Indoor Environmental Quality and its Effects on Human Sleep Quality

Hagen Fritz Kerry Kinney, PhD David Schnyer, PhD

Student Member ASHRAE

Zoltan Nagy, PhD

Associate Member ASHRAE

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

Achieving an adequate amount of good-quality sleep is essential for human health and well-being, including physiological processes, emotion regulation, physical development, quality of life \cite{hirshkowitz2015national}, and improving next-day performance (Gomes et al., 2011; Pereira et al., 2015). Lack of and disturbed sleep have been linked to negative health outcomes including obesity (Beccuti and Pannain, 2011), cardiovascular-related diseases (Cappuccio and Miller, 2017), and reduced life expectancy (Cappuccio et al., 2010). Achieving and maintaining sleep is a complex process that involves a variety of neurotransmitters and other signaling chemicals in conjunction with multiple organs in the human body. The primary internal influences affecting sleep include physical ailments like head and body aches in addition to a person's mental state such as feeling stressed, anxious, or depressed (Tsuno et al. 2005; Uhde et al., 2009). Primary environmental factors that tend to affect sleep include light, noise, and thermal comfort. Light's negative effect on sleep is a well-known phenomenon (Cho et al., 2013) as is the effect noises - soft, loud, constant, and intermittent - have on sleep (Hume et al., 2012). The relationship between thermal comfort and sleep also garners a considerable amount of attention including topics such as bedding insulation (Amrit, 2007), the relative humidity and temperature of the air (Lan et al., 2017), and a person’s internal body temperature (Kubota et al., 2002).

A potential external factor affecting sleep that has garnered some attention recently is indoor air quality (IAQ). Proper IAQ is paramount to the health of building occupants especially when considering people in developed nations spend, on average, nearly 90% of their time indoors (Klepeis et al., 1995). Indoor air is comprised of a mixture of pollutants generated indoors from a variety of processes and those from outdoor environments that penetrate indoors via infiltration, natural ventilation, and/or mechanical infiltration. Pollutant profiles in the indoor environment can be quite different than those outside because of unique indoor sources and the amount of ventilation with outdoor air that is provided. In general, poor IAQ can exacerbate or induce many illnesses relating to the respiratory (Lévesque et al., 2018) and cardiovascular systems (Chuang et al., 2017) in addition to negatively affecting occupants' moods (Hummelgaard et al., 2007), and productivity (Mujan et al., 2019).

The connection between IAQ and sleep is of interest because while asleep, a person is in a fragile state for an extended period. Under the current recommendation of 7 to 9 hours of sleep per night for adults, nearly one-third of a person's life is spent in their bedroom environment. Therefore, both acute exposures to air pollutants each night and the cumulative effects of these exposures are concerning. Recent studies have focused on characterizing the bedroom's IAQ by looking at chemicals and compounds emitted from bedding materials (Boor et al., 2017), the IAQ near the sleeping individual (Licina et al., 2017), and the concentration of pollutants in the bulk air (Zhang et al., 2018). These studies acknowledge the need for research that links the bedroom's environmental quality to the occupants' sleep qualities, but only a handful of studies have attempted to address this issue (Laverge and Arnold, 2011; Strom et al., 2016; Canha et al., 2017; Mishra et al., 2018; Liao et al., 2019). Many common pollutants associated with the indoor and outdoor environment can inflame airways affecting respiration while sleeping leading to the development or increase in severity of breathing-related sleep disorders. Additionaly, some pollutants can alter the development and/or structure of the brain (Lucchini et al., 2012; Costa et al., 2019) which might alter sleep architecture and quality.

There are two methods by which researchers can understand a subject's sleep quality: (1) through self-report measures like diaries or questionnaires administered before and/or after sleep, or (2) by using devices to derive key metrics of the subject's sleep. The gold standard for measuring sleep quality is through the use of polysomnography (PSG) which gives detailed information about a person's neurophysiological and cardio-respiratory state while sleeping. This information can be used to determine wake-fullness, rapid-eye-movement (REM) stages, and various non-REM stages. While PSG provides the most accurate measures of sleep quality, the method involves bulky machinery that may disrupt participants’ sleep, requires training to interpret the results, and is costly to conduct. To combat these issues, some companies have developed affordable wearable devices capable of measuring sleep quality. Recent products couple heart rate monitoring with movement detection to help estimate a few key sleep stages. These devices can provide useful insight into a subject's overall sleep quality and gross sleep quality parameters (Haghayegh et al., 2019). In a similar fashion, rapid development of affordable IAQ sensing technologies has made measuring indoor environmental quality (IEQ) easier than ever before, sparking interest in measuring conditions within the bedroom microenvironment. Recent studies highlight that new, commercially available IEQ sensors can be distributed at scale (Bekö et al., 2010; Cheng and Li, 2018). These sensors are also useful when measuring conditions over extended periods of time as they require less power to operate and less maintenance than higher-grade instruments.

In this paper, we leverage commercially available sensing technologies to measure both IAQ and sleep quality to understand the relationship between these fields amongst college-aged students living in Austin, TX. We start by describing the IEQ monitor that combines many of these low-cost sensors into an all-in-one device. We continue by describing the study where these devices along with wearable fitness trackers are distributed to participants who are also asked to rate their own sleep. Data from this study is presented after and used to probe the question of IAQ's affect on both measured and self-report sleep quality. Our research is novel in that we are measuring multiple components of the study population to help account for any confounding factors that might compromise the effects of IAQ on various sleep metrics measured by unobtrusive sleep-monitoring devices and ecological momentary assessments (EMAs).

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. Student participants were recruited across all discplines from the University of Texas at Austin (UT) and underwent an initial screening before being consented into the study. 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. Following enrollment, various devices were shipped to subsets of participants with instructions provided on how to set up and/or use them. Participants were instructed to go about their normal behaviors as devices passively collected data or participants were notified of a survey to complete. The study concluded when participants scheduled an exit interview with a study coordinator in early September 2020 and returned study materials back to UT.

Environmental Quality Monitoring

A one-time questionnaire called the Environment and Experiences (EE) survey was administered to participants to get an initisal impression of their indoor environment. The survey asked questions regarding pollutant exposures at home (smoking/vaping practices, pets, floor type, etc.) and cleaning habits (portable air cleaner use, disinfecting practices, etc.), to name a few. To monitor the IEQ of the participants’ bedrooms during the study period, we developed, calibrated, and deployed our own open source, research-oriented monitoring device called the Building EnVironment and Occupancy (BEVO) Beacon. We distributed 30 of these devices to a subset of the original 71 participants. The BEVO Beacon, pictured in Figure 1, includes a single-board micro-computer wired to six affordable, commercially available sensors; one 250 mm X 250 mm (1” X 1”) cooling fan; and a battery-powered clock which keeps time if the device is not connected to the internet. The micro-computer is housed in a separate chamber from the sensors where a fan provides cooling to the processing unit. The six IEQ sensors are either exposed directly to the ambient 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 (CO2), particulate matter with aerodynamic diameters less than 2.5 (PM2.5) and 10 (PM10) micrometers, total volatile organic compounds (TVOCs), nitrogen dioxide (NO2), 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 micro-computer but can be accessed remotely as long as the device is connected to WiFi.

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**Figure 1** The BEVO Beacon and its six main IEQ sensors.

The BEVO Beacons were shipped to participants on a rolling basis beginning June 1st, 2020 with the first device reaching its destination on June 3rd. After receiving the device, participants were asked to power-on the devices immediately. The BEVO Beacons were returned on a rolling basis starting September 1st, 2020.

Sleep Monitoring

As part of the study, all 71 participants were asked to download and use a smartphone application. The application is an open research platform (Torous et al. 2016) that provides digital phenotyping in the form of data collected from smartphone sensors and responses from Ecological Momentary Assessments (EMAs). EMAs were sent to participants four times a week, twice a day: once in the morning at 9:00 am and again in the evening at 7:00 pm. Both EMAs asked participants to rate various components of their mood on a four-point scale. The morning EMAs also included four questions to help determine self-report sleep metrics, asking participants to estimate their total sleep time (TST), sleep onset latency (SOL), number of awakenings (NAW), and restfulness on a four-point scale (0 – not very restful; 3 – very restful).

Commerical fitness tracking devices were distributed to the same 30 participants who received a BEVO Beacon. Participants were asked to create or use their existing accounts, which were linked to a secure server to store and give researchers the ability to monitor data collection. This particular fitness tracker included a heart rate monitor in addition to the standard accelerometer which helps to more accurately track sleep. Measurements obtained from the fitness tracker were used directly in addition to a few metrics that were derived from the sleep stage estimates given by the fitness tracker.

Pre-Processing IEQ Data

Upon receiving the devices, 3 sensors onboard each of the 30 BEVO Beacons were calibrated jointly in a mock house environment against laboratory grade monitors including the CO2, NO2, and PM (of all sizes). From the calibration, a linear model was fit to help correct measurements from these three sensors.

The BEVO Beacon, once powered, continuously monitors the environment. However, for this study we were only interested in data collected during periods when participants were home and in their bedrooms. The fitness trackers log sleep data, including the start and stop time, for any sleep event that the devices detect 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, the fitness tracker is worn around the wrist and travels with the participant whereas the BEVO Beacon remains stationary in the participants’ bedrooms. Therefore, there could be instances where the participants sleep in an environment other than the one the BEVO Beacon is monitoring. To correct for this, we cross referenced the addresses provided by the participants with GPS traces logged by the open research platform’s app. We were then able to further filter the IEQ dataset so as to only include nights when the participants were asleep at their homes i.e. the same location the BEVO Beacon was monitoring.

Results

IEQ and Device-Monitored Sleep Quality

By filtering the IEQ dataset to only include nights with device-monitored sleep and GPS traces to confirm that participants were home, we have a total of 278 nights of IEQ and sleep quality measurements across 15 unique participants. We lost a significant amount of data because participants might not have logged data from one of the three modalities (GPS from phone app, IEQ from BEVO Beacon, or sleep measurements from wearable) meaning the data logged on the other modalities could not be included in analysis. Figure 2 shows the number of nights measured by each of the BEVO Beacons in addition to which sensors collected data for each of those nights.



**Figure 2** Number of nights of measurements for each of the 15 BEVO Beacons after filtering for device-monitored sleep events and GPS traces confirming participants and BEVO Beacons are co-located.

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 |
| CO2 | 75.6 | 98.0 | 96.0 |
| CO/T/RH | 74.7 | 96.8 | 99.9 |
| NO2/T/RH\* | 67.0 | 91.4 | 85.3 |
| PM1 | 76.0 | 98.6 | 99.8 |
| PM2.5 | 75.9 | 98.5 | 99.8 |
| PM10 | 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

IEQ and Self-Report Sleep Quality

Since EMAs were only administed four times a week and incur a larger burden on the participants relative to the wearable which participants only have to remember to wear, we have fewer observations when participants are home, asleep, and completed the EMA the following morning. Data availability is shown for the 192 nights across 16 participants in Figure X. One more participant is present in this dataset compared to the device-monitored dataset because one of the devices was using an older operating system which invalidated the sleep metrics, but the device was still able to detect the start and stop times of the sleep event accurately.



**Figure X** Number of nights of measurements for each of the 15 BEVO Beacons after filtering for device-monitored sleep events, GPS traces confirming participants and BEVO Beacons are co-located, and EMAs completed upon waking.

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 PM2.5/PM10. However, the maximum values of PM measured are concerning, especially when considering that the PM1 and PM2.5 maximmum concentrations were greater than 70 g/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 NO2 concentrations are uncharacteristically high. Research measuring NO2 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 g/m3 (~9 ppb) across all homes measured (Franklin et al., 2006). The errors in our NO2 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 CO2 measurements on occasion and higher than expected temperature readings. The latter can be attributed to heat from the micro-computer processor which seems to increase the NO2 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 |
| CO2 (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 |
| NO2 (ppb) | 8186 | 112.52 | 75.20 | 0.00 | 66.44 | 111.84 | 646.48 | 3.58 | 12.94 |
| PM1 () | 13599 | 2.72 | 2.39 | 0.00 | 1.61 | 3.32 | 72.54 | 9.31 | 142.62 |
| PM2.5() | 13594 | 6.94 | 6.83 | 0.00 | 5.38 | 8.75 | 81.76 | 3.83 | 41.44 |
| PM10 () | 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 PM10 and PM2.5 measurements and the 0.93 correlation between PM2.5 and PM1 readings.

Discussion

Effect of IAQ on Sleep Quality

Device-Monitored versus Self-Report Sleep Measurements

Conclusion

Acknowledgement

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