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presented by

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Date: 26 July 2024

The Link between Buildings and Cognitive Performance

A dissertation presented

by

Sandra Dedesko

to

The Department of Population Health Sciences

in the Environmental Health Field of Study

in partial fulfillment of the requirements

for the degree of

Doctor of Philosophy

in the subject of Population Health Sciences

Harvard University

Cambridge, Massachusetts

July 2024

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The Link between Buildings and Cognitive Performance

ABSTRACT

In North America, buildings account for an estimated 40% of total energy use and carbon emissions (Nägeli et al., 2018) and are where people spend over 90% of their time (Klepeis et al., 2001). A historical focus on energy efficiency has led to strategies that often degrade indoor environmental quality and in turn, occupant health (A. K. Persily & Emmerich, 2012). Recent attention has shifted towards designing and operating buildings for human health, but there are still questions around the benefits of building operation for human occupants and how to balance these considerations with building energy expenditure. Building heating, ventilation, and air conditioning systems are one pervasive building component that are key to this balance since these systems consume substantial amounts of energy to thermally condition and ventilate indoor spaces, which in turn, impacts occupant health in many ways. Much of the current building stock is operated to conditions set forth by standards that are not designed to promote human health. Accordingly, substantial amounts of energy are being consumed to condition and ventilate spaces to settings that do not necessarily support occupants and their activities. In response to this, we investigate indoor air quality, as influenced by building ventilation and occupancy, and indoor thermal conditions, as influenced by space conditioning, as two main indoor exposures that are influenced by these systems and also impact occupant health. We then assessed occupant cognitive performance and perceptions of the indoor environment with participant test and survey responses collected through our smartphone-based research application. We used this acute exposure and outcome data to model associations between indoor air and thermal conditions and metrics of cognitive function and thermal sensation. Collectively, the model estimates show that lower carbon dioxide concentrations, achieved through higher outdoor ventilation, are consistently and significantly associated with improved cognitive test scores. For thermal conditions, we observe that a normative range of roughly 22-26 ºC can support cognitive performance and thermal sensation in a variety of settings and that temperatures above and below this range show evidence of decreasing cognitive test scores. The relationship between indoor air moisture and cognitive performance is less clear from this work. There is preliminary evidence that common thermal modeling approaches, such as the use of temperature and relative humidity as separate thermal variables or the use of pervasively used thermal comfort models, might underestimate the potential importance of indoor moisture with respect to occupant outcomes. We explore enthalpy as a potentially useful combined temperature and moisture metric and observe preliminary evidence of consistent associations between higher values of indoor enthalpy, up to approximately 55 kJ/kg, and improved cognitive test scores. Additional research is needed to understand how these associations might vary in wider exposure ranges, across different built environment settings and populations, and the potential implications for building energy expenditure. Overall, these collective results suggest that focusing on increasing outdoor air ventilation and maintaining temperatures within a normative range of approximately 22-26 °C, can support occupants and their activities in working and learning environments.

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CHAPTER 1: INTRODUCTION

History of Ventilation and Space Conditioning with Respect to Building Occupants

We spend a tremendous amount of time in buildings and energy to operate buildings. In North America, the average adult spends over 90% of their time indoors (Klepeis et al., 2001) and the building stock is responsible for an estimated 40% of total energy use and associated carbon emissions (Nägeli et al., 2018; DOE, 2015). As a result, buildings have a prominent impact on human health and the natural environment, making them both a problem and solution to the climate change and human health challenges we face.

The energy crisis of the 1970's spurred interest and efforts in designing and operating buildings in a more energy efficient manner (Coyle, 2014). With climate change being a major concern, multiple organizations have set greenhouse gas emission reduction goals, with one common target being an 80% reduction in 1990 greenhouse gas emissions by the year 2050 (Solano Rodriguez et al., 2017). Buildings are an essential part of achieving these reductions; accordingly, numerous mandatory and voluntary energy efficiency measures have been incorporated into the building stock (Barnes & Parrish, 2016; Subramanyam et al., 2017). Some recent examples include New York City's Local Law 97, which sets tiered reduction milestones in the years leading up to 2050 based on building size (Salimifard et al., 2022), and the city of Boston's Building Emissions Reduction and Disclosure Ordinance, which adopts a similar approach, but arrives at a net zero performance goal by 2050 (*City of Boston Climate Action Plan 2019 Update*, 2019).

When developing strategies to achieve these reductions, a common component to focus on is ventilation and space conditioning (i.e., heating, cooling, humidifying, and dehumidifying), since these processes consume substantial amounts of energy (Korolija et al., 2011; Pérez-

Lombard et al., 2008), with heating, ventilation, and air conditioning (HVAC) typically accounting for the largest energy end use in residential and commercial buildings in the United States of America (US DOE, 2015; Þórólfsdóttir et al., 2023). In attempts to reduce this energy expenditure, common building design and operation strategies have included constructing tighter building envelopes to reduce the amount of conditioned indoor air that is lost to the outdoors; installing more efficient HVAC systems and equipment; reducing the amount of ventilation air supplied to indoor spaces; and adjusting setpoint temperatures. While these strategies do reduce energy requirements, many do so at the expense of occupant health by degrading indoor air quality and indoor thermal conditions (Manuel, 2011; Militello-Hourigan & Miller, 2018; Shrestha et al., 2019).

Past research has described many scenarios where low ventilation rates and undesirable indoor thermal conditions impair occupant health and satisfaction in many ways. While there can be more extreme cases of negative health impacts depending on the exposure scenario (Smith, 2000), the more pervasive health effects seen across the North American building stock relate to reduced cognitive performance and "sick building syndrome", an umbrella term denoting a myriad of health symptoms, such as headaches, fatigue, and various forms of irritation, attributable to time spent in a certain building or buildings with poor indoor environmental attributes (Licina & Yildirim, 2021; Nag, 2019). Various studies have suggested a link between ventilation and health (Carrer et al., 2015) with evidence for improved cognitive performance under scenarios of lower indoor carbon dioxide (CO_2) concentrations (Allen et al., 2016; Cedeño Laurent et al., 2021; Coley et al., 2007; Fisk, 2017), a proxy measurement used to indicate higher ventilation rates and/or lower occupancies in field measurements, and reductions in symptoms falling under sick building syndrome with improved ventilation (Carrer et al., 2015; Seppanen et al., 1999; Sundell et al., 2011; Wargocki, 2013). In addition to ventilation and indoor air quality, the thermal conditions in indoor spaces have also been shown to influence performance, satisfaction, and physiologic symptoms falling under sick building syndrome. Numerous studies have suggested a link between indoor moisture and various symptoms (Jones et al., 2022), indoor air temperatures and cognitive function and work performance (Bueno et al., 2021; Cedeño Laurent et al., 2018; Cui et al., 2013; Jiang et al., 2018; Lan, Wargocki, & Lian, 2011; Porras-Salazar et al., 2018; Tanabe et al., 2013), and improved thermal comfort and reductions in sick building syndrome symptoms (Amin et al., 2015; Lan, Wargocki, Wyon, et al., 2011). Past work has also shown that perceptions of thermal satisfaction and the range of indoor thermal conditions deemed satisfactory is highly individual and varies based on numerous factors, such as sex assigned at birth, age, geographical location, and other individual differences (Arens et al., 2015; Karjalainen, 2012; Khovalyg & Ravussin, 2022; Lan, Wargocki, Wyon, et al., 2011).

Evidently, the indoor air and thermal conditions achieved in buildings often result in degraded physiologic health, cognitive performance, and overall satisfaction due to current HVAC operational practices. In North America, standards set forth by the American Society of Heating, Refrigeration and Air Conditioning Engineers (ASHRAE) are pervasively used in practice and effectively stipulate the system energy performance criteria, space conditioning settings (i.e., temperature and relative humidity, RH), and ventilation rates for much of the building stock. However, these standards are not developed for optimizing human health. While the standards *strive* to promote health where appropriate, it is explicitly stated that following such standards does not guarantee occupant health, comfort, or satisfaction (A. Persily, 2015). The ASHRAE standards focused on ventilation (62.1-2022 and 62.2-2022, Ventilation and Acceptable Indoor Air Quality and Ventilation and Acceptable Indoor Air Quality in Residential

Buildings, respectively) focus on "*acceptable"* indoor air quality based on emissions from occupants and building materials (ASHRAE 62.1-2020; Persily, 2015; Siegel, 2020), as opposed to enhanced indoor air quality for health promotion beyond basic hygienic and safety considerations, such as elevated cognitive performance and perceived satisfaction with indoor conditions. Moreover, the ASHRAE standard focused on thermal comfort (55-2020, Thermal Environmental Conditions for Human Occupancy) is based on a thermal comfort model and underlying experiments from the 1960's and 1970's (Fanger, 1973) that are not representative of the characteristics and thermal preferences of today's diverse building occupant populations, as found in more recent works. Not surprisingly, several studies have shown that the thermal comfort model outlined in ASHRAE-55 has low utility to satisfy the majority of diverse building occupants in practice in recent years (Cheung et al., 2019). Moreover, a meta-analysis applied a widely accepted model relating indoor temperature to work performance and found the model to have low predictive accuracy applied to a large, more recent dataset of more recent and varied indoor settings (Porras-Salazar et al., 2021). Evidently, standard HVAC operation, following these design standards and underlying research, does not result in indoor environmental conditions that optimize human health, particularly with respect to health considerations beyond ensuring basic safety and hygiene, such as cognitive performance and perceptions of satisfaction.

While the historical focus of HVAC operation and the associated standards has not been on human health, in recent years, and largely exacerbated by the coronavirus 2019 (COVID-19) pandemic, attention has shifted towards this consideration. The COVID-19 pandemic has highlighted buildings as an essential tool to protect and enhance human health and wellbeing, and not surprisingly, exacerbated the adoption of health-based strategies and building rating systems. There has been exponential adoption of voluntary health-focused rating systems (IWBI, 2021), the inclusion of buildings in governmental COVID-19 response strategies (The White House, 2022), the emergence of new guidance focused on COVID-19 risk reduction strategies (The Lancet COVID-19 Commission Task Force & on Safe Work, Safe School, and Safe Travel, 2022) and non-infectious air delivery rates (NADR) for reducing exposures (The Lancet COVID-19 Commission & Task Force on Safe Work, Safe School, and Safe Travel, 2022), and the introduction of new initiatives and funding opportunities to help improve the health impacts of buildings, including the US Environmental Protection Agency's Clean Air in Buildings Challenge (US EPA, 2022) and the United States Department of Education grant program to assist with implementing COVID-19 safety measures in schools (US DOE, 2021).

As the transition of COVID-19 throughout 2022 saw reductions in severe health impacts and the re-opening of various facilities, many questions emerged around building design and operation going forward (Navaratnam et al., 2022; Tranel, 2020). Health should continue to remain a priority, and now, also a more intentional component of building design and operation; however, many questions remain. Particularly, questions have emerged around the how to operate buildings for health considerations other than disease transmission, and how to balance these concerns with building energy consumption and environmental impacts (Cedeño-Laurent et al., 2018; MacNaughton et al., 2015; P. et al., 2018).

Research Focus

In response to these questions, this research focuses on investigating indoor air and thermal conditions, and how they relate to aspects of occupant health and wellbeing. Indoor air and thermal conditions are the exposures of interest since they are influenced by building HVAC systems and influence occupant health in-turn. The occupant outcomes of interest include metrics of cognitive performance and perceptions of satisfaction with various aspects of the indoor environment, since these are pervasive health considerations in working and learning environments where people spend significant portions of their time, and are also occupant outcomes of concern during more typical operational conditions, and not a period of heightened infection control where disease transmission measures should govern operational priorities. Measuring these exposures and outcomes and assessing associations between them will provide greater insights into the conditions that support building occupants. This will focus on indoor air quality and thermal conditions to help understand if higher ventilation rates have benefit beyond infection control and what temperatures help support modern and diverse building occupant populations and their activities. In turn, this might also elucidate an opportunity to save energy, or at least not waste it, since much of the current building stock is consuming substantial amounts of energy to condition and ventilate indoor spaces in a way that does not promote occupant health.

Research Framework

This research is composed of three investigations from two studies, as depicted in Figure 1 below. Each of these studies measures indoor air and/or thermal conditions and estimates associations with cognitive performance metrics, and in some cases, perceptions of satisfaction as a complementary assessment.

Study	Aim	Main Association
Classrooms for Health Study	1) Classroom Ventilation	CO_2 → Accuracy, Speed
	2) Classroom Thermal	Thermal conditions → Accuracy, Speed
CogFx Global Buildings Study	3) Global Creativity	CO_2, Thermal conditions → Creativity

Figure 1: Schematic of Research Framework

This collective investigation begins with the Classrooms for Health Study, which is a prospective, observational, longitudinal study of indoor environmental conditions and student cognitive performance and perceptions of the indoor environment over the 2022-2023 academic year at a Boston-based university. The first investigation from this study is presented in Chapter Two and consists of an investigation of indoor CO_2 concentrations, as influenced by occupancy and enhanced ventilation, and associations with cognitive test scores of speed and accuracy among graduate students attending classes in lecture halls with increased outdoor air ventilation rates in response to COVID-19. The goal of this work is to assess if increased ventilation rates for infection control have added benefits beyond reducing disease transmission.

A second investigation from the Classrooms for Health study, this time focused on indoor thermal conditions, is presented in Chapter Three. Since space conditioning is one of the two primary functions of a building's HVAC system operation, assessing associations between indoor thermal conditions and cognitive test scores among the same graduate students in the Classrooms for Health study provides complementary information for the ventilation assessment presented in Chapter Two. A second motivation for this thermal work stems from the aforementioned challenges in the current state of thermal modeling, mainly the low predictive accuracy observed from the use of conventional thermal comfort prediction models and models relating temperature to work performance. Accordingly, this investigation begins by calculating and comparing multiple characterizations of the indoor thermal environment from simple temperature and RH measurements in the classrooms. Next, we construct an analysis dataset of all thermal exposures, the same cognitive test scores of accuracy and speed from the ventilation study in Chapter Two, and now also participant's thermal sensation votes in the rooms they had class. This dataset allows for the exploration of associations among thermal variables, cognitive test scores, and thermal sensations. This work provides considerations for how to measure and characterize indoor thermal conditions, and how these characterizations relate to occupant health outcomes. This provides new insights for thermal modeling research, which has many known challenges, and also for practice, by elucidating a range of indoor thermal conditions that can support occupants and their activities while providing some flexibility for building operation.

Finally, Chapter Four presents the third investigation in this work, which extends beyond the Boston-based classrooms study in Chapters Two and Three, to investigate new cognitive performance metrics across six countries. This investigation stems from the CogFx Global Buildings study, which is a prospective, observational, longitudinal cohort study following 302 adult office worker participants, in 42 commercial office buildings, located in six countries, over the course of approximately one year. The larger study measured environmental conditions near participant's office workstations and collected participant responses to various cognitive tests and health surveys. The analysis in Chapter Four focuses on acute air and thermal exposures at participant workstations and estimates associations with scores of divergent creative thinking, an understudied cognitive process in the literature on this topic. By investigating a creative cognitive domain, and associations with both air and thermal conditions in more diverse study settings, this investigation extends beyond the scope of the Classrooms for Health Study to investigate how these associations might vary across diverse geographies and also in relation to an understudied cognitive process related to creativity, which is often thought to be a more inherent quality and therefore potentially less subject to influence from acute environmental exposures.

Collectively, these three investigations from two studies provide new insights on our understanding of how indoor conditions can influence cognitive function and perceived satisfaction. The overall findings from this work are summarized in Chapter Five, along with recommendations for future work to further this topic for both research and practice. Applying these findings to practice can help inform building operation to support human occupants and their activities, while also potentially identifying opportunities to conserve energy.

CHAPTER 2: ASSOCIATIONS BETWEEN CARBON DIOXIDE CONCENTRATIONS AND COGNITIVE TEST SCORES AMONG UNIVERSITY STUDENTS IN CLASSROOMS WITH INCREASED VENTILATION RATES FOR COVID-19 RISK MANAGEMENT

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Abstract

Past work demonstrating an association between indoor air quality and cognitive performance brought attention to the benefits of increasing outdoor air ventilation beyond code minimums. These same code minimums were scrutinized during the COVID-19 pandemic for their insufficient ventilation and filtration specifications. In this study, we investigate associations between indoor CO_2 concentrations, influenced by outdoor air ventilation and building occupancy, and cognitive test scores among graduate students attending lectures in university classrooms where infection risk management strategies, namely increased ventilation, had been implemented. We administered post-class cognitive function tests through a

smartphone application to participating students (54 included in analysis) over the 2022-2023 academic year in classrooms equipped with continuous indoor environmental quality monitors. Mixed effects statistical models show directionally consistent evidence that higher central and peak classroom CO_2 concentrations are associated with lower cognitive test scores over the measured range included in analysis (~440-1,630 ppm). The effect estimates are strongest for 95th percentile class CO_2 concentrations, representing peak class CO_2 exposures. This suggests that for schools and other indoor settings where in-person attendance is a priority, and therefore occupant density cannot be decreased, increasing outdoor air ventilation rates beyond code minimums can have benefit beyond airborne infection management by promoting student performance and learning.

Introduction

A growing body of evidence is demonstrating an association between indoor CO_2 concentrations and cognitive performance. The collective findings are mixed when CO_2 is experimentally altered in isolation (i.e., pure injection of CO_2 into the study environment), but more consistent when CO_2 concentrations vary due to changes in ventilation rates and building occupancy (Du et al., 2020). Although it is currently unclear how much of this observed association is due to a direct effect or indirect effect (e.g., unmeasured indoor parameter(s) associated with CO_2 that influence(s) cognitive function) of CO_2 on cognitive performance, this latter arm of evidence suggests that lower indoor CO_2 concentrations, resulting from higher outdoor air ventilation and/or lower building occupancy, are associated with improved cognitive performance (Du et al., 2020). Previous studies have observed this association in various built environment settings, including: work environments, such as commercial office buildings (Cedeño Laurent et al., 2021; Wargocki et al., 2000), simulated office environments (Allen et al., 2016; Maddalena et al., 2015), call centers (Tham, 2004; Wargocki et al., 2004), and work-from-home setups (Young et al. under review); education settings, including universities (Riham Jaber et al., 2017) and elementary schools (Haverinen-Shaughnessy & Shaughnessy, 2015; Wargocki & Wyon, 2007b, 2007a); residential settings, including private dwellings (Jareemit et al., 2017) and dormitories (Strøm-Tejsen et al., 2016); and chess tournament venues (Künn et al., 2019). These studies not only demonstrate an association in multiple building types, but also across varied building occupant populations and indoor CO_2 concentrations. While some past work has suggested that the impacts of air pollution on cognitive performance are especially pronounced among older populations (Gao et al., 2021; Künn et al., 2019), these studies provide evidence of an association among healthy school-aged children and young adults. Furthermore, the aforementioned studies focus on low CO_2 concentrations relative to exposure limits (e.g., 5,000 ppm) (X. Zhang et al., 2016) and normative industry targets (1,000 ppm) (Persily, 2020, 2021), which are often exceeded in the building stock (Fisk, 2017), and still demonstrate an association, with Cedeño Laurent et al. (2021) illustrating a linear, no-threshold association between increasingly lower indoor CO_2 concentrations, down to ambient atmospheric concentrations, and improved cognitive function.

These findings sparked new interest in increasing outdoor air ventilation rates, which was then exacerbated by the COVID-19 pandemic, where urgent concerns moved from pollutant dilution and even cognitive function to infection control due to SARS-CoV-2 spreading via airborne transmission (Allen & Marr, 2020; Melikov, 2020; Morawska et al., 2020; Sachs et al., 2020). Existing outdoor air ventilation targets in commonly used building design standards (ASHRAE, 2022) were not developed for infection control and accordingly, were insufficient to effectively reduce airborne transmission of SARS-CoV-2. In response, several new enhanced ventilation targets were proposed during the emergency phase of the pandemic (Allen & Ibrahim, 2021; Morawska et al., 2021; The Lancet COVID-19 Commission & Task Force on Safe Work, Safe School, and Safe Travel, 2022). At the formal end of the emergency phase, ASHRAE and the Center for Disease Control (CDC) both released ventilation targets focused on reducing the risk of indoor transmission of SARS-CoV-2 (ASHRAE, 2023a; CDC, 2023b). The CDC recommended five air changes per hour (ACH) (CDC, 2023b) and a CO_2 concentration above 800 ppm indicating a need to bring in more outdoor air (CDC, 2023a), while ASHRAE put forward recommendations for equivalent clean airflow rates per person that vary based on space type (ASHRAE, 2023a), but are well above rates in ASHARE Standard 62.1 (Fox, 2023). As public focus shifted from the pandemic and indoor transmission of respiratory pathogens, and pressures to reduce ventilation rates to conserve energy and meet climate targets continue, outstanding questions remain regarding the benefits of higher ventilation rates beyond infection control.

In this work, we address these questions by leveraging an opportunity to study the cognitive performance of graduate students attending classes in university lecture halls that had implemented enhanced ventilation rates in response to the COVID-19 pandemic. Schools are an especially important building type to investigate on this topic because: 1) they are one of the few building types where post-pandemic occupancy reflects pre-pandemic conditions; 2) remote and hybrid learning was found to negatively impact student academic progress during the pandemic (Callen et al., 2023); and 3) the COVID-19 pandemic emphasized the need and importance of upgrading school facilities to improve ventilation and indoor environmental quality for student health, wellbeing, and learning (Fisk, 2017; Levinson et al., 2021; Lumpkin & Jayaraman, 2022). Evidently, in-person learning is important for student progress; understanding how education facilities can be operated for student health and learning should be a priority. Accordingly, we investigate the associations between indoor CO_2 concentrations and cognitive test scores among graduate students attending classes in rooms with COVID-19 risk management measures, namely higher outdoor air ventilation rates and continuous indoor air quality monitors, in the greater Boston area.

Methods

Study Design

The implementation of COVID-19 re-opening strategies provided an opportunity to launch the Classrooms for Health Study, a prospective observational longitudinal cohort study that examines the influence of classroom conditions on various student health outcomes over the 2022-2023 academic year at a university in the greater Boston area. Several facility teams within the university had installed real-time indoor environmental monitors and increased ventilation rates, following advised targets of 30 cfm/person or 4-6 ACH, as part of their operational risk management strategies in response to COVID-19. This presented an opportunity to investigate the influence of increased ventilation on student performance. Students regularly attending classes in the monitored spaces completed cognitive function tests and perception surveys after classes using a smartphone-based research application, previously developed and utilized in past studies (Cedeño Laurent et al., 2021; Young et al., 2024). While multiple exposures and outcomes were collected, this work focuses on the acute associations between classroom CO_2 concentrations and student cognitive test scores. All study protocols were General Data Regulation-compliant, reviewed and approved by the Institutional Review Board at the Harvard

T.H. Chan School of Public Health, and reviewed and approved by the academic offices of participating students.

Study Population

Students from two graduate schools at the university were recruited for participation in this study through advertisements that were approved and administered by each school. Recruitment began in October 2022 at the first school and in January 2023 at the second school, depending on the timing of approvals, and remained open through the end of the academic year in May 2023. To enroll in the study, all participants had to meet eligibility criteria, which included: be a full-time student enrolled in a participating program at either school; regularly attend class in person; be between eighteen and 65 years of age; speak English; have a smartphone compatible with the study's research application; not be colorblind; not be a current smoker; and not have a known medical condition and/or take any medication that impacts their thermoregulation.

Exposure Assessment: Indoor Environmental Quality

The primary exposure of interest in this study is indoor CO_2. Classroom CO_2, along with dry bulb temperature (referred to herein as "temperature"), RH, total volatile organic compounds (TVOCs), and fine particulate matter ($PM_{2.5}$) were characterized using commercial-grade, real-time continuous monitors (pressure, sound, and a light metric are also measured, but these are not relevant to this analysis). Monitors were battery-powered and installed on classroom walls away from heat sources and windows, if present, and at the breathing height at the location of installation; however, many rooms were sloped downward towards the front of the room (i.e., stadium seating). All monitors came pre-calibrated and operated within the manufacturer-specified range of 4-40 °C and less than 85% RH. Therefore, all measured values should be within manufacturer-reported accuracies, which are: ±0.5 ºC at 25 ºC for temperature, ±3% for RH, ±50 ppm or 3% for CO_2 (when temperature is between 15-35 ºC and RH is between 0-80%), and ±10 μg/m^3 between 0 and 100 μg/m^3 for $PM_{2.5}$. The TVOC and CO_2 sensors require seven days of operation for self-calibration, and so no measurements within the first seven days of operation are used in the proceeding study analysis. The monitors provided data at a 5-minute interval for all parameters, except for $PM_{2.5}$, which is logged at a 10-minute frequency, for the entire study period. This data was then used to calculate summary statistics of central and peak temperature, RH, and CO_2 for the class periods included in analysis. Six of the class periods included in the final analysis were affected by missing CO_2 data. An issue with battery power caused one monitor to only record temperature and RH (a power-saving measurement mode) from March 8 through April 4, 2023. These missing values were replaced with the values from the monitor at that school with the strongest correlation (based on simple regressions and Spearman Rank correlations to account for potential bias), which happened to be from the monitor in the adjacent classroom. A summary of all measured classroom conditions (at the 5 and 10-minute measurement intervals) used to create the final analysis dataset is presented in the Results section and summaries of the calculated summary statistics used for the final analysis are presented in Appendix A.

Outcome Assessment: Cognitive Function

The outcome of interest in this investigation is cognitive performance. This was assessed by administering cognitive tests to participants through the smartphone-based research application. We were not permitted to engage with participants during class, so tests were sent immediately after their regularly scheduled classes and made available for a set period. This was originally set for two hours after class to ensure adequate participation time, but was later shortened to twenty minutes to better capture the influence of class exposures on cognitive performance (63% of responses in the original two-hour window were being done within the first twenty minutes anyways). Participants were informed of this change and always received a notification when each cognitive test became available and ten minutes prior to its expiration. Since class schedules varied among participants, the number and timing of cognitive tests on any given day varied among participants. In attempts to reduce participant burden and minimize study drop-out, a maximum of two cognitive tests per day were sent to any single participant. All tests were restricted to Tuesdays, Wednesdays, and Thursdays to control for "weekend-effects" that may influence cognitive performance (Barner et al., 2019; Cedeño Laurent et al., 2021; Hasler et al., 2012). Furthermore, study participation was "gamified" in attempts to motivate and retain participants. Each cognitive test was worth a number of study points, which were continuously tallied by study team members and rewarded to participants in the form of gift cards on an on-going basis.

The actual cognitive tests used include the Stroop Color Word Test (referred to herein as "Stroop") and the Arithmetic Test. These tests have been used extensively in research (Scarpina & Tagini, 2017), including past work that examined associations between environmental parameters and cognitive performance, due to their sensitivity to said exposure conditions (Cedeño Laurent et al., 2021; Saenen et al., 2016). The Stroop test presents text in a certain font color, and the participant is to identify the color of the font (not the written word) as quickly as possible (MacLeod, 2006; Stroop, 1992). The written word is typically a color (in this study "Red", "Blue", "Green", or "Purple"), but can also be "XXXX". A Stroop test can be a congruent condition when the written color matches the font color ("Blue" written in blue font), an incongruent condition where the written color does not match the font color ("Blue" written in green font), and a neutral condition where “XXXX” is presented as the text in any font color (e.g., “XXXX” in green font). A visual example of this is given in Figure 2 where the intended correct answer to this incongruent condition is green. In this study, each Stroop test consists of twenty of these trials, with various combinations of congruent, incongruent, and neutral conditions. The Stroop test evaluates selective attention and inhibitory control as it requires selection of relevant sensory information and inhibition of dominant information (Cedeño Laurent et al., 2021; MacLeod, 2006; McMorris, 2016; Stroop, 1992). Applying this to the example in Figure 2: one must inhibit the inclination to select the written word as the answer (“Blue”, in this example) and instead select the color of the font (green, in this example). The Arithmetic test is more familiar and asks participants to complete two-digit addition and subtraction prompts. For example, the correct answer for the “47+32” prompt in Figure 2 is 79. In this study, each Arithmetic test consists of ten of these individual trials. The Arithmetic test evaluates cognitive speed and working memory (Cedeño Laurent et al., 2021; Cragg et al., 2017; Y. Zhang et al., 2022), which is the ability to retain information in a readily usable way (Cowan, 2014).

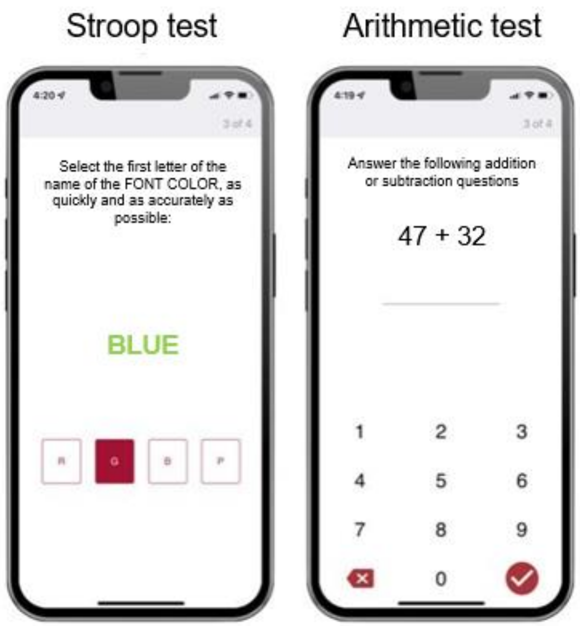

Figure 2: Example of Stroop (left) and Arithmetic (right) tests, as performed by participants in the study's smartphone research application.

Cognitive scores were calculated from the raw participant responses to both tests. Responses to all trials within a single test (twenty trials for a Stroop test and ten trials for an Arithmetic test) were used to calculate these cognitive metrics for each completed test. Speed and accuracy are the typical dependent variables of these tests (Liesefeld & Janczyk, 2019; MacLeod, 2006; McMorris, 2016), and so throughput, the number of correct responses per unit time (calculated by dividing the number of correct trials by the entire response time, and converting to units of n correct / minute), and response time, the total time taken to complete all trials within a test (in units of milliseconds), were calculated for each Stroop and Arithmetic test response. These metrics were chosen because they represent speed and accuracy in a manner that is straightforward both to calculate and interpret. Beyond these, additional metrics were calculated to represent the "Stroop effect", which is the difficulty in inhibiting the more automated process, which in this case is, naming the color of the font and not the written word

(Mitchell & Potenza, 2017; Scarpina & Tagini, 2017; Stroop, 1992), and manifests as increased errors and slowed response times when completing incongruent Stroop trials. Scores representing the Stroop effect are calculated in different ways depending on the type of Stroop test administered and author approach (Periáñez et al., 2021; Scarpina & Tagini, 2017). To represent the Stroop effect in this study, we calculate average response time (referred to herein as "Stroop incongruent response time") and percent correct responses per unit time for incongruent trials only (referred to herein as "Stroop incongruent throughput") since, in this study, trials were randomized with differing ratios of neutral, congruent, and incongruent prompts, and so these calculated metrics incorporate accuracy and speed in a standardized, consistent manner across all trials.

The calculated metrics were then cleaned prior to statistical analysis, following approaches in similar works (Cedeño Laurent et al., 2018, 2021). Trials where less than 25% of responses were correct were excluded as it was assumed that a genuine attempt at completing the test was not made. Responses with high response times, including a total Stroop test response time of 100,000 milliseconds (one minute and forty seconds) or more, and a total Arithmetic response time of 150,000 milliseconds (two and a half minutes), were excluded as these times suggest a possible distraction or interruption.

Covariate Measurement

In addition to administering the cognitive tests, the smartphone research application was also used to collect baseline and covariate data. Over the study period, a series of baseline surveys were sent to participants to gather information about their background and demographics. Furthermore, each cognitive test was paired with a short survey that included a question about whether each class was attended in-person or not. Responses to this question were used to ascertain whether participating students were in their scheduled classroom and exposed to the conditions measured by the in-room monitors.

Statistical Methods

Exposure, outcome, and covariate data were combined to create an analysis dataset of 273 observations from 54 participants, further described in Figure 3. Each observation in the analysis dataset includes the calculated cognitive test scores from a single response to a cognitive test, paired with the summarized class conditions that correspond to the class time and location of that cognitive test response. One dataset was created for each of the six calculated summary statistics (i.e., mean; median; 75th percentile; 95th percentile; standard deviation, SD; and coefficient of variation, CV) for class CO_2. Only tests that were paired with complete survey responses that indicated the participant attended their class in person are included in this analysis. A flowchart of inclusion criteria leading to the final analysis dataset is presented in Figure 3 below.

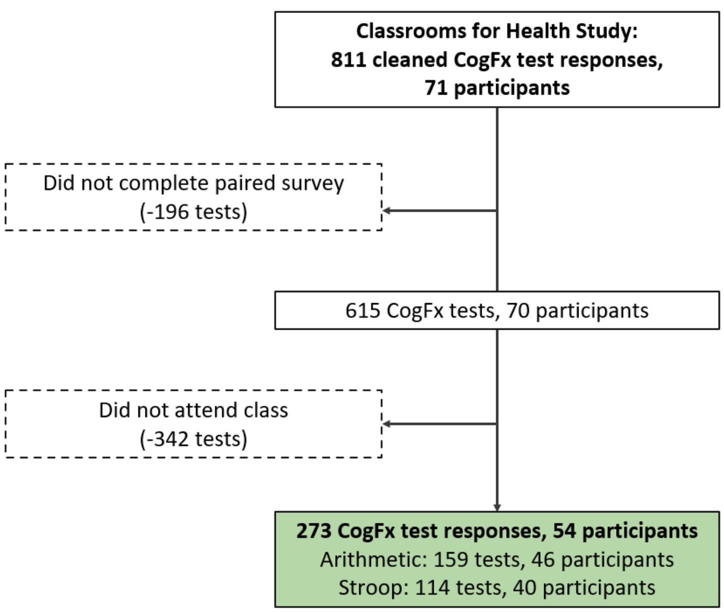

Figure 3: Flowchart showing data inclusion criteria that produced the final analysis dataset.

This analysis dataset was then used to construct a series of mixed effects statistical models to explore the associations between summarized classroom CO_2 concentrations and calculated cognitive scores. A separate model was constructed for each of the six calculated cognitive metrics, treating each as the outcome of interest in its respective model. A set of these six models was constructed for each calculated summary statistic (mean, median, 75th percentile, 95th percentile, SD, and CV) of class CO_2 concentrations. Distributions of all six cognitive scores were assessed for treatment in the models. Stroop throughput, Stroop incongruent throughput, and Arithmetic throughput followed normal distributions and were modeled as continuous variables using a linear model assuming a normal distribution. Stroop response time, Arithmetic response time, and Stroop average incongruent response times were log-transformed to meet the assumption of normality and then also modeled as continuous variables using a linear model assuming a normal distribution. Distributions were inspected for any lagging outliers that should be removed prior to running the models. The primary exposure of interest is classroom CO_2, which was modeled with a cubic regression spline to allow for non-linear associations. Since this study measured natural variations in classroom CO_2, the CO_2 exposure variable in the model incorporates the direct effect of CO_2 on cognitive performance and other unmeasured factors associated with natural variations in CO_2 via ventilation and occupancy (Cedeño Laurent et al., 2021; Du et al., 2020).

Models also include control for temperature and RH since these parameters could confound the association of interest as they are associated with variations in indoor CO_2 concentrations and cognitive performance, as demonstrated in past work (Cedeño Laurent et al., 2018; Lan et al., 2022a; Porras-Salazar et al., 2021; Seppänen et al., 2006). Temperature and RH were also initially modeled with cubic regression splines to allow for non-linear associations, which past research has sometimes observed for temperature (Dedesko et al., 2022; Seppänen et al., 2006). Classroom $PM_{2.5}$ and TVOC concentrations were not included in the models since measured values were low (i.e., mean and interquartile range values of 340 ppb and 161-435 ppb for TVOC and 0.5 ug/m^3 and 0-1 ug/m^3 for $PM_{2.5}$) and comparable among classrooms and therefore unlikely to influence the results (either via prediction or confounding). We controlled for school to account for statistical differences observed between environmental exposures and cognitive test scores, in addition to potential unmeasured differences, between schools.

Next, we controlled for learning effects in each of the six models by controlling for either the first test response for each participant or by controlling for test number for each participant (Cedeño Laurent et al., 2021; Goldberg et al., 2015; Young et al., 2024). We explored both control options for each of the six cognitive models and selected either first test or trial number based on the lower Akaike Information Criterion (AIC) value, as well as magnitude, direction, and statistical significance of the effect estimates (e.g., directionally consistent, increasing effect estimates with evidence of statistical significance would indicate continued learning effects beyond the first test and a need to control for trial number). Based on this exercise, we controlled for trial number in the four Stroop models and first test in the two Arithmetic models, which corresponds to our hypothesis that participants are less familiar with Stroop tests than Arithmetic tests and therefore continue to improve with continued test taking (i.e., trial number). Moreover, controlling for trial number in Stroop models helps to control for differences in the ratios of incongruent, congruent, and neutral prompts among trials. Finally, we included participant-specific random effects to account for correlations among cognitive test responses from the same participant over time.

Beyond this base model construction, we also conducted a series of sensitivity analyses to investigate the robustness of the base model estimates. Since the classrooms in this study are very similar, and actually identical at one of the schools, we ran a series of models where we included classroom-specific nested random effects (i.e., participant-specific random effects nested within classroom-specific random effects) to account for potential correlation among multiple responses from participants in the same classroom over time. Additionally, after running the base models for all six summary statistics of class CO_2, we conducted a temporal analysis to understand how the timing of various class CO_2 concentrations relate to the timing of the cognitive tests to help elucidate potential biological mechanisms of CO_2 underlying the modelled associations.

Results

Participants

A summary of the characteristics of participants included in analysis, except for one participant who did not complete the background survey, is presented in Table 1. As shown in the table, most participants were in their twenties (26 ± 3.5 years of age, on average), White or Asian (~45% and ~32%, respectively), and female sex assigned at birth (~74%). Approximately half of participants originated from the United States and the other half elsewhere.

Table 1: Participant Characteristics for Classrooms for Health CO_2 analysis

Characteristic	Overall (N=53)
Sex Assigned at Birth	
Female	39 (73.6%)
Male	12 (22.6%)
Prefer not to say	2 (3.8%)
Age	
Mean (SD)	26.2 (3.48)
Median [Min, Max]	26.0 [21.0, 42.0]
Hispanic, Latino, or Spanish Origin	
No: not of Hispanic, Latino/a/x, or Spanish origin	45 (84.9%)
Yes: another Hispanic, Latino/a/x, or Spanish origin	5 (9.4%)
Yes: Mexican, Mexican American, Chicano/a/x	2 (3.8%)
Yes: Puerto Rican	1 (1.9%)
Race	
Asian or Asian American	17 (32.1%)
Black or African American	6 (11.3%)
Some other race	4 (7.5%)
White or Caucasian	24 (45.3%)
White or Caucasian or Native Hawaiian or Other Pacific Islander	1 (1.9%)
White or Caucasian or Some other race	1 (1.9%)
US Origin	
No	26 (49.1%)
Yes	27 (50.9%)

Note: One of the 54 participants included in analysis did not complete the baseline survey and is therefore not included in the above table showing characteristics for 53 of 54 participants.

Exposures

A summary of all measured values of CO_2, temperature, and RH included in analysis are presented in Table 2. Summary tables for each of the calculated summary statistics used for association modeling are provided in Appendix A. Overall, class temperatures are within the range typically deemed "comfortable" for human occupants (interquartile range of 23-24 ºC) (*ANSI/ASHRAE Standard 55-2017*), but most mean RH values are below the recommended 30-60% range for indoor spaces (Arens et al., 2020). Most measured classroom CO_2 concentrations fell below 900 ppm (75th percentile value of 874 ppm), which is low compared to the levels previously observed in buildings (Fisk, 2017), but expected with higher levels of outdoor air ventilation.

Table 2: Summary of measured classroom conditions included in the analysis dataset.

Variable	Mean	SD	CV	Min	p25	p50	p75	p95	Max
Temperature (C)	23	1.2	0.053	20	23	23	24	25	29
RH (%)	25	7.1	0.29	11	19	24	30	37	47
CO_2 (ppm)	728	223	0.31	439	558	650	874	1175	1631

Outcomes

Calculated cognitive test scores indicate that on average, each Stroop trial takes 1.2 seconds (± 0.4) to complete and that fifty Stroop trials (± 19) would typically be completed per minute (average throughput). Each arithmetic trial takes approximately 5.1 seconds (± 1.8) and approximately twelve trials (± 4) are completed each minute, on average. The 114 Stroop test responses and 159 Arithmetic test responses included in this analysis occurred between November 2022 and April 2023.

Modeled Associations

Estimates from the adjusted models suggest that exposures to lower classroom CO_2 concentrations are associated with improved cognitive test scores. A visual representation of the observed associations between 95th percentile class CO_2 concentrations, representing peak exposures, and cognitive test scores are presented in Figure 4. Figures 4a and 4e show decreases in throughput with increasing CO_2 (95th percentile values), indicating a decrease in the number of correct trials completed per minute at higher peak CO_2 exposures for both Stroop and Arithmetic tests. Figures 4b and 4f show increases in response time with increasing average CO_2 (95th percentile values), indicating slower cognitive speed at higher peak CO_2 exposures. With respect to the Stroop effect, Figure 4c shows an increase in average incongruent response time with increasing 95th percentile CO_2 and Figure 4d shows a decrease in Stroop incongruent throughput with increasing 95th percentile CO_2. These two plots suggest that increases in peak indoor CO_2 concentrations are associated with an increase in the Stroop effect, which manifests as slowed response times and/or increased errors.

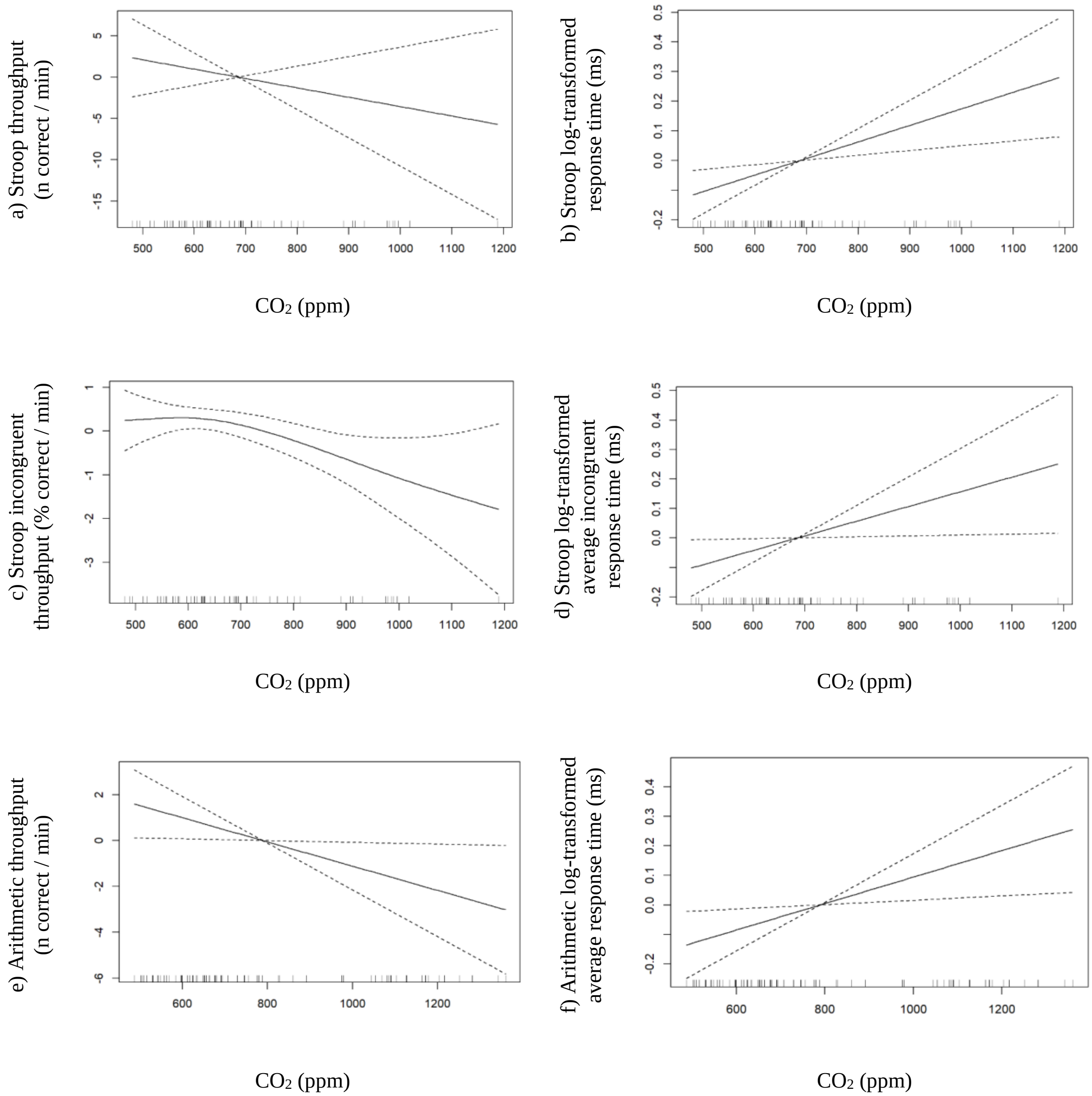

Figure 4: Plotted splines from mixed effects models showing the estimated associations between 95th percentile class CO_2 concentrations, representing peak exposures, and cognitive test scores. Models were adjusted for class temperature and RH, school, and learning effects, and included participant-specific random effects. All response time metrics are log-transformed to meet the assumptions of normality. All throughput metrics already met the assumptions of normality.

Since the plotted spline terms for indoor CO_2 show linear associations overall, the models were re-run with linear terms only. A summary of model estimates is presented in Table 3 with 95th percentile classroom CO_2 concentrations representing peak CO_2 exposures and mean classroom CO_2 concentrations representing central or average CO_2 exposures. The estimates show that a 100-ppm increase in peak classroom CO_2 (95^{th} percentile concentration) is associated with approximately one less correct Stroop trial per minute and approximately a 6% slower response time, while controlling for all other variables in the model. For arithmetic responses, we observe approximately one less correct arithmetic trial per two minutes and a 5% slower response time. For the model estimates using central (mean) CO_2 concentrations, we see weaker statistical evidence overall and similar or smaller estimated effect magnitudes. The adjusted R^2 value was ≤ 0.25 for all models.

Table 3: Effect estimates from mixed effects statistical models for the association between classroom CO_2 concentrations and calculated cognitive test scores among participants in this study.

	Per 100-ppm increase in CO_2		
Cognitive Test Outcome	Change in Outcome (95% CI)	p-value	
Peak Class Exposures: 95th percentile CO_2 concentration			
Stroop (n=113)			
Throughput (n correct / minute)	-1.13 (-3.4, 1.13)	0.33	
Incongruent throughput (% correct / minute)	-0.26 (-0.51, -0.012)	0.043	*
Response time (milliseconds) [a]	1.06 (1.02, 1.1)	0.0070	*
Average incongruent response time (milliseconds) [a]	1.05 (1.03, 1.08)	0.04	*
Arithmetic (n=159)			
Throughput (n correct / minute)	-0.53 (-1.01, -0.04)	0.034	*
Average response time (milliseconds) [a]	1.05 (1.01, 1.09)	0.019	*
Central Class Exposures: Mean CO_2 concentration			
Stroop (n=113)			
Throughput (n correct / minute)	-0.29 (-2.51, 1.94)	0.80	
Incongruent throughput (% correct / minute)	-0.17 (-0.42, 0.09)	0.20	
Response time (milliseconds) [a]	1.03 (0.99, 1.08)	0.093	·
Average incongruent response time (milliseconds) [a]	1.02 (0.99, 1.04)	0.53	
Arithmetic (n=159)			
Throughput (n correct / minute)	-0.52 (-1.06, 0.02)	0.060	·
Average response time (milliseconds) [a]	1.05 (1, 1.09)	0.037	*

[a] *Effect estimates in the table have been exponentiated (since outcome variables were log-transformed prior to model inclusion) and are therefore interpreted as factor changes in test outcomes.*

The results from the sensitivity analyses strengthen the above base model findings and provide further insights. Beginning with the models that include participant-specific random effects nested within classroom-specific random effects, we did not find evidence of classrooms explaining away the observed associations between CO_2 and cognitive tests scores, as the above model results held. Moving on to the assessment of models from all six summary statistics of class CO_2, models incorporating the SD or CV of classroom CO_2 concentrations showed no evidence of directionally consistent or statistically significant associations with cognitive test scores. Models using median (as another central CO_2 exposure statistic) and 75th percentile CO_2 concentrations (as another peak CO_2 exposure statistic) show directionally consistent, but statistically weaker, evidence of the associations observed with mean and 95th percentile CO_2 concentrations. Finally, after observing larger estimated effects and stronger statistical evidence from models using 95th percentile CO_2 concentrations, we investigated the timing and contextual implications for these peak (95th percentile value) CO_2 concentrations. One potential hypothesis was that 95th percentile CO_2 concentrations occur towards the end of class due to a continuous buildup of CO_2. Accordingly, we assessed the "time to peak" CO_2 concentration, defined as the minutes between the start of class and the time of occurrence of the 95th percentile CO_2 concentration in each class period included in analysis. The mean and median time to peak values are forty and 34 minutes, respectively, indicating that these 95th percentile CO_2 concentrations occur roughly in the middle of the eighty-to-ninety-minute classes examined in this study. Plots of temporal CO_2 concentrations during class periods in analysis were constructed and visually inspected and show a range of scenarios, such as 1) initial increases in CO_2 concentration towards a steady state concentration for most of the class and 2) greater variation in CO_2 concentrations, suggesting an influence of demand-controlled ventilation (Pistochini et al., 2023), which was in operation at one of the schools. Sample temporal CO_2 concentration plots for randomly selected classrooms and class periods in analysis are provided in Appendix A.

Discussion

Association between Indoor CO_2 and Cognitive Performance

In this prospective longitudinal observational study, lower peak and central indoor CO_2 exposure concentrations, resulting from higher outdoor air ventilation rates and/or lower occupancy, are associated with improved cognitive test scores among the young-adult graduate student participants attending classes in the monitored academic buildings. Modelled effect estimates are directionally consistent for all six cognitive outcomes analyzed for peak and central summary statistics of class CO_2 and have varying levels of statistical significance. These findings are particularly interesting given the small size of the analysis datasets (n=273) and low levels of indoor concentrations of CO_2, relative to other indoor environments where CO_2 concentrations above 1,000 ppm and even 2,000 ppm have been observed (Fisk, 2017) or are expected, based on ventilation rates commonly adopted in practice (Fox, 2023).

These findings are supported by past work that has found evidence of an association between indoor CO_2, as influenced by ventilation and/or occupancy, and cognitive performance metrics at low concentrations of CO_2. For example, one prospective observational longitudinal study following 302 office worker participants in six countries administered the same Stroop and Arithmetic tests over a wider range of higher indoor CO_2 concentrations (up to 2,500 ppm), but with most falling below 900 ppm (approximate 75th percentile value). Using a higher-powered analysis dataset (2,776 Stroop tests, 2,583 Arithmetic tests), these authors observed directionally consistent, and overall, statistically stronger evidence of lower cognitive performance with increasing CO_2 concentrations over the range of measured values. Interestingly, plotted spline terms from their general additive mixed models showed a linear, no-threshold association between increasing CO_2 concentrations and lower Stroop scores for both throughput and response time, suggesting that continuous decreases in indoor CO_2 concentrations, even towards the lowest feasible level (i.e., most of their measurements falling below 900 ppm), are associated with continuous improvements in cognitive performance (Cedeño Laurent et al., 2021). This agrees with the suggested effects at the low concentrations observed in this study, and other past works. A different study of 499 female students attending class at a university in Jeddah, Saudi Arabia found a statistically significant ($p<0.05$) decrease in cognitive performance (based on error %s from vigilance and memory tests) at 1,000 ppm CO_2 compared to 600 ppm CO_2, achieved via adjustments to the building's central ventilation system outdoor air provision, while holding other environmental conditions constant and adjusting for potential confounders (Riham Jaber et al., 2017). Moreover, an experimental study of 24 professional adult employees in an environmentally controlled office setup revealed an increase in scores (25% on average) in eight out of nine cognitive domains assessed by the Strategic Management Simulation Tool, when ventilation rates were increased from 20 cfm/person to 40 cfm/person (equating to indoor CO_2 concentrations of roughly 945 ppm vs. 550 ppm, respectively) (Allen et al., 2016).

Biological Mechanisms

While the collective findings suggest that higher indoor CO_2 concentrations are associated with lower cognitive performance, our findings around peak exposures provide additional insights for the potential biological mechanisms of CO_2 on cognitive performance. From our analysis, the effect estimates are largest in magnitude and strongest in terms of statistical significance for 95th percentile class CO_2 concentrations, suggesting that maximum indoor CO_2 concentrations, as opposed to average, might be more relevant to cognitive performance. Moreover, the finding that these 95th percentile concentrations vary in timing, but typically occur in the middle of class, and not exceptionally close to the occurrence of the post-class cognitive tests, raises further questions around our understanding of the biological mechanisms CO_2 exposures act through to influence cognitive performance. Many biological mechanisms have been suggested, including an inflammatory response (Thom et al., 2017b, 2017a); elevated heart rate and associated autonomic system changes (Rodeheffer et al., 2018; Snow et al., 2019; Zhang et al., 2016); direct changes to the cerebrospinal fluid environment in the brain (since CO_2 can cross the blood-brain barrier) (Cronyn, 2012); various physical symptoms, such as drowsiness and headache (Snow et al., 2019) that can impair cognitive abilities in-turn (Jacobson et al., 2019); and other biological mechanisms related to other parameters affected by ventilation and occupancy, such as bioeffluent concentrations (Maula et al., 2017) and/or the microbial composition of outdoor air (Meadow et al., 2014), that are at play and also not fully measured nor understood at this time. Although the exact mechanisms are not fully clear, the findings that peak CO_2 exposures appear to have stronger associations with cognitive test scores, while also not being exceptionally acute to the time of tests, suggests that there are lasting biological effects and that peak CO_2 exposures could have lingering associations with cognitive performance.

Limitations and Strengths

Although our findings are based on a limited study scenario and dataset, we observe statistically consistent and significant evidence that is robust to multiple sensitivity analyses and further supported by an established body of evidence. However, there are inherent limitations that cannot be addressed with additional analysis or support from other work. First, our study population is dominated by White and Asian females in their twenties, with high levels of education, which is not representative of other populations and limits the generalizability of these findings. Moreover, the monitored lecture halls in this study are at a well-funded and well-maintained university. The measured exposure concentrations in this study are low relative to concentrations previously found in other built environment settings (Fisk, 2017; Persily, 2020) and may not be representative of the range of CO_2 levels encountered in other buildings, especially schools where recent reports have highlighted the need for pervasive improvements to ventilation systems (Pampati et al., 2022). Also related to the exposures in this study is the inability to perform quality assurance, quality control (QAQC) testing prior to study measurements since the environmental monitors were already in place for operational, not research, purposes. However, as discussed in the methods section, all sensors came pre-calibrated to operate within the manufacturer-reported accuracies, and so the lack of QAQC testing is not a concern for our study's main focus of association modeling. Furthermore, since our exposures are continuous and errors are nondifferential with respect to the cognitive test scores, any bias in the modelled associations would be towards the null, meaning that the true, unbiased associations could be greater than those estimated in this work.

Moving on to the outcome, a main limitation is the lack of formal consensus on cognitive test scoring, which can limit comparison across studies but does not bias results within a study (Scarpina & Tagini, 2017). This is primarily a concern for metrics representing the Stroop effect, since throughput and response time metrics across all trials are more straightforward and objective to calculate. We tried to overcome these challenges by devising Stroop effect scores (i.e., Stroop incongruent throughput and response time) in a manner appropriate for test administration in this study, but potential differences should be kept in mind when comparing to other studies. Furthermore, although these cognitive test scores provide objective cognitive performance measures for analysis that are challenging to intentionally bias and representative of some types of testing students perform (e.g., math exams), they are not representative of the range of work performed in education environments. Other works have assessed basic domains of performance, such as basic activity level, but also more involved domains of cognitive performance, such as information usage, breadth of approach, strategy, and found similar associations between lower indoor CO_2 and/or higher ventilation rates and improved measures of performance (Allen et al., 2016). So, although we use circumscribed scores from cognitive tests designed for study administration, the results from this study and others suggest that CO_2 concentrations, as affected by ventilation and occupancy, are associated with both these isolated, objective cognitive test scores, and other types of work and performance more reflective of the range observed in real-world settings.

Finally, the classroom CO_2 concentrations in this study are a result of both ventilation rates and occupancy, neither of which are known. Class attendance varies substantially, making ventilation rates challenging to estimate and therefore recommend. Approximately 70% of all class average CO_2 concentrations in this study were below the CDC specified limit of 800 ppm (CDC, 2023). Converting ASHRAE's ventilation rates for infection control for education facilities to equivalent CO_2 concentrations, reveals slightly lower targets, ranging from 600-660 ppm (resulting from ventilation rates ranging from ~42-53 cfm/person), depending on the specific education setting (ASHRAE, 2023; Fox, 2023). Our study provides evidence of a benefit to maintaining indoor CO_2 concentrations at and below these targets, as we observe linear associations between continuous decreases in CO_2 towards ambient conditions and improved cognitive test scores. Future work that follows a similar study methodology, but sets and monitors specific ventilation rates could further narrow and strengthen these practical recommendations, which should eventually and ideally be contextualized against the energy expenditure required to ventilate indoor spaces to such conditions.

Despite these limitations, the study design and statistical approach provides consistent and statistically significant evidence that lower concentrations of central and peak indoor CO_2, resulting from higher ventilation rates and/or lower occupancy, are associated with improved cognitive test performance. The adjusted R^2 values indicate that up to 25% of the variation in cognitive test scores can be explained by the variables adjusted for in the model. So, while it is evident that there are other variables not included here that influence the cognitive test scores, the model outputs suggest that the few environmental factors and covariates included in our models are still associated with and important to cognitive performance. This builds upon past research that has demonstrated an improvement in student performance when ventilation rates are increased (Haverinen-Shaughnessy & Shaughnessy, 2015; Wargocki & Wyon, 2007b, 2007a). Additional research that addresses the aforementioned study limitations would help elucidate the range of effects possible in different educational settings beyond this present study. Extension of this research to schools with poor ventilation is especially important to understand the likely larger benefit to student learning and performance in schools that need it most. This is a tremendously important research precedence since in-person education is a post-pandemic priority and even this study of healthy young adult students in well-operated buildings showed that higher concentrations of indoor CO_2 are associated with lower cognitive test performance. Extension of this existing research could help further our understanding of the building operational conditions that improve student performance and health and, ideally, motivate upgrades to school facilities for students who could benefit the most.

Conclusion

This prospective, longitudinal observational study provides evidence that lower indoor CO_2 exposure concentrations, achieved via ventilation and occupancy, are associated with improved cognitive test scores among a young-adult graduate student population. The strongest statistical evidence for the associations with peak CO_2 concentrations and their typical occurrence in the middle of classes suggest that peak CO_2 exposures have pronounced and lasting effects on cognitive performance that are important to further understand and intervene upon. The classrooms in this study had implemented COVID-19 risk management strategies, namely increased outdoor air ventilation rates, which were in effect during the study period and suggest that higher outdoor air ventilation rates can help improve student learning and performance in educational settings. This study suggests a benefit of increased outdoor air ventilation, beyond infection control, even among healthy, young-adult students attending classes in well-operated and maintained facilities. The benefit to students could be even greater if ventilation upgrades are made in facilities with low levels of outdoor air ventilation.

CHAPTER 3: NEW CONSIDERATIONS FOR ASSESSING INDOOR THERMAL CONDITIONS: ASSOCIATIONS BETWEEN ENTHALPY, COGNITIVE FUNCTION, AND THERMAL SENSATIONS

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Abstract

Motivated by a body of recent evidence that has found discrepancies with established thermal models predicting comfort and work performance, we investigated multiple characterizations of thermal conditions and associations among thermal variables, cognitive performance, and thermal perceptions. Measurements of classroom dry-bulb temperature and RH were used to calculate a suite of eleven thermal variables, which were paired with thermal sensation votes and cognitive test responses from graduate students attending classes in these monitored spaces to create an analysis dataset of 273 observations from 54 participants. Results from Spearman Rank correlation coefficients, supported by factor analysis and principal component analysis, suggest that the eleven thermal variables cluster into three groups related to

indoor temperature, indoor RH, and indoor-outdoor differences. Accordingly, we observed distinct patterns of association for each group from a series of mixed effects statistical models. Indoor enthalpy appeared to incorporate the heat and moisture components of air in the most comprehensive, balanced manner, while also exhibiting consistent and strong associations with cognitive test scores and thermal sensation. Higher values of indoor enthalpy appear to be associated with improved cognitive test scores and warm sensations, and warm sensations appear to be associated with improved cognitive test scores. Additional research is needed to understand how these findings might differ when applied to different populations and built environment settings. The collective results posit new considerations for how we express the heat and moisture components of air with respect to occupant outcomes and how these outcomes can be supported through building operation.

Introduction

Indoor thermal conditions have a prominent influence on occupant satisfaction with the indoor environment (Arsad et al., 2023; Charles, 2003; Sherman, 1984), and buildings consume substantial amounts of energy to maintain comfortable thermal conditions for occupants. Commercial and residential buildings in the United States of America are estimated to consume and emit approximately 40% of primary energy and greenhouse gas emissions, respectively (Nägeli et al., 2018; US DOE, 2015), with space conditioning typically being the largest end use, accounting for anywhere from approximately 30-50% of all end use consumptions (U.S. Energy Information Administration, 2022, 2023). Accordingly, it's important that the energy used for space conditioning achieves the desired goal: primarily, providing thermally comfortable indoor spaces that support building occupants and their activities.

In North America, the historical occupant focus of indoor thermal conditions has been on achieving “thermal comfort”, which is often defined as “the condition of mind that expresses satisfaction with the thermal environment and is assessed by subjective evaluation” (ASHRAE, 2023) or “conditions wherein the average person does not experience the feeling of discomfort” (Olgyay et al., 2015). The Predicted Mean Vote (PMV) model (Fanger, 1967, 1970) is regarded as the most recognized thermal comfort model (Gilani et al., 2015) and is used globally (Li et al., 2020; Ruya & Augenbroe, 2018; Taleghani et al., 2013), as it has been incorporated into various standards used in building design and operation (ASHRAE, 2023; *ISO 7730: Ergonomics of the Thermal Environment*, 2015). The PMV model incorporates four indoor environmental variables (dry-bulb temperature; RH; mean radiant temperature, MRT; and air speed) with two individual thermal variables (clothing insulation and metabolic rate) to predict the mean thermal sensation (not preference) of a building occupant population (Fanger, 1970; Sherman, 1984). Although the PMV model is the most pervasively used in practice (Li et al., 2020) since its creation in 1970 (Fanger, 1970; van Hoof, 2008), there is growing evidence that it has low predictive accuracy when applied to more recent built environment settings. For example, one study used the world’s largest thermal comfort field study database to compare PMV model predictions to occupant thermal sensations votes and found that the PMV model had a low predictive accuracy of 34% while a completely random model had a predictive accuracy of 17% (Cheung et al., 2019). Although this model performance is low, it is not totally surprising considering more recent research moving towards individual thermal comfort models (Kim et al., 2018), noting that thermal comfort is a dynamic and highly individual sensation based on changing environmental conditions and individual physiological and psychological states (Arens et al., 2020; Karjalainen, 2012; Khovalyg & Ravussin, 2022; Lan et al., 2011).

This dilemma in thermal comfort models is similar to a related stream of indoor thermal research. While much of the building design industry's focus on indoor thermal conditions has historically been on ensuring thermal comfort, a growing body of evidence is also investigating how indoor thermal conditions influence cognitive function and/or work performance, with some studies suggesting a strong influence (Alajmi et al., 2015; Frontczak & Wargocki, 2011). Several earlier studies investigating indoor thermal conditions, thermal sensations, and cognitive function and/or work performance observed inverted U-shaped relationships between indoor temperature and work performance (L. Berglund et al., 1990; Lan et al., 2011; Seppänen et al., 2006), and also between thermal sensations and work performance (Jensen et al., 2009; Kosonen & Tan, 2004; Lan et al., 2011). Based on this early body of work, indoor temperatures around 22 ºC (Schiavon, 2022; Seppänen et al., 2006) and slightly cool to neutral thermal sensations (e.g., $-0.5 < PMV < 0$) (Jensen et al., 2009; Kosonen & Tan, 2004; Lan et al., 2011) were believed to promote cognitive performance. However, more recent studies on this topic challenge these earlier findings. A 2021 meta-analysis gathered objective measures of indoor air temperature and work performance, normalized the data, and assessed multiple models to represent the relationship between temperature and performance, including the model from the work that helped establish the ~ 22 ºC peaking, inverted U-shaped relationship (Seppänen et al., 2006), multiple regression models, the Maximum Adaptability framework, and various machine learning techniques. None of the model estimates reached statistical significance ($p>0.05$) and all had low predictive accuracies (maximum adjusted R^2 of 0.07), leading the authors to conclude that they are not suitable for accurate predictions and that other factors beyond just temperature are likely important to consider when assessing the relationship between thermal conditions and performance (Porras-Salazar et al., 2021). Indeed, others have noted that differences in building type, location, building occupant characteristics, and cognitive domain or work/task considered can all contribute to differences in these modeled associations (Luo et al., 2023; Periáñez et al., 2021; Porras-Salazar et al., 2021; Riham Jaber et al., 2017; Scarpina & Tagini, 2017; Schiavon, 2022). Similar to the challenges with thermal comfort modeling, it appears that associations between thermal conditions and work performance vary based on many factors and that it might not be possible to devise a representative relationship between just temperature and performance that can be accurately applied to a multitude of settings.

Interestingly, the collective findings from both streams of research on thermal conditions with respect to a) thermal comfort and b) cognitive function, arrive at similar conclusions: 1) established models aimed to predict these two outcomes have low predictive accuracy, and therefore utility, when applied to modern and varied built environment settings, and 2) the desired outcomes of thermal comfort and improved cognitive performance appear to vary based on individual and group/population-level factors. These findings pose many issues for built environment research and practice. First, due to the low predictive accuracy of the models underlying building design standards, much of today's building stock could be consuming unnecessary amounts of energy to achieve indoor thermal conditions that neither promote thermal comfort nor cognitive performance. Second, regardless of the predictive accuracy of thermal comfort or cognitive function models on a group or individual basis, indoor spaces (within zones) are still conditioned to a single setpoint temperature. Evidently, there is a need to understand how the thermal conditions achieved through building operation influence both thermal sensations and cognitive performance in a modern building occupant population to determine if there is a range of indoor thermal conditions that can promote both outcomes simultaneously, and also if these conditions can be elucidated through other characterizations of the indoor thermal environment, beyond the use of temperature and established thermal comfort model estimates, such as PMV, due to the aforementioned limitations. Accordingly, we investigate this topic by characterizing the indoor thermal environment with multiple thermal variables and then examine associations among thermal variables, participant thermal sensations, and participant cognitive test scores to assess how these different thermal variables associate with thermal sensations and cognitive function, and if there is an indoor thermal condition or range of conditions that can promote both outcomes.

Methods

Study Design

This was investigated through a prospective, observational, longitudinal cohort study over the 2022-2023 academic year at a Boston-based university. As a result of the COVID-19 pandemic, multiple schools within the university installed real-time, continuous indoor environmental quality monitors in classrooms as an ongoing risk management strategy. Since these monitors provided a continuous assessment of indoor environmental quality, recruiting graduate students attending class in these monitored spaces was an effective approach to investigate this topic. Participation primarily involved completing short thermal perception surveys and cognitive tests after their regularly scheduled classes using a smartphone-based research application that had been used in similar studies (Cedeño Laurent et al., 2021; Young et al., 2024). This outcome data was later paired with the measured class conditions for further analysis and association modeling. All study protocols were General Data Regulation-compliant, reviewed and approved by the Institutional Review Board at the Harvard T.H. Chan School of Public Health, and reviewed and approved by the academic offices of participating students.

Study Population

Participants were recruited from two schools at the University via advertisements approved and administered by each school. Study recruitment began at the first school in October 2022 and at the second school in January 2023, due to different approval timelines, and remained open until the end of the study in May 2023. To be eligible for study participation, a series of eligibility criteria had to be met, which included: be a full-time student in one of the participating academic programs, regularly attend class in person, be between eighteen and 65 years of age, have a smartphone compatible with the study application, not be colorblind, not be a current smoker, and not have a medical condition or take any medication that could impact one's thermoregulation.

Exposure Assessment: Indoor Thermal Conditions

Indoor thermal conditions are the primary exposure of interest in this study. Indoor dry-bulb temperature (referred to herein as "temperature") and RH are the two thermal variables measured by the indoor environmental monitors in the classrooms. The monitors also measure CO_2, TVOCs, $PM_{2.5}$, pressure, sound, and a light metric. Of all measured parameters, only temperature and RH are incorporated as exposure variables, and CO_2 as a confounder; all other measured variables were deemed inappropriate to this analysis as confounders or predictors due to theoretical rationale or a lack of variation or magnitude in the physical measurements. For example, while past work has shown olfactory perceptions to be intertwined with thermal perceptions (Fang et al., 1998b, 1998a, 2004), the class average TVOC and $PM_{2.5}$ concentrations were all low and comparable among classrooms (class average TVOC mean ± SD of 342 ±198 ppb; all class average $PM_{2.5}$ concentrations < 2 ug/m^3) and are therefore unlikely to predict or confound the results. According to the environmental monitor's manufacturer specifications, measurements are made at the following accuracies: ± 0.5 ºC at 25 ºC for temperature, ± 3% for RH, ± 50 ppm or 3% for CO_2 (when temperature is between 15-35 ºC and RH is between 0-80%). Although QAQC testing could not be conducted since monitors were already installed by facility teams for operational purposes, all classroom conditions remained within the range of recommended operating conditions of 4-40 °C and less than 85% RH, so the measurements should be within the manufacturer reported accuracies. Moreover, all sensors within the monitor came pre-calibrated and were given at least seven days of startup time (which is required for the CO_2 sensor due to its ongoing self-calibration method) before any measurements were included in the study dataset. All three variables were measured and logged at a 5-minute measurement frequency over the study period. One monitor logged only temperature and RH from March 8 through April 4, 2023 due to low battery power. Over this duration, the missing CO_2 values for this one room were replaced with the CO_2 measurements from the monitor with the strongest correlation (examined both with regressions and Spearman Rank correlations to account for potential bias), which appropriately, was the adjacent classroom. With the missing data replaced, class average values of all three variables were then calculated for each class period that corresponded to a participant response. Only six class periods in the final analysis dataset were affected by the missing CO_2 data.

The class average temperature and RH values were retained for direct analysis and also to calculate a suite of thermal variables for further exploration. The suite of eleven thermal variables includes indoor variables, consisting of: temperature (°C), RH (%), the partial pressure of water vapor (Pwv; units of kPa), humidity ratio (kg moisture/kg dry air), enthalpy (kJ/kg), dewpoint temperature (ºC), heat index (a combination of temperature and RH, expressed in ºC, to reflect the combined sensations of temperature and RH), and the estimated PMV score (unitless); and variables that contrast indoor conditions to those outdoors, including: temperature difference (⁰C), enthalpy difference (kJ/kg), and vapor pressure balance (VPB; units of kPa). All variables were calculated objectively using only the class average temperature and RH values, except for PMV, which was estimated using the comf package in R (Schweiker et al., 2024) and using a series of assumptions, including an average metabolic rate of 1.0 (corresponding to the seated desk work of students) (ASHRAE, 2023), an airspeed of 0.1 m/s (which is the default value for indoor spaces with low air speed, as confirmed by physical spot measurements), MRT equaling air temperature (since most classrooms in this study do not have exterior windows and past work has shown MRT to approximate air temperature in these spaces (Dawe et al., 2020)), and a clothing insulation value of 1.3 clo, calculated based on an estimated ensemble appropriate for the New England heating season, which this study spanned (Tartarini et al., 2020). These assumptions are representative of the study conditions and similar to the estimation approach used in other past work (A. Ahmed et al., 2009; Lan et al., 2011).

Outcome Assessment: Thermal Perceptions and Cognitive Function

The two outcomes of interest in this study are cognitive performance and thermal perceptions. We assessed both outcomes using the smartphone-based research application. Participants received a thermal perception survey, paired with a cognitive test to complete within a limited time after class. Participants were initially given two hours after class to complete the activities, but this was later shortened to twenty minutes to improve the acuteness of outcome responses with respect to class exposures. Supporting this change was the observation that 63% of completed study activities within the two-hour window were done within the first twenty minutes. Participants were made aware of the time changes and always received a notification on their smartphone when study activities became available and ten minutes prior to their expiration. Other efforts were made to promote participation, including gamifying study activities with points and awarding them as incentives on an on-going basis as accrued.

Thermal perceptions were assessed by administering short thermal surveys. We assessed responses to all core thermal questions, which informed our decision of focusing our analysis on participant's thermal sensations. This decision is further supported by recent work that has found the thermal sensation vote to be the most significant thermal comfort predictor (Lala et al., 2023). Our survey question asked participants how they felt in the room they just had class in for the majority of time and provided response options in the form of a seven-point Likert scale (i.e., "hot", "warm", "slightly warm", "neutral", "slightly cool", "cool", "cold", illustrated in Figure 5) following ASHRAE's thermal sensation scale (Arens et al., 2020), which is heavily utilized in thermal comfort research (Favero et al., 2023; Schweiker et al., 2017). Figure 5 presents this core question as participants received it through the study application. Due to the frequency of responses per category (most responses being "neutral", discussed further in Results), the more granular responses from the seven-point Likert scale were combined into three categories: "neutral" responses remained in their own category, termed "neutral"; the three responses on the warm side of neutral (i.e., "slightly warm", "warm", and "hot") were combined into the "warm" sensation group; and the three responses on the cool side of neutral (i.e., "slightly cool", "cool", and "cold") were combined into the "cool" sensation group. Herein, this outcome is referred to as "thermal sensation" with the three response options: "warm", "neutral", and "cool".

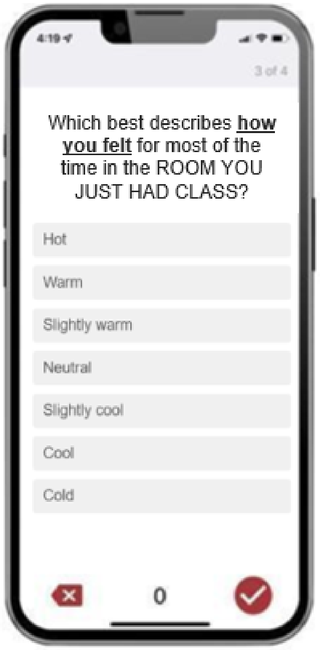


Figure 5: Example of the thermal sensation question and seven-point Likert scale response options participants received via the smartphone-based study application.

Cognitive performance was assessed by calculating various metrics from participant responses to validated cognitive performance tests. Two tests were used in this study, including the Stroop Color Word Test (referred to herein as "Stroop") and the Arithmetic test. The Stroop test assesses selective attention and inhibitory control while the Arithmetic test assesses cognitive speed and working memory. So, while we calculate similar metrics from the test responses, the two tests address different cognitive processes. The Stroop test in this study consists of twenty individual Stroop trials where in each trial, there is a text prompt and the participant must select the color of the font and not the written color. Figure 6 illustrates an example Stroop trial where the correct answer is "green". A Stroop trial can be congruent (where the font color matches the written color), incongruent (where the font color does not match the written color), and neutral (where the written text is not a color, but "XXXX"). The Arithmetic test is more familiar and consists of ten trials of two-digit addition and subtraction problems. Figure 6 also provides an example of an Arithmetic trial where the correct answer is “25”.

Responses to all trials in a single test (twenty for Stroop and ten for Arithmetic) were used to calculate various cognitive test scores. Accuracy and speed are the common dependent variables of these tests, so we calculate throughput, the number of correct responses per unit time (n correct / minute), and total response time (milliseconds) for responses to each test, accordingly. For Stroop responses, we calculate two additional metrics that aim to represent the “Stroop effect”, which refers to reductions in cognitive performance when inhibiting dominant information to select subservient information. In this study, the Stroop effect pertains to selecting the color of the font (subservient information) over the written word (dominant information) and manifests as slowed response times and/or reduced accuracy when completing incongruent trials. There are many metrics that can be calculated to represent the Stroop effect, and much variation in the approach based on how the test was administered and other decisions made by researchers (Periáñez et al., 2021; Scarpina & Tagini, 2017). In this study, ratios of incongruent, congruent, and neutral prompts are not equal across all Stroop tests, so we calculate “Stroop incongruent throughput” as the percentage of correct responses per unit time (% correct / minute) and average response time (milliseconds) for incongruent trials within each test. The calculated metrics were cleaned prior to analysis. Any test responses with less than 25% correct responses or a high response time (one minute and forty seconds for Stroop tests and two minutes and thirty seconds for Arithmetic tests) were excluded as it was likely that a genuine, distraction-free attempt was not made (Cedeño Laurent et al., 2021; Young et al., 2024).

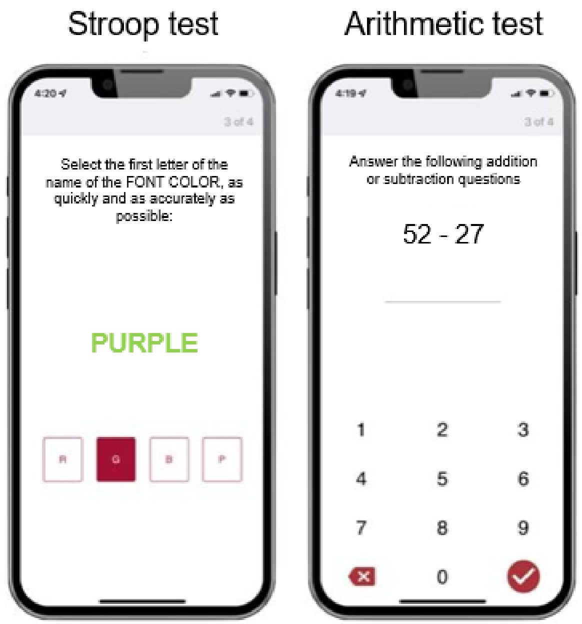


Figure 6: Example of Stroop and Arithmetic tests, as performed by participants in the study's smartphone research app. The correct Stroop response is "G" for "Green" and the correct Arithmetic response is "25".

Statistical Methods

After scoring and cleaning, calculated cognitive test scores and categorized thermal sensation responses were combined with class average exposure data to create an analysis dataset. Only responses where in-person class attendance was verified (via a survey question) and both the cognitive test and thermal perception survey were completed were included in the final analysis. This resulted in 273 observations from 54 unique participants, as depicted in Figure 7 below. The 114 Stroop test responses and 159 Arithmetic test responses included in this analysis occurred between November 2022 and April 2023.

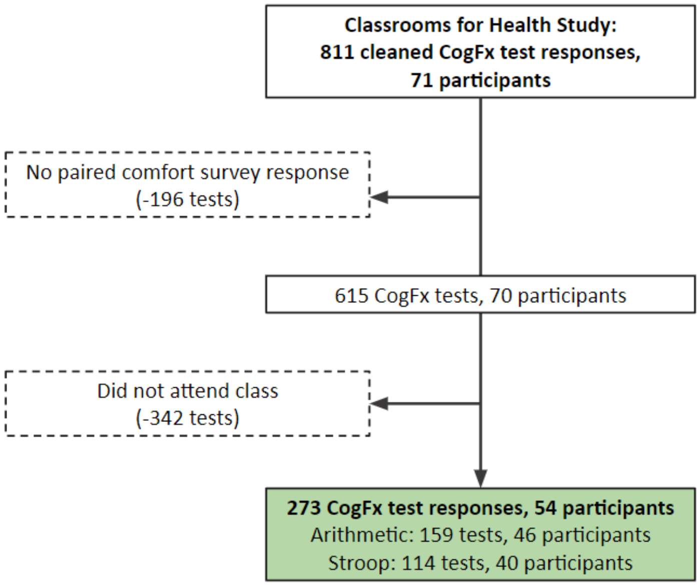


Figure 7: Flowchart showing data inclusion criteria that produced the final analysis dataset.

Summary statistics, distributions, and Spearman Rank correlation matrices were first examined to understand the exposure and outcome data. These preliminary findings (discussed further throughout section 3.0) motivated additional supporting analyses, including factor analysis and principal component analysis of the exposure variables. This preliminary work also informed a series of mixed effects statistical models that incorporated the eleven thermal variables (as exposures), six cognitive test scores (as outcomes), and three summarized thermal sensations (as exposures or outcomes) into different exposure-outcome pairings for association modeling. As described earlier, the two primary associations of interest include: 1) the associations between thermal conditions and cognitive test scores, and 2) the associations between thermal conditions and thermal sensations. As a complementary third association, we treated thermal sensations as an exposure and investigated its associations with the cognitive test scores. For each of these three associations, we constructed numerous models between each applicable exposure and outcome variable. For example, to investigate the association between thermal conditions and cognitive test scores, a model was constructed for every thermal variable and cognitive test score combination, resulting in 66 models (i.e., eleven thermal variables and six cognitive test scores). For the other investigated associations, we constructed eighteen models exploring the association between thermal sensations and cognitive test scores (three thermal sensation variables and six different test scores), and 33 models exploring the association between thermal conditions and thermal sensation (eleven thermal variables and three thermal sensations).

All models, regardless of exposure or outcome, controlled for class average CO_2 and school to control for confounding and potential differences between the two schools, respectively. Thermal exposures and CO_2 were modeled with cubic regression splines to allow for non-linear associations with the outcome of interest in each model. Participant-specific random effects were included to account for correlation among observations from the same individual over time. Beyond these general considerations, additional specifications were made based on the specific outcome.

For models with thermal sensation as the outcome, we constructed a series of binomial regression models for each of the three categorized sensations (i.e., cold, neutral, warm) as binary variables (e.g., cold or not, neutral or not, warm or not). For models with cognitive test scores as the outcomes, we used a linear model with a normal distribution to model each of Stroop throughput, Stroop incongruent throughput, and Arithmetic throughput. Stroop response time, Arithmetic response time, and Stroop average incongruent response time all had to be log-transformed to meet the assumptions of normality and were then assessed using linear models with a normal distribution. Additionally, we controlled for learning effects in all cognitive models by either controlling for the first test response or test number. For Stroop-based models, we controlled for test number since we consistently observed the presence of continued learning effects, based on statistically significant and increasing magnitudes of effect estimates with increasing test number. This decision was also supported by the lower AIC values for models that controlled for test number compared to models that controlled for first test. For Arithmetic-based tests, we consistently observed the opposite: there was no evidence of continued learning effects and the AIC values were lower for models that controlled for first test compared to models that controlled for test number. We controlled for first test in Arithmetic-based models accordingly.

Following base model construction, we conducted additional sensitivity analyses to further investigate our results. Considering the extent of literature citing perceptions of indoor air quality and thermal conditions to be intertwined (L. Berglund et al., 1990; Fang et al., 1998b, 1998a, 2004; Kerka & Humphreys, 1956), we conducted a supporting analysis to assess if air quality issues might be influencing our results focused on thermal sensations. Although the CO_2 concentrations (and TVOC and $PM_{2.5}$ measurements, but not included analysis) were low in this study, compared to other indoor environments (Fisk, 2017), we investigated potential correlations and associations between class average CO_2 concentrations and participant responses to survey questions asking about perceptions of indoor air quality. Responses to survey questions asking participants to rate the quality of indoor air and the presence of any air quality issues were paired with class average CO_2 concentrations in the same fashion as the analysis dataset. We then constructed boxplots, t-test and analysis of variance (ANOVA) tests, depending on the number of response options, and finally, simple logistic regression models. The logistic regression models incorporated a spline term for class average CO_2 as the primary exposure variable; controlled for temperature, RH, and school; and included participant-specific random effects. Two models were constructed: one with a binary outcome variable for IAQ rating being either good or bad, and another model using a binary indicator for the presence or absence of air quality issues. Beyond this olfactory investigation, we also ran a series of models that incorporated participant-specific random effects nested within classroom-specific random effects to account for potential correlations among multiple measurements from students in the same classrooms over time. Finally, we ran a series of models with just indoor RH (no paired temperature), outdoor enthalpy, and outdoor dewpoint temperature to assess if the associations we observed with indoor enthalpy were indeed distinct or an artifact related to some other variable. All data management, processing, and statistical analysis was conducted in Rstudio.

Results

Participant Characteristics

54 unique participants contributed data to the final analysis dataset. Participant characteristics are presented in Table 4 for 53 of these participants as one did not complete the background surveys. Most participants in this study are female (~74%), in their twenties (mean age of 26 ± 3.5 years), and White or Asian.

Table 4: Participant Characteristics for 53 of 54 Participants Included in Analysis

Characteristic	Overall (N=53)
Sex Assigned at Birth	
Female	39 (73.6%)
Male	12 (22.6%)
Prefer not to say	2 (3.8%)
Age	
Mean (SD)	26.2 (3.48)
Median [Min, Max]	26.0 [21.0, 42.0]
Hispanic, Latino, or Spanish Origin	
No: not of Hispanic, Latino/a/x, or Spanish origin	45 (84.9%)
Yes: another Hispanic, Latino/a/x, or Spanish origin	5 (9.4%)
Yes: Mexican, Mexican American, Chicano/a/x	2 (3.8%)
Yes: Puerto Rican	1 (1.9%)
Race	
Asian or Asian American	17 (32.1%)
Black or African American	6 (11.3%)
Some other race	4 (7.5%)
White or Caucasian	24 (45.3%)
White or Caucasian or Native Hawaiian or Other Pacific Islander	1 (1.9%)
White or Caucasian or Some other race	1 (1.9%)
US Origin	
No	26 (49.1%)
Yes	27 (50.9%)

Note: One of the 54 participants included in analysis did not complete the baseline survey and is therefore not included in the above table of 53 out of 54 participants.

Measured Classroom Conditions and Calculated Thermal Variables

A summary of the suite of calculated class average thermal variables and accompanying class average CO_2 concentrations used in the statistical analysis are presented in Table 5 below. Class average indoor temperatures range from 20-26 ºC, with a tight interquartile range of 23-24 ºC. On average, mean class CO_2 concentrations are low (i.e., mean and 75th percentile values are 710 and 775 ppm, respectively) compared to concentrations observed in past investigations (Fisk, 2017) and inferred from the temporal evolution of minimum standards, which much of today's building stock achieves or falls below (ASHRAE, 2022; Fox, 2023; Persily, 2002, 2015). The classrooms in this study had increased outdoor air ventilation rates as an infection risk management strategy (Dedesko et al., awaiting submission), which agrees with these low CO_2 values. Overall, class average RH is low (i.e., mean and 75th percentile values of 25% and 28%, respectively) compared to the range of 30-60% (ASHRAE, 2016) that is recommended for human health and comfort considerations (in addition to other built environment considerations, such as material durability). The two metrics, heat index and PMV, focused on characterizing human perceptions reveal that the heat index reflects a slightly lower temperature compared to dry-bulb air temperature itself and that all estimated PMV values are negative, suggesting that on average, this study population would have felt a cool sensation following the PMV approach.

Table 5: Summary Statistics for Class Average Indoor Conditions Included in Analysis (n=273)

Variable	Mean	SD	CV	Min	p25	p50	p75	p95	Max
Temperature (C)	23	1.2	0.051	20	23	23	24	25	26
RH (%)	25	6.8	0.28	12	19	25	28	36	46
CO_2 (ppm)	707	207	0.29	471	562	625	771	1176	1309
Heat Index (C)	22	1.2	0.055	19	22	22	23	24	25
PMV	-1.2	0.43	-0.35	-2.4	-1.4	-1.2	-0.96	-0.58	-0.21
Enthalpy (kJ/kg)	35	3.7	0.11	26	32	34	37	41	49
Pwv (kPa)	0.71	0.2	0.29	0.33	0.54	0.69	0.88	1.1	1.4
Humidity Ratio (kg water/kg dry air)	0.0044	0.0013	0.29	0.002	0.0034	0.0043	0.0054	0.0066	0.0087
Dewpoint (C)	1.6	4	2.5	-8.4	-1.6	1.7	5	7.8	12
Temperature Difference (C)	18	5.8	0.33	5.8	12	17	22	26	27
Enthalpy Difference (kJ/kg)	19	8	0.43	4.6	12	19	25	33	42
VPB (kPa)	0.062	0.22	3.6	-0.37	-0.061	0.026	0.16	0.41	0.88

After examining summary statistics, a Spearman Rank correlation matrix was constructed using the mean class conditions presented in Table 5. The Spearman-rank correlation coefficients are presented in matrix form in Figure 9, which shows three groupings of very tight correlations around temperature, RH, and indoor-outdoor differences. Due to the intensity of this clustering, we conducted factor analysis to further investigate these observed correlations in terms of latent factors (Schuster & Yuan, 2005). We began with six factors and followed the Kaiser rule where factors are eliminated when the Sum of Square (SS) loadings (Eigenvalues) are less than one, which indicates that these factors do not add additional information to the assessment. We ultimately arrived at three factors that account for 96% of the overall variance across all eleven variables, and whose factor loadings follow the three groups defined by Spearman Rank correlations. We also performed principal component analysis to assess linear composites of the variables and found similar results. These supplementary analyses confirm the three observed groupings, which we define and refer to herein as: 1) temperature-oriented variables, consisting of temperature, heat index, and estimated PMV; 2) moisture-oriented variables, consisting of RH, Pwv, humidity ratio, dewpoint temperature, and enthalpy; and 3) indoor-outdoor difference variables, consisting of the temperature difference, enthalpy difference, and VPB. We observe perfect 1:1 Spearman Rank correlations among all variables within the temperature-oriented group and low correlations with variables in the moisture-oriented group, suggesting that heat index and PMV estimates strongly reflect air temperature and not moisture. Similarly, for the moisture-oriented group, we observe strong positive Spearman Rank correlations among all variables within this group and low correlations with variables in the temperature-oriented group. Enthalpy is somewhat distinct as it has the lowest, but still strong, correlation with RH within this group (correlation coefficient of 0.86) and the strongest correlation with temperature in this group (correlation coefficient of 0.51), suggesting that enthalpy might incorporate the heat and moisture components of air in a distinct and more balanced and comprehensive manner than the other temperature and moisture-oriented variables. Finally, we observe the lowest correlation coefficients within the indoor-outdoor difference group, which combined with higher residual variance for the factor loadings in this group from our factor analysis, suggests higher variability within this group. Furthermore, indoor-outdoor difference variables show overall low negative correlations with the temperature and moisture-oriented variables, suggesting these variables provide distinct information compared to the other two groups.

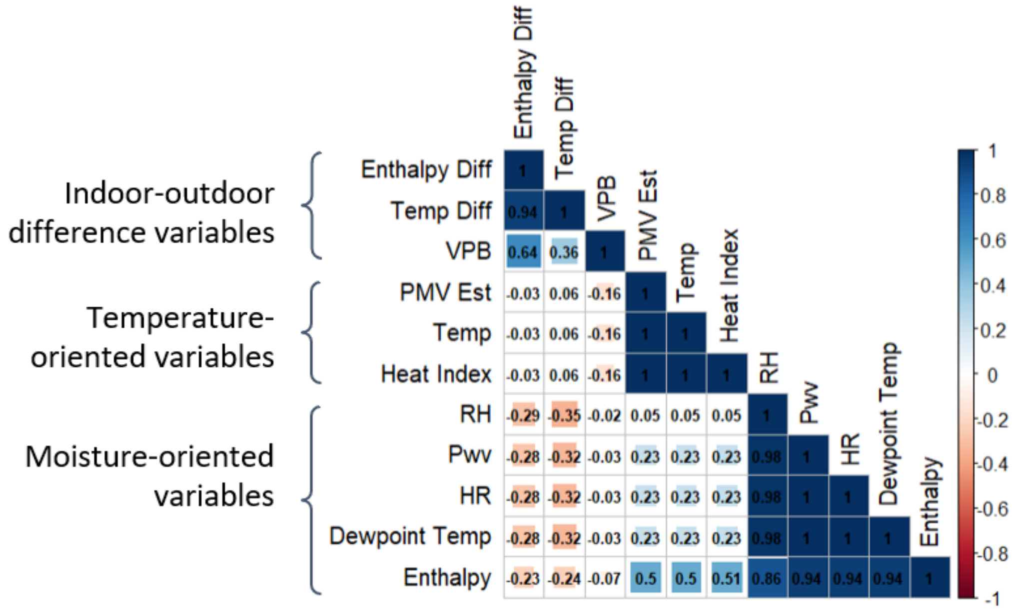
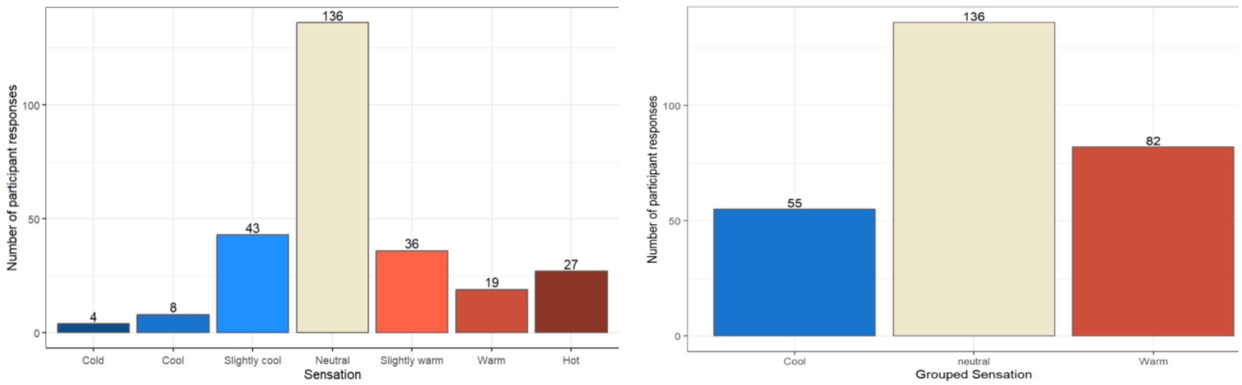


Figure 8: Spearman Rank Correlation Coefficients Showing Three Distinct Groupings Among Class Average Thermal Exposure Variables

Thermal Sensations and Cognitive Test Scores

Participant responses to the core thermal sensation question are presented in Figure 9 below, with the original seven-point Likert scale responses summarized on the left (Figure 9a) and the three categorized sensations summarized on the right (Figure 9b). As shown, 50% of thermal sensation responses were neutral, 30% were some sensation of warm, and 20% were some sensation of cool, which counters the PMV estimates that suggested most participants would feel a cool sensation. The small number of responses in the individual, more granular cold and warm sensation options in the seven-point Likert scale (Figure 9a) motivated the three sensation groupings shown in Figure 9b, as previously described, for the association modeling.



a. Original seven-point Likert scale response options

b. Summarized thermal groupings

Figure 9: Summary of participant's thermal sensations in the rooms they just had class.

Calculated cognitive test scores indicate that on average, one Stroop trial takes 1.2 seconds (± 0.4) to complete and that 50 (± 19) correct Stroop trials can typically completed per minute (i.e., average Stroop throughput). Focusing on incongruent Stroop trials only, to represent the Stroop effect, we observe an average response time of 1.3 seconds (± 0.5) per trial and a Stroop incongruent throughput metric of 4.1% / minute (±1.7). Each arithmetic trial takes approximately 5.1 seconds (± 1.8) to complete and approximately 12 correct trials (± 4) are completed each minute, on average (i.e., arithmetic throughput).

Modeled Associations

Since we observed such tight correlations among thermal variables within each of the three groups, it is not surprising that the modeled associations are similar among thermal variables within the same group. Accordingly, and for brevity, we discuss the overall pattern of association observed for each of the three thermal groups and then further illustrate these patterns by presenting more detailed results, including plotted splines and model estimates, for one representative thermal variable from the temperature and moisture-oriented groups. We discuss temperature (paired with RH as a separate independent variable) from the temperature-oriented group and enthalpy from the moisture-oriented group based on practical and theoretical rationale. Specifically, the use of temperature and RH as separate independent variables is common practice in association modeling and epidemiology, general built environment research, and real-world building assessments, and accordingly, we highlight temperature and RH to emphasize the implications of this approach. We select enthalpy from the moisture-oriented group due to the findings from the exposure assessment that it potentially incorporates both the heat and moisture components of air in a distinct and more complete manner and also the strength of the statistical evidence. We do not present detailed results for the indoor-outdoor difference group, as these variables showed little evidence of meaningful, consistent, or statistically significant associations. The results are presented with respect to the range of exposures and outcomes included in this analysis only. We refer to “statistically significant evidence” as results reaching the 0.05 alpha level, and “mixed evidence” as a combination/group of results reaching and not reaching the 0.05 and 0.1 alpha levels.

Associations between Thermal Variables and Cognitive Function

We first examined models estimating the associations between class average thermal conditions and cognitive test scores. Beginning with the moisture-oriented group, spline terms showing the modeled associations between indoor enthalpy and the six cognitive test scores are presented in Figure 10 below. The modeled associations suggest linear associations between enthalpy and arithmetic test scores (Figures 10 e-f), where increases in indoor enthalpy are associated with increases in throughput and decreases in response time. There is evidence of nonlinear associations between indoor enthalpy and the four Stroop scores (Figures 10 a-d); overall, we see suggestive evidence that higher enthalpy, over the 26-49 kJ/kg range examined in this analysis, is associated with better Stroop scores as we observe higher throughput scores and lower response times at the higher compared to lower enthalpy range. The model estimates are mixed in terms of statistical significance, as detailed for each spline term in Figure 10 below.

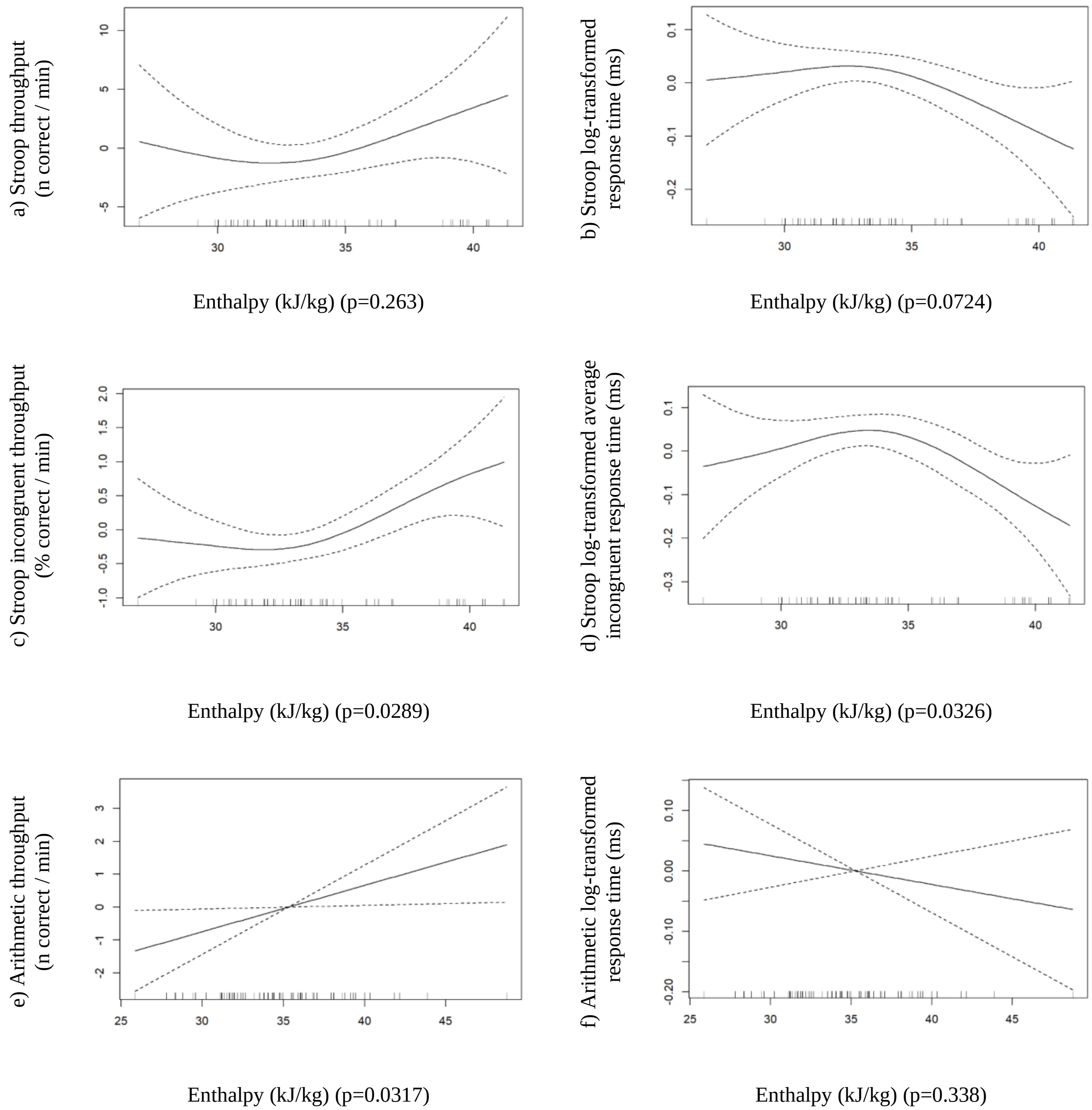


Figure 10: Plotted spline terms from adjusted mixed effects models showing the associations between indoor enthalpy and each of the six cognitive function scores. Associations appear nonlinear for Stroop scores and linear for arithmetic scores. For all scores, better cognitive scores (higher throughput or lower response times) are observed at the higher range of enthalpy compared to the lower range. Models are adjusted for class average enthalpy and CO_2, school, and learning effects, and include participant-specific random effects.

Moving on to the temperature-oriented variables, our models suggest that higher values of temperature-oriented variables are linearly associated with improved cognitive performance for all cognitive scores except Stroop throughput where we observe a nonlinear association with temperatures around 24 ºC being associated with the highest Stroop throughput scores for all three thermal variables in the temperature-oriented group. The modeled associations are inconsistent for RH. While in some instances, increases in RH appear to be associated with improved cognitive scores, there are many instances where the modeled spline terms suggest no association with cognitive scores. Statistically, the results are mixed for temperature and none of the accompanying RH splines reach any level of statistical significance. The set of models that includes temperature and RH as separate thermal exposure variables suggests a stronger association between temperature and cognitive test scores compared to RH and cognitive test scores. We present representative plotted spline terms for temperature and RH from this set of models in Appendix B. For the indoor-outdoor difference group, we do not find evidence of a consistent association with all six cognitive test scores for each of the exposure variables in this group, and accordingly, no meaningful pattern of an association for the group itself.

Associations between Thermal Variables and Thermal Sensation

Next, we examined the associations between the eleven thermal variables and three binary thermal sensation variables (warm or not, neutral or not, cool or not). Beginning with the moisture-oriented variables, we present a sample spline term in Appendix B, which shows suggestive evidence of indoor enthalpy values around 35 kJ/kg to be associated with neutral sensations. For temperature-oriented variables, we observe an inverted U-shaped association, peaking around 23-24 ºC, with feeling neutral as opposed to not, as shown in Appendix B. Appendix B also shows the complementary spline term for RH that suggests that an indoor RH of approximately 25% is associated with neutral sensations. Not surprisingly, we found higher values of both temperature and moisture-oriented variables to be associated with warm sensations, and lower values to be associated with cool sensations. We observe the strongest statistical evidence of associations for models predicting warm sensations, mixed evidence for models predicting cold sensations, and no statistically significant evidence for models predicting neutral sensations. Once again, we do not observe evidence of a consistent association between indoor-outdoor difference variables and thermal sensation.

Associations between Thermal Sensation and Cognitive Function

Finally, as a complementary assessment, we examine the modeled associations between thermal sensations (neutral or not, warm or not, cool or not) and cognitive performance (i.e., the six cognitive test scores). We find neither directionally consistent nor statistically significant evidence that feeling neutral as opposed to not is associated with cognitive test scores. Instead, we find directionally consistent evidence, with mixed statistical significance, that feeling warm as opposed to not is associated with improved correct responses per time, and lower response times. Conversely, feeling cool as opposed to not is associated with worse cognitive test scores (both correct responses per time and response time), but none of these effect estimates reach statistical significance at the 0.05 or 0.1 alpha levels. These model estimates are presented in Appendix B.

Sensitivity Analyses

Collectively, we found no evidence of a correlation or association between CO_2 and air quality perceptions, as boxplot distributions were similar, t-test and ANOVA results showed no significant differences between groups, and the regression models showed no evidence of an association (spline terms were nearly horizontal lines). The regression models also show little evidence of an association between temperature and RH with IAQ perceptions. This suggests that participants did not typically note issues with the indoor air quality and also that there does not appear to be olfactory interference with thermal perceptions. This furthers our confidence in this study's findings that indoor enthalpy appears to be associated with thermal sensations and cognitive performance, separately from any olfactory issues. We observed no differences between model estimates with and without classroom as a nested random effect. Finally, the series of models with just indoor RH (no paired temperature as a separate variable), outdoor enthalpy, and outdoor dewpoint temperature did not yield consistent or statistically significant evidence of associations, further strengthening our observations with indoor temperature and moisture-oriented variables, despite our small dataset and limited study scenario.

Discussion

In this work, we set out to assess the associations between 1) thermal conditions and cognitive performance, 2) thermal conditions and thermal sensation, and, as a complement, 3) thermal sensations and cognitive performance. In the process, we observed interesting relationships among thermal variables themselves, how they relate to cognitive performance and thermal sensations, and implications for our treatment and characterizations of thermal conditions.

Thermal Variable Groups

The first key finding of this analysis is that the thermal variables we examined cluster into three groups, correlated around indoor temperature, indoor moisture, and indoor-outdoor differences. Due to the intensity of this clustering, it was not surprising that from our model estimates, we then observed similar associations among thermal variables within each group.

Although in isolation, these thermal variables provide distinct information, the findings from this study reveal that when relating these thermal exposure variables to occupant outcomes (e.g., through statistical comparisons or association modelling), there are many considerations to account for. Within the temperature-oriented group, the perfect correlations (1.0) among temperature, heat index, and PMV estimates, and low correlations with RH (0.05) suggests that the additional step of calculating heat index or estimating PMV provides no additional information for association modelling beyond the use of the simple temperature measurements in this scenario, which spans a narrow range of indoor air temperature and moisture in these well-operated buildings. Furthermore, although both heat index and PMV incorporate RH into their calculations, these variables appear to be primarily driven by temperature under the conditions in our analysis, thus potentially underrepresenting indoor air moisture in these types of scenarios. This is not necessarily surprising for heat index, given its common use in outdoor settings at temperature and RH conditions much higher than those observed in this study and its stepwise pattern with low sensitivity to changes in temperature and moisture at lower values. Similarly, for the set of models that incorporate temperature and RH as separate independent thermal exposure variables, we observed directionally consistent and statistically stronger evidence of an association between temperature and the outcomes of interest compared to RH and the outcomes of interest. Temperature and RH are commonly modelled as separate independent variables (Bueno et al., 2021), but our findings suggest that this approach might emphasize the association of temperature and not the potential importance of indoor moisture with respect to these occupant outcomes. Indeed, past work has shown that considering temperature and RH separately is inadequate, as the two variables can move in different directions, further supported by the low Spearman correlation (0.05) observed in this work, yet work together on occupant outcomes (Rana et al., 2013). Evidently, the temperature-oriented variables, either heat index, estimated PMV, or temperature with RH as two separate independent variables, might not adequately represent both the heat and moisture of air, which turns our attention to the moisture-oriented variables. Within this group, we also observe strong positive correlations among variables within this group and consistent patterns of modelled associations. Enthalpy exhibited somewhat lower, but still strong, positive correlations with RH (0.86) and the strongest correlation with temperature (0.51) compared to all other variables in the moisture-oriented group. While we still observe overall consistent patterns of association among all variables within the moisture-oriented group, we observe the strongest statistical evidence of an association between enthalpy and cognitive test scores and also with thermal sensations. Although the analysis dataset is small, this collective evidence suggests that enthalpy might incorporate both air temperature and moisture in a more complete/representative manner that is distinct from the other variables and also more strongly associated with the outcomes of interest. Finally, all variables within the temperature and moisture-oriented groups were calculated using simple indoor measurements of temperature and RH. The indoor-outdoor difference variables required additional outdoor weather data to calculate but did not provide consistent evidence of meaningful associations with the outcomes of interest. This aligns with them being less proximate/related to the indoor exposures experienced by participants in their classrooms and observations from existing work where others have commented on the low utility of indoor-outdoor differences for predicting occupant comfort (Piasecki et al., 2020). Accordingly, obtaining outdoor weather data and calculating these variables is not essential for similar future efforts, as simple measurements of indoor temperature and RH can provide useful information as observed in this study.

Modeled Associations

Beyond the findings related to the thermal exposure variables themselves, we observed interesting patterns of modeled associations that raise many questions related to the influence of indoor air heat and moisture on human occupants. This study occurred over the heating season in the greater Boston area and the tight range of mean indoor temperatures (range of 20-26 ºC, IQR of 23-24 ºC) are within a range deemed "comfortable" (ASHRAE, 2023) and typical of most work environments (Földváry Ličina et al., 2018; Porras-Salazar et al., 2021). However, mean indoor moisture was low (range of 12-46%, IQR of 18-28 %) relative to the 30-60% RH range that is recommended for human comfort and health, among other building considerations (ASHRAE, 2016). Accordingly, the tighter range of air temperatures and larger range of RH measurements suggests a tighter range of heat and larger range of moisture in the air. While the temperature-oriented variables emphasize the heat component, and most moisture-oriented variables emphasize the moisture component, enthalpy incorporated both in the most balanced manner. Enthalpy is a measure of the total energy content of the air, including the sensible heat of dry air and the latent heat of moisture in the air (Dincer & Rosen, 2007; Stephens, 2016). Indoor enthalpy correlates more closely with the moisture-oriented variables, which, combined the tight range of temperatures and larger range of low indoor RH, suggests that in this study, increases in air moisture are likely responsible for the increases in enthalpy, which is observed to be associated with improved cognitive performance and warm sensations. This suggests that participants felt warmer and perform better with higher indoor air moisture, over the tight range of acceptable indoor temperatures and a larger, but also small, range of indoor RH observed in this study. More broadly, these findings suggest that indoor air moisture might be more influential to these outcomes than recent attention has devoted, since much past work has focused on indoor temperatures and/or a modeling approach that potentially underemphasizes the importance of moisture, as observed with the use of temperature and RH as separate independent exposure variables. Collectively, the findings from this investigation suggest that indoor moisture, particularly when expressed with its paired temperature as a conjugate metric and not as a separate, independent metric, as is the case with RH, might be more relevant to cognitive performance than past attention has given. These findings suggest that enthalpy might be a more complete representation of both the heat and moisture content of air with respect to these occupant outcomes and particularly important when trying to examine the indoor conditions that support occupants and their activities.

Comparison of the present study to past work is challenging due to the limited amount of published research that examines indoor enthalpy or thermal parameters beyond temperature and RH in the context of associations with cognitive performance and/or thermal sensations. A recent systematic literature review on the topic examined sixty studies that met inclusion criteria and found that 90% of studies utilized temperature; some works also assessed RH, CO_2, and other metrics of light and sound; and none of the reviewed studies assessed indoor enthalpy, dewpoint temperature, humidity ratio, vapor pressure, or indoor-outdoor differences (Bueno et al., 2021). One recent study examined associations between heat index and Stroop metrics and found nonlinear results (Young et al., 2024), while other occupational work has used wetbulb globe temperature meter readings to find an association between heat stress and impaired Stroop test scores (Mazloumi et al., 2014). A few previous studies examined indoor enthalpy and occupant satisfaction, but with respect to perceptions of indoor air quality and found that higher indoor enthalpy, beyond the range measured in our study, was associated with poorer perceptions of indoor air quality (Fang et al., 1998b, 1998a, 2004). A more recent study examined indoor enthalpy and occupant satisfaction (both with thermal and air quality conditions) under hot and humid conditions and found at high enthalpies, beyond those in the present study (>55 kJ/kg), dissatisfaction with air indoor air quality is greater than dissatisfaction with thermal conditions and that the Fanger models (percent dissatisfied, using PMV) underpredicted the level of dissatisfaction (Piasecki et al., 2020). These authors also note other motivating works where air acceptability decreased with increasing enthalpy, but above the range in our study (Toftum et al., 1998; Toftum & Fanger, 1999).

Mechanisms of thermal exposures on cognitive performance and thermal sensation

Although not focused on enthalpy, Harriman (2009) looks beyond indoor temperature and RH as individual parameters and discusses dewpoint temperature with respect to thermal comfort. He states that human comfort is driven by differences in dewpoint temperatures between the skin surface and surrounding ambient air. A bigger difference between the two indicates greater drying potential, which is beneficial when you want to release heat to cool off (i.e., during the cooling season), but detrimental when you want to conserve heat and not “dry out” to stay warm and comfortable (i.e., during the heating season). Relatedly, others have examined skin wettedness and also noted its importance to thermal comfort. One study examined participants during exercise and recovery and found skin wettedness to be more important to thermal behavior than core temperature (Vargas et al., 2018). Other studies have focused on more accurately representing skin wettedness and evaporative heat loss in thermal comfort models, yielding substantial improvements in model predictive accuracy. One study utilized the standard effective temperature model, with advanced human thermoregulation, to better represent skin wettedness and heat loss via evaporation at the skin surface into the PMV model. They then validated this model with the ASHRAE Global Thermal Comfort Database II and found the predictive accuracy to improve from 32% for the original PMV model to 64% for their modified model for a variety of building types and settings (S. Zhang & Lin, 2021). These authors also assessed related model modifications by other investigators who did not perform their own validations. They found that similar efforts, such as a PMV adaptation aimed at more accurately accounting for evaporative heat loss by basal sweating (Omidvar & Kim, 2020), improved PMV prediction accuracy by 49%. Evidently, skin wettedness and the associated evaporative heat loss with surrounding air shows promising importance for thermal comfort. In our study over the heating season, we observe mean class dewpoint temperatures ranging from -8.4 to 12 ºC, with an IQR of -1.6 to 5 ºC and a mean of 1.6 ºC ± 4 ºC. Harriman (2009) notes that a higher dewpoint means the air feels muggier and at lower dewpoints, symptoms, such as dry eyes and skin, start to emerge. He recommends maintaining a dewpoint between roughly -1.1 and 4.4 ºC during the heating season to help promote thermal comfort, while being mindful of the energy expenditure associated with this space conditioning. Most class mean dewpoint temperatures in our study fall within this range, and most participants voted feeling neutral, supporting Harriman's recommendation. However, some dewpoint temperatures in our study fall below this range, and beyond comfort, based on our association modeling, it appears that higher levels of indoor moisture could be beneficial to cognitive performance. Our findings with enthalpy could be related to these suggested thermoregulation mechanisms between skin wettedness and air via moisture exchange, especially given the high correlation between indoor enthalpy and dewpoint temperature (Spearman Rank correlation coefficient of 0.94). While we hypothesize skin-air moisture-based interactions as part of the underlying biological mechanisms of our modeled associations between moisture-oriented variables and occupant outcomes, it is likely that other mechanisms are at play with respect to indoor thermal conditions and thermal sensations and cognitive performance. Past studies have noted improved cognitive performance slightly beyond neutral sensations, which many authors attribute to mental arousal from stimulation caused by changes in brain temperatures (Kiyatkin, 2019; Tham & Willem, 2010). Furthermore, the improved cognitive peformance we observed with higher levels of indoor moisture could be due to reduced symptoms and perceptions of dryness, which would draw attention away from cognitive processes.

Sensitivity Analyses

After contrasting our findings to the existing literature, we conducted additional sensitivity analyses to further investigate our results. Collectively, we found no evidence of a correlation or association between CO_2 and air quality perceptions, as boxplot distributions were similar, t-test and ANOVA results showed no significant differences between groups, and the regression models showed no evidence of an association (spline terms were nearly horizontal lines). The regression models also showed little evidence of an association between temperature and RH with IAQ perceptions. This suggests that participants did not typically note issues with the indoor air quality and also that there does not appear to be interference with thermal perceptions. This furthers our confidence in this study's findings that indoor enthalpy appears to be associated with thermal sensations and cognitive performance, separately from any olfactory issues. From our analysis comparing model estimates with and without classroom as a nested random effect, we observe no differences, suggesting no correlation among responses from students in the same classroom over time. Finally, from the models with just indoor RH, outdoor enthalpy, and outdoor dewpoint temperature as thermal exposures, we did not find consistent or statistically significant evidence of associations, further strengthening our observations with indoor temperature and moisture-oriented variables, despite our small dataset and limited study scenario.

Limitations and Next Steps

Beyond study design, analysis methods, and sensitivity analyses, there are many inherent limitations in this work that must be addressed and considered when interpreting these results. First, our study consists primarily of White and Asian female participants in their mid-twenties. Past work has found females to prefer and perform better under warmer conditions compared to males (Byrne et al., 2005; Du et al., 2023; Haynes, 2007; Karjalainen, 2012; Parkinson et al., 2021) and that older individuals are more susceptible to the effects of thermal conditions (Dolcini et al., 2020), which means that the findings from this study might not apply to populations of more diverse sex and age. Relatedly, the effect of thermal conditions has been reported to vary based on task type/complexity, with many studies finding no association between temperature and simple tasks, but an association between temperature and complex tasks (Luo et al., 2023; F. Zhang et al., 2019). This implies that thermal conditions might not influence performance when the task is more straightforward and there could be more flexibility with indoor thermal conditions. Furthermore, the indoor spaces in this study are located in the Boston area and the measurement period included in analysis pertains to the heating season only. Accordingly, the low values of measured RH in our study and apparent benefit of higher indoor enthalpy (greater energy related to air temperature and particularly moisture) might not translate to other times of year and studies in cooling-dominant climates. Indeed, past work occurring in cooling-dominated settings found slightly cool sensations and/or lower indoor moisture to improve cognitive performance (R. Ahmed et al., 2022; Jensen et al., 2009; Kosonen & Tan, 2004; Lan et al., 2011, 2022), even among a similar population of female graduate students, age

16-23, but in Saudi Arabia (R. Ahmed et al., 2022). Similarly, it has been found that occupants prefer and adapt to indoor thermal conditions differently based on their regional background and typical climate (R. Ahmed et al., 2022; Kong et al., 2019), which again, implies that these results would differ based on population and location. Relatedly, the measured values of indoor temperature and RH fall within a tight range, and also low range with respect to RH, and so the finding that higher values of indoor enthalpy are associated with warm sensations and improved cognitive test scores are with respect to the range of indoor exposures in this study specifically. Other work that has examined hot and humid climates found the opposite, with lower values of temperature and moisture leading to improvements in occupant outcomes over the range included in their studies (R. Ahmed et al., 2022; Tian et al., 2021). Moreover, although we assess multiple thermal variables, we acknowledge that our assessment is limited to quantifications of air heat and moisture, which is not thermally comprehensive. Although we made a series of investigative field measurements of surface temperatures and airspeed, many limitations (i.e., accuracy and measurement range of the devices, no knowledge of participant locations to calculate MRT) prevented the use of these measurements in our analysis. While most rooms are interior with no windows to the outdoors and airspeeds were low, our assumptions for MRT and airspeed to calculate PMV are reasonable, but not fully accurate, along with our static assumptions for clothing insulation and metabolic rate, which are highly variable in practice (Rana et al., 2013). Future work could also assess these parameters for a more comprehensive assessment of indoor thermal conditions since the surface temperature scans did reveal some variation in indoor surface temperature from interior heat sources. Nevertheless, our results are still useful for research and practice where these involved field measurements are not possible and simple measurements of temperature and RH are available through in-room monitors and the building management system.

With respect to our outcome measures, there is the possibility of recall error as participants answered thermal surveys after class, but within a set time limit. Furthermore, the cognitive tests used enable the objective calculation of cognitive scores, but do not reflect the range of cognitive tasks and work performance performed in all environments. Finally, although our statistical models control for many potential confounders while also providing the flexibility to explore non-linear associations, interpreting the results is limited to comparing and contrasting the modeled associations and hypothesizing potential differences and/or explanations. While we observe more consistent and statistically stronger evidence of an association between enthalpy and the outcomes of interest, strengthened by our Spearman Rank correlation assessment and potential theoretical explanations from the literature, our small and limited analysis dataset does not allow for definitive conclusions. Ideally, future work would build upon our preliminary findings and hypotheses and investigate this topic more comprehensively with more diverse study settings, additional thermal variables, and overall larger datasets.

Despite these limitations, the study design and statistical approach instill confidence in our findings, which provide new considerations for the representation of the heat and moisture components of air with respect to occupant outcomes. Collectively, the statistical findings and theoretical explanations in the literature suggest that indoor moisture may be more important to these occupant outcomes than previously thought, and that the commonly used approach of investigating these outcomes with temperature and RH as separate independent variables might not elucidate this importance. Indeed, our models that followed the common approach of incorporating temperature and RH as separate variables emphasized temperature irrespective of an accompanying RH and underemphasized potential associations with RH. Indoor enthalpy emerged as the thermal variable with the most balanced correlation with temperature and RH and strong statistical association with cognitive performance and thermal sensations, which points to indoor moisture being more influential to these outcomes at lower enthalpies than previously examined (Toftum et al., 1998; Toftum & Fanger, 1999), positing a need to better incorporate indoor moisture into our understanding of the indoor environment and its impacts on occupants. Since enthalpy is straightforward and scalable to calculate with simple temperature and RH measurements, while also being strongly associated with cognitive performance and thermal sensations, it has high utility for future studies that investigate how the indoor environment influences occupant outcomes. Future work would ideally apply this approach to further understand how indoor moisture, and its quantification, influence occupant outcomes across a range of populations and built environment settings, beyond those examined in this study.

Conclusion

This prospective, observational, longitudinal study provides new insights surrounding the thermal variables we use to characterize the built environment and how they relate to occupant outcomes. We observe that indoor thermal variables cluster into three groups related to temperature, moisture, and indoor-outdoor differences and each of these groups exhibits distinct patterns of associations with cognitive test scores and thermal sensations. These findings suggest useful considerations for built environment research and practice, where in well-controlled buildings: 1) many thermal variables are so closely related that they provide little utility beyond one another; 2) for association modeling, temperature-oriented variables, including the common modeling approach of treating temperature and RH as separate exposure variables, do not fully represent a potentially important role of indoor moisture with respect to occupant outcomes; 3) a quantitative representation of indoor moisture with its paired temperature, as demonstrated with enthalpy, might be more important to cognitive performance and thermal sensations, than previously considered; and 4) higher values of indoor enthalpy, likely driven by increases in indoor air moisture in this study, and warm sensations could promote cognitive performance during the heating season. These considerations should be explored beyond the limited scope of this study to understand how these findings might vary with different study populations and built environment settings, and how the collective results could inform building operation to support occupant thermal comfort and cognitive performance.

CHAPTER 4: ASSOCIATIONS BETWEEN INDOOR ENVIRONMENTAL CONDITIONS AND DIVERGENT CREATIVE THINKING SCORES IN THE COGFX GLOBAL BUILDINGS STUDY

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Abstract

A growing body of evidence has demonstrated associations between indoor air and thermal conditions and various cognitive performance metrics. However, most of these cognitive metrics are measures of speed and accuracy using objective tests. Few studies on this topic have examined a creative cognitive process, despite its importance to most knowledge-based work. Accordingly, this work investigates associations between indoor air and thermal conditions and divergent creative thinking scores among adult knowledge workers in commercial office buildings across four countries over the course of approximately six months. Indoor environmental monitors at participant workstations provided local, acute exposures of indoor CO_2 and $PM_{2.5}$ concentration,s in addition to temperature and RH. Hourly averages of these

environmental parameters were calculated and paired with participant responses to the Alternative Uses Test, a validated assessment of divergent creative thinking, for incorporation into a series of mixed effects statistical models. The models show statistically significant evidence that increasing indoor CO_2 concentrations are associated with lower divergent creative thinking scores, even within the lower range of CO_2 concentrations observed in these buildings. Concentrations of $PM_{2.5}$ were also low, and there is suggestive evidence of impaired divergent creative thinking scores with increased $PM_{2.5}$ concentrations. The thermal estimates suggest a temperature range of roughly 22-26 ºC to be associated with higher divergent creative thinking test scores, while temperatures above and below this range are associated with decreases in these scores. Overall, the present study suggests that maintaining temperatures within a normative range and focusing on promoting indoor air quality can help promote creative thinking in working environments.

Introduction

For a typical office-based business, an estimated 1%, 9%, and 90% of annual business expenditure is devoted to energy, rent, and staff, respectively (BOMA, 2010; Bureau of Labor Statistics, 2011; International WELL Building Institute, 2017; Reichardt, 2016; Terrapin Bright Green LLC, 2012; US Department of Labor, 2010; World Green Building Council, 2014). While much attention has been devoted towards reducing building energy consumption through the sustainable buildings movement (Coyle, 2014; Solano Rodriguez et al., 2017), and many market drivers influence commercial rental rates (Brooks & McArthur, 2019; Devine et al., 2024), historically, little attention has been devoted to supporting worker performance, health, and wellbeing, despite staff being the main business expenditure and several studies citing billions of dollars in economic losses due to impaired worker health and performance (Fisk & Rosenfeld, 1997; Niemelä et al., 2006; Stewart, 2003).

In addition to the evidence outlining economic losses from building-related ill-health (Fisk et al., 2009; Niemelä et al., 2006; Niza et al., 2024; Rostron, 2008; Surawattanasakul et al., 2022), a related arm of research is demonstrating associations between various indoor environmental parameters and cognitive performance. Robust and growing evidence suggests that lower concentrations of indoor CO_2, achieved via lower occupancies and/or higher outdoor air ventilation rates, are associated with improved cognitive performance metrics in a variety of work-type settings (Allen et al., 2016, 2019; Cedeño Laurent et al., 2021; Du et al., 2020; Künn et al., 2023; Riham Jaber et al., 2017; Young et al., 2024); however it's been noted that the observed effects can vary by task type and population characteristics (Du et al., 2020; Rodeheffer et al., 2018; Satish et al., 2012). While some indoor air pollutants will vary with indoor CO_2 concentrations, there is additional evidence for associations between cognitive performance metric and other air quality parameters themselves, such as $PM_{2.5}$ (Ailshire & Crimmins, 2014; Cedeño Laurent et al., 2021; Saenz et al., 2018; Shehab & Pope, 2019; Wang et al., 2020; Weuve, 2012) and volatile organic compounds (Allen et al., 2016; Arikrishnan et al., 2023). For thermal conditions, past work has observed significant effects of indoor dry-bulb temperatures on multiple cognitive domains, including working memory (Maula et al., 2016), long-term memory (Cui et al., 2013), attention (Lan et al., 2011), mathematical processing (Cedeño Laurent et al., 2018; Lan et al., 2011), reasoning (Makinen et al., 2006; Palinkas et al., 2005), and processing speed (Schiavon et al., 2017). Most of these studies were narrowly focused in terms of study population characteristics, geography and climate, and indoor conditions. Not surprisingly, differences in the estimated thermal effects arise when comparing across studies with differences in the aforementioned factors. Some studies suggest variation in preferred thermal conditions by group and individual factors (Arsad et al., 2023; Kim et al., 2018; S. Zhang & Zhu, 2022), such as sex (Karjalainen, 2012; Parkinson et al., 2021), type of work performed (Luo et al., 2023; F. Zhang et al., 2019), and the potential influence of other indoor factors (Porras-Salazar et al., 2021).

Although there is evidence for the influence of indoor environmental conditions on worker health and performance, complemented by the estimated economic impacts, gaps remain in both research and practice. With respect to research, two main limitations across most studies in this space are: 1) the use of narrow study populations and settings, which limits the generalizability of study findings, and 2) the pervasive use of objective cognitive tests focused on speed and accuracy (Du et al., 2020; Porras-Salazar et al., 2021), which don't capture the full extent of knowledge work. Moving on to practice, in the field of occupational health and safety, organizations set threshold limit values to protect worker health from various exposures (Congressional Research Service, 2013; United States Government Accountability Office, 2012). These exposure limits typically apply to outdoor and industrial settings; are designed to prevent serious ill-health outcomes, such as preventing heat stroke among outdoor workers; and are related to physical types of work (Deveau et al., 2015; Paustenbach, 2001), and are therefore not applicable to knowledge-based work in office environments. Although there is growing attention on the potential for buildings to promote human health (Danivska et al., 2019; EPA, 2001; Heidari et al., 2017; United States Government Accountability Office, 2012), and emerging voluntary guidelines and standards promoting healthy building practices in general (Callway et al., 2020; Gostin et al., 2023; Heidari et al., 2017), there is still a need to elucidate the indoor environmental conditions that promote knowledge-based work to help fill the research gap and better inform building design and operation in practice.

Accordingly, this work aims to address these outstanding questions by investigating associations between acute indoor air and thermal exposures and divergent creative thinking among knowledge workers across multiple countries. In addition to being sparsely studied, creative thinking is important to study in this context because it's becoming an increasingly vital skill to businesses and it's not fully clear how it may be influenced by indoor office conditions. Although few studies have focused on a creative cognitive process, those that do show motivating evidence of associations between indoor air and thermal conditions and creative test scores (Arikrishnan et al., 2023; Young et al., 2024). While there are many inherent physiologic and genetic characteristics that appear to be associated with creativity (Moore et al., 2009), there is also evidence that creativity can increase with various lifestyle factors and training regimes (Blanchette et al., 2005; Haase et al., 2023; Hassevoort et al., 2020; Steinberg et al., 1997). Accordingly, this research will help elucidate whether indoor environmental conditions are another modifiable factor that can be used to promote creativity. This will be of high interest to businesses since creative thinking is ranked as one of the most sought-after skills (Van Laar et al., 2017) for both employees and employers, spanning a multitude of disciplines (Archibugi et al., 2013; World Economic Forum, 2023), and in the wake of business disruptions due to technological advancements (Aoun, 2017; Balková et al., 2022) and societal changes (Karwowski & Soszynski, 2008), such as COVID-19 (Zutshi et al., 2021). By investigating how indoor air and thermal conditions are associated with divergent creative thinking scores among adult office workers across multiple countries, this study aims to help address the aforementioned gaps in the scientific literature and also help inform how working environments can be designed and operated to promote creative thinking.

Methods

Study Design

This topic was investigated using a subset of data from the CogFx Global Buildings Study. The CogFx Global Buildings Study is a prospective, observational, longitudinal study that assessed indoor environmental conditions and various health outcomes among adult workers in commercial office buildings located in China, India, Mexico, Thailand, the United Kingdom (UK), and the United States of America (USA), over one year within the overall study period spanning May 2018 through March 2020. Indoor environmental conditions were assessed in buildings using real-time, continuous monitors. Health outcomes included various aspects of cognitive performance, physical health, and perceived satisfaction, which were assessed using participant responses to various tests and surveys that were administered using a smartphone-based research application. Each participant received a total of fifteen minutes of study activities each week. All activities were sent to participants during standard working hours (Monday-Friday, 9 am – 5 pm local time) based on either a schedule or the measured indoor environmental conditions (e.g., an activity was programmed to send if measured indoor conditions exceeded pre-specified thresholds). Participants were given one hour to complete each study activity and had to be physically present in their regular office building to complete it, which was enforced using geocoded locations and Global Positioning System (GPS) information collected by the smartphone-based research application. If the activity was not completed within the one-hour window, it was pre-programmed to be sent another day that week following either the same schedule or triggered conditions. The type of cognitive test sent to participants varied by rotating through the full suite of cognitive tests used in this study, with each test administered up to 36 times over the entire twelve-month study period; however the number of tests completed by each participant varied based on their participation. The measured indoor environmental conditions and participant responses to activities were available to pair for further analysis. All study protocols were General Data Regulation-compliant and were reviewed and approved by the Institutional Review Board at the Harvard T.H. Chan School of Public Health.

Study Population

Participant recruitment began by first identifying employers willing and able to participate, and then recruiting participants regularly working for participating employers. Employers were eligible to participate if they owned or leased space in a commercial office building, were willing and able to install continuous indoor environmental monitors within their space, and had ten or more employees. Once eligible employers were retained, eligible employees were recruited with a goal of at least ten participants per building with balanced demographics in terms of age and sex assigned at birth within each building. Employees were eligible to participate if they met the following criteria: be a full-time employee at a participating company, have an assigned workstation and work from it at least three days each week, be between the ages of eighteen and 64, speak at least one of the three study languages (i.e., Chinese, English, or Spanish), have a smartphone compatible with the research application, not be colorblind, and not be a current smoker.

Exposure Assessment: Indoor Environmental Quality

Indoor environmental parameters were measured using commercial-grade real-time continuous monitors installed at or near participants' workstations. The monitors were installed either by a study team member or an individual at the building with remote assistance from a study team member. All monitors were installed at the breathing zone height of a seated individual (0.8-1.5 m) and away from drafts, heat sources, and direct solar radiation. Due to various restrictions with sensor connectivity, communication, and security considerations, six different monitors had to be used across the full study, but each building received the same type of monitor. The monitors used are as follows: Harvard Healthy Buildings sensor/Academia Sinica or Awair Omni for India; Obotrons for Thailand; Harvard Healthy Buildings sensor or Awair Omni for the UK; and Harvard Healthy Buildings sensor, Awair Omni, Chemi-Sense CS-001, or Tongdy MSD-16 for the USA. All monitors measured the thermal and air quality parameters of interest, which are temperature, RH, CO_2, and $PM_{2.5}$. All sensors with manufacturer-report accuracies are within $\pm$1 C for temperature, $\pm$5% for RH, $\pm$15 ug/m^3 for $PM_{2.5}$, and $\pm$200 ppm for CO_2; additional details of sensor-specific performance are available in Table 1 for $PM_{2.5}$ and Table S1 for CO_2 in a related study (Jones et al., 2021). QAQC testing was conducted by study team members prior to installation for air quality parameters by co-locating at least one monitor of each of the six types with a recently calibrated reference instrument: TSI DustTrak, TSI Instruments, USA for $PM_{2.5}$ sensors; QTrak 7575; TSI Instruments, USA for CO_2 sensors. Co-located data was visually inspected to ensure agreement between the study monitors and reference instruments. Hourly averages of temperature, RH, CO2, and $PM_{2.5}$ were calculated for each outcome measure included in analysis, described in the following section, using data from the participant's assigned sensor, enforced by the geocoding described earlier, and for the hour corresponding to the timestamp of each specific outcome response. Following convention from similar efforts (Cedeño Laurent et al., 2021), the data was checked for values in ranges where sensor performance is limited (Demanega et al., 2021) and should be removed for analysis. This includes $PM_{2.5}$ measurements equal to or above 80 ug/m^3 and CO_2 measurements equal to or above 2,500 ppm; however no values in these ranges were observed in the final analysis dataset.

Outcome Assessment: Divergent Creative Thinking

The outcome of interest in this investigation is divergent creative thinking, which is ideation to problems with no standard solution (Madore et al., 2016). This study uses derived divergent creative thinking scores from participant responses to the Alternative Uses Test (AUT), a validated assessment of divergent creative thinking (Dippo & Kudrowitz, 2015; Guilford, 1967; Madore et al., 2016). The AUT works by prompting a participant with an everyday object (e.g., “brick”), referred to herein as a “prompt”, and then the participant has two minutes to come up with as many diverse uses for that object as possible (e.g., “doorstop”, “toy”, and “mallet” could all be uses for the “brick”). Herein, “token-response” refers to a single use proposed by a participant to an AUT “prompt”, and “collective-response” refers to the collection of “token-responses” to a single AUT “prompt” (e.g., all proposed uses a participant submits to a single AUT prompt). Using the above example, “brick” would be the “prompt”; “doorstop”, “toy”, and “mallet” would each be a “token-response” (3 in total); and “doorstop”, “toy”, and “mallet” would be the participant’s “collective-response”. While some forms of the AUT in past studies have provided further instructions to participants about how they should respond, such as requesting terse responses (Yin et al., 2019), in this study, no instruction as to the types of uses or how the uses should be described were specified. AUT prompts rotated through a set of verified objects for all participants.

Participant responses to the AUT were then used to calculate metrics of divergent creative thinking. While there is variation in the specific dimensions and associated scoring approaches used across studies (Dumas & Runco, 2018), this work focused on four common dimensions of divergent creative thinking (Alhashim et al., 2020; Beketayev & Runco, 2016; Shah et al., 2003; Stevenson et al., 2020; Tanis et al., 2018; Vartanian et al., 2019). These dimensions and what they intend to represent are as follows: 1) fluency: the number of proposed, valid uses per AUT prompt; 2) elaboration: the average level of detail across valid responses to a prompt; 3) originality: how unique the proposed use is; and 4) flexibility: the number of unique proposed uses (Madore et al., 2016).

To derive the divergent creative thinking scores for the four dimensions from the raw AUT responses, raw AUT token-responses were first reviewed and cleaned for various response issues. Two study team members performed the cleaning and reviewing and discussed the approach, process, and unique occurrences and questions, with supervision and review by a third study team member to promote consistency and quality control. The raw token-responses were first translated from Chinese and Spanish to standard American English, where applicable; cleaned for spelling errors and accidental characters; and grammatically streamlined for consistent comparison (e.g., converting all compound word forms to a single continuous word). Next the token-responses were cleaned and removed based on interpretability and appropriateness with respect to the prompt. Specific details of this approach and decisions are provided in Appendix C. Overall, the reviewers adopted a more “generous” than “strict” cleaning approach, meaning that, efforts to reasonably correct, decipher, and/or complete token-responses were taken as opposed to automatically removing any token-response that was incomplete in some way. All cleaning and reviewing done by the study team was blinded with respect to the exposures and participant and building characteristics.

Using the cleaned dataset, each collective-response to an AUT prompt was scored along the four dimensions of divergent creative thinking. Fluency is calculated using an automated script that sums the number of token-responses per AUT prompt (i.e., a fluency score is calculated for each AUT completed by a single participant). Elaboration is calculated using an automated script that sums the total number of words used in all participant token-responses to a single AUT prompt and then dividing by the number of participant token-responses to that AUT prompt to obtain the average number of words across all collective-responses. Flexibility and originality could not be scored with an automated script and were assessed by the two independent scorers and third reviewer. The first step in this process is to “transform” the unique participant token-responses into a standardized set of consistent function categories through an "encoding"-type process. Function categories were defined to encompass different participant token-responses that had the same use (e.g., the responses “beer” and “wine” would both fall under the function category “drink”). Flexibility is scored as the total number of distinct (coded) function categories across all token-responses to a single AUT prompt. Originality, intended to represent how “unique” the proposed use is, is calculated by awarding a point to each unique encoded proposed use function that occurred only once across all responses to a specific AUT prompt. This process resulted in 426 cleaned and scored AUT responses.

Statistical Methods

Cleaned exposure, outcome, and covariate data were combined to create an analysis dataset of 195 observations from 86 participants, further described in Figure 11. Each observation in the analysis dataset includes the calculated creative thinking scores from a single response to an AUT test, paired with the mean indoor conditions that correspond to the time and location of that AUT test response. This analysis dataset consists of complete case data only;

AUT responses where corresponding indoor exposure data was unavailable (due to sensors failing to record measurements during that time) are excluded from the main analysis. A flowchart of inclusion criteria leading to the final analysis dataset is presented in Figure 11 below.

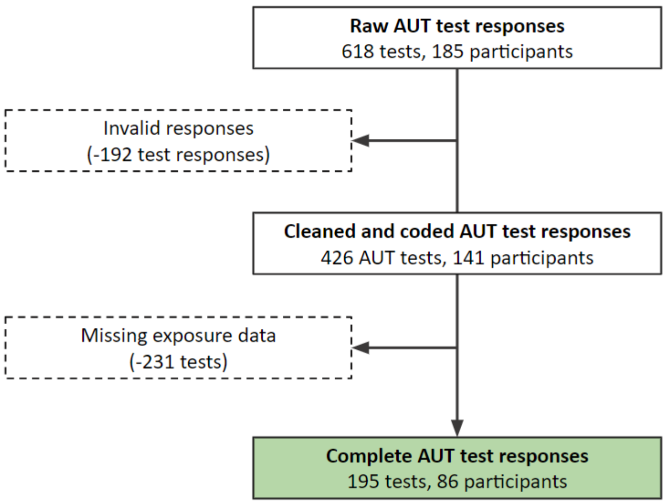


Figure 11: Flowchart showing data inclusion criteria that produced the final analysis dataset.

This analysis dataset was then used to construct a series of mixed effects models to explore the associations between acute indoor environmental exposures and divergent creative thinking scores. A separate model was constructed for each of the four calculated divergent creative thinking metrics, treating each as the outcome of interest in its respective model. Fluency, flexibility, and originality were each modeled with a quasi-Poisson distribution since these are count variables with over-dispersed variances. Elaboration was log-transformed to better meet the assumption of normality and was then modeled as a continuous variable using a linear model assuming a normal distribution. Acute CO_2 and $PM_{2.5}$ exposures are modeled as linear terms since past work has found linear associations without a threshold between these two parameters and cognitive performance metrics over a range of acute exposures similar to those observed in this study (Cedeño Laurent et al., 2021; Young et al., 2024). Indoor thermal exposures, modeled either using calculated enthalpy or measured temperature and RH as separate independent variables, were modeled using cubic regression splines to allow for non-linear associations that have been observed in past work (Seppänen et al., 2006; F. Zhang et al., 2019a). Correlations among indoor air quality parameters and thermal parameters were low and deemed acceptable to include in the same model. Correlations among multiple responses from the same participant over the study period were controlled for using participant-specific random effects. Models following this construction are termed the “minimally adjusted models” as they consistently produced the lowest AIC value and are deemed to best fit the given data. We also explored models that control for other potentially important confounders and predictors by controlling for learning effects and time in different ways. A series of models that extend beyond the minimally adjusted models and control for the first AUT response by each participant to account for potential learning effects (Cedeño Laurent et al., 2021; Goldberg et al., 2015), country, and time using a natural spline with two degrees of freedom were also constructed. These models are termed the “fully adjusted models” and produce higher AIC values, indicating worse fit than the minimally adjusted models. Model estimates are discussed below, along with additional sensitivity analyses to investigate potential variation in the results.

Results

Participants

As described in Figure 11, a total of 460 participants working in 42 buildings across all six countries enrolled in the CogFx Global Buildings Study. Of these 460 participants, 86 participants working in 22 different buildings in four countries, including India, Thailand, the UK, and the USA, are included in this analysis. Characteristics for 72 of these participants are summarized in Table 6 below. The other fourteen participants that contributed AUT responses to this analysis dataset did not complete the baseline survey and so their characteristics are unknown. As shown in Table 6, most participants included in this analysis who completed the baseline survey were in their twenties or thirties and have a high level of education. Balanced sex was achieved within each country and overall, but the study population is predominantly White and Asian. These participant characteristics are consistent with the broader pool of 185 participants that contributed an AUT response, regardless of whether it was included in analysis.

Table 6: Participant characteristics for the 72 participants included in this analysis that completed the baseline survey.

	India (N=11)	Thailand (N=2)	UK (N=15)	USA (N=44)	Overall (N=72)
Age					
Mean (SD)	29.5 (3.67)	30.5 (0.707)	30.0 (6.19)	34.5 (8.12)	32.7 (7.40)
Median [Min, Max]	29.0 [25.0, 35.0]	30.5 [30.0, 31.0]	28.0 [23.0, 42.0]	33.5 [21.0, 52.0]	31.0 [21.0, 52.0]
Gender					
Female	4 (36.4%)	1 (50.0%)	7 (46.7%)	25 (56.8%)	37 (51.4%)
Male	7 (63.6%)	1 (50.0%)	8 (53.3%)	19 (43.2%)	35 (48.6%)
Ethnicity					
Asian	11 (100%)	2 (100%)	0 (0%)	7 (15.9%)	20 (27.8%)
White	0 (0%)	0 (0%)	15 (100%)	29 (65.9%)	44 (61.1%)
Black or African American	0 (0%)	0 (0%)	0 (0%)	1 (2.3%)	1 (1.4%)
Hispanic, latin, or Spanish origin of any race	0 (0%)	0 (0%)	0 (0%)	1 (2.3%)	1 (1.4%)
Other	0 (0%)	0 (0%)	0 (0%)	2 (4.5%)	2 (2.8%)
Two or more races	0 (0%)	0 (0%)	0 (0%)	1 (2.3%)	1 (1.4%)
White/Asian	0 (0%)	0 (0%)	0 (0%)	2 (4.5%)	2 (2.8%)
White/Other	0 (0%)	0 (0%)	0 (0%)	1 (2.3%)	1 (1.4%)
Education					
4 year degree	3 (27.3%)	0 (0%)	2 (13.3%)	14 (31.8%)	19 (26.4%)
Doctorate	6 (54.5%)	2 (100%)	10 (66.7%)	17 (38.6%)	35 (48.6%)
Professional degree	2 (18.2%)	0 (0%)	1 (6.7%)	10 (22.7%)	13 (18.1%)
Master	0 (0%)	0 (0%)	1 (6.7%)	2 (4.5%)	3 (4.2%)
Some college	0 (0%)	0 (0%)	1 (6.7%)	1 (2.3%)	2 (2.8%)

Exposures

A summary of all one-hour averaged exposures of temperature, RH, CO_2, $PM_{2.5}$, and enthalpy included in analysis is presented in Table 7. Average acute exposures for thermal conditions are in line with building design standards focused on acceptable thermal conditions

(ASHRAE, 2023b). 85% of acute CO_2 exposures are below a commonly cited industry reference of 1,000 ppm (Persily, 2021) and most $PM_{2.5}$ exposures are low (median value of 3 ug/m^3). However, higher values of thermal conditions and air quality exposures exceed some thresholds in building design guidelines and standards and recommendations set for health considerations (ASHRAE, 2023b; CDC, 2023a; United States Environmental Protection Agency, n.d.).

Table 7: Summary of one-hour average office conditions corresponding to an AUT response included in analysis.

Variable	Mean	SD	CV	Min	p25	p50	p75	p95	Max
Temperature (C)	24	1.7	0.072	20	23	24	25	28	29
RH (%)	47	9.7	0.2	22	41	47	52	66	81
CO2 (ppm)	758	259	0.34	414	568	671	861	1279	1954
$PM_{2.5}$ (ug/m3)	4.5	4.8	1.1	0	0.55	3	7.3	12	31
Indoor Enthalpy (kJ/kg)	47	6.2	0.13	36	43	45	50	59	66

Examining measured values of indoor thermal and air quality parameters by country reveals some differences, as shown in Appendix C. For indoor air quality, indoor CO_2 exposures are comparable across countries, but $PM_{2.5}$ concentrations are noticeably elevated in India compared to the three other countries included in analysis. With respect to indoor thermal conditions, indoor temperature is highest in Thailand and indoor RH is elevated in India. Calculated indoor enthalpy is distinct in each country with minimal overlap in the interquartile ranges across all four countries, and indoor enthalpy being highest in India, followed by Thailand, the UK, and the USA in decreasing order.

Outcomes

Calculated creativity scores indicate that on average, a participant will produce approximately nine valid uses (fluency mean ± SD of 9.4 ± 4.4), using two words per token response (elaboration mean ± SD of 2.1 ± 1.0), with six different use categories (flexibility mean ± SD of 5.8 ± 2.5), and one original use category (originality mean ± SD of 1.6 ± 1.6). It has been suggested that all domains of divergent creative thinking increase with ideation, which implies that elaboration, flexibility, and originality should increase with fluency (Dumas & Runco, 2018; Tanis et al., 2018). A Spearman Rank correlation matrix was used to assess this and revealed that fluency was positively correlated with flexibility and originality (Spearman Rank correlation coefficient of 0.68 and 0.37, respectively), but weakly and negatively correlated with elaboration (Spearman Rank correlation coefficient of -0.03).

Modeled Associations

Results from the mixed effects models are presented below, first for indoor air quality and then for thermal parameters.

Indoor Air Quality

Exponentiated modeled effect estimates for the influence of CO_2 and $PM_{2.5}$ on the divergent creative thinking scores using both the minimally and fully adjusted models are presented in Table 8 below. There is directionally consistent evidence across all models that increases in acute indoor CO_2 concentrations are associated with a decrease in all four divergent creative thinking scores. Using the estimates from the minimally adjusted models, a 100-ppm increase in acute indoor CO_2 is associated with 3% (95% CI: 0-5%), 4% (95% CI: 1-6%), and 11% (95% CI: 5-16%) negative difference in the expected fluency, flexibility, and originality count scores, respectively; and an 11% decrease (95% CI: 5-16%) in the expected elaboration score. The estimates reach statistical significance at the 0.05 alpha level for minimally adjusted and fully adjusted models for flexibility, originality, and elaboration scores; the results reach statistical significance at the 0.1 alpha level for the minimally adjusted model estimate for fluency. For $PM_{2.5}$, the estimates are directionally consistent across all models where a 5 ug/m^3 increase in $PM_{2.5}$ is associated with decreases in all four divergent creative thinking scores. However, none of the effect estimates for $PM_{2.5}$ reach statistical significance at either the 0.05 or 0.1 alpha levels.

Table 8: Summary of exponentiated effect estimates for indoor air quality parameters from minimally and fully adjusted models. Minimally adjusted models control for hourly averaged indoor CO_2, $PM_{2.5}$, temperature, and RH, and include participant-specific random effects. Fully adjusted models control for hourly averaged indoor CO_2, $PM_{2.5}$, temperature, and RH; first test response; time (using a natural spline with two degrees of freedom); and include participant-specific random effects nested within building-specific random effects.

	Per 100 ppm increase in CO_2			Per 5 ug/m^3 increase in $PM_{2.5}$	
Test Outcome	Change (95% CI)	p-value		Change (95% CI)	p-value
Fluency (n=195)					
Min adjusted model	0.97 (0.94, 1.00)	0.06	.	0.99 (0.9, 1.08)	0.77
Fully adjusted model	0.97 (0.94, 1.01)	0.11		1.00 (0.91, 1.10)	0.98
Flexibility (n=195)					
Min adjusted model	0.96 (0.93, 0.99)	0.0053	*	0.99 (0.91 1.08)	0.83
Fully adjusted model	0.96 (0.93, 0.99)	0.0065	*	1.01 (0.92 1.11)	0.76
Originality (n=195)					
Min adjusted model	0.89 (0.83, 0.95)	0.0012	*	0.89 (0.74, 1.07)	0.22
Fully adjusted model	0.88 (0.82, 0.95)	0.00058	*	0.92 (0.76, 1.12)	0.43
Elaboration (n=195)					
Min adjusted model	0.89 (0.83, 0.95)	0.0012	*	0.89 (0.74, 1.07)	0.22
Fully adjusted model	0.96 (0.93, 0.99)	0.0087	*	0.96 (0.88, 1.05)	0.39

Indoor Thermal Conditions

Associations between indoor thermal conditions and divergent creative thinking were explored through a set of models using temperature and RH as independent variables and then through a set of models using calculated indoor enthalpy as a combined thermal parameter. Nonlinear associations between indoor thermal conditions and divergent creative thinking scores were observed and so plotted spline terms are presented below. Beginning with models using temperature and RH, Figure 12 shows that temperature appears to follow a non-linear association with all four divergent creative thinking scores. The association is comparable across all four scores and resembles a somewhat inverted U-shape where scores decrease at lower and higher temperatures and increase in the mid-temperature range included in this analysis. The curvature is slightest for fluency, greater for flexibility, and then greatest for originality and elaboration. The modeled association between temperature and fluency is fairly flat in a wider temperature range of 22-26 ºC, suggesting consistent fluency scores in that temperature range. However, for the other three scores with stronger curvature, it appears that temperatures around 25-26 ºC are associated with the highest scores, followed by an associated decrease. The complementary modeled spline terms for RH from these models are presented in Figure 13 below. These figures show linear associations between RH and all four cognitive scores with increasing RH associated with decreases in fluency, flexibility, and originality scores, and increases with elaboration scores. Overall, the effect estimates are suggestive as one spline term for temperature and another for RH reach statistical significance at the 0.05 alpha level.

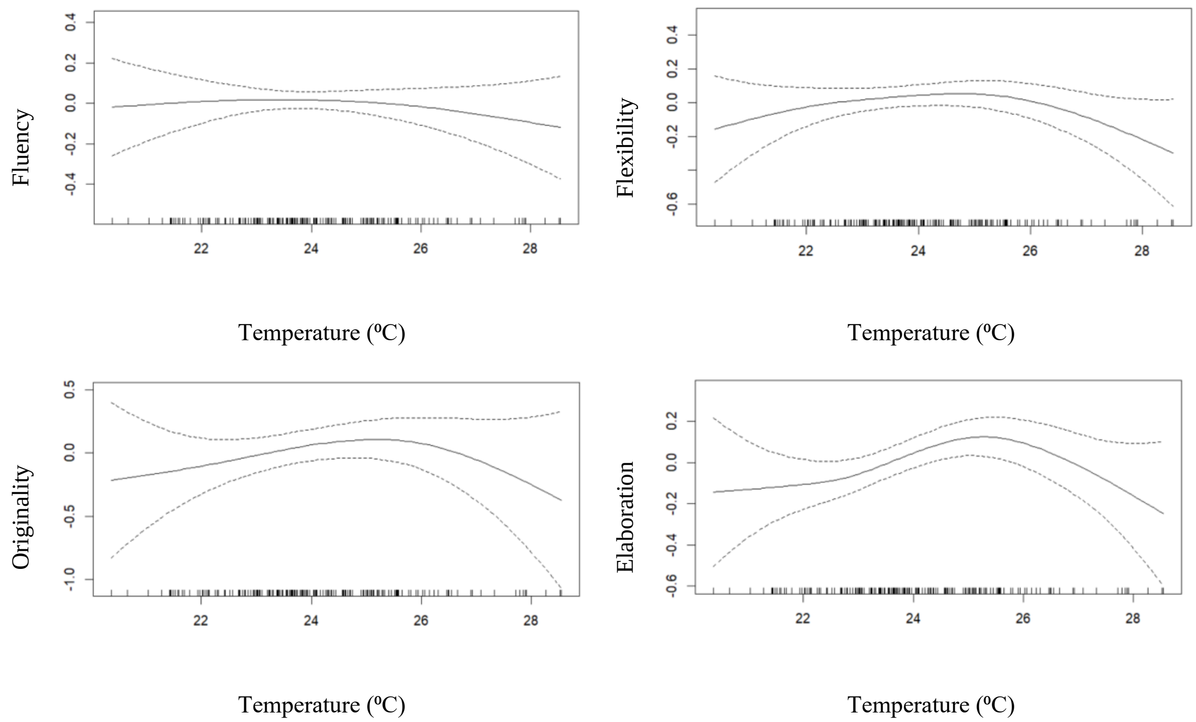


Figure 12: Associations between indoor temperature and divergent creative thinking scores using estimates from the minimally adjusted models. These minimally adjusted models control for CO_2, $PM_{2.5}$, temperature, RH, and a participant-specific random effect.

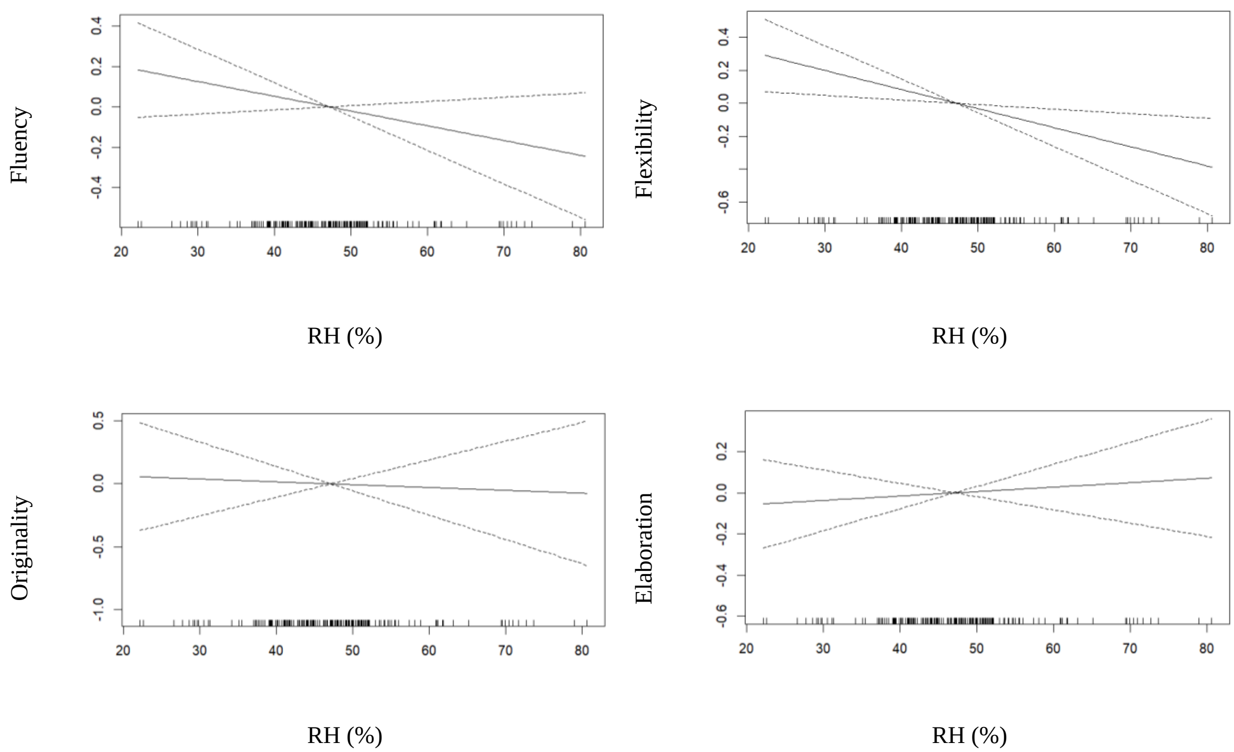


Figure 13: Associations between indoor RH and divergent creative thinking scores using estimates from the minimally adjusted models. These minimally adjusted models control for CO_2, $PM_{2.5}$, temperature, RH, and a participant-specific random effect.

Moving on to the set of models that utilizes indoor enthalpy in place of temperature and RH, the plotted spline terms (presented in Appendix C) are mixed in terms of direction, linearity, and statistical significance. Increasing indoor enthalpy appears linearly associated with decreases in fluency scores and increases in originality and elaboration scores. For flexibility, there is a slight non-linear association with a breakpoint around 45 kJ/kg and decreases in flexibility at higher and lower enthalpy. Only one spline term for enthalpy reaches statistical significance at the 0.1 alpha level (p=0.06). Since the exposure data shows minimal overlap in enthalpy data and differences in RH among countries, the data was subset by country to explore country-specific associations. Using observations from the USA only, we observe directionally consistent evidence that increasing indoor enthalpy (up to approximately 50 kJ/kg) is associated with increases in all four divergent creative thinking scores. Similarly, for the set of country-specific plots examining temperature and RH as separate independent variables, for the USA, increases in temperature (up to 26 ºC) are associated with increases in all four scores; the accompanying associations between RH (up to approximately 55%) and divergent creative thinking scores are fairly flat. The number of observations in the other countries limits the ability to examine within-country associations. With 37 observations for the UK and 30 for India, we observe preliminary suggestive evidence of different associations, but the results are inconsistent and data too few for strong inferences. With only five observations available for India, no within-country estimates can be generated with this dataset.

Discussion

This study provides evidence for how acute indoor air and thermal exposures influence divergent creative thinking among knowledge workers in commercial office buildings. For indoor air quality, there is statistically strong and consistent evidence that higher concentrations of indoor CO_2, as influenced by building ventilation and occupancy, are associated with decreases in divergent creative thinking scores. There is consistent, but suggestive evidence that higher indoor $PM_{2.5}$ concentrations are associated with lower divergent creative thinking scores. For temperature, a non-linear association is observed where lower and higher temperatures are associated with lower divergent creative thinking scores. The complementary modeled associations for RH are mixed, as are the overall estimates for enthalpy. Overall, worse indoor air quality and lower and higher temperatures appear to be associated with impaired divergent creative thinking, and the associations between indoor air moisture, modeled as either RH or as incorporated into enthalpy, appear inconclusive in this study.

When comparing these results to the literature, many consistent findings emerge. The strongest and clearest finding in this study is the association between CO_2 and divergent creative thinking, which aligns with a strong and growing body of evidence demonstrating an association between indoor CO_2, influenced by ventilation and occupancy, and cognitive performance. Past work has found lower concentrations of indoor CO_2, achieved via ventilation and occupancy, to be associated with worse performance in a variety of cognitive tests, indoor settings, and domains, including arithmetic tests that assess cognitive speed and working memory (Cedeño Laurent et al., 2021; Young et al., 2024), the Stroop test that examines cognitive speed and inhibitory control (Cedeño Laurent et al., 2021; Young et al., 2024); an investigation of nine domains assessed in the Strategic Management Simulation software tool, which includes basic activity level, applied activity level, focused activity level, task orientation, crisis response, information seeking, information usage, breadth of approach, and strategy (Allen et al., 2016); the quality of chess moves among players at an indoor tournament (Künn et al., 2023); and the speed at which students completed numerical and language-based tasks (Wargocki & Wyon, 2007b). Although the body of literature is robust on the association between indoor CO_2 and cognitive performance overall, few studies examine a creative cognitive domain. One study assessed fluency and originality using a different divergent creativity test (i.e., Serious Brick Play adapted from the LEGO Serious Play framework) and found higher levels of TVOCs to be associated with lower creativity scores among 92 adult participants in a simulated office environment over six weeks (Arikrishnan et al., 2023). Young et al. (2024) assessed convergent creative thinking (using the Compound Remote Associate Task, cRAT) among adult knowledge workers in work-from-home settings and found negative associations between home CO_2

concentrations and convergent creative thinking scores; however these effect estimates were not statistically significant.

The strong evidence of an association between the levels of CO_2 observed in this study and creativity are particularly interesting since: 1) the CO_2 concentrations in this study are low overall (75th percentile value of 861 ppm) relative to the range observed in other buildings and anticipated as a result of minimum ventilation standards (ASHRAE, 2022; Fisk, 2017; Fox, 2023), and 2) creativity has often been thought of as a more inherent quality. Many researchers have found certain brain structures (e.g., distinct brain hemisphere sizes) (Moore et al., 2009) and DNA characteristics (e.g., specific gene clusters and duplicate DNA strands) (Kraus et al., 2014; Ukkola-Vuoti et al., 2013) to be associated with higher creativity. Beyond biological characteristics, others have found that different mental conditions, such as bi-polar disorder (Kyaga et al., 2013), or trauma that causes changes to gene expression and functional brain changes can increase creativity (Levy-Gigi et al., 2013). Considering these inherent and substantial biological and mental conditions, it's somewhat surprising that acute CO_2 exposures show consistent and significant effects in this small dataset with a tight range of mainly low CO_2 exposure concentrations. The biological mechanisms that CO_2 acts through on cognitive performance in general, let alone creativity, are unclear, but it's possible that higher levels of CO_2 in the environment result in higher levels of CO_2 in the bloodstream, which have been shown to cause inflammation, drowsiness/fatigue, and dizziness, all of which, could reduce the divergent creative thinking scores we observed. Others have noted various lifestyle behaviors, such as regular exercise (Blanchette et al., 2005; Steinberg et al., 1997), good sleep (Lewis et al., 2018; Ritter et al., 2012), and a healthy diet (e.g., high fiber consumption and low sugar consumption) (Hassevoort et al., 2020) to promote creativity. It's possible that these behaviors help with alertness and reducing inflammation, similar to hypothesized processes CO_2 may be acting through. Evidently there are both inherent biological and genetic factors associated with creativity, in addition to dynamic, daily lifestyle factors and behaviors. While some individuals are inherently more creative than others, our use of participant-specific random effects in the models accounts for some of this variation, and so the strong evidence for CO_2 suggests that acute CO_2 exposures are another modifiable factor associated with creativity.

Moving on to $PM_{2.5}$, the lack of statistically significant findings between $PM_{2.5}$ and divergent creative thinking scores aligns with past work that only found statistically significant evidence between acute indoor $PM_{2.5}$ concentrations and cognitive performance metrics at $PM_{2.5}$ concentrations above 12 ug/m^3 and not below (Cedeño Laurent et al., 2021). The 95th percentile $PM_{2.5}$ value in this analysis dataset is 12 ug/m^3 and so it is not surprising that we find only suggestive evidence of lower $PM_{2.5}$ concentrations being associated with improved divergent creative thinking scores. Other past studies have also found statistically significant decreases in cognitive performance metrics to be associated with elevated $PM_{2.5}$, using both experimentally elevated indoor concentrations (Shehab & Pope, 2019) and longer-term spatially averaged outdoor concentrations (Ailshire & Crimmins, 2014; Gao et al., 2021; Wang et al., 2020), all of which examined larger ranges and higher comparative $PM_{2.5}$ concentrations than those in this study. These findings of impaired short-term cognitive performance and faster longer term cognitive decline with higher $PM_{2.5}$ concentrations (Weuve, 2012) are further supported by evidence of biological mechanisms that $PM_{2.5}$ acts through to impact cognitive outcomes. Higher concentrations of $PM_{2.5}$ have been associated with brain inflammation and markers of neurodegeneration (Ailshire & Crimmins, 2014; Calderón-Garcidueñas et al., 2012) and inhaled fine particles have a direct route to the brain via the olfactory route (You et al., 2022). Although our dataset is small and consists of low $PM_{2.5}$ concentrations, it's likely that the suggestive evidence of an association with $PM_{2.5}$ is due to these biological mechanisms.

Moving on to the thermal results, there is consistent evidence of an association for temperature. The non-linear associations between temperature and divergent creative thinking scores are similar to the inverted U and extended U or Maximum Adaptability Model (MAM), detailed in past works (Seppänen et al., 2006; F. Zhang et al., 2019b). For flexibility and originality scores, the associations appear somewhat similar to the inverted U-model, albeit with a higher temperature of around 25-26 ºC being associated with the highest scores, as opposed to the 22º C temperature widely adopted by Seppanen et al.'s original model based on non-creative, objective measures of cognitive performance (e.g., text processing, simple arithmetic, length of phone interactions) (Seppänen et al., 2006). For fluency and originality, a wider range of temperatures, spanning roughly 22-26 ºC appear to be associated with consistently higher scores, which follows more of the extended U or MAM that suggests human physiologic and adaptation is possible within a normative range of temperatures to remain comfortable and productive (F. Zhang et al., 2019b). This agrees with past work that has found decreases in cognitive performance at elevated temperatures during a heatwave (Cedeño Laurent et al., 2018), and at 27 ºC compared to 23 ºC, even when thermal comfort is maintained by clothing adjustment, (Lan et al., 2020). A recent study of adult knowledge workers in work-from-home settings found non-linear associations between heat index (calculated using temperature and RH) and various cognitive scores, with a breakpoint (either leveling off or decreasing) around a heat index value of roughly 25 ºC (Young et al., 2024). While this evidence suggests an upper temperature of around 25-26 ºC before decreases in performance are observed, this temperature will likely vary based on population and setting. For example, past work has found no "optimal" temperature when applying various thermal models to large datasets (Porras-Salazar et al., 2021), and thermal preferences are thought to be highly personal, and vary based on many dynamic and individual factors (Abdelrahman et al., 2022; Carlucci et al., 2018; Heschong, 1979; Kim et al., 2018; Kosonen & Tan, 2004). Moreover, some level of thermoregulation and adaptation is possible through vasodilation, sweating, and other physiologic cooling mechanisms with the environment, which can help extend the range of thermal conditions individuals can be exposed to before there are appreciable impairments in performance (Cedeño Laurent et al., 2018; Kong et al., 2019; F. Zhang et al., 2019b). Eventually though, temperatures that are too high or low can result in physiologic changes associated with increased stress, such as increased skin temperature and humidity, respiration rate, and heart rate; lower blood oxygen saturation and pNN50, a marker of heart rate variability; and changes to deep core and brain temperatures, which have been noted to impair cognitive processes (Abbasi et al., 2019; Khan et al., 2021; Lan et al., 2022b; F. Zhang et al., 2019b). The temperatures in this analysis are not extreme, but initial evidence of lower creative thinking scores is observed at the lower and higher temperatures, while a mid-range of roughly 22-26 °C appears to support creative thinking.

Moving on to indoor moisture, the complementary RH splines and enthalpy plots show inconsistent results, which suggests that the influence of indoor moisture is less clear. While a temperature range of 22-26 ºC in this study is found to support divergent creative thinking scores, the complementary indoor moisture levels remain to be known. The country-specific investigation shows consistent evidence for the USA where higher values of enthalpy are associated with increased cognitive scores, which is similar to the findings in Chapter Three. However, the range of temperature, RH, and calculated enthalpy exposures for the USA in this study and the results in Chapter Three span roughly the left half of the inverted U-shaped association. Although higher values of temperature and enthalpy, representing a combination of temperature and moisture, appear to promote performance to a point, we had insufficient country-specific data for Thailand, India, and the UK to investigate how these associations might differ by country in different thermal exposure ranges. Ideally future studies would have larger datasets to help elucidate the associations between indoor moisture and cognitive outcomes.

In addition to constructing both the minimally adjusted and fully adjusted sets of models, multiple sensitivity analyses were conducted to help assess the robustness of the model estimates. Using the minimally adjusted models as the base comparative set, additional models were constructed using varying incorporations of nested random effects, including participant ID, nested within building ID; and then also participant ID, nested within building ID, nested within country, to account for repeated measures and potential clustering. Results from models with both levels of nested random effects remained consistent with those from the base minimally adjusted models. Since we could not examine country-specific associations for Thailand due to limited data, we re-ran the minimally adjusted models with the 5 observations from Thai participants excluded and observed no appreciable changes in the model estimates. Next, we focused on a missing data analysis. Since 231 observations were removed from the analysis dataset due to missing environmental monitor data, we endeavored to replace as many of these missing indoor exposure conditions as possible to obtain a larger dataset for analysis. When available, missing exposure data were replaced with data from a sensor within the same building for the corresponding hour prior to completing the AUT test. For buildings with more than one available sensor, measurements from the sensor with the highest correlation with measurements from the missing sensor, when available over the larger study period beyond AUT data collection, were selected. This provided an additional 56 observations for analysis, bringing the total for this enlarged dataset to 251 observations from 105 participants. The results between minimally adjusted models using the main and enlarged analysis datasets are similar. Notably, the enlarged dataset includes a larger range of indoor temperatures (~20-30 ºC) and a more noticeable decline in divergent creative thinking scores is observed from the 26-30 ºC range, further strengthening the evidence for declines in performance above 26 ºC in this study. For enthalpy splines modeled with the enlarged dataset, we observe some changes to the shape of association, with roughly 45 kJ/kg possibly representing a combined value of temperature and moisture that could promote fluency and flexibility scores. Corresponding plots of the temperature and enthalpy splines from these models are provided in Appendix C. Finally, potential combined effects of indoor air quality parameters were investigated by incorporating interaction terms between CO_2 and $PM_{2.5}$ concentrations. Effect estimates for the interaction terms did not reach statistical significance and were effectively null in this analysis dataset, but could be explored in other scenarios with higher air pollutant concentrations where interactive effects could occur.

Despite the study design, robust statistical methods, and sensitivity analyses, there remain several limitations. First, the final AUT analysis dataset is small at 195 observations and consists of low levels of CO_2 and $PM_{2.5}$. This limits the statistical power overall and ability to examine associations within specific countries. Next, despite recruiting participants from six countries, the participants in the final analysis dataset are predominantly Asian and White, in their twenties and thirties, and have high levels of education, which is not representative of all working populations and limits the generalizability of these findings. With respect to the exposure data, although this analysis includes localized indoor air and thermal conditions, the parameters are not comprehensive. Our assessment does not include other potentially important air pollutants, such as volatile organic compounds (Allen et al., 2016; Arikrishnan et al., 2023), or the full suite of indoor environmental parameters related to the human-environmental heat balance, including MRT and air speed (André et al., 2024; ASHRAE, 2023b; Cen et al., 2024; d'Ambrosio Alfano et al., 2019), which could be potentially important to the findings, but were not feasible to assess in this geographically large and varied study, but would be useful to assess in future studies where feasible. Furthermore, the accuracy of the sensors themselves introduces uncertainty, which is of particular concern with respect to $PM_{2.5}$ as most hourly averaged concentrations fall within the maximum reported measurement uncertainty. This uncertainty is bi-directional and the exact magnitude is unknown, but it is another factor that limits the ability to assess associations with $PM_{2.5}$ in this work. Ideally, more accurate $PM_{2.5}$ sensors that have become available since the time of these measurements could be used in future investigations to overcome this issue and improve the ability to investigate associations between $PM_{2.5}$ and creativity scores. The variation in type of installed sensors introduces variability among measurements in terms of performance specifications. However, these variations are minor, as all sensor types used have similar performance characteristics and introduced uncertainty is comparable across sensor types. Furthermore, since the sensor accuracy is bi-directional, exposures are continuous, and measurements are not influenced by the AUT responses, the resulting potential bias introduced to the modeled associations is towards the null, which means that the estimated effect estimates might be reduced compared to the true, unbiased effects. A final challenge with the exposure assessment is the quantity of missing exposure data, which resulted in the exclusion of many observations from this analysis and reduced the power to detect statistically significant effects. Ideally advancements in sensor technology and communication protocols since the time of data collection in this study would help to overcome these issues, as observed in the Classrooms for Health Study.

Moving on to the outcome measure, many challenges stem from the AUT test itself and the lack of a standardized/consistent approach to scoring the raw measurements (Stevenson et al., 2020; Tanis et al., 2018). We attempted to overcome these issues by reviewing the literature and devising a scoring protocol that promotes an unbiased standardized process and minimizes subjectivity and potential biases. The cleaning and scoring exercise was: 1) done in an entirely blinded manner (participant information was anonymized and exposure data was not included), 2) conducted with two cleaners/scorers and one additional reviewer for consistency, 3) conducted in an objective automated process when possible (calculating fluency and elaboration scores with code), and 4) followed a standardized protocol to develop and assign use categories, thus making the manually assigned scores (flexibility and originality) more objective and less subject to bias. Despite these efforts, a degree of subjectivity remains in these scores due to the manual nature of the scoring process, in addition to other inherent limitations with the AUT and entailed scoring. Others have noted challenges with scoring AUT responses, including the influence of sample size on the scores (e.g., increasing sample size reduces the probability of generating original ideas) (Stevenson et al., 2020), a lack of clear instructions potentially causing different responses (e.g., participants were not instructed to respond in a terse or detailed manner, so elaboration could be a more individual stylist metric than an indication of creativity) (Yin et al., 2019), and lack of account for the usefulness and/or appropriateness of responses, defined in other studies of creativity using assessments other than the AUT as "quality" (Haase et al., 2023), which could allow participants to increase their fluency scores with minor modifications to proposed uses. Moreover, there is thought that domain familiarity, subject matter expertise, background, and lived experience could influence both the responses and scoring to AUT prompts (Alhashim et al., 2020). This could result in differences across populations, particularly in our study when interpreting different languages, or even among responses from a single individual, based on the different prompts and their familiarity/lived experience (Richardson et al., 2018; Rogers et al., 2023). Future work should look to clarify test instructions, systematize the number of prompts with sample size, include scorers with diverse backgrounds, and explore the incorporation of a usefulness/quality metric into the responses. To further overcome such issues, we explored the use of more objective scoring procedures such automated sentiment analysis (Gaspar & Alexandre, 2019), semantic distance analysis (Hass, 2017), and machine learning approaches (Stevenson et al., 2020), but these were not feasible for use in our scoring approach at the time of assessment (2021). New developments in such approaches, including supervised and unsupervised learning methods (Buczak et al., 2023) and an open platform for computing semantic distances (Beaty & Johnson, 2021), have become available and could be explored for use in future work.

Despite these limitations, our study includes many strengths related to design, AUT scoring method, and analysis techniques, which helps to overcome many of these limitations. This work provides new information for the associations between indoor air and thermal conditions and divergent creative thinking scores, a sparsely studied cognitive outcome that is more challenging and time intensive to score than other objective cognitive tests and measures. In addition to the modeled associations, this work also outlines a scoring protocol for the AUT in addition to newly developed scoring resources that other researchers can utilize. Ideally, future studies would extend this work by collecting larger datasets in additional environmental settings to explore potential differences in modeled associations, particularly with respect to thermal parameters, to better understand the influence of indoor moisture and the collective range in which thermal conditions can be adjusted to before there is no appreciable impact on cognitive outcomes and how this range might differ by populations, geographies, and over time with adaptation and acclimatization effects.

Conclusion

In this analysis of 86 adult knowledge worker participants across four countries, we observed that better indoor air quality is associated with improved cognitive performance, specifically for a creative cognitive domain. Statistically strong and consistent evidence shows that higher concentrations of indoor CO_2, resulting from building occupancy and ventilation, are associated with lower divergent creative thinking scores. For $PM_{2.5}$, statistically significant effects are not expected in this low concentration range, but there is suggestive evidence that lower concentrations of indoor $PM_{2.5}$ are associated with improved divergent creative thinking. For thermal conditions, there is evidence of an extended U relationship or MAM applying, where a temperature range of roughly 22-26 ^{o}C was found to promote fairly stable divergent creative thinking scores, with decreases in temperatures beyond this range. The results for RH, as a complementary independent variable to temperature, and enthalpy, as its own combined temperature and moisture variable, are mixed. There is preliminary evidence that these associations may vary by country, but this analysis dataset was too small and underpowered to investigate more thoroughly. While there is still research to be done to further understand the associations between different indoor air pollutants and creative thinking, and also thermal conditions, particularly with respect to indoor moisture, and cognitive performance, and how these associations may vary by individual, population, and geographic factors, this study adds to the body of literature that indoor air quality and thermal conditions influence cognitive performance, including creative domains. Work environments where creative thinking is important should look to prioritize outdoor air ventilation rates and maintain indoor temperatures within a reasonable range, albeit with some flexibility, which could help balance operational and energy considerations with promoting knowledge worker performance.

CHAPTER 5: CONCLUSION

This collective work investigated indoor environmental conditions influenced by building HVAC systems and their influence on occupant health outcomes that are reflective of typical working environments. Our investigations focused on indoor CO_2 concentrations, as influenced by building the ventilation component of HVAC operation, and indoor thermal conditions, as influenced by the space conditioning component of HVAC operation, and how these conditions are associated with metrics of cognitive performance and perceptions of satisfaction. The goal of this work is to help elucidate the conditions, and by inference, HVAC operation practices, that can help support building occupants and their activities in working and learning environments.

Summary of Findings

Chapter Two focused on indoor concentrations of CO_2 and associations with cognitive test scores among graduate students attending classes in lecture halls with increased outdoor air ventilation rates as a COVID-19 risk management strategy. Low concentrations of classroom CO_2 (measured class values ranging from ~440-1,630 ppm) were observed over the study period, which is expected with higher levels of outdoor air ventilation. Despite this low CO_2 exposure range, we still observed evidence of increases in classroom CO_2 being associated with lower cognitive performance, as assessed by metrics incorporating speed and accuracy scores from two administered cognitive tests. Interestingly, the associations were statistically stronger when using 95th percentile class exposure concentrations, as a measure of peak CO_2 exposures, compared to mean class CO_2 exposure concentrations, as a measure of average CO_2 exposures. Examining the temporal occurrence of class 95th percentile concentrations revealed that these peak exposures typically occur around the midpoint of class, as opposed to the very end. This suggests that higher concentrations of CO_2 are associated with lower cognitive test scores, and also that higher exposures have lasting cognitive effects.

Chapter Three complemented the CO_2 assessment in Chapter Two by examining indoor thermal conditions, the second main component influenced by HVAC operation, and an area of indoor environmental research that faces many challenges. This work began by calculating a suite of thermal variables from simple measurements of temperature and RH. Assessing these thermal exposure variables by evaluating Spearman Rank correlation coefficients, factor analysis, and principal component analysis revealed that all eleven thermal variables cluster into three groups that center around indoor air temperature, indoor air RH, and indoor-outdoor differences. We then examined a series of associations among thermal variables, cognitive test scores based on accuracy and speed, and thermal sensations. Not surprisingly, distinct patterns of association were observed for each of the three groups. Overall, we observed that higher values of enthalpy, a combined factor of air temperature and moisture, are associated with improved cognitive test scores over the exposure range included in this analysis. We also observed that warm sensations are associated with improved cognitive test scores, and that in-turn, higher values of enthalpy, over the range assessed in this study, are associated with warm sensations. The temperatures in this study encompass a tight range, as does RH, but to a lesser extent. Accordingly, the higher values of enthalpy in this study are likely a result of increases in indoor air moisture, suggesting that indoor moisture levels, in combination with air temperatures, are associated with cognitive performance. Models using indoor air temperature and RH as separate independent exposure variables similarly show that higher indoor air temperatures, up to 26 ^{o}C in this study, are associated with increased cognitive test scores and warm sensations, but appear to underemphasize the potential importance of indoor moisture. This work suggests that higher indoor air temperature and moisture can support human occupants in this specific study setting, which consisted primary of female occupants in the greater Boston area over the New England heating season. More generally, this investigation also provides new considerations for the characterization of indoor thermal conditions and implications for relating these conditions to occupant health outcomes.

Finally, Chapter Four extended beyond the Boston-based classrooms study and cognitive measures of speed and accuracy to examine divergent creative thinking among office worker participants in multiple countries. In this work, we examined acute hourly exposures of CO_2 and $PM_{2.5}$ as air quality parameters, and temperature and RH as thermal metrics. Most (e.g., 75% of) exposure values fell within low, normative ranges for buildings, but the upper exposure values were higher than those in the Classrooms for Health study, which provided a wider exposure range for assessment. Modeled associations showed statistically significant associations between increases in indoor CO_2 exposures and lower divergent creative thinking scores. The associations for $PM_{2.5}$ show directionally consistent, but statistically insignificant (at the 0.05 and 0.1 alpha levels), evidence of an association between higher $PM_{2.5}$ exposures and lower divergent creative thinking scores. However, past investigations have only found significant associations at exposures higher than those in this analysis, and the acute exposures were all within the limits of sensor accuracy, which substantially limits the confidence in the $PM_{2.5}$ assessment. With respect to thermal conditions, we observe an extended inverted U-shaped association or Maximum Adaptability framework holding, where temperatures between 22-26 ºC support higher divergent creative thinking scores, and temperatures above and below being associated with decreases in scores. The relationship between indoor moisture, either as a separate independent thermal variable or assessed in combination with temperatures and expressed as enthalpy, did not yield evidence of consistent or significant associations. Conducting country-specific models showed some evidence of associations within the USA in this study being similar to those in the classrooms study in Chapter Three, but our analysis dataset was underpowered to sufficiently investigate associations within the other two countries.

Recommendations for Future Research

The findings from and limitations in these studies set an agenda for future research on this topic. First, future studies would ideally investigate more diverse study populations. Although the CogFx Global Buildings Study encompassed six countries, the analysis population was similar to the Classrooms for Health analysis population, as both consisted of young adults who are predominantly White and Asian, and highly educated. Second, future work would ideally investigate built environment settings with larger exposure ranges where intervention could bring even greater benefit. Most buildings in these studies were well-operated and maintained and exposure concentrations were low. While this is interesting from a scientific perspective in that we still observed statistically significant and consistent results, at the same time, we are not observing the potential full magnitude of these indoor environmental-human health associations. From a practical perspective, we are potentially not observing the full impact of potential interventions, such as improved ventilation in schools that are currently poorly operated. Third, our measurement approach provided localized acute exposure assessment information, but did not measure the full suite of indoor exposures. Future investigations could enhance the suite of indoor thermal variables by assessing air speed and MRT for a more complete assessment. For air quality, additional air pollutants, such as specific volatile organic compounds, could be measured to explore associations between understudied air pollutants on this topic and cognitive performance. Related to thermal investigations would be additional work that investigates the role of indoor air moisture on occupant outcomes, with larger analysis datasets, larger exposure ranges, and varied study settings with respect to both time and place. While we see preliminary evidence of an association between enthalpy and occupant outcomes, this approach needs to be applied to more varied scenarios to better assess its usefulness and how it might vary. Finally, energy is a main motivator for this topic, but this work is energy suggestive, whereas future work would ideally be energy integrative. Indoor moisture is a priority for energy investigations as well, since many space conditioning processes are governed by moisture management. Future studies could incorporate building automation system information, work with building operators to tune system operation, and/or employ other modeling and measurement techniques to better assess the potential impacts on building energy consumption, to ideally balance with building operation for occupant health.

Implications and Concluding Remarks

While there are many limitations in this work, these investigations include many strengths in study design and analysis that instill confidence in the findings. When examining the collective findings, we observe the strongest evidence for an association between lower concentrations of indoor CO_2, as influenced by ventilation and occupancy, and cognitive test scores. This suggests that increasing outdoor air ventilation could support occupant performance in working and learning environments. Moving on to thermal conditions, it appears that maintaining temperatures in a normative range (e.g., 22-26 ^{o}C) can support occupants and their activities. The role of air moisture is less clear in this work, but there is preliminary evidence that the association might vary distinctly by setting (e.g., location, climate, study population), and that common approaches of assessing indoor air moisture with respect to occupant outcomes (e.g., PMV estimates, using temperature and RH as separate thermal variables) might underestimate its importance. Indoor enthalpy, a combined metric of air heat and moisture, shows promise to help overcome these issues and should be explored more fully in future work. While there is still work to be done to understand the role of indoor air moisture on typical occupant outcomes, this work suggests that focusing on enhancing indoor air quality, while maintaining indoor temperatures in a normative range can help support cognitive performance and thermal sensation. Focusing on increasing outdoor air ventilation and maintaining temperatures within a normative range can help provide some flexibility around building energy consumption, while also supporting occupants and their activities in working and learning environments.

APPENDIX A (FOR CHAPTER TWO)

Exposures: Additional Classroom Summary Statistics

Table 9: Summary table presenting summary statistics (mean, median, p75, p95, SD, CV) of all measured values of indoor temperature, RH, and CO_2 within class periods included in analysis. Summary statistics are based on summarized observations for 273 class periods included in final analysis (n=273 per summary statistic table).

Variable	Mean	SD	CV	Min	p25	p50	p75	p95	Max
Central Exposures: mean CO_2									
Temperature (C)	23	1.2	0.051	20	23	23	24	25	26
RH (%)	25	6.8	0.28	12	19	25	28	36	46
CO_2 (ppm)	707	207	0.29	471	562	625	771	1176	1309
Central Exposures: median CO_2									
Temperature (C)	23	1.2	0.051	20	23	23	24	25	26
RH (%)	25	6.8	0.28	12	19	24	28	36	46
CO_2 (ppm)	712	212	0.3	470	566	614	778	1184	1333
Peak Exposures: p95 CO_2									
Temperature (C)	24	1.2	0.05	21	23	24	25	25	27
RH (%)	25	7.1	0.28	12	20	25	28	37	46
CO_2 (ppm)	749	229	0.31	479	584	676	812	1230	1562
Peak Exposures: p75 CO_2									
Temperature (C)	24	1.2	0.05	20	23	24	24	25	27
RH (%)	25	7	0.28	12	19	25	28	37	46
CO_2 (ppm)	731	220	0.3	476	577	653	794	1200	1350
Exposure Variation: SD CO_2									
Temperature (C)	0.24	0.18	0.78	0.044	0.094	0.17	0.3	0.6	0.73
RH (%)	0.52	0.44	0.85	0.065	0.2	0.42	0.64	1.9	2.2

Table 9 (Continued)

CO_2 (ppm)	39	37	0.96	5.2	15	28	48	122	290
Exposure Variation: CV CO_2									
Temperature (C)	1	0.79	0.78	0.18	0.38	0.71	1.3	2.6	3.1
RH (%)	2	1.4	0.7	0.29	0.95	1.8	2.7	6.2	6.8
CO_2 (ppm)	5	3.7	0.74	0.99	2.4	4.1	6.5	11	28

Exposures: Temporal Classroom CO_2 Concentrations

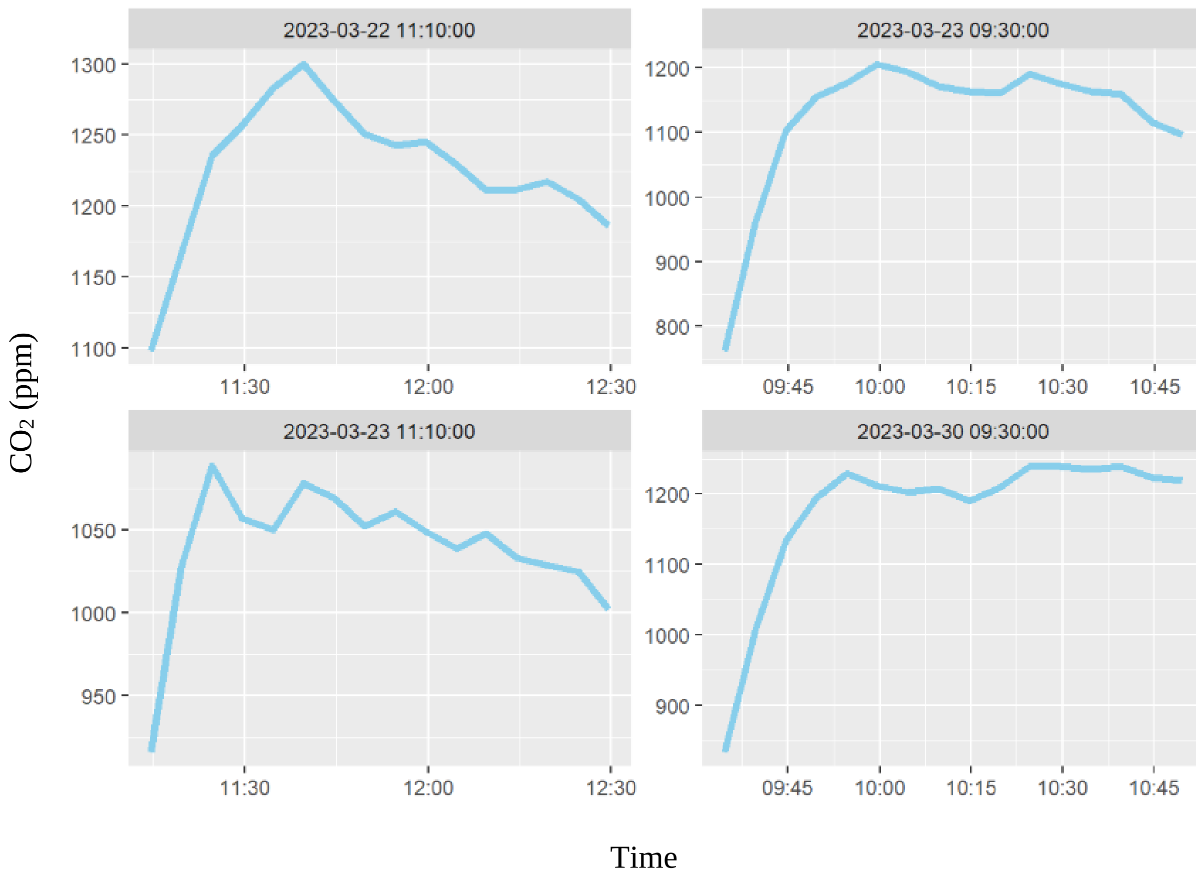


Figure 14: Sample of temporal classroom CO_2 concentrations for four class periods included in the study for one randomly selected classroom at School B.

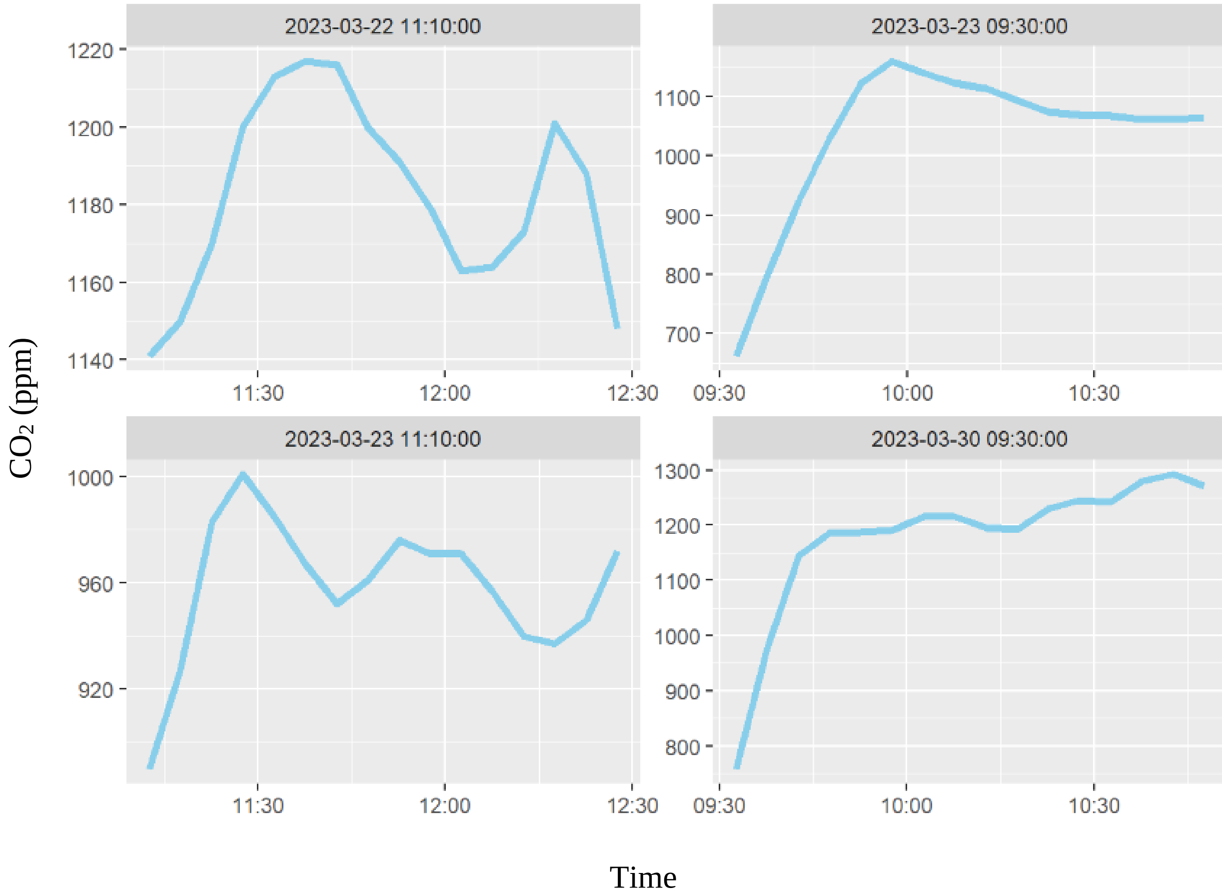


Figure 15: Sample of temporal classroom CO_2 concentrations for four class periods included in the study for a second randomly selected classroom at School B.

APPENDIX B (FOR CHAPTER THREE)

Associations between thermal conditions and cognitive test scores

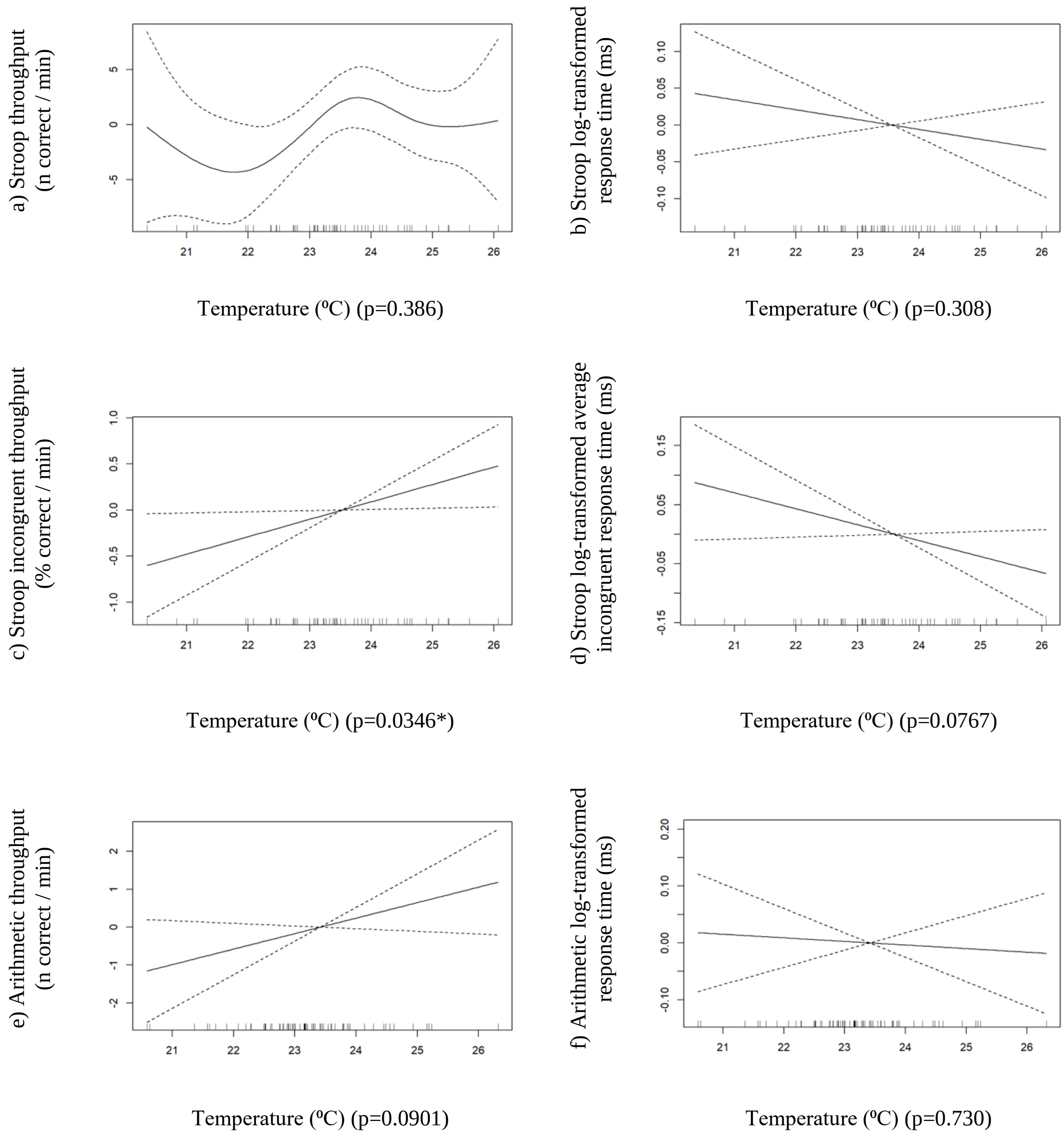


Figure 16: Plotted spline terms from adjusted mixed effects models showing the associations between indoor temperature and each of the six cognitive function scores. Models are adjusted for class average temperature, RH and CO_2, school, and learning effects, and include participant-specific random effects.

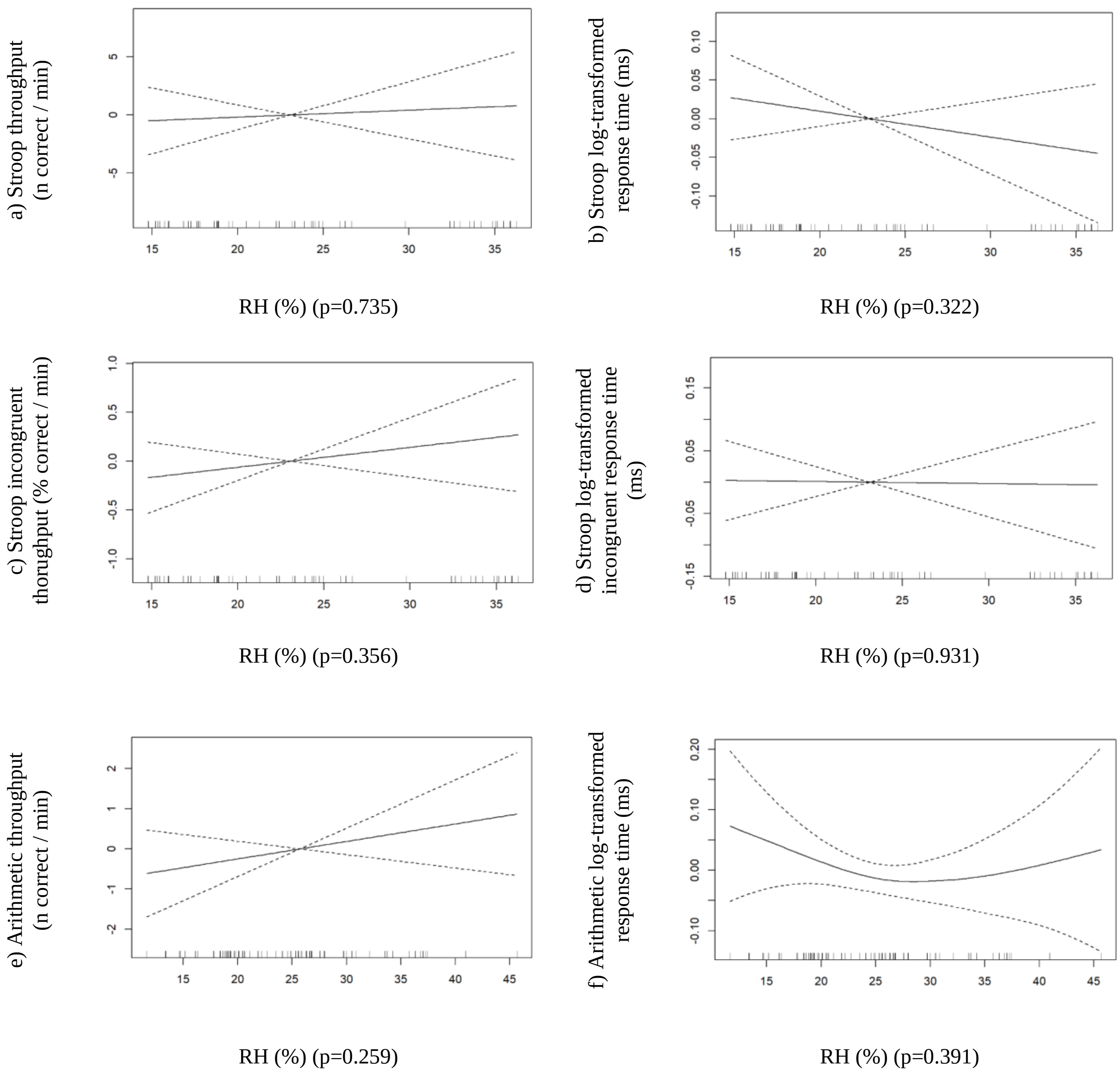
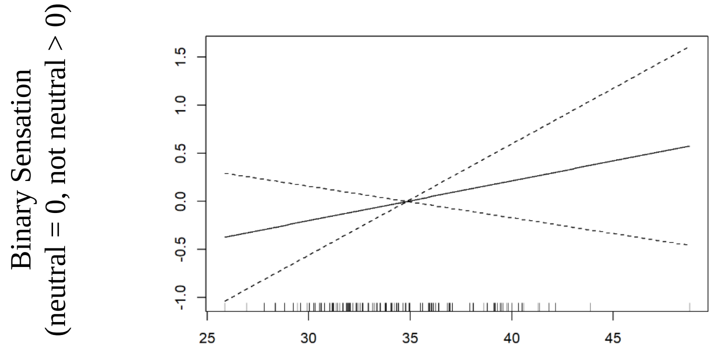
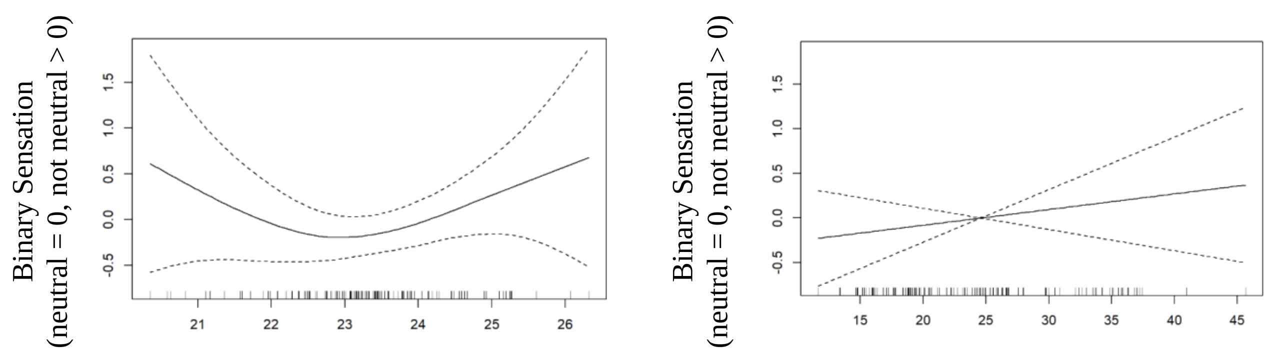


Figure 17: Plotted spline terms from adjusted mixed effects models showing the associations between indoor RH and each of the six cognitive function scores. Models are adjusted for class average temperature, RH and CO_2, school, and learning effects, and include participant-specific random effects.



Enthalpy (kJ/kg) (p=0.265)

Figure 18: Spline term showing the modeled association between class average enthalpy and neutral sensations. Models are adjusted for class average enthalpy and CO2, and school, and include participant-specific random effects.



a. Temperature (ºC) (p=0.197)

b. RH (%) (p=0.396)

Figure 19: Spline term showing the modeled association between class average temperature (a) and RH (b) and neutral sensations. Models are adjusted for class average temperature, RH, and CO2, and school, and include participant-specific random effects.

Table 10: Effect estimate summary from models exploring the associations between binary thermal sensations and cognitive test scores.

	Change in cognitive test score		
Cognitive tests, grouped by thermal sensation	Change (95% CI)	p-value	
Feeling neutral (as opposed to not)			
Stroop (n=113)			
Throughput (n correct / minute)	0.18 (-4.01, 4.37)	0.93	
Response time (milliseconds)	1.02 (0.95, 1.1)	0.61	
Incongruent throughput (% correct / minute)	-0.11 (-0.6, 0.38)	0.65	
Average incongruent response time (milliseconds)	1.05 (1, 1.09)	0.29	
Arithmetic (n=159)		0	
Throughput (n correct / minute)	-0.1 (-1.2, 1.01)	0.87	
Response Time (milliseconds)	0.99 (0.92, 1.08)	0.89	
Feeling warm (as opposed to not)			
Stroop (n=113)			
Throughput (n correct / minute)	2.02 (-2.76, 6.8)	0.41	
Response time (milliseconds)	0.94 (0.87, 1.1)	0.15	
Incongruent throughput (% correct / minute)	0.58 (0.03, 1.13)	0.04	*
Average incongruent response time (milliseconds)	0.91 (0.87, 0.96)	0.05	*
Arithmetic (n=159)			
Throughput (n correct / minute)	0.51 (-0.65, 1.01)	0.87	
Response Time (milliseconds)	0.98 (0.9, 1.07)	0.65	
Feeling cold (as opposed to not)			
Stroop (n=113)			
Throughput (n correct / minute)	-2.64 (-7.81, 2.52)	0.32	
Response time (milliseconds)	1.05 (0.95, 1.14)	0.34	
Incongruent throughput (% correct / minute)	-0.51 (-1.08, 0.06)	0.08	
Average incongruent response time (milliseconds)	1.04 (0.99, 1.1)	0.41	
Arithmetic (n=159)			
Throughput (n correct / minute)	-0.68 (-2.16, 0.81)	0.37	
Response time (milliseconds)	1.04 (0.93, 1.17)	0.44	

APPENDIX C (FOR CHAPTER FOUR)

Indoor Exposures by Country

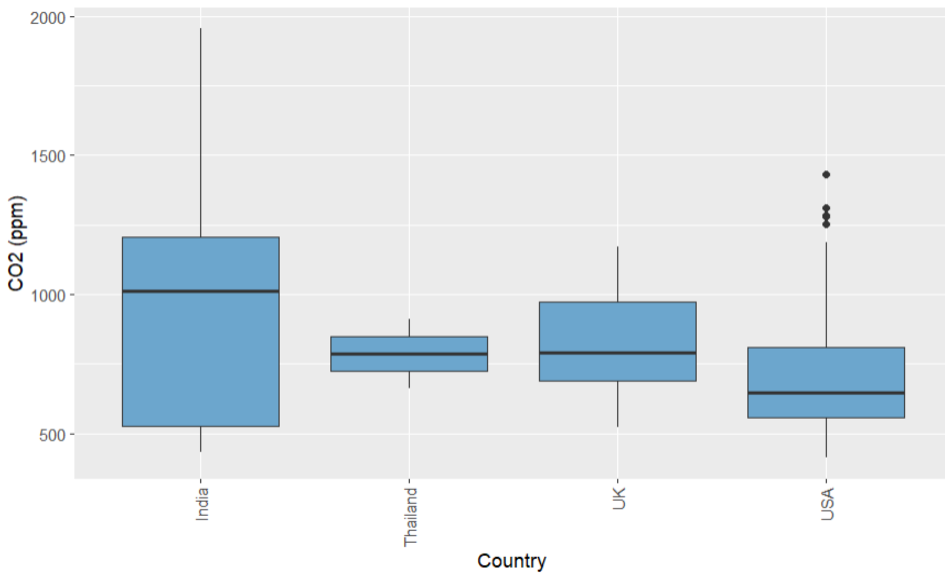


Figure 20: Country-specific boxplots summarizing acute exposures for the hourly-average CO_2 concentrations corresponding to valid AUT test responses included in analysis.

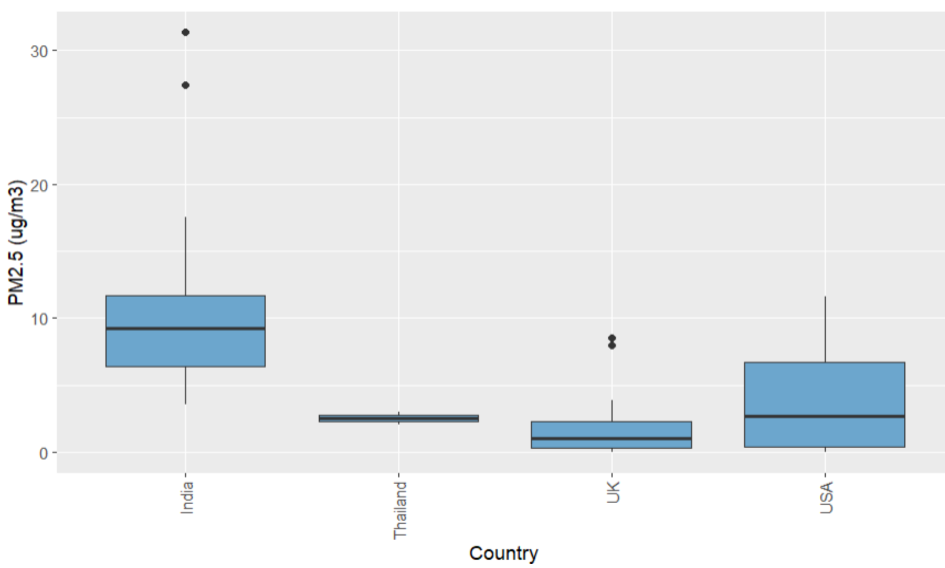


Figure 21: Country-specific boxplots summarizing acute exposures for the hourly-average $PM_{2.5}$ concentrations corresponding to valid AUT test responses included in analysis.

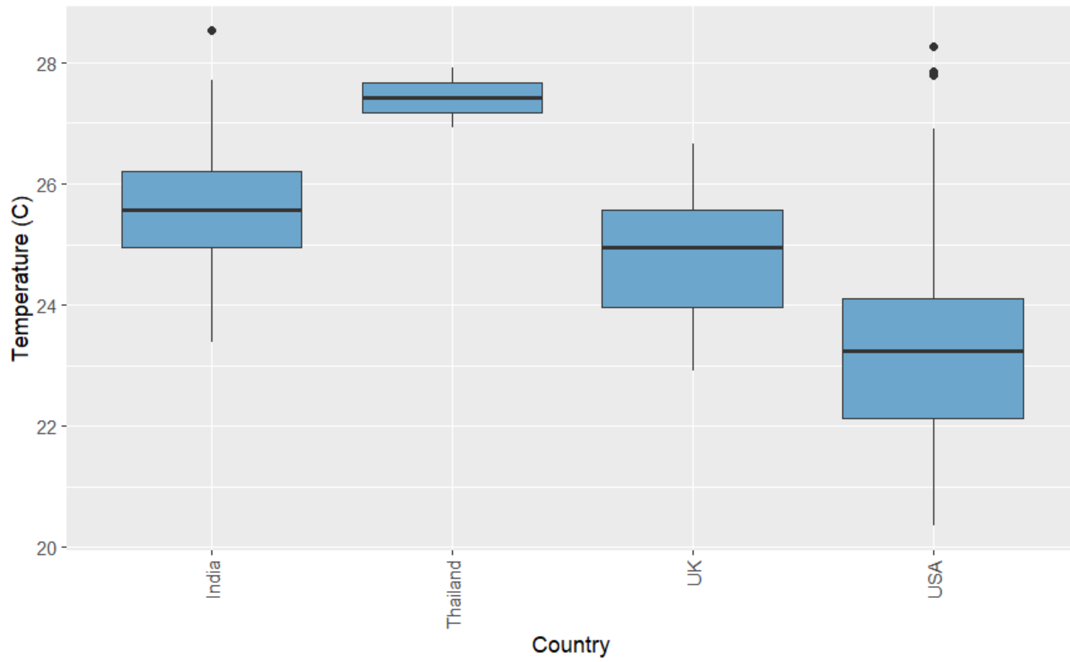


Figure 22: Country-specific boxplots summarizing acute exposures for the hourly-average temperatures corresponding to valid AUT test responses included in analysis.

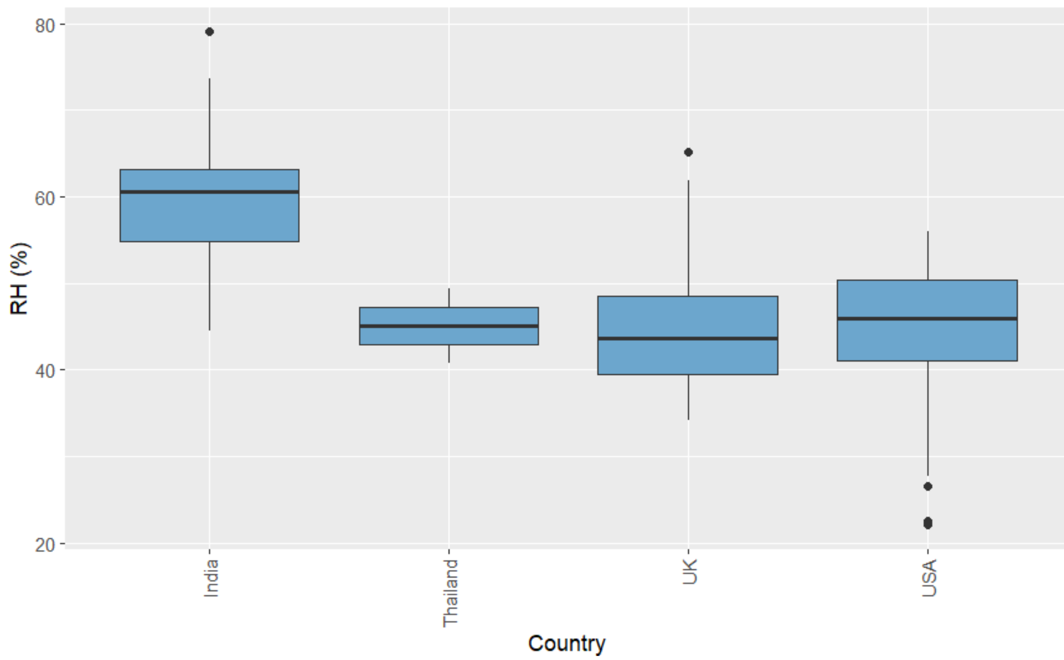


Figure 23: Country-specific boxplots summarizing acute exposures for the hourly-average RH values corresponding to valid AUT test responses included in analysis.

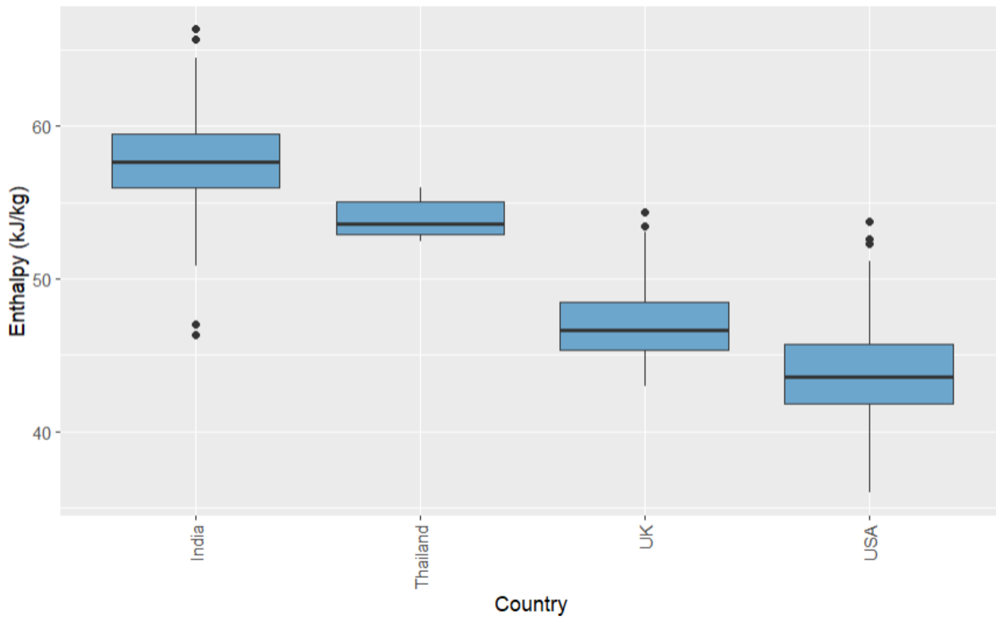


Figure 24: Country-specific boxplots summarizing acute exposures for the hourly-average calculated enthalpy values corresponding to valid AUT test responses included in analysis.

Details on Scoring the AUT

The token-responses were cleaned based on token-response content with respect to the prompt. Inappropriate/invalid token-responses, where the token-response has no possible relation, meaning, or use with respect to the prompt (e.g., the response "plan" to the prompt "key"), were removed, as were token-responses that were merely descriptions of the prompted object and not actual uses of it (e.g., "big sheet of paper" for the prompt "sheet of paper"). In some instances, the final token-response to a prompt appeared incomplete, likely due to the participant running out of time to complete the response. For these occurrences, the token-responses were retained and corrected when interpretable, but removed when they were not. There were also instances of collective-responses where all the contained token-responses were unclear or unrelated, or where they suggested that the participant had failed to understand the prompt or the purpose of the AUT. These collective-responses were removed entirely. In other cases, single token-responses that should have been two token-responses and two token-responses that formed a single coherent token-response were corrected accordingly. For example, "to shop” followed by “via the internet" was transformed into "to shop via the internet". Within a token-response, words that were redundant or ambiguous with respect to the overall response meaning were also removed.

Associations between indoor enthalpy and divergent creative thinking scores, complete case data

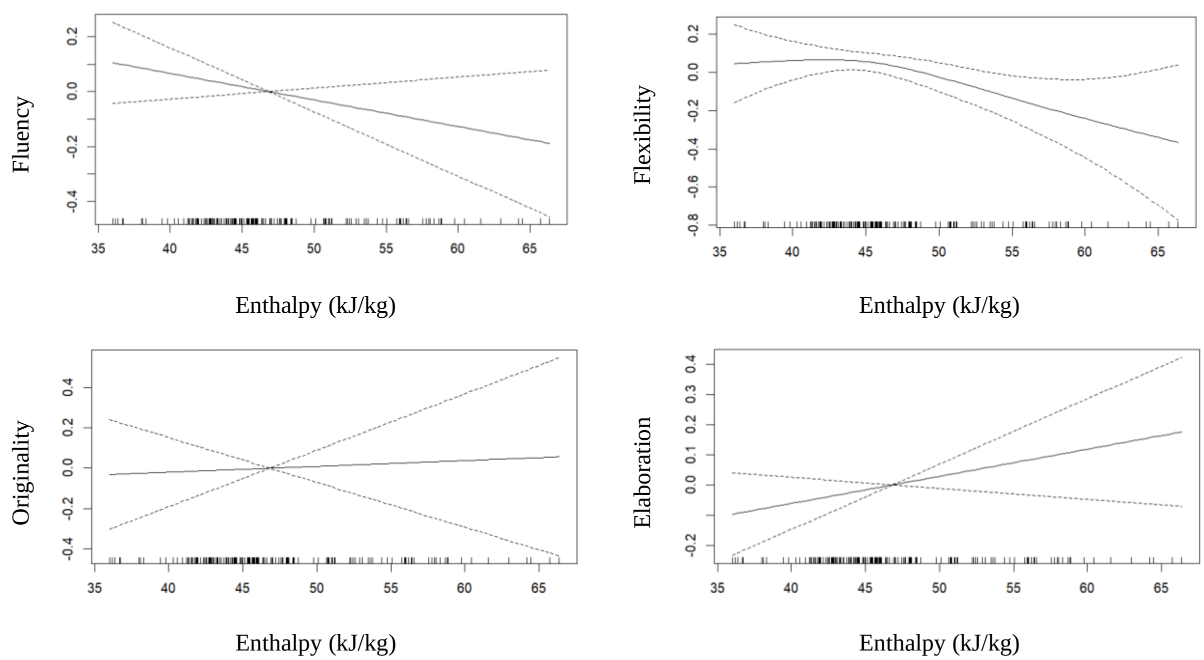


Figure 25: Associations between indoor enthalpy and divergent creative thinking scores using estimates from the minimally adjusted models and complete case data from all countries. Minimally adjusted models control for hourly averaged indoor enthalpy, CO_2, and $PM_{2.5}$, and include a participant-specific random effect.

Sensitivity Analysis: Replace missing data (+56 observations)

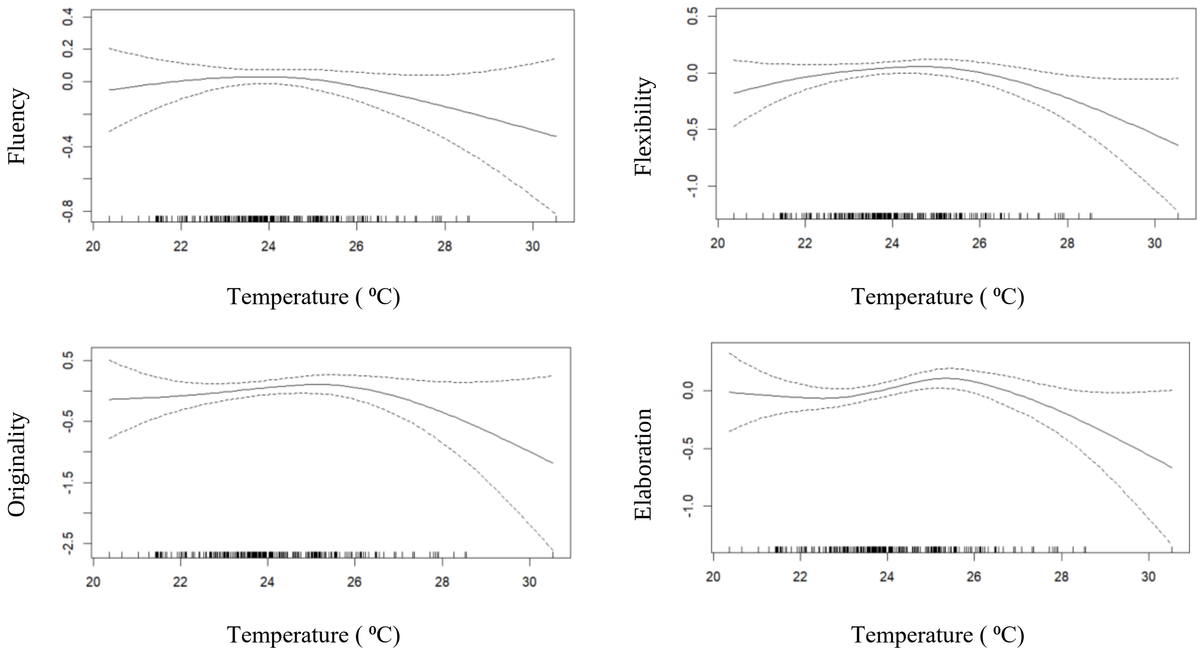


Figure 26: Associations between indoor temperature and divergent creative thinking scores using estimates from the minimally adjusted models, with replaced exposure data where available. Minimally adjusted models control for hourly averaged indoor temperature, RH, CO_2, and $PM_{2.5}$, and a participant-specific random effect.

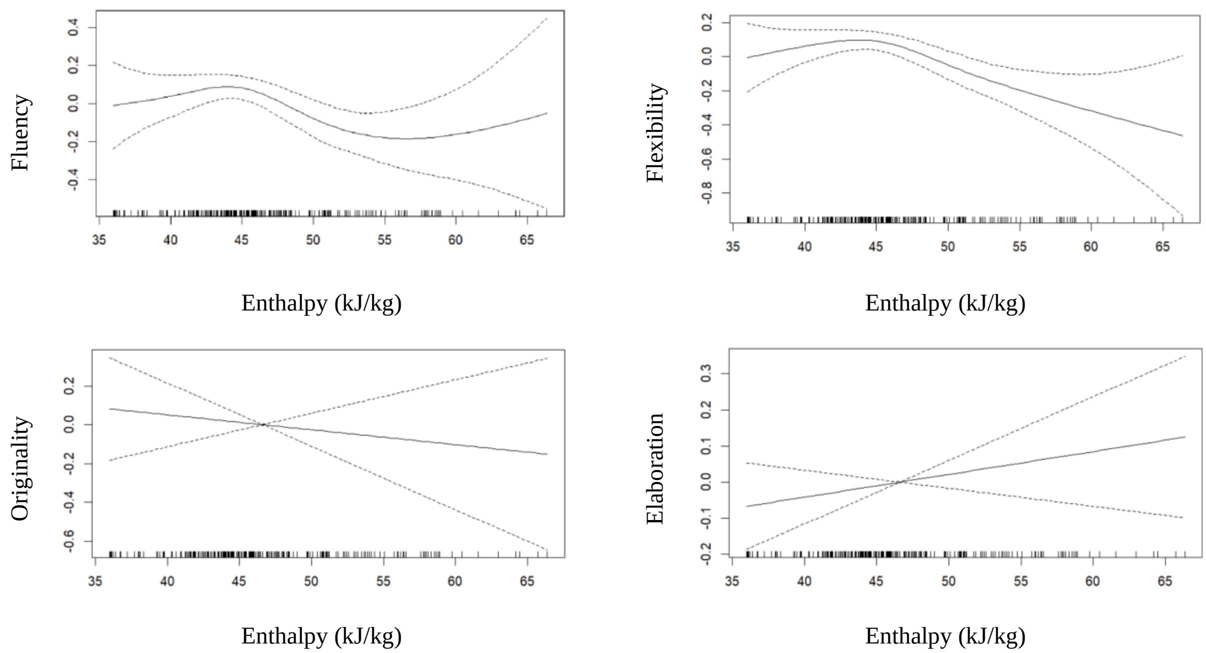


Figure 27: Associations between indoor enthalpy and divergent creative thinking scores using estimates from the minimally adjusted models, with replaced missing exposure data where available. Minimally adjusted models control for hourly averaged indoor enthalpy, CO_2, and $PM_{2.5}$, and a participant-specific random effect.

BIBLIOGRAPHY

1. Abbasi, A. M., Motamedzade, M., Aliabadi, M., Golmohammadi, R., & Tapak, L. (2019). The impact of indoor air temperature on the executive functions of human brain and the physiological responses of body. *Health Promotion Perspectives*, *9*(1), 55–64. https://doi.org/10.15171/hpp.2019.07

2. Abdelrahman, M. M., Chong, A., & Miller, C. (2022). Personal thermal comfort models using digital twins: Preference prediction with BIM-extracted spatial–temporal proximity data from Build2Vec. *Building and Environment*, *207*, 108532. https://doi.org/10.1016/j.buildenv.2021.108532

3. Ailshire, J. A., & Crimmins, E. M. (2014). Fine Particulate Matter Air Pollution and Cognitive Function Among Older US Adults. *American Journal of Epidemiology*, *180*(4), 359–366. https://doi.org/10.1093/aje/kwu155

4. Alhashim, A. G., Marshall, M., Hartog, T., Jonczyk, R., Dickson, D., van Hell, J., Okdun-Kremer, GÃ. E., & Siddique, Z. (2020). WIP: Assessing creativity of alternative uses task responses: A detailed procedure. *ASEE Annual Conference and Exposition, Conference Proceedings*, 1656.

5. Allen, J. G., & Ibrahim, A. M. (2021). Indoor Air Changes and Potential Implications for SARS-CoV-2 Transmission. *JAMA*, *325*(20), 2112. https://doi.org/10.1001/jama.2021.5053

6. Allen, J. G., MacNaughton, P., Cedeno-Laurent, J. G., Cao, X., Flanigan, S., Vallarino, J., Rueda, F., Donnelly-McLay, D., & Spengler, J. D. (2019). Airplane pilot flight performance on 21 maneuvers in a flight simulator under varying carbon dioxide concentrations. *Journal of Exposure Science & Environmental Epidemiology*, *29*(4), 457–468. https://doi.org/10.1038/s41370-018-0055-8

7. Allen, J. G., MacNaughton, P., Satish, U., Santanam, S., Vallarino, J., & Spengler, J. D. (2016). Associations of Cognitive Function Scores with Carbon Dioxide, Ventilation, and Volatile Organic Compound Exposures in Office Workers: A Controlled Exposure Study of Green and Conventional Office Environments. *Environmental Health Perspectives*, *124*(6), 805–812. https://doi.org/10.1289/ehp.1510037

8. Allen, J. G., & Marr, L. C. (2020). Recognizing and controlling airborne transmission of SARS-CoV-2 in indoor environments. *Indoor Air*, *30*(4), ina.12697. https://doi.org/10.1111/ina.12697

9. André, M., Schiavon, S., & Lamberts, R. (2024). Implementation of desk fans in open office: Lessons learned and guidelines from a field study. *Building and Environment*, *259*, 111681. https://doi.org/10.1016/j.buildenv.2024.111681

10. Aoun, J. E. (2017). *Robot-proof: Higher education in the age of artificial intelligence*. MIT Press.

11. Archibugi, D., Filippetti, A., & Frenz, M. (2013). Economic crisis and innovation: Is destruction prevailing over accumulation? *Research Policy*, *42*(2), 303–314. https://doi.org/10.1016/j.respol.2012.07.002

12. Arens, E., Hoyt, T., Zhou, X., Huang, L., Zhang, H., & Schiavon, S. (2015). Modeling the comfort effects of short-wave solar radiation indoors. *Building and Environment*, *88*, 3–9. https://doi.org/10.1016/j.buildenv.2014.09.004

13. Arikrishnan, S., Roberts, A. C., Lau, W. S., Wan, M. P., & Ng, B. F. (2023). Experimental study on the impact of indoor air quality on creativity by Serious Brick Play method. *Scientific Reports*, *13*(1), 15488. https://doi.org/10.1038/s41598-023-42355-z

14. Arsad, F. S., Hod, R., Ahmad, N., Baharom, M., & Ja'afar, M. H. (2023). Assessment of indoor thermal comfort temperature and related behavioural adaptations: A systematic review. *Environmental Science and Pollution Research*, *30*(29), 73137–73149. https://doi.org/10.1007/s11356-023-27089-9

15. ASHRAE. (2022). *ANSI/ASHRAE Standard 62.1-2022, Ventilation and Acceptable Indoor Air Quality*.

16. ASHRAE. (2023a). *ASHRAE Standard 241, Control of Infectious Aerosols*.

17. ASHRAE. (2023b). *Standard 55-2023—Thermal Environmental Conditions for Human Occupancy (ANSI Approved)*.

18. Balková, M., Lejsková, P., & Ližbetinová, L. (2022). The Values Supporting the Creativity of Employees. *Frontiers in Psychology*, *12*, 805153. https://doi.org/10.3389/fpsyg.2021.805153

19. Barner, C., Schmid, S. R., & Diekelmann, S. (2019). Time-of-day effects on prospective memory. *Behavioural Brain Research*, *376*, 112179. https://doi.org/10.1016/j.bbr.2019.112179

20. Beaty, R. E., & Johnson, D. R. (2021). Automating creativity assessment with SemDis: An open platform for computing semantic distance. *Behavior Research Methods*, *53*(2), 757–780. https://doi.org/10.3758/s13428-020-01453-w

21. Beketayev, K., & Runco, M. A. (2016). Scoring divergent thinking tests by computer with a semantics-based algorithm. *Europe's Journal of Psychology*, *12*(2), 210–220. https://doi.org/10.5964/ejop.v12i2.1127

22. Blanchette, D. M., Ramocki, S. P., O'del, J. N., & Casey, M. S. (2005). Aerobic Exercise and Creative Potential: Immediate and Residual Effects. *Creativity Research Journal*, *17*(2–3), 257–264. https://doi.org/10.1080/10400419.2005.9651483

23. BOMA. (2010). *Experience Exchange Report (EER)* [Benchmarking Reports]. BOMA International.

24. Brooks, M., & McArthur, J. J. (2019). Drivers of Investment in Commercial Real Estate Sustainability: 2006–2018. *Journal of Sustainable Real Estate*, *11*(1), 130–155. https://doi.org/10.22300/1949-8276.11.1.130

25. Buczak, P., Huang, H., Forthmann, B., & Doebler, P. (2023). The Machines Take Over: A Comparison of Various Supervised Learning Approaches for Automated Scoring of Divergent Thinking Tasks. *The Journal of Creative Behavior*, *57*(1), 17–36. https://doi.org/10.1002/jocb.559

26. Bureau of Labor Statistics. (2011). *Employer Costs for Employee Compensation new release*. United States Department of Labor.

27. Calderón-Garcidueñas, L., Kavanaugh, M., Block, M., D'Angiulli, A., Delgado-Chávez, R., Torres-Jardón, R., González-Maciel, A., Reynoso-Robles, R., Osnaya, N., Villarreal-Calderon, R., Guo, R., Hua, Z., Zhu, H., Perry, G., & Diaz, P. (2012). Neuroinflammation, Hyperphosphorylated Tau, Diffuse Amyloid Plaques, and Down-Regulation of the Cellular Prion Protein in Air Pollution Exposed Children and Young Adults. *Journal of Alzheimer's Disease*, *28*(1), 93–107. https://doi.org/10.3233/JAD-2011-110722

28. Callen, I., Carbonari, M. V., DeArmond, M., Dewey, D., Dizon-Ross, E., Goldhaber, D., Isaacs, J., Kane, T. J., Kuhfield, M., McDonald, A., McEachin, A., Morton, E., Atsuko, M., & Staiger, D. O. (2023). *Summer School As a Learning Loss Recovery Strategy After COVID-19: Evidence from Summer 2022* (CALDER Working Paper No. 2901-0823). Center for Education Policy Research, Harvard University.

29. Callway, R., Pineo, H., & Moore, G. (2020). Understanding the Role of Standards in the Negotiation of a Healthy Built Environment. *Sustainability*, *12*(23), 9884. https://doi.org/10.3390/su12239884

30. Carlucci, S., Bai, L., de Dear, R., & Yang, L. (2018). Review of adaptive thermal comfort models in built environmental regulatory documents. *Building and Environment*, *137*, 73–89. https://doi.org/10.1016/j.buildenv.2018.03.053

31. CDC. (2023a, May 11). *Improving Ventilation In Buildings*. https://www.cdc.gov/coronavirus/2019-ncov/prevent-getting-sick/improving-ventilation-in-buildings.html

32. CDC. (2023b, May 12). *Ventilation in Buildings*. https://www.cdc.gov/coronavirus/2019-ncov/community/ventilation.html#print

33. Cedeño Laurent, J. G., MacNaughton, P., Jones, E., Young, A. S., Bliss, M., Flanigan, S., Vallarino, J., Chen, L. J., Cao, X., & Allen, J. G. (2021). Associations between acute exposures to $PM_{2.5}$ and carbon dioxide indoors and cognitive function in office workers: A multicountry longitudinal prospective observational study. *Environmental Research Letters*, *16*(9), 094047. https://doi.org/10.1088/1748-9326/ac1bd8

34. Cedeño Laurent, J. G., Williams, A., Oulhote, Y., Zanobetti, A., Allen, J. G., & Spengler, J. D. (2018). Reduced cognitive function during a heat wave among residents of non-air-

conditioned buildings: An observational study of young adults in the summer of 2016. *PLOS Medicine*, *15*(7), e1002605. https://doi.org/10.1371/journal.pmed.1002605

35. Cedeño-Laurent, J. G., Williams, A., MacNaughton, P., Cao, X., Eitland, E., Spengler, J., & Allen, J. (2018). Building Evidence for Health: Green Buildings, Current Science, and Future Challenges. *Annual Review of Public Health*, *39*(1), 291–308. https://doi.org/10.1146/annurev-publhealth-031816-044420

36. Cen, C., Cheng, S., Tan, E., & Wong, N. H. (2024). Students' thermal comfort and cognitive performance in fan-assisted naturally ventilated classrooms in tropical Singapore. *Building and Environment*, *260*, 111689. https://doi.org/10.1016/j.buildenv.2024.111689

37. Chan, W. R., Heming, A., & Shannon, C. (n.d.). *P. Jacob Bueno de Mesquita, Ph.D.* 46.

38. Charles, K. E. (2003). *Fanger's thermal comfort and draught models* (p. 29 p.). [object Object]. https://doi.org/10.4224/20378865

39. *City of Boston Climate Action Plan 2019 Update*. (n.d.). 88.

40. Congressional Research Service. (2013). *Environmental Laws: Summaries of Major Statutes Administered by the Environmental Protection Agency* (RL30798). CRS Report Prepared for Members and Committees of Congress.

41. Cowan, N. (2014). Working Memory Underpins Cognitive Development, Learning, and Education. *Educational Psychology Review*, *26*(2), 197–223. https://doi.org/10.1007/s10648-013-9246-y

42. Coyle, E. D. (Ed.). (2014). *Understanding the global energy crisis*. Purdue University Press.

43. Cragg, L., Richardson, S., Hubber, P. J., Keeble, S., & Gilmore, C. (2017). When is working memory important for arithmetic? The impact of strategy and age. *PloS One*, *12*(12), e0188693. https://doi.org/10.1371/journal.pone.0188693

44. Cronyn, P. D. (2012). *Chronic Exposure to Moderately Elevated CO2 during Long-Duration Space Flight*.

45. Cui, W., Cao, G., Park, J. H., Ouyang, Q., & Zhu, Y. (2013). Influence of indoor air temperature on human thermal comfort, motivation and performance. *Building and Environment*, *68*, 114–122. https://doi.org/10.1016/j.buildenv.2013.06.012

46. d'Ambrosio Alfano, F., Olesen, B., Palella, B., Pepe, D., & Riccio, G. (2019). Fifty Years of PMV Model: Reliability, Implementation and Design of Software for Its Calculation. *Atmosphere*, *11*(1), 49. https://doi.org/10.3390/atmos11010049

47. Danivska, V., Heywood, C., Christersson, M., Zhang, E., & Nenonen, S. (2019). Environmental and social sustainability – emergence of well-being in the built environment, assessment tools and real estate market implications. *Intelligent Buildings International*, *11*(3–4), 212–226. https://doi.org/10.1080/17508975.2019.1678005

48. Dedesko, S., Jones, E. R., & Allen, J. G. (2022, June). Thermal Conditions and Associations with Divergent Creative Thinking Scores in Office Environments. *Proceedings, Indoor Air 2022, Kuopio, Finland*. Indoor Air 2022, Kuopio, Finland.

49. Demanega, I., Mujan, I., Singer, B. C., Anđelković, A. S., Babich, F., & Licina, D. (2021). Performance assessment of low-cost environmental monitors and single sensors under variable indoor air quality and thermal conditions. *Building and Environment*, *187*, 107415. https://doi.org/10.1016/j.buildenv.2020.107415

50. Deveau, M., Chen, C.-P., Johanson, G., Krewski, D., Maier, A., Niven, K. J., Ripple, S., Schulte, P. A., Silk, J., Urbanus, J. H., Zalk, D. M., & Niemeier, R. W. (2015). The Global Landscape of Occupational Exposure Limits—Implementation of Harmonization Principles to Guide Limit Selection. *Journal of Occupational and Environmental Hygiene*, *12*(sup1), S127–S144. https://doi.org/10.1080/15459624.2015.1060327

51. Devine, A., Sanderford, A., & Wang, C. (2024). Sustainability and Private Equity Real Estate Returns. *The Journal of Real Estate Finance and Economics*, *68*(2), 161–187. https://doi.org/10.1007/s11146-022-09914-z

52. Dippo, C., & Kudrowitz, B. (2015). The Effects of Elaboration in Creativity Tests as it Pertains to Overall Scores and How it Might Prevent a Person From Thinking of Creative Ideas During the Early Stages of Brainstorming and Idea Generation. *Volume 7: 27th International Conference on Design Theory and Methodology*, V007T06A007. https://doi.org/10.1115/DETC2015-46789

53. Du, B., Tandoc, M. C., Mack, M. L., & Siegel, J. A. (2020). Indoor CO_2 concentrations and cognitive function: A critical review. *Indoor Air*, *30*(6), 1067–1082. https://doi.org/10.1111/ina.12706

54. Dumas, D., & Runco, M. (2018). Objectively scoring divergent thinking tests for originality: A re-analysis and extension. *Creativity Research Journal*, *30*(4), 466–468.

55. EPA. (2001). *Healthy Buildings, Healthy People: A vision for the 21st century*. EPA.

56. Fisk, W. J. (2017). The ventilation problem in schools: Literature review. *Indoor Air*, *27*(6), 1039–1051. https://doi.org/10.1111/ina.12403

57. Fisk, W. J., Mirer, A. G., & Mendell, M. J. (2009). Quantitative relationship of sick building syndrome symptoms with ventilation rates. *Indoor Air*, *19*(2), 159–165. https://doi.org/10.1111/j.1600-0668.2008.00575.x

58. Fisk, W. J., & Rosenfeld, A. H. (1997). Estimates of Improved Productivity and Health from Better Indoor Environments. *Indoor Air*, *7*(3), 158–172. https://doi.org/10.1111/j.1600-0668.1997.t01-1-00002.x

59. Fox, J. (2023, July 7). *Equivalent Clean Airflow Rates from ASHRAE 241 Control of Infectious Aerosols (Part 2)*. https://itsairborne.com/ashrae-241-control-of-infectious-aerosols-part-2-equivalent-clean-airflow-rates-76a511769d4d

60. Gao, X., Coull, B., Lin, X., Vokonas, P., Spiro, A., Hou, L., Schwartz, J., & Baccarelli, A. A. (2021). Short-term air pollution, cognitive performance and nonsteroidal anti-inflammatory drug use in the Veterans Affairs Normative Aging Study. *Nature Aging*, *1*(5), 430–437. https://doi.org/10.1038/s43587-021-00060-4

61. Gaspar, A., & Alexandre, L. A. (2019). A Multimodal Approach to Image Sentiment Analysis. In H. Yin, D. Camacho, P. Tino, A. J. Tallón-Ballesteros, R. Menezes, & R. Allmendinger (Eds.), *Intelligent Data Engineering and Automated Learning – IDEAL 2019* (Vol. 11871, pp. 302–309). Springer International Publishing. https://doi.org/10.1007/978-3-030-33607-3_33

62. Goldberg, T. E., Harvey, P. D., Wesnes, K. A., Snyder, P. J., & Schneider, L. S. (2015). Practice effects due to serial cognitive assessment: Implications for preclinical Alzheimer's disease randomized controlled trials. *Alzheimer's & Dementia: Diagnosis, Assessment & Disease Monitoring*, *1*(1), 103–111. https://doi.org/10.1016/j.dadm.2014.11.003

63. Gostin, L. O., Hodge, J. G., & Gronvall, G. K. (2023). The Model State Indoor Air Quality Act. *JAMA*, *330*(16), 1525. https://doi.org/10.1001/jama.2023.17334

64. Guilford, J. P. (1967). Creativity: Yesterday, Today and Tomorrow. *The Journal of Creative Behavior*, *1*(1), 3–14. https://doi.org/10.1002/j.2162-6057.1967.tb00002.x

65. Haase, J., Hanel, P. H. P., & Gronau, N. (2023). Creativity enhancement methods for adults: A meta-analysis. *Psychology of Aesthetics, Creativity, and the Arts*. https://doi.org/10.1037/aca0000557

66. Hasler, B. P., Dahl, R. E., Holm, S. M., Jakubcak, J. L., Ryan, N. D., Silk, J. S., Phillips, M. L., & Forbes, E. E. (2012). Weekend-weekday advances in sleep timing are associated with altered reward-related brain function in healthy adolescents. *Biological Psychology*, *91*(3), 334–341. https://doi.org/10.1016/j.biopsycho.2012.08.008

67. Hass, R. W. (2017). Tracking the dynamics of divergent thinking via semantic distance: Analytic methods and theoretical implications. *Memory & Cognition*, *45*(2), 233–244. https://doi.org/10.3758/s13421-016-0659-y

68. Hassevoort, K. M., Lin, A. S., Khan, N. A., Hillman, C. H., & Cohen, N. J. (2020). Added sugar and dietary fiber consumption are associated with creativity in preadolescent children. *Nutritional Neuroscience*, *23*(10), 791–802. https://doi.org/10.1080/1028415X.2018.1558003

69. Haverinen-Shaughnessy, U., & Shaughnessy, R. J. (2015). Effects of Classroom Ventilation Rate and Temperature on Students' Test Scores. *PLOS ONE*, *10*(8), e0136165. https://doi.org/10.1371/journal.pone.0136165

70. Heidari, L., Younger, M., Chandler, G., Gooch, J., & Schramm, P. (2017). Integrating Health Into Buildings of the Future. *Journal of Solar Energy Engineering*, *139*(1), 010802. https://doi.org/10.1115/1.4035061

71. Heschong, L. (1979). *Thermal Delight in Architecture*. MIT Press. https://api.semanticscholar.org/CorpusID:109985491

72. International WELL Building Institute. (2017, February). *WELL @ Work: The Benefits of a WELL-Certified Office*. https://resources.wellcertified.com/articles/well-work-the-benefits-of-a-well-certified-office/

73. Jacobson, T. A., Kler, J. S., Hernke, M. T., Braun, R. K., Meyer, K. C., & Funk, W. E. (2019). Direct human health risks of increased atmospheric carbon dioxide. *Nature Sustainability*, *2*(8), 691–701. https://doi.org/10.1038/s41893-019-0323-1

74. Jareemit, D., Julpanwattana, P., & Choruengwiwat, J. (2017). Impact of Outdoor Air Exchange Rates on Sleep Quality and the Next-Day Performance with Application of Energy Recovery Ventilator. *Journal of Architectural/Planning Research and Studies (JARS)*, *14*(1), 21–32. https://doi.org/10.56261/jars.v14i1.104443

75. Jones, E. R., Cedeño Laurent, J. G., Young, A. S., Coull, B. A., Spengler, J. D., & Allen, J. G. (2022). Indoor humidity levels and associations with reported symptoms in office buildings. *Indoor Air*, *32*(1). https://doi.org/10.1111/ina.12961

76. Jones, E. R., Cedeño Laurent, J. G., Young, A. S., MacNaughton, P., Coull, B. A., Spengler, J. D., & Allen, J. G. (2021). The effects of ventilation and filtration on indoor PM2.5 in office buildings in four countries. *Building and Environment*, *200*, 107975. https://doi.org/10.1016/j.buildenv.2021.107975

77. Karjalainen, S. (2012). Thermal comfort and gender: A literature review: Thermal comfort and gender: a literature review. *Indoor Air*, *22*(2), 96–109. https://doi.org/10.1111/j.1600-0668.2011.00747.x

78. Karwowski, M., & Soszynski, M. (2008). How to develop creative imagination? *Thinking Skills and Creativity*, *3*(2), 163–171. https://doi.org/10.1016/j.tsc.2008.07.001

79. Khan, A. M., Finlay, J. M., Clarke, P., Sol, K., Melendez, R., Judd, S., & Gronlund, C. J. (2021). Association between temperature exposure and cognition: A cross-sectional analysis of 20,687 aging adults in the United States. *BMC Public Health*, *21*(1), 1484. https://doi.org/10.1186/s12889-021-11533-x

80. Kim, J., Schiavon, S., & Brager, G. (2018). Personal comfort models – A new paradigm in thermal comfort for occupant-centric environmental control. *Building and Environment*, *132*, 114–124. https://doi.org/10.1016/j.buildenv.2018.01.023

81. Kong, D., Liu, H., Wu, Y., Li, B., Wei, S., & Yuan, M. (2019). Effects of indoor humidity on building occupants' thermal comfort and evidence in terms of climate adaptation. *Building and Environment*, *155*, 298–307. https://doi.org/10.1016/j.buildenv.2019.02.039

82. Kosonen, R., & Tan, F. (2004). Assessment of productivity loss in air-conditioned buildings using PMV index. *Energy and Buildings*, *36*(10), 987–993. https://doi.org/10.1016/j.enbuild.2004.06.021

83. Kraus, C., Ganger, S., Losak, J., Hahn, A., Savli, M., Kranz, G. S., Baldinger, P., Windischberger, C., Kasper, S., & Lanzenberger, R. (2014). Gray matter and intrinsic network changes in the posterior cingulate cortex after selective serotonin reuptake inhibitor intake. *NeuroImage*, *84*, 236–244. https://doi.org/10.1016/j.neuroimage.2013.08.036

84. Künn, S., Palacios, J., & Pestel, N. (2019). Indoor Air Quality and Cognitive Performance. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3460848

85. Künn, S., Palacios, J., & Pestel, N. (2023). Indoor Air Quality and Strategic Decision Making. *Management Science*, mnsc.2022.4643. https://doi.org/10.1287/mnsc.2022.4643

86. Kyaga, S., Landén, M., Boman, M., Hultman, C. M., Långström, N., & Lichtenstein, P. (2013). Mental illness, suicide and creativity: 40-Year prospective total population study. *Journal of Psychiatric Research*, *47*(1), 83–90. https://doi.org/10.1016/j.jpsychires.2012.09.010

87. Lan, L., Tang, J., Wargocki, P., Wyon, D. P., & Lian, Z. (2022a). Cognitive performance was reduced by higher air temperature even when thermal comfort was maintained over the 24–28°C range. *Indoor Air*, *32*(1). https://doi.org/10.1111/ina.12916

88. Lan, L., Tang, J., Wargocki, P., Wyon, D. P., & Lian, Z. (2022b). Cognitive performance was reduced by higher air temperature even when thermal comfort was maintained over the 24–28°C range. *Indoor Air*, *32*(1). https://doi.org/10.1111/ina.12916

89. Lan, L., Wargocki, P., Wyon, D. P., & Lian, Z. (2011). Effects of thermal discomfort in an office on perceived air quality, SBS symptoms, physiological responses, and human performance: The effects of thermal discomfort on health and human performance. *Indoor Air*, *21*(5), 376–390. https://doi.org/10.1111/j.1600-0668.2011.00714.x

90. Lan, L., Xia, L., Hejjo, R., Wyon, D. P., & Wargocki, P. (2020). Perceived air quality and cognitive performance decrease at moderately raised indoor temperatures even when clothed for comfort. *Indoor Air*, *30*(5), 841–859. https://doi.org/10.1111/ina.12685

91. Levinson, M., Geller, A. C., & Allen, J. G. (2021). Health Equity, Schooling Hesitancy, and the Social Determinants of Learning. *The Lancet Regional Health - Americas*, *2*, 100032. https://doi.org/10.1016/j.lana.2021.100032

92. Levy-Gigi, E., Szabó, C., Kelemen, O., & Kéri, S. (2013). Association Among Clinical Response, Hippocampal Volume, and FKBP5 Gene Expression in Individuals with Posttraumatic Stress Disorder Receiving Cognitive Behavioral Therapy. *Biological Psychiatry*, *74*(11), 793–800. https://doi.org/10.1016/j.biopsych.2013.05.017

93. Lewis, P. A., Knoblich, G., & Poe, G. (2018). How Memory Replay in Sleep Boosts Creative Problem-Solving. *Trends in Cognitive Sciences*, *22*(6), 491–503. https://doi.org/10.1016/j.tics.2018.03.009

94. Liesefeld, H. R., & Janczyk, M. (2019). Combining speed and accuracy to control for speed-accuracy trade-offs(?). *Behavior Research Methods*, *51*(1), 40–60. https://doi.org/10.3758/s13428-018-1076-x

95. Lumpkin, L., & Jayaraman, S. (2022, October 24). Schools got $122 billion to reopen last year. Most has not been used. *The Washington Post*. https://www.washingtonpost.com/education/2022/10/24/covid-spending-schools-students-achievement/

96. MacLeod, C. M. (2006). Stroop Effect in Language. In *Encyclopedia of Language & Linguistics* (pp. 161–165). Elsevier. https://doi.org/10.1016/B0-08-044854-2/00871-3

97. MacNaughton, P., Pegues, J., Satish, U., Santanam, S., Spengler, J., & Allen, J. (2015). Economic, Environmental and Health Implications of Enhanced Ventilation in Office Buildings. *International Journal of Environmental Research and Public Health*, *12*(11), 14709–14722. https://doi.org/10.3390/ijerph121114709

98. Maddalena, R., Mendell, M. J., Eliseeva, K., Chan, W. R., Sullivan, D. P., Russell, M., Satish, U., & Fisk, W. J. (2015). Effects of ventilation rate per person and per floor area on perceived air quality, sick building syndrome symptoms, and decision-making. *Indoor Air*, *25*(4), 362–370. https://doi.org/10.1111/ina.12149

99. Madore, K. P., Jing, H. G., & Schacter, D. L. (2016). Divergent creative thinking in young and older adults: Extending the effects of an episodic specificity induction. *Memory & Cognition*, *44*(6), 974–988. https://doi.org/10.3758/s13421-016-0605-z

100. Makinen, T., Palinkas, L., Reeves, D., Paakkonen, T., Rintamaki, H., Leppaluoto, J., & Hassi, J. (2006). Effect of repeated exposures to cold on cognitive performance in humans. Physiology & Behavior, 87(1), 166–176. https://doi.org/10.1016/j.physbeh.2005.09.015

101. Maula, H., Hongisto, V., Naatula, V., Haapakangas, A., & Koskela, H. (2017). The effect of low ventilation rate with elevated bioeffluent concentration on work performance, perceived indoor air quality, and health symptoms. *Indoor Air*, *27*(6), 1141–1153. https://doi.org/10.1111/ina.12387

102. Maula, H., Hongisto, V., Östman, L., Haapakangas, A., Koskela, H., & Hyönä, J. (2016). The effect of slightly warm temperature on work performance and comfort in open-plan offices—A laboratory study. *Indoor Air*, *26*(2), 286–297. https://doi.org/10.1111/ina.12209

103. Mazloumi, A., Golbabaei, F., Mahmood Khani, S., Kazemi, Z., Hosseini, M., Abbasinia, M., & Farhang Dehghan, S. (2014). Evaluating Effects of Heat Stress on Cognitive Function among Workers in a Hot Industry. *Health Promotion Perspectives*, *4*(2), 240–246.

104. McMorris, T. (2016). History of Research into the Acute Exercise–Cognition Interaction. In *Exercise-Cognition Interaction* (pp. 1–28). Elsevier. https://doi.org/10.1016/B978-0-12-800778-5.00001-3

105. Meadow, J. F., Altrichter, A. E., Kembel, S. W., Kline, J., Mhuireach, G., Moriyama, M., Northcutt, D., O'Connor, T. K., Womack, A. M., Brown, G. Z., Green, J. L., & Bohannan, B. J. M. (2014). Indoor airborne bacterial communities are influenced by ventilation, occupancy, and outdoor air source. *Indoor Air*, *24*(1), 41–48. https://doi.org/10.1111/ina.12047

106. Melikov, A. K. (2020). COVID-19: Reduction of airborne transmission needs paradigm shift in ventilation. *Building and Environment*, *186*, 107336. https://doi.org/10.1016/j.buildenv.2020.107336

107. Mitchell, M. R., & Potenza, M. N. (2017). Stroop, Cocaine Dependence, and Intrinsic Connectivity. In *The Neuroscience of Cocaine* (pp. 331–339). Elsevier. https://doi.org/10.1016/B978-0-12-803750-8.00034-8

108. Moore, D. W., Bhadelia, R. A., Billings, R. L., Fulwiler, C., Heilman, K. M., Rood, K. M. J., & Gansler, D. A. (2009). Hemispheric connectivity and the visual–spatial divergent-thinking component of creativity. *Brain and Cognition*, *70*(3), 267–272. https://doi.org/10.1016/j.bandc.2009.02.011

109. Morawska, L., Allen, J., Bahnfleth, W., Bluyssen, P. M., Boerstra, A., Buonanno, G., Cao, J., Dancer, S. J., Floto, A., Franchimon, F., Greenhalgh, T., Haworth, C., Hogeling, J., Isaxon, C., Jimenez, J. L., Kurnitski, J., Li, Y., Loomans, M., Marks, G., … Yao, M. (2021). A paradigm shift to combat indoor respiratory infection. *Science*, *372*(6543), 689–691. https://doi.org/10.1126/science.abg2025

110. Morawska, L., Tang, J. W., Bahnfleth, W., Bluyssen, P. M., Boerstra, A., Buonanno, G., Cao, J., Dancer, S., Floto, A., Franchimon, F., Haworth, C., Hogeling, J., Isaxon, C., Jimenez, J. L., Kurnitski, J., Li, Y., Loomans, M., Marks, G., Marr, L. C., … Yao, M. (2020). How can airborne transmission of COVID-19 indoors be minimised? *Environment International*, *142*, 105832. https://doi.org/10.1016/j.envint.2020.105832

111. Navaratnam, S., Nguyen, K., Selvaranjan, K., Zhang, G., Mendis, P., & Aye, L. (2022). Designing Post COVID-19 Buildings: Approaches for Achieving Healthy Buildings. *Buildings*, *12*(1), 74. https://doi.org/10.3390/buildings12010074

112. Niemelä, R., Seppänen, O., Korhonen, P., & Reijula, K. (2006). Prevalence of building-related symptoms as an indicator of health and productivity. *American Journal of Industrial Medicine*, *49*(10), 819–825. https://doi.org/10.1002/ajim.20370

113. Niza, I. L., De Souza, M. P., Da Luz, I. M., & Broday, E. E. (2024). Sick building syndrome and its impacts on health, well-being and productivity: A systematic literature review. *Indoor and Built Environment*, *33*(2), 218–236. https://doi.org/10.1177/1420326X231191079

114. P., M., X., C., J., B., J., C.-L., J., S., A., B., & J., A. (2018). Energy savings, emission reductions, and health co-benefits of the green building movement. *Journal of Exposure Science & Environmental Epidemiology*, *28*(4), 307–318. https://doi.org/10.1038/s41370-017-0014-9

115. Palinkas, L. A., Makinen, T. M., Paakkonen, T., Rintamaki, H., Leppaluoto, J., & Hassi, J. (2005). Influence of seasonally adjusted exposure to cold and darkness on cognitive performance in circumpolar residents. *Scandinavian Journal of Psychology*, *46*(3), 239–246. https://doi.org/10.1111/j.1467-9450.2005.00453.x

116. Pampati, S., Rasberry, C. N., McConnell, L., Timpe, Z., Lee, S., Spencer, P., Moore, S., Mead, K. R., Murray, C. C., Deng, X., Iachan, R., Tripathi, T., Martin, S. B., & Barrios, L. C. (2022). Ventilation Improvement Strategies Among K–12 Public Schools—The National School COVID-19 Prevention Study, United States, February 14–March 27, 2022. *MMWR. Morbidity and Mortality Weekly Report*, *71*(23), 770–775. https://doi.org/10.15585/mmwr.mm7123e2

117. Parkinson, T., Schiavon, S., de Dear, R., & Brager, G. (2021). Overcooling of offices reveals gender inequity in thermal comfort. *Scientific Reports*, *11*(1), 23684. https://doi.org/10.1038/s41598-021-03121-1

118. Paustenbach, D. J. (2001). The History and Biological Basis of Occupational Exposure Limits for Chemical Agents. In R. Harris (Ed.), *Patty's Industrial Hygiene* (1st ed.). Wiley. https://doi.org/10.1002/0471435139.hyg041

119. Periáñez, J. A., Lubrini, G., García-Gutiérrez, A., & Ríos-Lago, M. (2021). Construct Validity of the Stroop Color-Word Test: Influence of Speed of Visual Search, Verbal Fluency, Working Memory, Cognitive Flexibility, and Conflict Monitoring. *Archives of Clinical Neuropsychology: The Official Journal of the National Academy of Neuropsychologists*, *36*(1), 99–111. https://doi.org/10.1093/arclin/acaa034

120. Persily, A. (2020, November 15). *Quit Blaming ASHRAE Standard 62.1 for 1000 ppm CO2*. https://tsapps.nist.gov/publication/get_pdf.cfm?pub_id=929997

121. Persily, A. (2021). Please Don't Blame Standard 62.1 for 1000 ppm CO2. *ASHRAE Journal*, *63*(2), 1–2.

122. Pistochini, T., Ellis, M., Meyers, F., Frasier, A., Cappa, C., & Bennett, D. (2023). Method of test for CO2-based demand control ventilation systems: Benchmarking the state-of-the-art and the undervalued potential of proportional-integral control. *Energy and Buildings*, *301*, 113717. https://doi.org/10.1016/j.enbuild.2023.113717

123. Porras-Salazar, J. A., Schiavon, S., Wargocki, P., Cheung, T., & Tham, K. W. (2021). Meta-analysis of 35 studies examining the effect of indoor temperature on office work performance. *Building and Environment*, *203*, 108037. https://doi.org/10.1016/j.buildenv.2021.108037

124. Reichardt, A. (2016). Operating Expenses and the Rent Premium of Sustainable Buildings. In A. Reichardt, *Sustainability in Commercial Real Estate Markets* (pp. 37–63). Springer Fachmedien Wiesbaden. https://doi.org/10.1007/978-3-658-11739-9_3

125. Richardson, M. B., Li, P., Gohlke, J. M., & Allison, D. B. (2018). Effects of Indoor Thermal Environment on Human Food Intake, Productivity, and Comfort: Pilot, Randomized,

Crossover Trial. *Obesity (Silver Spring, Md.)*, *26*(12), 1826–1833. https://doi.org/10.1002/oby.22328

126. Riham Jaber, A., Dejan, M., & Marcella, U. (2017). The Effect of Indoor Temperature and CO 2 Levels on Cognitive Performance of Adult Females in a University Building in Saudi Arabia. *Energy Procedia*, *122*, 451–456. https://doi.org/10.1016/j.egypro.2017.07.378

127. Ritter, S. M., Strick, M., Bos, M. W., Van Baaren, R. B., & Dijksterhuis, A. (2012). Good morning creativity: Task reactivation during sleep enhances beneficial effect of sleep on creative performance. *Journal of Sleep Research*, *21*(6), 643–647. https://doi.org/10.1111/j.1365-2869.2012.01006.x

128. Rodeheffer, C. D., Chabal, S., Clarke, J. M., & Fothergill, D. M. (2018). Acute Exposure to Low-to-Moderate Carbon Dioxide Levels and Submariner Decision Making. *Aerospace Medicine and Human Performance*, *89*(6), 520–525. https://doi.org/10.3357/AMHP.5010.2018

129. Rogers, C. J., Tolmie, A., Massonnié, J., & Thomas, M. S. C. (2023). Complex cognition and individual variability: A mixed methods study of the relationship between creativity and executive control. *Frontiers in Psychology*, *14*, 1191893. https://doi.org/10.3389/fpsyg.2023.1191893

130. Rostron, J. (2008). Sick building syndrome: A review of causes, consequences and remedies. *Journal of Retail & Leisure Property*, *7*(4), 291–303. https://doi.org/10.1057/rlp.2008.20

131. Sachs, J. D., Abdool Karim, S., Aknin, L., Allen, J., Brosbøl, K., Cuevas Barron, G., Daszak, P., Espinosa, M. F., Gaspar, V., Gaviria, A., Haines, A., Hotez, P., Koundouri, P., Larraín Bascuñán, F., Lee, J.-K., Pate, M., Polman, P., Reddy, S., Serageldin, I., … Bartels, J. G. E. (2020). Lancet COVID-19 Commission Statement on the occasion of the 75th session of the UN General Assembly. *The Lancet*, *396*(10257), 1102–1124. https://doi.org/10.1016/S0140-6736(20)31927-9

132. Saenen, N. D., Provost, E. B., Viaene, M. K., Vanpoucke, C., Lefebvre, W., Vrijens, K., Roels, H. A., & Nawrot, T. S. (2016). Recent versus chronic exposure to particulate matter air pollution in association with neurobehavioral performance in a panel study of primary schoolchildren. *Environment International*, *95*, 112–119. https://doi.org/10.1016/j.envint.2016.07.014

133. Saenz, J. L., Wong, R., & Ailshire, J. A. (2018). Indoor air pollution and cognitive function among older Mexican adults. *Journal of Epidemiology and Community Health*, *72*(1), 21. https://doi.org/10.1136/jech-2017-209704

134. Salimifard, P., Buonocore, J. J., Konschnik, K., Azimi, P., VanRy, M., Cedeno Laurent, J. G., Hernández, D., & Allen, J. G. (2022). Climate policy impacts on building energy use, emissions, and health: New York City local law 97. *Energy*, *238*, 121879. https://doi.org/10.1016/j.energy.2021.121879

135. Satish, U., Mendell, M. J., Shekhar, K., Hotchi, T., Sullivan, D., Streufert, S., & Fisk, W. J. (2012). Is CO_2 an Indoor Pollutant? Direct Effects of Low-to-Moderate CO_2 Concentrations on Human Decision-Making Performance. *Environmental Health Perspectives*, *120*(12), 1671–1677. https://doi.org/10.1289/ehp.1104789

136. Scarpina, F., & Tagini, S. (2017). The Stroop Color and Word Test. *Frontiers in Psychology*, *8*. https://doi.org/10.3389/fpsyg.2017.00557

137. Schiavon, S., Yang, B., Donner, Y., Chang, V. W.-C., & Nazaroff, W. W. (2017). Thermal comfort, perceived air quality, and cognitive performance when personally controlled air movement is used by tropically acclimatized persons. *Indoor Air*, *27*(3), 690–702. https://doi.org/10.1111/ina.12352

138. Seppänen, O., Fisk, W. J., & Lei, Q. (2006). *Effect of temperature on task performance in office environment.pdf*. Ernest Orlando Lawrence Berkeley National Lab. https://eta-publications.lbl.gov/sites/default/files/lbnl-60946.pdf

139. Shah, J. J., Smith, S. M., & Vargas-Hernandez, N. (2003). Metrics for measuring ideation effectiveness. *Design Studies*, *24*(2), 111–134. https://doi.org/10.1016/S0142-694X(02)00034-0

140. Shehab, M. A., & Pope, F. D. (2019). Effects of short-term exposure to particulate matter air pollution on cognitive performance. *Scientific Reports*, *9*(1), 8237. https://doi.org/10.1038/s41598-019-44561-0

141. Sherman, M. (1984). *Simplified Model of Thermal Comfort*.

142. Snow, S., Boyson, A. S., Paas, K. H. W., Gough, H., King, M.-F., Barlow, J., Noakes, C. J., & Schraefel, M. C. (2019). Exploring the physiological, neurophysiological and cognitive performance effects of elevated carbon dioxide concentrations indoors. *Building and Environment*, *156*, 243–252. https://doi.org/10.1016/j.buildenv.2019.04.010

143. Solano Rodriguez, B., Drummond, P., & Ekins, P. (2017). Decarbonizing the EU energy system by 2050: An important role for BECCS. *Climate Policy*, *17*(sup1), S93–S110. https://doi.org/10.1080/14693062.2016.1242058

144. Steinberg, H., Sykes, E. A., Moss, T., Lowery, S., LeBoutillier, N., & Dewey, A. (1997). Exercise enhances creativity independently of mood. *British Journal of Sports Medicine*, *31*(3), 240–245. https://doi.org/10.1136/bjsm.31.3.240

145. Stevenson, C., Smal, I., Baas, M., Dahrendorf, M., Grasman, R., Tanis, C., Scheurs, E., Sleiffer, D., & van der Maas, H. (2020). *Automated AUT scoring using a Big Data variant of the Consensual Assessment Technique*. University of Amsterdam. https://pure.uva.nl/ws/files/62306010/ABBAS_report_200711_final.pdf

146. Stewart, W. F. (2003). Lost Productive Time and Cost Due to Common Pain Conditions in the US Workforce. *JAMA*, *290*(18), 2443. https://doi.org/10.1001/jama.290.18.2443

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

148. Stroop, J. R. (1992). Studies of interference in serial verbal reactions. *Journal of Experimental Psychology: General*, *121*(1), 15–23. https://doi.org/10.1037/0096-3445.121.1.15

149. Surawattanasakul, V., Sirikul, W., Sapbamrer, R., Wangsan, K., Panumasvivat, J., Assavanopakun, P., & Muangkaew, S. (2022). Respiratory Symptoms and Skin Sick Building Syndrome among Office Workers at University Hospital, Chiang Mai, Thailand: Associations with Indoor Air Quality, AIRMED Project. *International Journal of Environmental Research and Public Health*, *19*(17), 10850. https://doi.org/10.3390/ijerph191710850

150. Tanis, C., Stevenson, C., & Baas, M. (2018). *Automatic Scoring of the Alternative Uses Task*.

151. Terrapin Bright Green LLC. (2012). *The Economics of Biophilia: Why Designing with Nature in Mind Makes Financial Sense*.

152. Tham, K. W. (2004). Effects of temperature and outdoor air supply rate on the performance of call center operators in the tropics. *Indoor Air, 14 Suppl 7*, 119–125. https://doi.org/10.1111/j.1600-0668.2004.00280.x

153. The Lancet COVID-19 Commission Task Force & on Safe Work, Safe School, and Safe Travel. (2022). *The First Four Healthy Building Strategies Every Building Should Pursue to Reduce Risk from COVID-19*. https://static1.squarespace.com/static/5ef3652ab722df11fcb2ba5d/t/62c87da27d568623d2b6ce0e/1657306531592/HPH-18706_LancetLessons_HealthyBuildings_HighRes-2.pdf

154. The Lancet COVID-19 Commission & Task Force on Safe Work, Safe School, and Safe Travel. (2022). *Proposed Non-infectious Air Delivery Rates (NADR) for Reducing Exposure to Airborne Respiratory Infectious Diseases*. https://static1.squarespace.com/static/5ef3652ab722df11fcb2ba5d/t/637740d40f35a9699a7fb05f/1668759764821/Lancet+Covid+Commission+TF+Report+Nov+2022.pdf

155. Thom, S. R., Bhopale, V. M., Hu, J., & Yang, M. (2017a). Increased carbon dioxide levels stimulate neutrophils to produce microparticles and activate the nucleotide-binding domain-like receptor 3 inflammasome. *Free Radical Biology & Medicine*, *106*, 406–416. https://doi.org/10.1016/j.freeradbiomed.2017.03.005

156. Thom, S. R., Bhopale, V. M., Hu, J., & Yang, M. (2017b). Inflammatory responses to acute elevations of carbon dioxide in mice. *Journal of Applied Physiology (Bethesda, Md.: 1985)*, *123*(2), 297–302. https://doi.org/10.1152/japplphysiol.00343.2017

157. Tranel, B. (2020). How Should Office Buildings Change in a Post-Pandemic World? *Gensler Research & Insight*. https://www.gensler.com/blog/how-should-office-buildings-change-in-a-post-pandemic-world

158. Ukkola-Vuoti, L., Kanduri, C., Oikkonen, J., Buck, G., Blancher, C., Raijas, P., Karma, K., Lähdesmäki, H., & Järvelä, I. (2013). Genome-Wide Copy Number Variation Analysis in Extended Families and Unrelated Individuals Characterized for Musical Aptitude and Creativity in Music. *PLoS ONE*, *8*(2), e56356. https://doi.org/10.1371/journal.pone.0056356

159. United States Environmental Protection Agency. (n.d.). *NAAQS Table*. Retrieved September 4, 2023, from https://www.epa.gov/criteria-air-pollutants/naaqs-table

160. United States Government Accountability Office. (2012). *WORKPLACE SAFETY AND HEALTH Multiple Challenges Lengthen OSHA's Standard Setting* (Report to Congressional Requesters GAO-12-330).

161. US Department of Labor. (2010). *Absences from work of employed full-time wage and salary*.

162. US DOE. (2015). Chapter 5: Increasing Efficiency of Building Systems and Technologies. *Quadrennial Technology Review*.

163. Van Laar, E., Van Deursen, A. J. A. M., Van Dijk, J. A. G. M., & De Haan, J. (2017). The relation between 21st-century skills and digital skills: A systematic literature review. *Computers in Human Behavior*, *72*, 577–588. https://doi.org/10.1016/j.chb.2017.03.010

164. Vartanian, O., Beatty, E. L., Smith, I., Forbes, S., Rice, E., & Crocker, J. (2019). Measurement matters: The relationship between methods of scoring the Alternate Uses Task and brain activation. *Current Opinion in Behavioral Sciences*, *27*, 109–115. https://doi.org/10.1016/j.cobeha.2018.10.012

165. Wang, J., Li, T., Lv, Y., Kraus, V. B., Zhang, Y., Mao, C., Yin, Z., Shi, W., Zhou, J., Zheng, T., Kinney, P. L., Ji, J., Tang, S., & Shi, X. (2020). Fine Particulate Matter and Poor Cognitive Function among Chinese Older Adults: Evidence from a Community-Based, 12-Year Prospective Cohort Study. *Environmental Health Perspectives*, *128*(6), 067013. https://doi.org/10.1289/EHP5304

166. Wargocki, P., & Wyon, D. P. (2007a). The Effects of Moderately Raised Classroom Temperatures and Classroom Ventilation Rate on the Performance of Schoolwork by Children (RP-1257). *HVAC&R Research*, *13*(2), 193–220. https://doi.org/10.1080/10789669.2007.10390951

167. Wargocki, P., & Wyon, D. P. (2007b). The Effects of Outdoor Air Supply Rate and Supply Air Filter Condition in Classrooms on the Performance of Schoolwork by Children (RP-1257). *HVAC&R Research*, *13*(2).

168. Wargocki, P., Wyon, D. P., & Fanger, P. O. (2004). The performance and subjective responses of call-center operators with new and used supply air filters at two outdoor air supply rates. *Indoor Air*, *14 Suppl 8*, 7–16. https://doi.org/10.1111/j.1600-0668.2004.00304.x

169. Wargocki, P., Wyon, D. P., Sundell, J., Clausen, G., & Fanger, P. O. (2000). The effects of outdoor air supply rate in an office on perceived air quality, sick building syndrome (SBS)

symptoms and productivity. *Indoor Air*, *10*(4), 222–236. https://doi.org/10.1034/j.1600-0668.2000.010004222.x

170. Weuve, J. (2012). Exposure to Particulate Air Pollution and Cognitive Decline in Older Women. *Archives of Internal Medicine*, *172*(3), 219. https://doi.org/10.1001/archinternmed.2011.683

171. World Economic Forum. (2023). *Future of Jobs Report*. World Economic Forum.

172. World Green Building Council. (2014). *Health, Wellbeing & Productivity in Offices: The next chapter for green buildings*. https://worldgbc.org/wp-content/uploads/2022/03/compressed_WorldGBC_Health_Wellbeing__Productivity_Full_Report_Dbl_Med_Res_Feb_2015-1.pdf

173. Yin, J., Arfaei, N., MacNaughton, P., Catalano, P. J., Allen, J. G., & Spengler, J. D. (2019). Effects of biophilic interventions in office on stress reaction and cognitive function: A randomized crossover study in virtual reality. *Indoor Air*, *29*(6), 1028–1039. https://doi.org/10.1111/ina.12593

174. You, R., Ho, Y.-S., & Chang, R. C.-C. (2022). The pathogenic effects of particulate matter on neurodegeneration: A review. *Journal of Biomedical Science*, *29*(1), 15. https://doi.org/10.1186/s12929-022-00799-x

175. Young, A., Parikh, S., Dedesko, S., Bliss, M., Xu, J., Zanobetti, A., Miller, S., & Allen, J. (2024). Home indoor air quality and cognitive function over one year for people working remotely during COVID-19. *Building and Environment*, 111551. https://doi.org/10.1016/j.buildenv.2024.111551

176. Zhang, F., De Dear, R., & Hancock, P. (2019a). Effects of moderate thermal environments on cognitive performance: A multidisciplinary review. *Applied Energy*, *236*, 760–777. https://doi.org/10.1016/j.apenergy.2018.12.005

177. Zhang, F., De Dear, R., & Hancock, P. (2019b). Effects of moderate thermal environments on cognitive performance: A multidisciplinary review. *Applied Energy*, *236*, 760–777. https://doi.org/10.1016/j.apenergy.2018.12.005

178. Zhang, S., & Zhu, N. (2022). Gender differences in thermal responses to temperature ramps in moderate environments. *Journal of Thermal Biology*, *103*, 103158. https://doi.org/10.1016/j.jtherbio.2021.103158

179. Zhang, X., Wargocki, P., & Lian, Z. (2016). Human responses to carbon dioxide, a follow-up study at recommended exposure limits in non-industrial environments. *Building and Environment*, *100*, 162–171. https://doi.org/10.1016/j.buildenv.2016.02.014

180. Zhang, Y., Tolmie, A., & Gordon, R. (2022). The Relationship between Working Memory and Arithmetic in Primary School Children: A Meta-Analysis. *Brain Sciences*, *13*(1), 22. https://doi.org/10.3390/brainsci13010022

181. Zutshi, A., Mendy, J., Sharma, G. D., Thomas, A., & Sarker, T. (2021). From Challenges to Creativity: Enhancing SMEs' Resilience in the Context of COVID-19. *Sustainability*, *13*(12), 6542. https://doi.org/10.3390/su13126542

182. Þórólfsdóttir, E., Árnadóttir, Á., & Heinonen, J. (2023). Net zero emission buildings: A review of academic literature and national roadmaps. *Environmental Research: Infrastructure and Sustainability*, *3*(4), 042002. https://doi.org/10.1088/2634-4505/ad0e80