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A longitudinal study of IAQ metrics and the efficacy of default HVAC ventilation

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ABSTRACT

People spend approximately 90% of their time indoors, making effective indoor air quality (IAQ) monitoring crucial for occupants' well-being. Traditional IAQ monitoring primarily focuses on carbon dioxide (CO_2) levels to inform the operation of Heating, Ventilation, and Air Conditioning (HVAC) systems. However, HVAC systems often overlook other critical IAQ metrics, such as volatile organic compounds (VOC), which may correspond better to occupant activities in some cases. This naturalistic study, conducted over four months at the University of Virginia, addresses this significant gap by observing changes in VOC and CO_2 levels across various times, events, and spaces, including conference rooms, single occupancy offices, and common open-space areas. We aimed to determine whether CO_2 can be the only representative of IAQ for dynamically adjusting the ventilation rates within this testbed. A key focus was on poor IAQ instances where CO_2 levels were below the recommended levels, but VOC concentrations exceeded them, potentially impacting occupants' health and well-being. Our results revealed that in the studied conference room, poor IAQ conditions prevailed 71% of the time during occupancy, in contrast to lower rates in single occupancy offices (11%, 7%, and 16%). Notably, while social events influenced CO_2 levels less, VOC levels significantly increased in all open-space areas. These findings challenge the conventional reliance on CO_2 monitoring for IAQ management, highlighting the necessity of incorporating comprehensive IAQ metrics in HVAC systems. The study underscores the critical need for dynamic HVAC systems that adapt to real-time IAQ conditions, a vital step towards enhancing indoor environmental quality in various settings.

1. Introduction and background

On average, Americans spend up to 90% of their time in indoor environments [1]. However, most buildings are not designed or operated to enhance our health and productivity [2]. Among the various factors affecting indoor environmental quality (IEQ), which includes noise, light, and indoor air quality (IAQ), the World Health Organization (WHO) [3] identifies IAQ as a critical element with substantial influence on occupant well-being, health, and performance. Recognizing its significance, WHO has outlined a range of symptoms known as Sick Building Syndrome (SBS), which include difficulty concentrating, skin irritation, and fatigue, commonly reported by occupants of many indoor spaces [4]. Recent research underscores the profound impact of IAQ on productivity, concentration, comfort, as well as physical and mental health [5–8]. Carbon dioxide (CO_2) and Volatile organic compounds (VOC) [9,10] are among the primary indoor air pollutants associated with SBS symptoms such as headache, fatigue [11,12] and asthma [13]. Other contributing factors include particulate matters such as $PM_{2.5}$ and PM_{10}, which may be more prevalent in residential buildings [14,15] during activities like cooking, in structures near high-traffic areas [16,17], or during extreme events such as wildfires [18].

According to the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) Standard 62.1, the primary source of indoor CO_2 emissions is human metabolism [19]. This gas is frequently used as the sole indicator of IAQ and guides the operation of advanced Heating, Ventilation, and Air Conditioning (HVAC) systems. Numerous studies have confirmed that elevated levels of indoor CO_2 are linked to symptoms such as fatigue and dizziness [20], as well as increases in blood pressure [21]. Furthermore, prior research has established a correlation between high indoor CO_2 levels and occupants' discomfort as well as a decrease in the performance of office workers [22].

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On the other hand, VOCs are compounds with high vapor pressure and low water solubility and are emitted as gases from certain solids or liquids. VOCs encompass a range of chemicals, some of which can have both short-term and long-term negative health impacts. Indoor concentrations of many VOC are consistently higher (up to ten times higher) than outdoors due to emissions from a variety of indoor sources, including paints, cleaning supplies, pesticides, building materials, and office equipment such as printers and copiers [23]. Previous studies have shown that the presence and activities of humans and beauty products could impact VOC levels in indoor environments [24,25]. These studies found associations between high levels of VOCs and SBS [26], especially when occupants are feeling negative emotional states such as stress [9]. The link between indoor VOC levels and occupant well-being has prompted further research aimed at developing reliable testing methods for pollutants emitted by both occupants and the products they use. One notable study by Bartzis et al. [27] evaluated the emission rates of consumer products in indoor settings. The authors selected items from different product classes, such as cleaning agents, air fresheners, and personal care products that are known to emit VOC, and implemented an inter-laboratory comparison by testing the same items in three different test chambers. Their findings revealed that the studied consumer products can significantly elevate VOC levels beyond healthy limits. Consequently, the study emphasized the need for standardized emission estimation protocols and called for more extensive, naturalistic data collection concerning human-emitted pollutants in indoor environments.

Several research studies have investigated the changes in IAQ factors across different building types, including schools [28], museums [29,30], cinemas [31], residential buildings [32–34], and hospitals [35]. Educational institutes are also considered one of the most important indoor environments to be studied regarding IAQ, given that, after residential settings, students and instructors spend considerable time there. [7,12,36,37]. These studies found that poor IAQ exacerbates allergic diseases and asthma across occupants and decreases their performance given the levels and duration of exposure to poor IAQ [28]. They also identified that indoor air pollutants are influenced by seasonal changes, time of day, and variations in occupancy level and behaviors [38]. For instance, in residential settings, certain activities, such as, cooking and painting have been identified as triggers for elevated levels of specific pollutants, notably VOCs [39].

The level of CO_2 in indoor environments has been studied for various applications, including its relevance to HVAC system performance and its impact on occupant well-being. Asif et al. [40] have evaluated the CO_2 level along with indoor temperature and relative humidity in an academic building over a period from March to June. Their research encompassed buildings with diverse HVAC systems and revealed that non-centralized HVAC systems often led to CO_2 levels that exceeded ASHRAE standards during occupied periods. In this study, they only considered CO_2 as the indoor air pollutant and evaluated classrooms with high (or medium) occupancy levels. In another study, Pantelic et al. [41] investigated the metabolically generated CO_2 effects on the "personal cloud" surrounding an individual. This study evaluated the relationship between the metabolic CO_2 concentration and the scenarios typically encountered in the office environment, such as working on a computer and talking. This research showed that occupants' presence and activities result in a higher metabolic CO_2 cloud around the occupants.

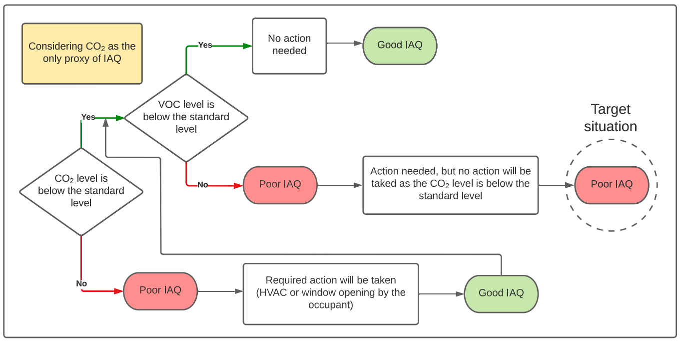
Other studies evaluated the relation between CO_2 level and occupants' performance. Several studies showed that exposure to moderate CO_2 levels (1000–2500 ppm) could impair certain attributes of decision making, such as gathering and utilization of information, even in the absence of other bio-effluents [42,43]. This is while some other studies found exposure to CO_2 at levels up to 3000 ppm without the presence of other indoor air pollutants, such as sources of VOC, did not cause occupants' cognitive performance degradation. With the presence of other bio-effluents and CO_2 at levels up to 3000 ppm, participants identified acute symptoms such as headache, fatigue, and difficulty in thinking clearly, and decreased certain indicators of cognitive functioning [44]. These findings show the importance of evaluating CO_2 levels alongside other indoor air pollutants, such as VOC.

A review study by Weschler et al. [45] showed that humans have a pronounced influence on the indoor chemistry they reside in, such as transferring skin oils to indoor surfaces, and specifically highlighted the occupants' influence on ozone levels is significantly large. The study emphasized the need for further research into the impact of human VOC emissions on the IAQ of enclosed spaces [45]. Another study [46] reviewed methodologies and approaches in previous studies for evaluating VOC levels. The paper highlighted that to obtain more reliable estimates of human exposure to VOC, there is a need for naturalistic studies over a long period of time, which can be done using suitable analytical techniques and low-cost sensors. In another study by Wang et al. [47], they implemented a controlled experiment in a climate-controlled chamber occupied by four seated human volunteers. They evaluated the effect of occupants' activities, clothing, age, and relative humidity and temperature on the VOC's emission rate. Their results showed that the occupants' clothing, as well as instructed movements, such as standing up and stretching, increased the VOC emission rates. The study also concluded that an increase in temperature and relative humidity results in higher VOC emissions.

Lin et al. [48] conducted an analysis of the influence of occupant behavior on IAQ, utilizing data from smart home sensors across two testbeds. The study focused on three representative pollutants, $PM_{2.5}$, formaldehyde, and methanol, representing outdoor and indoor pollutants that are associated with indoor materials and occupant activities. This study showed that activities that impact the ambient temperature, such as bathing and cooking, have more impact on the pollutants. This might be because the temperature caused by an activity may last longer than the activity itself; therefore, it can impact the IAQ even after the activity has ended. Other than the effect of occupants on the VOC level, Allen et al. [43] evaluated the effect of different levels of VOC on occupants' cognitive performance. In this study, results showed that VOC and CO_2 are independently associated with the cognitive functions of the studied subjects, and their cognitive functions scores were significantly higher where VOC and CO_2 levels were lower.

Previous studies have evaluated IAQ in a limited number of spaces for short periods of time. Limited studies capture the changes in IAQ in open space areas in buildings or enclosed spaces with a low number of occupants, such as single-occupancy offices. Additionally, most existing research only focuses on IAQ during occupied periods, neglecting to analyze how metrics fluctuate between occupied and unoccupied times [49]. When studies do account for occupancy, they typically rely on preset schedules for spaces like classrooms to determine occupied hours [40]. Also, limited studies have evaluated the changes in VOC and CO_2 exposure rates longitudinally. Addressing these gaps by simultaneously evaluating both CO_2 and VOC levels using affordable IAQ sensors could be a crucial step towards enhancing IAQ and fine-tuning ventilation systems. Over recent years, advancements in accurate and cost-effective Internet of Things (IoT) devices have effectively overcome the scarcity of monitoring indoor air pollutant concentration. Accordingly, by leveraging a network of affordable IAQ sensing systems, we have conducted a longitudinal study of CO_2 and VOC variations in multiple indoor spaces with diverse functionalities and occupancy profiles.

In light of the limitation of relying on CO_2 concentration as the sole indicator for IAQ management in ventilation systems, our study aimed to observe and analyze the patterns of CO_2 and VOC levels across various spaces within the University of Virginia's living lab. By examining these patterns in relation to occupancy levels, we sought to assess the adequacy of current ventilation strategies and the potential necessity for incorporating VOC measurements alongside CO_2 to better reflect IAQ conditions. Another objective is to evaluate the occupants'



(a) The flowchart showing the IAQ conditions and the corresponding ventilation actions

VOC level (200 ppb)	CO_2 level (1000 ppm)	Ventilation activated?	Poor IAQ?
Safe	Safe	No	No
Safe	Poor	Yes	No
Poor	Safe	No	Yes
Poor	Poor	Yes	No

(b) The truth table showing the IAQ conditions based on VOC and CO_2 levels

Fig. 1. The ventilation control logic and IAQ situation if CO_2 is considered as the only proxy of IAQ.

approximate exposure frequency to the ”poor IAQ” condition in single-occupancy offices and a conference room. Fig. 1 shows the rule-based logic for the identification of poor IAQ conditions. As this flowchart shows, poor IAQ conditions could be associated with CO_2 and VOC concentrations and the consequent ventilation actions. Towards these objectives, we gathered data on VOC and CO_2 levels across various indoor spaces, each characterized by different occupancy patterns. The study areas included three single-occupancy offices, two shared office spaces, a hallway, a kitchen and dining area, and a conference room. Our initial analysis examined the effectiveness of existing ventilation systems in mitigating VOC and CO_2 concentrations, quantifying the instances where these pollutants surpassed recommended levels. Subsequently, we focused on conditions of “poor IAQ”, defined as situations where CO_2 levels remain within the acceptable range, but VOC levels do not. As noted, Fig. 1 shows the occurrence of the poor IAQ situation based on the VOC and CO_2 levels. We reported the frequency with which the VOC and CO_2 exceeded their standard level and the occurrence of poor IAQ for the weekdays and weekend schedules of the HVAC system. To augment our analysis, we employed a support vector machine (SVM) model that uses VOC and CO_2 data to predict occupant presence in single-occupancy offices and the conference room. This predictive model enabled us to quantify the occupants’ exposure time to poor IAQ conditions.

2. Methodology

This study aims to evaluate whether considering CO_2 as the only proxy of IAQ to inform HVAC ventilation rates is enough for healthier building and indoor environments. This section provides an overview of the testbed and sensing system, data collection, and poor IAQ definition, followed by data processing and analysis.

2.1. Testbed and sensing system description

The data for this study was collected in the Living Link Lab (L-LL) located at the University of Virginia campus. The L-LL is a 17,000 sqft open space office building and is occupied by roughly 150 residents, including faculty, research scientists, graduate students, and staff. L-LL consists of 24 single-occupancy offices, four conference rooms with different capacities, one kitchen and arena space, and four connected main shared office spaces. Fig. 2(a) shows different areas in L-LL, and Fig. 2(b) shows photos of different locations of the testbed, including the arena and the kitchen area, the conference room, single-occupancy offices, and the residents’ shared offices. If there are events in this space, they typically take place in the arena, and food and drinks are usually served during events, and occupancy levels can increase by anywhere from 60 to 80 people. These events are typically scientific presentations or social events and gatherings for different celebrations during the year. Since 2018, the space has turned into a living lab where over 350 IoT devices have been deployed to monitor indoor environmental changes, energy consumption, and occupants’ interactions with different building systems. These sensors include appliance and electric circuit energy monitors, motion, and indoor environmental quality sensors, such as light, temperature, humidity, noise, CO_2, $PM_{2.5}$, and VOC levels [50]. Features and parameters of the sensors that are utilized in the L-LL for this study are summarized in Table 1. For this study, we used eight Awair Omni IEQ sensors in L-LL, of which three were located in the single-occupancy offices, one in the conference room, one in the hallway, one in each shared office space, and one in the kitchen area to collect the pollutants’ concentrations sampled every 10 s. In one of the single-occupancy offices and the conference room, one of each type of motion sensor was used to collect the occupancy status for four months (the entire study).

Table 1
Characteristics of sensors used.

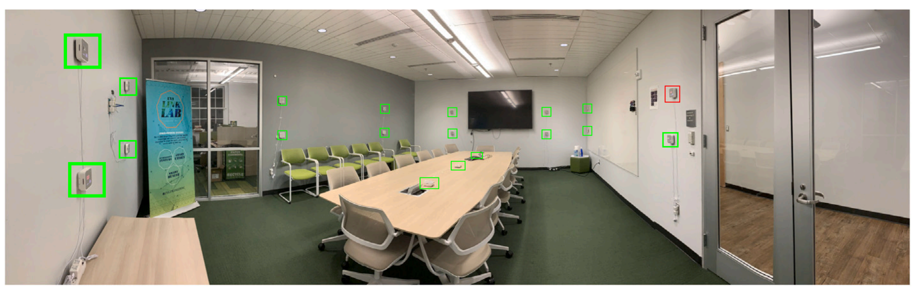
Sensor	Measurement	Value range	Error	Unit
EnOcean E9T-OSW	Motion	[0,255]	–	–
Dual Tech Ceiling Mount Sensor MOS-DT	Motion	[0,255]	–	–
Awair Element	CO_2 VOC	[400, 5000] [0, 60000]	±75ppm ±10%	ppm ppb

As shown in Fig. 3, to optimize sensor placement in single occupancy offices, we initially considered two locations: one closer to the occupant at a seating height of 3.94 ft and another further away at a standing height of 5.91 ft. Our analysis indicated that the data from both positions exhibited similar patterns, with readings typically within a 3%–5% range of each other. Notably, the sensor positioned closer to the occupant consistently registered slightly higher pollutant levels. Based on these findings, we decided to conduct the experiment using a single sensor placed near the occupant at the 3.94 ft seating height in each room. This positioning provides a more accurate representation of the pollutant concentration levels to which occupants are exposed. To optimize sensor placement in the conference room, we initially installed nineteen sensors at various locations and heights (3.94 and 5.91 ft) within the room. This pilot experiment was run during working hours (2.6 air changes per hour) for 10 days (separate from the main study). Upon analyzing the collected data, we observed that all sensor readings were remarkably consistent, deviating by only 3%–5% from each other. Utilizing both correlation analysis and random forest feature selection techniques, we identified one sensor (shown in red boxes in Fig. 3) as the most representative of the collective locations. This particular sensor’s significance was further underscored by its strategic positioning, away from the direct influence of any ventilation vents, ensuring that

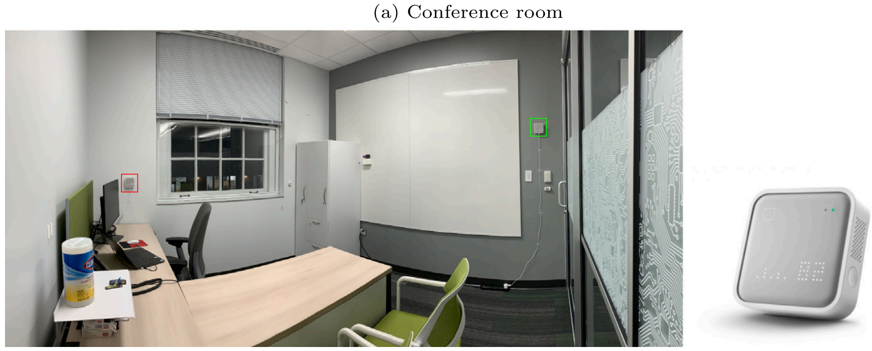
(a) Different locations of the hallways and the conference room in the lab; single-occupancy offices A and C are selected from zone A, and single-occupancy office B is selected from zone B.

(b) Top left: single-occupancy offices, top right: Arena & the kitchen area, bottom left: conference room, bottom right: shared office spaces

Fig. 2. Different locations of the L-LL.



(a) Conference room



(b) Single-occupancy office

(c) IAQ sensors

Fig. 3. IAQ sensors arrangement in the single occupancy offices and the conference room. Green and red boxes: IAQ sensors, red box: the selected location of the IAQ sensor for the data collection. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

its readings were not artificially impacted. Consequently, this location was selected for the experiment, balancing both statistical rigor and practical considerations in environmental monitoring.

2.2. Data collection

We recorded four months of VOC, CO_2, and motion sensor data during weekdays and weekends. We divided the data into two different conditions based on the HVAC systems' operation. The first one is the "working hours" condition that includes weekdays from 6:00 AM to 7:00 PM, in which the HVAC systems are preset to operate at a ventilation rate of 2.6 air changes per hour (ACH) across all zones. The second condition is "off hours", which includes the weekends and specific hours of weekdays (7:00 PM–6:00 AM) when the HVAC operations are preset at a lower air exchange rate of 1.5 ACH due to lower expected occupancy levels.

2.3. Poor IAQ definition

We have considered the limit level for both pollutants (CO_2 and VOC) based on the literature [42,43,52–54] on performance loss of the occupants at different levels of indoor air pollutants. Table 2 represents the impact of moderate and high levels of CO_2 and VOC on productivity loss according to the literature. For this study, we have considered the moderate level category, which considers adverse health and performance impacts at 1000 ppm for CO_2 and 200 ppb for VOC levels. In this study, we are specifically interested in incidents where CO_2 concentration is below the recommended levels while VOC levels exceed those recommendations. In these conditions, although the IAQ is poor for the occupants due to high VOC concentration, the HVAC system is not informed to operate at a higher rate since it is only actuated based on CO_2 levels.

Table 2
IAQ guidelines and productivity impacts.

Particles	Baseline	Moderate	High	Productivity effect
CO_2 (ppm)	600 [43]	1000 [42,43]	2500 [42]	−21% for every 400 past 600 [43], −44%–94% at 2500 [42]
VOC (ppb)	50 [43,51]	200 [52]	500 [43]	−13% at 100 [43]

To better understand the "poor IAQ" condition, Fig. 1 represents the potential scenarios that can happen if the ventilation system operates dynamically based on the CO_2 levels. As depicted, poor IAQ can happen in two ways: first, when CO_2 levels surpass recommended thresholds, prompting activation of the HVAC system. Second, when VOC levels alone exceed the recommended range, while CO_2 remains within acceptable limits, leading to an unresponsive HVAC system. In this paper, the term "poor IAQ" specifically denotes the latter case. To assess the necessity of incorporating VOC-level information into HVAC system operation, we quantify occurrences of the aforementioned poor IAQ conditions across various spaces within the L-LL. In essence, this longitudinal study aims to determine whether CO_2 measurements alone suffice for dynamically adjusting ventilation rates, or if the inclusion of VOC levels is essential for optimizing HVAC system performance.

2.4. Data processing and analysis

To analyze the data, we aggregated the high-frequency data over 15-min intervals by computing the average values of the 10-s readings. To effectively identify and remove outliers from the dataset, we replaced readings that fell outside the sensor's operational range (as detailed in Table 1) with the mean of the adjacent values, preceding and following the outlier. This approach ensured that any anomalous data potentially resulting from sensor errors did not skew our results. Additionally, we meticulously evaluated the plots of the pollutant time-series data to scrutinize any significantly distant data points from the main cluster. Our thorough examination revealed no such anomalies in the dataset. Also, we installed the sensors one week prior to the main study, ensuring they were adequately calibrated to the environmental conditions of the space.

Additionally, we addressed the missing values by substituting them with the mean of their immediate preceding and subsequent values. We then separated the aggregated data into two categories: working hours and off-hours, identifying periods during which CO_2 and VOC levels exceeded their respective recommended limits. Additionally, we assessed instances of poor IAQ, as defined in Section 2.3, across various locations for both working and off-hour conditions. Extending this analysis to both the kitchen area and the arena, we pinpointed time periods corresponding to scheduled events by referencing the lab's calendar. By analyzing CO_2 and VOC concentrations during these specific events, we aim to ascertain whether CO_2 alone serves as a sufficient proxy for IAQ under these particular conditions.

As noted, the second objective of our study is to evaluate the occupants' approximate exposure frequency to the "poor IAQ" condition in single-occupancy offices and the conference room. Towards this goal, we trained several machine learning models to predict the binary status of the occupancy levels (0 if there is not anyone in the area, and 1 if there is at least one occupant in the area) by using CO_2 and VOC levels as the features. We used the motion sensors installed in one of the single-occupancy offices and the conference room for the target variable ground truth. To find the best-fitted model, we trained five different models: SVM, Gaussian naive Bayes (GNB), logistic regression (LGR), random forest classifier (RFC), and k-nearest neighbors (k-NN). The best-fitted model for our data was an SVM model with a non-linear kernel (with an F1 score of 0.86). We evaluated the results using both linear and non-linear kernels for the SVM model, and the one with the Gaussian kernel (as a non-linear kernel) leads to higher accuracy. This model uses the radial basis function (RBF) as the Gaussian kernel. The details of the models we used for the occupancy detection task can be found in our paper [55]. Using the occupancy predictor model helped us find out the percentages of time that occupants were present and exposed to poor IAQ levels in the other two single-occupied offices, which were not equipped with motion sensors. For fine-tuning the SVM model in these offices, we used the occupants' calendar data for a limited time as the occupancy ground truth.

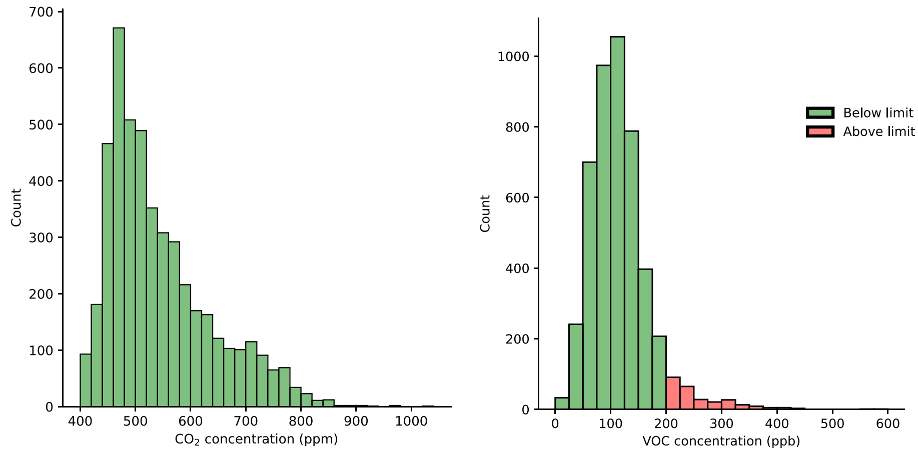
3. Results

This section provides the findings from the analysis of the data collected from three single-occupancy offices, a conference room, and shared office spaces, examined both during working hours and off-hours. Subsequent subsections will detail the frequency with which CO_2 and VOC levels exceed recommended thresholds, as well as instances of poor IAQ – i.e. when VOC concentrations surpass the recommended level, but CO_2 levels remain within the acceptable range. These subsections show that poor IAQ happens most often in enclosed, shared areas with a high number of occupants, such as conference rooms. Furthermore, our findings highlight that the HVAC system may fail to address the poor IAQ conditions 6 to 30 percent of the time across different zones and space types. These findings suggest that we can considerably improve the IAQ levels during the occupied periods by dynamically operating the HVAC systems based on both VOC and CO_2 data in targeted zones.

3.1. Single-occupancy offices

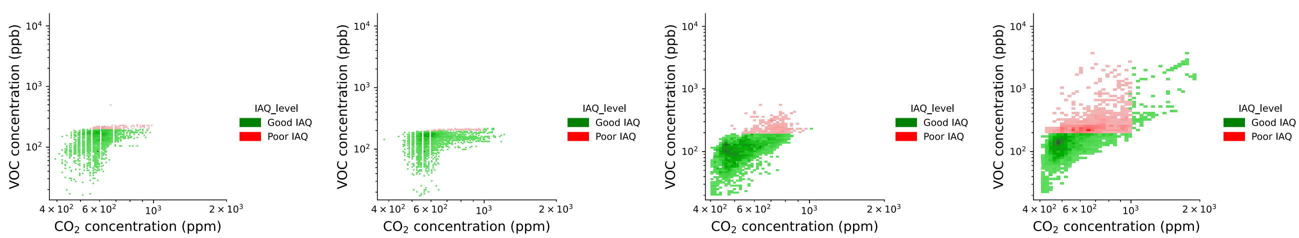
In this section, we evaluate the VOC and CO_2 levels of three single-occupancy offices and assess how often these pollutants exceed the recommended thresholds. Fig. 4 provides a histogram that depicts the frequency distribution of VOC and CO_2 concentrations in Office C during working hours over a four-month data collection period. The data reveals that CO_2 levels ranged between 400 and 1000 ppm, while VOC levels varied from 0 to 600 ppb in this specific office. Peaks in the histograms indicate that the most common concentration ranges for CO_2 and VOC are 460–480 ppm and 100–125 ppb, respectively — both of which fall beneath their recommended levels. It also shows that CO_2 level never exceeded its recommended level in this room, while the red bars in the VOC histogram indicated the occurrence of VOC levels above the recommended level (6% of the time). We presented the histograms for VOC and CO_2 concentrations of the other two single-occupancy offices in the appendix section (Figs. A.1 and A.2). Tables 3 and 4 display the percentage of time these pollutants exceeded the recommended thresholds during working and off-hours, respectively. In these tables, the frequency of poor IAQ situations in the third row is sometimes lower than the frequency of VOC levels exceeding their recommended limits in the second row. This difference occurs because instances where CO_2 levels have already triggered ventilation due to their high levels are excluded from the calculation of poor IAQ frequency when VOC levels also exceed their recommended limits. Across the single-occupancy offices, the CO_2 concentration is below the identified moderate range during both working hours and off hours; however, this is not the case for the VOC concentration. We can see that the VOC levels are above the limit level at 6%, 3%, and 6% of the time in offices A, B, and C, respectively, during working hours.

During off hours, single-occupancy offices A, B, and C experienced elevated VOC levels, with the accumulation surpassing recommended



(a) CO_2 concentration (b) VOC concentration

Fig. 4. Histograms of CO_2 and VOC concentration in single-occupancy office C.



(a) Single-occupancy office A (b) Single-occupancy office B (c) Single-occupancy office C (d) Conference room

Fig. 5. IAQ situation in single-occupancy offices and the conference room during working hours.

Table 3
Percentage of time pollutants exceeded recommended levels and poor IAQ occurs during working hours.

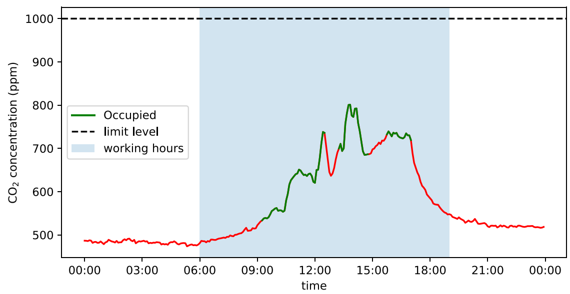
Pollutant	Office A	Office B	Office C	Conference room	Hallway	Arena	Shared office space 1	Shared office space 2
CO_2 (%)	0	0	0	3	0	0	0	0
VOC (%)	6	3	6	37	8	24	15	16
Poor IAQ (%)	6	3	6	34	8	24	15	16

Table 4
Percentage of time pollutants exceeded recommended levels and poor IAQ occurs during Off hours.

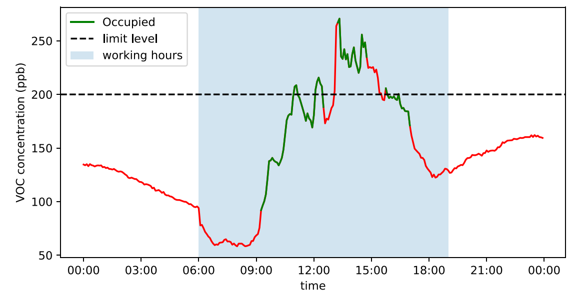
Pollutant	Office A	Office B	Office C	Conference room	Hallway	Arena	Shared office space 1	Shared office space 2
CO_2 (%)	0	0	0	2	0	0	0	0
VOC (%)	33	18	19	30	15	36	30	22
Poor IAQ (%)	33	18	19	28	15	36	30	22

thresholds 33%, 18%, and 19% of the time, respectively. To obtain information about the poor IAQ situation in which air cleaning actions would not be taken, we need to assess the values of the two pollutants jointly. Fig. 5 (plot a-c) shows the joint plot of CO_2 and VOC concentrations for single-occupancy offices, and Table 3 shows the percentage of time that the IAQ is in poor condition during working hours. Notably, instances where both CO_2 and VOC levels surpassed the recommended limits are also marked in green in Fig. 5. The reason is that when CO_2 is above the recommended level, the ventilation system would be activated as they consider this pollutant as the only proxy of IAQ. Conversely, instances marked in red indicate periods where only VOC levels are elevated, leading to their accumulation due to the absence of ventilation response, adversely affecting occupants' well-being and performance. The highest frequency of poor IAQ happens in offices A and C, which is 6% for both offices during working hours. This shows that the IAQ in these offices is poor 6% of the time during the normal weekday schedule in which the HVAC system is operating at a 2.6 ACH air exchange rate.

The results of our SVM model and motion sensor data (where they were available) show that during working hours, 11%, 7%, and 16% of the occupied time, there was at least one occupant in the single-occupancy offices A, B, and C, respectively, while the IAQ was poor. These values correspond to a daily average exposure of 45, 20, and 40 min for each occupant in single-occupancy offices A, B, and C, respectively. Fig. 6 shows a time series plot of VOC and CO_2 levels of a working day in a single-occupancy office with the occupied timeframes. As shown in Fig. 6, both VOC and CO_2 levels exhibit a gradual increase following the arrival of an occupant. During the occupied time, the VOC level can exceed the recommended moderate level, while the CO_2 level stays below the recommended level. Evaluating occupied

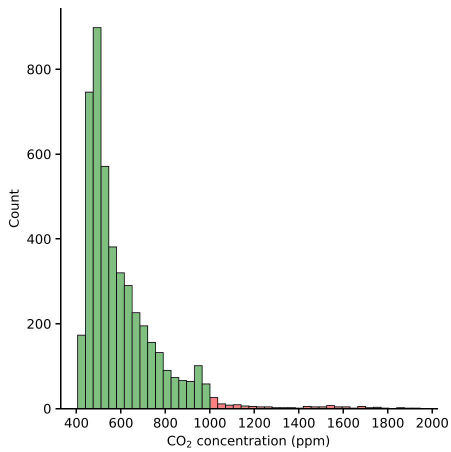


(a) CO_2 level

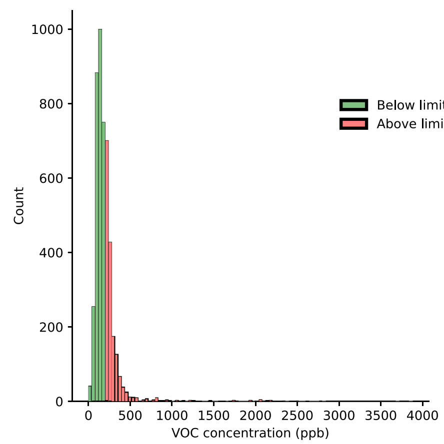


(b) VOC level

Fig. 6. CO_2 and VOC time series data during a working day in a single-occupancy office.



(a) CO_2 concentration



(b) VOC concentration

Fig. 7. Histograms of CO_2 and VOC concentration in the conference room. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

periods on other days also showed the same pattern of VOC and CO_2 concentration.

3.2. Conference room

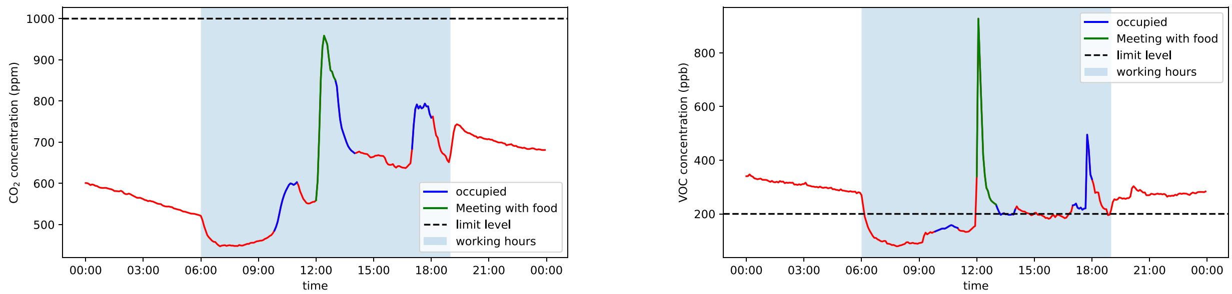
Figs. 7(a) and 7(b) present histograms depicting VOC and CO_2 concentrations in the conference room, respectively. The histograms reveal that CO_2 levels ranged from 400 to 2000 ppm, while VOC levels varied between 0 and 4000 ppb. Notably, the most frequent concentrations for CO_2 and VOC were 480-520 ppm and 120-160 ppb, respectively, both of which fall below their respective recommended limits. The red bars in these plots signify instances where pollutant levels exceeded recommended guidelines. As detailed in Table 3, VOC levels surpassed the recommended limit 37% of the time during working hours in the conference room, compared to just 3% for CO_2 levels. Fig. 5 (plot d) illustrates that poor IAQ conditions prevailed 34% of the time during working hours — a concerning statistic given the room's frequent turnover. Utilizing both the room's calendar and motion sensors for occupancy detection, we discovered that during 71% of the occupied time in working hours – equivalent to 3 h and 50 minutes – the room experienced poor IAQ conditions. Further, calendar data and other metrics suggest that the room typically accommodates more than one occupant when IAQ is in poor condition. These values showed significant periods in which occupants have meetings in the conference room, but the HVAC system is not circulating enough air to improve the IAQ levels. Evaluating the poor IAQ during off hours shows that 28% of the time, the space has poor IAQ levels.

Fig. 8 shows the average levels of VOC and CO_2 for four representative Mondays during the data collection period, focusing specifically on days when recurring meetings were scheduled in the conference room. The number of people and their activities in the room varied across different meetings, leading to fluctuating levels of VOC and CO_2 concentrations. For example, in the meeting at 12–1 PM, food was served every week, resulting in higher levels of VOC. As illustrated in Fig. 8, the presence of occupants led to increases in both VOC and CO_2 levels. However, the CO_2 concentrations remained within acceptable range throughout the day, unlike VOC levels, which frequently exceeded the recommended thresholds. Like the single-occupancy offices, the conference room also experienced elevated VOC levels from 7 PM to 6 AM, which directly resulted from the reduced ventilation rates. During this period, the accumulation of VOC occasionally resulted in poor IAQ. Similar patterns in fluctuations of CO_2 and VOC levels are evident in the conference room across other days of the week.

3.3. Open-space areas

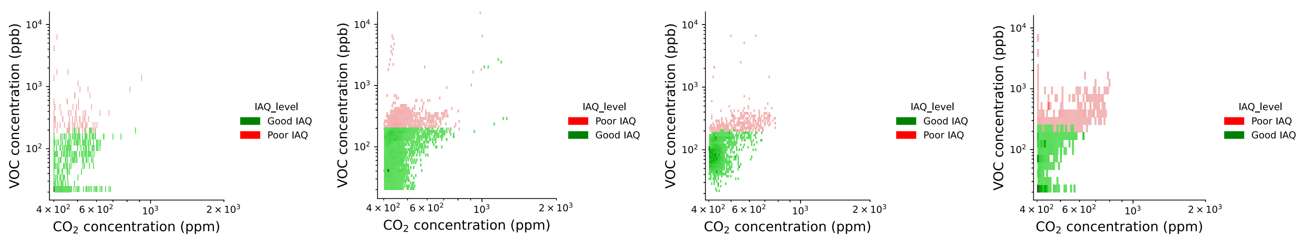
Fig. 2(a) shows the locations of four different open-space areas, including the shared office spaces occupied by graduate students. Fig. 9 shows the poor IAQ conditions in each of these four spaces. In this figure, the x-axis represents CO_2 concentration, while the y-axis reflects VOC levels. Red dots in Fig. 9 mark instances in which VOC concentrations exceeded the recommended threshold of 200 ppb, even as CO_2 levels remained below their advised limit of 1000 ppm.

Table 3 quantifies the percentage of working hours during which poor IAQ was observed across these areas. Values in this table reveal that the poor IAQ situation happens more often near the kitchen and dining area. In this area, 24% of the time, the air quality was poor during working hours. It is important to note that occupants do not typically spend long periods near this area; therefore, their exposure to higher levels of VOC in this space is limited. In shared office spaces 1



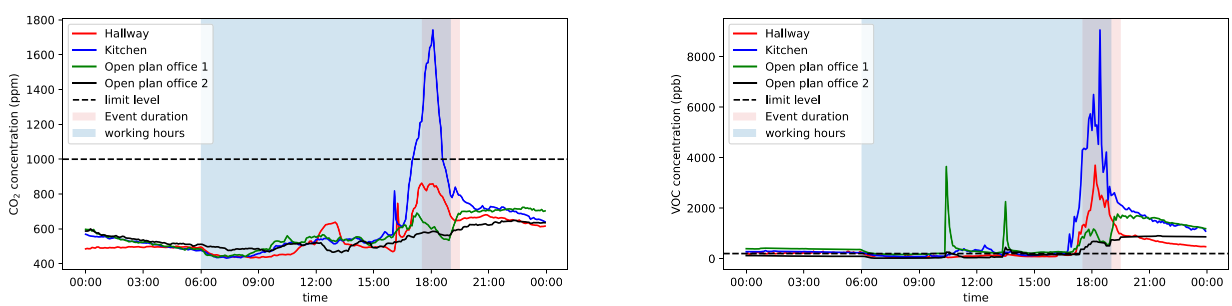
(a) CO$_2$ level (b) VOC level

Fig. 8. The average CO$_2$ and VOC time series data during a working day for four weeks in the conference room.



(a) Entrance Hallway (b) Kitchen and arena (c) shared office space 1 (d) shared office space 2

Fig. 9. Poor IAQ situation of the open-space areas during working hours.



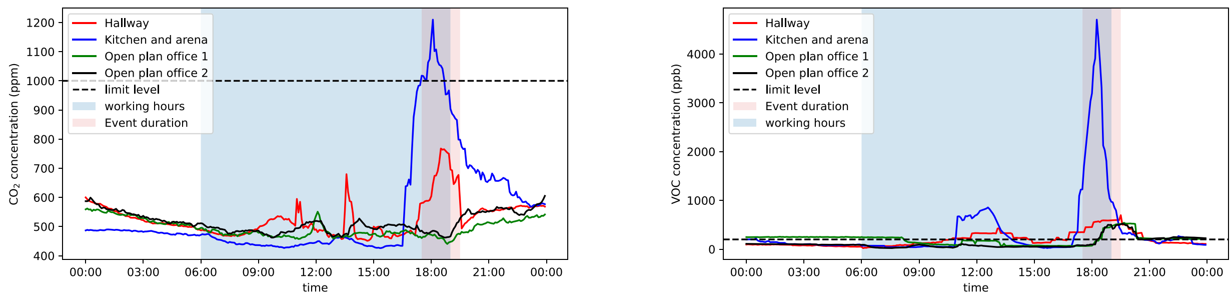
(a) CO$_2$ level (b) VOC level

Fig. 10. Average CO$_2$ and VOC time series data during days of four social events in the arena.

and 2, the IAQ levels were poor at 15% and 16% of the time during working hours, respectively. This area is where the occupants work at their desks for long periods. The entrance corridor, which benefits from regular influxes of fresh air, recorded the lowest incidence of poor IAQ at 8% during working hours. Our findings show that these values are at higher rates during the off hours when the HVAC system operates at a lower air exchange rate. During off hours, which include weekdays from 7 PM to 6 AM and all day on weekends, the VOC levels in various areas increased due to reduced ventilation rates. This led to sporadic VOC accumulation, exceeding recommended levels and resulting in poor IAQ. Specifically, the incidence of poor IAQ during these off hours was recorded at 15% in the hallway, 36% in the kitchen area, and 30% and 22% in shared office spaces 1 and 2, respectively. As shown in both Table 3 and 4, it is noteworthy that CO$_2$ levels never surpassed their recommended limits (happened less than 1% of the time only during the events in the arena), neither during working hours nor off-hours.

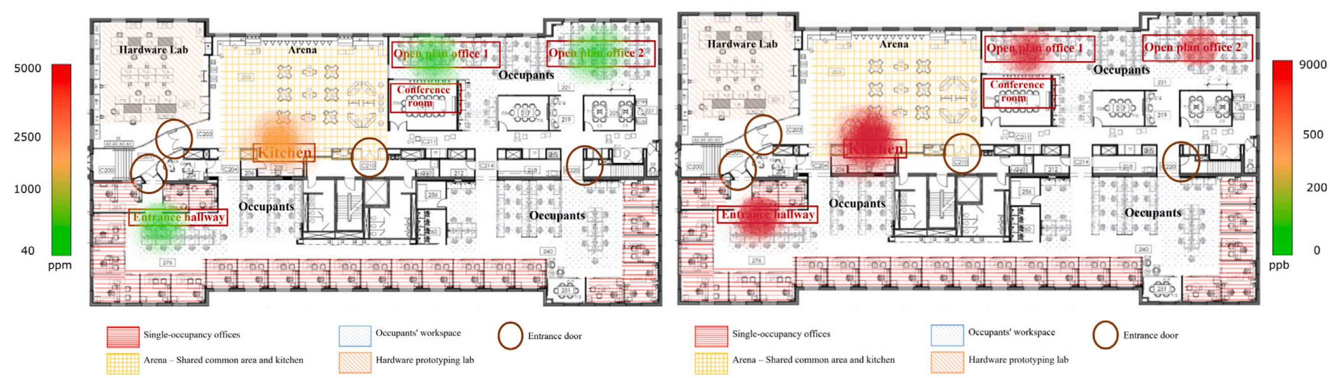
During the data collection period, the L-LL arena and kitchen area hosted three events and one large gathering, each beginning around 5:00 PM and ending around 7:30 PM. To assess pollutant levels during these occasions, we took the raw data and averaged it into five-minute intervals for both CO$_2$ and VOC on the event days. Fig. 10 displays the 24-h average concentrations observed on those specific dates. Two of the events had an attendance of roughly 70–80 people, while the remaining two drew between 30-40 participants. Food was also served in all four events. For comparative purposes, Fig. 11 isolates the pollutant levels from the smaller events (30–40 attendees). In these smaller gatherings, CO$_2$ peaked at 1200 ppm, and VOC reached around 4000 ppb—levels that are appreciably lower than those observed in larger events, where CO$_2$ hit 1800 ppm, but VOC soared to an alarming value around 8000 ppb, as shown in Fig. 10. The average of the VOC level in the event location was 4078 ppb during the event period.

A significant observation shown in Fig. 10 is that the ventilation system failed to mitigate VOC concentrations in any of the open-space areas by the end of the day. As previously mentioned, during off hours, there was an increase in VOC levels in these areas, with accumulations sometimes exceeding recommended levels. Notably, following such events, VOC concentrations remained above the recommended threshold until 6 AM, when the ventilation systems resumed operation with a higher ACH rate to cleanse the air of indoor pollutants. This is while CO$_2$ was above the standard level only in the arena for about 90 min during the events. As we can see in Fig. 10, VOC concentrations initially spiked in the arena and gradually permeated other lab spaces, a pattern not seen with CO$_2$, which remained elevated for a much shorter duration and was confined mainly to the arena where the events were happening. Based on the preset schedule of the lab's ventilation system, the HVAC systems switched to a lower ventilation speed at 7:00 PM, regardless of the pollutant level or occupancy levels. This contributed to VOC concentrations staying above the recommended levels for nearly



(a) CO_2 level (b) VOC level

Fig. 11. Average CO_2 and VOC time series data during days of two social events with approximate 30 attendees.



(a) CO_2 level distribution (b) VOC level distribution

Fig. 12. CO_2 and VOC distribution over the lab during an event.

six hours post-event across all lab spaces. As shown in Fig. 11, when the event is smaller with fewer attendees, the ventilation systems decreased the VOC level to the recommended level about an hour after the event ended. As we can see, even in smaller events, the VOC level increased all around the lab, despite the CO_2 level, which only surpassed the recommended range in the event area.

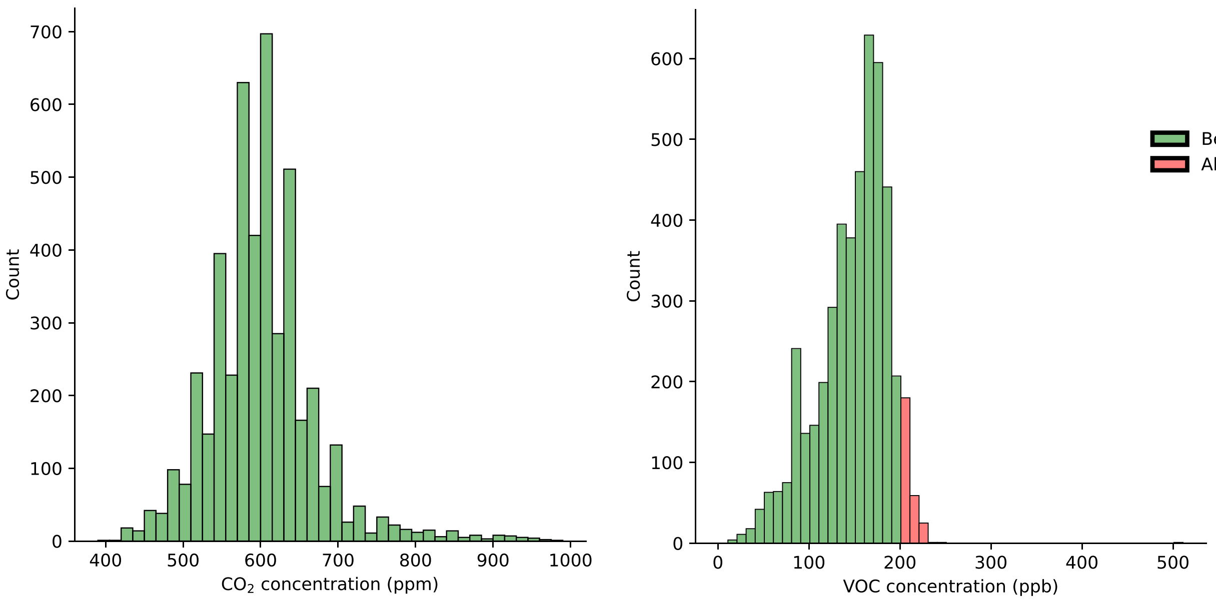
Fig. 12 provides an alternative visualization of pollutant levels and their distribution across various open-plan locations within the lab during these events. This heatmap illustrates the peak levels for both VOC and CO_2 levels at each location. The least affected area by the spread of VOC is shared office space 2, in which the VOC level went up to 520 ppb in smaller events and 905 ppb in larger events. As indicated in Fig. 12, the CO_2 levels across different lab areas are comparatively less influenced by the events. This could likely be attributed to a lower concentration of people outside the main event area.

The entrance hallway is the most impacted area for CO_2 concentration, following the main event arena. In this hallway, CO_2 levels peaked at 862 ppm in larger events and 767 ppm in smaller events — levels that still fall below the recommended level as defined in this study. Notably, the entrance hallway and the arena are the only two areas where CO_2 levels exhibited an increase due to event activities. Even so, in the entrance hallway, the CO_2 concentrations remained below the recommended level. Upon examining the IAQ both during and after these events, it becomes evident that the current preset HVAC system operations are inadequate for addressing the dynamic changes in space utilization. Specifically, the system struggled to purify the air expediently even once the events, particularly the larger ones, ended.

4. Conclusions and discussion

This study investigated the spatiotemporal variations of CO_2 and VOC levels as primary indicators of poor IAQ over four months in a multi-functional institutional building. We examined the influence of occupant presence, activities, and HVAC system ventilation rates on pollutant concentrations in diverse spaces within the University of Virginia's living lab. CO_2 levels above 1000 ppm and VOC levels exceeding 200 ppb were considered poor levels of these pollutants. Our analysis, conducted during both working and off-hours, assessed the frequency of poor IAQ events and the effectiveness of using CO_2 as the sole metric for IAQ and ventilation adjustments. We identified instances where poor IAQ conditions were not detected by the HVAC system due to its reliance on CO_2 levels alone, despite elevated VOC concentrations.

The assessment of IAQ across various zones within our testbed reveals that poor IAQ conditions are relatively infrequent in single-occupancy offices during working hours. The highest value obtained in these offices for poor IAQ situation is 6% of working hours. Also, using the machine learning models for occupancy presence showed that in the same office, the IAQ was poor during 16% of the occupied time. These values were higher in the conference room with the occurrence of poor IAQ during 34% of the working hours and 71% during the occupied periods (during working hours). Evaluating this situation in open plan spaces showed that the highest occurrence of poor IAQ condition was in the kitchen and arena (24% of the time during working hours), where occupants eat their food and hold gatherings and events. Next in line were shared office spaces 1 and 2, showing poor IAQ for 15% and 16% of working hours, respectively. As these spaces are primarily occupied by graduate students who spend extended periods at their individual desks, enhancing ventilation rates in these spaces becomes particularly crucial. The poor IAQ situation only occurs 8% of the time during working hours in the entrance hallway. This area did not host many students at the time of data collection and is located near one of the



(a) CO_2 concentration (b) VOC concentration

Fig. A.1. Histograms of CO_2 and VOC concentration in office A.

main entrance doors where the occupants are in transit rather than stationary. During off hours, VOC levels were elevated due to the lower ventilation rates, and as a result, every area, except the conference room, experienced a higher frequency of poor IAQ conditions compared to their working-hour counterparts.

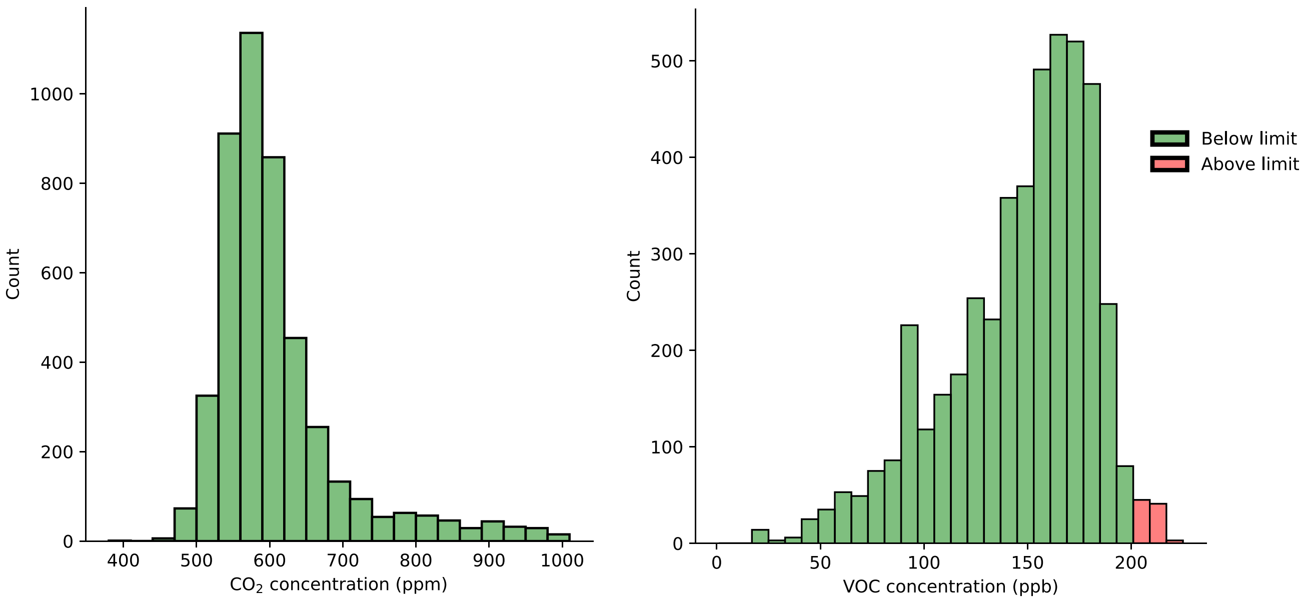
Our analysis of pollutant levels during social events in the lab underscores the necessity of including VOC as key factors in determining ventilation rates. Based on our results of evaluating different locations of the lab with different applications, occupancy levels, and patterns, we conclude that it is essential to consider VOC in automating HVAC systems in areas with more occupants, such as conference rooms and shared office spaces. Our results show that a preset schedule of the HVAC operations and considering CO_2 as the only signal for ventilation rates is insufficient for cleaning indoor air of high occupancy areas. Also, dynamic operation logic with VOC consideration for ventilation systems is needed to clean the indoor air during social events. This is while areas with fewer occupants, such as single-occupancy offices, are less prone to poor IAQ (up to 16% of occupancy period) even with the preset schedules of ventilation systems.

For controlling the HVAC operation, rather than considering only the values we obtained for poor IAQ frequency, we need to consider the exposure duration of the occupants to these compounds as well. For instance, although poor IAQ is more frequent in the kitchen area than in shared office spaces 1 and 2 – where graduate students typically work at their desks – the latter still demands close attention. This is because the potentially severe health impacts of long-term exposure to elevated VOC levels are a concern for students who spend extended periods at their desks. In contrast, individuals who merely pass through the hallway or the kitchen experience shorter exposure times. Therefore, some spatial intelligence of how different spaces are utilized is also important for the future optimization of HVAC operations.

5. Future work

The prevailing assumption that a research lab that hosts graduate students remains largely unoccupied during off-hours does not align with the actual observations made in this particular lab. It has been observed that the lab is frequently active, with several occupants or even meetings taking place on weekdays after 7:00 PM and on weekends. Conversely, there are time slots during traditional working hours – specifically between 6:00 and 9:00 AM – when the lab, especially the single-occupancy offices and conference rooms, is sparsely occupied. Despite this, the HVAC system continues to operate on its preset schedule, which is clearly not the most efficient approach. These observations underscore the need for dynamic HVAC operation based on the real-time IAQ and occupancy levels. Implementing such an approach could not only improve air quality but also contribute to energy conservation by reducing ventilation rates in unoccupied areas. Using time series models to forecast the occupancy status in advance can also save energy by cleaning the area with lower ventilation rates whenever no occupants are expected for a set period of time. Other than forecasting the occupancy status, by forecasting the CO_2 and VOC level, we can better inform the operation and air exchange rates of the HVAC systems as well.

Rather than the occupancy binary status, information regarding the number of occupants can also help automate the HVAC operations. In one of our previous studies [56], we quantified the performance loss cost (dollar cost) of each occupant based on the information on CO_2, VOC, $PM_{2.5}$, and temperature level in the area. This means that by having information regarding the number of occupants in the area, we can estimate the total performance loss cost of the occupants based on the IEQ condition. Towards this goal, we equipped the L-LL with an occupancy counter sensor to gain information about the number of occupants in the area rather than only the binary status of the occupancy. We are using non-intrusive sensors, which use Time of Flight technology to count people anonymously. In our future studies, we will use this to prioritize the HVAC systems schedules based on the number of occupants in the area, total productivity loss, and the IAQ condition rather than only considering the IAQ condition. This will help balance the occupants' total productivity loss and the energy cost when automating the HVAC operations. Also, in our future work, we plan to fine-tune our SVM model for predicting occupancy status in additional conference rooms, leveraging the model initially trained on four months of IAQ and occupancy data from the original conference room in this paper.



(a) CO_2 concentration (b) VOC concentration

Fig. A.2. Histograms of CO_2 and VOC concentration in office B.

CRediT authorship contribution statement

Mahsa Pahlavikhah Varnosfaderani: Writing – review & editing, Writing – original draft, Visualization, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Arsalan Heydarian:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Funding acquisition, Conceptualization. **Farrokh Jazizadeh:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Arsalan Heydarian reports financial support was provided by Trane Technologies Company LLC. Arsalan Heydarian reports financial support was provided by National Science Foundation.

Data availability

To protect personal data, we will provide access upon understanding the requester's identity, purpose, and extent of data needed. This ensures participant privacy.

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Appendix. VOC and CO_2 histograms of single-occupancy of offices A and B

See Figs. A.1 and A.2.

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