle sensor for urban PM-monitoring, in: 3rd International Conference on Atmospheric Dust, 2018.

[14] A. Mukherjee, L. Stanton, A. Graham, P. Roberts, Assessing the utility of low-cost particulate matter sensors over a 12-week period in the Cuyama Valley of California, Sensors 17 (2017) 1805.

[15] H.-Y. Liu, P. Schneider, R. Haugen, M. Vogt, Performance assessment of a low-cost PM2. 5 sensor for a near four-month period in Oslo, Norway, Atmosphere 10 (2019) 41.

[16] L. Spinelle, M. Gerboles, M.G. Villani, M. Aleixandre, F. Bonavitacola, Field calibration of a cluster of low-cost commercially available sensors for air quality monitoring. Part B: NO, CO and CO2, Sensor. Actuator. B Chem. 238 (2017) 706–715.

[17] F. Udrea, J. Gardner, S.Z. Ali, M.F. Chowdhury, I. Poenaru, IR Emitter and NDIR Sensor, Google Patents, 2014.

[18] A. Ortiz Perez, B. Bierer, L. Scholz, J. Wöllenstein, S. Palzer, A wireless gas sensor network to monitor indoor environmental quality in schools, Sensors 18 (2018) 4345.

[19] A.P. Kaduwela, A.P. Kaduwela, E. Jrade, M. Brusseau, S. Morris, J. Morris, V. Risk, Development of a low-cost air sensor package and indoor air quality monitoring in a California middle school: detection of a distant wildfire, J. Air Waste Manag. Assoc. (2019) 1015–1022.

[20] D. Thomas, B. Mistry, S. Snow, M. Schraefel, Indoor Air Quality Monitoring (IAQ): A Low-Cost Alternative to CO $$ _ {2} $$ Monitoring in Comparison to an Industry Standard Device, Science and Information Conference, Springer, 2018, pp. 1010–1027.

[21] Y. Wang, J. Li, H. Jing, Q. Zhang, J. Jiang, P. Biswas, Laboratory evaluation and calibration of three low-cost particle sensors for particulate matter measurement, Aerosol. Sci. Technol. 49 (2015) 1063–1077.

[22] A. Cavaliere, F. Carotenuto, F. Di Gennaro, B. Gioli, G. Gualtieri, F. Martelli, A. Matese, P. Toscano, C. Vagnoli, A. Zaldei, Development of low-cost air quality stations for next generation monitoring networks: calibration and validation of PM2. 5 and PM10 sensors, Sensors 18 (2018) 2843.

[23] H.-M. Liu, H.-C. Wu, H.-C. Lee, Y.-H. Ho, L.-J. Chen, A system calibration model for mobile PM2. 5 sensing using low-cost sensors, in: 2017 IEEE International Conference on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData), IEEE, 2017, pp. 611–618.

[24] D.B. Curtis, B. Meland, M. Aycibin, N.P. Arnold, V.H. Grassian, M.A. Young, P. D. Kleiber, A laboratory investigation of light scattering from representative components of mineral dust aerosol at a wavelength of 550 nm, J. Geophys. Res.: Atmosphere 113 (2008).

[25] S. Sousan, K. Koehler, L. Hallett, T.M. Peters, Evaluation of consumer monitors to measure particulate matter, J. Aerosol Sci. 107 (2017) 123–133.

[26] F. Karagulian, M. Barbiere, A. Kotsev, L. Spinelle, M. Gerboles, F. Lagler, N. Redon, S. Crunaire, A. Borowiak, Review of the performance of low-cost sensors for air quality monitoring, Atmosphere 10 (2019) 506.

[27] T. Sauerwald, T. Baur, M. Leidinger, W. Reimringer, L. Spinelle, M. Gerboles, G. Kok, A. Schütze, Highly sensitive benzene detection with metal oxide semiconductor gas sensors–an inter-laboratory comparison, Journal of Sensors and Sensor Systems 7 (2018) 235–243.

[28] C. Zuidema, C.S. Schumacher, E. Austin, G. Carvlin, T.V. Larson, E.W. Spalt, M. Zusman, A.J. Gassett, E. Seto, J.D. Kaufman, Deployment, calibration, and cross-validation of low-cost electrochemical sensors for carbon monoxide, nitrogen oxides, and ozone for an epidemiological study, Sensors 21 (2021) 4214.
[29] A. Baldelli, M. Jeronimo, M. Tinney, K. Bartlett, Real-time measurements of formaldehyde emissions in a gross anatomy laboratory, SN Applied Sciences 2 (2020) 1–13.
[30] A. Baldelli, M. Jeronimo, B. Loosley, G. Owen, I. Welch, K. Bartlett, Particle matter, volatile organic compounds, and occupational allergens: correlation and sources in laboratory animal facilities, SN Applied Sciences 2 (2020) 1–14.
[31] D.H. Hagan, G. Isaacman-VanWertz, J.P. Franklin, L.M. Wallace, B.D. Kocar, C. L. Heald, J.H. Kroll, Calibration and Assessment of Electrochemical Air Quality Sensors by Co-location with Regulatory-Grade Instruments, 2018.
[32] M. Azhdarzadeh, F.M. Shemirani, C.A. Ruzycki, A. Baldelli, J. Ivey, D. Barona, T. Church, D. Lewis, J.S. Olfert, W.H. Finlay, An atomizer to generate monodisperse droplets from high vapor pressure liquids, Atomization Sprays (2016) 26.
[33] L.A. Ferraz-Albani, A. Baldelli, C.J. Knapp, W. Jäger, R. Vehring, D.S. Nobes, J. S. Olfert, L.W. Kostiuk, Enhanced evaporation of microscale droplets with an infrared laser, J. Heat Tran. 139 (2017).
[34] A. Baldelli, R. Vehring, Analysis of cohesion forces between monodisperse microparticles with rough surfaces, Colloid. Surface. Physicochem. Eng. Aspect. 506 (2016) 179–189.
[35] S. Amaral, J. de Carvalho, M. Costa, C. Pinheiro, An overview of particulate matter measurement instruments, Atmosphere 6 (2015) 1327–1345.
[36] X. Yu, Y. Shi, T. Wang, X. Sun, Dust-concentration measurement based on Mie scattering of a laser beam, PloS One 12 (2017), e0181575.
[37] I.N. Tang, Chemical and size effects of hygroscopic aerosols on light scattering coefficients, J. Geophys. Res.: Atmosphere 101 (1996) 19245–19250.
[38] A. Mirzaei, S. Leonardi, G. Neri, Detection of hazardous volatile organic compounds (VOCs) by metal oxide nanostructures-based gas sensors: a review, Ceram. Int. 42 (2016) 15119–15141.
[39] J. Keizer, The nonequilibrium electromotive force. II. Theory for a continuously stirred tank reactor, J. Chem. Phys. 87 (1987) 4074–4087.
[40] J. Hauke, T. Kossowski, Comparison of values of Pearson's and Spearman's correlation coefficients on the same sets of data, Quaest. Geogr. 30 (2011) 87–93.
[41] A. Moreno-Rangel, T. Sharpe, F. Musau, G. McGill, Field evaluation of a low-cost indoor air quality monitor to quantify exposure to pollutants in residential environments, Journal of Sensors and Sensor Systems 7 (2018) 373–388.
[42] A.E. ASTM, 2597/2597M-14: Standard Practice for Manufacturing Characterization of Digital Detector Arrays, ASTM International, West Conshohocken, Pennsylvania, 2014.
[43] Z. Li, Q. Wen, R. Zhang, Sources, health effects and control strategies of indoor fine particulate matter (PM2. 5): a review, Sci. Total Environ. 586 (2017) 610–622.
[44] C.J. Weschler, Ozone in indoor environments: concentration and chemistry, Indoor Air 10 (2000) 269–288.
[45] P.S. Myles, J. Cui, I. Using the Bland–Altman Method to Measure Agreement with Repeated Measures, Oxford University Press, 2007.
[46] T. Zheng, M.H. Bergin, K.K. Johnson, S.N. Tripathi, S. Shirodkar, M.S. Landis, R. Sutaria, D.E. Carlson, Field evaluation of low-cost particulate matter sensors in high-and low-concentration environments, Atmospheric Measurement Techniques 11 (2018) 4823–4846.
[47] A. Manikonda, N. Zíková, P.K. Hopke, A.R. Ferro, Laboratory assessment of low-cost PM monitors, J. Aerosol Sci. 102 (2016) 29–40.
[48] D.H. Hagan, J.H. Kroll, Assessing the accuracy of low-cost optical particle sensors using a physics-based approach, Atmospheric Measurement Techniques 13 (2020) 6343–6355.
[49] A. Baldelli, B. Couch, B. Loosley, K. Bartlett, Occupational exposure of librarians to mold spores and metal particles: a real-time case study, SN Applied Sciences 3 (2021) 1–14.
[50] T. Yasuda, S. Yonemura, A. Tani, Comparison of the characteristics of small commercial NDIR CO2 sensor models and development of a portable CO2 measurement device, Sensors 12 (2012) 3641–3655.
[51] C.R. Martin, N. Zeng, A. Karion, R.R. Dickerson, X. Ren, B.N. Turpie, K.J. Weber, Evaluation and environmental correction of ambient CO2 measurements from a low-cost NDIR sensor, Atmospheric measurement techniques 10 (2017).
[52] Y. You, Z. Bai, C. Jia, Z. Wan, W. Ran, J. Zhang, Measuring air exchanges rates using continuous CO2 sensors, Proceedings of Clima (2007).
[53] O. Seppänen, W. Fisk, M. Mendell, Association of ventilation rates and CO2 concentrations with health andother responses in commercial and institutional buildings, Indoor Air 9 (1999) 226–252.
[54] V. Militello, C. Casarino, A. Emanuele, A. Giostra, F. Pullara, M. Leone, Aggregation kinetics of bovine serum albumin studied by FTIR spectroscopy and light scattering, Biophys. Chem. 107 (2004) 175–187.
[55] H.J. Rickenbacker, W.O. Collinge, V. Hasik, A. Ciranni, I. Smith, P. Colao, A. L. Sharrard, M.M. Bilec, Development of a framework for indoor air quality assessments in energy conservation districts, Sustainable Cities and Society 52 (2020) 101831.
[56] L. Mølhave, G. Clausen, B. Berglund, J. De Ceaurriz, A. Kettrup, T. Lindvall, M. Maroni, A. Pickering, U. Risse, H. Rothweiler, Total volatile organic compounds (TVOC) in indoor air quality investigations, Indoor Air 7 (1997) 225–240.
[57] N.B. Goodman, A.J. Wheeler, P.J. Paevere, P.W. Selleck, M. Cheng, A. Steinemann, Indoor volatile organic compounds at an Australian university, Build. Environ. 135 (2018) 344–351.
[58] L. Zhang, F. Tian, C. Kadri, B. Xiao, H. Li, L. Pan, H. Zhou, On-line sensor calibration transfer among electronic nose instruments for monitoring volatile organic chemicals in indoor air quality, Sensor. Actuator. B Chem. 160 (2011) 899–909.
[59] S. Abraham, X. Li, A cost-effective wireless sensor network system for indoor air quality monitoring applications, Procedia Computer Science 34 (2014) 165–171.
[60] S. Högdahl, Placing VOC Sensors forAssessing Air Quality: A CFD Study of Indoor VOC Distribution, 2018.
[61] V.L. Erickson, Demand response based VOC environmental control through wireless sensor networks, in: Proceedings of the International Conference on Wireless Networks (ICWN), the Steering Committee of the World Congress in Computer Science, Computer, 2018, pp. 3–9.
[62] A. Schütze, T. Baur, M. Leidinger, W. Reimringer, R. Jung, T. Conrad, T. Sauerwald, Highly sensitive and selective VOC sensor systems based on semiconductor gas sensors: how to? Environments 4 (2017) 20.
[63] M. Leidinger, T. Sauerwald, W. Reimringer, G. Ventura, A. Schütze, Selective detection of hazardous VOCs for indoor air quality applications using a virtual gas sensor array, Journal of Sensors and Sensor Systems 3 (2014) 253.
[64] J. Obermeier, P. Trefz, K. Wex, B. Sabel, J. Schubert, W. Miekisch, Electrochemical sensor system for breath analysis of aldehydes, CO and NO, J. Breath Res. 9 (2015), 016008.
[65] A. Gonzalez, A. Boies, J. Swason, D. Kittelson, Field calibration of low-cost air pollution sensors, Atmos. Meas. Tech. Discuss. (2019) 1–17, 2019.
[66] N. Afshar-Mohajer, C. Zuidema, S. Sousan, L. Hallett, M. Tatum, A.M. Rule, G. Thomas, T.M. Peters, K. Koehler, Evaluation of low-cost electro-chemical sensors for environmental monitoring of ozone, nitrogen dioxide, and carbon monoxide, J. Occup. Environ. Hyg. 15 (2018) 87–98.
[67] T. Nomura, Y. Fujimori, M. Kitora, Y. Matsuura, I. Aso, Battery operated semiconductor CO sensor using pulse heating method, Sensor. Actuator. B Chem. 52 (1998) 90–95.
[68] W.M. Alberts, Indoor air pollution: NO, NO2, CO, and CO2, J. Allergy Clin. Immunol. 94 (1994) 289–295.
[69] B. Urasinska-Wojcik, T.A. Vincent, M.F. Chowdhury, J.W. Gardner, Ultrasensitive WO3 gas sensors for NO2 detection in air and low oxygen environment, Sensor. Actuator. B Chem. 239 (2017) 1051–1059.