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Performance assessment of low-cost environmental monitors and single sensors under variable indoor air quality and thermal conditions

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ABSTRACT

Recent technological advancements have enabled the development and deployment of low-cost consumer grade monitors for ubiquitous and time-resolved indoor air quality monitoring. With their reliable performance, this technology could be instrumental in enhancing automatic controls and human decision making. We conducted a comprehensive performance evaluation of eight consumer grade multi-parameter monitors and eight single-parameter sensors in detecting particulate matter, carbon dioxide, total volatile organic compounds, dry-bulb air temperature, and relative humidity. In the controlled chamber, we generated eight air pollution sources, each at two thermodynamic conditions — cool and dry (20 ± 1 °C, 30 ± 5%), and warm and humid (26 ± 1 °C, 70 ± 5%). The majority of tested devices under-reported reference particle measurements by up to 50%, provided acceptable responses for carbon dioxide within 15% and diverging results with poor quantitative agreement for total volatile organic compounds. Despite the reported disparities in quantitative agreements, most of the low-cost devices could detect source events and were strongly correlated with the reference data, suggesting that these units could be suitable for measurement-based indoor air quality management. Most of the tested devices have also proven to competently measure air temperature (within+/-0.6 °C) and relative humidity (within+/-5% RH) and maintained a stable measurement accuracy over the two thermodynamic conditions.

1. Introduction

Increasingly strict energy efficiency requirements for buildings have led to tightening of building envelopes to reduce uncontrolled outdoor air infiltration. As a result, unless adequate ventilation is provided, air pollutants emitted inside buildings could be present at higher concentrations due to less dilution [1]. This has exacerbated concerns about health effects from indoor exposures to air pollutants. Some indoor air pollutants can be recognized by their immediate impacts on our body, such as throat irritation or watery eyes [2]. Others, which often bypass the human olfactory radar, are not necessarily benign. According to the US Environmental Protection Agency, some health impacts like respiratory diseases, heart disease, and cancer can show up years after exposure [3]. This highlights the importance of proper indoor air quality (IAQ) management including monitoring of air pollutants.

According to ASHRAE Standard 62.1–2019 [4], acceptable indoor air quality has "air in which there are no known contaminants at harmful concentrations, as determined by cognizant authorities, and with which a substantial majority (80% or more) of the people exposed do not express dissatisfaction". Multiple field studies, however, showed that buildings often do not meet even the minimum standard requirements [5]. Even when average concentrations in a building meet requirements, air pollutants are often non-homogeneously distributed which may result in elevated exposures at some locations [6–8].

The European Respiratory Society (ERS) has identified particulate matter ($PM_{2.5}$ and PM_{10}), volatile organic compounds (VOCs) and carbon dioxide (CO_2) as key air pollutants [9]. Most of these indoor pollutants derive from indoor or outdoor anthropogenic sources [9] and

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their control can be achieved either by limiting or eliminating the emitting source(s) or through adequate ventilation and filtration. To assure adequate control, IAQ monitoring is an important aspect that can trigger the right chain of actions, via real-time feedback to encourage human actions or through direct activation of automated control devices. While there is no universal air pollutant metric established that benchmarks indoor air quality [10], indoor CO_2 concentrations have been used as an indicator of human bio-effluents in occupied buildings and as a control metric for rooms equipped with demand-controlled ventilation [11]. However, in buildings with low or no occupancy, or where other air pollutant sources which emit VOCs or particles are problematic, ventilation control based on CO_2 concentration only may not be sufficient [12]. This highlights the importance of monitoring multiple relevant air pollutants.

Historically, indoor air quality monitoring has been performed by professionals with certified reference instruments [13]. The high capital cost and large size makes such devices unsuitable for ubiquitous and continuous IAQ monitoring in buildings [14]. Recently, technological advances in metal oxide semiconductors (MOS) for the detection of gaseous compounds [15], light scattering for particles [16], and non-dispersive infrared (NDIR) spectroscopy for the measurement of carbon dioxide [17] allowed the development of low-cost sensors and consumer grade monitors. These monitors are typically designed for the real-time monitoring of air temperature and relative humidity, along with several IAQ parameters, commonly including $PM_{2.5}$, PM_{10}, CO_2 and total VOCs (TVOCs) [18]. Some of the consumer grade monitors include sensors for other gases, such as carbon monoxide, nitrogen dioxide, ozone, or other parameters such as air pressure and sound level. The commonly available consumer grade monitors typically store data on IoT servers, and the measurements can be visualized through the web or mobile applications. The increased availability on the market of such consumer grade monitors and single low-cost sensors (devices that measure individual IAQ parameters and send data to a logger) has drawn the attention of many researchers.

To date, several studies examined the performance of low-cost sensors and monitors in detecting the PM indoors [19–25] and outdoors [26–29]. Singer et al. [20] tested the performance of low-cost air quality monitors in detecting fine particles from residential sources. They found a quantitative agreement within a factor of two for most of the sources but very little response for particles with an optical diameter below 0.3 μm. These results were recently confirmed by Wang et al. [19]. Other studies found that the performance of the integrated PM sensors into consumer grade monitors can be influenced by the air temperature and relative humidity [30,31]. The accuracy of CO_2 measurement with low-cost NDIR sensors, frequently deployed within consumer grade monitors, was also found to be dependent on the air temperature and relative humidity [32]. Beyond direct measurements, some devices estimate CO_2 concentration from TVOC measurements, resulting in substantial errors [33]. The TVOC measurement itself with metal oxide semiconductor or photoionization detector (PID) sensors is known to suffer from cross-sensitivity to confounding compounds [34]. The VOCs comprise a large group of chemicals ranging from harmless cooking odors to hazardous compounds such as aromatics (e.g. benzene, toluene, xylene), and aldehydes (e.g. formaldehyde and acetaldehyde), which makes the detection and monitoring of VOCs a challenge, along with exposure quantification.

Several studies examined sensor performance that in addition to air quality include other parameters of indoor environment, such as thermal comfort [34–36]. Moreno-Rangel et al. [37] evaluated five "Foobot" monitors in measuring residential air temperature, relative humidity, $PM_{2.5}$, CO_2, and TVOC; the study found a sufficient accuracy for all sensors except for CO_2 that was not recorded by a dedicated sensor but derived through an algorithm from the TVOC data. Beyond this work, we know relatively little about overall performance of consumer grade low-cost monitors and sensors. Additionally, the available knowledge is limited when it comes to dynamic performance of these units under variable seasons and associated thermodynamic conditions.

To bridge the knowledge gap, we evaluated the performance of various IAQ monitors and sensors under a controlled range of indoor air pollution and thermal conditions. In an environmental chamber, we tested the response of eight consumer grade multi-parameter monitors in measuring PM, CO_2, and TVOC emitted from eight common indoor sources. We also tested their response to the two main thermo-hygrometric parameters, namely air temperature and relative humidity. To add value to the study, eight single-parameter low-cost sensors for air temperature, relative humidity, CO_2, and PM were included in the performance evaluation. Monitoring data from the tested units were compared with measurements from research or professional-grade instruments. All the tests were performed at two distinct thermodynamic conditions: warm & humid; cool & dry.

2. Methods

2.1. The chamber setup

Performance evaluation of low-cost consumer grade monitors and single-parameter sensors was conducted in an environmental chamber with an interior volume of 63.3 m^3 (Fig. 1) located in Fribourg, Switzerland. The chamber is equipped with a dedicated heating, ventilation, and air conditioning (HVAC) system that enables control of air temperature, relative humidity, ventilation rate, and airflow distribution. The conditioned air was supplied through a 2-stage media filter to eliminate nearly all exogenous airborne particle contributions from outdoors to the chamber. The air was supplied through six floor-mounted diffusers and exhausted via six diffusers on the ceiling.

The HVAC was turned off 2 min before the start of a pollutant generation and monitor testing, so that the air exchange was provided solely by infiltration (mean air change rate during the experiments was 0.34 h^{-1}). Each experiment lasted for 1 h with continuous data acquisition. Air pollutant generation triggered the start of each experiment, which, depending on the source, lasted from 15 min to 1 h within the experiment time. After each 1-h experiment, ventilation was turned on until air pollutant concentrations dropped to the same level as before the generation. Research and consumer grade monitors were placed on the table at the height of 75 cm above the ground. The monitors were positioned nearly equidistant from the air pollutant source generation area (Fig. 1). To ensure the maximum uniformity of the air pollutant distribution, two pedestal mechanical fans were used, both pointing towards chamber walls. To maintain the steady climatic conditions during the measurements, internal heat sources were minimized.

2.2. Test activities

The performance of the consumer grade monitors and individual sensors was tested under two thermodynamic conditions — warm and humid (26 ± 1 °C, 70 ± 5%) and cool and dry (20 ± 1 °C, 30 ± 5%). Temperature and relative humidity values represent the values at the start of the experiments with maximum deviations for each condition. The selected thermodynamic properties of the air are commonly encountered indoors in many climates around the world. By applying this methodology, the performance assessment was conducted at the two opposite ends of the standard thermal comfort zone [38,39]. Recordings from the tested units were compared with measurement data from research and professional grade monitors.

Eight common indoor air pollution sources were simulated inside the test chamber, each at the two distinct indoor climate conditions (total of 16 experiments). Sources were chosen to cover a broad range of particle sizes, from ultrafine (≤0.1 μm) to coarse particles (<10 μm), and to cover the concentration ranges of interest for TVOC and CO_2. Common household activity such as frying was excluded as there is sufficient data already existing in literature [19,20,22,40].

The summary of air pollution sources and the highest 1-min resolved

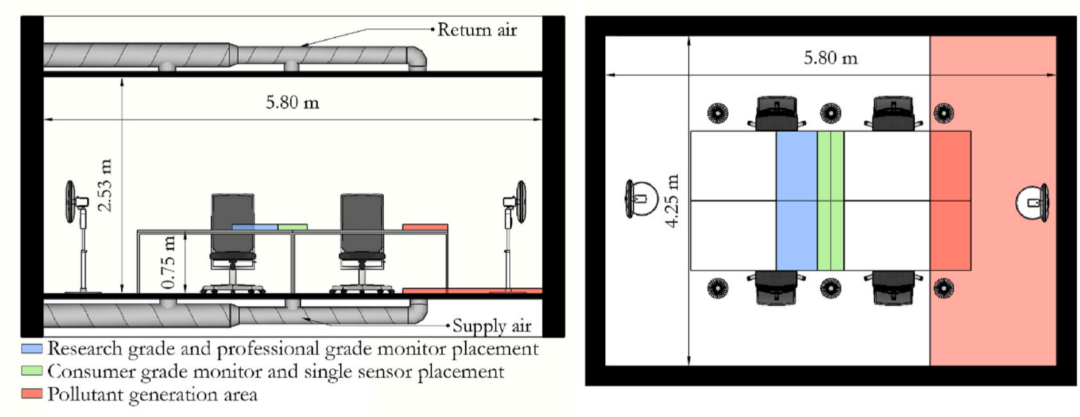

Fig. 1. Plan and profile view of the environmental chamber, including the position of the air pollutant release, consumer grade monitors and single sensors, research grade monitors, and professional grade monitors.

air pollutant concentrations for the given experimental conditions is reported in Table 1.

2.3. Reference measurement equipment

For reference monitoring of time- and size-resolved particle levels we deployed a Grimm Model 1371, Aerosol Technik (miniWRAS). The miniWRAS combines an optical light scattering sensor unit that counts particles in 31 bins from 0.25 to 35 μm and an electrical mobility analyzer that resolves particles in 10 bins from 10 to 193 nm. Measurements were taken at 1-min intervals. The calibration of the miniWRAS was verified using monodispersed 1.005 μm and 2.005 μm diameter polystyrene latex particles (PSL, Thermal Scientific, 405 US), with error below 10%. The use of a particle counter to determine particle mass concentrations requires the adoption of a particle density. It is known that depending on the pollutant source, particle density could vary significantly [19]. However, during this study, no mass-based measurement was performed and the particle mass concentration from miniWRAS was determined assuming spherical particles having a density of 1.68 g/cm^3 for all experiments. We also performed a complementary set of analyses with adjusted source dependent densities to quantify the degree of bias introduced owing to the constant density assumption.

The LI-COR 850 Biosciences gas analyzer (LI-COR) was used for the reference measurements of CO_2 and relative humidity. The LI-COR has a CO_2 measurement range of 0–20′000 ppm and the manufacturer-specified accuracy within 1.5% of reading. The LI-COR directly measures water vapor in the air (accuracy of 1.5%), which is used together with atmospheric pressure and dry bulb air temperature values to compute the relative humidity. The calculated error of the instrument,

Table 1
Description of simulated activities and resulting air pollutant highest 1-min concentration reported by the research and professional grade reference monitors.[a]

Source	Condition	Activity Description	PM_1	PM2.5	PM10	Total counts	CO_2	TVOC
			μg/m³	*μg/m³*	*μg/m³*	*#/cm³*	*ppm*	*ppb*
Candle burning	**Cool & Dry**	Six candles (scented and unscented mix) were lit by two matches and blown out after 1 h	89	106	117	3.2×10^4	928	39
	Warm & Humid	Eight candles (scented and unscented mix) were lit by two matches and blown out after 1 h	110	114	122	7.8×10^4	998	151
Mosquito coil burning	**Cool & Dry**	Two mosquito coils were burned for 30 min inside the chamber and then removed.	2346	2384	2387	5.5×10^5	623	352
	Warm & Humid	One mosquito coil was burned for 15 min inside the chamber and then removed.	512	515	517	1.5×10^5	499	113
Wood lacquer drying	**Cool & Dry**	A 0.45 × 0.45 m^2 wood board was extensively coated with oil-based wood lacquer and placed inside the chamber. The board was kept inside for the entire duration of the experiment (60 min).	4	6	10	3.1×10^3	532	10435
	Warm & Humid	A 0.45 × 0.45 m^2 wood board was extensively coated with oil-based wood lacquer and placed inside the chamber. The board was removed after 15 min.	2	2	2	1.5×10^3	459	3781
Room deodorant injection	**Cool & Dry**	A conventional automatic room deodorant was used with a	34	36	44	8.3×10^3	578	229
	Warm & Humid	maximum scent setting. Deodorant sprayed at 8-min intervals.	3	5	11	1.5×10^3	460	347
Essential oil heating	**Cool & Dry**	Two cups with water and essential oil were heated by candles	10	10	10	1.4×10^4	559	237
	Warm & Humid	lit by matches.	30	31	31	4.7×10^4	551	388
Carpet vacuuming	**Cool & Dry**	Three carpets (1.2 × 0.5 m^2) were placed inside the chamber.	6	49	727	1.4×10^3	1065	163
	Warm & Humid	The carpets were vacuumed for 15 min.	8	43	592	3.0×10^3	865	259
Popcorn cooking	**Cool & Dry**	80 g of popcorn kernel and 20 g of sunflower oil were used to	291	413	643	1.5×10^5	930	83
	Warm & Humid	prepare popcorn over an electric stove.	127	244	450	5.6×10^4	631	296
CO_2 injection	**Cool & Dry**	Chamber was sealed, and the CO_2 was injected from a pure	7	9	28	2.6×10^3	3784	89
	Warm & Humid	CO_2 cylinder until it reached the desired concentration.	4	5	15	2.8×10^3	3900	111

[a] Reported concentrations were obtained with the following research and professional grade instruments: Grimm miniWRAS for particles, LI-COR 850 for CO_2 and RH, and GrayWolf AdvancedSense Pro for TVOC, 1-min resolved data (see their description in section 2.3).

Table 2
Technical specification of individual sensors embedded in the low-cost consumer grade monitors and the associated price.

Monitor/reporting interval	Retail price[a]		Temperature	RH	PM size	PM concentration	TVOC	CO_2
AirVisual Pro (*AirVisual*) **- 10 s - 5 min.**	$269	**Range[e]**	0–40 °C	0–95%	0.3–2.5 μm	not specified	–	400–10′000 ppm
		Sensor	Sensirion SHT30		AirVisualM25b		–	SenseAir S8 or LP8
Awair 2nd Edition[b] (*Awair*) **- 10 s.**	$199	**Range[e]**	−40 to 125 °C ±0.2 °C	0–100% ±2%	0.3–2.5 μm	0–1′000 μg/m^3 ±15 μg/m3 or ±15%	0-60′000 ppb ± 10%	400–5′000 ppm ±75 ppm or 10%
		Sensor	Sensirion SHT30		Honeywell HPMA115S0-XXX		Sensirion SGP30	Amphenol Telaire T6703-5 K
Clarity Node[c] (*Clarity*) **- 2.5 min.**	$1000	**Range[e]**	15–45 °C; ±1 °C	30–85%, ±5%	0.3–10 μm	0–1′000 μg/m^3 ±10 μg/m^3 or ±10%	–	–
		Sensor	not specified	not specified	Plantower PMS 6003		–	–
Foobot (*Foobot*) **- 5 min.**	$199	**Range[e]**	15–45 °C ±1 °C	30–85% ±5%	0.3–2.5 μm	0–1′300 μg/m^3 ±20%	Precision ±10%	estimated from TVOC
		Sensor	Sensirion SHT20		SHARP GPY1010AU0F		iAQ-Core C	iAQ-Core C
Kaiterra Laser Egg + CO2 (*Kaiterra*) **- 1 min.**	$199	**Range[e]**	−20 – 100 °C	0–99%	0.3–2.5 μm	1–999 μg/m^3 ±10%	–	400–10′000 ppm
		Sensor	Sensirion SHT30		Plantower PMS 3003		–	SenseAir S8 or LP8
uHoo[d] (uHoo) **- 1 min.**	$329	**Range[e]**	−40 °C–85 °C ±0.5 °C	0–100% ±3%	0.3–2.5 μm	0–200 μg/m^3 ±15 μg/m^3 or ±10%	0-1′200 ppb ± 10 ppb or ±5%	400–10′000 ppm ± 50 ppm or ±3%
		Sensor	Bosch BME280		Shinyei ppd42		CSS811	ELT T110
Netatmo (inside unit) **(*Netatmo_i*)** **- 5 min.**	$165	**Range[e]**	0 °C–50 °C ±0.3 °C	0–100% ±3%	–	–	–	0–5′000 ppm ±50 ppm ≤1′000 ppm, ±5% > 1′000
		Sensor	Sensirion SHT20		–	–	–	MH-Z14 NDIR CO2 Module
Netatmo (outside unit) **(*Netatmo_o*)** **- 5 min.**		**Range[e]**	−40 – 65 °C ±0.3 °C	0–100% ±3%	–	–	–	–
		Sensor	Sensirion SHT20		–	–	–	–

[a] The retail price was recorded in March of 2020.
[b] Currently offered as Awair Element at lower price of $149 - August 2020.
[c] Has the ability to detect NO_2: 0–1000 ppb, which was not tested.
[d] Has the ability to detect NO_2: 0–1000 ppb, O_3: 0–1000 ppb and CO: 0–1000 ppb which was not tested.
[e] Measurement accuracy ranges were specified by the consumer grade monitor manufacturer.

including the atmospheric data is ±2%. The reference measurements for CO_2 concentrations and relative humidity were taken at 10 s intervals and averaged over 1 min. The instrument response was confirmed through exposure to calibration gases at 0 and 1′500 ppm.

For TVOC measurements, no true reference was considered owing to the current technological limitations for measuring time-resolved TVOCs [41]. As an alternative, two professional grade TVOC monitors were deployed: a) GrayWolf AdvancedSense Pro with an IQ-610 Indoor Air Quality Probe with a 10.6 eV lamp (named here as GW) and a range of 0.02–20 ppm; and b) Aeroqual Photoionization Detector (PID, abbreviated as AerPID) with a 10.6 eV lamp and a range of 0.01–20 ppm and a factory accuracy calibration of $< \pm 0.2$ ppm +10%. A lamp inside the PID sensor emits photons of UV light to ionize the targeted gases that generate electrically charged ions. The ions are attracted by an electric field and result in an electrical current proportional to the VOC concentration. Both GW and AerPID were calibrated by the manufacturer against isobutene in synthetic air three months before the experiments. Also, a one-point calibration with synthetic air was done for the GW TVOC sensor right before starting the experiments. The TVOC concentrations were recorded with 10-s resolution for GW and 1-min for the AerPID. The GW data were averaged at 1-min intervals. Apart from TVOCs, GW IQ-610 has sensors that detect CO, CO_2, relative humidity and dry bulb temperature. There sensors were not calibrated nor used in subsequent analyses.

A thermal anemometer (Model 425, Testo) with an air velocity probe and a data logger (Model 435, Testo) were used to acquire room dry bulb temperature. The hot wire anemometer uses an NTC thermistor with a range of −20 to +70 °C, and reported accuracy ±0.2 °C. Air temperature measurements were taken at 1-s intervals and averaged over 1 min. Before the experiments, the probe and the logger were calibrated in the Testo official laboratory. Technical specifications of the reference equipment are reported in Table S1.

2.4. Low-cost consumer grade monitors

Table 2 summarizes the model, type, and technical specifications of the seven consumer grade monitors and one enterprise grade monitor tested in the experiments. Because the majority of relevant information was not accessible directly from the manufacturer, the monitors had to be disassembled to retrieve sensor information. The monitors were selected considering online available devices for the measurements of indoor air quality, having a price between US$165 and US$329. An additional more expensive monitor available for enterprises only (Clarity Node, US$1000) was included in the experiment. The increased price can be attributed to the presence of a continuous network calibration model which other low-cost monitors lack. Also, Clarity measures nitrogen dioxide levels which other monitors, except for uHoo, do not.

2.5. Single low-cost sensors

Measurements were additionally performed with eight single low-cost sensors that can capture levels of particulate matter, carbon dioxide, air temperature, and relative humidity. The sensors were chosen according to in-house availability, personal interest in specific technologies, and their widespread use in consumer grade monitors. Also, sensors (except SHT31) were specifically chosen not to overlap with the sensors already tested within the monitors. Table 3 summarizes the information about sensor type, measurement range, particle size range, accuracy, and price.

2.6. Data processing

Before the experiments, the consumer grade monitors were set up with help from manuals, datasheets, and direct communication with manufacturers to ensure their optimal use. While some units were ready-to-use, others required a multi-day self-calibration before their deployment. All the monitors synchronized their internal clocks to an official time when connected to the internet and their cloud servers. Their synchronization was checked before and after the experiments. All low-cost monitors were concurrently operated without any time lag. Single sensor monitors were turned on at least 1 h prior to experiments allowing the sensors enough time to stabilize. Single sensors were shut down at the end of the last experiment each day. Single sensors needed additional equipment to transmit and log data. SCD40 was run using the manufacturers evaluation kit which connected directly to a PC with the manufacturer's proprietary software. SPS30 was controlled over Arduino Mega (UART) running the MIT written code from GitHub. K30, SHT31 and SDS018 were initiated from a custom board based on Arduino architecture, with the code provided by the manufacturer. The temperature from the thermistor Lit92 was derived from the voltage drop through the Steinhart-Hart [42] equation with the β coefficient provided by the manufacturer. OPC-N3 and OPC-R1 were connected directly to a PC and used manufacturers software for data logging.

AirVisual, Awair, and Kaiterra monitors possess the ability to show current environmental data on integrated displays, while others (Clarity, Foobot, uHoo, Netatmo_i/o) require an internet connection and a mobile application. Only the AirVisual can store data locally, with access through SAMBA protocol. All other monitors store data on IoT servers. Data retrieval was straightforward from Foobot, Clarity, Netatmo_i/o, and Kaiterra, for which an integrated interface option through web user accounts was available. The Awair does not have a proprietary web interface, and the data had to be retrieved through the manufacturer's support. To access the uHoo data, a business level account at an additional cost was required. The monitors had the following data recording intervals: 5 min (Foobot and Netatmo_i/o), 2.5 min (Clarity), 1 min (Kaiterra and uHoo), 10 s (Awair) and variable intervals from 10 s to 5

Table 3
Technical specifications of single low-cost sensors.

Sensor	Parameter	Measurement range/Size range	Accuracy	Single unit price
Sensirion SCD40 (SCD40)	Air temperature	−40 °C–120 °C	±0.5 °C (0–50 °C)	Not yet available
	Carbon dioxide	0 - 40′000 ppm	±50 ppm ±5%	
	Relative humidity	0–100%	±2% RH (0–100%)	
Sensirion SHT31-D (SHT31)	Relative humidity	0–100%	±2% (0–100%)	$14.50
CO2meter K30 (K30)	Carbon dioxide	0 - 10′000 ppm	±30 ppm ± 3%	$85.00
Littelfuse 11492 (Lit92)	Air temperature	−55 °C–150 °C	±0.2 °C (0–70 °C)	$16.50
Sensirion SPS30 (SPS30)	Particulate matter (size resolved)	0 - 1′000 μg/m^3 0.3–10 μm	max of ±10% and ±10 μg/m^3	$46.70
Alphasense OPC-N3 (OPC–N3)	Particulate matter (size resolved)	0 - 2′000 μg/m^3 0.35–40 μm	±15% (TSI 3300)	$305.00
Alphasense OPC-R1 (OPC-R1)	Particulate matter (size resolved)	0 - 1′500 μg/m^3 0.35–12.4 μm	±15% (TSI 3300)	$116.00
NovaFitness SDS018 (SDS018)	Particulate matter (PM_{10}, $PM_{2.5}$)	0 - 1′000 μg/m^3 0.3–10 μm	max of ±15% and ±10 μg/m^3	$26.80

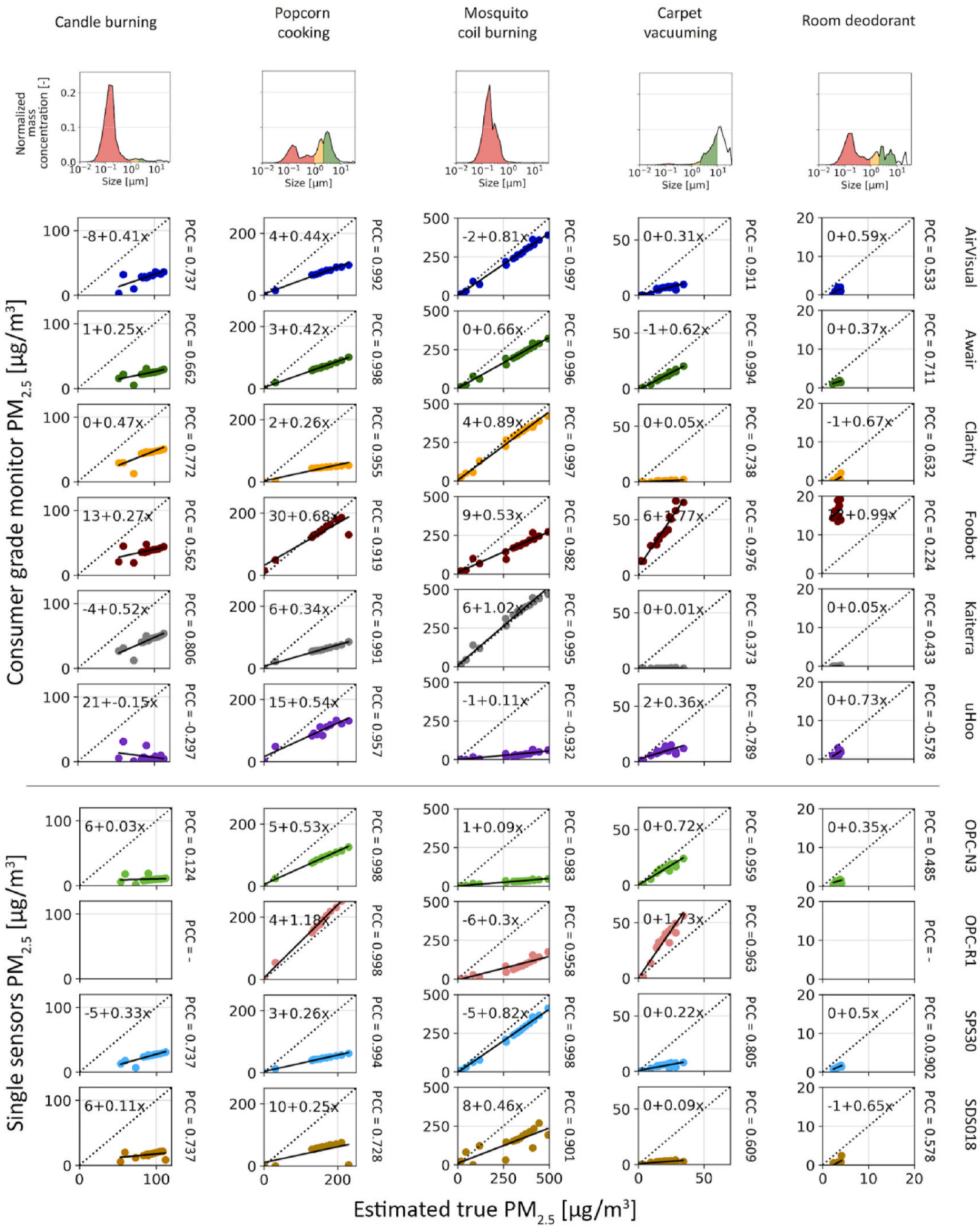

Fig. 2. Mass distribution over size, scatter plot and linear regression line for $PM_{2.5}$ mass concentration – warm and humid conditions. 5-min resolved data. PCC = Pearson's correlation coefficient. Equation of the regression line (with intercept and slope) is reported for each experiment and device. The green, yellow and red colors of the PM mass distribution over the particle size correspond to the following particle size ranges (in μm): 10–2.5, 2.5–1, <1. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

min (AirVisual). Single sensors required PC connection and the use of proprietary software to log data. They had different data logging time-steps, namely 1 min for SHT31, K30, Lit92, and SDS018, 3 s for SPS30, 2 s for SCD40, and 1 s for OPC-N3 and OPC-R1. The processing and analyses of data were done with Python 3.7.0 [43,44]. Due to the different time resolutions of the tested units, all data of sensors that sampled at frequency <1 min were converted into average 1-min values and this time resolution was used to generate all the line graphs for the pollutants. For all the scatter plots and the processing of air temperature data, 5-min averaged data were used, while the relative humidity results were obtained with 15-min averaged data.

2.7. Data analyses

The linear regression lines and the Pearson correlation coefficients (PCC) were computed using the NumPy package of Python [45] and 5-min averaged data. To understand the quantitative response of the low-cost monitors and sensors relative to the reference instruments, the

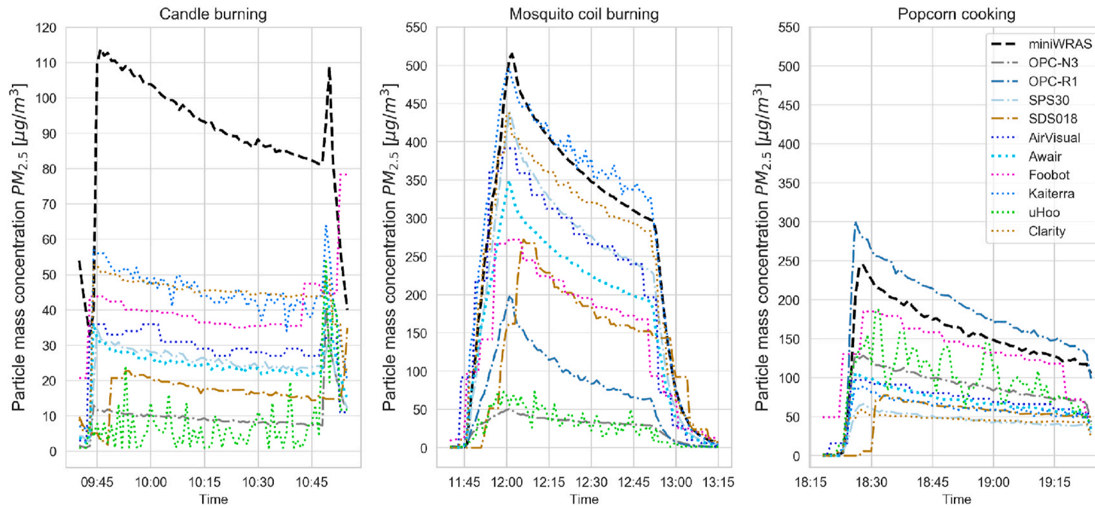

Fig. 3. Particle mass concentration $PM_{2.5}$ for candle burning (left) mosquito coil burning (center), popcorn cooking (right) in warm and humid conditions, 1-min resolved data.

regression coefficients were calculated with the NumPy *polyfit()* function which fits the dataset with a polynomial equation using the least-squares method. The order of the equation was set to 1, and the function returned the slope (regression coefficient, β) and the intercept of the regression line. To determine the PCC, the NumPy *corrcoef()* function was used. A correlation coefficient close to 1 indicates a strong correlation, while a unitary regression coefficient suggests a good accuracy of the measurement data. In practice, a good correlation means that a tested device responds proportionally to concentration changes, while a good accuracy indicates a quantitative agreement with a reference instrument. For IAQ measurements in this study, the positive correlation was rated as very strong for PCC ≥0.8, strong for 0.6 = PCC <0.8, moderate for 0.4 = PCC <0.6, weak for 0.2 = PCC <0.4 and very weak for 0 < PCC <0.2 [46]. Concerning the thermo-hygrometric parameters, the measurement was considered acceptable if the mean absolute error (MAE) compared to the reference was less than 0.5 °C for air temperature and less than 5% RH for relative humidity [38]. For the IAQ parameters, namely PM, CO_2, and TVOC, no acceptance range was considered. The performance of the tested devices in terms of quantitative agreement with the reference data was additionally assessed through the comparison of the mean relative error (MRE) across devices.

3. Results

All results for the IAQ parameters PM, CO_2, and TVOC are first reported for the warm and humid conditions. Insights about the seasonal performance comparison are presented in subsection 3.4.

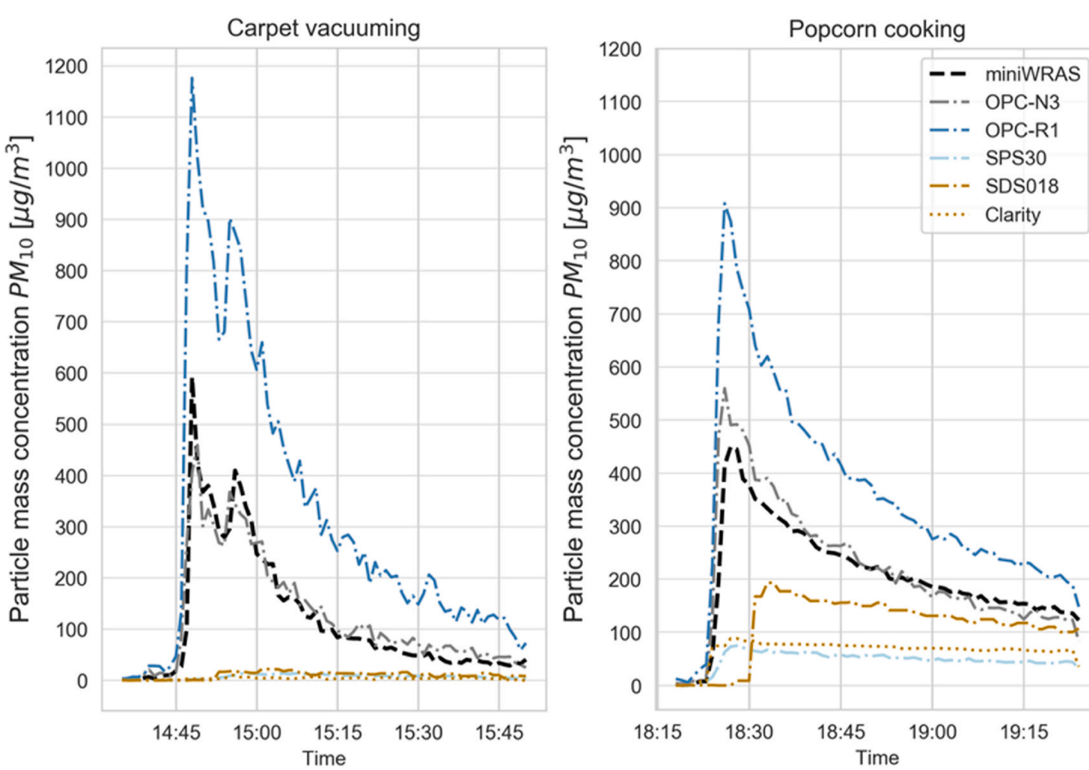

Fig. 4. PM_{10} mass concentration during carpet vacuuming (left) and popcorn cooking (right) in warm and humid conditions, 1-min resolved data.

3.1. Particulate matter

The 16 experimental runs summarized in Table 1 generated a broad range of pollutants, including particulate matter of different sizes, as outlined in Fig. 2. Combustion of candles and mosquito coils generated a substantial number of fine and ultrafine particles with the diameter mode at 0.2 μm. Popcorn cooking created the most widespread particle size distribution with the most considerable fraction of emitted mass centered at 3.0 μm. Vacuuming produced the highest particle mass concentration with the diameter mode at 13.1 μm. Room deodorant, candles, mosquito coil, and popcorn all contributed to the generation of fine particles with widely varied fine particle emissions. Room deodorant generated the lowest particle concentration with a peak $PM_{2.5}$ of 4 μg/m^3, while mosquito coil burning resulted in the highest $PM_{2.5}$ concentration of 515 μg/m^3. As shown in Fig. 2, most of the consumer grade monitors responded to particle concentration changes with a strong correlation to the miniWRAS data. For each monitor, quantitative agreement varied across the sources.

Fig. 3 shows the dynamic variation of $PM_{2.5}$ between the miniWRAS and the consumer grade monitors and single sensors for candle burning, mosquito coil burning, and popcorn cooking. The peak particle concentration for candle burning encompasses the effect of lighting the match at the beginning and extinguishing the candles at the end of the experiment, as each instantly elevated the particle concentration. The results show that the majority of consumer grade monitors under-reported $PM_{2.5}$ (relative to the reference monitor) in case of sources dominated by fine particles. For the candle burning activity, Clarity and Kaiterra were the closest to the reference concentration. They under-reported the reference on average by 52% and 53% respectively, followed by Foobot with 57%, and AirVisual and Awair with 67% and 73%, respectively. The uHoo showed by far the worst results with an MRE of 90% and PCC of −0.30. For mosquito coil burning that produced the $PM_{2.5}$ concentrations up to 492 μg/m^3, we observed that all monitors exhibited very strong correlation to the miniWRAS data (PCC > 0.9) and different quantitative response: Kaiterra was the closest to the reference with an MRE of 11%, followed by Clarity (MRE = 12%), AirVisual (MRE = 31%), Awair (MRE = 37%) and Foobot (MRE = 44%). Even in this scenario, the uHoo monitor did not detect the majority of generated particles and under-reported particle concentration on average by 90%, meaning it cannot be used for reliable measurements of fine particulate matter. In the case of popcorn cooking, the consumer grade monitors were strongly correlated (PCC > 0.97) with MRE within 70% for all monitors. Foobot performed the best with the MRE of 19% compared to the reference. Interestingly, in the case of popcorn cooking, uHoo performed much better than during other activities and showed similar results as the rest of consumer grade monitors, suggesting a lower sensitivity of the Bosch PM sensor to sub-micron particles.

Among the single sensors tested, the two Alphasense sensors, OPC-N3 and OPC-R1, showed very strong correlations for $PM_{2.5}$ concentrations (PCC > 0.90) for all the particle sources except for candle burning and room deodorant. Depending on the pollutant source, different quantitative agreements between the OPC-N3 and the miniWRAS were found: MRE of 43% for popcorn cooking, 88% for candle and 89% for mosquito coil burning. The OPC-R1 also under-reported the reference values during mosquito coil burning by 77% ($\beta = 0.30$), while it over-reported the reference by 20% in case of popcorn cooking ($\beta = 1.18$). The SPS30 was also very strongly correlated with miniWRAS for $PM_{2.5}$ concentrations reporting PCC above 0.80 for all particle sources. The SPS30 under-reported fine particle concentration by 24% during mosquito coil burning, by 71% during popcorn cooking and by 73% during candle burning. The SDS018 sensor responded to concentration changes, although with a delay in time of around 5–10 min, resulting in significantly lower correlation coefficients (PCC = 0.09–0.65) depending on the source type.

Most of the tested consumer grade monitors do not report particle concentrations in size range larger than 2.5 μm. Clarity is the only monitor that has this ability. As shown in Fig. 4, coarse particulate matter generated from the vacuuming activities peaked at 592 μg/m^3. The Clarity monitor showed little to no response to PM_{10} variation (MRE = 93%, PCC = 0.42). For popcorn, the PM_{10} concentration peaked at 450 μg/m^3 and the Clarity monitor under-reported PM_{10} on average by 63% with strong correlation (PCC = 0.78), thus exhibiting better performance compared to the vacuuming test.

The single low-cost sensors OPC-N3 and OPC-R1 were very strongly correlated with reference miniWRAS concentration (PCC > 0.90) for PM_{10}. The OPC-N3 exhibited closer quantitative response (MRE = 31% for popcorn cooking and 38% for vacuuming), while OPC-R1 over-reported the reference values resulting in an MRE of 115% in case of popcorn cooking and 212% for vacuuming. Similar to Clarity, SPS30 and SDS018 sensors under-reported the PM_{10} concentration in case of vacuuming activity by 89% and 84%, respectively. Even the correlation with the reference data was weak (PCC < 0.30). A significantly better relationship was found for the SPS30 sensor during popcorn cooking (PCC = 0.92), although the sensor was still under-reporting the concentration by 75% on average. The SDS018, indeed, showed a much better quantitative agreement (MRE = 43%) but no positive correlation (PCC = −0.10) because of the time delay.

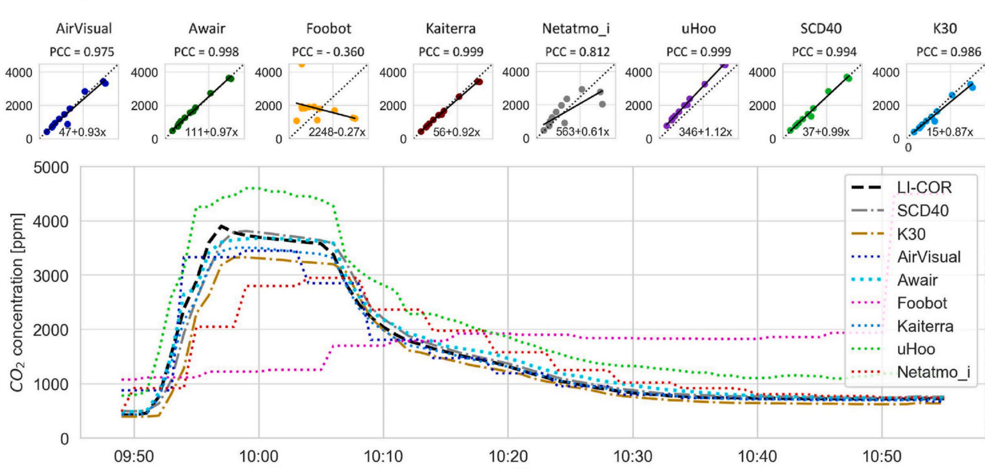

Fig. 5. CO_2 scatter plots with linear regression lines (top, 5 min-resolved data) and concentration in time (bottom, 1-min resolved data) for warm and humid conditions.

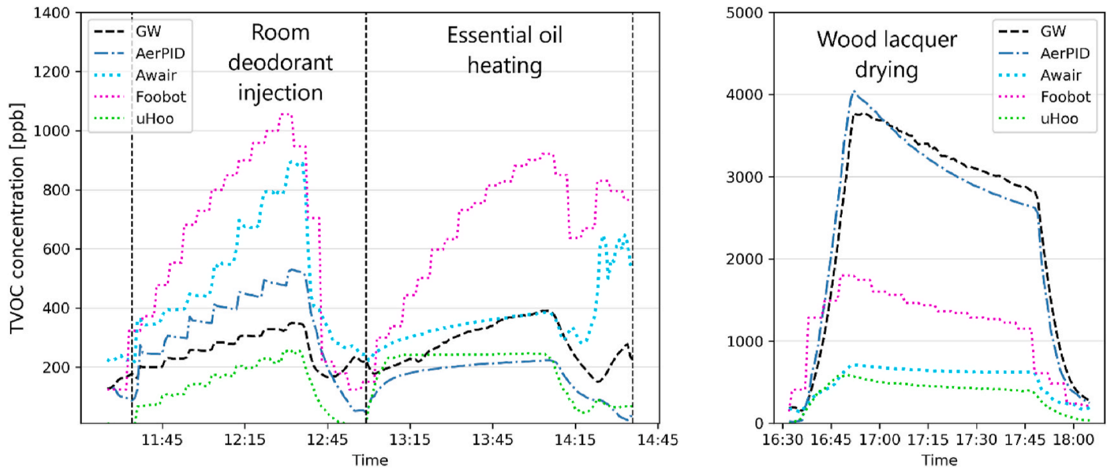

Fig. 6. TVOC concentration in time for different pollutant sources in warm and humid conditions, 1-min resolved data.

Table 4
Overview of mean relative error (MRE) of consumer grade monitors in different seasons and associated thermodynamic conditions.

	$PM_{2.5}$		CO_2		TVOC	
Monitor	Cool&Dry	Warm&Humid	Cool&Dry	Warm&Humid	Cool&Dry	Warm&Humid
AirVisual	78%	55%	9%	11%		
Awair	50%	55%	7%	8%	43%	84%
Clarity	50%	57%	–	–		
Foobot	91%	128%	38%	122%	153%	146%
Kaiterra	43%	56%	5%	3%		
Netatmo_i	–	–	15%	24%		
uHoo	97%	70%	31%	48%	60%	57%

3.2. Carbon dioxide (CO_2)

Fig. 5 represents the results of the performance assessment of low-cost CO_2 monitors and single-parameter sensors relative to the reference monitor. The performance of the tested units was good with PCC >0.80 and β in the range of 0.61–1.12 except for the Foobot monitor. All the consumer grade monitors except uHoo reported peak values under the reference. Considering the whole duration of the experiment, the Kaiterra under-reported the reference CO_2 concentration with an MRE of 3%, the Awair of 8%, the AirVisual of 11%, the Netatmo_i of 24% and the uHoo of 48%. The peak concentration recorded by Netatmo_i had a delayed response relative to all other monitors. Thus, the PCC for Netatmo_i was ~0.80, while all other monitors' PCC exceeded 0.97. The Foobot showed by far the worst results with no positive correlation (PCC = −0.36) and MRE = 122%, meaning that it cannot reliably be used to monitor CO_2 concentrations.

The tested single sensors, namely SCD40 and K30, were very strongly correlated (PCC = 0.99 for both) with the LI-COR data. The SCD40 was the most accurate as its reported peak concentration deviated from the reference just by 3%, and the MRE was 6%, while the K30 under-reported the CO_2 concentration by 12% on average and showed a short time delay. The CO_2 increase was also observed for candle burning and essential oil heating activities, although not significant enough to merit further analysis when compared to CO_2 injection.

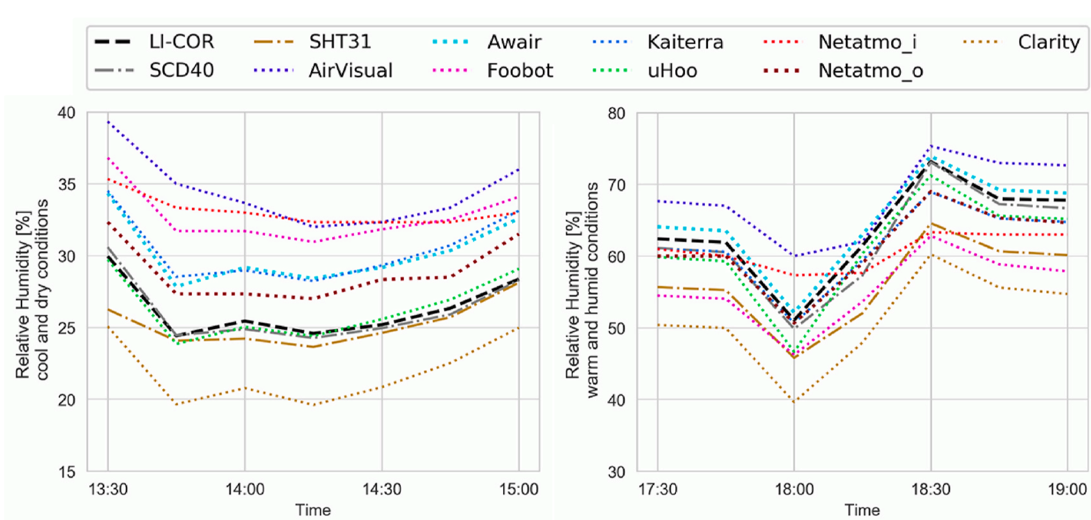

Fig. 7. Dynamic variation of relative humidity in cool and dry conditions (left) and warm and humid conditions (right), 15-min resolved data.

3.3. Total volatile organic compounds (TVOC)

Fig. 6 shows that the professional grade monitors (GW and AerPID) were very closely correlated in their response to each major source. The quantitative response varied up to two times depending on the source, despite being calibrated with the same chemical. GW showed the highest response during oil wood lacquer drying at 3′781 ppb. All the other activities produced lower TVOC concentrations in the range from 5 to 530 ppb. Generally, all consumer monitors showed good dynamic responses to different source activities. Despite the absence of true reference values, the low-cost monitors responded to the sources with similar time-response as PIDs. A comparison between consumer grade monitors and professional grade monitors reveals that all consumer grade monitors under-reported the TVOC peak levels generated from wood lacquer drying. This may be due to oversaturation of the sensors since the TVOC concentrations exceeded 4 ppm. During the injection of room deodorant, the Foobot over-reported the TVOC concentration measured by AerPID by 99% and GW by about 164%, while the Awair over-reported AerPID values by 54% and GW by 99%. The uHoo reported the lowest concentrations, with an MRE of 62% compared to AerPID and 47% compared to GW. While heating the essential oil, the Foobot over-reported the TVOC concentration by 215% compared to AerPID and 106% compared to GW. The Awair mostly reported close to GW (MRE = 17%) and the uHoo close to AerPID (MRE = 27%). In all, despite the relatively high disparity in recorded TVOC levels, all the units had a reliable dynamic response to TVOC concentration changes.

3.4. Comparison of IAQ sensor performance in different thermodynamic conditions

To evaluate the performance of consumer grade monitors in different climatic conditions, the MRE to reference was calculated and compared. As presented in Table 4, Awair proved to be the most stable monitor overall while having sensors in all of the categories. An equally high performance for PM and CO_2 was shown by Kaiterra which did not measure TVOCs. AirVisual and uHoo showed 20% higher MRE in cool and dry conditions for PM measurements while the opposite can be said for Foobot. When measuring CO_2, the most deviation was shown by Foobot with more than 80% of a difference and with significant error in both conditions. uHoo had an offset at 17% with better performance in cool and dry conditions. Overall, it can be observed that similar magnitudes of MRE compared to reference were observed for the tested monitors during the different seasons. This finding is supported by a one-year long evaluation of 3 consumer grade monitors which determined minimal measurement dependence on temperature and relative humidity and minimal drift [47]. Even so, it needs to be stated that the majority of monitors were slightly closer to reference in cool and dry conditions for $PM_{2.5}$ and CO_2 and in warm and humid conditions in case of TVOC.

3.5. Relative humidity (RH)

The relative humidity variations inside the chamber during both simulated seasons are shown in Fig. 7. The LI-COR reported relative humidity values from 24% to 30% RH (mean = 26% RH) for cool and dry and 51%–73% RH (mean = 64% RH) for warm and humid conditions. The tested devices followed the reference values well and responded to changes in the relative humidity. The majority of tested consumer grade monitors and single sensors were very strongly correlated with reference data (PCC > 0.8), except for Netatmo_i (PCC = 0.73) in cool and dry conditions. Despite the good correlation for the majority of devices, different quantitative responses could be observed. Some of the monitors, namely Awair, Kaiterra, Netatmo_o, and uHoo reported acceptable values with MAE below 5% RH in both seasons. Others, such as AirVisual, Foobot and Netatmo_i, reported relative humidity with an MAE compared to the reference between 5.5 and 8.3% RH, in both seasons. The response of the Clarity monitor was acceptable in cool and dry conditions (MAE = 4.3% RH) while it was outside the acceptance range by under-reporting the reference by 12.5% on average in warm and humid conditions.

When it comes to the single-parameter sensors, the SHT31 sensor reported very close to the reference in cool and dry conditions (MAE = 1.1% RH), while it exhibited higher errors during warm and humid conditions (MAE = 7.4% RH). The SCD40 performed well in both seasons and resulted in an MAE of 0.3% RH in cool and dry and 1.4% RH warm and humid conditions. In summary, the majority of tested units overestimated the reference RH in cool and dry conditions and underestimated the reference in warm and humid conditions. The MAE comparison for two thermodynamic conditions indicates that half of the tested devices reported with higher accuracy in cool and dry conditions, while the other half was closer to the reference in warm and humid conditions.

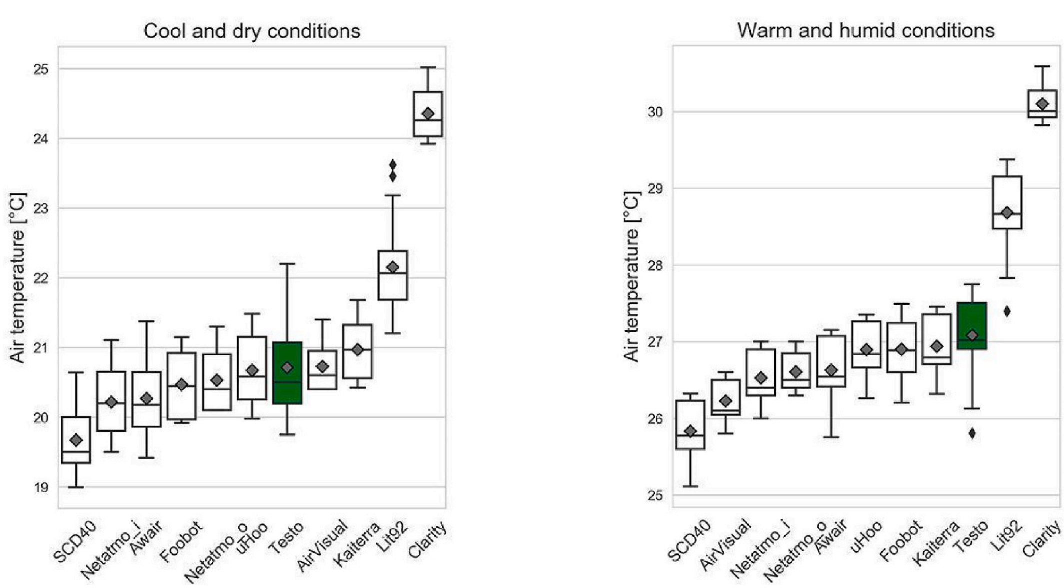

Fig. 8. Comparison of air temperatures during one day of the experiment in cool and dry conditions (left) and warm and humid conditions (right), 5-min resolved data.

3.6. Air temperature

The results of air temperature variations captured by different monitors and single-parameter sensors during the two thermodynamic conditions are reported in Fig. 8. The air temperature during cool and dry conditions varied from 19.7 °C to 22.2 °C (mean = 20.7 °C), and 25.8 °C–27.7 °C (mean = 27.1 °C) during warm and humid conditions according to the reference Testo thermometer. The majority of tested devices exhibited strong to very strong correlation with the reference temperature data (PCC > 0.6). Moderate correlation resulted from Foobot in warm and humid conditions (PCC = 0.55), while the AirVisual and the Netatmo_o exhibited weak correlation in cool and dry conditions (PCC = 0.37 and 0.35, respectively). A very weak correlation emerged from the Clarity monitor in cool and dry conditions. Many of the tested consumer grade monitors showed an acceptable quantitative agreement compared to the reference: Awair, Foobot, and uHoo deviated from the reference by less than 0.5 °C on average in both seasons and thus complied with ISO 7726 [48]. Kaiterra had a MAE of 0.2 °C in warm and humid conditions and reached a MAE of 0.6 °C in cool and dry conditions. AirVisual, Netatmo_i and Netatmo_o had MAE around 0.5 °C in cool and dry conditions. In the remaining conditions, the MAE of AirVisiual and Netatmo_i/o were still below 0.9 °C from the reference. The Clarity reported significantly higher errors, ranging from as much as 2.5 °C–4 °C during both thermodynamic conditions with an MAE of 3.6 °C in cool and dry and 3.0 °C in warm and humid conditions.

The single-parameter sensors performed differently — SCD40 underreported mean air temperature difference to the reference of 1.0 °C in cool and dry and 1.3 °C in warm and humid conditions, while the Lit92 sensor overestimated the air temperature on average by 1.4 °C in cool and dry and 1.6 °C in warm and humid conditions. Out of 10 tested devices, 5 had lower MAE in cool and dry conditions and the remaining in warm and humid conditions.

4. Discussion

The results acquired in the test activities reaffirm the fact that optical light scattering technology used in low-cost PM sensors cannot cover the whole particle size spectrum commonly emitted from indoor sources. Singer et al. [21] evaluated 2 research grade and 7 consumer grade monitors and concluded that consumer grade monitors have semi-quantitative responses (50–200%) to the majority of tested pollutants and all of the devices had little or no response to events in which generated particles had the optical threshold of 0.3 μm. This was confirmed in the study of Wang et al. [20] which reported the limit of particle detection at around 0.25 μm. According to specifications, the majority of consumer grade monitors are supposed to register particles with optical diameter between 0.3 μm and 2.5 μm. Depending on the pollutant source and associated particle size distribution, a closer agreement with the reference was found in case of optical particle diameter ranging from 1 μm to 2.5 μm where the majority of tested devices reported around 50% of reference concentration at the worst. The agreement diminished when the sources were dominated by submicron particles (<1 μm) and during activities that generate coarse particles (e.g. vacuuming). Studies [20,21] also report that optical monitors (consumer, professional and research grade) may be under-reporting the mass concentration of larger particles generated from vacuuming if they have higher density. However, owing to the polydisperse nature of particle sources indoors, the response of most of the sensors was time correlated. Strong correlation with reference data was found also by Li et al. [24] for the tested consumer grade monitors. This means that the devices are dynamically keeping track of concentration changes and can be used to detect an event despite poor quantitative agreement. Analyzed data suggests no consistent bias for $PM_{2.5}$ sensors. End-users should be made aware that the PM data from the current low-cost sensors needs to be understood as an indication of a state change or a rough estimation rather than actual concentration in indoor environments.

According to their specifications, Clarity and single sensors SPS30, OPC-R1 and OPC-N3 have the ability to detect PM_{10}. Our results showed that Clarity's sensor Plantower PMS 6003 and SPS30 are in the sub $50 category and that they can barely detect any PM_{10} concentration changes. Kaittera uses the Plantower 3003 which has the ability to detect PM_{10} but the manufacturer chooses not to relate that data to the end-user. OPC-R1 with the double, and the OPC-N3 six-time higher price both correlate well to the reference, with OPC-R1 still in the price range to be considered for a low-cost consumer grade monitor integration. At their current state, Clarity and SPS30 cannot be used for determining PM_{10} concentrations. Improvements in the algorithms used to determine PM mass concentrations from optical particle counting are needed to improve measurement accuracy for coarse-mode particles.

An additional analysis was carried out to evaluate the effect of adopting different source dependent particle densities for the reference miniWRAS. To calculate the mass concentration of particles, the default densities of 1.68 g/cm^3 for miniWRAS was adjusted with experimental values from literature for each pollutant source. For the majority of tested devices, the $PM_{2.5}$ concentration was closer to the reference data with adjusted density in case of candle burning, popcorn cooking and mosquito coil burning, regardless from the season, as reported in Table S3.

The consumer grade monitors and sensors evaluated in the experiments include non-dispersive infrared (NDIR) technology to detect CO_2 concentrations in the indoor environment except the Foobot. Despite the same price range, the Foobot has no dedicated sensor and estimates the CO_2 concentration from the TVOC data with the use of an algorithm. As a result, all the sensors except Foobot were very strongly correlated with the reference (PCC > 0.8). Foobot's very poor performance is a direct consequence of manufacturers design choice and suggests that currently there is no alternative to a dedicated CO_2 sensor. The uHoo had a consistent offset from the reference which is indicative of a systematic instrument error. The manufacturer could possibly correct this error with the use of better calibration procedures and algorithms in future software updates. Despite the very strong correlation, Netatmo_i had a poor dynamic response as it took ~15 min in both conditions to approach the reference, thereby not capturing the peak CO_2 event, which is not acceptable. Unlike other tested sensors, the CO_2 sensor inside Netatmo_i was introduced to the market over seven years ago. The results from newer devices suggest that the low-cost sensing technology has matured and is becoming more accurate and reliable. It is important to note that all of the tested CO_2 sensors, except Awair, include automatic baseline correction (ABC). At initial device startup, ABC can take from a week up to two weeks which makes the whole procedure cumbersome. Further, devices go into ABC mode once a week. This could result in erroneous readings in environments that do not periodically reach global background outdoor CO_2 levels, particularly in buildings that are occupied continuously or have low enough ventilation and short periods without occupancy. The data output on CO_2 concentrations from the majority of the tested modern low-cost sensors can be used with confidence in decision making if the ABC requirements are met.

TVOCs are composed of a multitude of volatile organic compounds, and each pollutant source is generating different kinds of VOCs. A comprehensive study showed that TVOC sensors have different sensitivity to various VOC sources, depending on their working principle [41]. This was shown to be most evident for PID sensors, which can be expected to produce agreeable results to laboratory air sampling only when measuring specific groups of compounds which they are calibrated for. This explains different responses of the monitors and poor seasonal replication in different experiments. Consumer grade monitors managed to capture TVOC concentration changes in time and could be adopted to detect events. Similar to PM sensors, end-users should be made aware of the inaccuracies of absolute values.

In all tested monitors and single sensors, relative humidity and air

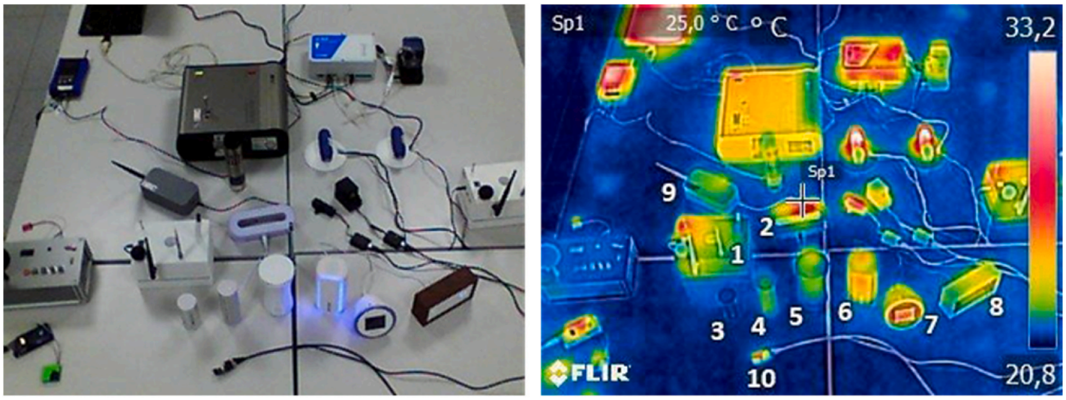

Fig. 9. Experimental setup taken with regular camera (left) and thermal imaging camera (right), (1 - Lit92, 2- AirVisual, 3 - Netatmo_o, 4 - Netatmo_i, 5 - uHoo, 6 - Foobot, 7 - Kaiterra, 8 - Awair, 9 – Clarity, 10 – SCD40).

Table 5
Overall performance grading of consumer grade monitors.

	Rating for MRE or MAE[a]							Rating for PCC[b]						
Monitor	$PM_{2.5}$	PM_{10}	CO_2	TVOC	RH	T	Average	$PM_{2.5}$	PM_{10}	CO_2	TVOC	RH	T	Average
AirVisual	4	–	5	–	2	4	3.8	5	–	5	–	5	3	4.5
Awair	5	–	5	5	4	5	4.8	5	–	5	5	5	5	5.0
Clarity	5	5	–	–	1	1	3.0	5	4	–	–	5	2	4.0
Foobot	1	–	1	1	1	5	1.8	5	–	1	5	5	3	3.8
Kaiterra	5	–	5	–	4	5	4.8	4	–	5	–	5	4	4.5
Netatmo_o	–	–	–	–	4	5	4.5	–	–	–	–	5	3	4.0
Netatmo_i	–	–	4	–	2	4	3.3	–	–	5	–	5	4	4.7
uHoo	3	–	3	5	5	5	4.2	4	–	5	5	5	5	4.8

[a] The rating for the MRE or MAE is calculated in relation to the other monitors' performance.
[b] The rating for the PCC is calculated with the same scale for all parameters as described in section 2.7 [46].

temperature were measured by a single sensor. This sensor integrates two components, a capacitive relative humidity sensor and the band gap air temperature sensor. Interestingly, the majority of the units use the Sensirion SHT sensors from series 2 (Foobot, Netatmo_i, Netatmo_o) and 3 (AirVisual, Kaiterra, Awair), which suggests a trend on the market. However, the best performance was shown by uHoo and its Bosch BME 280 sensor practically being true to the reference. There is no logical clustering of measurements with regards to the SHT sensor series. This indicates that consumer grade monitor manufacturers use different procedures for sensor calibration and use custom signal conversion algorithms. Additional reasoning for the result disparities may be caused by variable algorithms employed to compensate for internal heat gains inside the custom-built monitor shells that affect final readings and justify the result disparities. The air temperature was reported accurately by most of the tested devices, with 3 out of 8 consumer grade monitors being within+/-0.5 °C from the reference air temperature in both seasons and all the monitors being within+/-0.6 °C from the reference regardless of the season, except for Clarity in both climatic conditions and for AirVisual in warm and humid conditions. These results confirm the suitability of consumer grade monitors, apart from Clarity, to monitor the air temperature inside buildings. The AirVisual and Kaiterra represent the monitors with color displays with a higher heat output as shown in Fig. 9. Our results suggest that the air temperature measurements were well compensated for the local heat production, except for Clarity. On the other hand, the Lit92 sensor was installed on a housing that accommodated multiple single sensors and was in proximity of a microcontroller with a power converter. The heat output from the microcontroller likely interfered with the air temperature field which led to overestimated temperature values.

To better summarize the performance of consumer grade monitors in both thermodynamic conditions, we developed an overall performance grading. First, the performance of the monitors was averaged across all 16 experimental conditions. Then, according to the classification for MRE ($PM_{2.5}$, PM_{10}, CO_2 and TVOC) or MAE (relative humidity and temperature) and PCC, each monitor was given a grade from 1 to 5. This was done by dividing the range between the minimum and maximum MRE or MAE for each parameter into 5 categories where the grade 1 was assigned to the worst and 5 to the best category. The score was averaged across two test thermodynamic conditions. For the PCC, the 5 categories were based on the rating introduced in chapter 2.7. Table 5 shows the summarized performance for each monitor. The MRE, MAE and PCC data used for the monitor ranking are given in the supplement Table S2.

Among the tested consumer grade devices, Awair scored the highest in our rating scale for monitoring pollutants, air temperature, and relative humidity; and it also scored highly for measuring TVOC concentrations, unlike many other monitors. The Kaiterra monitor scored just a bit lower but lacks the ability to report more than one gaseous pollutant (in this case TVOC). A slightly lower performance was shown by the uHoo and AirVisual monitors, followed by Netatmo_i, but the latter monitor lacked the ability to report PM and TVOC. The Clarity came in second to last despite not monitoring CO_2 and TVOC. However, these results need to be considered carefully. We determined that the device was connected to the proprietary device hub used for calibration, but when data log was analyzed, we discerned that no calibration from the network to the device was received which could account for the erroneous measurements. Foobot showed the worst overall performance, especially in the IAQ category, and the Netatmo_o exhibited a good overall performance for relative humidity and temperature but is not monitoring any of the pollutants. Contrary to the expectation, monitors on the lower price spectrum had the best performance in the tested categories. End-users should not regard the price of the low-cost monitors as an indicator of their performance.

Seasonal comparison did not show a clear influence of indoor thermodynamic conditions on the accuracy and stability of the measurements. Each device displayed comparable performance in both conditions. The main differences could be observed between devices, when measuring individual parameters regardless of the condition.

While interpreting the reported results, several limitations must be acknowledged. Only a single new device of each model was tested and their durability and consistency over time was not considered. The study did not evaluate the impact of automatic baseline correction on CO_2 sensor performance and did not consider the effect of intermittent high to very low ambient RH changes. Further, the performance assessment did not consider the quality and richness of the real-time data reporting interface, nor the accessibility and availability of the measured data. For PM measurements, miniWRAS was not adjusted with the true size of particles with gravimetric measurements, and the default density of 1.68 g/cm^3 was used. There was no true reference for the TVOC measurement. Professional grade monitors were simply used to determine the responsiveness of the low-cost units to VOC alterations. Lastly, the exact replication of the experiments in both hygro-thermal conditions was not feasible. Nonetheless, our primary intention was to provide a wide and relatively similar air pollutant concentration range per season, without attention in matching the two conditions.

5. Conclusions

This paper presents a comprehensive performance evaluation of low-cost consumer grade monitors and single-parameter sensors in detecting five indoor environmental parameters – particulate matter, carbon dioxide, total volatile organic compounds, dry-bulb air temperature and relative humidity. Eight experiments were chosen to simulate indoor air pollutant sources that were carried out at two distinct climatic conditions – cool & dry, and warm & humid.

For PM measurements, despite MRE exceeding 100% for some devices, the dynamic responses were time-correlated for the majority of tested devices — meaning that the low-cost units could be used to detect concentration changes of particulate matter spanning from 0.3 to 2.5 μm. On average, the best performing monitor deviated from the reference by a factor of two. Among the single sensors, OPC-R1 provided the best results for $PM_{2.5}$, while the OPC-N3 proved to be the best for PM_{10} monitoring. The majority of the tested units performed well in detecting CO_2 concentrations up to 3′500 ppm resulting in errors within 25% from the reference, with the best monitors performing within 3% from the reference. Foobot and uHoo monitors failed to accurately report the CO_2 concentration, with the mean relative error exceeding 30%. Low cost TVOC monitors Awair, Foobot and uHoo showed a strong correlation with the professional grade monitors despite a poor quantitative agreement. For relative humidity, the majority of tested devices gave time-correlated and acceptable results within 5% difference from the reference with the tendency to over-report relative humidity in cool and dry conditions and under-report it in warm and humid conditions. The uHoo, SCD40 and SHT31 showed the best performance with less than 0.6% RH difference, while the Clarity was the worst in class resulting in a 12% difference from reference. The air temperature was reported within+/-0.5 °C from the reference temperature in both seasons by 3 out of 8 consumer grade monitors and within+/-0.6 °C by the majority of tested devices. Seasonal comparison revealed that the majority of consumer grade monitors displayed comparable performance in both conditions, with the majority of consumer grade monitors being slightly closer to reference in cool and dry conditions for PM and CO_2 and in warm and humid conditions for TVOC.

Recent technological advancements have opened up an opportunity for more effective indoor air quality control and management. The present study suggests that the majority of the tested low-cost consumer grade monitors have the potential to be used to secure adequate indoor environments by triggering the right chain of actions. This could be accomplished either via a feedback loop to encourage human actions or through integration in a building management system with automated controllers and devices. To assure continuous improvement of low-cost environmental sensing technology, future work should focus on the examination of the longitudinal performance of these units, development of quality control algorithms that minimize errors and remove bias, and development of the standards and guidelines for their testing.

Declaration of competing interest

The authors 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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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.buildenv.2020.107415.

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