

Indoor Environmental Quality and its Effects on Human Sleep Quality

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ABSTRACT

Sleep is essential for multiple aspects of a person's well-being and can be affected by a person's physical and mental state in addition to the environment they sleep in. To date, the majority of research analyzing the relationship between a person's sleep quality and indoor environment has focused on environmental parameters such as temperature, relative humidity, light, and noise. However, in recent years, a few key studies have identified indoor air quality (IAQ) as a potential contributor to sleep quality. The recent interest in IAQ's effect on sleep quality has been sparked by the introduction of multiple affordable sensing technologies in both the IAQ and sleep quality fields. In this study, we combine five, commercially available IAQ sensors into one device that we provided to participants to measure their IAQ in addition to temperature, relative humidity, and light. Participants were provided with wearable sleep monitoring devices and were also asked to fill out four-question surveys in the morning to get a sense of two types of sleep quality: device-monitored and self-reported. We found that certain pollutants such as NO₂, CO, and PM_{2.5} altered device-monitored sleep metrics like sleep efficiency when comparing nights with low versus high pollutant concentrations. When considering self-reported sleep metrics, we found that participants rated their sleep as more restful when CO₂ concentrations were low, but we did not see this relationship with any other measured pollutant. Results from our study indicate that there is merit in measuring both device-monitored and self-report sleep quality as a function of exposure to multiple indoor air pollutants in the sleeping environment.

INTRODUCTION

Achieving an adequate amount of good-quality sleep is essential for human health and well-being as it affects physiological processes, emotion regulation, physical development, and quality of life (Hirshkowitz et al., 2015), and improves 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 known 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 that noises - soft, loud, constant, and intermittent - have on sleep (Hume et al., 2012). The relationship between thermal comfort and sleep has also garnered a considerable amount of attention with studies investigating bedding insulation (Amrit, 2007), the relative humidity

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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 only recently received attention 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, 87% of their time indoors (Klepeis et al., 1995). Indoor air contains a mixture of pollutants generated indoors from a variety of processes as well as pollutants 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 outdoor air ventilation that is provided. In general, poor IAQ can exacerbate or induce a variety of 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).

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 a 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 examining 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 occupant's sleep quality, but only a handful of studies have attempted to address this issue (Laverge and Arnold, 2011; Strom et al., 2016; Mishra et al., 2018; Liao et al., 2019; Xiong et al. 2020). Many common pollutants associated with the indoor and outdoor environment can inflame airways affecting respiration while sleeping leading to the development or worsening of breathing-related sleep disorders. In addition, 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 measure 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, various companies have developed affordable wearable devices capable of measuring sleep quality. Newer 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 and gross sleep quality parameters (Haghighy et al., 2019). In a similar fashion, rapid development of affordable 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) and can be useful when measuring conditions over extended periods of time as they require less power and maintenance to operate than higher-grade instruments.

In this paper, we leverage commercially available sensing technologies to measure both IEQ 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 were distributed to participants who were asked to rate their own sleep. Data from this study is presented and used to probe the question of IAQ's effect on measured and self-report sleep quality. Our research is novel in that we are measuring multiple components of IAQ and employing two methods of sleep quality monitoring to understand the effects of IAQ on sleep quality.

METHODOLOGY

This research project was a subset of a larger study aimed at understanding student behaviors and environmental

exposures throughout the course of their day using numerous affordable and mobile sensing technologies. Student participants were recruited across all disciplines 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 surveys 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 was administered to participants to get an initial impression of their indoor environment such as 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 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 (PM_{2.5}) 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.

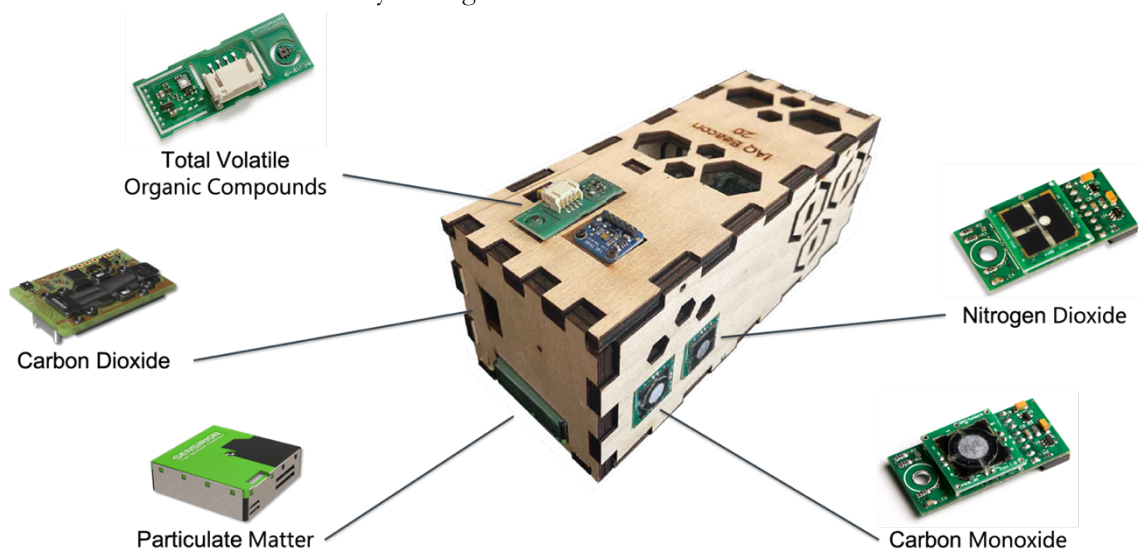


Figure 1 Our all-in-one IEQ-monitoring device, the BEVO Beacon, and its five main IAQ sensors. Temperature and relative humidity are measured by the Carbon Monoxide and Nitrogen Dioxide sensors.

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 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).

Commercial 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. 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 derived from the sleep stage estimates produced by the fitness tracker. The primary sleep metrics include sleep efficiency (SE) defined as the percentage of time asleep when in bed and the ratio of REM stage sleep to all other stages i.e., non-REM (nREM).

Pre-Processing IEQ Data

When BEVO Beacons were returned, 3 sensors onboard each of the devices were calibrated jointly in a 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.

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 lasting longer than 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 fixed in participants' bedrooms. There could be instances where 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 from the participants' phones logged by the open research platform. We were then able to further filter the IEQ dataset 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, the dataset consists of a total of 278 nights of IEQ and sleep quality measurements across 15 unique participants. A significant amount of data was lost 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), invalidating the remaining data from other modalities. 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.

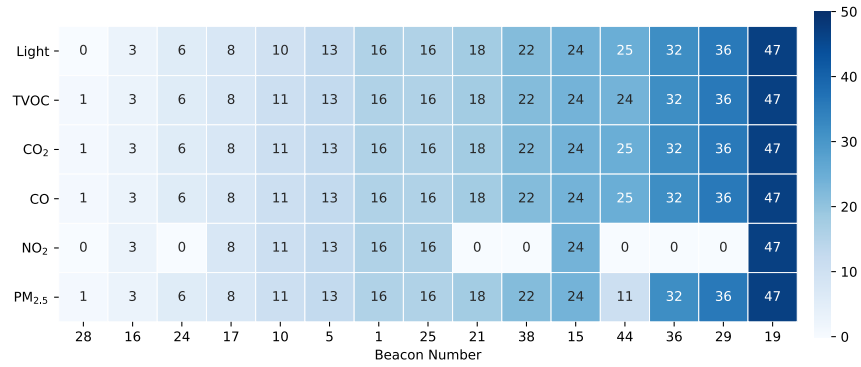


Figure 2 Number of nights of measurements for each of the 15 BEVO Beacons after filtering for device-monitored sleep events and GPS traces confirming participants and BEVO Beacons are co-located.

Examining the data on an aggregate basis, we can determine if the distributions of device-monitored sleep metrics differ for nights when a measured parameter is low or high based on established or assumed thresholds given in Table 1. We determine if the measurement for a certain parameter is low or high depending on the median value measured during an individual's sleep event. Figures 3 and 4 show the distributions of sleep efficiency and REM:nREM ratios, respectively, for each of the pollutants measured by the BEVO Beacon in addition to temperature. Numbers above each of the violin plots indicate the p-value from a t-test of means between the distributions. Values less than or equal to 0.05 are highlighted.

Table 1. Pollutant Thresholds for Determining Low/High Pollutant Levels

	Threshold	Organization	Notes	Citation
Temperature	27°C /80.6°F		Median nightly concentration from study	
TVOC	200 ppb	WHO	Twice the sensory irritation limit	WHO, 2010
CO ₂	1100 ppm	ASHRAE	Based on standard 62.2	ASHRAE, 2019
CO	4 ppm	WHO	Based on minimum 24-hour exposure limit	WHO, 2010
NO ₂	25 ppb	EPA and WHO	Half the EPA NAAQS (to account for indoors) and WHO 1-hour exposure limit	US EPA, 2010; WHO, 2010
PM _{2.5}	1.5 µg/m ³		Median nightly concentration from study	

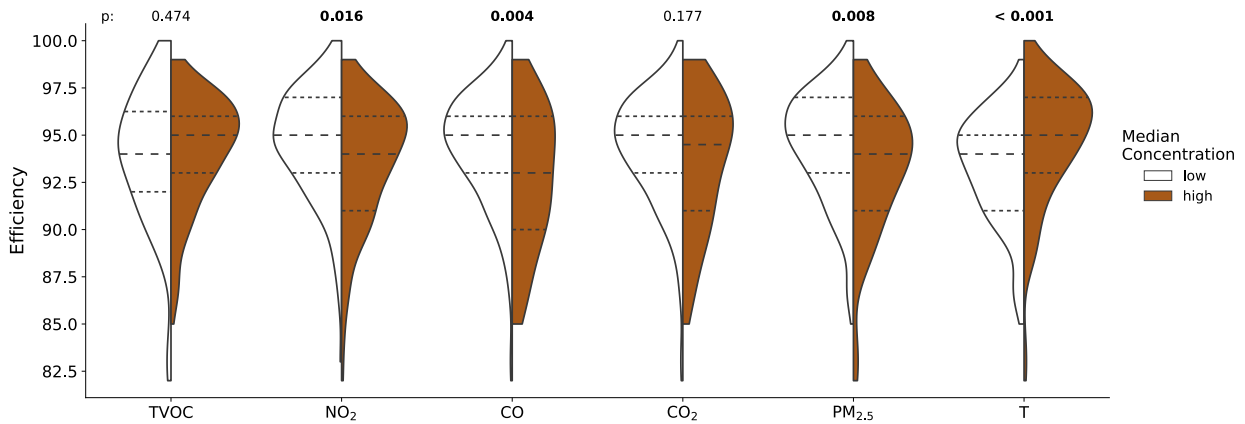


Figure 3 Distributions of SE for nights when IEQ parameters are below or above thresholds in Table 1. Values above the violin plots indicate p-values from a t-test on the difference of means between the two distributions.

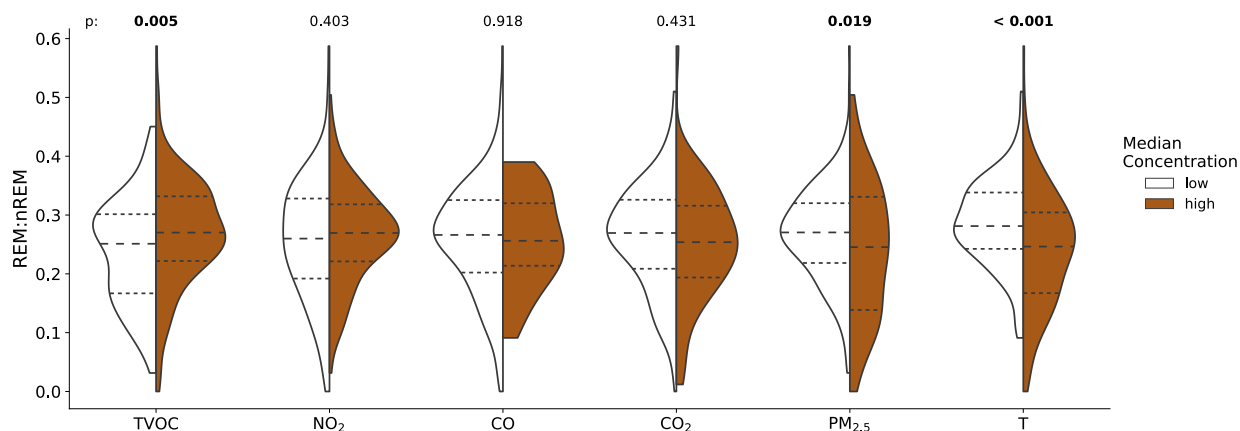


Figure 4 Distributions of REM:nREM for nights when IEQ parameters are below or above thresholds in Table 1. Values above the violin plots indicate p-values from a t-test on the difference of means between the two distributions.

IEQ and Self-Report Sleep Quality

Since EMAs were only administered four times a week and incur a larger burden on the participants relative to a wearable device, there are 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 5.

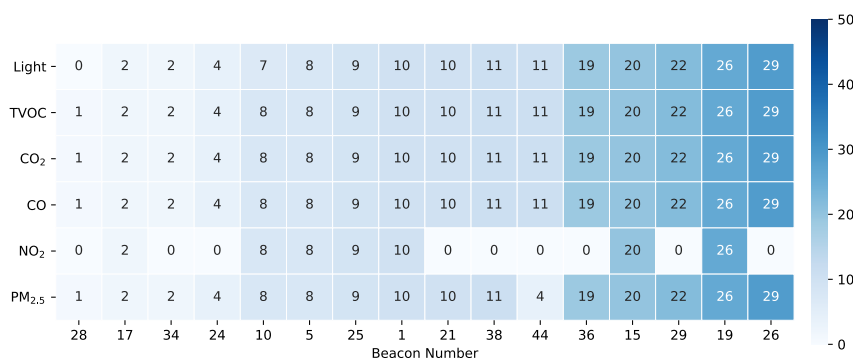


Figure 5 Number of nights of measurements for each of the 15 BEVO Beacons after filtering for GPS traces to confirm participants and BEVO Beacons are co-located and EMAs were completed upon waking.

For the self-reported sleep metrics, we focus on two of the possible four: SOL, or the amount of time participants reported it took them to fall asleep, and self-reported restfulness on a 4-point scale. Following a similar analysis to that conducted for device-monitored sleep metrics, Figure 6 highlights any significant differences in the distributions of self-reported SOL for nights when concentrations of the measured IEQ parameters were low or high.

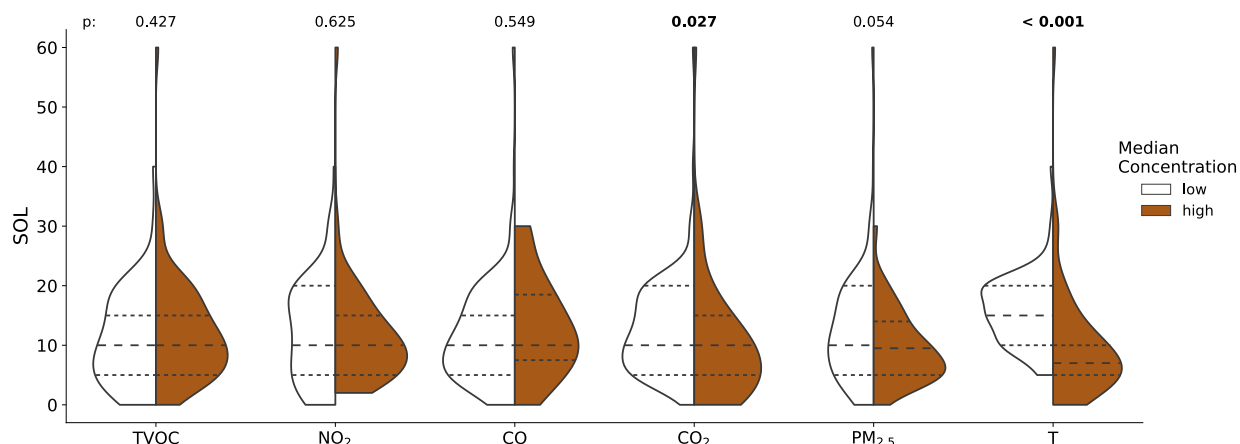


Figure 6 Distributions of self-reported SOL ratios for nights when the given IEQ parameter value is below or above the thresholds given in Table 1. P-values from a t-test on the difference of means between the two distributions are given above the corresponding IEQ parameter.

Rather than look at restfulness on a four-point scale, we combine scores of 0 and 1 into a “negative” rating while 2 and 3 constitute “positive” ratings. Figure 7 shows how the measurements of the IEQ parameters from the BEVO Beacon differ for the nights participants rate their restfulness as either negative or positive.

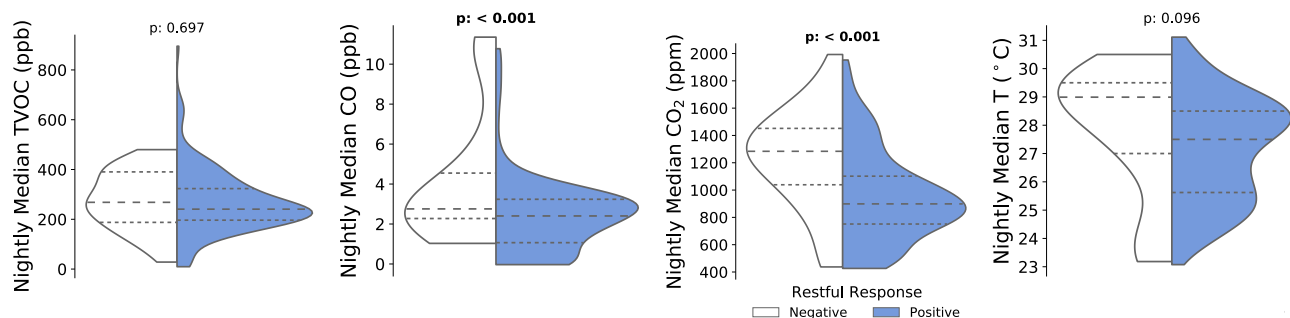


Figure 7 Distributions of median pollutant and temperature measurements for nights when participants rate their restfulness as either negative (0 and 1) or positive (2 and 3) on the morning EMA when they awoken. Only results where t-statistics on the means could be calculated between the distributions are included with p-values given above each violin plot.

DISCUSSION

Effect of IEQ on Sleep Quality

Device-Monitored Sleep. When considering device-monitored sleep metrics, there appears to be a significant decrease in SE, according to the data in Figure 3, when concentrations of NO₂, CO, and PM_{2.5} are elevated. There are no studies that explicitly study indoor NO₂ or CO and device-monitored sleep quality, but PM_{2.5} has been studied and shown to negatively affect sleep efficiency according to PSG (Liao, 2019), confirming the results observed in the current study. However, we also observed a significant increase in sleep efficiency at elevated temperatures which contrasts with the expected trend and the results reported in a similar study by Xiong et al., 2020 that measured bedroom air temperatures similar to those measured in this stud.

Based on the results presented in Figure 4, TVOCs seem to increase the relative percentage of time spent in REM

sleep compared to non-REM sleep. TVOCs represent a complex and often unknown mixture of compounds so understanding the relationship between TVOCs on sleep quality is more nuanced, however recent studies indicate TVOCs do not produce significant changes in sleep quality when compared to PSG (Liao, 2019). Although some studies have hypothesized that NO₂ could disrupt normal sleep architecture by interfering with neurotransmitters in the brain, the results here show no significant differences in the ratio of REM:nREM for low and high concentration nights. We do see that PM_{2.5} concentrations tend to reduce the ratio of REM:nREM sleep suggesting that perhaps PM_{2.5} is altering sleep architecture by either increasing severity of breathing-related sleep disorders or those associated with signaling in the brain. Important to note is that CO₂ shows no significant differences in SE or REM:nREM ratios under low and high conditions which contradicts many of the results found in similar studies (Strom et al., 2016; Mishra et al., 2018; Xiong 2020) that use devices to monitor sleep quality. CO₂ tends to be a good proxy for ventilation so we would expect some significant differences in sleep metrics especially considering other pollutants in our study exhibited significant differences between sleep metrics at low and high concentrations. Lastly, elevated nightly temperatures indicate a significant decrease in the time spent in REM, which was recently corroborated (Xiong, 2020).

Self-Reported Sleep. Measurements of SOL proved to be lower for nights with elevated measurements of CO₂, PM_{2.5}, and temperature according to the data presented in Figure 6. This relationship suggests that people are able to fall asleep quicker when the concentrations of CO₂ are elevated which is a possibility considering increased CO₂ concentrations are known to cause subjective and objective indicators of drowsiness (Snow et al., 2018). Like CO₂, PM has been implicated in causing fatigue in multiple studies of indoor environments, most notably offices (Nezis et al., 2019). While cooler temperatures might promote more efficient sleep, warming prior to bed has been shown to decrease SOL in young adults free of known sleep conditions (Raymann et al., 2007).

The effect of CO₂ on sleep quality is significant when considering the restfulness scores from the EMAs. Figure 7 highlights that for nights when participants rate their restfulness as poor, the median CO₂ concentration for that night is significantly higher than when they rate their sleep more restful. The same relationship is apparent when considering the CO distributions although the difference in the shape of the distributions is not nearly as dramatic as those for the CO₂ results. Strom et al. (2016) reported significant improvements in participants' restfulness score when the CO₂ concentrations were lower, while Mishra et al. (2018) found that increased concentrations of CO₂ reduced the self-report depth of sleep but had no correlation to self-reported restfulness. Xiong et al. (2020) report no correlation between any self-reported sleep metric and CO₂. As for the temperature and TVOC levels measured in the current study, there was not significant difference between the distributions during negative and positive restfulness nights. For the remaining two pollutants, t-statistics could not be calculated and are not shown.

CONCLUSION

In this study, we highlighted the importance of a properly controlled indoor environment as it relates to sleep quality. Many common indoor air pollutants like CO₂ and particulate matter, which have been hypothesized to affect sleep through direct or indirect means, have been shown here to alter both device-monitored and self-reported sleep amongst a healthy, young adult population sleeping in their normal environment free from bulky monitoring equipment that might bias results. We also show that other, less-studied pollutants, like NO₂ and CO might have equally important consequences on sleep quality. There also appears to be differences in IAQ's effect on sleep quality when considering the type of sleep quality measurement (i.e., device-monitored or self-report) indicating that studies should be conducted to analyze both measurements of sleep quality. We plan to continue to probe the relationship between indoor air pollution and sleep quality by monitoring different groups of individuals with more robust instrumentation to assess whether an individuals' sleep qualities are more or less susceptible to indoor air pollution.

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