INDOOR AIR QUALITY, SLEEP QUALITY AND NEXT-DAY COGNITIVE PERFORMANCE

by

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ABSTRACT

PHILIP ZENDELS. Indoor Air Quality, Sleep Quality and Next-Day Cognitive Performance. (Under the direction of JANE F. GAULTNEY)

Sleep is important for numerous regulatory processes of health and cognition and sleep impairments can lead to impairments in these outcomes. Sleep and breathing disorders such as Obstructive Sleep Apnea (OSA) have been well documented in impairing sleep, health and cognitive outcomes. While breathing disorders such as OSA have been well documented in their outcomes, the relationship has not been studied much for healthy breathers. Other factors surrounding the sleep environment of an individual, such as the temperature of their bedroom, ambient light exposure and noise have been shown to contribute to poorer sleep and cognitive performance but little work has examined the quality of the bedroom air. Additionally, research suggests that poor air quality leads to cognitive impairment. This study investigated the relationship between bedroom air quality, sleep quality and cognition. Sixty-one participants used two devices to record particulate matter and carbon dioxide (CO_2) within their bedroom, wore an actigraph, and completed a daily sleep diary and cognitive battery for three days. Results were analyzed via a multi-level mediation regression to examine the direct and indirect relationships of air quality on cognition through sleep within and between participants. High CO_2 was found to negatively influence both objective and subjective sleep quality as well as directly but not indirectly reducing working memory performance. More sleep disturbances were found to impair working memory performance. This research highlights the importance of having clean air within sleep environments and the importance of breathing during sleep for individuals, regardless of sleep disorder diagnosis.

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LIST OF ABBREVIATIONS

CO_2	Carbon Dioxide
OSA	Obstructive Sleep Apnea
PM	Particulate Matter
PM_{10}	Particulate Matter of 10 microns in diameter or larger
$PM_{2.5}$	Particulate Matter of 2.5 microns in diameter or larger
PSQI	Pittsburgh Sleep Quality Index
RH	Relative Humidity
SE	Sleep Efficiency
SES	Socioeconomic Status
SOL	Sleep Onset Latency
WASO	Wake After Sleep Onset
WHO	World Health Organization
WM	Working Memory

Introduction

Sleep is an important mechanism for regulating numerous physiological, emotional, and cognitive facets of our life. A plethora of research has shown that impaired sleep quality is associated with decrements in higher cognitive functions such as memory, decision making, and other aspects of executive functioning (Lowe, Safati & Hall, 2017). Many factors can contribute to sleep problems, including genetic predisposition to sleep disorders, physiological health, and behaviors surrounding sleep (Akinnusi, Saliba, Porhomayon & El-Solh, 2012; Kerkhof, 2018; Sehgal & Mignot, 2012). Healthy sleep hygiene behaviors and conditions, such as minimizing nighttime screen exposure and having a suitably dark and quiet bedroom free of distraction, promote higher quality sleep (Lin et al., 2007). Though there have been many studies investigating environmental conditions conducive to sleep (e.g. light or noise exposure), few have looked into how air quality may affect the rest one receives at night (Urlaub, Grün, Foldbjerg & Sedlbauer, 2015). Additionally, factors that contribute to nighttime breathing such as sleep disordered breathing impair cognitive abilities, though few studies have looked into the role of air quality in this relationship (Beebe & Gozal, 2002; Rana et al., 2016).

Because about a third of our lifetime is spent asleep, and sleep is such a critical component of health, ensuring healthy sleep behaviors is important for promoting our optimal functioning (Tobaldini et al., 2017). For conditions that can be modified, such as the bedroom environment, it is important to understand what conditions best promote health and functioning by promoting high quality sleep. Although evidence points to the importance of a dark and quiet sleeping space, the importance of bedroom air quality for healthy sleep has little empirical evidence. Cognitive impairments as a result of poor sleep pose safety risks in driving and may cost industries billions of dollars each year in reduced productivity, making understanding factors that contribute to optimal sleep especially critical (Goel et al., 2009; Zak & Winn, 2016).

Air Quality

Over the past few decades, evidence has accumulated on the dangers of low levels of air pollutants, such as harmful gasses and particulate matter, for optimal human health. High concentrations of even common gaseous pollutants, such as carbon dioxide (CO_2), can lead to symptoms such as fatigue, headaches, and respiration difficulties through Sick Building Syndrome (Redlich, Sparrer & Cullen, 1997; Zhang, Zhao, Nordquist & Norback, 2011). Particulate matter, including organic and mineral compounds ranging from nanometers to micrometers in size, have adverse effects on health, leading to higher rates of morbidity and mortality related to respiration across many groups (Lippmann, 2012). The health concerns raised by these contaminates have led to guidelines and regulations recommending lower levels of pollutants in the ambient (outdoor) environment. For example, the World Health Organization (WHO) recommended 10 micrograms per 10 cubic meters or less of particulate matter of 2.5 micrometers ($PM_{2.5}$) averaged across a year and 20 micrograms per 10 cubic meters or less of particulate matter of 10 micrometers (PM_{10}) averaged across a year (Colvez, Castex, Carriere, 2003). Presently, there are no guidelines for indoor air quality. A few past studies have recognized the importance of studying air quality as it relates to sleep, including looking into how various ventilation patterns can promote better indoor air quality at night, though none have captured the multi-faceted aspects of both air quality and sleep (Canha, Lage, Candeias, Alves & Almeida, 2017; Strøm-Tejsen et al., 2016; Urlaub et al., 2015). Though there is a clear effect of air quality on health, the effects of air contaminants on sleep have not been sufficiently explored.

Poor air quality, such as high concentrations of particulate matter, can have both short and long term negative health consequences. Short term exposure has found to cause respiratory problems and constrict blood flow, and long term exposure is linked to chronic health conditions such as eczema and cancer (Lippmann 2012; Pope et al., 2002). Chronic exposure to particulate matter is especially a problem in communities of lower socioeconomic status (SES), leading to further health inequities between populations (Jerrett et al., 2001; Jerrett et al. 2005). Inflammation, irritation, and damage to the respiratory system caused by pollutants such as particulate matter may be especially relevant in causing breathing disruptions, and evidence suggests that greater ambient air pollution could be linked with higher rates of obstructive sleep apnea (OSA) as a result of this (Billings, Gold, Szpiro, Aaron & Jorgensen, 2019).

In the developed world, individuals spend the majority of their time indoors, sleeping in a bedroom, working in an office, indoor eating, school, recreation, and more (Almeida-Silva, Wolterbeek & Almedia 2013). Indoor environments often suffer from poor air circulation due to lack of ventilation, with air contaminants not able to diffuse into the atmosphere (Canha, Lage, Candeias, Alves & Almeida, 2017). Because of this, it is especially important to analyze how indoor air quality may impact health outcomes; however, unlike ambient air quality there are few regulations on indoor air quality in place for optimal health. Research is mixed on the relationship between ambient and indoor air quality, with some studies finding indoor air quality changes following external conditions on a delay, others finding little to no correlation due to differences in ventilation and higher concentration of compounds (Han et al., 2015; Hänninen, Rumrich & Asikainen, 2017; Krebs et al., 2021). Both the amount of time spent indoors and the ease of manipulating indoor air conditoins compared to the external environment lend themselves to more research investigating the effects of indoor air quality on health.

Sleep

Sleep is an essential behavior for optimal health, assisting in maintaining homeostasis, regulating metabolism, supporting the immune system, allowing for adequate respiration, and promoting mental health (Besedovsky, Lange & Born, 2011; Del Rio João, de Jesus, Carmo & Pinto, 2018; Tobaldini et al., 2017; Taheri, et al., 2004; Vyazovskiy, 2015). Additionally, sleep is essential for mental well-being and cognitive functioning, with insufficient or inefficient sleep associated with impairments to memory, executive functioning, perception, attention, emotion regulation, and more (Goel et al., 2009; Lowe et al., 2017). Neuroimaging studies have shown deficits in brain regions critical for many aspects of cognition following sleep deprivation, such as the prefrontal cortex, thalamus, hippocampus and limbic system, further evidence for sleep's important roles in cognitive ability (Goel et al., 2009). Many of these cognitive processes, such as those involved with memory and executive functioning, require not just adequate sleep duration, but also high quality sleep (Lo et al., 2012; Rana et al., 2016).

Though sleep duration is an important and easy to understand measurement for sleep, a variety of other components of sleep, including the time it takes to fall asleep, the amount of times one wakes up throughout the night, perceived sleep restfulness, and sleep fragmentation all contribute to sleep quality (Buysse et al., 1989). Additionally, impairments to breathing such as OSA can cause sleep fragmentation, prevent restorative sleep, and induce greater daytime sleepiness (Beebe & Gozal, 2002). Sleep quality and duration are often measured objectively via technology such as electroencephalograms or actigraphs, which record neural and physical activity, respectively. Subjective reports for sleep quality are often also taken, with reports such as the Pittsburgh Sleep Quality Index (PSQI) encompassing a wide range of variables that affect sleep (Buysse et al., 1989). Though objective measures such as actigraphs and subjective reports present different types of data, both collect important information on sleep efficiency, the amount of time spent asleep relative to the amount of total time in bed. This indicator of sleep fragmentation can be used as a predictor of cognitive- and health-related outcomes.

Sleep hygiene is a collection of health behaviors and bedroom conditions that promote better quality and longer duration sleep (Lin et al., 2007). Measures of sleep hygiene feature different subcomponents, but many include limiting arousing activities prior to bed, limiting eating and drinking before bed, having consistent bed times and wake times, and having an environment that promotes sleep. Sleep environments often specify a bedroom free of distractions and being adequately dark, quiet, and cool enough for one to rest as these can interrupt sleep, reset the circadian rhythm, and reduce slow wave sleep, respectively (Caddick, Gregory, Arsintescu & Flynn-Evans, 2018; Lin et al., 2017). Despite studies showing poor ventilation of bedrooms as a potential health risk, little effort has been put into including clean air as an environmental component of sleep hygiene (Canha et al., 2017; Strøm-Tejsen et al., 2016).

Research has begun to explore the importance of air quality in sleep environments, though many studies include limited variables. Sleep disordered breathing such as OSA may impair cognitive function and individual health by preventing adequate oxygen flow throughout the night (Spruyt et al., 2009). Environmental conditions such as low oxygen due to high altitude have shown similar effects (Bazurto Zapata, Meza, Jaramillo, Gomez & Duque, 2014). CO_2 is often used as a single variable to measure air quality, and some research has found that excessive levels of CO_2 indoors causes negative effects on sleep quality (Caddick et al., 2018; Hui, Wong & Mui, 2008; Urlaub et al., 2015). However, whether CO_2 has objective effects on sleep is debated, as Urlaub et al. (2015) explain in their review of indoor air quality and sleep.

Other studies have explored other elements of indoor air quality, finding that bedroom environments frequently have levels of CO_2 and other pollutants outside of recommended levels (Canha et al., 2017). Though evidence has linked other pollutants in the external environment to higher prevalence of OSA, research has yet to determine if pollutants beyond CO_2 in the internal environment may impair sleep in general (Billings et al., 2019).

Cognition

Cognitive ability is important for optimal performance in academic and professional settings, thus it is important to minimize impairments. A variety of cognitive abilities such as memory, decision making, executive functioning, and more all perform optimally when an individual obtains adequate sleep duration and quality. Executive functioning, the ability to start, examine, change, and stop actions to achieve their goals, may be especially vulnerable to insufficient or ineffective sleep (Tucker, Whitney, Belenky, Hinson & Van Dongen, 2010). Working memory (WM), the ability to manage different types of information for use and long-term encoding, is impaired following sleep deprivation (Frenda & Fenn, 2016). Sleep-related cognitive impairments have been estimated to cost over 60 billion dollars a year due to inadequate memory consolidation and evaluation strategies (Zak & Winn, 2016). Impairments to executive functioning can also pose safety risks. For example, sleep-deprived individuals demonstrate worse driving performance, and are at higher risk for accidents, endangering the driver and those around and possibly costing an additional 50 billion dollars to the economy each year (Goel et al., 2009). With this in mind, receiving adequate sleep is clearly important for optimal cognitive performance to promote productivity and safety.

A variety of studies have looked into specific mechanisms of sleep's impact on cognition. Neuroimaging studies have found a variety of brain regions critical for cognition with changes in activity as a response to sleep deprivation. The prefrontal and parietal cortices as well as the thalamus and basal ganglia have all shown differences that result in poorer logical skills, language processing, spatial navigation, inhibition control and decision making when individuals receive insufficient sleep (Goel et al., 2009). Sleep deprivation may impact the hippocampus by altering neuron connectivity, impairing the ability for individuals to correctly form episodic memory (Goel et al., 2009). Sleep quality impairments, such as waking throughout the night, and disrupted breathing, have also been shown to inhibit memory consolidation and inhibitory control, even when individuals received healthy durations of sleep throughout the night (Beebe & Gozal, 2002; Rana et al., 2016).

Though not as abundant in the literature as sleep mechanisms that support cognitive function, a few studies have found that poor air quality can also impede advanced thinking tasks. High concentrations of $PM_{2.5}$ in the outdoor environment can cause neuroinflamation, resulting in poorer mental health and cognitive impairment to memory (Fonken et al., 2011). In a review of indoor air quality literature, Tham (2016) found that higher concentrations of air pollutants reduced worker productivity and caused lower scores on cognitive batteries and WM tasks. Ambient exposure to $PM_{2.5}$ and carbon monoxide impair cognition and worker productivity in populations with asthma (Lavy, Ebenstein & Roth, 2014). Additionally, research indicates that children have lower cognitive outcomes and achieve lower test scores when ambient levels of $PM_{2.5}$ and ozone are high (Shier, Nicosia, Shih & Datar, 2019).

Present Study

The present study hopes to expand the work of existing studies by linking air quality, sleep, and next morning cognitive performance. It is hypothesized that there will be an indirect effect of air quality on cognitive performance via sleep. Specifically, higher levels of particulate matter and CO_2 levels will be associated with lower sleep duration and worse sleep quality, which will in turn predict lower next day cognitive performance. This builds upon previous research linking the three concepts of indoor air quality, sleep, and cognition, expanding on the work of Strøm-Tejsen et al. (2016) by including predictors such as particulate matter for air quality and using a variety of cognitive measures to examine effects.

Methods

Participants

This study collected data from 61 (sample size determined by a power analysis) individuals from around University of North Carolina, Charlotte. Data collection took place between February and November of 2021. The sample was 42.62% male (1.64% transgender), and the mean age for participants is 23.15 (*SD* = 4.69; range 18-34). The majority of the participants identified as white or Caucasian (59.02%). Participants were recruited through the SONA system and general recruiting. Participants recruited via the UNC Charlotte SONA system received course credit for participating. In addition, all participants received up to fifty dollars for completion of all tasks requested. Snowball sampling was used to attract other participants including graduate students and non-students. Participants were not eligible for the study if they had any sleep or breathing disorders. Data about participants can be found in Table 1.

Procedures

Participants signed up online and filled out a brief survey including demographic information, as well as reporting on any abnormalities in sleep and breathing, such as disorders or medication they might take. Following this, participants scheduled a time to meet with the researcher of this study in order to sign a consent form, be briefed on the purpose of the study, the requirements for participation, and to collect baseline sleep survey data. After signing a return agreement, they were loaned three devices for measurement of air quality and sleep. As data were collected during the COVID-19 pandemic, the researcher wore gloves and wiped down all devices with disinfectant before and after they were transferred to participants and masks were worn at all times. Over the next three days, participants were instructed to follow any normal preferences for sleep behavior and room ventilation that they would normally have. Each morning, after participants woke up, they filled out a brief survey reporting on subjective sleep quality as well as perform a short cognitive battery (20 minutes). If participants missed a day (*N* = 8), they were allowed to hold on to the devices for one extra day beyond the standard three to repeat the procedure. The baseline measures took about 20 minutes to complete, and the morning sleep questions and cognitive battery also took about 20 minutes each morning.

An instruction sheet was provided to explain how to wear, set up, and use each of the devices provided in the study, as well as instructions on how to take the morning sleep survey and the cognitive battery. The instructions also informed participants about the way they earned their incentive. Participants received an actigraph wrist watch, as well as a PurpleAir PA-II monitor and an Autopilot APCEMDL CO2 Monitor to track sleep and air quality, respectively. The instruction sheet provided information on how to allow proper airflow for the devices to function. At the end of the three days, participants once again met with the researcher to return the devices. The data was then reviewed by the researcher, and participants were emailed with their compensation based on completeness; seven dollars for each day of complete data and an additional twenty nine dollars for completing the whole study. In order to protect participants' identity, they were assigned a short numeric/letter string to be used as their identifier. Participants used this identifier to sign in to the cognitive battery and morning sleep questions. A master list linking their names and their chosen ID was maintained in a separate file. Data collected were stored anonymously in the cloud with no identification information associated with the data, and has been password protected to ensure data are confidentially stored.

Measures

Air Quality. Carbon dioxide (CO_2) has long been used as an indicator for indoor air quality, and has been analyzed for its health consequences in high concentrations in studies of health and sleep quality (Strøm-Tejsen et al., 2016; Zhang et al., 2011). Participants were provided with an AutoPilot APCEMDL CO2 Monitor (Hydrofarm, Petaluma, CA) which uses 2-channel infrared gas sensors, a device that has been used in previous literature to examine indoor air quality (Barnwell, 2021). This device takes measurements at five second intervals and stores data on temperature (°C), relative humidity (RH) (%), and CO_2 (ppm). The temperature range for the device is from 0 to +50 °C, with an accuracy of ±0.1°C, humidity data can be collected in ranges from 5% to 95% ±1%, and CO_2 ranges from 0 to 5,0000 ±50ppm. The device was left plugged in to record data for the duration of the three days of the study. Data were downloaded from the device's SD card by the experimenter after it was returned to the researcher and the average CO_2 of each night while the participant slept was calculated.

Participants also received a PurpleAir PA-II (PurpleAir), a device that has been shown to accurately measure particulate matter concentration in the ambient environment (Magi, Cupini, Francis, Green & Hauser, 2019). This device tracks particulate matter from a wide range of sizes, including both $PM_{2.5}$ and PM_{10}. Particulate matter is considered a dangerous pollutant by the WHO, and has been shown to impair cognitive performance in multiple studies, hence its inclusion in this study (Lavy et al., 2014; Shier et al., 2019; WHO, 2005). The measurement range is from 0.30 to 10 µm, and it has a 98% efficiency rate for particles greater than 0.50 µm (Singer & Delp, 2018) in which it scans for individual counts of molecules ($N_{.3\text{-}10.0}$). Its effectivity is maintained from 0 to 500 µg of particles per cubic meter of air when measuring weight of particulates (PM). The temperature range for the thermometer on the device goes from -40 to 85°C, the pressure range includes 300 to 1,100 hPa, and the relative humidity (RH) is tracked with a tolerance of 3%. Data were recorded from the device at ninety second intervals and were stored digitally until downloaded when the device was returned.

Sleep Quality. Sleep Quality was measured using both objective and subjective measures. Upon waking each morning, participants reported their duration of sleep in a sleep diary available from the National Sleep Foundation (Byrne, 2015) with the time they went to bed, time they woke up, report on any sleep disturbances, and report on how rested they feel on a three point Likert Scale (refreshed, somewhat refreshed, or fatigued). Additionally, sleep quality was assessed via four questions taken from the Medical Outcomes Scale (MOS; Hays, Martin, Sesti & Sprizter, 2005). All of these items are on a six point Likert scale of frequency ranging from "All of the Time" to "None of the Time." Three of these items were reverse coded. Higher scores represent more sleep disturbances throughout the night. Data on sleep quality, including total sleep duration, awakenings throughout the night, and sleep efficiency (percentage of time in bed asleep), were measured objectively using an Actigraph wGT3X-BT (ActiGraph). Sleep quality was objectively estimated as number of awakenings and by calculating the amount of time one was asleep divided by their total time resting in bed the previous night (i.e. sleep efficiency (SE)). These actigraphs use an accelerometer and light sensor to detect information about the wearer's activity, including whether they are awake or asleep and sitting or standing. This specific model has been shown to accurately assess sleep when worn on the non-dominant wrist (Lee & Tse, 2019). Data were stored on the actigraphs, and were downloaded after their return.

Eriksen Flanker Task. The Eriksen flanker task was designed in order to assess executive functioning (Eriksen & Eriksen 1974). This is measured by a target stimuli being presented at a fixed location, flanked by surrounding irrelevant stimuli, and participants must decipher the condition and respond whether certain targets are present. There are two types of trials presented; in congruent trials, surrounding distractors will match target stimuli while in incongruent trials, surrounding distractors will represent the opposite stimuli. This type of task has previously been used in sleep studies in order to examine executive functioning and inhibition (Renn & Cote, 2013). This task was taken from an implementation created by PsyToolkit (Stoet 2010; Stoet 2017), and participant's data were stored anonymously via their assigned ID online through cloud services.

Go/No-Go Task. The go/no-go paradigm has been a measure used in multiple studies to assess executive functioning (Criaud & Bounlinguez, 2012). This is a simple task where participants are presented with a screen that displays either a signal for them to 'go' or press a key or 'no-go' and take no action. It is a measure of one's ability to inhibit their behaviors. Previous studies have examined performance changes on this task following sleep impairments (Renn & Cote, 2013). This task was taken from an implementation created by PsyToolkit (Stoet 2010; Stoet 2017), and participant's data were stored anonymously via their assigned ID online through cloud services.

N-back Task. The N-back task has been used to assess individual's WM by quickly presenting updating information. This task was originally created by Kirchner (1958). Participants are told a number of items which they must remember back from a list presented (the "N") and are presented items in the list one at a time. After each item, participants respond with whether the same item was present N-items ago. This study will use a 3-back task, participants must remember the previous three items viewed and report with whether the current item viewed was the third one back (not prior to the third nor either of the previous two). Previous studies have found that sleep can affect performance in lower values of N, such as a 3-

back task (Terán-Pérez et al., 2012). This task was taken from an implementation created by PsyToolkit (Stoet 2010; Stoet 2017), and participant's data were stored anonymously via their assigned ID on online through cloud services.

Effort Investment. Level of cognitive effort participants are willing to invest will be measured with a modified version of the Math Effort Task presented by Engle-Friedman et al. (2003). Participants were presented with five levels of difficulty to choose from for simple addition mental math problems that they are to complete without the use of aids. Each level of difficulty presents a different range of three numbers (1-3, 3-9, 7-15, 7-25, 7-35) to be added and numbers are presented for .8 seconds at a time. Participants have 15 seconds to answer the problem. Participants were presented with six problems.

Plan of Analysis

Particulate matter counts per volume were standardized and averaged to create a composite score for analyses. Additionally, composite scores were created for executive functioning were created by standardizing the Go No-go score and the Eriksen flanker task score and combining these with standardized reaction times, where higher scores show higher executive functioning. The process was done for the 3-back outcomes. Analyses were completed in SPSS 27 (IBM Corporation, Almonk, NY) using the MLMed macro. Each participant's data on air quality were averaged across each of three nights.

A mixed model mediation analysis was run to analyze the data across the three days. This used a 1-1-1 model with an example shown in Figure 1. Level two contained participant level and demographic variables (between subjects) and level one was variance within participants across the three days. Demographic variables that were significantly correlate with air quality outcomes were added as level 2 variables, while daily temperature and humidity acted as covariates on the first level. Separate analyses were conducted for CO_2 and a standardized total of PM. The analysis explored whether air quality predicted cognitive outcomes through objective and subjective measures of sleep. Separate analyses were used to analyze subjective and objective data.

Results

Table 1 shows demographic details about the participants in this sample. Participants were primarily women, white, undergraduate students and lived in houses. Participants were recruited from the university SONA system as well as notice via flyers and emails. No significant correlations were observed between gender and any focal variables or student status and any focal variables. Because many individuals lived in houses or private apartments, few participants shared their bedroom with a roommate. Number of roommates was also not correlated significantly with any focal variables.

Table 2 shows descriptive statistics for focal variables in the study before composite variables were created. Rooms were typically normal temperature and humidity for indoor environments. Carbon Dioxide was high for indoor environments (*M* = 1325.55) though it had a high variability (*SD* = 499.70) and Particulate Matter was low. Participants generally reported mediocre subjective sleep quality. Objective sleep time was low (*M* = 410.67 minutes, *SD* = 69.71) but objective sleep efficiency remained at healthy levels for most participants (*M* = 89%, *SD* = 5%), being above the advised 85% (Miller et al., 2014). Figure 2 shows an example of one night of CO_2 data. Figure 3 shows an example of Particulate Matter data across a three-day period. Figure 4 shows an example of sleep data across the three-day period. Scores on the executive function measures (Go No-go task and Eriksen flanker task) tended to be better than scores on the WM (3-back) task.

Table 3 shows bivariate correlations of the raw focal variables of the study. Higher CO_2 was associated with high relative humidity, more time awake after sleep onset, more counts of waking after sleep onset (WASO), and slower WM reaction time. Warmer temperatures were associated with more correct answers on the Go No-go task and longer reaction times on the Go

No-go task. Higher humidity was associated with longer objective sleep time and lower motivation. Particulate matter measures were positive and significantly intercorrelated as expected. Lower subjective feelings of being well-rested after sleep were correlated with more subjective sleep disturbances, less time awake after objective sleep onset, greater sleep efficiency, and longer reaction times on the Eriksen flanker task. Objective sleep measures, including sleep onset latency (SOL), WASO and sleep efficiency, were all intercorrelated in expected directions. More time awake after the initial sleep onset was also associated with better performance on the Go No-go task. Greater count of instances of waking after the initial sleep onset was correlated with longer reaction times on the Go No-go task, but better performance on the Go No-go task.

Type of domicile was included as a covariate. In a regression predicting air quality outcomes, individuals who were white were significantly more likely to have lower CO2 (b = -227.35, p < .01) than individuals who did not identify as white, with living status in a house, dorm or apartment being run as covariates. PM was predicted by living in an apartment (b = 2.57, p < .01), but not in a dorm or by race. In outcomes examining an interaction between race and air quality (a term created by centering, then multiplying the two together), neither race nor the interaction term predicted WM outcomes, though CO_2 did (b = -.001, p < .01). For executive functioning, race, CO2, and the interaction term were not significant predictors.

Tables 4 and 6 show associations of CO_2 with objective and subjective sleep outcomes. No facets of air quality or selected demographic covariates significantly predicted total sleep time. Between participants, CO_2 was the only significant predictor (b = -.003, p < .05; Table 4) for objective sleep efficiency; individuals who slept in rooms with higher concentrations of CO_2 had poorer overall sleep efficiency. Within participants (across the three nights), temperature was a significant predictor (*b* = .09; $p < .05$; Table 6) for the subjective restorative properties of sleep from the sleep diary; individuals felt less refreshed on nights where their room was warmer than on nights when their room was cooler. Between participants, humidity (*b* = -.13, $p < .05$; Table 6) and CO_2 (*b* = .003, $p < .01$; Table 6) were significant predictors of subjective sleep disturbances. Participants in rooms with higher humidity reported fewer sleep disturbances and participants in rooms with greater concentrations of CO_2 reported more sleep disturbances.

Tables 5 and 7 show results between the direct relationships of both CO_2 and sleep outcomes onto cognitive outcomes. In the analysis including objective sleep predictors, CO_2 was the only significant between subjects predictor (*b* = -.0008, $p < .05$; Table 5) of WM; participants in rooms with greater concentrations of CO_2 had poorer performance on WM assessments. Race was the only significant predictor of executive functioning (*b* = -1.13, $p < .05$; Table 5); individuals who identified as non-white or Caucasian had lower scores on measures of executive functioning.

With subjective sleep predictors, a similar finding emerged for executive functioning, with race (*b* = -1.01; $p < .05$; Table 7) the only significant predictor. WM, sleep disturbances (*b* = -.30; $p < .05$; Table 7) significantly predicted WM within participants (across the three nights); higher self-reported sleep disturbance was associated with worse WM. Between participants, CO_2 (*b* = -.0009; $p < .05$; Table 7) and living in a university dormitory as opposed to a house (*b* = -1.24; $p < .05$; Table 7) were significant predictors of WM. Individuals who slept in rooms with higher concentrations of CO_2 performed worse on WM measures and individuals who slept in dormitories performed worse on WM measures.

PM count ($N_{.3\text{-}5.0}$) was not a significant predictor for any outcomes of sleep or cognitive performance in any of the models. In both models for objective and subjective sleep, significant direct effects between CO_2 and sleep were observed (a pathway) as well as between sleep and cognitive performance (b pathway). Additionally, CO_2 was shown to significantly predict cognitive performance directly (c' pathway). Despite these findings, no significant effects were observed as indirect effects from CO_2 to cognitive performance (c pathway). This provides partial support for our hypothesis in the direct effects of CO_2 on sleep and some aspects of next day cognition, the prediction of indirect effects were not supported.

Discussion

Our hypothesis was that worse air quality parameters would predict cognitive impairment indirectly through measures of sleep. While we were unsuccessful in finding this, we did find that high concentrations of CO_2 did predict both objective poorer sleep efficiency and subjectively more sleep disturbance issues in direct relationships, suggesting air quality does impact sleep. Greater subjective sleep disturbances as well as higher CO_2 predicted poorer performance on WM. Though there were no significant indirect effects, this confirmed direct effects for the *a* pathway (air quality onto sleep), the *b* pathway (sleep quality onto cognition) and the *c'* pathway (air quality onto cognition). One possible explanation for the lack of indirect effects was the limitations of our sample size, given that data were collected for only three nights. In a pilot study conducted by Strøm-Tejsen et al. (2016), a week of data allowed more within-subject variability and possibly more opportunity to observe effects. Small effect size in analyses of CO_2 were likely due to the metric (parts per million), and not necessarily indicative of a negligible effect.

Though our findings mostly replicated past literature on the relationship between carbon dioxide and sleep, no significant findings were found relevant to PM. This is most likely due to the low concentration of PM most individuals experienced; the average PM $N_{2.5}$ experienced overnight was below the threshold of 10 molecules per dL of air for clean air (M = 6.39; SD = 12.01) as recommended by the World Health Organization, meaning most participants had clean air (Colvez et al., 2003). Further research should continue to investigate the role of PM and sleep due to the prevalence of other breathing disorders linked to high PM exposure, as well as geographically linked differences in air quality (Jerret et al., 2001). Past research indicates that particulate matter exposure is linked with greater risk for developing chronic respiratory conditions such as allergies and asthma as well as more severe symptoms in individuals who already have these conditions that are exposed (Sompornrattanaphan et al., 2020). Additionally, research is finding increasing overlap between sleep related breathing disorders (OSA) and chronic breathing disorders (asthma), further reason that investigating PM 2.5's role on sleep should be continued (Madama, Silva & Matos 2015). A potential future direction includes observing only peak PM concentrations for individual participants, such as the highest 10% of readings per individual, to investigate whether those experience brief exposure to high concentrations of PM may be more vulnerable to sleep loss than those with consistently low concentrations of PM.

Our findings did show a significant effect of racial identity on executive functioning. Given the observed relationships between race and air quality, we suspect that this is not an effect of race directly but rather a result of individuals within our sample identifying as people of color living in environments that had poorer ventilation or other environmental factors impacting air quality (as indicated by the nonsignificant interaction of race and CO2). Non-white individuals within the United States have been historically exposed to more outdoor air pollutants, have older housing maintenance systems and are more likely to experience mold problems, all potentially contributing to health disparities (Cook, Argenio & Lewinsky-Desier, 2021; Louisias & Matsui 2020). Other social determinants of health may also play a role; though our study did not collect data on SES, past research indicates that lower SES is related to poorer performance in some cognitive measurements (Elliott & Bachman, 2018), exposure to worse air quality (Jerrett et al., 2005) and worse sleep (Ruggiero et al., 2020). Given these associations of SES and poorer air quality, further research into the disparities between individuals of different demographics with air quality and health is needed (Jerrett et al., 2001).

Other demographic details may be of note for future studies to investigate in the relationship of air quality and sleep. Risk for OSA increases in middle aged and older adults. Assuming a relationship between air quality and breathing disorders, connections of air quality, sleep and cognitive performance may be more evident in an older population (Billings et al., 2019; Bseikri, Lo & Guilleminault, 2015). Given that our findings show cognitive impairment in poorer air quality and that individuals with sleep related breathing issues may already face cognitive impairment (Spryut et al., 2009) it is important to ensure that proper ventilation and maintenance of indoor air quality is kept in place around vulnerable populations. Institutions such as retirement homes and hospitals that may already have individuals vulnerable to cognition impairments from sleep should maintain proper ventilation and employ methods to reduce CO2 concentrations (Almeida-Silva et al., 2014). Similarly, college dorms also require proper ventilation methods. Given the number of individuals present in close proximity in high density housing, the potential for increased CO2, compromised air quality and sleep may contribute to student performance.

The present study has several strengths. The longitudinal nature ensured that data collected would be representative of multiple days of air quality, sleep quality and cognitive performance and would not be due to outliers of days where participants may have had particularly bad air or sleep quality. Additionally, the availability and ease of setting up equipment allowed participants from a wide variety of housing to participate. Since participants were instructed to go about their normal sleep schedule within their own bedrooms, the data have more ecological validity than would have been the case with an artificial schedule or location. All of the air quality equipment has high accuracy and validity while being relatively affordable. Collection objective air quality data and both objective and subjective sleep parameters allowed greater insight into the sleep experience. Though data was collected during the COVID-19 pandemic, much of the study was able to continue as normally as it was largely conducted independently with only brief meetings to pick up and drop off equipment.

However, it is not without limitations. Though analyzing multiple nights of data was a strength, longer durations (a week) including weeknight and weekend data may have been more representative of standard sleep schedules. This study allowed for natural variability within air quality based on individuals' normal sleeping preferences, but did not have any form of control and thus suffered from a lack of variability, especially surrounding PM. Online morning surveys and cognitive batteries allowed for some potential issues where participants would leave cognitive assessments running in the background but may not have engaged with them. Lastly, the nature of the COVID-19 pandemic may have caused other stressors as well as atypical housing density that could have affected sleep or cognitive outcomes.

Further research into whether air quality interventions to reduce air pollutants such as CO2 impact subsequent sleep and cognition should be explored. Among these are: improved ventilation and filtration methods, air circulation methods (having a fan on, having windows and doors open) and possibly introduction of plants into bedroom environments. Prior research has indicated that indoor plants can be used to reduce the concentration of indoor Carbon Dioxide and improve cognitive performance such as attention (Kin, Yeo & Lee, 2020; Su & Lin, 2015). Further research should also be explored involving other air pollutants, such as Particulate Matter in settings with greater variability, as well as other indoor pollutants including Carbon Monoxide, Formaldehyde and Volatile Organic compounds (Cahna et al., 2017). Additionally, data collection should be expanded to wider demographics including those of larger age ranges, race and ethnicity, health status and more.

People spend about a third of their lifetime sleeping, and a majority of their time is spent indoors. Inadequate ventilation can lead to accumulation of air pollutants even in an indoor environment, which inhibits the body's ability to obtain clean air throughout the night. CO_2 especially can impair both objective and subjective sleep quality, leading to lower sleep efficiency and more reported sleep disturbances. CO_2 also appears to contribute to impaired WM performance, as does sleep quality. While we were unable to find evidence to support our hypothesis of an indirect effect of sleep quality mediating the relationship between air quality and cognitive performance, we were able to find support for direct relationships between each of those variables. The cost of sleep deprivation can be high for health and cognitive outcomes, even among individuals who otherwise have no diagnosed sleep or breathing disorders. Future research should continue to investigate how indoor air quality affects health, sleep and performance outcomes.

Table 1
Demographic variables of sample

Variable	Mean ± SD	Range
Age	23.15 ± 4.69	18-34
Gender (%)		
Male	26 (42.62)	
Female	34 (55.73)	
Transgender	1 (1.64)	
Race (%)		
White/Caucasian	36 (59.02)	
Black/African American	8 (13.11)	
Asian American	12 (19.67)	
Mixed Race/Other	5 (8.20)	
Student Status (%)		
Undergraduate	33 (54.10)	
Graduate	14 (22.95)	
Non-student	14 (22.95)	
Living Arrangement (%)		
On-campus dorm	12 (19.67)	
Apartment	18 (29.51)	
House	31 (50.82)	
Roommates	.46 ± .59	0-3

Note. N = 61.

Table 2

Descriptive statistics for focal variables

	Mean	Std. Deviation	Range
1. CO_2 (ppm)	1325.55	499.70	636.89-4050.53
2. Temperature (F)	70.90	3.36	60.90-81.38
3. Relative Humidity (%)	49.87	7.82	27.43-73.30
4. PM .3	1176.51	1138.70	1.58-9223.37
5. PM .5	364.29	345.91	.52-4271.56
6. PM 1.0	63.10	84.89	.00-1395.47
7. PM 2.5	6.39	12.01	.00-206.04
8. PM 5.0	1.34	2.38	.00-32.36
9. Restorativeness	2.05	0.53	1.00-3.00
10. Sleep Disturbances	9.41	3.60	4.00-20.00
11. SOL (minutes)	5.62	7.17	.00-110.00
12. TST (minutes)	410.67	69.71	55.00-736.00
13. WASO Time (minutes)	47.45	24.25	6.00-320.00
14. WASO Count	17.37	6.89	2.00-42.00
15. SE	0.89	0.05	54.30%-98.20%
16. GNG incorrect	0.03	0.02	.00-.10
17. GNG RT (ms)	677.09	66.95	477.43+956.71
18. EFT score	0.90	0.09	.00-1.00
19. EFT RT (ms)	761.88	112.50	504.50-2000.00
20. 3B score	0.72	0.15	.07-.94
21. 3B RT	921.40	232.63	469.78-1903.00

Note. N = 61. CO_2 = Carbon Dioxide. ppm = parts per million. PM = Particulate Matter counts per 10 dL of air. Restorativeness = How refreshed individuals felt after waking. SOL = Sleep onset latency. TST = Total Sleep Time. WASO = Wake after sleep onset. SE = Sleep Efficiency. GNG = Go No-GO. RT = Reaction Time. EFT = Erikson Flanker Task. 3B = 3-back task. Motivation Difficulty = difficulty selected for motivation task (1-5). Motivation score = proportion of correct answers.

Table 3

Bivariate correlations of focal variables

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1. CO2																				
2. Temp	-0.06																			
3. Relative Humidity	.31*	0.08																		
4. PM .3	-0.05	-0.16	-0.18																	
5. PM .5	-0.04	-0.22	-0.10	.93**																
6. PM 1.0	-0.02	-0.26	-0.11	.91**	.95**															
7. PM 2.5	0.00	-0.23	-0.14	.89**	.82**	.94**														
8. PM 5.0	0.01	-0.20	-0.12	.89**	.80**	.83**	.88**													
9. Restorativeness	0.01	0.09	-0.13	-0.13	-0.16	-0.22	-0.16	-0.02												
10. Sleep Disturbances	0.24	-0.12	-0.17	-0.16	-0.10	-0.12	-0.11	-0.08	.404**											
11. SOL	0.03	-0.03	-0.14	-0.03	-0.09	-0.04	0.00	-0.03	-0.04	-0.04										
12. TST	.30*	0.06	.26*	-0.19	-0.15	-0.14	-0.17	-0.21	-0.11	-0.04	-0.13									
13. WASO Time	.39**	0.09	0.17	0.07	0.13	0.15	0.08	-0.05	-.28*	0.15	-0.07	0.19								
14. WASO Count	.37**	0.05	0.15	-0.01	0.12	0.08	-0.06	-0.10	-0.20	0.07	-0.24	.38**	.72**							
15. SE	-0.25	-0.10	-0.03	-0.09	-0.11	-0.15	-0.12	0.01	.26*	-0.16	-.28*	0.19	-.84**	-.50**						
16. GNG incorrect	-0.02	-.30*	-0.10	0.03	0.00	0.09	0.18	0.14	-0.04	0.00	-0.06	-0.25	-.26*	-.30*	0.15					
17. GNG RT	-0.09	.28*	0.23	-0.12	-0.06	-0.14	-0.20	-0.22	0.02	0.04	0.00	0.21	0.22	.29*	-0.12	-.61**				
18. EFT score	0.10	-0.02	0.08	0.09	0.08	0.06	0.06	0.11	-0.10	-0.04	0.04	-0.05	-0.16	-0.14	0.07	-0.15	-0.19			
19. EFT RT	-0.09	0.22	0.06	-0.02	-0.04	-0.08	-0.09	-0.14	.26*	0.05	0.00	0.03	0.11	0.13	-0.09	-0.16	.50**	-.57**		
20. 3B score	-0.23	0.11	-0.16	0.15	0.18	0.17	0.13	0.08	0.02	-0.03	-0.17	-0.05	0.00	-0.04	0.02	-0.08	-0.06	0.12	-0.13	
21. 3B RT	.28*	-0.05	0.10	-0.17	-0.18	-0.19	-0.17	-0.17	-0.01	0.01	0.06	0.18	-0.01	0.11	0.04	-0.13	0.11	0.09	0.12	-.79**

Note. N = 61. *$p < .05$. **$p < .01$. CO2 = Carbon Dioxide. ppm = parts per million. PM = Particulate Matter counts per 10 dL of air. Restorativeness = How refreshed individuals felt after waking. SOL = Sleep onset latency. TST = Total Sleep Time. WASO = Wake after sleep onset. SE = Sleep Efficiency. GNG = Go No-Go. RT = Reaction Time. EFT = Erikson Flanker Task. 3B = 3-back task.

Table 4

Carbon Dioxide effects on objective sleep outcomes

	Sleep Efficiency b	Sleep Efficiency SE	Total Sleep Time b	Total Sleep Time SE
Level 1 – Within				
Intercept	113.33**	14.61	325.54	212.93
Temperature	-.42	.33	-9.99	5.30
Humidity	.11	.15	1.78	.75
CO2	-.00	.00	.02	.03
Level 1 – Between				
Temperature	-.29	.20	-.00	2.87
Humidity	.03	.08	1.48	1.17
CO2	-.003*	.001	.02	.02
Level 2				
Race	-1.05	1.27	-30.64	18.51
Apartment	-3.56	1.47	-35.59	21.48
Dorm	1.12	1.68	8.31	24.44

Note. $N = 61$. b = effect size. SE = Standard Error. $^{*}p < .05$. $^{**}p < .01$

Table 5

Carbon Dioxide and Objective Sleep effects on Working Memory and Executive Function

	Working Memory b	Working Memory SE	Executive Function b	Executive Function SE
Level 1 – Within				
Intercept	.92	6.42	-.45	7.56
Temperature	-.04	.10	.06	.11
Humidity	.05	.04	-.05	.05
CO2	-.00	.00	.00	.00
SE	-.02	.03	-.01	.03
TST	-.00	.00	-.00	.00
Level 1 – Between				
Temperature	.01	.06	-.03	.07
Humidity	-.00	.02	-.00	.03
CO2	-.0008*	.0004	.00	.00
SE	.00	.04	.04	.05
TST	-.00	.00	-.00	.00
Level 2				
Race	-.26	.39	-1.13*	.46
Apartment	.08	.47	-.12	.55
Dorm	-1.26	.51	-.45	.60

Note. *N* = 61. *b* = effect size. *SE* = Standard Error. **p* < .05. ***p* < .01

Table 6

Carbon Dioxide effects on subjective sleep outcomes

	Restorativeness b	Restorativeness SE	Sleep Disturbances b	Sleep Disturbances SE
Level 1 – Within				
Intercept	2.01	1.69	24.73	11.01
Temperature	.09*	.04	.02	.07
Humidity	-.00	.02	.00	.03
CO2	-.00	.00	-.00	.00
Level 1 – Between				
Temperature	.01	.02	-.17	.15
Humidity	-.01	.01	-.13*	.06
CO2	.00	.00	.003**	.001
Level 2				
Race	.20	.15	1.08	.95
Apartment	-.20	.17	-1.30	1.11
Dorm	-.05	.19	-1.15	1.26

Note. *N* = 61. *b* = effect size. *SE* = Standard Error. $^{*}p < .05$. $^{**}p < .01$

Table 7

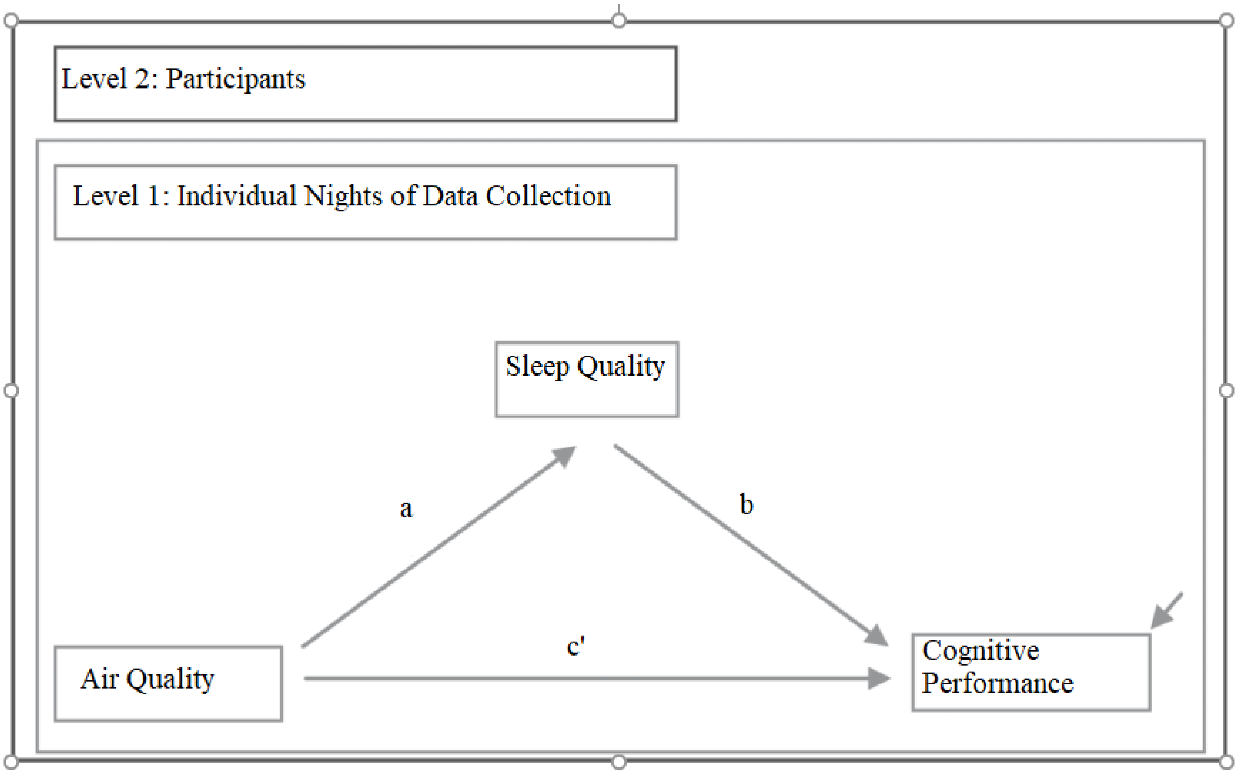
Carbon Dioxide and Subjective Sleep effects on Working Memory and Executive Function

	Working Memory b	Working Memory SE	Executive Function b	Executive Function SE
Level 1 – Within				
Intercept	.46	4.69	4.79	5.57
Temperature	.01	.09	.12	.11
Humidity	.03	.04	-.05	.05
CO2	-.00	.00	.00	.00
Restorativeness	.01	.24	-.26	.28
Sleep	-.30*	.13	-.14	.15
Disturbances				
Level 1 – Between				
Temperature	.01	.06	-.04	.07
Humidity	.00	.03	-.01	.03
CO2	-.0009*	.0004	.00	.00
Restorativeness	.16	.39	-.26	.46
Sleep	.02	.06	-.02	.07
Disturbances				
Level 2				
Race	-.29	.40	-1.01*	.47
Apartment	.16	.46	-.20	.54
Dorm	-1.24*	.51	-.47	.61

Note. N = 61. b = effect size. SE = Standard Error. *$p < .05$. **$p < .01$

Figure 1

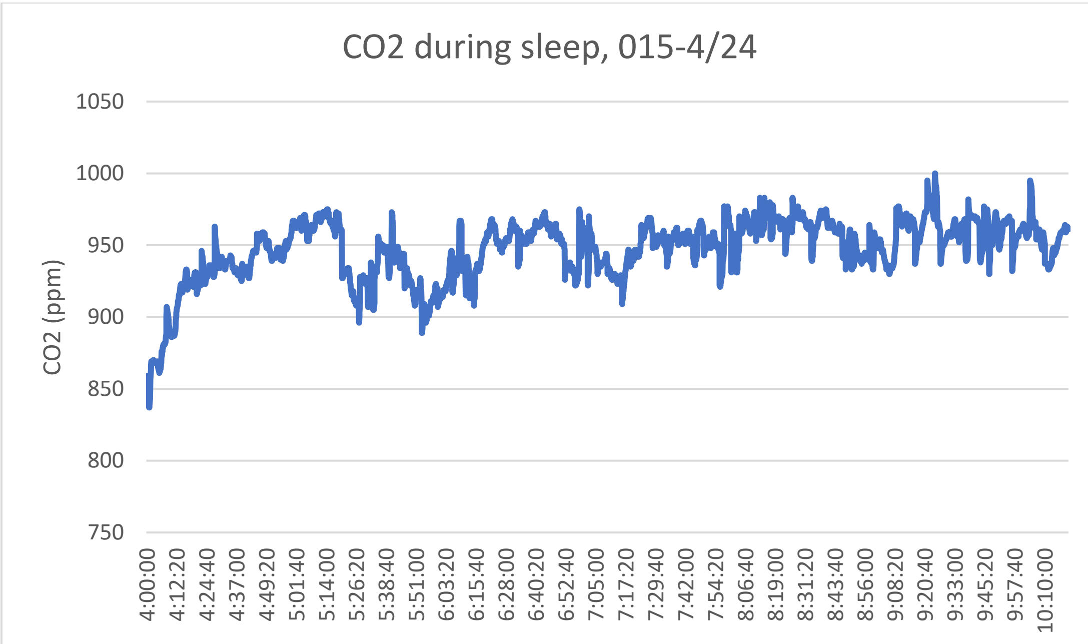
Study Model



Note. Pathways of statistical analysis for the multilevel mediation.

Figure 2

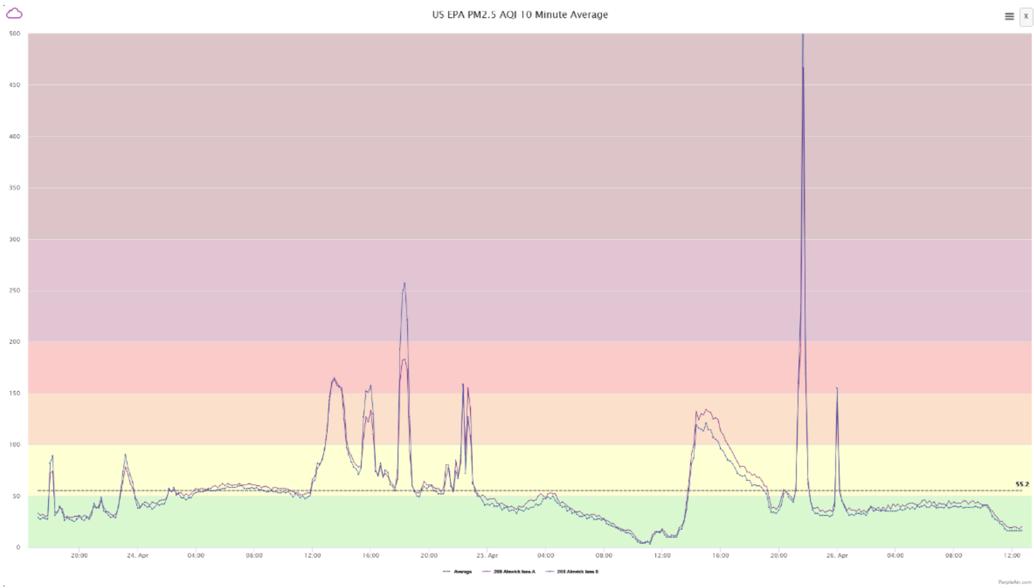
Example CO_2 Count for one participant over one night



Note. Time shown between participant's bed time and wake time.

Figure 3

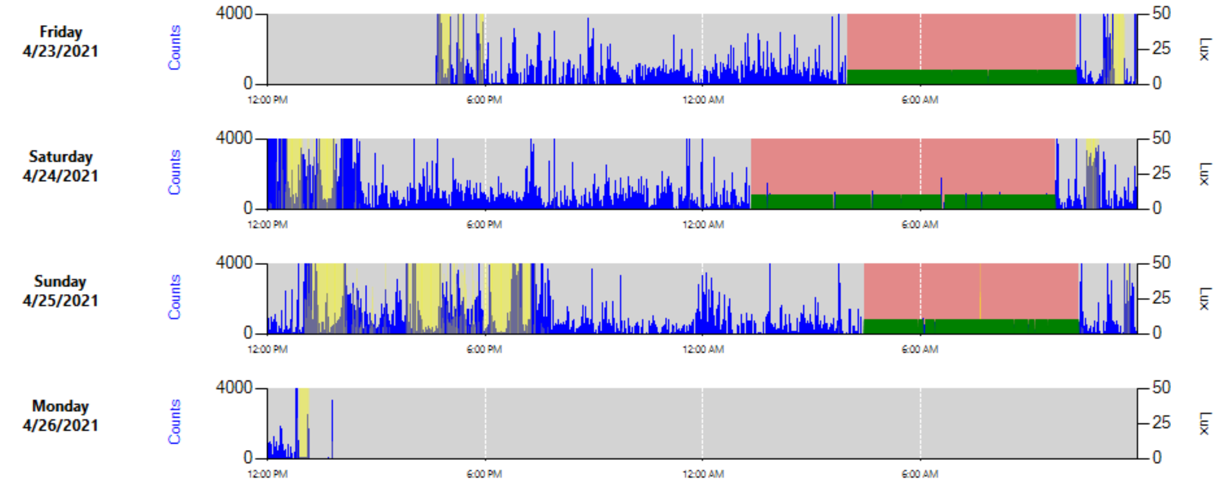
Example Particulate Matter Count for one participant



Note. Observations from entire duration of participation.

Figure 4

Example sleep of one participant over three nights



Note. Observations from entire duration of participation.

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