UC Berkeley

Indoor Environmental Quality (IEQ)

Title

Personal CO2 bubble: Context-dependent variations and wearable sensors usability

Permalink

https://escholarship.org/uc/item/2hc0396w

Authors

Ghahramani, Ali Pantelic, Jovan Vannucci, Matthew et al.

Publication Date

2019-03-01

DOI

10.1016/j.jobe.2018.11.015

Copyright Information

This work is made available under the terms of a Creative Commons Attribution-NonCommercial-ShareAlike License, available at https://creativecommons.org/licenses/by-nc-sa/4.0/

Peer reviewed

Personal CO₂ Bubble: Context-dependent Variations and Wearable Sensors Usability

Ali Ghahramani¹, Jovan Pantelic¹, Matthew Vannucci¹, Lorenza Pistore^{1,2}, Shichao Liu^{1,3}, Brian Gilligan⁴, Soheila Alyasin⁵, Edward Arens¹, for the Wellbuilt for Wellbeing Project Team⁶

Abstract

High CO₂ concentration in inhaled air has been shown to negatively impact work performance and increase acute health symptoms. As respiratory CO₂ is constantly exhaled, it may not dissipate in surrounding air in absence of adequate air movement and is instead re-inhaled into the airways (breathing in a CO₂-rich bubble). In this study, we explored the impacts of context-dependent factors such as office activities, desk settings, and personal differences on the inhalation zone CO₂ concentration and on concentrations at a below-neck wearable sensor. While all factors were found to significantly impact measurements at both measuring points, desk settings (empty desk, desk with a fan, desk with laptop, desk with monitor) was found to be the most dominant factor. Presence of a small portable desk fan was found to significantly reduce the CO₂ concentration. On average, we observed a 177 ppm reduction in CO₂ concentration when using a fan, which is 25 ppm higher than the background CO₂ measurement (650 ppm). Among 41 test subjects, we found distinct relationships between the inhalation zone CO₂ concentration and the wearable sensor measurements and, by applying a hierarchical clustering algorithm, we found 4 clusters of relationships. While below-neck wearable sensors could be used as an exact measure of inhalation of CO₂ concentration for 29% of the subjects, we identified a boundary point (917 ppm) separating high and low inhalation zone CO₂ concentration measurements.

Keywords: CO₂ exposure; personal indoor air quality; inhalation zone CO₂ concentration; occupant behavior; wearable CO₂ sensor; ubiquitous sensing;

¹ Center for the Built Environment, University of California, Berkeley, Berkeley, CA, USA

² Faculty of Science and Technology, Free University of Bozen-Bolzano, Bolzano, Italy

³ Department of Civil and Environmental Engineering, Worcester Polytechnic Institute, MA, USA

⁴ General Services Administration, Washington DC, USA

⁵ Allergy Research Center, Department of Pediatrics, Shiraz University of Medical Sciences, Shiraz, Iran

⁶ The members of the Wellbuilt for Wellbeing Project Team appear at the end of the article

1. Introduction

According to the Occupational Safety and Health Administration (OSHA 2012) and the American Conference of Government Industrial Hygienists (ACGIH 2011), the maximum recommended occupational exposure to CO₂ concentrations for an 8-hr workday is 5000 ppm. Exposure to an indoor concentration above 5000 ppm carries potential health risks. American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) Standard 62.1, "Ventilation for Acceptable Indoor Air Quality" also addresses CO₂ levels that target occupant satisfaction from the odor perspective. The standard states that an indoor CO₂ concentration of 700 ppm above outdoor air levels is the accepted threshold given the activities found in typical office buildings so, considering that outdoor CO₂ concentrations range from 300 to 500 ppm, the indoor CO₂ concentrations should not exceed a range of 1000 to 1200 ppm [1]. CO₂ levels can be used to adjust outdoor air supply flow rate as a proxy for ventilation [2]. Higher levels of CO₂ within the range found in normal indoor settings are associated with perceptions of poor air quality, increased acute health symptoms (e.g., headache, mucosal irritation), slower work performance [3-6], and increased absenteeism [7, 8]. Recent studies have shown that increase in indoor CO₂ concentration in indoor environments could negatively impact productivity and especially decision making [9, 10]. Their results show that a 400 ppm increase in CO₂ is associated with a 21% decrease in a typical participant's cognitive scores across a variety of tests [11]. Results also suggest that at approximately 950 ppm (levels that are common in indoor spaces and considered acceptable by ASHRAE 62.1), statistically significant declines in cognitive function scores are observed [11]. With the increased interest in occupant productivity and wellbeing and evolution of system-centric to human-centric standards, these results suggest the importance of understanding the environmental and personal factors impacting the inhaled CO₂ and monitoring the exact inhalation zone CO₂ concentrations between upper indoor levels and outdoor levels.

The primary source of CO₂ in office buildings is respiration of the building occupants [12]. In a sedentary condition, the total exhaled volume (~6 L/min) of air contains 4-5% CO₂, a 100-fold increase compared to the inhaled ambient air [13]. It is commonly assumed that the generated CO₂ quickly dissipates into the surrounding air, making the CO2 concentration uniform throughout the indoor environment. However, the exhaled respiratory (i.e., metabolic) CO₂ distribution around the human face and body is not uniform [14, 15]. Higher particle concentrations in a person's breathing zone was first reported as a "personal cloud" by Ozkaynak et al. in the late 90s [16]. Subsequent research examined various pollutants such as ozone and trace CO₂ from prior exhalations in the breathing zone and found significant differences from the background levels [14, 17]. The pollutant concentration in the inhalation zone is a function of both the physical characteristics of the human body and its environment, and the occupants' dynamic traits (i.e., occupants' dynamic breathing patterns) [14, 17, 18]. In addition, the thermal plume flow generated by the temperature gradient adjacent to the body can lead to a high concentration of suspended particles in the breathing zone [19, 20], up to 1.6-13 μg/m3 [20, 21]. In summary, a polluted breathing zone exists for various pollutants when there is insufficient air movement or human movement. A high concentration of CO₂ can happen in any type of environment because it is respiratory-induced. Figure 1 depicts results from Computation Fluid Dynamics simulation showing qualitative visualization of a high CO₂ concentration in the inhalation zone.

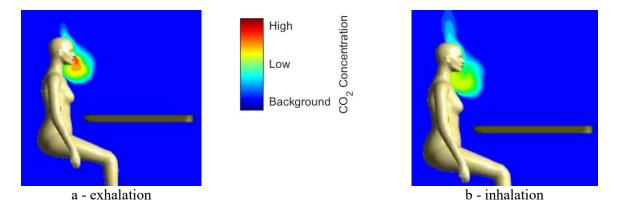


Fig 1. Respiratory CO₂ concentration in the breathing zone (a. during exhalation, b. during inhalation) forming a bubble

Body posture and nose- and mouth geometry are static factors that influence shape and concentration of the CO₂ bubble. Dynamic factors are occupant activity (spatial motions), indoor environment/furniture geometry, and air movements in the microclimate. Static and dynamic factors make a collective impact on the inhalation zone concentration, making it different from the background level.

The current study was designed to investigate the impacts of office activities, desk settings, and personal differences on the inhalation zone CO₂ concentration and on concentrations at a below-neck wearable sensor, and the ability of neck-worn wearable CO₂ sensors to measure inhalation zone CO₂ concentration. For ground truth we measured the inhaled CO₂ concentration at the nostril for several dynamic and static factors: activity (e.g., looking straight, looking down, steady speaking by counting numbers, and freestyle), desk settings (e.g., empty desk, desk with a rotating fan, desk with a desktop monitor, and desk with a laptop), and personal differences (i.e., inherent and experiential factors unique to each individual). We used an n-way ANOVA to assess the statistical relationships between the factors in the inhalation zone CO₂ concentration. The measurements from the wearable CO₂ sensor were then compared to the inhalation zone concentration measurements.

The paper is structured as follows. In Section 2, we describe our data collection procedure and statistical analysis tool used for studying impacts of different factors affecting inhalation zone CO₂ concentrations. Section 3 and 4 cover the results and statistical analysis of measurements for the inhalation zone concentration and wearable sensor, including the use of the hierarchical clustering algorithm. A comparison between measurements taken for inhalation zone and wearable sensor CO₂ concentrations are presented in Section 5, and Section 6 discusses the generality of the results.

2. Methods and experimental procedure

There were 41 participants recruited to perform different office activities in a controlled climate chamber while wearing a sensor to measure the CO_2 concentration in the inhalation zone. The climate chamber, located at the Center for the Built Environment (CBE) in UC Berkeley, USA, has dimensions of 5.4 m \times 5.4 m \times 2.65 m (length \times width \times height). A mixing ventilation was supplied by a single, 4-way ceiling mounted diffuser, and exhausted from a single ceiling exhaust grille. The air-exchange rate, measured by the CO_2 tracer gas decay, was controlled to be 4 hr⁻¹ for all experiments. The dry-bulb temperature was 22 \pm 0.5 °C, and the relative humidity was 40 \pm 5%.

Each participant performed four different breathing activities under four different desk settings (see Table 1). The participants were asked to sit on a chair behind a desk and: (1) breathe while "looking straight" ahead; (2) repetitively count from 1 to 10 while looking straight, "counting numbers"; (3) breathe while "looking down" at the desk; (4) behave freely, in "freestyle," without restrictions on activity. Each activity was done for 5 minutes. These activities were designed to simulate regular office activities, such as looking at a desktop monitor, writing a document by hand, talking on a phone, or behaving in an unfocused manner. The desk settings were: (1) an empty desk, (2) an empty desk with a rotating fan, (3) a desk with a desktop computer monitor, and (4) and a desk with an open laptop. Table 1 summarizes all activities tested under different desk settings. There were 3 activity/setting combinations not explored (desk + fan with looking down, desk + fan with freestyle, and desk + laptop looking down), as they are not typically seen in workplace environments, and this was taken into consideration in the analysis sections.

Table 1. Subject activities during different desk settings

Desk settings	Activities
Empty desk	Looking straight, looking down, counting numbers, free style
Desk + fan	Looking straight, counting numbers
Desk + desktop monitor	Looking straight, looking down, counting numbers, free style
Desk + laptop	Looking straight, counting numbers, free style

Figure 2 shows the inhalation zone measurement location, and wearable sensor placement on a participant. The inhalation zone CO₂ concentration was measured using a LI-820 CO₂ Gas Analyzer (LiCOR, Lincoln, NE, USA). The LiCOR sensor has an accuracy of <3 % in its operating temperature of -20° to +45°C. The sampling rate was 1 Hz and was reported in 1 second sample bins. The LI-820 sampling was driven by a GilAir Plus Personal Air Sampling Pump (Gilian, St. Petersburg, FL, USA), operating at a flow rate of 1 l/min. The sampling tube was attached to a pair of goggles, and the tip of the tube extended 1 cm above the nostrils and pointing downwards. The wearable CO_2 sensor has an accuracy of ± 30 ppm. All the sensors used in this study were calibrated by the company and tested against each other side-byside. The background CO₂ concentration was measured using a Telaire, T6713 CO₂ module (Mouser Electronics, Mansfield, TX, USA), which has an accuracy of 30 ppm + 3 % of the reading. Measurements were taken every 5 s, and the sensors had a response time of < 3 min for a 90 % step change. A standard flat-screen monitor 60.96 cm by 51.69 cm was used in the "desk + desktop monitor" scenario, and a laptop with a screen size of 35.56 by 17.43 cm was used in the "desk + laptop" scenario. An Oscillating Table Holmes Lil Blizzard Fan 18 cm in diameter was used in the table fan experiments (Figure 2). The fan was set to oscillate over a 180° angle. The lowest fan speed was used in the experiment to avoid causing the subject any discomfort due to the air velocity.

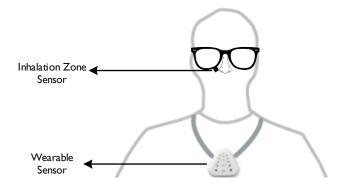






Fig 2. Inhalation zone measurement and wearable sensors settings

On average, there were 2818 data points for each person at each scenario (i.e., each desk setting and activity type). Accordingly, we calculated the mean and standard deviation of both personal inhalation zone CO₂ and wearable sensor and used them for visualizations, statistical analysis, and clustering analysis later in this paper. Only 38 of the 41 total test subjects had complete datasets required to carry out the statistical analysis described below.

2.1. Correlation analysis for factors impacting personal inhalation zone CO₂ and wearable CO₂ sensor

In order to assess the impact of desk settings, occupant activity, and personal differences on the personal inhalation zone CO₂ and the wearable CO₂ sensor measurements, we used an n-way Analysis of Variances (n-way ANOVA). N-way ANOVA is a generalization of a one-way ANOVA. N-way ANOVA helps determine if the means in a set of data (i.e., inhalation zone CO₂ or wearable sensor measurements) differ with respect to groups (levels) of multiple factors (e.g., desk settings, activity). N-way ANOVA model can be written as:

$$y_{ijkr} = \mu + \alpha_i + \beta_j + \gamma_k + (\alpha\beta)_{ij} + (\alpha\gamma)_{ik} + (\beta\gamma)_{jk} + (\alpha\beta\gamma)_{ijk} + \varepsilon_{ijkr}$$
 Equation 1

Where y_{ijkr} is an observation of the response variable. μ is the grand mean of the observations. i represents group i of factor A, i = 1, 2, ..., I. j represents group j of factor B, j = 1, 2, ..., J, k represents group k of factor C, and r represents the replication number, r = 1, 2, ..., R. α_i , β_j , and γ_k are the deviations of groups of factor A from the μ due to factor A, B, and C respectively.

Since we are not interested in the inter-relationships of the factors, we ignore $(\alpha\beta)_{ij}$, $(\alpha\gamma)_{ik}$, $(\beta\gamma)_{jk}$, and $(\alpha\beta\gamma)_{ijk}$ terms. ϵ_{ijkr} represents the random disturbances which are assumed to be independent, normally distributed, and with constant variance.

For each factor, the ANOVA provides the sum-of-squares, the degrees of freedom, the mean square, and the F ratio. Each F ratio is the ratio of the mean-square value for that source of variation to the residual mean square (with repeated-measures ANOVA, the denominator of one F ratio is the mean square for matching rather than residual mean square). If the null hypothesis (not statistically significant impact) is true, the F ratio is likely close to 1.0. If the null hypothesis is not true, the F ratio is likely greater than 1.0. The F ratios are not very informative by themselves unless degrees of freedom are closely matched. In such cases, the higher the F metric, the higher impact of the factor on the dependent variable. In addition, if the p-value is less than 0.05, the variable has a statistically significant impact on the dependent variable.

2.2. Estimation of inhalation zone CO₂ concentration via wearable sensors and hierarchical clustering

We used a hierarchical clustering algorithm to examine whether there are groups of people showing similar patterns of relationships between inhalation zone CO₂ and wearable sensor measurement. Specifically, we used the bottom-up hierarchical clustering approach (i.e., Agglomerative) where each data point starts in its own cluster (a single cluster), and the closest data points, based on a defined distance measure, pairs up into new clusters and are merged as one moves up the hierarchy. The distance measure used was Euclidean distance (i.e., L2 norm) defined in Equation 2:

$$L_2(x,y) = \sum_{i=1}^{n} |x_i - y_i|^2$$
 Equation 2

Where x_i and y_i are the components of the x and n is the number of dimension.

Using the complete link criteria, data pairs in close proximity are linked into a new cluster. The complete link uses the L2 norm distance measure to determine the proximity of data points to each other. As data points are paired into binary clusters, the newly formed clusters are grouped into larger clusters until a hierarchical tree is formed.

$$D(c_1, c_2) = \max_{x_1 \in c_1, x_2 \in c_2} D(x_1, x_2)$$
 Equation 3

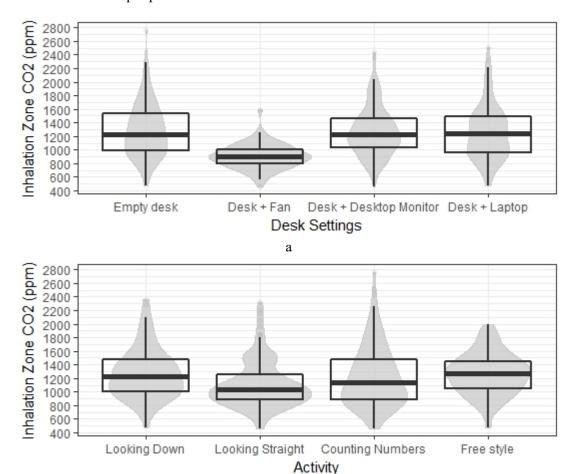
Where D is distance between two clusters, x_1 and x_2 are data points in c_1 and c_2 .

After forming the complete tree, we have to decide where to cut the tree based on expert understanding of the data and assign a limited number of classes to the objects. In this step, an arbitrary number, based on the observation of the data and the shape of the tree, is selected and used to prune branches off the bottom of the hierarchical tree and assign all the objects below each cut to a single cluster. This

creates partitions in the data. The complete method forces n-dimensional spherical clusters with consistent diameter.

3. Inhalation zone CO₂ measurements results

Figure 3 shows the mean personal inhalation zone CO₂ distributions for different desk settings, activity, and subjects. As it can be seen in Figure 3a, having an empty desk, desk with monitor, and laptop are not considerably different. However, the condition including fan is considerably different (~400 ppm lower median value compared to other cases). In addition, the distribution of CO₂ concentration during the desk with fan scenario is considerably smaller. In Figure 3b, the looking down and free style activity are very similar since most of the subjects used their smartphone (looking down at its screen) in this period. In both periods, the CO₂ concentration was relatively higher. Looking straight had a relatively lower CO₂ concentration while counting numbers had a much wider variability. When counting numbers, the exhaled air moves straight from the mouth in a jet like fashion, increasing concentration in the inhalation zone compared to the nose exhalation during breathing (Pantelic et al., 2018). Figure 3c demonstrates the variability of measurements for all the test participants and suggests that there are considerable variations in the median values and per person.



b

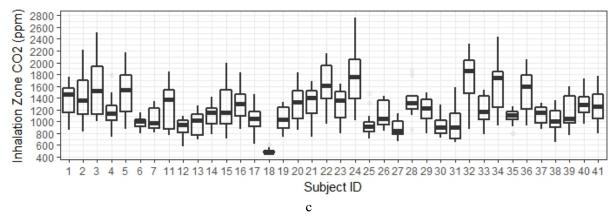


Fig 3. Mean personal inhalation zone distributions with respect to (a) desk settings, (b) activity, and (c) subject ID

3.1 Correlation analysis for factors impacting personal inhalation zone CO₂ concentration

Table 2 and 3 summarizes the n-way ANOVA analysis for the personal inhalation zone CO₂. As it can be seen in Table 2, all the factors have significant impacts on the personal inhalation zone CO₂. Desk setting has the highest impact, followed by personal differences denoted as subject IDs, and activity level. Similarly, in the Table 3, all the factors have statistically significant impacts on the personal inhalation zone CO₂, but the ranking of the factors is (1) personal variations (i.e., subject IDs), (2) activity, and (3) desk setting.

Table 2. N-way ANOVA for mean personal inhalation zone CO₂.

Factor	Degrees of Freedom	F	p
Subject ID	37	11.03	~0
Desk Settings	3	34.65	~0
Activity	3	2.59	0.05

Table 3. N-way ANOVA for standard deviation of personal inhalation zone CO₂.

Factor	Degrees of Freedom	F	p
Subject ID	37	8.88	~0
Desk Settings	3	3.67	0.0125
Activity	3	6.99	0.0001

4. Wearable CO₂ sensor measurements results

Figure 4 shows the mean wearable sensor CO₂ measurements for different desk settings, activity, and subjects. As it can be seen in Figure 4a, similar to the inhalation zone CO₂, using a fan reduces the CO₂ measurement by ~100 ppm. However, the empty desk, desk with monitor, and laptop scenarios are all lower (~600 ppm) than inhalation zone CO₂ and desk with fan is ~300 ppm lower. In Figure 4b, the looking down and freestyle activity are similar, and higher than looking straight and counting numbers. When looking straight while breathing or counting, exhaled air is dominantly dispersed away from the wearable sensor, which is reflected by the lower CO₂ concentration measurements of the wearable sensor. Results also suggest that when counting numbers, exhaled air moves away from the mouth and from the wearable

sensors resulting in even lower measure concentration. Similar to inhalation zone CO₂, Figure 4c suggests that there are variabilities in median values and also variations per person. There are many test subjects where low variations in the measurements were observed which suggests that the sensors were located somewhere outside the high concentration CO₂ bubble.

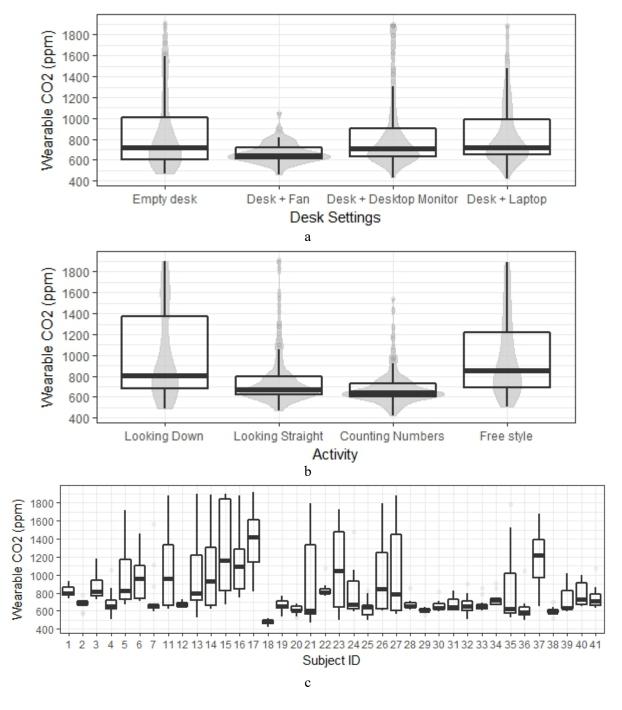


Fig 4. Mean wearable sensors distribution with respect to (a) desk settings, (b) activity, and (c) and subject ID

4.1. Correlation analysis for factors impacting wearable CO₂ sensor measurements

Table 4 and 5 summarizes the n-way ANOVA analysis for the wearable CO₂ sensor measurements. As it can be seen, all factors have statistically significant impact on the wearable CO₂ measurements. Activity has the highest impact on both mean and standard deviation of the measurements, and it is followed by the subject IDs and desk settings.

Table 4. N-way ANOVA for mean wearable CO₂ sensor measurements.

Factor	Degrees of Freedom	F	p
Subject ID	37	9.55	~0
Desk Settings	3	3.79	0.01
Activity	3	40.59	~0

Table 5. N-way ANOVA for standard deviation of wearable CO₂ sensor measurements.

		_	
Factor	Degrees of Freedom	F	p
Subject ID	37	6.25	~0
Desk Settings	3	5.06	0.0019
Activity	3	21.76	~0

Comparing the results from personal inhalation zone and wearable sensors, we can point out that desk setting is the most influential factor on the actual personal inhalation zone CO₂. However, even though empty desk with fan creates a significant difference in CO₂ measurements, because activity impact grows as the sensor is located further from the breathing zone, desk settings does not come out on top for wearable measurements and is replaced by the activity factor.

4.2. Analysis of wearable sensor CO₂ concentration measurements via hierarchal clustering

To better understand the relationship between measurements from wearable sensors, we applied a clustering algorithm to detect if there are groups of people who show similar patterns of relationships between inhalation zone CO_2 concentration and wearable sensor measurement. In order to feed the data collected into the hierarchical clustering algorithm, the data sets were reshaped into a new table where the rows represented the wearable CO_2 measurements during each activity and desk settings. We had 41 subjects and therefore needed to have 41 rows, but only 35 of the 41 participants had complete data sets, so we ended up having 35 rows where wearable measurements were available for all the activities.

Based on the differences and expert opinion, we decided to cut the tree at 4 clusters (Figure 5). The y-axis is a metric for determining the degree of similarity among either individual data points or clusters. These suggest that wearable sensors have 4 distinct inhalation zone CO₂ concentration signatures. These results suggest that the relationship is heavily dependent on personal factors that make each test subject unique/unpredictable and on desk settings and on occupant activity.

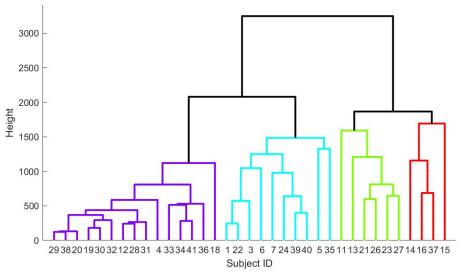


Figure 5. Hierarchical clustering for the personal wearable data and cutoff at 4 clusters

Among the four clusters we have classified in Figure 5, 2 clusters (clusters 3 and 4) have high sensitivity of wearable sensor to actual inhalation zone CO₂ measurements. Two other clusters sometimes demonstrate little to no change in inhalation zone CO₂ measurements.

The four cluster distributions and values for each scenario have been demonstrated in Figure 6. The mean concentration values for each of the four clusters were taken across 13 scenarios of activity and desk settings (as shown in Figure 6) and were calculated as 654, 843, 991, and 1156 ppm for clusters 1, 2, 3, and 4 respectively. Therefore, we took the midpoint between cluster 2 and cluster 3 (917 ppm) as the point where the clusters' sensitivity changes considerably.

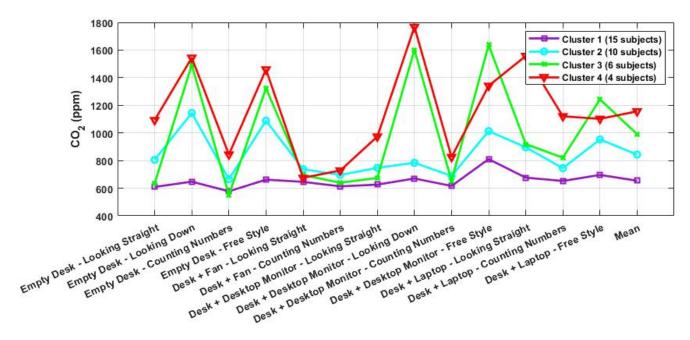


Figure 6. Scenario mean values for 4 clusters

5. Comparing inhalation zone with wearable sensor CO₂ concentration measurements

Based on clustering, we examined the temporal distribution of inhalation zone and wearable sensor CO₂ concentration measurements. Figure 7 shows two different cases: results from subject 16 demonstrates high correlation between the subjects' inhalation zone CO₂ concentration measurements and wearable sensor measurements whereas the results for subject 29 demonstrates a case where wearable sensor measurements are different than their inhalation zone CO₂ concentration measurements. Results for subject 29 show that wearable sensor measurement is independent from the inhalation zone CO₂ concentration. Subject 29 belongs to cluster 1, the largest cluster consisting of 15 test subjects, which suggests that, in 43% of the cases, wearable sensor measurement is independent of the inhalation zone concentration. This implies that, although a sensor worn around the neck represents a realistic position for practical application of wearable sensors, the sensor placement does not adequately reach the CO₂ bubble due to personal, static and dynamic factors. In the CFD analysis we performed (not shown), we observed that a small difference in the exhalation angle could cause a substantial difference in the shape of the CO₂ bubble. Further studies are necessary in order to understand the range of factors influencing the shape of the CO₂ bubble.

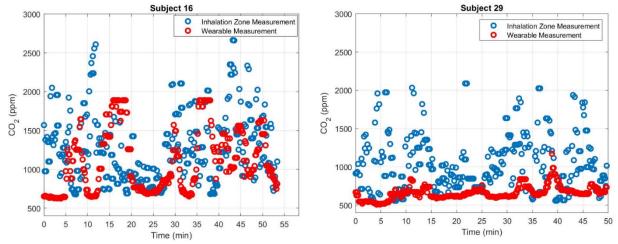


Figure 7. Inhalation zone and wearable CO₂ measurements for two subjects

To better understand the relationship between measurements from personal inhalation zone and wearable sensor CO₂ concentration, Figure 8 demonstrates the time-matched personal inhalation zone CO₂ concentration with measurements from the wearable sensors. The mean of the 13 values from each scenario are taken for each of the 4 experiment configurations. Each point in Figure 8 represents inhalation zone CO₂ concentration and wearable sensor measurements for an occupant in a specific desk setting and activity level.

Results show that in 82.7% of cases, wearable sensors were capturing a value smaller than the inhalation zone CO₂ concentration. The relationship between different activities or desk settings is reflected by their respective data distributions. There was no specific shared experiment related reason that explains why the wearable sensor could not detect high CO₂ concentration in each cluster. As it can be seen in Figure 8, wearable sensor measurements cannot capture inhalation zone concentration via a monotonic function. After analyzing the collected data, we determined 917 ppm as the transition point that most reasonably separates the data. As seen in Figure 8, if the measurements are above 917 ppm, in almost all cases (93%)

of cases), the inhalation zone CO_2 is greater than 917 ppm. However, if the wearable measurement is less than 917, there are many cases in which the inhalation zone CO_2 is less than 917 (28% of the time). The wearable CO_2 measurement is always the lower bound for the inhalation zone CO_2 concentration. It should also be noted that 917 ppm is a function of background CO_2 level (median 650 ppm in the current study with a variation of indoor CO_2 levels for about 100 ppm (\pm 50 ppm), depending on the exhalation rate of the occupants and uncertainty of the sensors used). In summary, measurement of personal inhalation zone CO_2 concentration via a sensor mounted around the neck is not a generalizable solution to a personal inhalation zone CO_2 measurement, but the actual inhalation zone CO_2 are consistently higher than the measurements from the wearable device (82.7% of cases). In order to use this type of wearable sensors effectively, we would need to develop personalized models that can measure inhalation zone CO_2 concentration with reasonable accuracy for \sim 30% of the occupants. Our future work will focus on finding the optimal sensor location that will provide reasonable tradeoff between accuracy of inhalation zone predications and quantity of subject predictions that can be made.

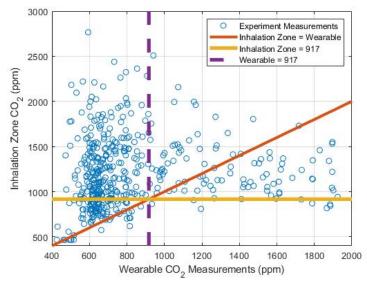


Figure 8. Inhalation zone CO₂ vs wearable measurements in different in desk settings and activities

6. Discussion

In this study, we investigated the potential of wearable sensors to evaluate the inhalation zone CO₂ concentration as a function of activity, desk settings, and personal differences. We used scenarios that realistically mimic regular office work conditions. However, the number of activities and desk settings might be expanded to generate more generalizable results. In addition, the number of test subjects selected was 41, but could be increased in future studies to take into account specific individual traits or physical conditions. Several factors such as gender, age range, body mass, fitness, metabolic rate, nasal pathways structure, and breathing habits are involved in the personal differences. Since these variables are many, with possibly mixed effects, we could not and did not intend to distinguish the impacts of each parameter separately and grouped all of them into personal differences. Studying the impacts of personal traits mentioned above are major future studies that help understanding the inhalation zone CO₂ exposure. The air speed in the breathing zone for scenarios with a fan was below 0.1 m/s and for the scenarios with a rotating fan was about 0.5 m/s. Therefore, the results from this study suggests that the personal CO₂ bubble exists in environments with a regular ventilation system, and a proper air movement system is needed to

create a breeze strong enough to burst the bubble. It should also be noted we only tested one fan condition, since our goal was to evaluate personal CO₂ sensing can be used for exposure estimation a purpose of this study. In addition, stronger desk fans, ceiling fans, and different sources of air movement in a room can help bursting the CO₂ faster. As future research direction, we plan to explore the optimal fan and air movement settings for minimizing the CO₂ in the breathing zone while maximizing energy efficiency and maintaining personal thermal comfort.

With the development of knowledge about indoor air quality impact on productivity, health, and well-being, there is growing need for accurate real-time knowledge of inhalation zone CO₂ exposure. Wearable sensors have the potential to provide a solution for this technical demand. Through statistical investigation of our gathered data in Figure 8, we suggest that a wearable sensor could be used to get a rough estimate of the inhalation zone CO₂ concentration based on the 917 ppm threshold. If the wearable measurements are greater than 917 ppm, then the inhalation zone concentration is at least 917 ppm. Otherwise, the wearable measurement is the lower bound of the inhalation zone concentration. Despite the sensor's limited applications as a wearable device, one might argue based on the high CO₂ concentrations measured from this study that we need personalized sensors or better ventilated workstation designs to monitor and lessen the buildup of CO₂ respectively. It further suggests that a room background measurement is more easily obtained by wearable sensors than previously expected. Given the looseness of the terms microenvironment and inhalation zone CO₂ (i.e. entire building types have been used as a microenvironment, and in current IAQ practices exposure almost never includes the self-exposure that we explored here) [22, 23], the 'background' signal we derive from the wearable sensor is more representative of actual inhalation zone CO2 than the background signal taken from a wall mounted sensor. Though wearable sensors do not offer a viable method for obtaining personal inhalation zone CO₂ measurement it can potentially be integrated into pre-existing systems to contribute to better indoor air quality [24]. Wearable sensors offer the possibility of relaying real time data to other indoor devices, such as ceiling or desk fans, that can activate and lessen the CO₂ concentration in personal CO₂ bubbles via directed air movements. Focused air movements are likely to burst personal CO₂ bubbles and disperse the gas further out the inhalation zone, decreasing the likelihood of CO₂ re-inhalation, which can lead to increased office work productivity. Aside from increasing productivity in work environments, using fans to lessen CO₂ concentrations can also function as a significant tool that helps ensure occupant safety and wellbeing in homes [25, 26]. A previous study shows that properly ventilated homes can help decrease the risk of sudden infant death syndrome (SIDS), the leading cause of postneonatal mortality rate in the United States, by correctly mitigating the build-up of CO₂ around the breathing zone of infants and decreasing their vulnerability to suffocation due the re-inhalation of carbon-rich air [27]. In addition, configuring wearable CO₂-measuring devices to communicate with other operational devices improves our understanding in the spread of airborne diseases and in the assessment of the level of volatile organic compounds that can undermine our wellbeing at home. Other aspects of indoor environmental quality such as thermal comfort have a closely related cognitive impacts on building occupants [28] which can be mitigated via fans, windows, and other personal comfort devices [22, 29, 30]. In addition, integration of HVAC systems to a multi-objective optimization where personal CO₂ concentrations, thermal comfort and energy consumption [31-33] can further improve occupants overall indoor environmental quality and reduce building energy consumption [34-37]. Time varying personal preferences in terms of thermal comfort [38-40] may compete with air quality requirements, which needs further research [41-43]. The glass-mounted sensing system can also use infrared sensors to monitor personal thermal comfort in a non-intrusive manner [44, 45].

As discussed in the Introduction section, the impact of reducing CO₂ in the inhalation zone carries significant improvements for cognitive performance. Using a fan and refraining from looking down at the desk or a smartphone could significantly reduce the CO₂ concentration. However, further studies are needed to gain a deeper understanding of the relationship between improvements in cognitive performance, and individual and organizational productivity. The current models available in the standards suggest that roughly 21% of the sample population is expected to face a decrease in cognitive scores in response to an average increase of 400 ppm in CO₂ levels, though trace amounts of volatile organic compounds (VOC) and ozone were noted as possible altering agents affecting the determination of cognitive performance [8]. Further development in wearable CO₂-measuring devices may better track/standardize the incremental effects of CO₂ levels on cognitive performance at smaller concentration intervals which are not specified by current standards.

7. Conclusion

This study was pursued in response to the premise that measuring CO₂ concentrations is important for air quality, occupant health and building occupant productivity. One avenue to measuring indoor CO2 concentrations is via wearable sensors. Our experiment specifically explored the feasibility of using a neckworn wearable sensor to measure the CO₂ concentrations in the inhalation zone. Our methodology involved designing environments with different activity and desk configurations to mimic that of typical work space scenarios. In doing so, we created both static (desk settings) and dynamic (occupant activity) components of work office conditions that would produce similar CO₂ concentrations found in real life situations. From the different scenarios tested, our data suggests that desk settings often have the greatest impact in the measured concentrations, although we need further research on the impact that each test subject's personal characteristics may have on the execution of the activity. The results from this study also suggests that the personal CO₂ bubble exists in environments with a regular ventilation system, and a proper air movement system is needed to create a breeze strong enough to burst the bubble. To better understand the relationship between inhalation zone concentrations and wearable sensor concentrations, we implemented hierarchal clustering from which we discovered 4 distinct clusters of test subjects that share similar CO₂ concentration measurements in the same configuration of desk setting and activity. Results reveal that in 82.7% of cases, wearable sensor measurements consistently measured lower CO₂ concentration values than actual inhalation zone measurements. Through further analysis, it appears that 917 ppm was the defining point separating the data in a 650 ppm background. For the neck-worn wearable sensor, measurements above that concentration were consistently greater than 917 ppm and measurements below were consistently lower than 917 ppm. Despite explosion of IOT based sensing, the need for accurate monitoring of personal CO₂ concentrations remains. Access to real-time data pertaining to CO2 concentrations around occupant inhalation zones can significantly aid occupant productivity and health. Integration of such wearable devices, whether located around the neck or otherwise [46], can improve the quality of the occupant's workspace experience.

8. Acknowledgement

This study was funded by the U.S. General Services Administration (GSA) under interagency agreement # GX0012829 with the U.S. Department of Energy and Lawrence Berkeley National Laboratory. GSA's Wellbuilt for Wellbeing Group is a multidisciplinary research project team (GSA Contract # GS-00-H-14-AA-C-0094) consisting of the following members: Kevin Kampschroer, Judith Heerwagen and Brian Gilligan of GSA. Esther Sternberg, Perry Skeath, Casey Lindberg, and Matthias Mehlof the University of

Arizona Institute on Place and Wellbeing. Bijan Najafi, Javad Razjouyan, Hyoki Lee, and Hung Nguyen of the Baylor College of Medicine Interdisciplinary Consortium on Advanced Motion Performance (iCAMP). Sudha Ram, Faiz Curim and Karthik Srinivasian of the University of Arizona INSITE Center for Business Intelligence and Analytics. Kelly Canada of LMI Inc. Priya Saha, Rebecca Goldfinger-Fein, Alicia Darbishire, and Mills Wallace of the Federal Occupantional Health Service. Davida Herzl, Reuben Herzl, Melissa Lunden, Nicole Goebel, and Scott Andrews of Aclima Inc.

9. References:

- [1] ASHRAE Standard, Standard 62.1-2010 (2010). Ventilation for Acceptable Indoor Air Quality, Atlanta, GA, American Society of Heating, Refrigerating and Air-Conditioning Engineers, Inc (2010).
- [2] W.J. Fisk, CO2 monitoring for demand controlled ventilation in commercial buildings (2010).
- [3] C.A. Erdmann, M.G. Apte, Mucous membrane and lower respiratory building related symptoms in relation to indoor carbon dioxide concentrations in the 100-building BASE dataset (2004).
- [4] C.C. Federspiel, W.J. Fisk, P.N. Price, G. Liu, D. Faulkner, D.L. DiBartolomeo, D.P. Sullivan, M. Lahiff, Worker performance and ventilation in a call center: analyses of work performance data for registered nurses, Indoor air. 14 (2004) 41-50.
- [5] O. Seppänen, W. Fisk, M. Mendell, Association of ventilation rates and CO2 concentrations with health andother responses in commercial and institutional buildings, Indoor air. 9 (1999) 226-252.
- [6] P. Wargocki, D.P. Wyon, J. Sundell, G. Clausen, P.O. Fanger, The effects of outdoor air supply rate in an office on perceived air quality, sick building syndrome (SBS) symptoms and productivity, Indoor air. 10 (2000) 222-236.
- [7] D.K. Milton, P.M. Glencross, M.D. Walters, Risk of sick leave associated with outdoor air supply rate, humidification, and occupant complaints, Indoor air. 10 (2000) 212-221.
- [8] D.G. Shendell, Associations between classroom CO₂ concentrations and student attendance in Washington and Idaho (2012).
- [9] U. Satish, M.J. Mendell, K. Shekhar, T. Hotchi, D. Sullivan, S. Streufert, W.J. Fisk, Is CO2 an indoor pollutant? Direct effects of low-to-moderate CO2 concentrations on human decision-making performance, Environmental health perspectives. 120 (2012) 1671-1677.
- [10] P. MacNaughton, J. Spengler, J. Vallarino, S. Santanam, U. Satish, J. Allen, Environmental perceptions and health before and after relocation to a green building, Building and Environment. 104 (2016) 138-144.
- [11] J.G. Allen, P. MacNaughton, U. Satish, S. Santanam, J. Vallarino, J.D. Spengler, Associations of Cognitive Function Scores with Carbon Dioxide, Ventilation, and Volatile Organic Compound Exposures in Office Workers: A Controlled Exposure Study of Green and Conventional Office Environments, Environmental health perspectives. 124 (2016) 805-812.

- [12] C.A. Erdmann, K.C. Steiner, M.G. Apte, Indoor carbon dioxide concentrations and sick building syndrome symptoms in the BASE study revisited: Analyses of the 100 building dataset (2002).
- [13] S.I. Fox, Human Physiology 9th Editon, McGraw-Hill press, New York, USA, 2006.
- [14] A. Melikov, J. Kaczmarczyk, Measurement and prediction of indoor air quality using a breathing thermal manikin, Indoor air. 17 (2007) 50-59.
- [15] D. Rim, A. Novoselac, Occupational exposure to hazardous airborne pollutants: Effects of air mixing and source location, Journal of occupational and environmental hygiene. 7 (2010) 683-692.
- [16] H. Ozkaynak, J. Xue, J. Spengler, L. Wallace, E. Pellizzari, P. Jenkins, Personal exposure to airborne particles and metals: results from the Particle TEAM study in Riverside, California, Journal of exposure analysis and environmental epidemiology. 6 (1996) 57-78.
- [17] R. Corsi, J. Siegel, A. Karamalegos, H. Simon, G. Morrison, Personal reactive clouds: Introducing the concept of near-head chemistry, Atmospheric Environment. 41 (2007) 3161-3165.
- [18] D. Licina, A. Melikov, C. Sekhar, K.W. Tham, Transport of gaseous pollutants by convective boundary layer around a human body, Science and Technology for the Built Environment. 21 (2015) 1175-1186.
- [19] M. Salmanzadeh, G. Zahedi, G. Ahmadi, D. Marr, M. Glauser, Computational modeling of effects of thermal plume adjacent to the body on the indoor airflow and particle transport, Journal of Aerosol Science. 53 (2012) 29-39.
- [20] D. Licina, Y. Tian, W.W. Nazaroff, Emission rates and the personal cloud effect associated with particle release from the perihuman environment, Indoor air. 27 (2017) 791-802.
- [21] X. Li, K. Inthavong, Q. Ge, J. Tu, Numerical investigation of particle transport and inhalation using standing thermal manikins, Building and Environment. 60 (2013) 116-125.
- [22] L. Stabile, M. Dell'Isola, A. Frattolillo, A. Massimo, A. Russi, Effect of natural ventilation and manual airing on indoor air quality in naturally ventilated Italian classrooms, Building and Environment. 98 (2016) 180-189.
- [23] M. Macarulla, M. Casals, M. Carnevali, N. Forcada, M. Gangolells, Modelling indoor air carbon dioxide concentration using grey-box models, Building and Environment. 117 (2017) 146-153.
- [24] A.D. Fontanini, U. Vaidya, B. Ganapathysubramanian, A methodology for optimal placement of sensors in enclosed environments: A dynamical systems approach, Building and Environment. 100 (2016) 145-161.
- [25] H. Zhang, J. Xie, H. Yoshino, U. Yanagi, K. Hasegawa, N. Kagi, Z. Lian, Thermal and environmental conditions in Shanghai households: Risk factors for childhood health, Building and Environment. 104 (2016) 35-46.

- [26] D.L. Johnson, R.A. Lynch, E.L. Floyd, J. Wang, J.N. Bartels, Indoor air quality in classrooms: Environmental measures and effective ventilation rate modeling in urban elementary schools, Building and Environment. 136 (2018) 185-197.
- [27] K. Coleman-Phox, R. Odouli, D. Li, Use of a fan during sleep and the risk of sudden infant death syndrome, Archives of Pediatrics & Adolescent Medicine. 162 (2008) 963-968.
- [28] W. Liu, W. Zhong, P. Wargocki, Performance, acute health symptoms and physiological responses during exposure to high air temperature and carbon dioxide concentration, Building and Environment. 114 (2017) 96-105.
- [29] M. Yao, B. Zhao, Window opening behavior of occupants in residential buildings in Beijing, Building and Environment. 124 (2017) 441-449.
- [30] F. Naspi, M. Arnesano, L. Zampetti, F. Stazi, G.M. Revel, M. D'Orazio, Experimental study on occupants' interaction with windows and lights in Mediterranean offices during the non-heating season, Building and Environment. 127 (2018) 221-238.
- [31] A. Ghahramani, S.A. Karvigh, B. Becerik-Gerber, HVAC system energy optimization using an adaptive hybrid metaheuristic, Energy and Buildings. 152 (2017) 149-161.
- [32] A. Ghahramani, F. Jazizadeh, B. Becerik-Gerber, A knowledge based approach for selecting energy-aware and comfort-driven HVAC temperature set points, Energy and Buildings. 85 (2014) 536-548.
- [33] A. Makhoul, K. Ghali, N. Ghaddar, Desk fans for the control of the convection flow around occupants using ceiling mounted personalized ventilation, Building and Environment. 59 (2013) 336-348.
- [34] A. Ghahramani, K. Dutta, B. Becerik-Gerber, Energy Trade Off Analysis Of Optimized Daily Temperature Setpoints, Journal of Building Engineering (2018).
- [35] A. Ghahramani, K. Zhang, K. Dutta, Z. Yang, B. Becerik-Gerber, Energy savings from temperature setpoints and deadband: Quantifying the influence of building and system properties on savings, Applied Energy. 165 (2016) 930-942.
- [36] A. Ghahramani, K. Dutta, Z. Yang, G. Ozcelik, B. Becerik-Gerber, Quantifying the influence of temperature setpoints, building and system features on energy consumption (2015) 1000-1011.
- [37] C. Bolchini, A. Geronazzo, E. Quintarelli, Smart buildings: A monitoring and data analysis methodological framework, Building and Environment. 121 (2017) 93-105.
- [38] A. Ghahramani, C. Tang, Z. Yang, B. Becerik-Gerber, A Study of Time-Dependent Variations in Personal Thermal Comfort via a Dynamic Bayesian Network, in: Sustainable Human–Building Ecosystems, pp. 99-107.
- [39] A. Ghahramani, C. Tang, B. Becerik-Gerber, An online learning approach for quantifying personalized thermal comfort via adaptive stochastic modeling, Building and Environment. 92 (2015) 86-96.

- [40] Z. Wang, R. de Dear, M. Luo, B. Lin, Y. He, A. Ghahramani, Y. Zhu, Individual difference in thermal comfort: A literature review, Building and Environment (2018).
- [41] S. Ahmadi-Karvigh, A. Ghahramani, B. Becerik-Gerber, L. Soibelman, One size does not fit all: Understanding user preferences for building automation systems, Energy and Buildings. 145 (2017) 163-173.
- [42] S. Ahmadi-Karvigh, A. Ghahramani, B. Becerik-Gerber, L. Soibelman, Real-time activity recognition for energy efficiency in buildings, Applied Energy. 211 (2018) 146-160.
- [43] Y. Wu, H. Liu, B. Li, Y. Cheng, D. Tan, Z. Fang, Thermal comfort criteria for personal air supply in aircraft cabins in winter, Building and Environment. 125 (2017) 373-382.
- [44] A. Ghahramani, G. Castro, S.A. Karvigh, B. Becerik-Gerber, Towards unsupervised learning of thermal comfort using infrared thermography, Applied Energy. 211 (2018) 41-49.
- [45] A. Ghahramani, G. Castro, B. Becerik-Gerber, X. Yu, Infrared thermography of human face for monitoring thermoregulation performance and estimating personal thermal comfort, Building and Environment. 109 (2016) 1-11.
- [46] A. Ghahramani, J. Pantelic, C. Lindberg, M. Mehl, K. Srinivasan, B. Gilligan, E. Arens, Learning occupants' workplace interactions from wearable and stationary ambient sensing systems, Applied Energy. 230 (2018) 42-51.