Ventilation and Indoor Air Quality in Residential Bedrooms

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ABSTRACT

Few studies have investigated human exposure to indoor air pollutants during sleep even though humans spend about a third of the day asleep in the same environment. In this study, we use consumer-grade sensors to measure key indoor air pollutants and use carbon dioxide to estimate ventilation rates so that we can better understand the human sleep microenvironment. We developed a sensing platform capable of measuring light levels, temperature, relative humidity, carbon dioxide, particulate matter (PM2.5 and PM10), total volatile organic compounds, carbon monoxide, and nitrogen dioxide. The device was distributed to 29 university students living in Texas from early June to early September 2020. Data were collected continuously at 1-minute intervals in their bedroom environments. Participants were also provided a wristband to be worn at all times. The wristband was used to determine when participants were asleep which allowed us to limit the data analysis to truly sleeping times and exposure. A survey administered at the beginning of the study period provided insight into the home environment including questions regarding roommates, pets, cooking habits, air filter use, etc. which provides context to the collected data.

INTRODUCTION

In developed nations, humans can spend between 80% and 90% of their time indoors (Schweizer et al., 2007). This fact coupled with the idea that potentially hazardous pollutant concentrations often rise to levels higher than those found outdoors means that human exposures in the indoor environment are of great importance. Within the indoor environment, humans spend a considerable amount of time in their bedroom microenvironment given that the CDC recommends adults get at least 7 hours of sleep each night, which equates to nearly one-third of a person's life. However, little research has been done to extensively characterize the sleep microenvironment (Boor et al., 2017).

Recent and rapid development of affordable sensing technologies has made measuring indoor environmental quality (IEQ) easier than ever before and has sparked interest in measuring conditions, primarily ventilation and CO_2 concentrations, within the bedroom microenvironment. For instance, researchers were able to leverage 80 devices to measure CO_2 concentrations across 500 homes for 2 days and 2 nights and estimate ventilation rates (Bekö et al., 2010). In a similar study, CO_2 measurements in over 400 homes were made to estimate natural ventilation rates (Cheng and Li, 2018). These two studies illustrate the scale of study that can be conducted using affordable, commercially available sensors. These sensors can also be useful when measuring conditions over long periods of time as they require less power to operate and less maintenance than higher-grade instruments.

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In this study, our aim was to characterize multiple indoor air pollutants and the ventilation rate across different residences for an extended period of a few months. To do so, we developed and deployed an IEQ monitor capable of measuring multiple indoor air pollutant concentrations to gain a better understanding of the types of pollutants people are exposed to in their bedroom microenvironments. Alongside these devices, participants in the study also received wearable sleep monitors and reported their GPS coordinates through an open-source smart phone app. We used these two devices to ensure the IEQ readings used in analysis were from periods when participants were asleep and home. In addition to reporting bulk IEQ measurements, we were also able to use the CO_2 concentrations measured by our devices to estimate ventilation rates in many of the participants' bedrooms. This research is unique in that we are able to pinpoint and use data only from periods when participants were asleep in their bedroom microenvironments. In addition, we can use data provided by participants to more accurately determine ventilation rates using low-cost sensors deployed in the wild.

METHODOLOGY

This research project was a subset of a larger study aimed at understanding student's behaviors and environmental exposures throughout the course of their day using numerous affordable and mobile sensing technologies. However, the scope of this project is limited to devices, variables, and participants that were studied in order to help address environmental exposures in participants' bedrooms.

Student participants were recruited from the University of Texas at Austin (UT) and underwent an initial screening before being consented into the study. Enrollment interviews that consisted of researcher-guided surveys to better understand the individual and their behaviors were conducted over a period of two weeks with full enrollment completed by May 1st, 2020. A total of 71 participants were initially enrolled with two participants opting to drop out during the course of the study. The study concluded when participants scheduled a virtual meeting with a study coordinator in early September 2020 for an exit interview and to coordinate shipping study materials back to UT.

Environmental Quality Monitoring

To get an initial impression of the environment participants lived in, a one-time virtual questionnaire called the Environment and Experiences (EE) survey was administered asking various questions regarding pollutant exposures at home (smoking/vaping practices, pets, floor type, etc.) and cleaning habits (portable air cleaner use, disinfecting practices, etc.). To monitor the IEQ of the participants' bedrooms during the study period, we developed, calibrated, and deployed our own monitoring device called the Building EnVironment and Occupancy (BEVO) Beacon. We distributed 29 devices to a subset of the 71 participants. The BEVO Beacon, pictured in Figure 1, includes a Raspberry Pi 3B+ (RPi) wired to six affordable, commercially available sensors; one 250 mm X 250 mm (1" X 1") cooling fan; and a battery-powered clock to keep time when the device is not connected to WiFi. Within the BEVO Beacon, the RPi is housed in a separate chamber from the sensors where the fan provides air to help cool the RPi processor. All six sensors are either exposed directly to the air or have inlets that pull from outside the wooden housing. The sensors on the BEVO Beacon measure temperature, relative humidity (RH), light levels, carbon dioxide (CO_2), particulate matter with aerodynamic diameters less than 2.5 ($PM_{2.5}$) or 10 (PM_{10}) micrometers, total volatile organic compounds (TVOCs), nitrogen dioxide (NO_2), and carbon monoxide (CO). Each sensor attempts to take 5 readings over a period of 10 seconds, logs the average of these readings, and then sleeps for 50 seconds providing data at a one-minute resolution. Data are stored locally on the RPi but can be accessed remotely if the BEVO Beacon is connected to WiFi.
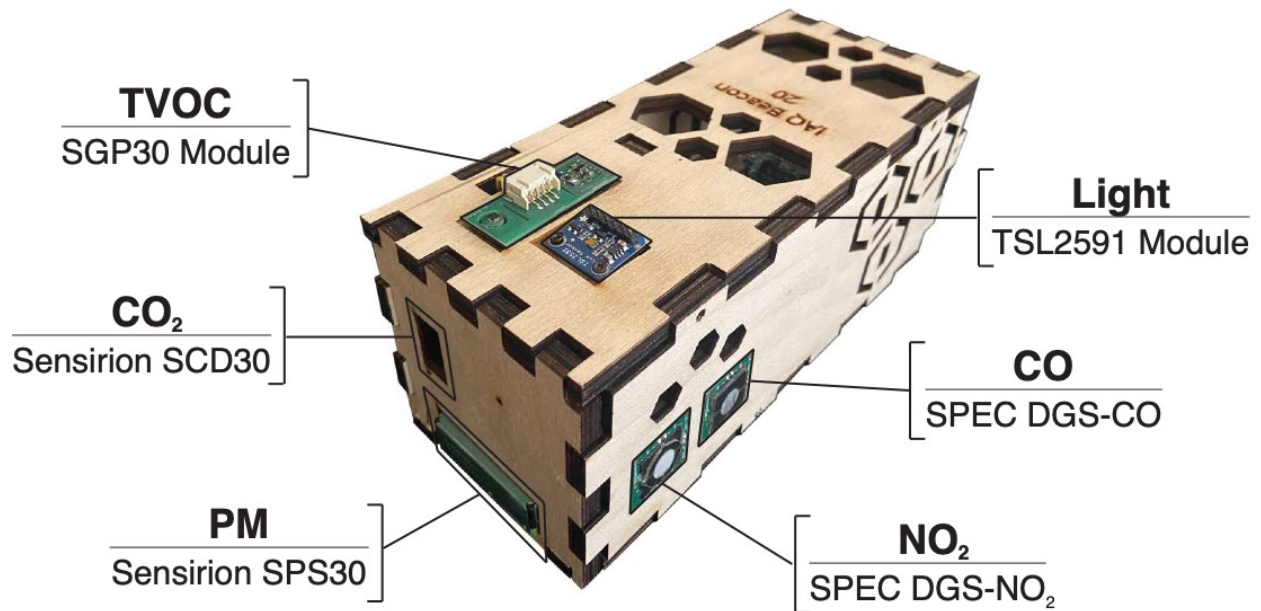
Figure 1   The BEVO Beacon and the 6 sensors, the primary variable they measure, and the sensor name.

The BEVO Beacons were sent out on a rolling basis starting June 1st, 2020 with the first device reaching its destination on June 3rd. Upon arrival, participants were asked to plug in the devices immediately. Some participants opted to delay powering the devices on or unplugged them before the study ended in September. The BEVO Beacons were returned on a rolling basis starting September 1st, 2020.

Mobile Sensing

As part of the study, all 71 participants were asked to download and use the Beiwe smartphone application. The Beiwe Research Platform (Torous et al. 2016) provides digital phenotyping in the form of data collected from smartphone sensors and responses from Ecological Momentary Assessments (EMAs) that researchers can schedule and send via the app. Data collected by the app were periodically pushed to a secure server accessible by the reserachers to monitor participation and data collection.

Fitbit Inspire HR devices were distributed to the same 29 participants who received a BEVO Beacon. Participants were asked to create or use their existing accounts, which were linked to a Fitabase server to securely store and allow researchers to monitor the data collected. This particular model of Fitbit includes a heart rate monitor in addition to the standard accelerometer which helps to more accurately track the wearer's sleep.

Pre-Processing IEQ Data

The BEVO Beacon, once powered on, continuously monitors the environment. However, for this study we were only interested in data collecting during periods when participants were home and in their bedrooms. Fitbit logs sleep data, including the start and stop time, for any sleep event that the device detects lasting a minimum of 3 hours. We used the start and stop timestamps to restrict the IEQ data from BEVO Beacons to only these periods. However, we cannot guarantee that participants are sleeping in the same environment that the BEVO Beacon is monitoring. To correct for this, we cross referenced the data provided by the participants with GPS traces logged by the Beiwe app. By comparing the longitude and latitude values measured by Beiwe to those corresponding to the participants' location,

the IEQ data can be futher filtered so as to only include nights when the participants were asleep at their homes i.e. the same location the BEVO Beacon is monitoring.

Ventilation Estimates

Ventilation in the spaces can be estimated under two conditions: (1) a constant CO_2 concentration is reached for an extended period of time or (2) an uninterrupted decay of CO_2 concentrations corresponding to when participants leave their bedrooms. In either case, a single-zone mass balance is used to represent the space:

$$V\frac{dC}{dT} = pQC_0 - QC + E \tag{1}$$

Where V is the volume, p is the penetration factor for CO_2, Q is the flow rate into and out of the space, C_0 is the outdoor CO_2 concentration, C is the indoor CO_2 concentration, and E is the CO_2 emission rate. Considering the first case when CO_2 concentrations are constant, Eq. 1 simplifies as the rate terms goes to zero. After rearranging:

$$\lambda = \frac{E}{V(C - pC_0)} \tag{2}$$

Where λ is the air exchange rate defined as $\frac{Q}{V}$ and is the variable we are interested in determining.

The second condition is more complicated since the rate term in Eq. 1 is still included. The final equation for an inert gas, such as CO_2, is given by:

$$C_t = C_{t=0}e^{-\lambda t} + \left(pC_0 + \frac{E}{\lambda V}\right)\left(1 - e^{-\lambda t}\right) \tag{3}$$

However, we can further simplify Eq. 3 since we are estimating the ventilation without an occupant in the space and assuming CO_2 from other sources, like recirculation or other occupants, is negligible. Therefore, the emission term goes to zero and we can rearrange to get:

$$C_t = C_{t=0}e^{-\lambda t} + pC_0\left(1 - e^{-\lambda t}\right) \tag{4}$$

To solve Eq. 4 for λ we can employ an iterative solution where λ is systematically varied until we minimize the error between the measured CO_2 concentrations and the concentrations, C_t, calculated by Eq. 4. Under either scenario, we must use the CO_2 concentrations measured by the BEVO Beacon, calculate E for each participant, and make a few key assumptions about the remaining variables.

The CO_2 emission rate, E, was calculated adapting the model presented in Persily and Jonge (2017). The model requires knowledge of the participants body-mass-ratio (BMR), and the temperature and pressure in the space. The BMR is dependent on the age, sex, and weight of the individual, which we know from the enrollment surveys (age and sex) and Fitbit (weight). We can use the average temperature measured by the BEVO Beacon during either the constant CO_2 or decay periods and can assume the pressure is constant at sea level conditions.

For the remaining values, we assumed the following: p is equal to 1, C_0 is 400 ppm, and V is constant but varies depending on the type of housing the participant lives in. For participants in apartments, we used dimensions of 3 m X 3.4 m X 2.7 m (10' X 11' X 9') whereas for those living in stand-alone houses, we approximated the bedroom dimensions as 3.4 m X 3.6 m X 2.7 m (11' X 12' X 9'). Participants did not provide the layout of their bedrooms but did indicate their housing type in the EE survey.

RESULTS AND DISCUSSION

Of the 29 BEVO Beacons deployed, 26 were returned with usable data. The data completeness and summary of values are highlighted in the following sections.

Data Completeness

After downloading the raw data from all BEVO Beacon devices, data were first downsampled to five-minute averages since delays associated with connecting to individual sensors caused measurements to be made at inconsistent time intervals rather than at each minute. Data completeness can be viewed in two ways: (1) amount of data collected over the period during which individuals had their BEVO Beacon devices or (2) amount of data collected over the period when BEVO Beacons were powered on. We present the results for both in Table 1 separated by sensor. The first two columns consider data collected during all hours of the day. The percentage of data collected during the study period is heavily reliant upon the participants' willingness and ability to keep the device plugged in. A few participants also moved during the study, meaning data was unusable for the period after the participant moved since the environment they were in changed. However, Table 1 shows that the devices are quite reliable when powered on with the light sensor performing the worst with 17% data loss and the PM sensor performing the best with <2% data loss.

Considering all participants, there were a total of 1892 nights during the study period. Of these nights, 219 of them were when participants were home and asleep according to the GPS and Fitbit data. We include a third column in Table 1 highlighting the percentage of data collected by each sensor for these 219 nights. With the exception of the CO_2 and NO_2 sensor, the reliability of measurements increased when only considering the nights when participants were home and asleep with the largest improvement in the light sensor's reliability (+10%).

Table 1. Data Completeness by Sensor

	Percentage of Data Collected:		
	During study period	While device is operating	When participants are sleeping at home
Light	64.2	83.3	93.5
TVOC	73.7	95.6	98.7
CO_2	75.6	98.0	96.0
CO/T/RH	74.7	96.8	99.9
NO_2/T/RH*	67.0	91.4	85.3
PM_1	76.0	98.6	99.8
$PM_{2.5}$	75.9	98.5	99.8
PM_{10}	75.8	98.4	99.7
Total	73.2	95.3	97.0

* Only 15 of the 26 BEVO Beacons summarized in this table had this sensor – results for this sensor only include these 15 BEVO Beacons

Summary of Data Collected

A summary of the aggregate data collected by the BEVO Beacons during the evenings when participants were home and asleep is shown in Table 2. The light and CO levels were very low for much of the measured period which is understandable considering light levels are low during the evenings and gas stoves, the primary source of household CO, would typically not be in operation during these hours. PM of all sizes are also within safe bounds for the majority of the dataset – 75th percentile values lower than EPA's ambient air quality standard for $PM_{2.5}$/PM_{10}. However, the maximum values of PM measured are concerning, especially when considering that the PM_1 and $PM_{2.5}$ maximmum concentrations were greater than 70 μg/m³ at least for a brief moment. However, these values are not unheard of as PM1/PM2.5 concentrations can easily exceed the maximums measured here if occupants are burning candles/incense (Lee and Wang 2006) or cooking (see Torkmahalleh et al. 2017 and references within). Of the variables measured, the NO_2 concentrations are uncharacteristically high. Research measuring NO_2 in urban homes found median values of 6 ppb in the cleanest environment and 24 ppb in a more polluted urban location (Algar et al., 2004). In research comparing homes with and without gas stoves, researchers found a geometric mean concentration of 16.2 μg/m³ (~9 ppb) across all homes measured (Franklin et al., 2006). The errors in our NO_2 concentrations are due, in part, to the ±15% accuracy and resolution of 20 ppb which are characteristic of the sensors used. However, the primary cause is due to poor pre-

calibration of the sensors. The sensors require constant power to operate effectively and if powered off for periods of greater than a day, need to be re-calibrated in a clean environment. Facility restrictions during the spring of 2020 due to SARS-CoV-2 pandemic limited our ability to calibrate this sensor effectively. The remaining sensors operated as expected with a few exceptions for certain BEVO Beacons including low CO_2 measurements on occasion and higher than expected temperature readings. The latter can be attributed to heat from the RPi processor which seems to increase the NO_2 and CO sensors' temperature measurements by 0.5°C to 1°C.

Table 2. Summary of Data from All BEVO Beacons During the Evenings

	n*	mean	median	minimum	25%	75%	maximum	skewness	kurtosis
Light (lux)	12737	2.59	0.00	0.00	0.00	1.36	74.91	4.26	22.71
T (°F/°C)	13389	26.66	27.00	18.65	25.00	28.00	31.72	-0.31	-0.29
RH (%)	13597	43.29	42.50	30.80	40.00	46.00	62.93	0.54	0.52
TVOC (ppb)	13449	271.40	243.72	0.00	184.36	338.56	1393.20	1.72	6.56
CO_2 (ppm)	12954	951.11	890.41	400.2	746.28	1158.08	2281.53	0.70	0.58
CO (ppm)	13606	0.85	0.00	0.00	0.00	0.39	13.09	2.26	4.22
NO_2 (ppb)	8186	112.52	75.20	0.00	66.44	111.84	646.48	3.58	12.94
PM_1 ($\mu g/m^3$)	13599	2.72	2.39	0.00	1.61	3.32	72.54	9.31	142.62
$PM_{2.5}$ ($\mu g/m^3$)	13594	6.94	6.83	0.00	5.38	8.75	81.76	3.83	41.44
PM_{10} ($\mu g/m^3$)	13588	10.82	10.90	0.00	8.84	13.75	92.66	1.88	16.82

* n refers to the number of 5-minute measurements made during the evenings when participants were home and asleep across all devices/participants

To see how sensitive each variable measured on the BEVO Beacon is to the others, we created a correlation matrix in Figure 2 considering only the values measured when participants were asleep and at home. For the most part, the measured variables seem to be very weakly correlated if not independent from one another with the exception of the PM measurements. Typically, if the concentration of a larger-sized particulate matter concentration is high, the subsequent PM size concentrations will also be high which can be seen by the 0.99 correlation between PM_{10} and $PM_{2.5}$ measurements and the 0.93 correlation between $PM_{2.5}$ and PM_1 readings.
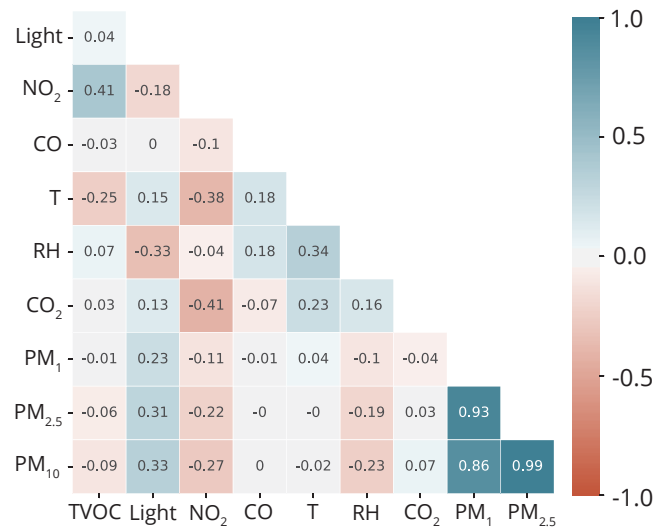

Figure 2 Correlation matrix between the measured variables on the BEVO Beacon where negative/red values indicate an inverse correlation and positive/blue values indicate a direct correlation.

Ventilation Rates

In this section, we present the ventilation rates estimated from Eqs. 2 and 4. If the CO_2 concentration at any point in the evening fell below 600 ppm, these nights were removed since either the sensor was operating poorly, or the participant was not sleeping in the same room as the BEVO Beacon.

Rates Based on Constant CO_2. To apply Eq. 2, we first identified periods of approximately constant CO_2 concentration by looking for differences between consecutive measurements that were within ±10 ppm over a period of at least an hour. We also ensured that the change in consecutive temperature measurements over these periods was less than or equal to zero which served as a proxy for HVAC operation i.e. if the temperature was not increasing, we assumed the HVAC was operating. The average temperature over such a period was also used as input, amongst other constant variables like BMR, to determine E for each individual/beacon pair for each night. Using this estimate for E, the average CO_2 concentration from the corresponding period, and assumed values for p, C_0, and V we estimated values for λ denoted as burnt orange circles in Figure 3.

Rates Based on CO_2 Decay. The decay method we employed required that the room be unoccupied. Therefore rather than using IEQ measurements during the evening when participants would have been in the room asleep, we used CO_2 measurements for a period of 3 hours after Fitbit reported the participant woke up. If the CO_2 concentration decreased consistently over a period of at least 1 hour during this 3-hour window, we would apply Eq. 4 iteratively to find the λ value the minimized the error between the measured and estimated CO_2 concentrations. We did not have to estimate E nor V for this method and assumed the same values for p and C_0. The resulting ventilation rates are shown as navy diamonds in Figure 3.
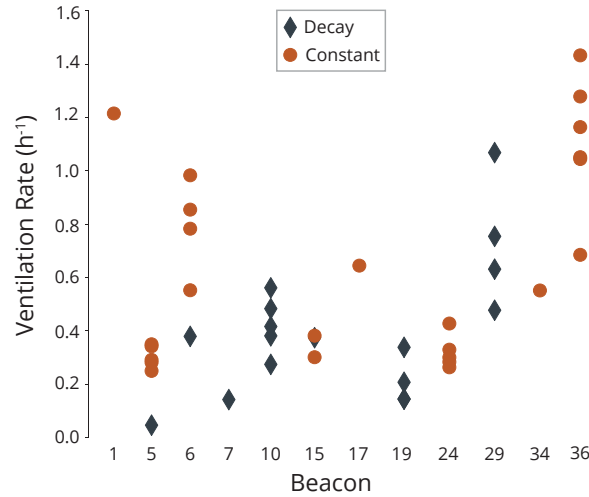
Figure 3   Estimated ventilation rates using the constant and decay methods for CO_2 (Eqs. 2 and 4, respectively).

Discussion of Ventilation Estimates. Ventilation rates are only estimated for 42 out of the 219 possible nights using data from 12 beacons. The remaining nights and beacons did not contain periods of at least an hour with constant or consistently decaying CO_2 measurements. Of the 12 BEVO Beacons highlighted in Figure 3, devices 5, 6, and 15 produced results from using both ventilation estimation methods while the remaining only had results from using one of the two methods.

The ventilation rates estimated from either method are within typical bounds and no estimates were removed or flagged as outliers in this analysis. A recent review paper on bedroom ventilation found that a majority of the measured ventilation rates in bedroom microenvironments were between $0.2 - 0.7$ h^{-1} (see Sekhar et al., 2020 and references

within), which fall within ASHRAE 62.2 minimum ventilation requirements.

We cannot be certain if either method is under- or over-predicting the ventilation rates since of the three devices that have results from both methods, the majority are estimated from the constant CO_2 method and only one datapoint comes from the decay method. The range of ventilation rates measured by the constant method ($0.25 - 1.43$ h^{-1}) is higher than those measured by the decay method ($0.05 - 1.07$ h^{-1}), but this could be a consequence of the environments measured and not the methods.

The assumptions made in both of these methods deserve some scrutiny as changes to V and C_0 could significantly alter the results in Figure 3. While the assumption of V is rather safe, the value of C_0 could be low given the environment. Many of our participants lived in shared housing units in an urban environment so the background CO_2 concentration could be higher than what is typically assumed simply because the home contains more sources of CO_2. Based on the measured CO_2 concentrations in each of the rooms, it is unlikely that any of the participants featured here shared their bedroom microenvironment with another person except for the owner of BEVO Beacon 7. This participant indicated they did share their space with another person, which was taken into account in the calculation of the one ventilation rate from this device shown in Figure 3. When comparing measurments from BEVO Beacon 7 to the other devices, the concentrations are consistently between 100 ppm – 400 ppm higher which supports the assumption that the other bedroom microenvironments contain only single occupants. Finally, further sensitivity analysis on the V, C_0, and E parameters is warranted, but is beyond the scope of this report.

CONCLUSION

Data collected from this study highlight the concentrations of a few key indoor air pollutants and other environmental parameters from 26 unique bedroom microenvironments across Texas from early June to the end of August. In addition, ventilation rates were estimated using both a constant and decay method for CO_2 based upon a static and dynamic single-zone mass balance, respectively, of the bedroom space. Data were collected by devices built in-house using affordable, commercially available sensors provided to participants to measure their bedroom microenvironments. We hope to improve the capabilities of these devices by updating the software to read from sensors more consistently and apply machine learning methods to refine the sensors' outputs. The work here serves as a preliminary analysis of a rich dataset that could be used to explore relationships across multiple data modalities such as how the sleep quality measured from Fitbit varies according to a few or many aspects of IEQ measured by the BEVO Beacons.

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