Building and Environment 214 (2022) 108835

Contents lists available at ScienceDirect

Building and Environment

journal homepage: www.elsevier.com/locate/buildenv

Data fusion of mobile and environmental sensing devices to understand the effect of the indoor environment on measured and self-reported sleep quality

Hagen Fritz [a], Kerry A. Kinney [a], Congyu Wu [b], David M. Schnyer [b], Zoltan Nagy [a,*]

[a] Department of Civil, Architectural and Environmental Engineering, University of Texas at Austin, Austin, TX 78712, United States of America
[b] Department of Psychology, University of Texas at Austin, Austin, TX 78712, United States of America

ARTICLE INFO

Keywords:
Air quality
Exposure
Field study
Low-cost sensors
Wearables

ABSTRACT

The Indoor Air Quality (IAQ) of the bedroom environment has recently garnered attention since air pollution can affect sleep. Previous studies investigated IAQ and sleep quality in controlled environments which impacts both self-reported and measured sleep quality. Studies within a participant's home environment are ecologically valid and reduce participant bias. Here, we study 20 participants over 77 days in Austin, TX. We monitored five components of IAQ using the BEVO Beacon, a calibrated purpose-built environmental monitor, and measured participant sleep quality through wearable activity trackers and 4-question surveys sent four times a week. We found significant decreases in sleep quality during nights with elevated CO, CO_2, and temperature. Elevated CO was associated with a mean increase in 0.9 self-reported awakenings and decreases in device-measured sleep time of 21.6 min and sleep efficiency of 0.6%. Increased CO_2 and temperature were associated with decreases in device-measured sleep time of 17.5 and 15.2 min, respectively. Elevated $PM_{2.5}$ and TVOCs concentrations were associated with overall improvements in sleep quality. Participants reported a mean of 4.4 fewer awakenings and had a 1.1% increased in measured sleep efficiency for nights with elevated $PM_{2.5}$. Elevated TVOCs were associated with an increase in sleep time of 14.5 min. These findings indicate a need to study the relationship between these aggregate IAQ measures and sleep quality more closely. Our results also indicate that pollutants can independently affect sleep quality regardless of the CO_2 measurements. Compared to literature, our study is the longest and includes the most IAQ parameters.

1. Introduction

We examine the relationship between sleep quality and indoor air quality (IAQ) using field experiments. An adequate amount of good-quality sleep is essential for human health and well-being, as sleep affects physiological processes, emotion regulation, physical development, quality of life [1], and next-day performance [2,3]. Poor sleep quality has been shown to degrade cognitive performance and impair brain function [4,5].

Internal factors that influence sleep include physical ailments like head and body aches in addition to a person's mental state such as feelings of stress, anxiety, or depression [6–8]. External factors include light, noise, thermal comfort, medication, and situations that disrupt normal circadian rhythm including jet-lag or shift-based work. Light's negative effect on sleep is a well-known phenomenon [9,10], similar to the effect noise has on sleep [11,12]. The relationship between thermal comfort and sleep focuses on topics such as the relative humidity and temperature of the bedroom air [13,14], bedding insulation [15,16], and the body's internal temperature [17].

A potential external factor that likely affects sleep is IAQ, which has recently attracted the attention of researchers. IAQ includes variables such as temperature and relative humidity in addition to the mixture of air pollutants within the indoor environment. Indoor air contains a variety of pollutants, some generated indoors and others that penetrate inside via infiltration or ventilation.

Considering humans can spend nearly 90% of their time indoors [18], good IAQ is an important health consideration. Poor IAQ can exacerbate or induce many illnesses related to the respiratory [19,20] and cardiovascular systems [21,22] in addition to negatively affecting occupants' moods [23,24], productivity [25], and performance [26,27]. These effects are noteworthy because many commonly-occurring pollutants can inflame airways [28,29], affecting respiration while sleeping or worsen pre-existing conditions like asthma. Pollutants can also alter the development and/or structure of the brain [30] which not only affects cognition [31] but might alter sleep architecture and quality [32].

* Corresponding author.
E-mail address: nagy@utexas.edu (Z. Nagy).

https://doi.org/10.1016/j.buildenv.2022.108835
Received 8 November 2021; Received in revised form 6 January 2022; Accepted 23 January 2022
Available online 10 February 2022

Acronyms

CO	Carbon Monoxide
CO_2	Carbon Dioxide
EMA	Ecological Momentary Assessment
GSQS	Groningen Sleep Quality Scale
IAQ	Indoor Air Quality
IoT	Internet of Things
MI	Mutual Information
NAW	Number of Awakenings
$PM_{2.5}$	Particulate Matter with aerodynamic diameter less than 2.5 μm
PSG	Polysomnography
PSQI	Pittsburgh Sleep Quality Index
REM	Rapid-Eye Movement
RH	Relative Humidity
RPi	Raspberry Pi 3B+
SE	Sleep Efficiency
SOL	Sleep Onset Latency
SWS	Short Wave Sleep
TST	Total Sleep Time
TVOC	Total Volatile Organic Compound

Studying the effects of indoor air pollution on sleep is a challenging task. Both IAQ and sleep quality monitoring devices are typically bulky, expensive, and require training to operate effectively [33]. However, advances in sensing technology have enabled the creation of more affordable and less obtrusive devices that can make addressing the question of IAQ's effect on sleep quality easier. Consumer-grade sensors – also referred to as low-cost sensors – do not have any universal definition in the IAQ field, but are typically thought to cost less than a few hundred USD [34]. Consumer-grade sensors now exist for a variety of common air pollutants, which have been assessed in both laboratory and field experiments (see [35] and references within). While these devices have drawbacks in terms of accuracy, many researchers have developed methods to calibrate sensor measurements and improve sensor reliability [35]. The ease of using these sensors has led to the creation of devices that leverage multiple, consumer-grade sensors for researcher-oriented applications [36].

In the sleep monitoring domain, consumer-grade wearable fitness trackers have become widely available and have found their way into the research domain. These devices use accelerometers, often along with heart rate monitors, to measure sleep quality and provide high-level information regarding sleep stages. Outputs from "sleep-staging" devices have been compared with self-report [37], accelerometer [38], and Polysomnography (PSG) [39] measurements of sleep quality and deemed to provide reasonably accurate measurements. In either domain, the affordability of consumer-grade sensors allows researchers to monitor many participants for a fraction of the cost that traditional monitoring would entail.

Our work is motivated by these recent advances in sensing technology, which now allow researchers to distribute IAQ and sleep monitoring devices to a large number of participants in their home environments. Thus, we can collect data over a longer time frame in a natural home environment without imposing undue burden on participants.

1.1. Related works

Initial IAQ studies focused on characterizing compounds emitted from bedding materials [40,41], the IAQ near the sleeping individual [42,43], and the concentration of pollutants in the bulk air [44]. Only a handful of studies (Table 1) have attempted to address the relationship between IAQ and sleep quality directly.

Pioneering studies investigating the relationship between IAQ and sleep quality focused on CO_2 and the effect of altering ventilation rates by comparing sleep quality during nights with and without enhanced natural ventilation [45–47]. These studies monitored sleep quality using technologies ranging from simple surveys to PSG – the gold standard of sleep monitoring – and found that participants tended to have fewer awakenings and a more restful sleep during nights with better ventilation. A controlled study in which participants were asked to sleep in mock bedroom environments under different CO_2 concentrations drew similar conclusions: SOL increased and the amount of time spent in Short Wave Sleep (SWS) decreased [48]. Rather than investigating how manipulating CO_2 concentrations affects sleep, one study simply monitored CO_2 and sleep quality over a longer period of time and noticed a similar decrease in SWS [49].

The primary issue with these and many of the studies listed in Table 1 is they only monitor CO_2 concentrations and use these measurements as a proxy for IAQ. The studies that consider other indoor air pollutants either measure over a short period [47] or do not incorporate a measure of objective sleep quality [50].

1.2. Contributions

In this paper, we leverage multiple, consumer-grade Internet of Things (IoT) sensing technologies to measure four commonly occurring indoor air pollutants, in addition to temperature and relative humidity, in an extended field experiment to understand how components of IAQ affect the sleep quality of university students. We also consider activity and mood data gathered through mobile sensing technology to determine the influence these factors might have on sleep metrics. This study's effort to address the effect of IAQ on sleep quality is novel in that we are measuring multiple commonly-occurring indoor air pollutants over the longest period for a study of this type to date in participants' home environments.

2. Methodology

2.1. Study design

We recruited student participants from the University of Texas at Austin (UT) who underwent a virtual enrollment interview before being consented into the study. During appointments, participants registered their mobile devices using the Beiwe™ smartphone application (Section 2.2) to gather real-time self-report data in the subjects' natural environments [53]. Following enrollment, Fitbit wearable activity devices (Section 2.3) and home environment monitors – the Building EnVironment and Occupancy (BEVO) Beacons (Section 2.4) – were sent to participants on a rolling basis (Fig. 1). Originally, 29 participants were enrolled, but because of missing data or a lack of overlap between the devices' measurements, only 20 participants are considered.

2.2. Self-reported mood and sleep

The Beiwe Research Platform™ [54] is a smartphone app that provides digital phenotyping from data collected by smartphone sensors and EMA responses. EMAs were distributed to participants on Monday, Wednesday, Friday, and Sunday in the mornings at 9:00 am and evenings at 7:00 pm. Morning EMAs included questions regarding the participant's mood and self-report sleep (See Table A.2) whereas evening EMAs only asked about mood. Participants could chose to respond to the EMAs at any time after they were distributed, but would expire if a newer EMA was sent.

Table 1
Summary of study parameters included in previous research examining indoor air pollution and sleep quality. The final entry highlights the parameters associated with this study.

Ref.	IAQ Parameters	Participants	Study Env.	Study Length	Sleep Quality Monitoring	
					Device-Measured	Self-Report
[45]	CO_2	8 university students	dorm	28 days	actigraphy	weekly and daily surveys
[46]	CO_2	14 (pilot) and 16 (main) university students	dorm	10 days	Sensewear Armband [51] and actigraphy	sleep diary, daily GSQS, and weekly PSQI
[47]	CO_2, PM, TVOCs, T	27 young adults	dorm	4 days	Fitbit Charge 2™, PSG	daily GSQS
[50]	CO_2, PM, T	24 university students	dorm	30 days	N/A	daily survey
[49]	CO_2, T	48 adults	homes	5 days	Fitbit Charge 2™	daily survey
[48]	CO_2	10 young adults	clinic	54 days	PSG	daily survey
[52]	CO_2, T	104 adults	homes	1 day	Fitbit Alta 2	survey
This Study	CO_2, CO, PM, TVOCs, T	20 university students	homes	77 days	Fitbit Inspire HR™	survey asked 4 times per week

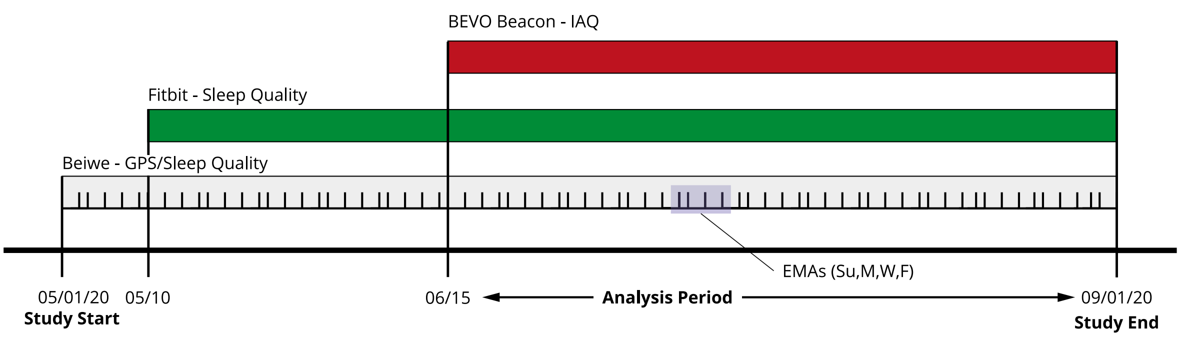

Fig. 1. Periods of measurement for each of the three modalities over the course of the study period. For the analysis, we consider the 77 days from 06/15 to 09/01 when participants had Fitbit and BEVO Beacons and were actively responding to EMAs sent 4 times a week.

Fig. 2. Sleep measurements were calculated by (a) Fitbit Inspire HR™ devices and self-reported through surveys distributed through the (b) Beiwe™ Smartphone App.

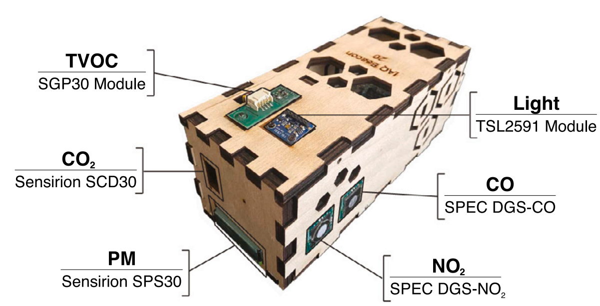

Fig. 3. The BEVO Beacon, the six sensors included on the device, the primary variable each sensor measures, and the individual module names.

2.3. Device-monitored sleep quality

Fitbit Inspire HR™ devices (Fig. 2) were distributed to all participants to monitor activity and sleep quality. Participant accounts were linked to the Beiwe™ server where data from the smartphones were also securely stored. Participants were encouraged to wear their Fitbit as often as possible, only removing it to charge. This particular model of Fitbit includes a heart rate monitor and the standard accelerometer to help track sleep more accurately.

The three sleep metrics measured in the study are shown in Table 2. We include TST and Sleep Efficiency (SE) parameters as provided by Fitbit. The third parameter was derived to address the limitations of Fitbit-measured sleep stages: Fitbit devices can accurately detect awake and Rapid-Eye Movement (REM) stages, but the distinction between light and deep is not as clear [57]. For this reason, we combined the light and deep stages into one category denoted as non-REM, and consider the ratio of REM to nREM sleep as a way of normalizing the sleep stage measurements.

2.4. Indoor environmental quality monitoring

To monitor IAQ in the participants' bedrooms during the study period, we developed, calibrated, and deployed the BEVO Beacon. The BEVO Beacon, pictured in Fig. 3, includes a Raspberry Pi 3B+ (RPi) wired to five consumer-grade air quality sensors; a light sensor; one 250 mm × 250 mm cooling fan; and a battery-powered clock to keep time when the device is not connected to the internet. Within the BEVO Beacon, the RPi is housed in a separate chamber from the sensors where a fan provides air to help cool the RPi's processing unit. The five air quality sensors measure temperature, Relative Humidity (RH), CO_2, Particulate Matter with aerodynamic diameter less than 2.5 μm ($PM_{2.5}$), Total Volatile Organic Compounds (TVOCs), and Carbon Monoxide (CO). Each sensor is enabled sequentially, scans the environment synchronously, and stores the average measurement from five scans on the RPi. The device determines the number of seconds required to scan five

Table 2
Sleep quality parameters self-reported on EMAs and derived from Fitbit Inspire HR™ measurements. Recommendations for each parameter corresponding to young adults are also provided.

Sleep Metric	Modality	Description	Calculation from Fitbit	Recommendation	Reference
SOL	EMA	Time to fall asleep	–	<30 min	[55]
NAW	EMA	Number of times waking >5 min	–	<2	[1]
Restfulness	EMA	4-point scale	–	>2	–
TST	EMA, Fitbit	Time spent asleep	Light + Deep + REM	7 to 9 h	[1]
SE	Fitbit	Ratio of sleep time to time in bed	$\frac{\text{TST}}{\text{Time in Bed}} \times 100$	85% to 95%	[55]
REM:nREM	Fitbit	Ratio of REM to nREM	$\frac{\text{REM}}{\text{Light+Deep}}$	0.25 to 0.33	[56]

times with each sensor and then sleeps for a certain time to ensure measurements are taken each minute. Participants were asked to place the device in their bedroom approximately one meter above the ground and out of the path of direct sunlight if possible. Each IAQ sensor on the BEVO Beacon, temperature, and RH was calibrated using the techniques described further in Appendix. The calibration resulted in individual, linear least-squares regression models per sensor on each BEVO Beacon to correct measurements.

2.5. Data fusion for occupancy detection

Since Beiwe™ and Fitbit are mobile sensing technologies, we obtain sleep data from participants regardless of the environment they sleep in. However, the BEVO Beacon is always monitoring a participant's original location. Since we were only interested in data collected during periods when participants were home and asleep in their bedrooms, we use data fusion across the three modalities to produce a single dataset. We use the term "data fusion" to refer to the process of integrating multiple data sources to create a more accurate and useful dataset compared to any individual data source component [58]. The dataset we create includes summarized IAQ measurements during Fitbit-detected sleep events that we can guarantee occurred at the participants' homes by either cross-referencing GPS coordinates or examining CO_2 concentrations. We describe these methods further in Sections 2.5.1 and 2.5.2. In either case, IAQ data from the BEVO Beacon were first restricted to sleep periods detected by Fitbit devices.

2.5.1. Smartphone GPS and address comparison

We cross-referenced the latitude and longitude coordinates from participant addresses with the GPS data provided by their smartphones gathered by the Beiwe™ application. Beiwe™ records GPS data at continuous intervals while the smartphone has power and internet or cellular connection. We considered GPS coordinates during Fitbit-detected sleep events only. We average the coordinates from each night and consider the participant home if their coordinates are within 50 meters of their corresponding address. We conducted this process for each Fitbit-detected sleep event across all participants.

2.5.2. Carbon Dioxide monitoring

Since GPS data were not available for each Fitbit-detected sleep event, we used CO_2 and temperature measurements to assess if participants were occupying their bedrooms to increase the number of nights available for analysis. To start, we calculated the change in CO_2 concentration at each timestamp during a sleep event for all participants. If more than 50% of the calculated CO_2 changes were greater than 0 – indicating an increase in the overall concentration – we included the night for analysis since increases in CO_2 indicate that a person is likely occupying the space. This process was instrumental to providing more data for analysis from nights when GPS data were missing.

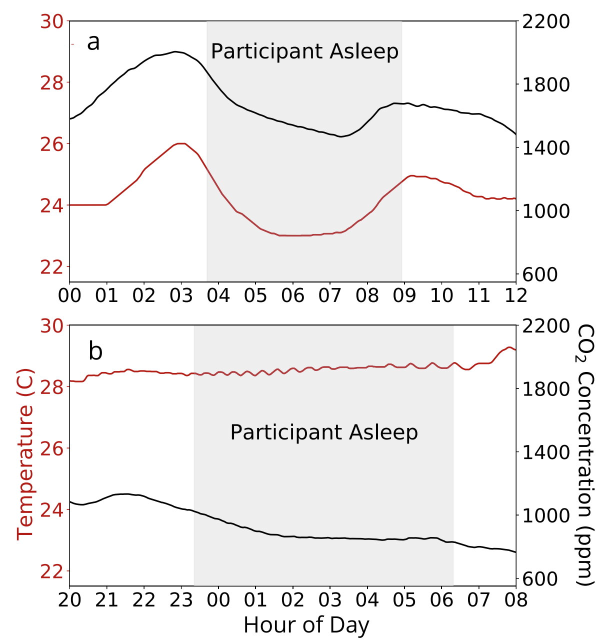

Fig. 4. Temperature and CO_2 variation for two exemplary nights when CO_2 concentrations were decreasing on average. Data from (a) were included because variations in temperature and CO_2 correspond whereas data in (b) were not included.

There were instances when CO_2 concentrations during sleep events would exhibit more erratic behavior and decrease on average. For these nights, we used the temperature measurements as a proxy for operation of the air conditioning unit and thus ventilation. We visually inspected these nights to see if there were instances when the temperature and CO_2 concentrations followed similar trends. If both variables were decreasing, we assumed the ventilation was active and removing CO_2 at a rate greater than what the participant was emitting while asleep. If temperatures were not decreasing, but CO_2 concentrations were decreasing or remaining constant, we concluded the participant was not in the room, and discarded the night from further analysis. Fig. 4 shows two nights of CO_2 and temperature data that exemplify the two scenarios described previously. This process not only provided more nights for analysis, but also helped identify two participants who had placed the BEVO Beacon in a common area and not their bedrooms.

2.6. Analysis of IAQ parameters during sleep

We conduct the analysis of IAQ's effect on sleep quality by aggregating all measurements made across each of the 20 participants. Using the IAQ data from time periods when participants were home and asleep,

Table 3
Thresholds for determining nights with low or high IAQ parameter measurements.

Parameter	Threshold	From	Notes	Reference
TVOC	200 ppb	WHO	Twice sensory irritation	[59]
CO_2	1100 ppm	ASHRAE	Based on Standard 62.2	[60,61]
CO	4 ppm	WHO	Maximum 24-hour exposure	[62]
$PM_{2.5}$	6 μg/m^3	US EPA	Half NAAQS annual exposure	[63]
Temperature	27 °C (80.6 °F)	This Study	median nightly concentration[a]	

[a]The median concentration was calculated using measurements made by all devices during Fitbit-detect sleep events.

we determine if a certain IAQ parameter is low or high by comparing the median value for that night to thresholds established by various organizations or based on data collected during this study (Table 3). If the median value was below the threshold, we labeled that night as "low" for that particular IAQ parameter or "high" otherwise. We then compare the distributions of Fitbit-measured sleep metrics and self-reported TST and SOL for nights when a certain IAQ parameter was low or high.

We take a different approach when considering the self-reported NAW and restfulness scores since these were reported as discrete values. We flip the analysis and start by determining nights when participants self-report their sleep quality as either satisfactory or poor based on recommendations provided in Table 2. We then compare the distribution of IAQ parameters between nights when participants slept well or poorly based on a given sleep metric.

2.7. Analysis of non-IAQ parameters during sleep

We conducted an exploratory analysis to determine the extent to which various components of activity and mood affected Fitbit-measured and self-reported sleep quality. Datasets were generated for each modality and combined with the available sleep data from Fitbit and EMAs separately to produce two datasets per sleep monitoring type. Each feature within the datasets was then systematically compared to each sleep metric using Mutual Information (MI). MI generalizes the correlation coefficient by quantifying the amount of information, or reduction in uncertainty, from one random variable given knowledge of another:

$$MI(X;Y) = \int_y \int_x P_{(XY)}(x,y) \log \frac{P_{(XY)}(x,y)}{P_X(x)P_Y(y)} \tag{1}$$

where $P_{(XY)}(x,y)$ is the joint probability density between variables X and Y and $P_X(x)$ and $P_Y(y)$ are the marginal probability densities for X and Y, respectively. MI is based on information entropy and higher entropy values indicate a greater uncertainty in the random variable. In terms of entropy, Eq. (1) can be expressed by

$$MI(X;Y) = H(X) - H(X|Y) \tag{2}$$

where $H(X)$ is the entropy of variable X and $H(X|Y)$ is the conditional entropy of X given Y. If X and Y are independent variables, $H(X|Y) = H(X)$ and the MI score is 0. If variable X explains Y completely, $H(X|Y) = 0$ and the MI score is equal to the entropy of variable X. Therefore, when comparing a feature to a sleep metric target, higher values of MI indicate a stronger relationship between the variables. We apply MI over traditional techniques to determine correlation because the functional shape of the relationship between non-IAQ and sleep variables is not known. MI provides a way of avoiding any assumptions on the functional relationship between variables.

3. Results

In the following sections, we summarize the data measured by the Fitbit devices, EMAs, and BEVO Beacon before analyzing the relationships between IAQ parameters and sleep quality in Section 3.2. The subsequent sections focus on the relationships between sleep quality and non-IAQ parameters and those between Fitbit and self-report measures of sleep in Sections 3.3 and 3.4, respectively.

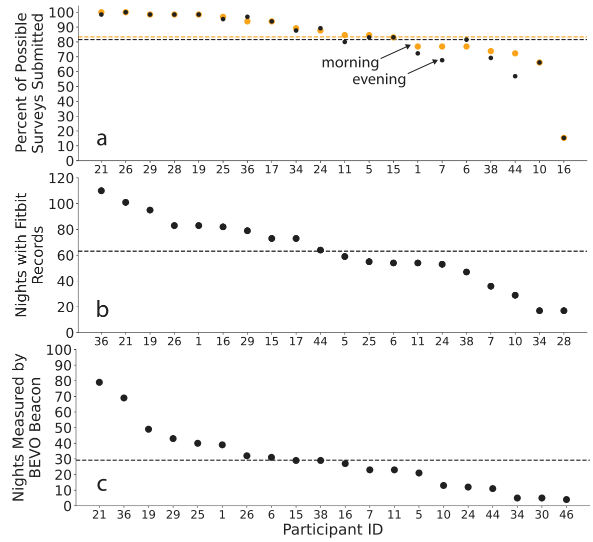

Fig. 5. Nights of available sleep data from (a) EMAs given as percent completed of the possible 65 and (b) Fitbit shown as the number of nights recorded. The dashed lines represent the mean submission rate.

3.1. Data availability and summary by modality

3.1.1. Self-report sleep metrics

The percentage of possible morning and evening surveys submitted by each participant is shown Fig. 5a. The 20 participants submitted a total of 1078 morning and 1046 evening EMAs. All participants submitted at least 9 of the possible 65 EMAs of each type distributed over the study period. Participants 21 and 26 submitted all 65 of the morning EMAs and participant 21 submitted all possible evening EMAs. The mean submission percentages for morning and evening EMAs were 83.4% and 81.6%, respectively.

The results for the four self-report sleep metrics (Figs. 6a–d) indicate that participants reported, on average, satisfactory sleep quality for each metric. Just over half (59.1%) of TST measurements fall within in the recommended 7 to 9 h of sleep [55] with an average of 6.8 h each night. Only 8.9% of our participants reported a SOL greater than 45 min, which is considered a marker for poor sleep quality [55]. 60.8% of participants have satisfactory NAWs, defined as 1 or less waking moments that last longer than 5 min [55]. Lastly, the median restfulness score was 3, indicating that participants tended to report their restfulness as "very much".

3.1.2. Device-monitored sleep metrics

Fig. 5b shows the number of nights of data for each participant rather than a percentage because participants had their Fitbit devices over varying periods of time depending on the mailed and return dates. A total of 1264 nights were measured across all 20 participants with a mean of 63 nights per participant, ranging between 17 to 110 nights.

The summary of the three Fitbit-monitored sleep metrics, shown in Figs. 6e–g, indicate our participants had generally satisfactory sleep quality. Results for TST, SE, and REM:nREM ratios are all normally

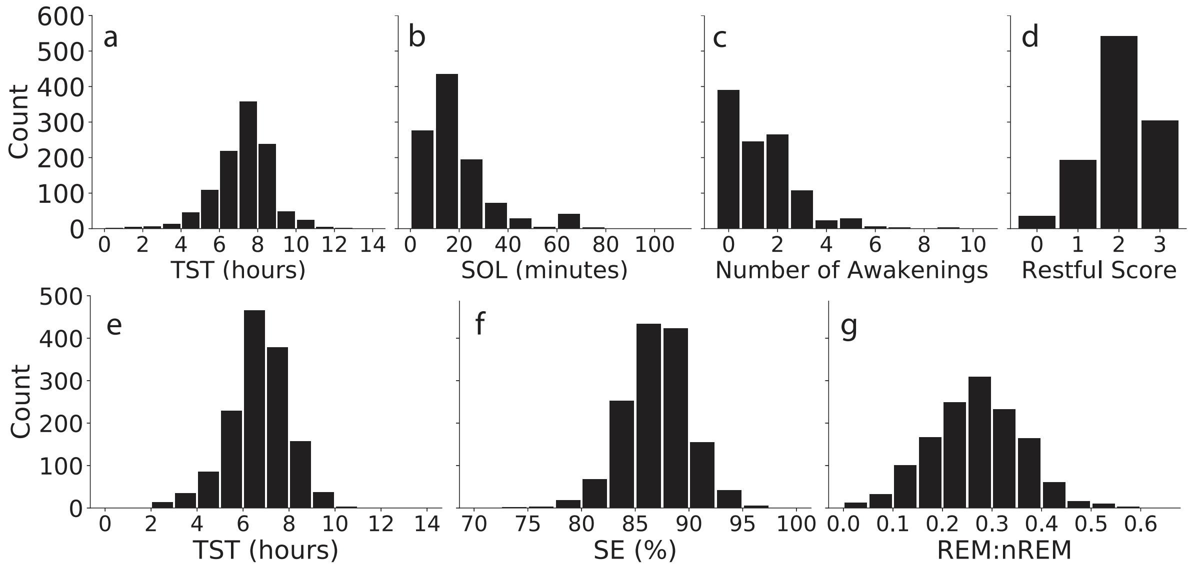

Fig. 6. Distributions of sleep metrics collected over the course of the entire study. The top row (a–d) corresponds to self-report metrics and the bottom row (e–g) are those derived from Fitbit measurements.

distributed around mean values within recommended ranges for young adults (see Table 2). TST measurements from Fitbit are slightly lower than self-report with 38.4% of measured values within the 7 to 9 h range. Only 2.6% of TST are greater than 9 h while the remaining 59.0% are less than 7 h. Only two nights measured by Fitbit indicated a SE less than 75%, corresponding to poor sleep quality [55] otherwise the mean SE was 87.0%. Adults should spend between 20% and 25% of the time they are asleep in REM [56], indicating ideal REM:nREM is between 0.25 to 0.33. The mean REM:nREM ratio measured in this study was 0.27 with 35.6% of the measured ratios lying within 0.25 to 0.33. The majority of REM:nREM ratios were less than 0.25 (40.0%) indicating a lack of REM sleep while the remaining 24.4% had ratios greater than 0.33.

3.1.3. Indoor air quality

Fig. 5c shows the number of nights that IAQ measurements were recorded by each BEVO Beacon. Across the 20 individuals, we have a total of 584 nights with IAQ measurements when participants are confirmed home by GPS and asleep according to Fitbit. The occupancy detection described in Section 2.5.2 helped provide an additional 81 nights from 14 individuals that would have originally been excluded due to a lack of GPS data. More detail on the measurements made by the BEVO Beacons are provided in Appendix.nonum Appendix. In Fig. 7, we illustrate one typical night of data collected for one participant across all three modalities. The consistent fluctuation of the temperature measurements indicates the activity of the ventilation system which can also be seen in the plots for CO, CO_2, and TVOCs. At 7:00, the device begins measuring low levels of sunlight and the final plot shows the participant waking up nearly an hour later. Fitbit measurements indicate an irregular cycle of sleep staging with a TST of 7.4 h and what appears to be one significant waking period at 6:40. The participant submits their EMA just after distribution at 9:00, responding that they slept approximately 7 h and woke once, which is consistent with Fitbit measurements.

Fig. 8 shows the correlation matrix between the five IAQ parameters measured by all BEVO Beacons. We use the correlation matrix to understand if any clear relationship exists between IAQ parameters. If there are strong relationships, we can simplify the subsequent analysis by using only a subset of the IAQ parameters. However, none of the IAQ parameters exhibited strong relationships with another, at least on an aggregate basis. We also examined the correlation matrix amongst the same parameters per device to understand if pollutants in a certain participant's environment exhibited different behavior. At the device level, only one recurring strong ($r^2 > 0.70$), negative relationship between temperature and CO was evident for four devices. We identified five other strongly correlated IAQ parameters amongst different devices, but each relationship was specific to just one device. The lack of consistently strong correlations between IAQ parameters on each device justifies our use of all five parameters for exploring their relationship to sleep quality. In addition, we conducted factor analysis to further understand if using all five IAQ parameters was merited. This analysis suggests using 3 factors instead of all 5 parameters, but the factor loadings are not easily interpreted in the context of the IAQ parameters and only explain 72.2% of the total variance. Including a fourth factor increases this value to 88.2%, but again the factor loadings do not indicate distinct groups and therefore, we simply include all five IAQ parameters.

Table 4
Summary of the effects of increased IAQ parameters on self-report and Fitbit-measured sleep metrics.

IAQ Parameter	Sleep Quality Metrics	
	Self-Report	Fitbit
↑ TVOC	–	↑ TST, ↑REM:nREM
↑ CO	↑ NAW	↓ TST, ↓ SE
↑ CO_2	↓ restful, ↓ SOL	↓ TST
↑ $PM_{2.5}$	↑ restful, ↓ NAW	↑ SE, ↓REM:nREM
↑ T	↓ TST, ↓ NAW, ↓ SOL	↓ TST

3.2. IAQ and sleep quality

This section contains the main findings of this study and have been summarized in Table 4. We detail the individual analyses of IAQ parameters on self-report sleep quality in Section 3.2.1 and on Fitbit-monitored sleep quality in Section 3.2.2.

3.2.1. Self-report sleep

Fig. 9 highlights the distributions of self-reported TST and SOL for nights when concentrations of the measured IAQ parameters were low or high. Fig. 9a indicates that distributions of TST differ in their shape depending on the low or high IAQ parameter, but mean TST tend to be similar. There were more nights with low median CO

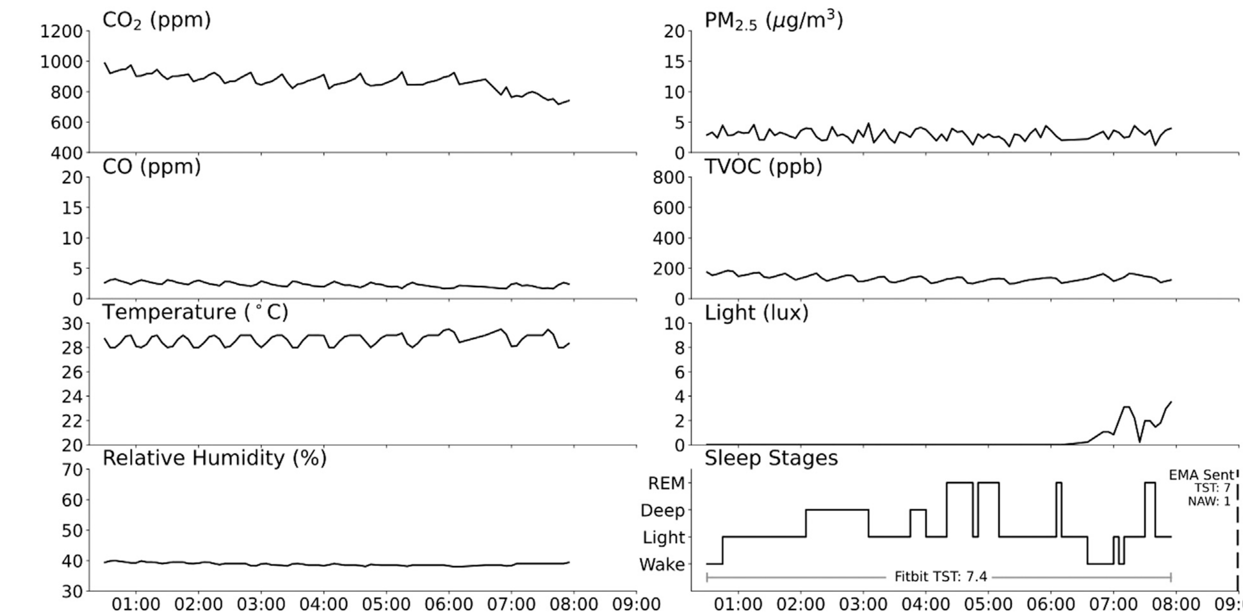

Fig. 7. Representative night of IAQ and sleep time series measurements for one participant. EMA scores on TST and NAW are give in the bottom right panel.

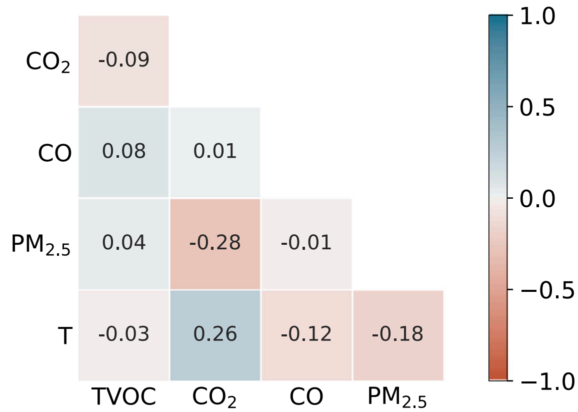

Fig. 8. Correlation matrix of the IAQ measurements aggregated across all participants.

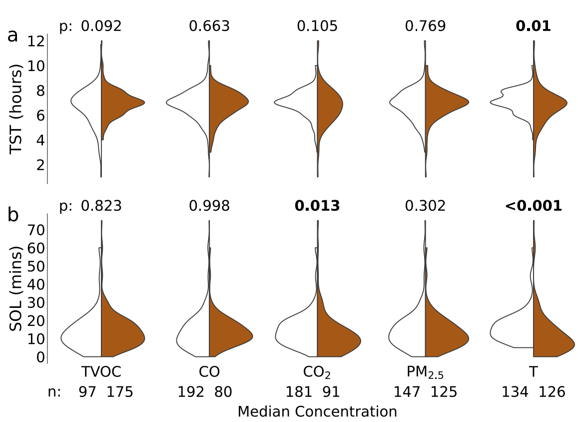

Fig. 9. Distributions of self-reported TST and SOL for nights when median pollutant concentrations were below or above thresholds listed in Table 3. Values above each violin indicate p-values from a t-Test on the means of the distributions where bold values indicate p-values < 0.05. Numbers at the bottom indicate the number of nights in each distribution.

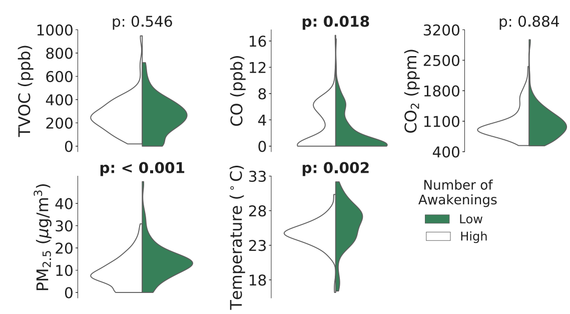

Fig. 10. Distributions of median IAQ measurements for nights when participants self-report their NAW as low or high. Values above each violin indicate p-values from a t-Test on the means of the distributions where bold values indicate p-values < 0.05. There were 128 and 144 nights with low and high NAW, respectively.

and CO_2 concentrations than high whereas the opposite was true for TVOC measurements. There were nearly the same number of low and high median nights when considering $PM_{2.5}$ and temperature. Only temperature seems to have a significant effect on self-reported TST – warmer temperatures resulted in a shorter sleep time of 23.4 min on average. We also observed that nights with warmer temperatures, as well as elevated CO_2, resulted in decreased SOL of 3.5 and 4.6 min, respectively. These relationships suggest that participants were able to fall asleep more quickly when ventilation rates were low.

Figs. 10 and 11 illustrate the distributions of IAQ measurements for negatively and positively reported NAW and restfulness, respectively. IAQ measurements for each night were grouped based on positive or negative scores of NAW or restfulness. We then conducted a t-Test of means between the distributions of IAQ parameters to assess if participants tended to report differently at lower or higher IAQ measurements.

Fig. 10 illustrates that the distributions of median CO measurements tend to be 0.9 ppm higher on average for nights when participants report more awakenings which suggests that elevated CO might disturb sleep. The bi-modal distributions of CO for nights with low and high NAW indicate that many of the CO measurements that were made during the study were low. If we were to neglect nights with low median CO concentrations, the relationship between elevated CO and increased awakenings would be even more pronounced. A similar, but

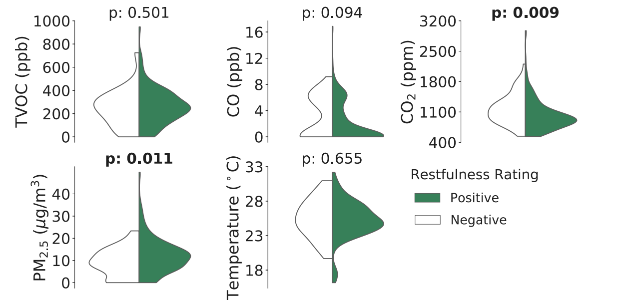

Fig. 11. Distributions of median IAQ measurements for nights when participants self-report their restfulness as positive or negative. Values above each violin indicate *p*-values from a t-Test on the means of the distributions where bold values indicate *p*-values < 0.05. There were 48 and 224 nights with low and high restfulness, respectively.

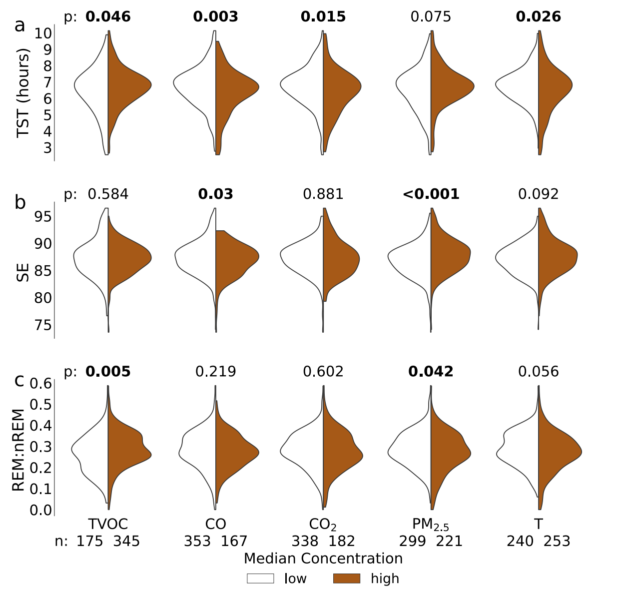

Fig. 12. Distributions of Fitbit-measured sleep metrics for nights when median pollutant concentrations were below or above thresholds listed in Table 3. Values above each violin indicate *p*-values from a t-Test on the means of the distributions where bold values indicate *p*-values < 0.05. Numbers at the bottom indicate the number of nights in each distribution.

less extreme bi-modal distribution exists between CO_2 concentrations and high NAW. Excluding nights with low median CO_2 concentrations would indicate a relationship between elevated CO_2 and increased NAW. The other two relationships of note in Fig. 10 indicate an opposite association, i.e. participants tended to report fewer awakenings on nights with elevated $PM_{2.5}$ and temperature measurements. $PM_{2.5}$ concentrations and temperature measurements were 4.4 μg/m^3 and 1.1 °C higher, on average, for nights participants reported fewer awakenings.

Fig. 11 highlights pollutant concentrations on nights when participants rate their restfulness as positive or negative. The distributions of CO measurements are bi-modal as before, but indicate poorer sleep quality at lower concentrations although the relationship is not as strong. CO_2 concentrations were an average 150.4 ppm higher on nights when participants indicated their sleep was not restful.

3.2.2. Fitbit-monitored sleep

Here we examine the distributions of the three Fitbit-derived sleep metrics during nights with low and high median IAQ measurements in Fig. 12. Generally, the distributions of Fitbit-derived parameters tend to be similar for nights with low and high IAQ parameters indicating relatively minor influences of the IAQ parameters measured in this study on sleep. Numbers at the bottom of the figure indicate the number of nights with low or high median IAQ measurements. The ratios of low and high median concentration nights per parameter are similar to those shown in Fig. 9 but with more observations. TVOC concentrations tended to be higher than the threshold while CO and CO_2 concentrations were typically lower than the thresholds we identified. $PM_{2.5}$ and temperature measurements were more evenly split between low and high median values.

Fig. 12a illustrates the distributions of TST, which show relatively similar shapes to those for self-reported TST. However, nearly all IAQ parameters are significantly associated with Fitbit-derived TST. At higher measurements of CO_2, CO, and temperature the mean TST is 17.5, 21.6, and 15.2 min shorter, respectively. As for the remaining pollutants, mean TST increased by 14.5 and 12.3 min when concentrations of TVOCs and $PM_{2.5}$ were elevated. Mean SEs (Fig. 12b) were 0.6% lower at elevated concentrations of CO and nights with the highest SE occurred during evenings with the lowest CO concentrations. In contrast, elevated $PM_{2.5}$ concentrations measured in this study indicate a statistically significant increase in mean SE of 1.1% on average. While our data suggest relationships between CO or $PM_{2.5}$ and SE, the differences are minor and near the resolution of the Fitbit device's measurement of SE. However, we are considering the mean SE aggregated across all participants which might attenuate the larger variations in SE experienced by the same participant on more and less polluted nights. We did not observe any statistically significant relationship between CO_2 or temperature and SE despite these parameters typically implicated in disrupting sleep. Lastly, Fig. 12c indicates elevated $PM_{2.5}$ and warmer temperatures tend to reduce the ratio of REM:nREM sleep by 1.6% in each case.

3.3. Relationships between sleep quality and other study variables

The relationships between Fitbit-measured or self-reported sleep metrics and variables related to mood and activity were explored to understand if any significant relationships should be accounted for. We were able to identify 11 non-IAQ parameters related to mood and activity that could potentially affect participants' sleep qualities. However no metric of Fitbit-measured nor self-report sleep quality produced a significant MI score when compared against mood or activity. The strongest relationships we identified were between variables from each sleep monitoring modality, the largest of which was between the two measurements of TST (see Section 3.4). This relationship is natural and produced a MI score of 0.41 which helped to generate a baseline that other MI scores could be compared against. No measure of mood or activity produced a MI score greater than 0.1 when compared to any metric of sleep quality. Since none of the MI scores were significant enough, we did not control for any non-IAQ parameter.

3.4. Fitbit-measured versus self-reported sleep metrics

The only direct comparison between sleep metrics that can be analyzed is between TST since it is provided by both Fitbit and EMAs. The TST reported by each modality for each participant is shown in Fig. 13. Only 19 of the 20 participants are shown because one participant only recorded Fitbit sleep data. Points for each individual, shown in black, and those across all participants, shown in gray, tend to group near the one-to-one line with a few noticeable deviations primarily recorded by Participant 5 and one instance each for Participants 10 and 24. Regardless of these exceptions, all plots indicate a positive correlation. Sleep-staging Fitbit devices are accurate when measuring TST in healthy populations [38,64], therefore poor agreement amongst some measurements is likely due to participants' biases and their tendency to report TST on a half-hour resolution.

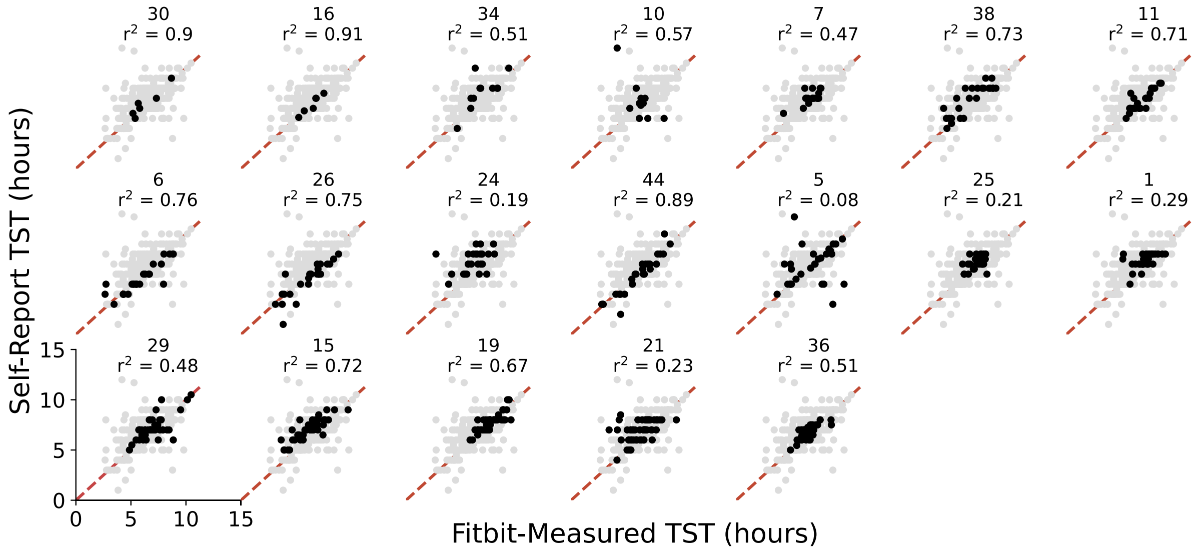

Fig. 13. Comparison of TST measured by self-report and Fitbit per participant. Participant measurements are shown as darker points where the lighter background represents all 1060 measurements across participants. r^2 values are given above individual plots where applicable.

Comparing other self-report to Fitbit-measured sleep metrics, there is no significant correlation between related measurements. Self-report NAW had no discernible relationship with Fitbit-measured SE, wake time, or wake percent nor did the self-report restfulness score with related Fitbit metrics such as REM:nREM and SE. We could not accurately compare self-reported SOL to any Fitbit-derived SOL for reasons described in Section 4. The lack of relationships across modalities highlights the importance of including both device-monitored and self-reported components of sleep quality.

4. Discussion

4.1. Comparison to related studies

The study detailed in this paper builds upon similar research (Table 1) with a few notable differences. We monitor CO, a previously unaccounted for pollutant, alongside other pollutants like $PM_{2.5}$ and TVOCs which are currently poorly represented in the related literature. We identified statistically significant relationships between all three of these pollutants and sleep quality. Previous studies primarily focus on CO_2, highlighting that CO_2 serves as a proxy for overall IAQ. However, results from this study indicate that pollutants like TVOCs and CO can independently affect sleep quality regardless of the CO_2 measurements. Our study also differs in that we monitor participants over the longest period of time to date for a study of this type. Monitoring participants over a period of 77 days increases the amount and variety of data we measure, enhancing the statistical strength to our findings. This study is one of the few that measures IAQ parameters in participants' apartments or houses unlike others that measure in sleep clinics or student dormitories. In Table 5 we provide a summary of the effects these studies identified including our results as the bottom entry for each parameter.

TVOCs were the only IAQ parameter that did not present a statistically significant relationship with any of the self-reported sleep metrics. Decreased TVOC concentrations measured in our study indicated a decrease in TST, but the relationship is not as strong as others. For the remaining sleep metrics, TVOC concentrations follow very similar distributions for nights with satisfactory or poor sleep quality. However, when considering the Fitbit-measured sleep metrics, elevated TVOC concentrations were related to increases in TST and the ratio of REM to nREM. Although REM:nREM increased at elevated TVOC concentrations, the mean ratio remains between the recommended 0.25 – 0.33 range [56] meaning that we cannot say that sleep quality worsened or improved. However, other research has shown that exposure to essential oils, which contain an abundance of VOCs [65], can alter the amount of time spent in various stages of sleep [66,67]. A recent study also found that TST increased in healthy university-aged subjects who typically experienced poor sleep quality when exposed to orange and lavender essential oils [68]. While our participants did not report any use of essential oils during the study period, many of the same VOCs that constitute these products could be present in their bedroom environments, leading to the changes in sleep staging and TST we found. We were only able to identify one related study that considered TVOC measurements, but their work indicates no relationship between TVOCs and any metric of sleep quality measured objectively by PSG and actigraphy [69]. This study does not report the TVOC measurements so we cannot compare the concentrations to understand if our environments were more or less polluted.

Like TVOCs, elevated $PM_{2.5}$ concentrations were generally associated with improvements in sleep quality – both self-reported and Fitbit-measured – although the effects are mild. The explanation for this effect is not as clear as with TVOCs. Considering related studies, researchers in [50] report no effect of $PM_{2.5}$ on sleep quality, while results from [47] indicate opposite outcomes to what we found. We believe that the lower $PM_{2.5}$ concentrations measured in our study alongside the potential differences in composition could explain the conflicting outcomes. Since $PM_{2.5}$ is an aggregate measurement of all aerosolized liquid and solid particles less than 2.5 μm in diameter, we cannot be sure about the particles' chemical and physical properties which, like VOCs found in essential oils, could improve sleep quality. In addition, increased $PM_{2.5}$ concentrations could be associated with one or multiple confounding variables that outweigh the negative effects $PM_{2.5}$ imparts on sleep quality. Activities like cooking generate high concentrations of $PM_{2.5}$ [70] but have been shown to improve affect [71] and decrease anxiety [72] which could lead to improvements in sleep.

We could find no previous study that investigated the effect of indoor CO on device-measured or self-reported sleep quality which makes our findings between CO and both measures of sleep quality unique. However, CO is produced from cigarette smoking [73] and many researchers have investigated the effects of second-hand exposure to tobacco smoke on sleep quality, finding that elevated second-hand smoke and poor sleep quality are modestly related (see [74] and references within). There are many components of second-hand tobacco

Table 5

Summary of the effects of increased IAQ parameters measured in this study on self-reported and device-measured sleep metrics measured in the related works listed in Table 1. We include our findings in bold on the bottom row for each parameter. The value in the Number of Studies column includes our work.

IAQ Parameter	Number of Studies	Sleep Quality Metrics Self-Report	Device-Measured
↑ TVOC	2	–	–
		–	**↑ TST, ↑ REM:nREM**
↑ CO	1	–	–
		↑	**↓ TST, ↓ SE**
↑ CO_2	9	↑ NAW, ↓ restful, ↑ SOL, ↑ drowsy	↓ SWS, ↑ SOL, ↓ SE
		↓ restful, ↓ SOL	**↓ TST**
↑ $PM_{2.5}$	3	–	↑ NAW, ↓ SE
		↑ restful, ↓ NAW	**↑ SE, ↓ REM:nREM**
↑ T	5	–	↓ SWS, ↓ REM, ↓ SE
		↓ TST, ↓ NAW, ↓ SOL	**↓ TST**

smoke – including VOCs and PM – that might be contributing to this effect, but CO is likely a major influencing factor. CO still within typical ranges [75] can lead to the onset of headaches and dizziness which would make initiating and maintaining sleep more challenging.

CO_2 is the only parameter that is measured consistently across all studies listed in Table 1. CO_2 is common amongst all these studies because CO_2 can be thought of as a proxy for ventilation and therefore overall IAQ. If CO_2 is high, ventilation is often poor, and therefore concentrations of other, more hazardous compounds might also be high. Although we measured self-reported restfulness on a different scale than any of the related works, our results indicating a relationship between elevated CO_2 and lower restfulness are mirrored in many of the related works [45–48,76]. However, we found a decrease in SOL at higher CO_2 concentrations while other studies reported increases in both self-reported [46] and device-measured [48] SOL. Elevated CO_2 has a known influence on subjective and objective drowsiness [77] which could explain the reduced SOL. We also consider the median CO_2 concentration from the sleep event which could have occurred much later in the evening whereas the CO_2 concentration during the initial hour of the sleep event is more relevant to SOL.

The final parameter we consider is temperature. In regards to the related studies we identified, a few also analyzed temperature's effect on sleep quality, but we do not have any relationships that we can directly compare. Researchers using Fitbit devices found decreases in SWS [52] in addition to the amount of time spent in REM sleep and SE [49]. Although we used similar devices, we did not detect changes in sleep-staging in response to temperature, but did measure decreases in TST. These two studies also measured subjective sleep metrics, but found no association between these metrics and temperature while we found that self-reported NAW, SOL, and TST all decreased at higher temperatures. Many studies exist that directly analyze the relationship between bedroom temperature and sleep quality, finding that warmer temperatures reduced TST [78], reduced objective and subjective SOL [79] and increased wakefulness [80]. While our findings mirror those in the first two studies, we identified decreases in self-reported NAW at warmer temperatures. Perhaps overall wakefulness increases which can be measured by advanced monitors such as PSG, but participants are not able to remember these instances of waking.

This study, along with [49], is one of two that uses low-cost, consumer-grade sensors on a device developed by the research team to monitor IAQ conditions. However, the device used in [49] only provides measurements regarding CO_2 and temperature whereas we leverage a wide variety of IAQ sensors that can monitor five pollutant species, light, temperature, and relative humidity. Indeed devices developed by other researchers do not have similar capabilities [81,82] although they do provide similar accuracy amongst the sensors that they do include. In addition, one of the primary issues with similar devices is that their sensors are they are not calibrated [83]. The BEVO Beacon is in the minority of devices that has been calibrated against reference monitors or gas standards (see Appendix.nonum Appendix for more detail).

4.2. Limitations

The value of using low-cost, consumer-grade IAQ sensors alongside Fitbit devices is the ability to rapidly develop and distribute devices at scale to various participants and monitor them over an extended period without too much concern if the device is lost or damaged. The primary limitation with the BEVO Beacon and Fitbit device is their accuracy relative to their research-grade counterparts. In terms of IAQ, measuring the true concentration of a certain pollutant is valuable, but we were concerned with how significant changes in IAQ parameters during the evening and over time could affect sleep quality. In this way, we can still draw valid conclusions by examining the relative change in pollutant concentrations. However, we want to emphasize the importance of properly calibrating consumer-grade IAQ sensors to a reference monitor.

It is important to mention that we were able to discern relationships between IAQ and sleep quality in bedrooms with relatively low-pollution conditions. For example, the concentrations of $PM_{2.5}$ measured in this study were low relative to those reported in related studies of the bedroom environment [47]. We expect the relationships between some of the measured indoor air pollutants and sleep metrics would be even more pronounced if conditions in the participants' bedrooms yielded greater variation in pollutant concentrations as well as higher values. Increased pollutant variability and concentrations would exacerbate the underlying mechanisms that caused participant sleep quality to deteriorate. Additionally, this and related studies focus on acute variation in IAQ parameters during the night, but a longitudinal study that assesses the cumulative exposures to varying degrees of pollutant concentrations might be equally illuminating.

Many papers have assessed the validity of using sleep-staging Fitbit devices like the version used in this study to monitor sleep, comparing against self-report, actigraphy, and PSG measurement techniques (see [64] and references within). These studies indicate sleep-staging Fitbit devices show promise especially when measuring REM sleep and sleep metrics like TST and SE [38]. However, the Fitbit devices used in this study did not provide an accurate measurement of SOL. To obtain a proper measurement for SOL from the Fitbit devices used in this study, participants needed to manually activate sleep monitoring on their devices prior to sleep. We did not require them to do so and thus, we do not report a device-monitored SOL.

We also want to highlight the importance of properly defining the metrics for self-reported sleep quality. A participant's bias when reporting their sleep quality can be just as illuminating as what a device might measure and provide other, valuable insight. For instance, the relationships between self-reported NAW and IAQ do not correspond with those between Fitbit-measured SE and IAQ even though NAW and SE are metrics for wakefulness. However, being able to compare self-report to device-monitored metrics provides researchers with the ability to uncover bias within participants' responses. Incorporating standardized metrics, surveys, or questions of self-report sleep quality into the study design is also important for comparison across studies and reproducibility. Surveys like the Pittsburgh Sleep Quality Index (PSQI) and Groningen Sleep Quality Scale (GSQS) have been vetted and used in a wide variety of studies in addition to the related works listed in Table 1. Due to the already high level of participant burden in our study which incorporated other extended surveys assessing the mental health of our participants, we did not include surveys like the PSQI but advocate for them in related, future studies.

While our analysis with MI did not indicate any appreciable relationship between mood or activity with sleep quality, there are still a wide variety of variables that are suspected or known to affect sleep that we were not able to control for. One of the primary goals of this study was to monitor participants in their own sleep environments to collect ecologically valid data. However, doing so means we are not able to monitor factors such as screen time, caffeine/alcohol consumption, and bedding that have been linked to changes in sleep quality [15,84,85]. Student participants likely have consistent schedules and behaviors during the summer semester. Therefore, participants might have grown accustomed to the effects that these daily and evening routines would impose on their sleep quality.

5. Conclusion

Our study highlights the importance of good IAQ during sleep, showing that both device-monitored and self-report measures of sleep quality can be negatively affected by increased pollutant concentrations and temperatures in the bedroom environment, even under typical conditions. We used a combination of five consumer-grade air quality sensors on a device of our own creation in conjunction with Fitbit wearable devices and EMAs to monitor 20 individuals over a period of 77 days in their home environments. We were able to show that, on an aggregate basis, sleep quality metrics such as TST, SE, the ratio of REM to nREM, and self-report SOL and restfulness were affected, to varying degrees, by IAQ parameters. Generally, elevated CO, CO_2, and temperature were associated with a worsening in sleep quality while increased concentrations of TVOCs and $PM_{2.5}$ were related to improvements in sleep quality.

This study indicates the importance of properly controlling IAQ in occupied bedroom microenvironments. The wide array of negative effects that poor sleep quality can impose on an occupant's mental and physical health warrants that care be given to IAQ control even if the effects of air pollution on sleep quality are minimal. The simplest way to ensure satisfactory IAQ in bedrooms is to ensure ventilation is constantly provided to the space either through natural or mechanical means. Providing extra natural ventilation might not be practical depending on the season or climate conditions. However, studies like this one shed light on the issue which hopefully influences occupants to open windows or doors when comfortable ambient conditions are met. On the other hand, excess mechanical ventilation might not be financially feasible for the occupant nor is the practice sustainable. Therefore, smart homes can leverage findings from this and related studies to understand what are tolerable limits to set on common indoor air pollutants measured in the bedroom environment so as to ensure a more restful sleep. These limits might also vary by individual creating an optimization problem that may be solved with sophisticated machine learning methods like reinforcement learning.

While parameters like light and noise are important for a good night's sleep, a greater concern for good air quality could lead to an even better sleep. While this study addresses several common indoor pollutants, future studies should consider monitoring other indoor air pollutants such as ozone or oxides of sulfur/nitrogen. With the increasing availability of affordable consumer-grade IAQ sensors, researchers should be able to monitor and include a wide variety of IAQ parameters in future studies. Researchers must recognize the limitations of these sensors to ensure the device is able to produce the quality of measurements needed to make concrete conclusions. In addition, participants that reside in more polluted areas or those with more pronounced sources of indoor and/or outdoor air pollution should be targeted to more aptly determine the extent of indoor air pollution's effect on sleep quality. Comparing less polluted environments to more heavily polluted ones is another method that would help address the extent of indoor air quality's effect on sleep quality. This study illustrates the value of using consumer-grade sensors in both the IAQ and sleep quality monitoring domains, to measure a greater number of participants over an extended period of time in the participants' real environments.

CRediT authorship contribution statement

Hagen Fritz: Visualization, Methodology, Data curation, Conceptualization, Writing – original draft. **Kerry A. Kinney:** Conceptualization, Formal analysis, Methodology, Project administration, Resources, Supervision, Writing – review & editing. **Congyu Wu:** Writing – review & editing, Validation, Methodology, Investigation, Conceptualization. **David M. Schnyer:** Methodology, Supervision, Validation, Writing – review & editing. **Zoltan Nagy:** Writing – review & editing, Supervision, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgment

This work was supported by Whole Communities—Whole Health, a research grand challenge at the University of Texas at Austin, United States.

Appendix. Additional figures and tables

A.1. Participant demographics

The relevant demographic information regarding the 20 participants from this study are provided in Table A.1. 80% of the participants identified as female and the remaining 20% identified as male. Ages ranged from 19 to 27 with a median age of 20 years. Participants lived in only one of two dwelling types: 30% resided in apartments and the remaining 70% lived in standalone homes.

A.2. Ecological momentary assessment

The questions for both the morning and evening EMAs are shown in Table A.2. Both EMAs asked participants to rate four aspects of their current mood – level of content, stress, loneliness, and sadness – on a four-point scale. In addition, participants were asked to rate their energy level on a five-point scale. The morning EMA also asked four questions regarding sleep quality, provided in the second half of Table A.2. The questions for TST, SOL, and NAW were free-response where participants could enter any numerical value when reporting. The last sleep question on restfulness was on a similar four-point scale to that of mood.

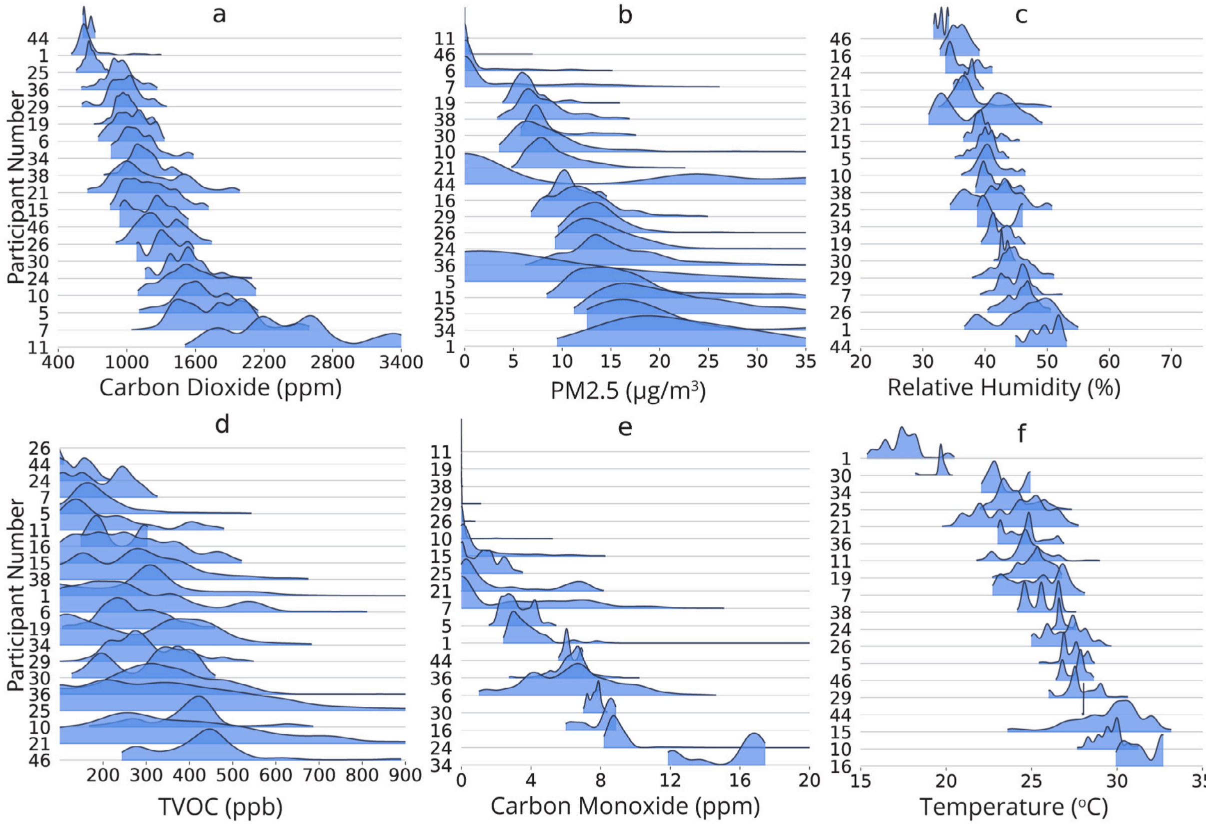

Fig. A.1. Distribution of IAQ parameters measured during Fitbit-detected sleep events ordered by increasing mean.

Table A.1
Participant demographic information.

Participant Number	Sex	Age	Building Type
1	F	27	Apartment
5	F	20	House
6	F	20	House
7	M	26	Apartment
10	F	19	House
11	F	20	House
15	F	19	House
16	F	19	Apartment
19	M	20	House
21	M	19	House
24	F	20	House
25	M	25	Apartment
26	F	19	House
29	F	20	House
30	F	19	Apartment
34	F	20	Apartment
36	F	21	House
38	F	19	House
44	F	19	House
46	F	19	House

A.3. Sensors on the Building EnVironment and Occupancy Beacon

Table A.3 highlights the IAQ sensors used on the Building EnVironment and Occupancy (BEVO) Beacon. Each of these sensors are single, bare units with minimal commercial software included and must be programmed and wired to a microcontroller. Given the wide variety of available consumer-grade IAQ sensors, we opted for sensors that used inter-integrated circuit communication protocol since these types of sensors were easier to integrate with the Raspberry Pi microcontroller. Sensors of a similar cost tend to perform with similar specifications to those we highlight in Table A.3. For an in-depth discussion on the performance of these sensors, we direct the reader to studies that have compared the performance of low-cost $PM_{2.5}$ [86,87], CO and CO_2 [88], and TVOC [89] sensors.

A.4. Calibration

We calibrated each of the IAQ parameters listed in Table A.3 except for the NO_2 and RH measurements which we did not use in the primary analysis. For each parameter we developed a linear regression model of the form $y_i = \alpha + \beta x_i$ by comparing measurements on each sensor to a reference monitor. For each parameter, we conducted three 2-hour long experiments and averaged the α and β coefficients from each of these experiments to produce the final model. The environment in which we calibrated the sensors depended on the parameter in question.

We calibrated the $PM_{2.5}$ and CO_2 sensors by co-locating all 20 BEVO Beacons with the corresponding research-grade monitor (TSI Aerodynamic Particle Sizer Model 3321; LI-COR Model 6252) in a full-scale experimental home environment (UTest House at UT Austin's Pickle Research Center). We injected particles (PTI Arizona Test Dust A1) into the space through the use of a hand-operated nebulizer at two points during the experiment. CO_2 concentrations of approximately 1500 ppm were generated in the space by using a pressurized CO_2 cylinder.

TVOC sensors were calibrated to output the same values by defining the reference measurement as the average TVOC concentration from all 20 devices at each timestamp. All BEVO Beacons were placed in the same 27 m^3 chamber and TVOC concentrations were generated by a researcher occupying the space for 30 min after an initial blank period of 30 min. We used a human researcher as our source for TVOCs because many consumer-grade TVOC sensors are sensitive to compounds in exhaled breath and we also wanted to ensure that sensors were calibrated towards the most likely source of TVOCs encountered during the field study.

Table A.2
Questions asked on the morning and evening EMAs sent through the Beiwe smartphone application.

Mood - Morning and Evening EMA					
Content					
RIGHT NOW, I am feeling CONTENT:					
0: Not at all	1: A little bit	2: Quite a bit	3: Very much	4: SKIP QUESTION	
Stress					
RIGHT NOW, I am feeling STRESSED:					
0: Not at all	1: A little bit	2: Quite a bit	3: Very much	4: SKIP QUESTION	
Loneliness					
RIGHT NOW, I am feeling LONELY:					
0: Not at all	1: A little bit	2: Quite a bit	3: Very much	4: SKIP QUESTION	
Sadness					
RIGHT NOW, I am feeling SAD:					
0: Not at all	1: A little bit	2: Quite a bit	3: Very much	4: SKIP QUESTION	
Energy					
RIGHT NOW, my ENERGY LEVEL is:					
0: Low energy	1: Somewhat Low Energy	2: Neutral	3: Somewhat high energy	4. High energy	5: SKIP QUESTION
Sleep Quality - Morning EMA Only					
Total Sleep Time					
How many hours did you sleep LAST NIGHT:					
Numeric Free Response					
Sleep Onset Latency					
How long, in minutes, did it take you to fall asleep LAST NIGHT?					
Numeric Free Response					
Number of Awakenings					
How many times do you remember waking up LAST NIGHT?					
Numeric Free Response					
Restfulness					
How restful was your sleep LAST NIGHT?					
0: Not at all restful	1: Slightly restful	2: Somewhat restful	3: Very restful	4: SKIP QUESTION	

Table A.3
Specifications of the sensors installed on the BEVO Beacon.

Model	Variable(s) measured	Accuracy	Measurement range	Cost
Sensirion SCD30	CO_2	±(30 ppm + 3% of MV[a])	0–40,000 ppm	75 USD
	T	±(0.4 °C + 0.023 × (MV − 25 °C))	40–70 °C	
Sensirion SPS30	PM_1	±10 μg/m^3 (<100 μg/m^3)	0–1,000 μg/m^3	75 USD
	$PM_{2.5}$	±10 μg/m^3 (<100 μg/m^3)		
	PM_4	±25 μg/m^3 (<100 μg/m^3)		
	PM_{10}	±25 μg/m^3 (<100 μg/m^3)		
Sensirion SVM30	TVOC	15% of MV	0–60,000 ppb	50 USD
	T	±1 °C	5–55 °C	
SPEC DGS CO	CO	15% of MV	0–1000 ppm	75 USD
	T	±0.4 °C	−10–85 °C	

[a]Measured Value.

We calibrated each CO sensor through a step-calibration process by using a 10 ppm CO gas standard that we diluted with zero air gas (ZAG) to yield 0, 1, 2, and 4 ppm CO concentrations. Batches of 3 BEVO Beacons were placed in a 5 L chamber and allowed to run for 24 h with pure ZAG supplied to the chamber. After this period, we ran each step in the calibration span for 2 h. Taking the middle 60 min from each span, we calculated the average CO measurement made by each BEVO Beacon and developed the linear model parameters to correct those readings to the true value.

Each temperature sensor on the BEVO Beacons was calibrated in a 10 L incubator. We varied the temperature from approximately 21 °C to 32 °C and used a reference (Michell Instruments S8000) to compare the sensor readings to. We did not calibrate the temperature sensors outside this range since the majority of measurements from pilot studies fell within this range.

A.5. Distributions of nightly IAQ measurements

Fig. A.1 shows the distribution of calibrated IAQ measurements, ordered by increasing mean, for each BEVO Beacon measured during Fitbit-detected sleep events. Not all participants recorded usable data for each IAQ parameter for every night. We do not include CO_2 nor CO data from Participants 16 and 46, respectively, due to hardware issues that caused the sensor to read out the same, erroneous value during the entire study. These data were also not used in the primary analysis.

References

[1] M. Hirshkowitz, K. Whiton, S.M. Albert, C. Alessi, O. Bruni, L. DonCarlos, N. Hazen, J. Herman, P.J.A. Hillard, E.S. Katz, et al., National sleep foundation's updated sleep duration recommendations, Sleep Health 1 (4) (2015) 233–243, http://dx.doi.org/10.1016/j.sleh.2014.12.010.

[2] A.A. Gomes, J. Tavares, M.H.P. de Azevedo, Sleep and academic performance in undergraduates: a multi-measure, multi-predictor approach, Chronobiol. Int. 28 (9) (2011) 786–801, http://dx.doi.org/10.3109/07420528.2011.606518.

[3] S.I.R. Pereira, F. Beijamini, R.A. Vincenzi, F.M. Louzada, Re-examining sleep's effect on motor skills: How to access performance on the finger tapping task? Sleep Sci. 8 (1) (2015) 4–8, http://dx.doi.org/10.1016/j.slsci.2015.01.001.

[4] Q.F. Song, X.X. Liu, W.N. HU, X.C. Han, W.H. Zhou, A.D. LU, X.Z. Wang, S.L. WU, Night sleep duration and risk of cognitive impairment in a Chinese population: a cross-sectional study, Biomed. Environ. Sci. 30 (10) (2017) 749–757, http://dx.doi.org/10.3967/bes2017.100.

[5] L. Shi, S.-J. Chen, M.-Y. Ma, Y.-P. Bao, Y. Han, Y.-M. Wang, J. Shi, M.V. Vitiello, L. Lu, Sleep disturbances increase the risk of dementia: a systematic review and meta-analysis, Sleep Med. Rev. 40 (2018) 4–16, http://dx.doi.org/10.1016/j.smrv.2017.06.010.

[6] N. Tsuno, A. Besset, K. Ritchie, Sleep and depression, J. Clin. Psychiatry (2005) http://dx.doi.org/10.4088/JCP.v66n1008.

[7] T.W. Uhde, B.M. Cortese, A. Vedeniapin, Anxiety and sleep problems: emerging concepts and theoretical treatment implications, Curr. Psychiatry Rep. 11 (4) (2009) 269–276.

[8] E.K. Lee, A.B. Douglass, Sleep in psychiatric disorders: where are we now? Canadian J. Psychiatry 55 (7) (2010) 403–412, http://dx.doi.org/10.1177/070674371005500703.

[9] T.S. Horowitz, B.E. Cade, J.M. Wolfe, C.A. Czeisler, Efficacy of bright light and sleep/darkness scheduling in alleviating circadian maladaptation to night work, Am. J. Physiol. Endocrinol. Metab. 281 (2) (2001) E384–E391, http://dx.doi.org/10.1152/ajpendo.2001.281.2.E384.

[10] J.R. Cho, E.Y. Joo, D.L. Koo, S.B. Hong, Let there be no light: the effect of bedside light on sleep quality and background electroencephalographic rhythms, Sleep Med. 14 (12) (2013) 1422–1425, http://dx.doi.org/10.1016/j.sleep.2013.09.007.

[11] M. Zaharna, C. Guilleminault, et al., Sleep, noise and health, Noise Health 12 (47) (2010) 64, http://dx.doi.org/10.4103/1463-1741.63205.

[12] K.I. Hume, M. Brink, M. Basner, et al., Effects of environmental noise on sleep, Noise Health 14 (61) (2012) 297, http://dx.doi.org/10.4103/1463-1741.104897.

[13] Y. Wang, Y. Liu, C. Song, J. Liu, Appropriate indoor operative temperature and bedding micro climate temperature that satisfies the requirements of sleep thermal comfort, Build. Environ. 92 (2015) 20–29, http://dx.doi.org/10.1016/j.buildenv.2015.04.015.

[14] L. Lan, K. Tsuzuki, Y. Liu, Z. Lian, Thermal environment and sleep quality: A review, Energy Build. 149 (2017) 101–113, http://dx.doi.org/10.1016/j.enbuild.2017.05.043.

[15] U.R. Amrit, Bedding textiles and their influence on thermal comfort and sleep, AUTEX Res. J. 8 (4) (2007) 252–254.

[16] M. He, Z. Lian, P. Chen, Evaluation on the performance of quilts based on young people's sleep quality and thermal comfort in winter, Energy Build. 183 (2019) 174–183, http://dx.doi.org/10.1016/j.enbuild.2018.10.040.

[17] T. Kubota, M. Uchiyama, H. Suzuki, K. Shibui, K. Kim, X. Tan, H. Tagaya, M. Okawa, S. Inoué, Effects of nocturnal bright light on saliva melatonin, core body temperature and sleep propensity rhythms in human subjects, Neurosci. Res. 42 (2) (2002) 115–122, http://dx.doi.org/10.1016/S0168-0102(01)00310-8.

[18] N.E. Klepeis, W.C. Nelson, W.R. Ott, J.P. Robinson, A.M. Tsang, P. Switzer, J.V. Behar, S.C. Hern, W.H. Engelmann, The national human activity pattern survey (NHAPS): a resource for assessing exposure to environmental pollutants, J. Expo. Sci. Environ. Epidemiol. 11 (3) (2001) 231–252, http://dx.doi.org/10.1038/sj.jea.7500165.

[19] P.J. Franklin, Indoor air quality and respiratory health of children, Paediatr. Respir. Rev. 8 (4) (2007) 281–286, http://dx.doi.org/10.1016/j.prrv.2007.08.007.

[20] B. Lévesque, V. Huppé, M. Dubé, R. Fachehoun, Impact of indoor air quality on respiratory health: results of a local survey on housing environment, Public Health 163 (2018) 76–79, http://dx.doi.org/10.1016/j.puhe.2018.06.015.

[21] L.-Y. Lin, H.-C. Chuang, I.-J. Liu, H.-W. Chen, K.-J. Chuang, Reducing indoor air pollution by air conditioning is associated with improvements in cardiovascular health among the general population, Sci. Total Environ. 463 (2013) 176–181, http://dx.doi.org/10.1016/j.scitotenv.2013.05.093.

[22] H.-C. Chuang, K.-F. Ho, L.-Y. Lin, T.-Y. Chang, G.-B. Hong, C.-M. Ma, I.-J. Liu, K.-J. Chuang, Long-term indoor air conditioner filtration and cardiovascular health: a randomized crossover intervention study, Environ. Int. 106 (2017) 91–96, http://dx.doi.org/10.1016/j.envint.2017.06.008.

[23] J. Hummelgaard, P. Juhl, K. Sæbjörnsson, G. Clausen, J. Toftum, G. Langkilde, Indoor air quality and occupant satisfaction in five mechanically and four naturally ventilated open-plan office buildings, Build. Environ. 42 (12) (2007) 4051–4058, http://dx.doi.org/10.1016/j.buildenv.2006.07.042.

[24] N. Fiedler, K. Kelly-McNeil, P. Ohman-Strickland, J. Zhang, J. Ottenweller, H.M. Kipen, Negative affect and chemical intolerance as risk factors for building-related symptoms: a controlled exposure study, Psychosom. Med. 70 (2) (2008) 254–262, http://dx.doi.org/10.1097/PSY.0b013e31816074f4.

[25] I. Mujan, A.S. Andelković, V. Munćan, M. Kljajić, D. Ružić, Influence of indoor environmental quality on human health and productivity-a review, J. Clean. Prod. 217 (2019) 646–657, http://dx.doi.org/10.1016/j.jclepro.2019.01.307.

[26] M.J. Mendell, G.A. Heath, Do indoor pollutants and thermal conditions in schools influence student performance? A critical review of the literature, Indoor Air 15 (1) (2005) 27–52, http://dx.doi.org/10.1111/j.1600-0668.2004.00320.x.

[27] O.A. Seppänen, W. Fisk, Some quantitative relations between indoor environmental quality and work performance or health, Hvac R Res. 12 (4) (2006) 957–973, http://dx.doi.org/10.1080/10789669.2006.10391446.

[28] J.-W. Kwon, H.-W. Park, W.J. Kim, M.-G. Kim, S.-J. Lee, Exposure to volatile organic compounds and airway inflammation, Environ. Health 17 (1) (2018) 1–8, http://dx.doi.org/10.1186/s12940-018-0410-1.

[29] M.E. Billings, D. Gold, A. Szpiro, C.P. Aaron, N. Jorgensen, A. Gassett, P.J. Leary, J.D. Kaufman, S.R. Redline, The association of ambient air pollution with sleep apnea: The multi-ethnic study of atherosclerosis, Ann. Am. Thorac. Soc. 16 (3) (2019) 363–370, http://dx.doi.org/10.1513/AnnalsATS.201804-248OC.

[30] L.G. Costa, T.B. Cole, K. Dao, Y.-C. Chang, J.M. Garrick, Developmental impact of air pollution on brain function, Neurochem. Int. 131 (2019) 104580, http://dx.doi.org/10.1016/j.neuint.2019.104580.

[31] L. Calderón-Garcidueñas, E. Leray, P. Heydarpour, R. Torres-Jardón, J. Reis, Air pollution, a rising environmental risk factor for cognition, neuroinflammation and neurodegeneration: the clinical impact on children and beyond, Rev. Neurol. 172 (1) (2016) 69–80, http://dx.doi.org/10.1016/j.neurol.2015.10.008.

[32] R. Lucchini, D. Dorman, A. Elder, B. Veronesi, Neurological impacts from inhalation of pollutants and the nose–brain connection, Neurotoxicology 33 (4) (2012) 838–841, http://dx.doi.org/10.1016/j.neuro.2011.12.001.

[33] J. Chi, W. Cao, Y. Gu, Recent progress in sleep quality monitoring and non-drug sleep improvement, Front. Hum. Neurosci. 14 (2020) 21, http://dx.doi.org/10.3389/fnhum.2020.00021.

[34] A.C. Rai, P. Kumar, F. Pilla, A.N. Skouloudis, S. Di Sabatino, C. Ratti, A. Yasar, D. Rickerby, End-user perspective of low-cost sensors for outdoor air pollution monitoring, Sci. Total Environ. 607 (2017) 691–705, http://dx.doi.org/10.1016/j.scitotenv.2017.06.266.

[35] F. Karagulian, M. Barbiere, A. Kotsev, L. Spinelle, M. Gerboles, F. Lagler, N. Redon, S. Crunaire, A. Borowiak, Review of the performance of low-cost sensors for air quality monitoring, Atmosphere 10 (9) (2019) 506, http://dx.doi.org/10.3390/atmos10090506.

[36] J. Saini, M. Dutta, G. Marques, Indoor air quality monitoring systems based on internet of things: A systematic review, Int. J. Environ. Res. Public Health 17 (14) (2020) 4942, http://dx.doi.org/10.3390/ijerph17144942.

[37] J. Liu, W.T. Wong, I.M. Zwetsloot, Y.C. Hsu, K.L. Tsui, Preliminary agreement on tracking sleep between a wrist-worn device fitbit alta and consensus sleep diary, Telemed. E-Health 25 (12) (2019) 1189–1197, http://dx.doi.org/10.1089/tmj.2018.0202.

[38] S. Haghayegh, S. Khoshnevis, M.H. Smolensky, K.R. Diller, R.J. Castriotta, Performance assessment of new-generation fitbit technology in deriving sleep parameters and stages, Chronobiol. Int. 37 (1) (2020) 47–59, http://dx.doi.org/10.1080/07420528.2019.1682006.

[39] E.D. Chinoy, J.A. Cuellar, K.E. Huwa, J.T. Jameson, C.H. Watson, S.C. Bessman, D.A. Hirsch, A.D. Cooper, S. Drummond, R.R. Markwald, Performance of seven consumer sleep-tracking devices compared with polysomnography, Sleep (2021) http://dx.doi.org/10.1093/sleep/zsaa291.

[40] J. Laverge, A. Novoselac, R. Corsi, A. Janssens, Experimental assessment of exposure to gaseous pollutants from mattresses and pillows while asleep, Build. Environ. 59 (2013) 203–210, http://dx.doi.org/10.1016/j.buildenv.2012.08.020.

[41] B.E. Boor, M.P. Spilak, J. Laverge, A. Novoselac, Y. Xu, Human exposure to indoor air pollutants in sleep microenvironments: A literature review, Build. Environ. 125 (2017) 528–555, http://dx.doi.org/10.1016/j.buildenv.2017.08.050.

[42] B.E. Boor, M.P. Spilak, R.L. Corsi, A. Novoselac, Characterizing particle resuspension from mattresses: chamber study, Indoor Air 25 (4) (2015) 441–456, http://dx.doi.org/10.1111/ina.12148.

[43] 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 (4) (2017) 791–802, http://dx.doi.org/10.1111/ina.12365.

[44] N. Canha, C. Teixeira, M. Figueira, C. Correia, How is indoor air quality during sleep? A review of field studies, Atmosphere 12 (1) (2021) 110, http://dx.doi.org/10.3390/atmos12010110.

[45] J. Laverge, A. Janssens, Analysis of the influence of ventilation rate on sleep pattern, in: Indoor Air 2011, ISIAQ, 2011.

[46] P. Strøm-Tejsen, D. Zukowska, P. Wargocki, D.P. Wyon, The effects of bedroom air quality on sleep and next-day performance, Indoor Air 26 (5) (2016) 679–686, http://dx.doi.org/10.1111/ina.12254.

[47] C. Liao, M. Delghust, J. Laverge, Association between indoor air quality and sleep quality, in: 33rd Annual Meeting Of The Associated-Professional-Sleep-Societies, Vol. 42, SLEEP, Oxford Univ Press Inc, 2019.

[48] X. Xu, Z. Lian, J. Shen, T. Cao, J. Zhu, X. Lin, K. Qing, W. Zhang, T. Zhang, Experimental study on sleep quality affected by carbon dioxide concentration, Indoor Air 31 (2) (2021) 440–453, http://dx.doi.org/10.1111/ina.12748.

[49] J. Xiong, L. Lan, Z. Lian, R. De Dear, Associations of bedroom temperature and ventilation with sleep quality, Sci. Technol. Built Environ. 26 (9) (2020) 1274–1284, http://dx.doi.org/10.1080/23744731.2020.1756664.

[50] N. Zhang, B. Cao, Y. Zhu, Indoor environment and sleep quality: A research based on online survey and field study, Build. Environ. 137 (2018) 198–207, http://dx.doi.org/10.1016/j.buildenv.2018.04.007.

[51] D. Andre, R. Pelletier, J. Farringdon, S. Safier, W. Talbott, R. Stone, N. Vyas, J. Trimble, D. Wolf, S. Vishnubhatla, et al., The Development of the Sensewear Armband, a Revolutionary Energy Assessment Device to Assess Physical Activity and Lifestyle, BodyMedia Inc, 2006.

[52] X. Zhang, G. Luo, J. Xie, J. Liu, Associations of bedroom air temperature and CO2 concentration with subjective perceptions and sleep quality during transition seasons, Indoor Air (2021) http://dx.doi.org/10.1111/ina.12809.

[53] S. Shiffman, A.A. Stone, M.R. Hufford, Ecological momentary assessment, Annu. Rev. Clin. Psychol. 4 (2008) 1–32, http://dx.doi.org/10.1146/annurev.clinpsy.3.022806.091415.

[54] J. Torous, M.V. Kiang, J. Lorme, J.-P. Onnela, New tools for new research in psychiatry: a scalable and customizable platform to empower data driven smartphone research, JMIR Ment. Health 3 (2) (2016) e16, http://dx.doi.org/10.2196/mental.5165.

[55] M. Ohayon, E.M. Wickwire, M. Hirshkowitz, S.M. Albert, A. Avidan, F.J. Daly, Y. Dauvilliers, R. Ferri, C. Fung, D. Gozal, et al., National sleep foundation's sleep quality recommendations: first report, Sleep Health 3 (1) (2017) 6–19, http://dx.doi.org/10.1016/j.sleh.2016.11.006.

[56] B.M. Altevogt, H.R. Colten, et al., Sleep Disorders And Sleep Deprivation: An Unmet Public Health Problem, National Academies Press, 2006.

[57] E.J. de Bruin, C. van Run, J. Staaks, A.M. Meijer, Effects of sleep manipulation on cognitive functioning of adolescents: a systematic review, Sleep Med. Rev. 32 (2017) 45–57, http://dx.doi.org/10.1016/j.smrv.2016.02.006.

[58] D.L. Hall, J. Llinas, An introduction to multisensor data fusion, Proc. IEEE 85 (1) (1997) 6–23, http://dx.doi.org/10.1109/5.554205.

[59] World Health Organization (WHO), Air Quality Guidelines For Europe, WHO Regional Office for Europe, Copenhagen, 2000.

[60] ASHRAE, ANSI/ASHRAE standard 62.2-2019: Ventilation and acceptable indoor air quality in residential buildings, 2019.

[61] S. Bonino, Carbon dioxide detection and indoor air quality control., Occup. Health Saf. (Waco, Tex.) 85 (4) (2016) 46–48.

[62] World Health Organization (WHO), WHO guidelines for indoor air quality: selected pollutants, World Health Organization. Regional Office for Europe, 2010.

[63] United States Environmental Protection Agency, Timeline of particulate matter (PM) national ambient air quality standards (NAAQS), 2013, www.epa.gov/pm-pollution/timeline-particulate-matter-pm-national-ambient-air-quality-standards-naaqs.

[64] S. Haghayegh, S. Khoshnevis, M.H. Smolensky, K.R. Diller, R.J. Castriotta, Accuracy of wristband fitbit models in assessing sleep: systematic review and meta-analysis, J. Med. Internet Res. 21 (11) (2019) e16273, http://dx.doi.org/10.2196/16273.

[65] N. Nematollahi, S.D. Kolev, A. Steinemann, Volatile chemical emissions from essential oils, Air Qual. Atmos. Health 11 (8) (2018) 949–954, http://dx.doi.org/10.1007/s11869-018-0606-0.

[66] N. Goel, R.P. Lao, Sleep changes vary by odor perception in young adults, Biol. Psychol. 71 (3) (2006) 341–349, http://dx.doi.org/10.1016/j.biopsycho.2005.07.004.

[67] A.S. Lillehei, L.L. Halcon, A systematic review of the effect of inhaled essential oils on sleep, J. Altern. Complement. Med. 20 (6) (2014) 441–451, http://dx.doi.org/10.1089/acm.2013.0311.

[68] H. Kawai, S. Tanaka, C. Nakamura, T. Ishibashi, A. Mitsumoto, Effects of essential oil inhalation on objective and subjective sleep quality in healthy university students, Sleep Biol. Rhythms 16 (1) (2018) 37–44, http://dx.doi.org/10.1007/s41105-017-0121-y.

[69] Z. Liang, M.A. Chapa-Martell, Accuracy of fitbit wristbands in measuring sleep stage transitions and the effect of user-specific factors, JMIR MHealth UHealth 7 (6) (2019) e13384, http://dx.doi.org/10.2196/13384.

[70] M.-P. Wan, C.-L. Wu, G.-N.S. To, T.-C. Chan, C.Y. Chao, Ultrafine particles, and PM2. 5 generated from cooking in homes, Atmos. Environ. 45 (34) (2011) 6141–6148, http://dx.doi.org/10.1016/j.atmosenv.2011.08.036.

[71] S. Fitzsimmons, L.L. Buettner, A therapeutic cooking program for older adults with dementia: Effects on agitation and apathy, Am. J. Recreat. Ther. 2 (4) (2003) 23–33.

[72] K.H. Hill, K.A. O'Brien, R.W. Yurt, Therapeutic efficacy of a therapeutic cooking group from the patients' perspective, J. Burn Care Res. 28 (2) (2007) 324–327, http://dx.doi.org/10.1097/BCR.0B013E318031A24C.

[73] N. Djulančić, V. Radojičić, M. Srbinovska, The influence of tobacco blend composition on carbon monoxide formation in mainstream cigarette smoke, Arch. Ind. Hyg. Toxicol. 64 (1) (2013) 107–113, http://dx.doi.org/10.2478/10004-1254-64-2013-2250.

[74] F. Safa, M. Chaiton, I. Mahmud, S. Ahmed, A. Chu, The association between exposure to second-hand smoke and sleep disturbances: A systematic review and meta-analysis, Sleep Health 6 (5) (2020) 702–714, http://dx.doi.org/10.1016/j.sleh.2020.03.008.

[75] P.W. Francisco, S. Pigg, D. Cautley, W.B. Rose, D.E. Jacobs, S. Cali, Carbon monoxide measurements in homes, Sci. Technol. Built Environ. 24 (2) (2018) 118–123, http://dx.doi.org/10.1080/23744731.2017.1372806.

[76] A. Mishra, A. van Ruitenbeek, M. Loomans, H. Kort, Window/door opening-mediated bedroom ventilation and its impact on sleep quality of healthy, young adults, Indoor Air 28 (2) (2018) 339–351, http://dx.doi.org/10.1111/ina.12435.

[77] S. Snow, A. Boyson, M. Felipe-King, O. Malik, L. Coutts, C.J. Noakes, H. Gough, J. Barlow, et al., Using EEG to characterise drowsiness during short duration exposure to elevated indoor Carbon Dioxide concentrations, BioRxiv (2018) 483750, http://dx.doi.org/10.1101/483750.

[78] L. Lan, L. Pan, Z. Lian, H. Huang, Y. Lin, Experimental study on thermal comfort of sleeping people at different air temperatures, Build. Environ. 73 (2014) 24–31, http://dx.doi.org/10.1016/j.buildenv.2013.11.024.

[79] L. Pan, Z. Lian, L. Lan, Investigation of sleep quality under different temperatures based on subjective and physiological measurements, Hvac R Res. 18 (5) (2012) 1030–1043, http://dx.doi.org/10.1080/10789669.2012.667037.

[80] E.H. Haskell, J.W. Palca, J.M. Walker, R.J. Berger, H.C. Heller, The effects of high and low ambient temperatures on human sleep stages, Electroencephalogr. Clin. Neurophys. 51 (5) (1981) 494–501, http://dx.doi.org/10.1016/0013-4694(81)90226-1.

[81] Q. Huang, C. Mao, Y. Chen, A compact and versatile wireless sensor prototype for affordable intelligent sensing and monitoring in smart buildings, in: Computing In Civil Engineering 2017, 2017, pp. 155–161, http://dx.doi.org/10.1061/9780784480830.020.

[82] G. Kolumban-Antal, V. Lasak, R. Bogdan, B. Groza, A secure and portable multi-sensor module for distributed air pollution monitoring, Sensors 20 (2) (2020) 403, http://dx.doi.org/10.3390/s20020403.

[83] H. Chojer, P. Branco, F. Martins, M. Alvim-Ferraz, S. Sousa, Development of low-cost indoor air quality monitoring devices: Recent advancements, Sci. Total Environ. 727 (2020) 138385, http://dx.doi.org/10.1016/j.scitotenv.2020.138385.

[84] L. Hale, S. Guan, Screen time and sleep among school-aged children and adolescents: a systematic literature review, Sleep Med. Rev. 21 (2015) 50–58, http://dx.doi.org/10.1016/j.smrv.2014.07.007.

[85] M.M. Thakkar, R. Sharma, P. Sahota, Alcohol disrupts sleep homeostasis, Alcohol 49 (4) (2015) 299–310, http://dx.doi.org/10.1016/j.alcohol.2014.07.019.

[86] B.C. Singer, W.W. Delp, Response of consumer and research grade indoor air quality monitors to residential sources of fine particles, Indoor Air 28 (4) (2018) 624–639, http://dx.doi.org/10.1111/ina.12463.

[87] Z. Wang, W.W. Delp, B.C. Singer, Performance of low-cost indoor air quality monitors for PM2. 5 and PM10 from residential sources, Build. Environ. 171 (2020) 106654, http://dx.doi.org/10.1016/j.buildenv.2020.106654.

[88] L. Spinelle, M. Gerboles, M.G. Villani, M. Aleixandre, F. Bonavitacola, Field calibration of a cluster of low-cost commercially available sensors for air quality monitoring. Part b: NO, CO and CO2, Sensors Actuators B Chem. 238 (2017) 706–715, http://dx.doi.org/10.1016/j.snb.2016.07.036.

[89] A. Polidori, V. Papapostolou, H. Zhang, Laboratory Evaluation of Low-Cost Air Quality Sensors, South Coast Air Quality Management District, Diamondbar, CA, USA, 2016.