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## Investigation of indoor air quality in university residences using low-cost sensors†

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Exposure to air pollutants can cause serious adverse effects on human health; thus, indoor air quality (IAQ) is an important health and safety concern for occupants. A significant fraction of university students live in institution-managed residences. The length of time they spent in the residences, along with the negative impact of air pollutants on their health and academic performance, necessitate the need for continuous monitoring of IAQ in student residences. This study represents the first application of a low-cost sensors (LCS) network in university residences. Four major IAQ parameters (*i.e.*, particulate matter (PM<sub>2.5</sub>), carbon dioxide (CO<sub>2</sub>), temperature, and relative humidity) were monitored in five residences in a Canadian university for five months. Questionnaires were used to investigate students' lifestyles and their relationship with air pollutants. The results of this study show that indoor activities, such as cooking and humidifier use, can generate indoor PM<sub>2.5</sub> with daily average concentrations higher than the maximum exposure limit recommended by the US Environmental Protection Agency. The study also found that the building ventilation behavior and outdoor temperature affected the indoor CO<sub>2</sub> and PM<sub>2.5</sub> concentrations. Additionally, a correlation between indoor and outdoor PM<sub>2.5</sub> concentrations indicated the impact of outdoor air on indoor air quality. Besides these scientific findings, this study demonstrated that spatiotemporally-resolved, personalized IAQ provided by LCS could benefit the controlling and mitigation of the risks associated with indoor air pollutant exposure. An LCS network can serve as an affordable strategy to monitor students' living environment on university campuses.

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### Environmental significance

Indoor air pollutants can cause serious health problems. People spend approximately 90% of their time indoors, and this fraction is higher for students living in campus residences. However, the IAQ study at student residences has been absent from the literature. This study used a low-cost air quality sensor network to monitor IAQ in student residences for the first time. Our study found that indoor activities, building ventilation, outdoor air, and weather could influence IAQ. Some of these factors elevated indoor pollutant levels above the recommended daily exposure limits. Thus, our study demonstrated that IAQ monitoring using a low-cost sensor network could help to control pollutant levels and mitigate the risks of exposure.

## 1 Introduction

Air pollution is a leading risk factor for human morbidity and mortality.<sup>1</sup> According to the world health organization (WHO),<sup>2</sup> household air pollution exposure contributes 2 million deaths annually. This number surpasses those due to the use of tobacco, AIDS, tuberculosis, and malaria.<sup>3</sup> Air pollution generally consists of a complex mixture of substances that generate adverse effects on human health. The impact of air pollution is not restricted to outdoor areas. The US Environmental Protection Agency (US EPA) states that indoor air can be more polluted than outdoor air, and indoor air quality (IAQ) is one of the top

five environmental public health risk factors.<sup>4</sup> Numerous species can contribute to the deterioration of IAQ levels, including particulate matter (PM), volatile organic compounds (VOCs), gasses (O<sub>3</sub>, CO, CO<sub>2</sub>, NO<sub>2</sub>, and SO<sub>2</sub>), and biological particles such as pollen, bacteria, and fungi.<sup>5,6</sup> Some research indicates that people spend approximately 90% of their time indoors, which is expected to be even higher for students living in campus residences.<sup>7</sup> It is estimated that over 1.6 million full-time students were enrolled in 2018–2019 across Canada, and this number has grown by 18% over the past decade.<sup>8</sup> The same report also presented an analysis of the student accommodation of the 13 largest post-secondary institutions in Canada, showing that 11.4% of full-time students were residing in university-run student accommodation, and the percentages are increasing daily. Students in residences are particularly vulnerable to indoor air pollution as they have little control over their living spaces and are unaware of potential risks associated

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with IAQ. Finding a reliable and low-cost method for measuring IAQ to monitor pollutants and their impacts on students' health is crucial, but there are very few such attempts reported in the literature. For example, the effect of ventilation on IAQ of the student dormitories in China was researched by Yang *et al.*<sup>7</sup> and Li *et al.*<sup>9</sup> Liang *et al.*,<sup>10</sup> studied the biological responses of the dorm students associated with traffic emission using high-resolution metabolomics. There is a lack of studies that performed continuous measurements of IAQ in the actual living spaces of students. Particularly, the measurement of indoor air pollutants at Canadian university student residences has been absent from the literature. Most of Canadian universities experience harsh winter conditions and may face unique challenges in maintaining IAQ during winter months.

Traditionally, air pollutant concentration monitoring has relied on expensive government-authorized regulatory monitoring sites, which are often located far from individual sources. Air pollutant concentrations can exhibit significant spatiotemporal variability depending on the origins and features of that environment.<sup>11</sup> The existing monitoring instruments cannot capture these variations.<sup>12</sup> Continuous, spatiotemporally resolved, and personalized information on indoor pollutants can elucidate the trends of air pollutants in students' living places, which serve as health indicators. The real-time data could also educate the occupants and help them take action and seek resources to control and mitigate those indoor pollutants.<sup>13</sup> However, efforts to collect comprehensive IAQ data are limited by the cost and size of reference-quality monitors, sample analysis, and data processing. In recent years, low-cost sensors (LCS) have become an alternative that allows continuous air quality measurements on both the community and individual levels.<sup>14</sup> These devices are portable, affordable, and user-friendly.<sup>15</sup> In the last few decades, numerous studies have demonstrated applications and limitations of LCS, such as guidelines for implementing an LCS network, improving the resolution of concentration coverage, air quality monitoring in the indoor environment, and outdoor measurement, *e.g.*, detecting wildfire emissions.<sup>7,16,17</sup> LCS needs to be calibrated, and data must be interpreted with care to avoid inaccuracies.<sup>18–20</sup> EPA suggested that these sensors cannot be used for regulatory monitoring but for non-regulatory, supplemental, or informational monitoring applications. Nonetheless, air quality monitoring through LCS can provide useful information for a variety of applications, such as assessing the impacts of technology, long-term health impact studies, citizen participation in research, empowering regulatory decision-making through the incorporation of data science techniques, and providing guidance in real-time.<sup>21,22</sup>

Among the most common indoor pollutants, particles with an aerodynamic diameter smaller than 2.5  $\mu\text{m}$  ( $\text{PM}_{2.5}$ ) and  $\text{CO}_2$  are frequently monitored.  $\text{PM}_{2.5}$  and  $\text{CO}_2$  have unique sources indoors; and as such, their indoor concentrations serve as effective indicators of IAQ.  $\text{PM}_{2.5}$  can travel within the airway and deposit or settle in the tracheobronchial portion of the lungs and even smaller particles in the gas-exchange volume of the lungs. The indoor  $\text{PM}_{2.5}$  concentration varies considerably from less than 10  $\mu\text{g m}^{-3}$  to hundreds of  $\mu\text{g m}^{-3}$ , which can

cause serious health problems,<sup>7,23</sup> ranging from fatigue, headache, and eye irritation to more severe outcomes such as infections, asthma, lung function impairment, lung cancer, and cardiovascular diseases.<sup>24,25</sup> In regard to  $\text{CO}_2$ , while being a good indicator of pollutants emitted by humans,<sup>26</sup>  $\text{CO}_2$  has historically been treated as an indicator for ventilation/infiltration rates, which has an impact on IAQ.<sup>27,28</sup> Growing evidence shows that exposure to a  $\text{CO}_2$  concentration of 500–5000 ppm can cause various physiological changes in circulatory and autonomic systems, and numerous unpleasant responses were also reported, including drowsiness, lethargy, stuffiness, and a feeling that the air is stale.<sup>29</sup> Impairment of the cognitive performances including decision-making and problem-solving, could begin at 1000 ppm even with short-term exposure.<sup>28–31</sup> For university and college students, such symptoms can negatively affect their academic performance.<sup>27,31</sup> The concentration and the trend of indoor pollutants are influenced by various factors such as outdoor air, occupancy, occupant behavior patterns, building materials, building practice, ventilation, and air exchange rates.<sup>32,33</sup> For these reasons,  $\text{PM}_{2.5}$  and  $\text{CO}_2$  concentrations are expected to vary from building to building, and potentially from unit to unit. Reference-grade instruments cannot offer the coverage required to monitor IAQ in such diverse student residences, while LCS has the potential to fulfill this purpose.

The overall objective of this study was a continuous application of an LCS sensor network to investigate the IAQ of university student residences. The measurement campaign was conducted in five student residence buildings on a Canadian university campus during the winter season for five months. Specifically, the study aimed to address potential sources of indoor pollutants (*i.e.*, occupant's activities, outdoor air, *etc.*) and the factors influencing indoor pollutant concentration (*i.e.*, occupancy, ventilation system, outdoor temperature, *etc.*). To our best knowledge, this study will be the first to assess the IAQ of student residences using LCS. These findings will significantly enhance our understanding of the indoor environment of the student residences and help facilitate health-related awareness. Furthermore, this new sensing technology will reduce the monitoring cost and provide the occupants with personalized information on IAQ.

## 2 Materials and methods

### 2.1 Sensor configuration

The LCS consists of a PM sensor (Nova SDS011, V1.3), a  $\text{CO}_2$ /temperature/relative humidity (RH) sensor (Sensirion SCD30), and a microcontroller (ESP8266 NodeMcu) (Fig. 1). The details of the choice and the design of the sensor unit will be found in ESI Table S1.† All the components were enclosed inside a small hexagonal wooden box with a length and height of 38.1  $\times$  6.9 cm, making the sensor compact and suitable to fit in a residential environment. According to the manufacturer's information, the SDS011 sensor can measure particles with diameters between 0.3 and 10  $\mu\text{m}$  in the air by using the principle of light scattering.<sup>34</sup> A fan is used to draw air into the measurement cavity through an inlet with a flow rate of 20–35



ccm. Light distribution is induced when particles go through the detecting area. The scattered light is transformed into electrical signals, amplified, and processed. The number and diameter of particles can be obtained by analysis because of the signal waveform. Particle counters inside the sensors provide the mass concentration of PM in micrograms per cubic meter ( $\mu\text{g m}^{-3}$ ), with a measurement range of 0–999.9  $\mu\text{g m}^{-3}$ , and measurement error was a maximum of 15% and  $\pm 10 \mu\text{g m}^{-3}$  (at 25 °C and 50% RH) with a particle resolution of 0.3  $\mu\text{g m}^{-3}$ . A few previous studies have evaluated the performance of SDS011 sensors against reference instruments under various conditions.<sup>35–37</sup>

Sensirion SCD30 is integrated with CO<sub>2</sub>, humidity, and temperature measuring capacities on the same sensor module, making it a good fit for compact air quality sensors. The CO<sub>2</sub> sensor utilizes nondispersive infrared (NDIR) detection, which is a relatively proven technology for CO<sub>2</sub> measurement. The manufacturer claims that the accuracy of the CO<sub>2</sub> sensor is  $\pm 30$  ppm.<sup>38</sup> The measurement capacity of Sensirion SCD30 for CO<sub>2</sub>, Temperature, and RH were 0–40 000 ppm, –40 °C to 70 °C, and 0–100%, respectively.

The sensor was combined with the Internet of Things (IoT) (Fig. 1) and data management services, which provide real-time data for environmental monitoring.<sup>39</sup> In this study, the IAQ data from the sensors were captured for every 30 s. The micro-controller includes the ESP8266 Wi-Fi system-on-chip (SoC) firmware.<sup>40</sup> ESP8266 NodeMcu transferred the sensor data to ThingSpeak, an IoT analytics platform service, in real-time. ThingSpeak allows aggregating, visualizing, and analyzing live data streams in the cloud. Real-time data was also made available to each study participant to monitor IAQ in their own

residence. Data was then downloaded by the research team and analyzed by Igor Pro 8 (WaveMetrics).

## 2.2 Sensor quality control

Although the demand for affordable air quality monitoring using LCS has grown exponentially, it is widely known that sensor data quality is highly variable.<sup>22</sup> A key consideration for all LCS networks is that the sensors should be well-calibrated, and performance needs to be well-characterized. This process helps to conduct the operation of the sensors efficiently and improves data accuracy. In this study, we conducted careful quality control for sensors before sending them to participants, which included sensor power status, connectivity to Wi-Fi networks, data uploading, and data reliability. In particular, to check the sensor performance, PM sensor calibration was done before (pre-campaign) and after (post-campaign) deployment.

For calibrating the SDS011 sensor, all sensors were collocated in an unoccupied office with a research-grade optical particle counter (OPC, GRIMM 11C), which measures particles within a range from 0.25  $\mu\text{m}$  to 32  $\mu\text{m}$ . The room door and window were closed during calibration, and a fan was used to homogenize the air. An ultrasonic humidifier was used to generate the aerosol particles. Particles generated from the ultrasonic humidifier had been studied in detail in one of our previous publications.<sup>41</sup> The particles are comprised of common salts and minerals found in drinking water. The size distribution of particles appears unimodal, with a mean diameter of 100 to 200 nm. We chose humidifier particles for calibration because it is a safe and simple way to generate particles with a wide range of concentrations. As will be discussed later, humidifier use has been identified as a major source of particles

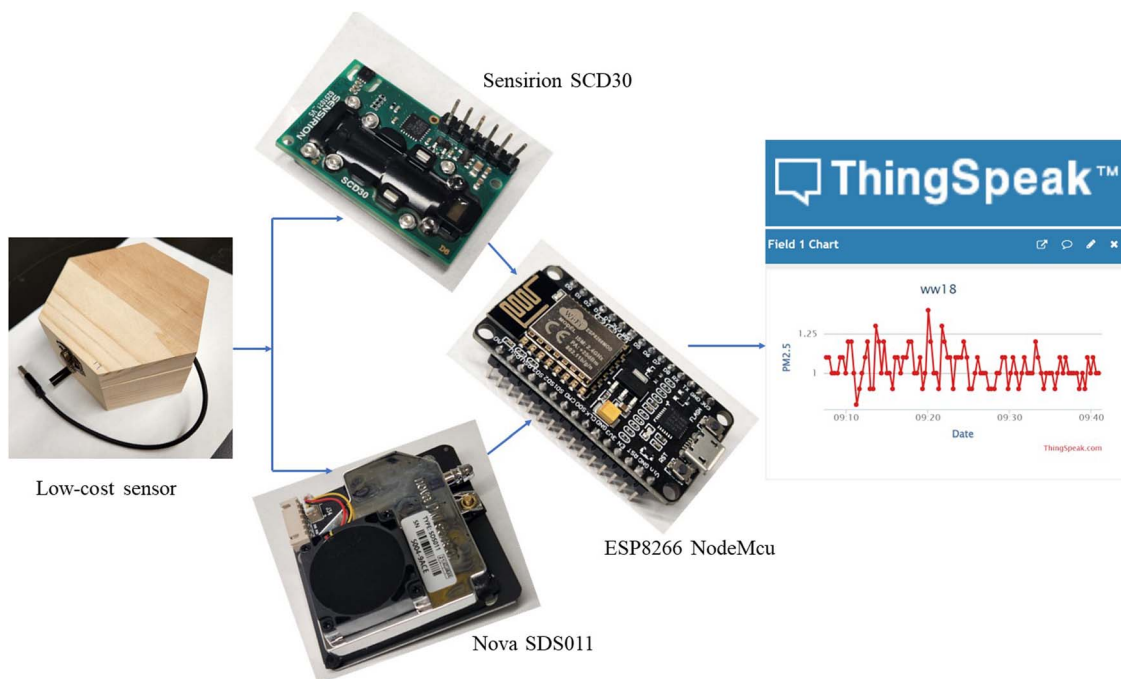


Fig. 1 Schematics of major components of the low-cost air quality sensor used in this work.



in student residences. However, we acknowledge that the calibration may not fully represent the entire spectrum of indoor aerosol, as the performance of LCS was found to vary under different conditions (*i.e.*, RH) and emitting sources (*i.e.*, size, density, and refractive index of the PM).<sup>42,43</sup> The humidifier was operated in the office until the PM<sub>2.5</sub> concentration reached 100 to 150  $\mu\text{g m}^{-3}$ . The ventilation of the office was centrally controlled by the building, with a consistent air exchange rate of 1.8 h<sup>-1</sup>, as measured in our previous study.<sup>44</sup> The natural decay of particles due to ventilation was monitored with both SDS011 sensors and the OPC. As per manufacturer specification, the SDS011 sensor could also measure PM<sub>10</sub>. However, it has been found that PM<sub>10</sub> measurements can be inaccurate compared to the reference instruments, especially if PM distribution shifts towards larger particles.<sup>45,46</sup> Herein, we focus only on the PM<sub>2.5</sub> data in our study. While PM<sub>10</sub>, PM<sub>1</sub>, or ultrafine PM have also been of increasing concern and studied in numerous literature, we did not investigate these in our work.

RH can be a major source of measurement error for PM sensors.<sup>41</sup> When the sample particles are hygroscopic in nature, they uptake more water under high RH conditions and can be subsequently treated as larger particles, leading to an overestimation of particle mass concentrations. Furthermore, water uptake can change the refractive index and density of the aerosol, making measurement more complex.<sup>15,18,47,48</sup> The manufacturer limits the operating range of the SDS011 sensor in terms of RH to 0–70%. Several studies observed significant positive artifacts in particle number and mass concentrations at RH above 75%.<sup>47,49,50</sup> In the current work, we confirmed that the RH was much below 75% and thus excluded any potential impact of RH on the PM<sub>2.5</sub> data.

In addition, an inter-comparison of CO<sub>2</sub> concentration measurement was done between the sensors to check the consistency and reliability of the SCD30 sensor's data. The experiment was conducted in the same manner in the unoccupied office, with dry ice used as the source of CO<sub>2</sub>. When all the sensors reported a CO<sub>2</sub> concentration of around 3000 ppm, the dry ice tray was removed from the office, and the windows were opened. The natural decay of CO<sub>2</sub> concentration was monitored until it reached approximately 580 ppm. The CO<sub>2</sub> concentration did not reach the ambient background of approximately 420 ppm (ref. 51) which was assumed due to the recirculation of indoor air from the building. A previous study has found that the SCD30 could underestimate the CO<sub>2</sub> concentration measurement under reduced pressure (approximately 85 kPa).<sup>1</sup> However, we didn't correct the SCD30 sensor's CO<sub>2</sub> data because the atmospheric pressure in Edmonton was 90 to 96 kPa during the study period (December 2021 to April 2022).<sup>52</sup> The graph of inter-comparison of SCD30 sensors using dry ice can be found in ESI, Fig. S1.† The inter-comparison study of the RH and temperature measurement were also done during the pre-and post-campaign PM calibration.

## 2.3 IAQ monitoring with LCS

**2.3.1 Recruitment of participants.** This study was conducted through the engagement of the university student

residence services and the student community. Thirty-six study participants from the university residences were recruited through classroom visits and advertisements with the help of student residence service and residence assistant staff (RAs). Classroom visits targeted large, first-year chemistry classes; thus, a significant fraction of participants were first-year undergraduate students. Prior to the recruitment, human research ethics approval was obtained from the University of Alberta Research Ethics Office (Pro00112541). Consent was taken from the participants for the data collection, where they acknowledged that (a) they understood the benefits and risks involved in this research, (b) who would have access to their information, (c) they had the freedom to withdraw from the study at any time, and (d) information confidentiality. Each participant was given a \$100 gift card at the end of the study to incentivize participation and completion of the study.

**2.3.2 Target buildings.** IAQ monitoring was conducted in five student residences from December 2021 to April 2022. The buildings were selected based on their different air ventilation systems and internal living arrangements. The residences differ from each other by permission or prohibition of student cooking; heat and energy recovery ventilation system (HRV); heating, ventilation, and air conditioning system (HVAC); and natural ventilation (NV) through the window. The residence rooms had a window, a bathroom, and a single occupant (the participant), whose daily activities were not disturbed by the experiments. Herein, the five residences are represented as residences A to E throughout this paper, and Table 1 lists some of their aspects relevant to this study. Other general information about these buildings is provided in the ESI, Table S2.†

**2.3.3 Participant engagement and questionnaires.** We trained the participants in the installation and maintenance process of the LCS. They were also provided with a troubleshooting checklist to handle the technical failure of the sensors. Participants were provided with a ThingSpeaks link to the real-time data of their own IAQ, with an aim to help them understand the factors responsible for the air quality trend in their surroundings. The sensors were connected to the residence's Wi-Fi network and placed in the student's living space. We asked the participants to set up the sensors at half the room's height and far from any heating or possible air pollutant sources, *i.e.*, cooking stove and humidifier. The participants were given questionnaires at the two-month mark and at the end of the study through Google Form. These questions were related to the lifestyle habits of the students inside the room, including cooking frequency and time, opening and closing windows, using a humidifier or diffuser, candle, cleaning, and dates when they moved from their residences. The entire list of questionnaires can be found in the ESI, Table S3.† The response rate of the questionnaires was 100%. The questionnaire data assisted in perceiving the possible indoor air pollutant sources and thus guided the interpretation of sensor data. We also communicated with individual participants for specific information in order to analyze the sensor data, such as the cooking time, humidifier use time, type of humidifier, and type of water used in the humidifier, *etc.*





Table 1 Feature of the five student residences

Name of the residence	No. of sensor	Study period	Cooking	Ventilation
Residence A	8	December 2021 to March 2022	Not allowed	HVAC
Residence B	8	December 2021 to March 2022	Not allowed	HRV and HVAC <sup>a</sup>
Residence C	8	December 2021 to March 2022	Allowed	HVAC
Residence D	5	December 2021 to March 2022	Allowed	HVAC
Residence E	7	March 2022 to April 2022	Not allowed	NV <sup>b</sup>

<sup>a</sup> In addition to the HVAC system in the building, in-suite HRV system is installed in each individual unit. <sup>b</sup> The building uses perimeter heating, and there are no air ducts in individual units. Air ventilation relies on the window to outdoor and the door to the corridor.

### 3 Results and discussion

#### 3.1 LCS sensor performance evaluation

Fig. 2(A) depicts the sensor and OPC-measured  $\text{PM}_{2.5}$  data obtained from the pre-campaign calibration. From this graphical figure, it was observed that when  $\text{PM}_{2.5} < 100 \mu\text{g m}^{-3}$ , the sensor and OPC measured values agreed with each other, but when  $\text{PM}_{2.5} > 100 \mu\text{g m}^{-3}$ , the sensors overestimated  $\text{PM}_{2.5}$  values compared to the OPC. A similar disagreement was observed

during the post-campaign calibrations (Fig. 2(B)), where a higher PM concentration was used. Calibration at higher PM concentrations also caused an increase in the inter-sensor data variability. Furthermore, Fig. 3(A) and (B) represent the box plot of slope and coefficient of determination ( $R^2$ ) values from the linear regression calibration model for the pre-and post-campaign calibration study. The linear regression model was built for each sensor measurement (y-axis) against the research grade instrument (OPC) (x-axis), with the slope and  $R^2$  values obtained from the fitting. The US EPA  $\text{PM}_{2.5}$ -based testing report recommends slope and  $R^2$  as two of the accuracy metrics to evaluate the performance of the sensors, with recommended values of  $1.0 \pm 0.35$  and  $>0.70$ , respectively.<sup>22,47</sup> In the pre-and post-calibration when  $\text{PM}_{2.5}$  was below  $100 \mu\text{g m}^{-3}$ , the slopes were  $1.15 \pm 0.08$  and  $0.97 \pm 0.14$  and were within the US EPA recommended slope range. However, when  $\text{PM}_{2.5}$  was above  $100 \mu\text{g m}^{-3}$ , some sensors overestimated the results compared to OPC, thus not meeting the US EPA recommended slope requirements. The slope was found  $1.33 \pm 0.18$  and  $1.44 \pm 0.18$  for pre-and post-campaign calibration, respectively. On the other hand,  $R^2$  results for both pre-and post-campaign met the US EPA recommended range. The reason behind the over-estimation and higher inter-sensor data variability at  $\text{PM}_{2.5}$  beyond  $100 \mu\text{g m}^{-3}$  is unknown. Previous studies showed that a magnitude of factors could lead to an overestimate of the sensor data, including atmospheric conditions (*i.e.*, RH and temperature), source of aerosol for calibration, the density, morphology, refractive index of the aerosol, and pattern of aerosol size distribution.<sup>15,48,49</sup> However, we studied the effect of RH and temperature as described below and assumed that the PM measurement was not affected by these properties. Numerous studies considered different methods for correcting these biases when they faced variable aerosol composition and size.<sup>43,48,53</sup> In our study when the sensor data was  $>100 \mu\text{g m}^{-3}$ , we applied a sensor-specific correction factor determined from our calibration. Given that the agreement between sensors and OPC was reasonable  $<100 \mu\text{g m}^{-3}$ , no correction factor was applied when the data was  $<100 \mu\text{g m}^{-3}$ . An example of how the correction factor helps to make the LCS PM data in agreement with OPC PM data when the PM concentration was  $>100 \mu\text{g m}^{-3}$  can be found in the ESI, Fig. S2.† We also operated the SDS011

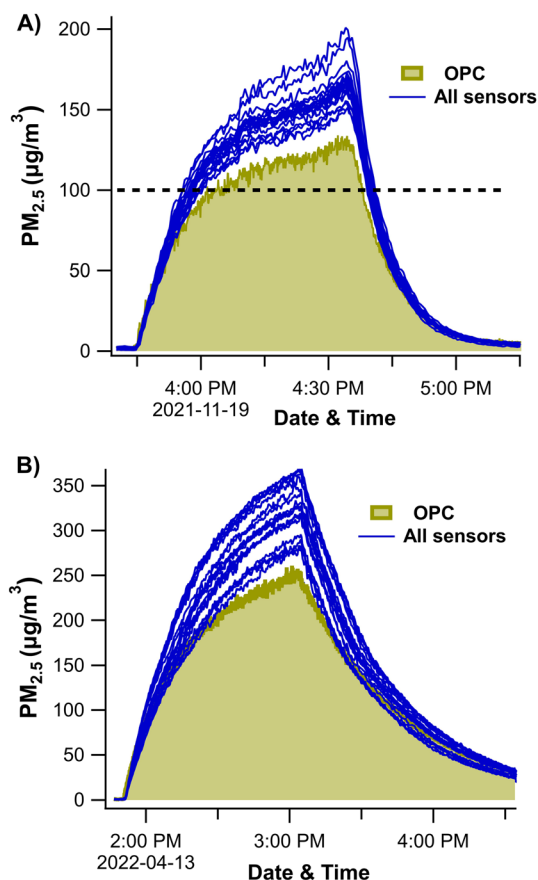


Fig. 2 SDS011 sensors and OPC measured  $\text{PM}_{2.5}$  concentration for pre-campaign (A) and post-campaign calibration (B).



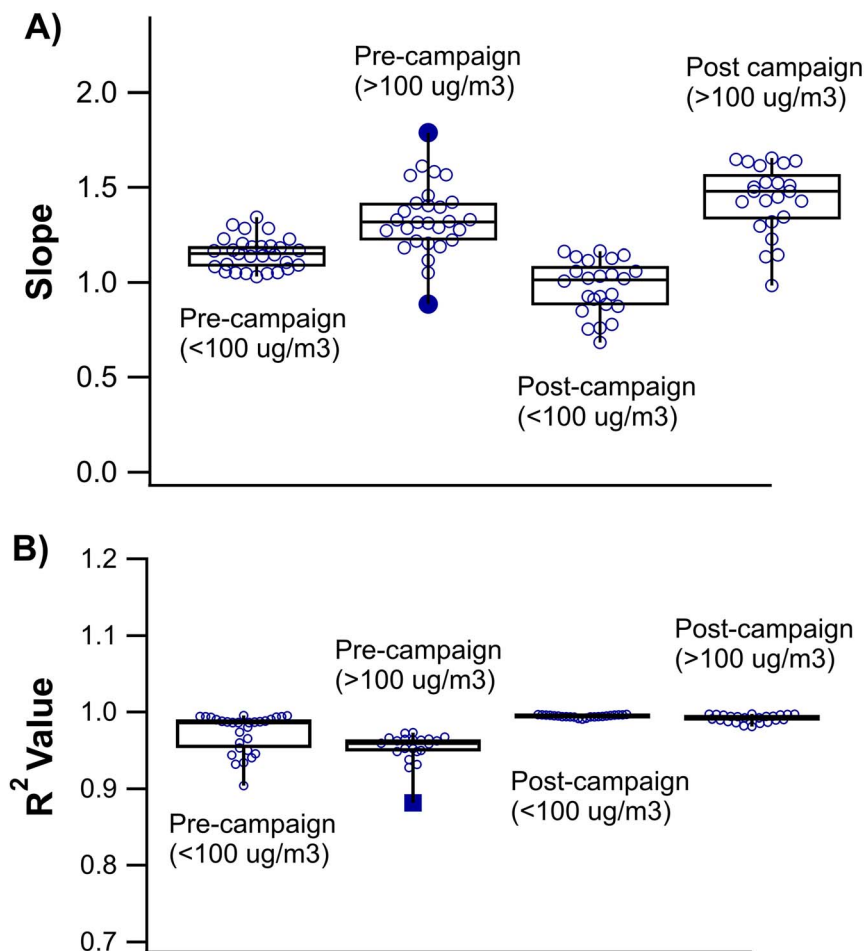


Fig. 3 Slope (A) and  $R^2$  values (B) for pre-calibration and post-calibration study.

sensors in the office without the humidifier for 24 hours to measure the limit of detection (LOD) for  $PM_{2.5}$ , which was found to be  $0.6 \mu\text{g m}^{-3}$ . The method used to calculate the LOD was adapted from previous literature.<sup>54,55</sup> LOD was the lowest concentration above which hourly averaged concentrations exceed their standard deviations by a factor of 3 more than 95% of the time.

For the  $CO_2$ , RH, and temperature data (SCD30 sensor), we did not perform an inter-comparison with reference instruments. Instead, all sensors were collocated in the unoccupied office to check the sensor data precision and reliability.<sup>19,35,56,57</sup> Precision of the collocated sample was measured with a coefficient of variations (CV%) for hourly averaged data.<sup>19,22,47</sup> (Table 2). Lower CV values indicate more precise measurements of the

sensors, with the US EPA recommending a targeted CV of  $\leq 30\%$ .<sup>22</sup> The calculated CV values for RH and temperature data for post and pre-campaign were relatively low. Besides that, CV (%) of  $CO_2$  concentrations of the collocated sensors (post-campaign only) was found at 7.53%, which is within the US EPA recommendation.

However, we found that the hourly average temperature in the studied residences was recorded at  $26.5 \pm 2 \text{ }^\circ\text{C}$ , which is 2–3  $^\circ\text{C}$  higher than the actual temperature and is assumed to be influenced by self-heating and internal conditions within the sensor unit.<sup>47</sup> In addition, the hourly averaged RH in the studied residence's room was 10–17%. As will be discussed later in this work, the lower RH resulted from cold outdoor temperatures. However, it is also likely that the internal temperature in sensor units has biased the measured RH low. An overestimation of 2–3  $^\circ\text{C}$  temperature could result in a 2–3% underestimation of the RH reading of our sensor.

Table 2 Coefficient of variation, CV (%) for 1 h average data between the LCS

Parameters	Pre-campaign, CV (%)	Post-campaign, CV (%)
Temperature	2.32	3.25
RH	5.38	9.98
$CO_2$	5.38	9.98

### 3.2 Sensor data quality

Fig. 4 shows the data availability for 29 sensors (from residences A to D) in the studied period. The color scale represents the number of data points uploaded by each sensor. Although the connectivity of all sensors was verified during calibrations,



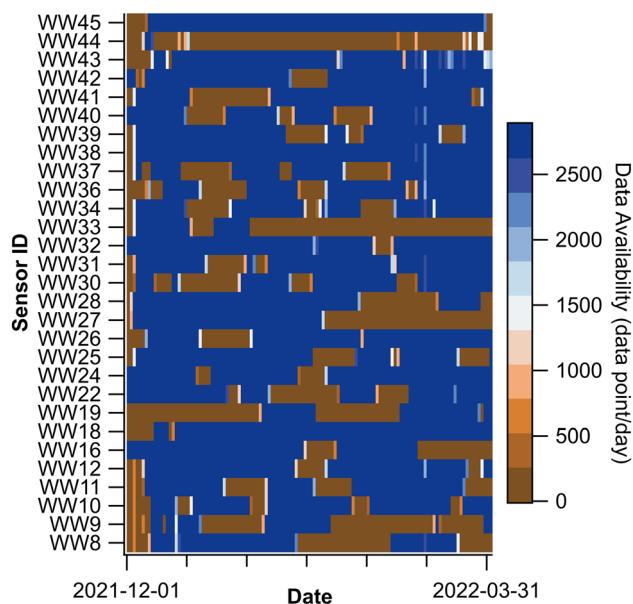


Fig. 4 Sensor data availability during the study period. The y-axis is comprised of individual sensor units deployed in residences A to D. The color scale represents the number of data points uploaded daily.

obtaining complete time series in actual residences was highly challenging since the sensors went offline occasionally. The main reason for data incompleteness was the instability or loss of the residence's Wi-Fi, resulting in the sensor's data collection being interrupted randomly. The data unavailability related to the wireless connection of the sensor was also reported previously in some studies.<sup>17,47,57</sup> A reboot of the sensor would usually solve the problem, but we did not have access to the actual residences and had to contact the participants to reboot the sensors, which sometimes took a long time. The data availability of 7 sensors from residence E was >99%. They are excluded from Fig. 4 because sensors were deployed at a different time (Table 1).

The other factors that influenced the missing data were (1) Winter break (from the end of December 2021 to the first week of January 2022) and (2) the University's switching to online classes due to COVID-19 (from January 2022 to February 2022). ESI Fig. S3† shows the number and percentage of sensors online at each given time, where a sensor is considered online if the data was recorded for at least 10 hours daily. Many students left their residences during these periods, and Wi-Fi issues forced some sensors offline. As these students were not in place, it was impossible to reboot the sensors for that period. Beyond these two periods, 70–90% of sensors were online for the duration of the investigation (ESI, Fig. S3†).

Besides data availability, a few limitations of our study should be noted here. We had no control over the activities of the participants and had to rely on the questionnaire's feedback to find possible sources. Additionally, we could not track the exact location of sensors in each residence. Although we provided basic instructions upon sensor deployment, it was up to the participants to choose the location of the sensor.

Relatedly, we had to assume that the sensor data was representative of IAQ in that specific residence; *i.e.*, the air was well-mixed inside the room. This assumption may not be true if the sensor was located too close to a source or a sink, and if the air mixing is insufficient. Overall, the LCS network was able to collect sufficient and reliable data during the measurement period. However, we could not avoid a certain degree of data loss and uncertainties related to factors beyond our control.

### 3.3 Factors affecting indoor pollutants

This study explored indoor activities and outdoor parameters that had a profound impact on IAQ, including occupancy and occupant activities, ventilation system (air exchange rate), and outdoor air quality.

**3.3.1 Impact of occupancy.** We identified an occupied and an unoccupied period based on the responses to our questionnaire. The unoccupied period was when the participants left the residences during the Winter break (23 December to 29 December), and the occupied period was from 1 to 21 December. The average CO<sub>2</sub> and PM<sub>2.5</sub> recorded from all sensors in residences A to D during these two periods were obtained and presented in Fig. 5(A) and (B). In residences A and B, the average PM<sub>2.5</sub> was found in unoccupied rooms at 1.8 and 1.5 μg m<sup>-3</sup>, whereas in occupied rooms, PM<sub>2.5</sub> concentration was found 2.7 and 2.8 μg m<sup>-3</sup>, respectively. On the other hand, the PM<sub>2.5</sub> concentrations were found 1.9 and 1.0 μg m<sup>-3</sup>

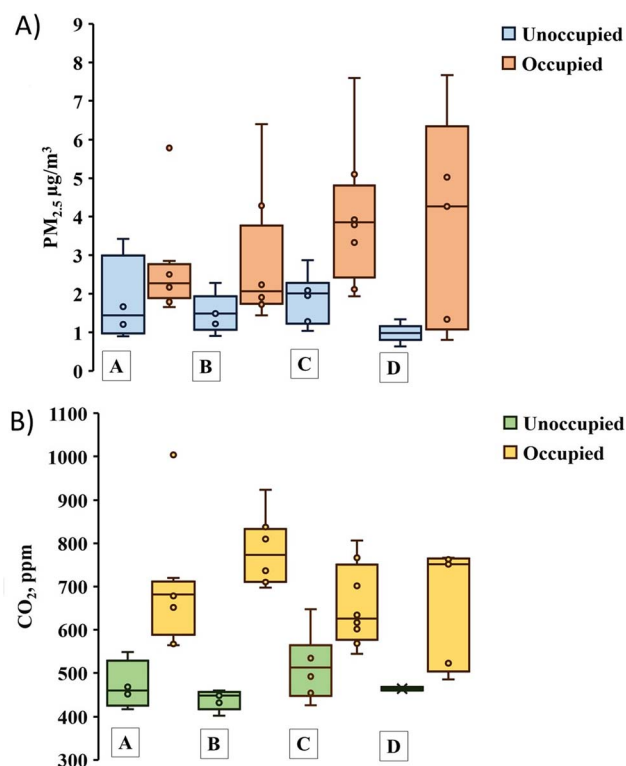


Fig. 5 Effect of occupancy on indoor PM<sub>2.5</sub> concentration (A) and CO<sub>2</sub> concentration (B): residences A–D were mechanically ventilated where residences A and B prohibited cooking, and residences C and D allowed cooking.



(unoccupied) and  $4.0 \mu\text{g m}^{-3}$  and  $3.8 \mu\text{g m}^{-3}$  (occupied), respectively, in residences C and D. It is likely that cooking in residences C and D led to an increase in the  $\text{PM}_{2.5}$  level during the occupied period compared to residence A and B (cooking is prohibited). According to the questionnaire's response, due to the low outdoor temperature ( $-10 \text{ }^\circ\text{C}$  to  $-32 \text{ }^\circ\text{C}$ ) none of the participants who cooked also opened the window during this time period; thus, the contribution of any outdoor sources during the cooking period would be negligible.

In addition,  $\text{CO}_2$  concentrations were found to be 472 and 493 ppm, and 695 and 781 ppm in unoccupied and occupied conditions in residences A and B, respectively. Meanwhile, those in residences C and D were found 515 and 464 ppm (unoccupied) and 655 and 658 ppm (occupied), respectively. The  $\text{CO}_2$  concentration differences between occupied and unoccupied rooms are mainly because of the exhalation of the occupants. A statistical test (*t*-test) was also performed to compare the  $\text{PM}_{2.5}$  and  $\text{CO}_2$  concentrations for occupied and unoccupied conditions. Except for the  $\text{PM}_{2.5}$  concentrations in residence A, the statistical results of the *P* value from the *t*-test founds less than 0.05 which indicates a statistically significant (at 95% confidence level) difference of  $\text{PM}_{2.5}$  and  $\text{CO}_2$  concentrations between occupied and unoccupied conditions in residences A–D (Table S4†). As such, it was believed that the occupants' activities, including their mere presence within the room, are the main driving factor behind the higher  $\text{PM}_{2.5}$  and  $\text{CO}_2$  levels in the occupied space. Moreover, the lower differences and low level of  $\text{PM}_{2.5}$  in these two conditions indicate the good ventilation behavior of these four buildings, which is explained further below.

National Ambient Air Standards by US EPA recommended a short-term exposure (24 hour or daily average) limit of  $\text{PM}_{2.5}$  at  $35 \mu\text{g m}^{-3}$ , and the long-term exposure limit (annual average) is  $12 \mu\text{g m}^{-3}$ .<sup>58</sup> Health Canada does not suggest a specific maximum exposure limit but recommends the indoor  $\text{PM}_{2.5}$  to be kept at the minimum and lower than  $\text{PM}_{2.5}$  outdoors.<sup>59</sup> On the other hand, the maximum daily exposure limit of  $\text{CO}_2$  recommended by Health Canada for residential occupants is 1000 ppm to protect against health impacts.<sup>27,60</sup> In this study,  $\text{PM}_{2.5}$  and  $\text{CO}_2$  concentrations are generally found lower than the 24 h exposure standard, there can be specific sources causing high concentrations which are discussed later.

**3.3.2 Impact of ventilation system.** This study also assessed the influence of ventilation systems on indoor particle concentrations in residential buildings as the ventilation process is also a significant factor that helps to maintain ideal IAQ. The actual ventilation rates would be affected by a number of more complex factors, such as the specific location of the room in the block, as well as the ventilation path. However, we did not include this question in the survey. As previously shown in Table 1, buildings A–D have mechanical ventilation (MV) systems (HRV and HVAC), whereas building E has NV (windows). Fig. 6(A) and (B) represent the averaged  $\text{PM}_{2.5}$  and  $\text{CO}_2$  concentrations for one month (March 2022) of all sensors deployed in five residences to elucidate the potential effects of MV and NV systems on indoor pollutants concentration. The indoor  $\text{PM}_{2.5}$  concentration of residence E was found  $2.2 \mu\text{g m}^{-3}$

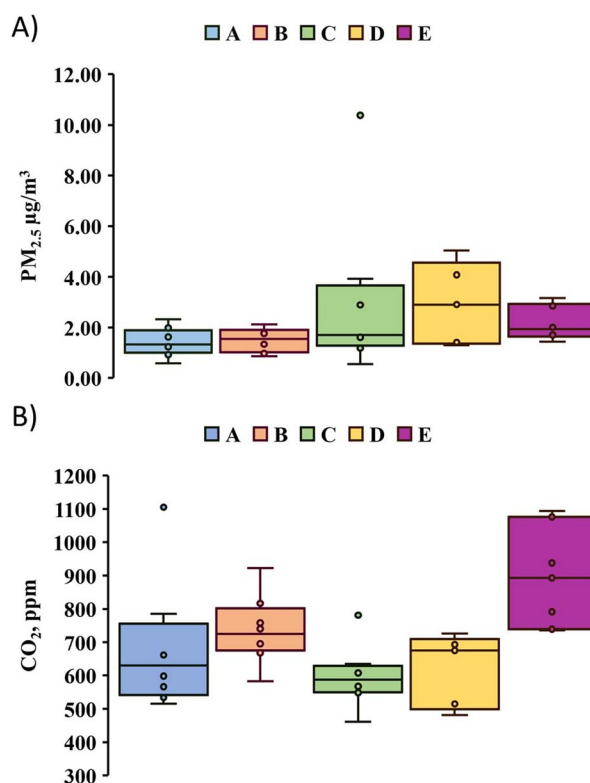


Fig. 6 Effect of MV (residence A–D) and NV (residence E) on indoor  $\text{PM}_{2.5}$  (A) and  $\text{CO}_2$  (B) concentration.

which was close to the  $\text{PM}_{2.5}$  concentration recorded in other residences; residence A ( $1.4 \mu\text{g m}^{-3}$ ), residence B ( $1.5 \mu\text{g m}^{-3}$ ), residence C ( $3.0 \mu\text{g m}^{-3}$ ) and residence D ( $3.0 \mu\text{g m}^{-3}$ ). In addition, according to the *t*-test result, the *P* values for the ventilation effects on the indoor  $\text{PM}_{2.5}$  and  $\text{CO}_2$  concentrations of residence A–B compared with residence E were found  $<0.05$ . However, for residences C, and D, the *P* value was found  $>0.05$  which is likely due to the contribution of cooking inside the room (Table S4†).

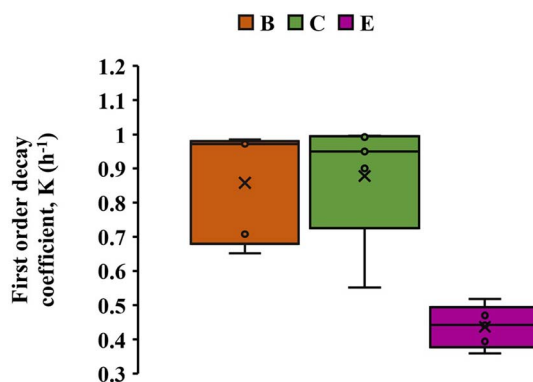


Fig. 7 First order decay coefficient (*K*) of  $\text{PM}_{2.5}$  generated from five events of humidifier use in residence B, C, and E. Note that B and C employ MV, while E employs NV.





On the other hand, CO<sub>2</sub> concentration (895 ppm) in residence E was higher than other residences (679, 738, 595, and 618 ppm in residence A, B, C, and D, respectively). Furthermore, the *P* values for the indoor CO<sub>2</sub> concentration of residences A–D compared with residence E were found <0.05 (Table S5†). Overall, the statistical results of the *P* value indicate the effects of ventilation systems (MV vs. NV) on differences in indoor PM<sub>2.5</sub> and CO<sub>2</sub> concentration. It was hypothesized that NV led to a slower air exchange rate and caused a higher indoor CO<sub>2</sub> concentration in residence E. The decay rate of PM<sub>2.5</sub> concentration (generated from the humidifier) in residences B, C, and D was obtained to test this hypothesis. Five humidifier use events were collected from each of these three residences, with the average first order coefficient (*K*) calculated and presented in Fig. 7. We indeed found a smaller *K* value in residence E compared to those in B and C, which have a MV system. In residences B and C, the average *K* values for the five humidifiers using events were found to be  $0.86 \pm 0.16 \text{ h}^{-1}$  and  $0.88 \pm 0.19 \text{ h}^{-1}$ , respectively. However, *K* was found to be almost half of those values ( $0.44 \pm 0.06 \text{ h}^{-1}$ ) in residence E. The *P* value for *K* was found 0.002 for both B and C residences with respect to residence E, which statistically proved the slower air exchange and ventilation rate in residence E. These results indicate that the reliance on NV in this residence can lead to the accumulation of indoor pollutants.

HVAC/HRV systems offer consistent ventilation and contribute to thermal comfort in the indoor environment.<sup>64</sup> The capability of MV to maintain better indoor air quality over NV was studied in several studies. Park *et al.*, mentioned that MV reduced the indoor to outdoor (I/O) ratios of PM concentration by 26% for submicron particles and 65% for fine particles compared with NV.<sup>62</sup> Results of this study confirm that MV with filtration can significantly reduce indoor particle levels and maintain good IAQ.

**3.3.3 Major sources of indoor PM<sub>2.5</sub>.** This study revealed several indoor activities that could be significantly contributing to indoor pollutant levels.<sup>63</sup> It is well established that using a humidifier, smoking, candling, cleaning and cooking are among the main sources of indoor pollutants.<sup>63,64</sup> Smoking and candling were scarce in our study. According to self-claimed information provided on our survey, only one participant smoked e-cigarettes, three participants used candles, and none indicated combustible tobacco smoking (prohibited in all residences). Two out of the five residences studied allowed students to cook inside their rooms using an electric stove, and according to the survey, 82% of students in these residences chose to cook with variable frequencies. In addition, about 25% of students used humidifiers, and as we have already discussed earlier, humidifiers generate a considerable amount of PM<sub>2.5</sub>. Our study identified cooking and humidifiers as two dominant sources of indoor pollutants, particularly for PM<sub>2.5</sub> in students' living spaces.

**3.3.3.1 Humidifier.** As the investigation was carried out during the winter seasons, indoor RH reached as low as  $7 \pm 3\%$  during the cold weather. We note that this value is likely biased low due to the self-heating of the sensor, as discussed previously. From the questionnaires, we found that participants used



Fig. 8 Effect of humidifier on indoor PM<sub>2.5</sub> emission. Data from one sensor is shown here as a case study.

a humidifier during the winter to alleviate low humidity-induced discomfort (such as skin drying, irritation of mucous membranes, dry eyes, and static electricity). Different studies showed that the portable humidifier could serve as an indoor PM<sub>2.5</sub> emitter.<sup>41,65</sup> Our study investigated the sensor data of those who used an ultrasonic humidifier. The time profiles of PM<sub>2.5</sub> and RH data recorded from one example sensor over a period of ten days are shown in Fig. 8. The pink shaded area indicates the projected period of humidifier use, as indicated by a sharp increase in both RH and PM<sub>2.5</sub>. The RH value was down to a minimum of 4% when the occupant was prompted to use a humidifier, which managed to increase the room humidity to approximately 20%. During humidifier usage, the mass concentration of indoor PM<sub>2.5</sub> reached 100 to 180  $\mu\text{g m}^{-3}$ , which aligns with findings from existing literature.<sup>41</sup> As discussed earlier, a sensor-specific correction factor was applied to the data when PM<sub>2.5</sub> concentration reached  $>100 \mu\text{g m}^{-3}$  to avoid a bias observed during calibration. The 24 hour averaged PM<sub>2.5</sub> concentrations during these 10 days of humidifier operation were between 15.0 to 49.6  $\mu\text{g m}^{-3}$ , which indicates that humidifier can result in indoor PM<sub>2.5</sub> concentrations exceeding the US EPA's acute daily average ambient air quality standard limit of 35  $\mu\text{g m}^{-3}$ .<sup>58</sup> The end of humidifier use was followed by a gradual decay of both the PM<sub>2.5</sub> concentrations and RH, likely through deposition, air circulation, and ventilation, with PM<sub>2.5</sub> eventually reaching its background level ( $<2.0 \mu\text{g m}^{-3}$ ).

According to personal communication with the participant, tap water was used in the humidifier. Lau *et al.*<sup>41</sup> and Guo *et al.*<sup>65</sup> found that suspended and dissolved materials and compounds contained in the charging water of the humidifier could be released as PM<sub>2.5</sub>. They also found that when using tap water, an ultrasonic humidifier released 22 times more PM<sub>2.5</sub> than an evaporative humidifier. Ultrasonic humidifiers produce water droplets as a cool fog and leave dissolved minerals in the mist as ultrafine particles, mostly  $<1 \mu\text{m}$ . Elements and ions, including Ca<sup>2+</sup>, Na<sup>+</sup>, Mg<sup>2+</sup>, K<sup>+</sup>, Cl<sup>-</sup>, Si<sup>4+</sup>, Al<sup>3+</sup>, Fe<sup>2+</sup>, OH<sup>-</sup>, CO<sub>3</sub><sup>2-</sup>, HCO<sub>3</sub><sup>-</sup> *etc.*<sup>66</sup> and microbial particles could be present in the tap water used for humidification.<sup>67–69</sup> There is no WHO or government health-based regulatory guidance or standards limit of the mineral content of tap water because they are unlikely to have adverse health effects when ingested; however, they can



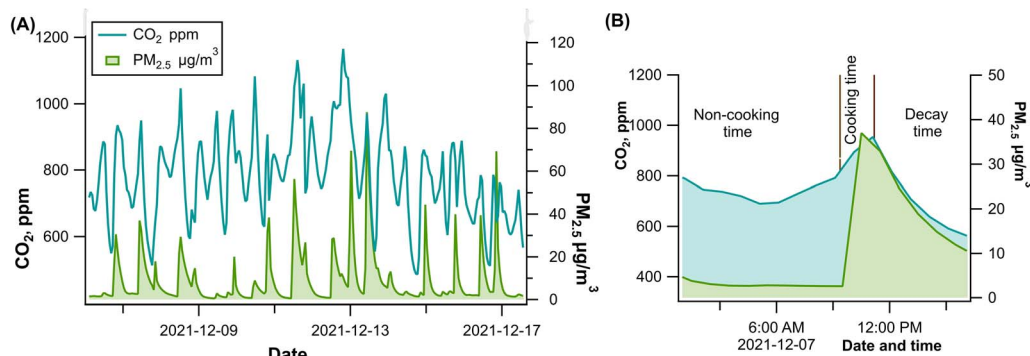


Fig. 9 (A) Cooking emission of indoor PM<sub>2.5</sub> and CO<sub>2</sub> measured by LCS during a 12 day period and (B) a one-day period from that 12 days, highlighting the differences between non-cooking time, cooking time, and decay rate.

potentially cause issues when inhaled into the lungs as aerosol particles or white dust.<sup>67,70,71</sup> The US EPA conceptual model (US EPA, 2016) considered the inhalation of treated tap water as an important route of human exposure to contaminants. Student residents should be encouraged to use water with low levels of mineral and other dissolved components to limit inhalation exposure to potentially harmful components. Alternatively, an evaporative humidifier can be used because it does not generate as much PM as an ultrasonic humidifier.<sup>41</sup>

**3.3.3.2 Cooking.** Several studies reported that cooking is one of the largest indoor PM emission sources.<sup>72,73</sup> Cooking emission primarily contributes to the fine particles (PM<sub>2.5</sub>) and ultrafine particles.<sup>74–76</sup> A Health Canada study showed that indoor particle concentration increased 65 times during cooking compared to background levels.<sup>74</sup> As such, cooking activity can adversely affect IAQ and occupant health. In this paper, we showcase PM<sub>2.5</sub> emission from cooking by presenting data from a participant who cooked regularly. Fig. 9(A) illustrates the PM<sub>2.5</sub> time profile from the sensor during a 12 day period. Fig. 9(B), which shows a one-day period, highlights the differences between non-cooking time (12.0 am to 9.30 am) and cooking time (9.30 am to 11.30 am) PM<sub>2.5</sub> levels. Results show that the PM sensor detected the start and end of the emissions of PM<sub>2.5</sub> from cooking. In the non-cooking period, the room PM<sub>2.5</sub> concentration was between 1.0–4.0 µg m<sup>-3</sup>. Cooking gave rise to hourly averaged concentrations between 28.7 and 87.6 µg m<sup>-3</sup>, and the maximum daily average was calculated to be 22.1 µg m<sup>-3</sup>.

We also observed a higher CO<sub>2</sub> concentration during the cooking period than the non-cooking time (sleeping time), resulting from the occupant's rapid movement inside the room. According to a study, the body uses more oxygen during fast action and muscles work.<sup>77</sup> and produces more CO<sub>2</sub>. The CO<sub>2</sub> level increased to an hourly average concentration of around 1000 ± 150 ppm when the PM<sub>2.5</sub> was also at the peak point.

It is important to note that for some participants who cooked, we did not observe a significant increase in PM<sub>2.5</sub> during the cooking time and didn't find any significant difference between the non-cooking and cooking hours. It is evident from existing literature that the extent of PM<sub>2.5</sub> emission is associated with cooking temperature, methods, type of stove

and appliances, types of food, fat, and oil.<sup>77–79</sup> Among the different types of cooking methods, frying, deep-frying, roasting, broiling, sauteing, toasting, baking, or burning of food generates these airborne particles.<sup>75</sup> Different cooking styles and food may explain the difference in PM<sub>2.5</sub> concentrations observed among participants who cooked. With the assistance of real-time IAQ monitoring, the occupants could take necessary mitigation measures such as using the stove venting hood properly, using NV, MV, portable air cleaner, and even adjusting the cooking methods to reduce the indoor PM<sub>2.5</sub> level as well as other cooking generated pollutants.<sup>72,80,81</sup>

Overall, The discussions from this section show that indoor sources, such as humidifiers and cooking, could contribute to an episodic but drastic increase in indoor PM<sub>2.5</sub> concentrations. Their impact on the overall average PM<sub>2.5</sub> concentration is present but moderate; however, the short-term impact cannot be neglected.

**3.3.4 Effect of outdoor air.** Although several indoor activities can cause spikes in indoor PM concentration, ambient or outdoor sources can also contribute to indoor PM concentration. Fig. 10 illustrates the time profiles of the hourly average data of the residence sensors with that of the nearest outdoor PurpleAir (PA) sensor which is 500 m away from the studied indoor sensor. PA sensor is a widely deployed LCS network across the globe.<sup>48</sup> PA's PM sensor operates under a similar principle to our LCS but is manufactured by a different vendor. The specific PA we selected was deployed and maintained by Alberta Capital Airshed, the local organization overseeing the local air quality monitoring network. The comparison was done for the sampling period of February 24, 2022, to March 6, 2022. Although PA PM<sub>2.5</sub> concentration data were considered for comparison with the indoor PM<sub>2.5</sub> concentration trend, not for quantitative comparison, a correction equation recommended by US EPA<sup>82</sup> was applied to correct the PA sensor PM<sub>2.5</sub> data to make it more comparable to our indoor LCS PM<sub>2.5</sub> data, thus reducing data accuracy concerns. To avoid biases in the sensor data by different indoor PM<sub>2.5</sub> sources, the sensors were selected from the two residences where cooking was prohibited and the time when no humidifiers were used. As shown in Fig. 10, the indoor and outdoor PM<sub>2.5</sub> concentrations exhibited a clear correlation albeit the indoor concentrations were lower





Fig. 10 Hourly variations of indoor  $PM_{2.5}$  level with outdoor  $PM_{2.5}$  level, during weekdays and weekends. The outdoor PurpleAir data was treated with corrections recommended by the US EPA.<sup>62</sup>

and appeared to be delayed compared to those outdoors, likely due to the infiltration process. The study period is further divided into weekdays (Monday–Friday) and weekends (Saturday–Sunday). Generally, both outdoor and indoor  $PM_{2.5}$  concentrations were higher during weekdays, likely due to traffic and industrial emissions. Our study found evidence that such outdoor sources can be affecting IAQ in student residences. A similar trend was observed during the rest of the study period; however, the indoor–outdoor correlation was disturbed when IAQ was dominated by indoor sources as discussed in previous sections.

Residences A and B had HRV and HVAC ventilation systems. During the investigation period, the windows were kept open about 4–13% of the day; thus, the effect of NV was considered a negligible contribution to indoor  $PM_{2.5}$ . However, based on the weekday's  $PM_{2.5}$  concentration trend, the indoor  $PM_{2.5}$  concentration level was found low compared to the outdoor  $PM_{2.5}$  concentration which indicates the efficient filtration efficiency of both ventilation systems in these two residences.

Overall, we found that outdoor air pollutants can be the major influence on indoor IAQ when there are no significant indoor sources present (*e.g.*, cooking and humidifier use). Building ventilation and filtration systems play a critical role in eliminating air pollutants of outdoor origin. In this study, the MV systems in the two studied buildings were successful in keeping  $PM_{2.5}$  concentration below the recommended daily acute exposure limit.

**3.3.5 Impact of outdoor temperature on the ventilation system.** In this study, we observed episodes of elevated indoor  $CO_2$  levels when the outdoor temperature was very low.

According to data collected by a regulatory monitoring station (sensor located about 3.7 km from the studied residence), from December 2021 to January 2022, the outdoor temperature was recorded to be  $-20$  °C to  $-30$  °C (Fig. 11). At that time, it appears that the ventilation systems (HVAC) of residences A and D faced technical challenges, with the build-up of  $CO_2$  observed for certain periods. According to questionnaires, the proportion of occupants who opened the window during that time was low due to the cold outdoor climate conditions. For instance, during that cold period, residence A recorded a 24 hour average indoor  $CO_2$  level of up to 1434 ppm, which is higher than the maximum daily indoor exposure limit.<sup>60</sup> A similar challenge was observed during mid to late January in both residences. It is important to note that the  $CO_2$  concentration remained at the background level if a specific residence was not occupied during this time (*e.g.*, purple trace in residence D). These observations indicate that challenges associated with the MV systems trapped air pollutants of indoor origin.

The daily average  $PM_{2.5}$  concentrations during this observation period were not elevated as those of  $CO_2$ . For residence A, the averaged  $PM_{2.5}$  (23 December to 4 February) was found at  $1.8$   $\mu\text{g m}^{-3}$ . However, from 17 January to 4 February the indoor  $PM_{2.5}$  concentration in residence D was increased, and average concentrations were recorded at  $8.6$   $\mu\text{g m}^{-3}$ . It was considered that in residence D, cooking raised the  $PM_{2.5}$  concentration along with insufficient ventilation. The higher  $PM_{2.5}$  in residence D provides an additional indication that indoor air pollutants were trapped inside during this cold period. Besides  $PM_{2.5}$ , there are other pollutants indoors, as introduced earlier.<sup>6</sup> These pollutants could also accumulate due to insufficient air



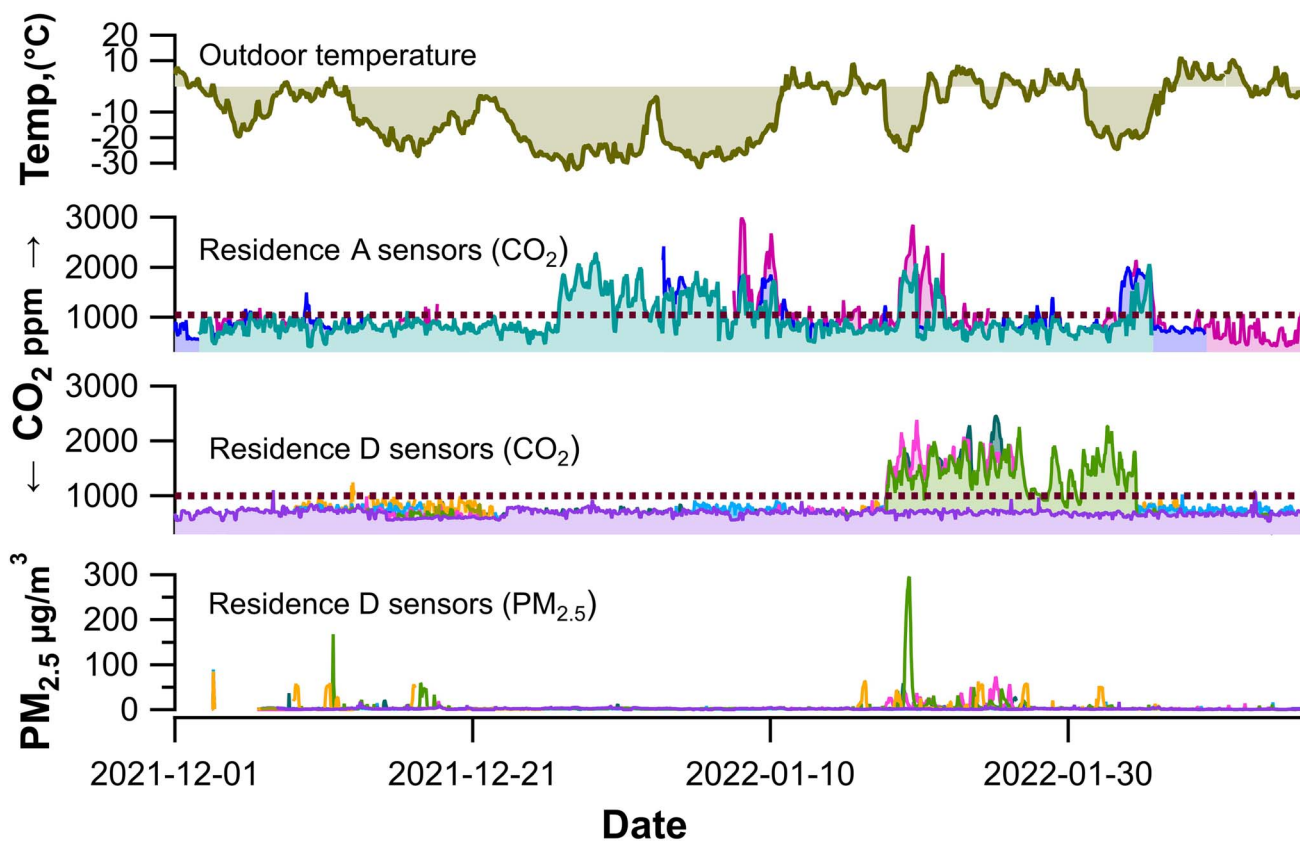


Fig. 11 Impact of outdoor temperature and ventilation on indoor pollutants  $\text{CO}_2$  and  $\text{PM}_{2.5}$  concentration. Impact of outdoor temperature and ventilation on indoor pollutants ( $\text{CO}_2$  and  $\text{PM}_{2.5}$ ) concentration.

ventilation rate. Our study shows that extremely cold weather may pose a concern for IAQ in student residences due to less NV (closed windows) and challenges associated with MV systems in cold temperatures. Such challenges may have been common for campuses located in the cold climate zone; however, they may have remained unrecognized due to the lack of affordable IAQ monitoring methods.

## 4 Conclusions

A major fraction of college and university students spend most of their time in school-managed student residences, and thus exposure to indoor air pollutants must be continuously monitored and managed. In this study, we applied an LCS network to monitor IAQ parameters in university student residences. A total of 36 sensors were deployed in five student residences with a variety of conditions. The sensors were operated in the actual living spaces of study participants for up to five months. This study represents the first application of an LCS network in university residences. Long-term monitoring of IAQ in the actual living spaces of students, conducted simultaneously by multiple sensors, was achieved for the first time. Overall, this study suggests that LCS can offer continuous, spatiotemporally-resolved IAQ data for a fraction of the cost of typical research-grade instruments. However, these inexpensive sensors have limitations and need to be characterized under realistic

conditions. As demonstrated in this work, collocation and calibration with a research-grade instrument were able to ensure reasonable data quality.

A number of discoveries were made in this study. The data indicated that cooking and humidifier use were the two dominant sources of indoor  $\text{PM}_{2.5}$ , the concentration of which surpassed the recommended daily exposure limit during such events. Besides that, the study found strong correlations between outdoor and indoor  $\text{PM}_{2.5}$ . Although the outdoor air was not as significant as a source compared to cooking and humidifier use, events of elevated outdoor pollutants (*e.g.*, wildfire smoke in the summer) can potentially govern IAQ parameters. The building ventilation behavior and outdoor temperature were also found to affect the indoor  $\text{CO}_2$  and  $\text{PM}_{2.5}$  concentrations. In particular, it was observed that the ventilation systems in certain residences faced challenges when the outdoor temperature was approaching  $-20\text{ }^\circ\text{C}$  and lower. Such situations may be common for residences located in cold climate and would not have been noticed without the deployment of LCS. As such, the results of this study underscore the need for basic measures of indoor air pollution control paired with ongoing air monitoring within the residence facility and the importance of future air monitoring studies aimed within these facilities. The LCS network has the potential to fulfill this purpose. It is expected to benefit the students for mitigating the risks of high pollutant exposure and the building management





for optimizing the building ventilation and energy consumption.

## Conflicts of interest

There are no conflicts to declare.

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