Building and Environment 257 (2024) 111551

Contents lists available at ScienceDirect

Building and Environment

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

Home indoor air quality and cognitive function over one year for people working remotely during COVID-19

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ARTICLE INFO

Keywords:
Occupational
Remote
IEQ
Productivity
Buildings
Ventilation

ABSTRACT

The coronavirus disease 2019 (COVID-19) pandemic triggered an increase in remote work-from-home for office workers. Given that many homes now function as offices despite not being designed to support office work, it is critical to research the impact of indoor air quality (IAQ) in homes on the cognitive performance of people working from home. In this study, we followed 206 office workers across the U.S. over one year under remote or hybrid-remote settings during 2021–2022. Participants placed two real-time, consumer-grade indoor environmental monitors in their home workstation area and bedroom. Using a custom smartphone application geofenced to their residential address, participants responded to surveys and periodic cognitive function tests, including the Stroop color–word interference test, Arithmetic two-digit addition/subtraction test, and Compound Remote Associates Task (cRAT). Exposures assessed included carbon dioxide (CO_2) and thermal conditions (indoor heat index: a combination of temperature and relative humidity) averaged over 30 min prior to each cognitive test. In fully adjusted longitudinal mixed models ($n \leq 121$), we found that indoor thermal conditions at home were associated with cognitive function outcomes non-linearly ($p < 0.05$), with poorer cognitive performance on the Stroop test and poorer creative problem-solving on the cRAT when conditions were either too warm or too cool. Most indoor CO_2 levels were <640 ppm, but there was still a slight association between higher CO_2 and poorer cognitive performance on Stroop ($p = 0.09$). Our findings highlight the need to enhance home indoor environmental quality for optimal cognitive function during remote work, with benefits for both employees and employers.

1. Introduction

The beginning of the coronavirus disease 2019 (COVID-19) pandemic triggered a major shift in work routines. For many office workers, their homes were abruptly forced into serving as all-purpose indoor environments, merging their personal life and work life into one location [1]. As office workers grew accustomed to remote work-from-home (WFH) over the next several years and as pandemic restrictions eased, opinions about the long-term practice of WFH diverged. Preferences about working at the office versus at home vary for a plethora of reasons related to virus exposure, work flexibility, productivity, work setup, social connection, mental well-being, family, and accessibility [2–10]. The main consensus is that long-term WFH does not universally work for everyone [6,11,12], and that different workers will require different types of support for optimizing their work life [13]. It is expected that some level of flexibility with WFH for office workers will become a permanent feature of many company policies – pandemic or no – in order to recruit and retain talent [14]. Given that many homes will continue to multitask as offices, without the buildings originally being designed to support office work, the question remains: Does the indoor home environment support effective cognitive performance while working, and how can home environments be optimized for remote work?

Prior research, mostly focused on office buildings, has shown that indoor air quality (IAQ) acutely influences the cognitive function of office workers. Indoor carbon dioxide (CO_2) is generated from people

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https://doi.org/10.1016/j.buildenv.2024.111551
Received 1 September 2023; Received in revised form 15 April 2024; Accepted 18 April 2024
Available online 24 April 2024
0360-1323/

breathing and is mostly influenced by occupancy levels and building ventilation rates. Accordingly, CO_2 has often been used in studies as an indicator of outdoor air ventilation rates and thus the general indoor dilution of pollutants, including volatile organic compounds (VOCs) and fine particulate matter ($PM_{2.5}$), although its accuracy as a surrogate for ventilation depends on the building volume, space type, occupant density, and other occupancy characteristics [15–17]. CO_2 may also act as an independent indoor pollutant on its own [17–20]. A review of 37 experimental studies suggested that CO_2 can affect multiple dimensions of cognitive function, with more consistent evidence when CO_2 was manipulated by adjusting ventilation rates as opposed to by pure injection into the air [17]. A recent meta-analysis of 15 experimental studies found stronger effects on complex cognitive tasks as opposed to simple cognitive tasks, based on exposure to pure CO_2 [21]. In our previous observational study about the cognitive function of office workers in real office buildings in six countries around the world, we reported that higher indoor concentrations of both CO_2 and $PM_{2.5}$ in office buildings were associated with worse performance on cognitive function tests during the course of one year; the CO_2 could have acted as a surrogate for a different (true) causal agent, not just as its own causal agent [22]. Most other studies of office worker cognitive function took place in experimental simulated office rooms with controlled IAQ under a small number of different exposure conditions. Their findings indicated associations of CO_2 conditions with worse decision-making performance [20] and cognitive function [19,23], associations of outdoor air ventilation rates with worse performance in decision-making [24], simulated office tasks [25], and cognitive function [19], and associations of $PM_{2.5}$ levels with worse performance in tasks of memory and logical thinking [26]. In addition to indoor pollutants, there is research evidence of non-linear impacts of thermal discomfort, particularly hot or cold temperatures, on cognitive function [23,27] and student performance [28–31]. Improving IAQ in office buildings for better cognitive function not only benefits the employees, but also the organization. Because of increased employee productivity and presenteeism, enhanced ventilation in offices has been shown to provide financial benefits to the employer that far outweigh any energy costs associated with enhanced ventilation [32].

Homes have distinct IAQ profiles compared to office buildings. For one, homes may experience higher levels of certain indoor pollutants from cooking, candle use, smoking, and other sources not typically found in commercial office spaces [33,34]. Many residential buildings may also have poorer mechanical outdoor air ventilation (if any), air filtration, or thermal insulation [33,35] compared to commercial office buildings [36]. A recent review found that outdoor air ventilation rates measured in about 10,000 homes had a geometric mean of 0.5 air changes per hour (i.e., a volume of air equivalent to half the home enters every hour), based on data mostly from North America, northern Europe, and China [35]. There is a sparsity of comparative data to commercial office spaces, but the 2019 building design standards from the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) would have equated to required air change rates, at minimum, of approximately 0.32–0.35 for single-family or multi-family homes versus nearly double, 0.6, for office spaces (assuming default occupancy and 8-foot ceilings) [37–39]. In practice, the actual air change rates in buildings also depend on how the systems are designed, installed, and operated.

Emerging research has identified a possible relationship between the indoor environment of homes and work performance at home. One study found that home environments with comfortable working spaces and access to greenery were associated with improved perceptions of WFH productivity among respondents to an online survey instrument [1]. Another found that higher thermal satisfaction at home was associated with better self-reported WFH productivity for a manufacturing company in Japan [40]. A third study in the U.S. reported that university students living in residential buildings without air conditioning had worse cognitive function during heat waves than those living in air conditioned buildings [30]. However, to our knowledge there are no studies about the impact of IAQ measured in homes on objective assessments of cognitive performance.

Major research gaps remain about how IAQ in residences affects the cognitive function of office workers while working from home, which could inform solutions for healthier home workplace environments with benefits to employees and employers alike. There is a critical need for studies that evaluate continuous measures of multiple IAQ parameters, inside real buildings, as occupancy behaviors change, over several seasons, with objectively measured outcomes of cognitive function in the working-age population. Thus, the focus of our study was to characterize real-time home indoor concentrations of CO_2, $PM_{2.5}$, temperature, and relative humidity and to investigate their associations with cognitive function test performance of office workers while working from home in the U.S. over 12 months during 2021–2022.

2. Material and methods

2.1. Study design

This investigation was part of the longitudinal Home-Work Study that prospectively followed 206 office workers in the United States while they were working in remote or hybrid settings during the COVID-19 pandemic. Participants were enrolled on a rolling basis and followed for one year upon their enrollment (starting between May–December 2021). The participant outcomes monitored included cognitive function, productivity, mental well-being, sleep quality, and physical activity. We shipped participants two real-time, consumer-grade indoor environmental monitors to place in their home workstation area and bedroom (Awair Omni, San Francisco, CA, USA) and a Fitbit watch to wear during the study (Fitbit Charge 4, San Francisco, CA, USA). We also developed a custom smartphone research application (app) that enrolled and consented participants, sent push notifications for periodic in-app surveys or cognitive function tests, monitored their paired sensor data, and tallied their compensation points. To maximize responses, in-app surveys and tests were set to automatically resend on certain future days if missed by a participant the first time. Cognitive function outcomes included a suite of four tests measuring cognitive performance or creativity. Participants were usually sent one or two app-based cognitive function tests almost every week, and these tests were geofenced such that they could only be taken when the phone was located at the home address.

Participants were asked to complete a series of surveys throughout the study period, including one demographics survey that asked about covariates used in our statistical analysis. The other surveys were outside the scope of this paper apart from population descriptives, but included more one-time baseline surveys; recurring surveys about productivity and mental health every two to three weeks; and surveys about hybrid work status every two weeks (to obtain information about their hybrid work schedule and any home changes). The one-time surveys included questions about financial stress, work, lifestyle, medical conditions, social support, personality (including extraversion and creativity indicators), home behaviors (including cleaning, air quality factors, and product uses), typical location during each hour of a day, building factors to the best of their knowledge (including type, ownership, layout, flooring, gas appliances, exhaust fans, temperature control, ventilation systems, air drafts, air filtration, maintenance issues, and water/mold issues, among many other questions), and home workstation factors (including ergonomics, lighting, nature/biophilia, setup of workstation, distractions, privacy, and noise). The study protocol was reviewed and approved by the Institutional Review Board at the Harvard T.H. Chan School of Public Health.

2.2. Study population

Participants comprised a convenience sample of knowledge workers, as they were recruited through advertisements on the LinkedIn website (Sunnyvale, CA, USA) and through a company-wide newsletter to U.S. employees of Ernst & Young (New York, NY, USA). Inclusion criteria queried in the eligibility survey were: lived in the U.S.; were between 22 and 64 years of age; had a full-time, permanent employment position doing desk-based computer work; were currently conducting full or partial remote work at home for a least the next several months; lived in a house, apartment, townhouse, or condominium; had no smokers in the household; read English fluently; did not have a color vision deficiency (for participation in a color-based cognitive function test); had a smartphone; had a stable Wi-Fi connection at home (for the monitors); and agreed to use the provided devices.

Fig. 1 summarizes the exclusion criteria for data used in this paper's analysis about indoor air quality and cognitive function. Data from a final 131 participants covering 3781 cognitive tests were used, after excluding potentially invalid cognitive test responses (as described in a later section), missing IAQ data at time of cognitive test, and test responses that had only one trial for a particular test type and participant (due to longitudinal design and learning effects).

2.3. Indoor air quality exposure assessment

We provided participants with two new Awair Omni indoor environmental monitors, one for near their bed and one for near their home workstation. The Awair Omnis are consumer-grade monitors intended for the public to gain real-time access to environmental measurements and are typically relatively low in cost. The sensors measured concentrations in 5-min intervals for CO_2, $PM_{2.5}$, temperature, and relative humidity, measured via non-dispersive infrared detector (with automatic background calibration), laser-based light scattering particle sensor, and complementary metal-oxide semiconductor sensor for the latter two, respectively [41]. Other measured parameters not considered in this analysis include total VOCs (because of less standardized methods), noise levels, and light intensity (the latter two were less related to air quality). Occasional missing data occurred due to the device disconnecting from Wi-Fi, as we describe further in the Statistical Analyses section. Once disconnected, the device had to be rebooted by the participant via the device app, which we periodically monitored and instructed participants on when and how to do so.

Participants were given written and video instructions on how to properly place the monitors at breathing-zone height near the target area (bed or workstation), ensure sufficient airflow around the devices, prevent obstruction from nearby objects (i.e., within two inches), and avoid places with unrepresentative conditions (e.g., dust, dampness, clutter, excess heat, excess cold, direct light, and corners with little airflow).

Each sensor within the Awair Omni unit comes batch-tested and pre-calibrated from the manufacturer (Honeywell Sensing for the $PM_{2.5}$ sensor) or has an automatic background self-calibration protocol during operation (Telaire for the CO_2 sensor). We conducted additional quality control and quality assurance (QA/QC) for 10 % of the monitors before subsequent shipment to participants. For batches of seven to 11 of those randomly selected monitors at a time, we monitored the four air quality parameters in a typical home bedroom for 30 min with windows closed followed by 30 min with the window open (for almost-outdoor CO_2 levels); we visually confirmed that the shapes of the parameter curves were parallel across devices over time and that the CO_2 levels approached background outdoor concentrations (~400–500 ppm). In

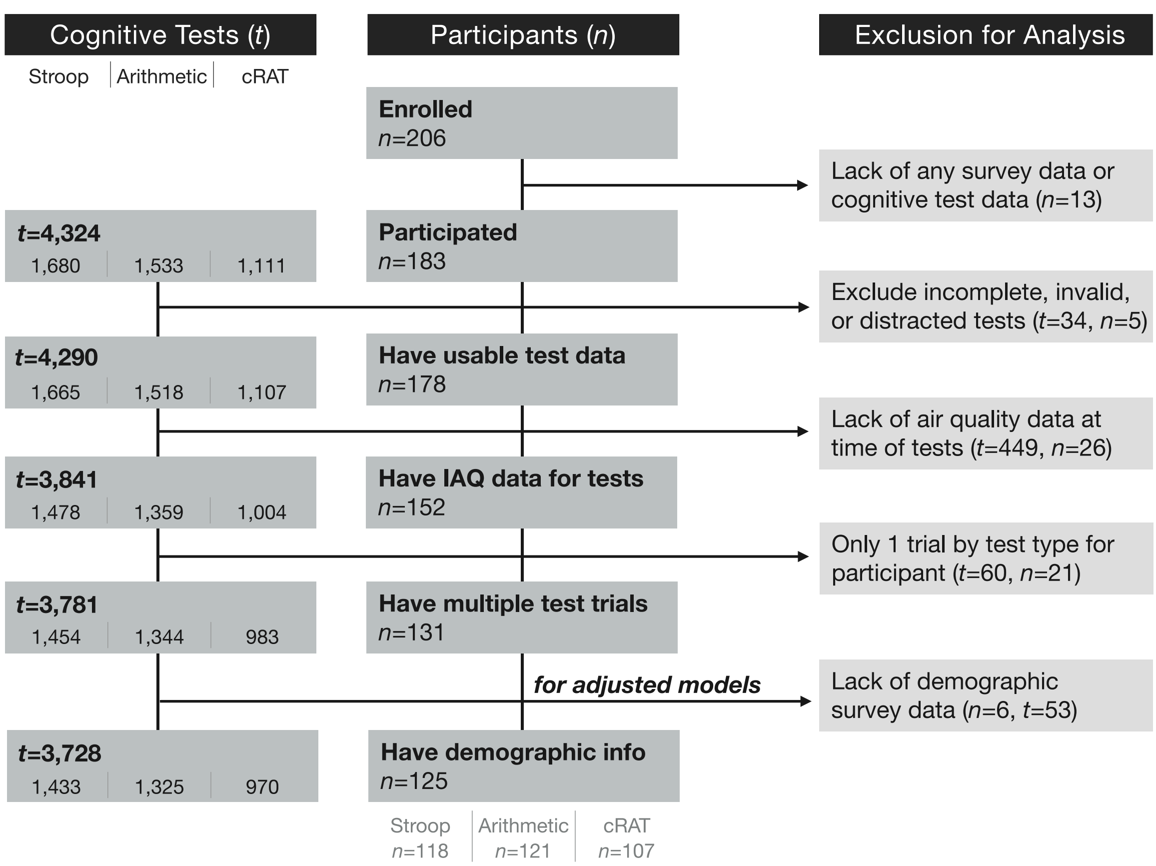

Fig. 1. Summary of exclusion criteria for participants and cognitive test data used in the final analysis of this paper about the association between indoor air quality and cognitive function (using Stroop, Arithmetic, and cRAT creativity tests). Note: n = number of participants; t = number of cognitive test responses from participants.

our observations, no monitors failed the co-location comparisons.

The Awair sensor specifications reported supported measurement ranges of 400–5000 ppm for CO_2, 0–1000 μg/m^3 for $PM_{2.5}$, -40–125 °C for temperature, and 0–100 % for relative humidity. We excluded air quality measurements that had any values outside the range (<0.1 % of data). The reported sensor accuracy was ±75 ppm for CO_2 (with 1 ppm output resolution), ±15 μg/m^3 for $PM_{2.5}$ (1 μg/m^3 resolution), ±0.2 °C for temperature (with 0.015 °C resolution), and ±2 % for relative humidity (with 0.01 % resolution) [41]. Most (93 %) of the $PM_{2.5}$ data during the study period had concentrations below 15 μg/m^3 (the accuracy limit), so we decided to exclude this exposure parameter from statistical models.

Because temperature and relative humidity are interrelated parameters that together influence perceptions of thermal comfort, we estimated the heat index as a combined exposure of interest using the *weathermetrics* package in R, based on the algorithm by the U.S. National Weather Service in its online heat index calculator [42,43]. Heat index is a measure of what the apparent temperature feels like to the body based on both relative humidity and air temperature. In essence, it adjusts the air temperature value based on the effects of air moisture (humidity) [42,43].

2.4. Cognitive function outcome assessment

Participants completed four types of self-administered, visual cognitive tests within the study smartphone app: Stroop [44,45], Arithmetic [22], Compound Remote Associates Task (cRAT) [46,47], and Alternative Uses Task (AUT) [48] (Fig. 2). For this analysis, we focused on the first three types of tests, which have entirely objective scoring (without the need for subjectively judging or cleaning the results) and are thus easily scalable measures. All tests were designed to take approximately 2 min in our app. The app provided an instruction screen before the participants pressed *start*. Feedback on accuracy of answers was not given during the tests.

The Arithmetic test in our study consisted of two-digit addition and subtraction problems that measure cognitive speed and working memory [22]. Each test prompted 10 math problems immediately after each other, and participants were instructed to answer as quickly and as accurately as possible. Prompts were randomized within test trials for all types of tests. The performance metric calculated for the Arithmetic tests was cognitive throughput (number of correct responses per minute).

The Stroop test is a color–word test that measures cognitive speed, selective attention, working memory, and inhibitory control (ability to inhibit cognitive interference). It is an interference test in that the participant must try to inhibit an easier automated thought process (reading the written color word on the screen) and instead perform a less automated task (naming the *font* color of the word) [44,45]. In our app, each test (or "trial") prompted 20 immediate rounds in which a color was written as a word on the screen and the displayed font color of that text was either the same ("congruent stimuli") or different ("incongruent stimuli") from the written color word; some of the prompts were also "neutral stimuli" in which simply "XXXX" was written in a particular displayed font color. As quickly and as accurately as possible, the participant was instructed to click the icon option that matched the *displayed* font color, not the written word. The color options were blue, red, green, and purple. Performance metrics for Stroop test responses were calculated as cognitive throughput (number of correct responses per minute for congruent and incongruent prompts), throughput interference inhibition (throughput in congruent and neutral rounds subtracted from throughput in incongruent rounds), and inhibitory control based on the following equation modified from a previous publication [44,45]:

$$inhibitory\ control = \frac{1}{time + 2 * \frac{time * \#\ errors}{\#\ prompts}}$$

where time refers to the total time (minutes) taken for all prompts and where we took the inverse of the previously published formula so that higher scores indicated better cognitive function (in line with the direction of effect for our other metrics).

The cRAT is a word-pairing test of convergent creative thinking, remote association, and insight problem solving [46,47,49]. In our study, each cRAT trial prompted eight creativity problems in which the screen displayed three words that form compound words (or semantic associations) with a fourth linkage word that the participant must think of. For example, given a prompt with the words "fountain, baking, pop", the correct answer would be "soda," which forms the compound words "soda fountain", "baking soda", and "soda pop." The solutions are

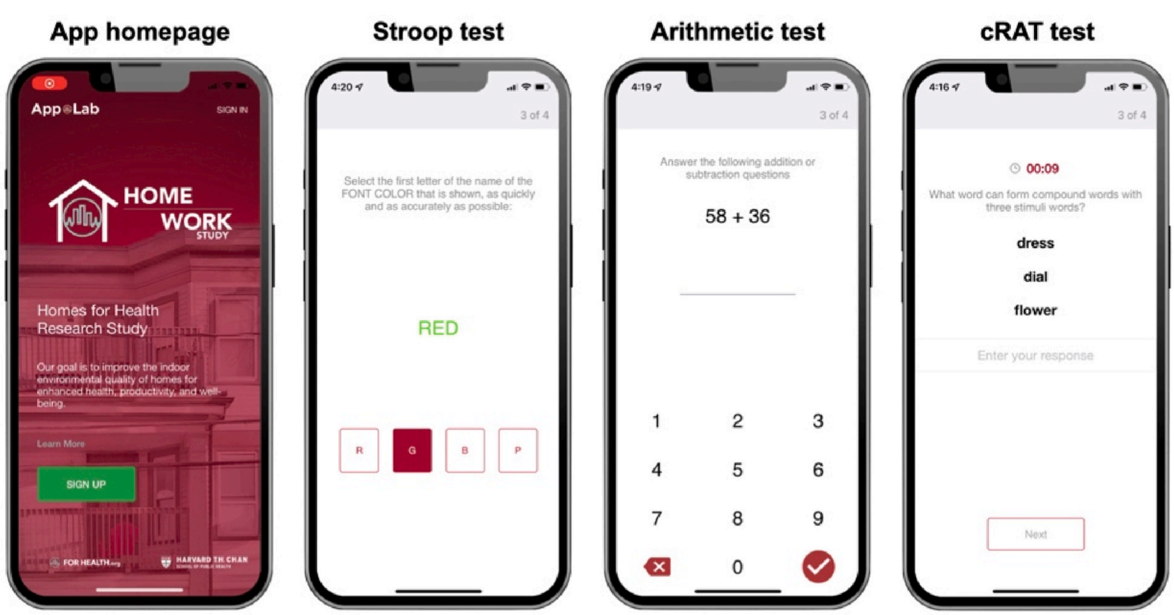

Fig. 2. Screenshots of example cognitive function test prompts within our custom study app for the a) Stroop, b) Arithmetic, and c) cRAT tests. Note: the Stroop example is of an incongruent prompt (the solution is the font color green, even though the word reads "red"). The solution for the cRAT example is "sun". The solution for the Arithmetic test is 94. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

unambiguous, one-word answers. The cRAT test requires creative thought by misdirecting someone's information retrieval: the first information considered in attempting a solution is usually not the correct answer, and thus the participant must access more distantly related information and may have the 'aha!' moment without knowing how they came to the answer [3]. The possible cRAT prompts had variable difficulty levels and were randomly selected at trial runtime from a published study of 300 predefined sets of words [3]. A participant was not shown a particular prompt more than once. While the Stroop and Arithmetic tests did not have a time limit per question, each cRAT test had a limit of 15 s per prompt before the test would automatically advance to the next prompt. The performance metric for the cRAT test was creative throughput (number of correct solutions per minute).

All cognitive tests were limited to work hours during Monday–Friday. Cognitive tests were scheduled to be sent on Tuesdays–Thursdays (to avoid weekend edge effects), but the tests could reappear in the app on other future days (also Tuesdays–Thursdays) if they were missed the first time. The geofencing restriction on cognitive tests to the participant's residential address helped ensure that the cognitive tests were capturing performance during business hours at home. We aimed for participants to receive approximately two of the cognitive function tests each week (except every third week, one was replaced with a mental health survey). Although most tests were regularly scheduled, sometimes the tests were designed to be triggered by the app upon the sensor-based indoor air quality values reaching a certain threshold, to increase the range in environmental conditions captured. The triggered tests occurred during any weekday (Monday–Friday), as there was no way to limit them to a specific set of weekdays as was done for the scheduled tests. These triggered tests consisted of one cognitive test type per threshold condition over a few-week period towards the end of their study participation: $PM_{2.5} < 6\ \mu g/m^3$, $PM_{2.5} > 12\ \mu g/m^3$, $PM_{2.5} > 50\ \mu g/m^3$, $CO_2 < 600$ ppm, $CO_2 > 950$ ppm, temperature $<20\ ^\circ C$, temperature $>26\ ^\circ C$, and $20\ ^\circ C <$ temperature $<26\ ^\circ C$. These triggered tests were not always responded to if the person's phone was not geolocated at home or if the air quality never matched the condition. If a participant missed the triggered time window, the test would be triggered again the next time the condition was met.

We excluded cognitive test responses that were incomplete, potentially invalid (<25 % accuracy in Stroop or Arithmetic trial), or potentially distracted (response time longer than 5 s per Stroop prompt or 15 s per Arithmetic prompt on average). Because of the longitudinal nature of our study question and the need to control for first-test learning curve effects, we only included data for a particular test type for a participant if they had at least two trial responses during the study period (Fig. 1). The final data set for analysis consisted of, on average, 12 trials per participant (range: 2–26 per participant) for the Stroop test, 11 trials per participant (range: 2–27) for the Arithmetic test, and 9 trials per participant (range: 2–17) for the cRAT test. All our cognitive function metrics can be interpreted as higher scores indicating better cognitive function and lower scores indicating worse cognitive function.

2.5. Statistical Analyses

2.5.1. Exposure variable selection

To inform our selection of exposure variables in statistical models, we calculated Spearman correlation coefficients between indoor air quality parameters (Fig. S1). Then, for each parameter, we also evaluated the correlations between different time frames of the measured parameter: the average, maximum, and 95th percentile concentration summarized for the 15 min, 30 min, 60 min, one week, and two weeks periods leading up to the timestamp of the cognitive test response (Fig. S2). Due to the strong correlations between different summary statistics across time frames of less than an hour, and our focus on *acute* associations, we were confident that the 30-min average concentrations of parameters were representative of acute exposure before a cognitive test. The exposure variables were thus 30-min averages of CO_2 and heat index (the combined indicator calculated from temperature and relative humidity). As described above, we did not include the $PM_{2.5}$ parameter because most concentrations were below the accuracy limit of the sensor for that parameter. We had prioritized exposure data from the monitors placed in the home workstations of the participants, but if missing, we used any available data from the monitors in the bedrooms.

2.5.2. Mixed models

To investigate associations between the IAQ exposures and each continuous metric of cognitive function, we employed generalized additive mixed models (GAMMs). GAMMs are an extension of generalized additive models, which allow for non-linearity in associations, and mixed effects models, which account for correlated data, such as due to repeat measurements of individuals over time. In the GAMM models, we included the participant identifier as a random intercept to account for expected correlations between measurements taken from the same individual over the course of a year. The cognitive function metric for the cRAT test needed to be log-transformed to achieve more normally distributed data based on histograms; before log-transformation, some zero values were converted to 0.01 to be able to take logs. The CO_2 and heat index exposure variables were added to the models as non-linear terms using penalized splines without specifying the degrees of freedom. Our results present both minimally adjusted and fully adjusted models. In minimally adjusted models, we controlled for several time-varying covariates: weekday (Monday, Friday, Mid-Week), participant's trial number for that test type as a learning effect (continuous), day of the year (penalized spline), and hour of day in local participant time zone (continuous). Hour of day was first added as a penalized spline but was changed to linear based on the resulting spline graph with one effective degree of freedom. In fully adjusted models, we also adjusted for several potential baseline confounders that we identified based on scientific literature and expert knowledge and that we categorized as: highest level of education completed (some/full college, graduate school), age (continuous linear based on result of penalized spline), gender (male, non-male), and race (White, Asian, Black, multiple or other races).

To improve interpretability of the results and effect estimates, we then conducted linear piecewise mixed models. The spline curves for the exposure variables from the GAMM models were evaluated for linearity (defined as one effective degree of freedom [edf]) and then used to inform the specification of linear CO_2 terms and piecewise linear heat index terms in these linear mixed models. We selected a piecewise breakpoint at the mean of 23 °C (73.4 °F) for the heat index variable (the median was 21 °C), which was near the points of slope change for the heat index splines for multiple outcomes from the primary models. The piecewise models were otherwise identical to the GAMM models. For the Stroop and Arithmetic metrics, model results are presented as the change in score associated with a 400-ppm increase in CO_2 or with a 10°C-increase in heat index. For the cRAT test, model results are presented as the *percent* change in score because the metric was log-transformed prior to analysis.

In secondary GAMM analysis, instead of the summarized heat index exposure variable, we used both temperature and relative humidity parameters together in a non-linear bivariate thin plate spline [50]. We evaluated the significance and non-linearity (based on effective degrees of freedom) of the resulting three-dimensional spline plot to determine the interaction of temperature and relative humidity in the associations with cognitive function.

In sensitivity analyses, we additionally controlled for the following covariates in all sets of primary models: living situation (alone, with roommates, with domestic partner), home type (single-family house, multiplex house, small apartment building [2–9 units], large apartment building [10+ units]), forced-air central cooling and/or heating system (yes, no), children under the age of 18 (yes, no), and Hispanic ethnicity (yes, no). The results were similar in statistical significance, direction, and approximate magnitude. To assess potential interactions of CO_2

with heat index, we conducted two separate sensitivity analyses. First, we performed the primary GAMM models with a bivariate thin plate spline between CO_2 and heat index, instead of as two separate exposure splines. The result showed only two effective degrees of freedom for the spline for each outcome (i.e., no significant interaction), and visual examination of the three-dimensional spline plots also indicated no interaction (Fig. S4). Second, in adjusted linear mixed models, we added an interaction term for the linear heat index and the presence of a forced-air central cooling or heating system (which could influence both carbon dioxide and temperature simultaneously), but there was no evidence of a significant interaction. Thus, we maintained our primary models as described.

All statistics were performed in R (version 4.1.2). Statistical significance was evaluated at $\alpha = 0.05$, and suggestive evidence (borderline) was defined as $\alpha = 0.10$.

3. Results

3.1. Study population

Table 1 summarizes characteristics of the participants in the Home-Work Study. Characteristics were similar between all participants and the subset of participants included in our final analysis for this paper (Table S1). Participants in our final analysis had a slight majority of female gender identity (57 %) and a range of ages (22–60 years old) (Table 1). They were mostly of White (64 %) or Asian (33 %) race, and there were 4 % of Black race and 8 % of Hispanic, Latino, or Spanish ethnicity. The majority (66 %) lived with a domestic partner, while 16 % lived alone and 18 % with roommates. Approximately a third had children under the age of 18. This population was also highly educated, with around 58 % holding a graduate degree.

Table S2 and Table S3 provide further living, work, and building characteristics. In terms of their work, the participants worked in a variety of institutions, including private for-profit companies (73 %), non-profit organizations (9 %), academic institutions (9 %), and government (5 %). Fields of work varied, with most in consulting (18 %), research (14 %), engineering (10 %), accounting (7 %), program/product management (6 %), information technology (5 %), and operations (5 %), among other fields. About half of participants (49 %) had a job that became remote in response to the pandemic, while the others had a job that was already fully (23 %) or partially (24 %) remote. The home workstations of the participants were in a designated home office (42 %), bedroom (19 %), living area (19 %), dining room (8 %), or other rooms. The home buildings mostly consisted of single-family houses (57 %) and apartment buildings (43 %), with about half of homes (55 %) being owned instead of rented. According to the self-report by participants of their home buildings, less than half of homes had mechanical, forced-air central cooling (28 %) or heating (45 %) systems, although misclassification depending on participant understanding was possible. A selection of other survey questions about the building, including ventilation, thermal control, and air filtration, are provided in the supplementary tables.

3.2. Indoor air quality

Table 2 provides summary statistics for the indoor air quality parameters. These concentrations are visualized in Fig. S3 for all time points during the study and in Fig. 3 for all the 30-min-averaged concentrations at the time of cognitive test responses. Absolute indoor CO_2 concentrations were usually between 414 and 1390 ppm (5th and 95th percentiles, respectively) in the participant homes across all time points, with half the values less than 632 ppm (Table 2). The temperature was usually between 17 and 26 °C (between 36 and 79 °F), and relative humidity was usually between 26 and 67 %. The combined heat index estimate tended to occur between 16 and 27 °C (between 61 and 81 °F). Concentrations of $PM_{2.5}$ remained low during the study, usually never above 21 μg/m^3 (the accuracy limit for the sensor was only ± 15 μg/m^3) and so this parameter was not included in statistical models.

Table 1
Population characteristics for the participants included in the final analysis of the paper.

	Statistic	Participants in This Analysis
DEMOGRAPHICS (*N* = 125)		
Gender identity	n (%)	
Female		71 (57 %)
Male		52 (42 %)
Non-binary		2 (1.6 %)
Other gender identity		0 (0 %)
Age	Median [Range]	33 [22–60]
Race(s)	n (%)	
White or Caucasian		80 (64 %)
Asian or Asian American		41 (33 %)
Black or African American		5 (4 %)
American Indian or Alaska Native		1 (0.84 %)
Native Hawaiian or Other Pacific Islander		0 (0 %)
Other race		4 (3.2 %)
Hispanic, Latino, or Spanish origin	n (%)	
No		115 (92 %)
Yes: Mexican, Mexican American, Chicano		3 (2.4 %)
Yes: Cuban		2 (1.6 %)
Yes: Puerto Rican		1 (0.8 %)
Yes: another origin		4 (3.2 %)
Born in the United States	n (%)	
Yes		85 (68 %)
No		40 (32 %)
Highest educated level received	n (%)	
Graduate school: doctorate degree		11 (8.8 %)
Graduate school: master's degree		56 (45 %)
Graduate school: professional degree		6 (4.8 %)
4-year college bachelor's degree		45 (36 %)
Some college, technical school, or associate's degree		7 (5.6 %)
High school diploma or GED		0 (0 %)
Less than high school		0 (0 %)
LIVING SITUATION (*N* = 125)		
Housemate situation	n (%)	
Domestic partner		83 (66 %)
Other housemates		22 (18 %)
Live alone		20 (16 %)
Total # people living in home	Median [Range]	2 [1–7]
Children	n (%)	
No		84 (67 %)
Yes		41 (33 %)
BUILDING SITUATION (*N* = 119)		
Type of home	n (%)	
Single-family house		60 (50 %)
Single-family house attached to other (s)		8 (6.7 %)
Apartment building with 2–9 units		20 (17 %)
Apartment building with 10+ units		31 (26 %)
Home occupancy type	n (%)	
Owned		65 (55 %)
Rented		51 (43 %)
Occupied without ownership or rent		3 (2.5 %)

3.3. Associations between indoor thermal conditions and cognitive function

The real-time indoor heat index concentrations at home during the 30 min prior to a cognitive function test were significantly or suggestively associated with participant performance for four different outcomes: cognitive throughput (in Stroop test), better ability to inhibit cognitive interference (two other metrics in Stroop test), and better creative problem-solving throughput (in cRAT test). In generalized additive mixed models, the non-linear spline terms (Fig. 4 and Fig. S5) for

Table 2
Summary statistics for indoor air quality parameters measured by Awair Omni real-time monitors in the home workstation and bedroom areas of the participant homes during one-year periods between May 2021 and December 2022.

Parameter	Units	Sensor Range	Median (5th–95th Percentile) [Range]			
			Average During 30 Minutes Before Cognitive Tests (N_s = 131)	All 5-Minute Timepoints		
				All Sensors (N_s = 314)	All Workstation Sensors (N_s = 159)	All Bedroom Sensors (N_s = 155)
			N_t = 3781	N_t = 25,495,879	N_t = 13,103,817	N_t = 12,392,062
CO_2	ppm	400–5000	678 (445–1410) [400–2540]	632 (414–1390) [400–5000]	610 (414–1300) [400–5000]	656 (415–1480) [400–5000]
$PM_{2.5}$	μg/m^3	0–1000	2.65 (0.57–21.7) [0–819]	2.27 (0.267–20.9) [0–1000]	2.27 (0.33–17.8) [0–1000]	2.24 (0.2–25.3) [0–1000]
Temperature	°C	−40–125	22 (17.9–26.2) [7.77–31.8]	21.8 (17.2–26.3) [0–43]	21.7 (17.1–26.4) [0–43]	21.8 (17.2–26.1) [0–41.8]
Relative humidity	%	0–100	46 (24.7–64.1) [11.8–91.4]	49.2 (25.6–66.9) [0–99]	48.6 (25.1–66.2) [0–99]	49.8 (26.1–67.6) [0–99]
Estimated heat index	°C		21.5 (17–26.5) [6.5–32]	21 (16–27) [0–52]	21 (16–27) [0–41]	21 (16–26) [0–52]

	All 5-Minute Timepoints and Sensors (N_s = 314)			
	Spring (Mar–May)	Summer (Jun–Aug)	Autumn (Sep–Nov)	Winter (Dec–Feb)
	N_t = 5,735,635	N_t = 6,018,168	N_t = 7,951,374	N_t = 5,790,702
CO_2	638 (415–1390) [400–5000]	625 (413–1330) [400–5000]	650 (414–1470) [400–5000]	612 (415–1350) [400–5000]
$PM_{2.5}$	2.13 (0.179–23.0) [0–1000]	2.33 (0.23–14.8) [0–1000]	2.37 (0.333–17.0) [0–1000]	2.20 (0.276–36.1) [0–1000]
Temperature	21.6 (17.2–25.6) [0.16–43.0]	23.4 (19.2–27.7) [7.16–39.8]	21.7 (17.5–25.9) [0–37.8]	20.4 (15.9–24.6) [0–41.8]
Relative humidity	45.0 (24.7–61.4) [7.43–93.7]	52.8 (39.7–68.5) [10.8–98.0]	53.3 (32.6–69.6) [0–99.0]	38.5 (20.4–62.1) [0–99.0]
Estimated heat index	21 (16–25) [0–42]	23 (19–28) [5–52]	21 (17–26) [0–40]	20 (15–24) [0–42]

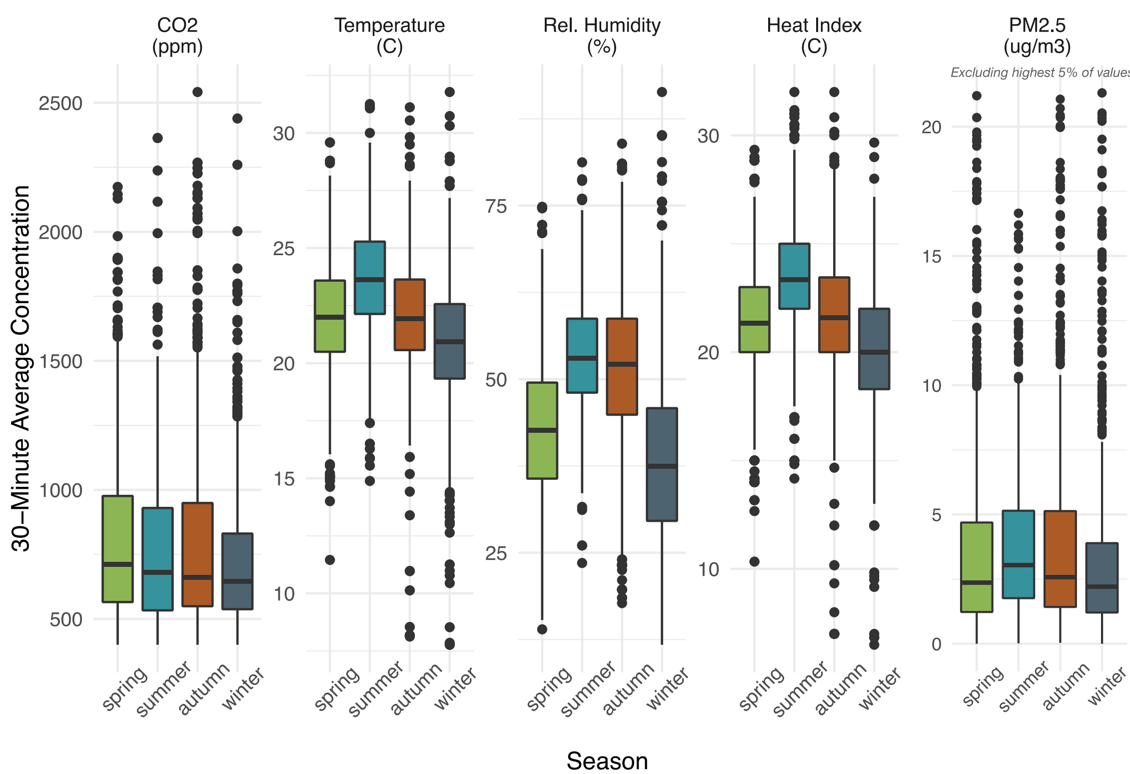

Fig. 3. Boxplots summarizing 30-min-prior average concentrations of residential indoor air quality parameters linked to 3781 cognitive tests taken by 131 participants while working from home during one-year study periods between May 2021 and December 2022. Note: For $PM_{2.5}$, we only included the lower 95 % of values to improve visualization of the boxplot. Spring = March, April, May; Summer = June, July, August; Autumn = September, October, November; Winter = December, January, February.

indoor heat index appeared linearly increasing with the Stroop test metrics until reaching a plateau, with a slight decrease towards the tail end for the inhibitory control metric only, although data were scarcer at those higher indoor heat levels. There was more of an upside-down U-shaped curve between indoor heat index and creative throughput in the cRAT test, with the inflection point around 22–23 °C. Thus, the relationships between heat index and cognitive function metrics were non-linear for the Stroop and cRAT tests, which informed our subsequent

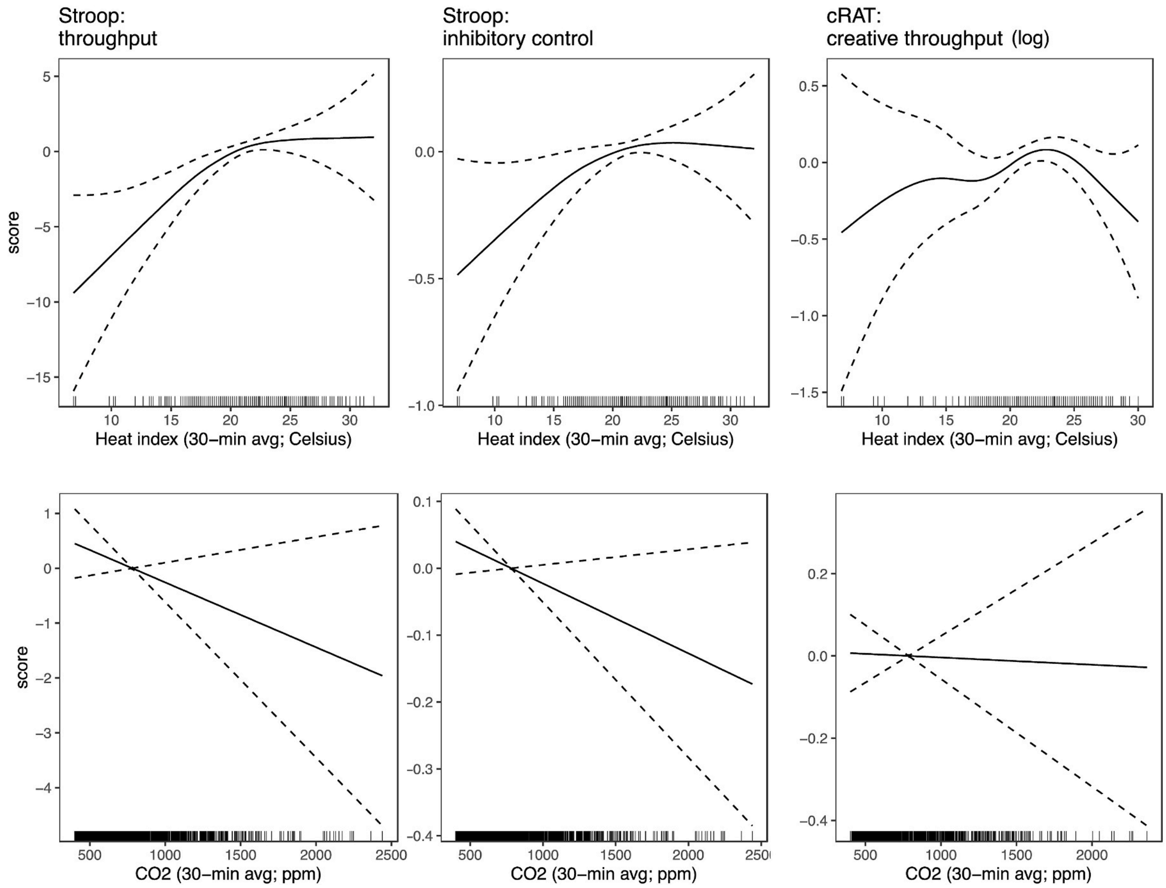

Fig. 4. Spline curves from fully adjusted generalized additive mixed models for the association between 30-min average indoor air quality parameters and acute cognitive function outcomes among 125 participants during a one-year longitudinal period.
Note: Spline curves for all outcomes are provided in Fig. S5. Dotted lines represented 95 % confidence intervals. Black vertical bars at the bottom of each graph show where the actual data points lie. The effective degrees of freedom were 1 for carbon dioxide and 2–3 for heat index.

modeling decisions. Table 3 presents the results from linear mixed models, using the indoor CO_2 exposure variable as a linear term and the heat index as piecewise linear (<23 °C versus ≥23 °C), which was chosen based on the patterns of the non-linear splines.

Indoor thermal comfort had beneficial or harmful associations with cognitive function depending on whether the heat index was too hot or too cold (while considering relative humidity) (Table 3). Restricted to levels *above* 23 °C (73.4 °F) in our models, a warmer heat index was significantly associated with worse creative throughput and suggestively associated with worse cognitive throughput and worse ability to inhibit cognitive interference. However, restricted to levels below 23 °C (73.4 °F), a warmer heat index was associated with better cognitive throughput, better ability to inhibit cognitive interference, and better creative throughput.

Specifically, among heat indices above 23 °C, a 1 °C higher indoor heat index was associated with 11 % fewer correct solutions per minute in the cRAT creative problem solving test (95 % CI: −18 %, −3.1 %; $p < 0.01$), adjusted for trial number, weekday, day of year, local hour of day, age, gender, race, and education (Table 3). In the Stroop color-word test, a 1 °C higher indoor heat index among indices above 23 °C was associated with 0.58 fewer correct responses per minute (95 % CI: −1.2, 0.00025; $p = 0.050$), a 0.038 worse score on cognitive interference inhibitory control (95 % CI: −0.083, 0.0064; $p = 0.093$), and 0.65 fewer correct responses per minute in incongruent trials with color–word interference (after subtracting congruent/neutral reference trial throughput) (95 %: −1.3, −0.0018; $p = 0.050$) (Table 3).

On the other side, restricted to heat indices *below* 23 °C, a 1 °C warmer indoor heat index was associated with 4.4 % more correct solutions per minute in the cRAT creative problem-solving test (95 % CI: 0.33 %, 8.5 %; $p < 0.05$), 0.49 more correct responses per minute in the Stroop color-word test (95 % CI: 0.20, 0.77; $p < 0.001$), a 0.026 better score on cognitive interference inhibitory control in the Stroop test (95 % CI: 0.0038, 0.048; $p < 0.05$), and 0.57 more correct responses per minute in incongruent trials with color–word interference (after subtracting reference trial throughput) in the Stroop test (95 % CI: 0.26, 0.89; $p < 0.001$). There were no significant associations with throughput in the Arithmetic test.

Our further delineation of parameters involved in thermal comfort indicated that indoor temperature and relative humidity have complex *interactive* effects in associations with certain cognitive function outcomes (Fig. S6). In fully adjusted mixed models, the bivariate thin plate spline of the interaction between temperature and relative humidity was significantly ($p < 0.05$) and non-linearly ($edf>2$) associated with throughput ($edf = 4.1$; $p = 0.00093$) and inhibitory control ($edf = 2.6$; $p = 0.022$), as well as linearly with throughput interference inhibition ($edf = 2.0$; $p = 0.00013$) in the Stroop test. There was no significant interaction observed for the Arithmetic ($edf = 4.4$, $p = 0.13$) or cRAT ($edf = 2.0$, $p = 0.18$) metrics. The three-dimensional spline graphs are presented in Fig. S6.

3.4. Associations between indoor CO_2 and cognitive function

Real-time indoor CO_2 concentrations during the 30 min before cognitive function test responses were below 640 ppm in at least half of instances (Table 2) and were not statistically significantly associated with outcomes in this suite of tests; however, there was suggestive

Table 3
Results from longitudinal mixed models for the association between the acute average concentrations of indoor air quality parameters in the 30 min prior to a test and the cognitive function outcomes among participants while working from home during one-year periods between May 2021 and December 2022.

Outcome Metric	Number of Tests (t) and Participants (n)	Covariates	Change in outcome [95 % confidence interval] (p)		
			CO_2	Heat Index <23 °C (73.4 °F)	Heat Index ≥23 °C (73.4 °F)
			Per 400 ppm increase	*[Piecewise] Per 1°C increase*	
Stroop					
Cognitive throughput	$n = 122$, $t = 1454$	Min. adjusted	−0.408 [-1.07, 0.254] (p = 0.23)	**0.489 [0.206, 0.772] (p=0.00073)** [e]	**−0.541 [-1.11, 0.0315] (p=0.064)**[b]
	$n = 118$, $t = 1433$	Fully adjusted	−0.509 [-1.17, 0.153] (p = 0.13)	**0.486 [0.203, 0.769] (p=0.00080)** [e]	**−0.575 [-1.15, 0.000247] (p=0.050)**[b]
Inhibitory control	$n = 122$, $t = 1454$	Min. adjusted	−0.0354 [-0.0866, 0.0159] (p = 0.18)	**0.0265 [0.00463, 0.0484] (p=0.018)** [c]	−0.0370 [-0.0814, 0.0075] (p = 0.10)
	$n = 118$, $t = 1433$	Fully adjusted	**−0.0445 [-0.0958, 0.00683] (p=0.090)**[b]	**0.0257 [0.00382, 0.0476] (p=0.021)** [c]	**−0.0384 [-0.0831, 0.00639] (p=0.093)**[b]
Throughput interference inhibition	$n = 122$, $t = 1454$	Min. adjusted	−0.408 [-1.15, 0.333] (p = 0.28)	**0.574 [0.258, 0.89] (p=0.00039)** [e]	**−0.600 [-1.24, 0.0398] (p=0.066)**[b]
	$n = 118$, $t = 1433$	Fully adjusted	−0.522 [-1.26, 0.218] (p = 0.17)	**0.571 [0.255, 0.887] (p=0.00041)** [e]	**−0.645 [-1.29, -0.00177] (p=0.050)** [c]
cRAT					
Creative throughput[a]	$n = 110$, $t = 983$	Min. adjusted	−1.57 % [-10.7 %, 8.48 %] (p = 0.75)	**4.59 % [0.583 %, 8.75 %] (p=0.025)** [c]	**−11 % [-18.1 %, -3.25 %] (p=0.0063)** [d]
	$n = 107$, $t = 970$	Fully adjusted	−0.953 % [-10.2 %, 9.21 %] (p = 0.85)	**4.35 % [0.334 %, 8.53 %] (p=0.034)** [c]	**−10.9 % [-18.1 %, -3.13 %] (p=0.007)** [d]
Arithmetic					
Cognitive throughput	$n = 126$, $t = 1344$	Min. adjusted	0.00698 [-0.215, 0.229] (p = 0.95)	0.0306 [-0.058, 0.119] (p = 0.50)	0.0934 [-0.087, 0.274] (p = 0.31)
	$n = 121$, $t = 1325$	Fully adjusted	0.011 [-0.212, 0.234] (p = 0.92)	0.0141 [-0.0751, 0.103] (p = 0.76)	0.101 [-0.0812, 0.283] (p = 0.28)

Note: Minimally adjusted models were controlled for only time-varying variables: trial number, weekday category, local hour of day, and a spline for the day of year. Fully adjusted models were additionally controlled for baseline variables: age, gender, race, and education. Exposures were calculated as averages in the 30 min prior to the test response.
[a] This outcome was log-transformed before analysis and thus the estimates are presented as percent changes in the outcome.
[b] $P < 0.10$.
[c] $p < 0.05$.
[d] $p < 0.01$.
[e] $p < 0.001$.

evidence of an association between higher CO_2 concentrations and slightly lower cognitive inhibitory control in the Stroop test (Table 3). Specifically, a 400-ppm increase in CO_2 was associated with a 0.045 worse score on cognitive interference inhibitory control in adjusted models (95 % CI: −0.096, 0.0068; $p = 0.09$). Furthermore, there were non-significant but negative linear relationships between CO_2 concentrations and cognitive function in the Stroop and cRAT tests, indicating a direction of effect that aligns with our hypothesis (higher CO_2 associated with worse cognitive function). In the spline-based models in Fig. 4 and Fig. S5, higher CO_2 exposure was non-significantly and linearly associated with slightly worse cognitive throughput, inhibitory control, and cognitive interference inhibition in the Stroop test. The CO_2 spline always resulted in one effective degree of freedom, indicating linearity in the relationships with outcomes. The relationship was around null (nearly flat) for cRAT creative throughput and Arithmetic throughput.

4. Discussion

In this study, we followed the real-time indoor air quality and cognitive function for around 200 office workers at home over one year during COVID-19. We found that indoor thermal conditions and possibly CO_2 concentrations while working from home may influence cognitive function, based on two brain tests that target cognitive speed, selective attention, working memory, cognitive interference, creative thinking, remote association, and insight problem solving.

4.1. Indoor thermal conditions

Thermal conditions at home were related to cognitive function in complex ways. For one, indoor temperature and relative humidity synergistically interacted with each other in the association with cognitive function, suggesting that both are important, non-independent indoor environmental parameters. In addition, the indoor heat index, a measure of apparent temperature adjusted for relative humidity, was *non-linearly* associated with certain cognitive function outcomes. For two of the outcomes, a higher heat index was associated with better cognitive function performance among cooler thermal conditions but with worse cognitive function among warmer thermal conditions after some threshold (although our data became scarcer at high thermal conditions). This non-linearity aligns with previous research finding an inverted U-shaped curve between temperature and cognitive performance in which both hot and cold exposure have negative impacts compared to neutral temperatures, and effects may differ slightly depending on the type of cognitive task (e.g., reasoning versus attentional) [27,28].

Although the physiological mechanisms between thermal conditions and cognitive function are still not fully understood, experimental evidence suggests that cognitive function relies upon a dynamic interaction between the sympathetic and parasympathetic nervous systems [31], and that too-warm thermal discomfort can shift the cardiovascular autonomic control more towards sympathetic activity [51,52]. The 'sweet spot' of indoor setpoints for thermal neutrality is different for each individual, based upon the role of clothing, adaptation, age, sex, fluctuating metabolic rates, and other complex factors [28]. The inter-individual variability in thermoregulation is a reason some have called for technologies that offer personalized thermal conditioning in buildings [53].

4.2. Indoor carbon dioxide levels

Apart from thermal conditions, there was suggestive evidence that indoor CO_2 levels in residences were also associated with a poorer ability to inhibit cognitive interference, even with most CO_2 levels below 640 ppm. The relatively low levels of CO_2 in this study may have precluded stronger statistical significance.

Over half of the homes in our study were single-family houses and the homes had a median of two residents, which suggests that relatively high building volumes [54] and low occupancies [55] likely played a role in the low CO_2 levels observed. Ventilation rates could have contributed as well, but we did not visit homes to directly measure ventilation rates or envelope air tightness or to inspect ventilation systems. Therefore, it is possible that CO_2 was not a comprehensive proxy for general IAQ in the homes in our study and could have contributed to weaker statistical findings than if we had directly evaluated ventilation or other indoor pollutants.

Nonetheless, our finding of potential negative associations between indoor CO_2 and cognitive function in home environments aligns with some previous research focused on office environments. For example, our previous study of 302 office workers found lower throughput and slower response time (based on the same Stroop test) in association with higher CO_2 levels in their office buildings over one year across the U.S., India, China, Thailand, Mexico, and the U.K [22]. Most other research leveraged controlled chambers or office replicates in experimental study designs. Results were not always consistent, but some studies demonstrated negative associations of indoor CO_2 concentrations or poor ventilation rates with human performance on tests of cognitive function [19,23], decision making [20,24], and simulated office tasks [25]. In one study, different categories of artificially elevated pure CO_2 levels revealed significant reductions in seven domains of cognitive function (15 % lower scores at 945 ppm CO_2 and 50 % lower at 1400 ppm, compared to 550 ppm target) [19] and at least six domains of decision-making performance (11–23 % lower scores at 1000 ppm CO_2 and 44–94 % lower at 2500 ppm, compared to 600 ppm) [20]. Another experimental study tested airplane pilots in a flight simulator and found that as ultra-pure CO_2 decreased from 2500 ppm while ventilation rates stayed the same, there was a 1.52 higher odds of passing a flight maneuver at 1500 ppm CO_2 and 1.69 higher odds at 700 ppm [18]. Research of young children in school has shown adverse links between indoor CO_2 or poor ventilation and test scores [29,56]. Thus, lower CO_2 levels – whether as a direct pollutant or indirect indicator of IAQ – may have important benefits for the cognitive performance of occupants across a diverse range of indoor built environments.

Paired with the previous body of literature, our study adds to the growing evidence that low CO_2 and enhanced clean outdoor air ventilation may improve human cognitive function. Ventilation benefits more than just the occupants: previous work from our research program showed that enhanced office ventilation yields financial benefits to employers from improved employee health, productivity, and presenteeism, and these benefits greatly exceed the ventilation energy costs [32]. For example, doubling the ventilation rate from 20 to 40 cfm/person in office buildings was estimated to cost less than \$40 per person per year across all U.S. climate zones investigated, while the improvements in employee cognitive performance by 8 % would be equivalent to a \$6500 increase in productivity per person per year. Energy recovery ventilation systems were shown to support this enhanced ventilation with nearly neutralized environmental impact [32]. Solutions to support enhanced IAQ in homes during remote work would also benefit employees and employers alike.

4.3. Strengths and limitations

There are several limitations to note for this study. The generalizability of our convenience sample is limited to highly educated knowledge workers (all with education after high school and roughly half with a masters or doctoral degree), who were working from home in the U.S. during the COVID-19 pandemic and who were mostly of White or Asian race. IAQ parameters and ventilation systems in the relatively higher-income homes in this study were likely better at controlling indoor conditions (e.g., 86 % of homes had thermostat control of cooling) than is typical for lower-income homes in the U.S. or other countries and thus has limited generalizability. The participants also had access to their real-time IAQ data if sought, and they could have taken steps to reduce pollutant levels or could have potentially biased their cognitive performance. These potentially well-controlled or low-occupancy IAQ conditions may partly contribute to the lower or no statistical significance found for associations of CO_2 levels with worse cognitive function outcomes. Indoor CO_2 and temperature are universal conditions in any indoor building environment, but care should still be taken when generalizing our findings to non-residential buildings or lower-income homes. The low concentrations of $PM_{2.5}$ in the homes in this study did not allow us to investigate associations between indoor $PM_{2.5}$ and cognitive function, as our previous global study of the cognitive function of office workers in the U.S., China, India, and U.K. did with a wider range of $PM_{2.5}$ pollution. The accuracy range of the IAQ sensors limited our ability to evaluate low-level $PM_{2.5}$ exposure below 15 $\mu g/m^3$. These monitors were low-cost devices purchased new in 2020. Although there is some measurement error for these commercial-grade devices, research has found them to be strongly correlated with reference data from research-grade instruments (e.g., correlation coefficient of 0.998 for CO_2 by Awair monitors) [57]. Exposure measurement error by the devices or by the participants' placement of the devices would likely only be non-differential with respect to the outcomes, as all participants had the same type of monitors and were blinded to the accuracy results of their cognitive function tests over the entire study period. The monitors did have issues with disconnecting from WiFi networks at random, which contributed to missing data (about 10 % based on Fig. 1). However, there were two monitors for each participant to pull data from, and we did periodically monitor disconnections and instruct participants on how to re-connect the monitors. Another limitation was that the sampling occurred entirely remotely, so we did not visit homes or collect direct measurements beyond the monitors and surveys. For example, we were unable to measure ventilation rates or inspect ventilation systems to supplement the indoor air pollutant data. However, the remote sampling strategy was beneficial during the pandemic and enabled us to safely recruit a large sample of participants from a wide geographical area within the U.S. We also did not directly survey individual participants' thermal comfort or behaviors that modify comfort, such as clothing, but rather focused on objective sensor measurements; other future studies could focus on thermal perceptions. Finally, our study only evaluated exposures inside homes and did not capture potential lagged exposures external to the home, such as in the outdoors, occasional office days (for some participants), or other buildings.

There are important strengths and novelties in this study. This is the first study to investigate objectively measured home indoor air quality and cognitive function outcomes for people working remotely from home, which has only become more important since the COVID-19 pandemic. The study design recruited 206 workers in real home dwellings across the U.S., not in a simulated office room experiment as most prior studies have done. Our study sensors monitored *multiple* IAQ parameters in real time *at* the home workstation of the participants and used the same model of sensor for every participant. We followed the IAQ and repeated participant outcomes longitudinally over one year, covering all seasons with a high spatiotemporal resolution. The study employed a relatively large sample size and focused on working-age adults, unlike many previous studies of students or elderly adults.

Furthermore, our custom smartphone study app enhanced the engagement and compliance of participants with study activities. For example, the cognitive function tests within the app were geofenced so that they could only be taken while at the home address, ensuring that the outcomes aligned with the parallel IAQ measurements. Study activities were sent with app push notifications to improve responses and were gamified via a compensation points system to motivate each activity. Finally, the rich data from this cohort will support future research, including investigation of the impacts of complex demographic, building, and behavioral factors on mental well-being while working from home.

5. Conclusion

In summary, the indoor air quality in home environments played an important role in the cognitive performance of office workers while working remotely from home during the COVID-19 pandemic. Both too-warm and too-cold indoor thermal conditions were associated with poorer cognitive throughput and creative problem-solving. There was also suggestive evidence of an association between higher indoor CO_2 concentrations and a poorer ability to inhibit cognitive interference. Similar to some previous research of office environments, our results of home environments highlight the potential benefits of lower CO_2 as a proxy for optimizing the cognitive performance and creativity of building occupants. These findings support building systems and standards that maintain low CO_2 concentrations based on promoting optimal health and cognitive function, with benefits reaped to occupants and employers alike. Our current study also emphasizes the importance of considering individual variability of diverse populations in the practices and technologies for thermal conditioning of buildings. Finally, the increase in remote or hybrid remote work since the beginning of the COVID-19 pandemic raises the question of the potential financial benefits to and roles of employers in supporting interventions for healthier work environments at home for their employees.

CRediT authorship contribution statement

Anna S. Young: Writing – review & editing, Writing – original draft, Visualization, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Shivani Parikh:** Writing – review & editing, Methodology, Investigation, Conceptualization. **Sandra Dedesko:** Writing – review & editing, Methodology, Investigation, Conceptualization. **Maya Bliss:** Writing – review & editing, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Jiaxuan Xu:** Writing – review & editing, Investigation. **Antonella Zanobetti:** Writing – review & editing, Methodology, Formal analysis. **Shelly L. Miller:** Writing – review & editing, Methodology, Conceptualization. **Joseph G. Allen:** Writing – review & editing, Supervision, Methodology, Funding acquisition, 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.

Data availability

The data that has been used is confidential.

Acknowledgments

We would like to thank Mahala Lahvis, Jose Vallarino, Rachel Steiner, Tara Tyrell, Jose Guillermo Cedeño Laurent, Piers MacNaughton, Yu Wang, Winnie Chin, Naila Segule, and Jie Yin for their help during this study. This research was conducted with support from NIEHS T32 ES007069, NIEHS P30 ES000002, NIOSH T42 OH008416, and gifts from VELUX, Carrier Global Corporation, and Procter & Gamble. The content is solely the responsibility of the authors and does not necessarily represent the official views of the funders or their affiliated agencies. The funders were not involved in decisions about study design, data collection, data analysis, data interpretation, data presentation, or manuscript writing. The authors declare no known competing interests.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.buildenv.2024.111551.

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