Impact of Car-Cabin Physical Environments on Driving Performance: A Multimodal Approach

by

Chao Wang

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APPROVED:

Professor Shichao Liu
Worcester Polytechnic Institute
Advisor

Professor Richard Lopez
Worcester Polytechnic Institute
Committee Member

Professor Nan Ma
Worcester Polytechnic Institute
Committee Member

Professor Erin T. Solovey
Worcester Polytechnic Institute
Committee Member

Professor Xiaojun Cheng
Boston University
Committee Member

Dr. John C. Elson
Ford Motor Company
Committee Member

Professor Yingzi Lin
Northeastern University
Committee Member

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Abstract

This PhD dissertation investigates the relationship between Indoor Environmental Quality (IEQ) and human cognitive performance, addressing critical knowledge gaps with significant implications for various domains, such as the in-car environment, driving performance, and secondary cognitive task performance (e.g., navigation) during driving. My research comprises three distinct projects, each contributing to a comprehensive understanding of this complex relationship. The first project involves a systematic literature review that emphasizes the substantial impact of IEQ factors, including indoor air quality, thermal environments, lighting conditions, noise condition, and non-light visual factors, on cognitive performance. These findings underscore the paramount importance of monitoring and enhancing these environmental aspects to sustain optimal cognitive proficiency. The review work inspired me to resolve the inconsistencies in results identified in the literature through rigorous experimental design and neuroimaging techniques. In particular, the second project of this dissertation investigates the effects of CO_2 levels and body odors on driving performance using a driving simulator, areas not extensively explored previously. Using electroencephalography (EEG) and functional near-infrared spectroscopy (fNIRS), the study reveals the influence of these factors on driving and cognitive performance. Most specifically, it was found that body odor positively affects N-back task response accuracy while elevated CO_2 up to 3500 ppm does not reduce driving performance significantly. The study notes that body odor decreases $(\theta+\alpha)/\beta$ and θ/β ratios, suggesting heightened alertness and attention. The third project focuses on the impact of thermal environment, interior lighting at night, and their interplay (Hue-Heat Hypothesis) on driving performance. While the results do not support Hue-Heat Hypothesis) in general and report limited impact of interior lighting at night, enhanced temperature exhibits a significant influence on drivers' in-car environment perception, physiological states, and deterioration on N-back task response accuracy. Additionally, increased temperatures correlate with higher EEG Delta band power spectral density and reduced Beta, indicating diminished mental engagement during driving. Collectively, this dissertation documents variations in driving data, survey responses, task performance, physiological states, and brain responses under different conditions. My dissertation fills crucial gaps in our understanding of how CO_2 levels, body odor, interior lighting at night, and temperature influence driving performance and secondary cognitive task related to driving. The findings contribute to ongoing efforts to optimize the in-car environment for enhanced driving experiences. Future investigations will aim to classify brain responses and physiological reactions to varied air quality, interior lighting, and temperature conditions.

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Wang, C., Zhang, F., Wang, J., Doyle, J. K., Hancock, P. A., Mak, C. M., & Liu, S. (2021). "How indoor environmental quality affects occupants' cognitive functions: A systematic review". Building and Environment, 107647

Wang, C., Lin, Y., Ptukhin,Y., & Liu, S. (2023). "Air quality in the car: how CO_2 and body odor affect drivers' cognition and driving performance?". Science of Total Environment, 168785

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Chapter 1: Introduction

1.1. Problem statement

The relationship between Indoor Environmental Quality (IEQ) and human cognitive functions has been a focal point of scholarly interest over recent years, as highlighted by numerous studies (Allen et al., 2016a; Coley et al., 2007a; Hygge & Knez, 2001a; Mendell & Heath, 2005a; Witterseh et al., 2004a). Cognitive functions encompass the brain-based capabilities necessary for carrying out tasks across a spectrum of complexity (Angevaren et al., 2008). These functions are crucially linked to learning, memory, reasoning, and problem-solving processes, with each function playing a vital role in assimilating new information (Staal, 2004). Given the considerable amount of time individuals spend indoors for educational or professional purposes, the IEQ can markedly influence cognitive functions, thereby affecting learning outcomes and work productivity. Previous literature reviews have categorized IEQ factors into several key areas, including indoor air quality (IAQ), thermal conditions, lighting, acoustics, office design and layout, biophilia and views, aesthetics, and the location and facilities available, underscoring their significant impact (Al Horr et al., 2016a; Fisk & Seppanen, 2007; Frontczak & Wargocki, 2011). The relationship between IEQ factors and cognitive function has been extensively studied; however, the results have frequently been inconsistent, especially in terms of how indoor air quality (IAQ) or thermal conditions affect cognitive functions. A potential reason for this variability is the limitations of traditional research methodologies, attributed to variations in research methodologies, participant demographics, the complexity of environmental settings, and constraints in measurement approaches (Hygge & Knez, 2001a; Mendell & Heath, 2005a; Witterseh et al., 2004a). Additionally, the utilization of surveys or computerized cognitive assessments, which may not effectively measure real-time brain activity or capture the nuanced effects of indoor environmental conditions on cognitive processes.

In addition, the earlier investigations predominantly took place within building environments. One example is the research on body odor that is a unique identifier of an individual and comprises a complex mix of numerous volatile organic compounds (VOCs) across various chemical classes (Gallagher et al., 2008). Their presence offers a crucial measure of air quality degradation in vehicle cabins due to passenger metabolism. Nevertheless, the impact of body odor on driving performance has been rarely studied. Driving performance encompasses the driver's capability to safely and efficiently maneuver the vehicle, make timely decisions, and react appropriately to diverse driving scenarios (Savino, 2009).

Heat and light have been separately identified as factors influencing cognitive function (Keis et al., 2014a; Knez, 1995; Schiavon et al., 2017a; F. Zhang & Dear, 2017). Additionally, the hue-heat hypothesisHeat and light have been separately identified as factors influencing cognitive function (Keis et al., 2014a; Schiavon et al., 2017a; F. Zhang & Dear, 2017) [ref]. Additionally, the hue-heat hypothesis that the color temperature of lighting can elicit perceptual and emotional reactions similar to those experienced with actual temperature changes (Mogensen & English, 1926), suggests a potential interactive effect on cognitive function. The hypothesis has been thoroughly investigated across various fields such as experimental psychology, applied psychology, and psychological ergonomics, focusing on how color temperatures might influence thermal comfort and perception (Berry, 1961; Fanger et al., 1977; Huebner et al., 2016; Toftum et al., 2018; Winzen et al., 2014). Therefore, despite the limited number of studies, the literature has reported the interactive effects of temperature and light on cognition in buildings perception (Huebner et al., 2016; Toftum et al., 2018; Winzen et al., 2014). In nowadays, interior ambient lighting has recently become a feature of luxury vehicles, aimed at enriching the driving experience and eliciting positive emotional responses from occupants (T. Kim et al., 2021; Park et al., 2016). Prior studies have demonstrated that interior ambient lighting, even when positioned outside the direct line of sight, can positively affect several facets of the driving context (Caberletti et al., 2010; van Huysduynen et al., 2017). However, more research is needed to better understand the impact of temperature, lighting and their interaction on driving performance.

Exploring the impact of in-car air quality, lighting conditions, and thermal environment, on drivers' cognitive state and driving performance is of crucial for public safety. Optimizing the car-cabin physical environment can potentially reduce car accidents that led to 2.1 million emergency department visits for injuries in one year, 2020 (CDC, 2023).

1.2. Research Objectives

This dissertation seeks to understand the intricate relationship between IEQ factors—such as air quality, thermal conditions, and lighting—and cognitive functions critical to learning and work, with a particular focus on driving performance. By addressing limitations in current research methodologies and employing neuroimaging tools like Electroencephalography (EEG) and functional Near-Infrared Spectroscopy (fNIRS), the dissertation endeavors to provide deeper insights into how IEQ impacts driving and cognitive performance, contributing to a broader understanding of environmental influences on human cognitive processes.

The overall objectives of this dissertation can be summarized as:

1) Bridge the divide between the IEQ factors and human cognitive performance, as well as discern whether distinct cognitive functions exhibited varying responses to diverse indoor environmental conditions.
2) Explore the impact of car-cabin physical environment, specifically focusing on CO_2 levels, body odors, thermal environment, and interior night lighting on driving performance and cognition.

One investigation supports the first objective:

A) In this investigation of review work, my research delved into various aspects of this relationship, aiming to comprehend how factors such as ventilation, thermal conditions, noise, and lighting impact cognitive function. Additionally, I sought to discern whether distinct cognitive functions, encompassing attention, perception, memory, language, and higher-order skills, exhibited varying responses to diverse indoor environmental conditions. This review work applies a specific text-mining approach to extract knowledge from thousands of identified and relevant published papers. My research also pursued the identification of limitations within prevailing IEQ and cognition studies, thus providing a roadmap for future research endeavors.

Two investigations support the second objective:

B) The first investigation was dedicated to exploring the impact of car-cabin variables, specifically focusing on CO_2 levels and body odors emanating from both drivers and/or passengers, on driving performance and cognition. Furthermore, I harnessed physiological sensors to scrutinize the influence of CO_2 and body odor on drivers' cognitive performance and physiological states. In light of this challenge, I employed two powerful and complementary neuroimaging techniques, namely EEG and fNIRS. My primary research question was to scrutinize the intricate interplay between CO_2 concentrations, body odors, and their influences on driving performance using a driving simulator, as well as subjective evaluations of the environment.

C) In the second investigation, I aimed to investigate the effect of temperature and interior lighting at night on driving performance, as well as the validation of the Hue-Heart Hypothesis within the context of driving. I systematically manipulated temperature and lighting conditions within the car cabin to observe their effects on driving performance, driver acceptance of the environment, alertness, and mood.

This dissertation provides a summary of the interconnections between the three investigations described in **Error! Reference source not found.**. Each investigation also resulted in one or more m anuscripts, presented in condensed form in the Summary of Methods and Research (Chapter 3) and in full in Appendices A-E. In Appendix A, the journal article "How indoor environmental quality affects occupants' cognitive functions: A systematic review" (published in *Building and Environment*), addresses the goals described in Objective 1, Investigation A. In Appendix B, the journal article "Air quality in the car: how CO_2 and body odor affect drivers' cognition and driving performance?" addresses the research goals described in Objective 2, Investigation B (published in *Science of Total Environment*). In Appendix C, the manuscript "Can EEG and fNIRS detect the effects of CO_2 exposure on drivers' cognition and driving performance?" In Appendix C, the manuscript "The influence of in-car air quality on drivers' brain states with hybrid fNIRS and EEG" (in preparation for submission to *Neuroimaging*) addresses the research goals described in Objective 2, Investigation B. In Appendix D, the article "Interactive Effects of Interior Ambient Light and Thermal environment on Comfort, Emotion, and Driving Performance" (in preparation for submission to *Science of Total Environment*) addresses research goals of Objective 2, Investigation C.

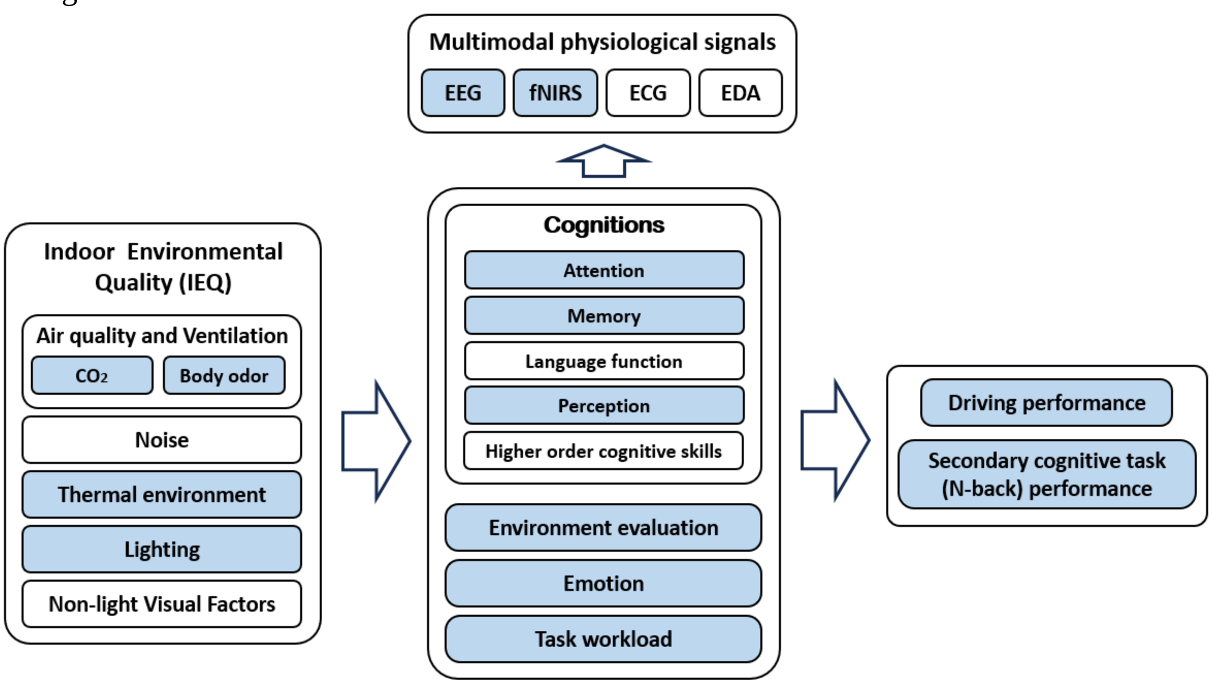


Figure 1. Illustration of the connections between the three research investigations conducted in the dissertation. The items with light blue color filled are included in this dissertation.

Chapter 2: Literature Review

This chapter provides a summary of selected sections from the literature reviews related to all the investigations detailed in Appendices A – D.

2.1. Indoor Environmental Quality

Given the considerable time individuals spend indoors for education or work, especially during the pandemic lockdowns, the quality of the indoor environment (IEQ) plays a crucial role in influencing occupants' cognitive functions, subsequently affecting their learning and work performance. Comprehensive reviews (Al Horr et al., 2016a; Fisk & Seppanen, 2007; Frontczak & Wargocki, 2011) have categorized the factors contributing to IEQ into several key areas, including indoor air quality (IAQ), thermal conditions, lighting, acoustics, office layout, biophilic design and external views, aesthetic appeal, as well as the building's location and available amenities. These factors collectively represent the major elements that impact the well-being and cognitive performance of indoor occupants.

A significant volume of research has demonstrated that factors such as poor indoor air quality (Mendell & Heath, 2005b), inadequate ventilation (Allen et al., 2016b; Coley et al., 2007b), unsuitable thermal conditions (Cui et al., 2013a; Lan et al., 2010), lighting condition (Hygge & Knez, 2001b), noise environment (Jahncke et al., 2011; Sundstrom et al., 1994), and layout of indoor space (Haynes, 2008) can negatively impact both learning and work performance. Despite the comprehensive insights provided by these and other key studies on the subject (Choi et al., 2014; Haverinen-Shaughnessy & Shaughnessy, 2015; Servilha et al., 2014; Wargocki & Wyon, 2007), there is a noted gap in their analysis concerning the differentiation of cognitive task types. This differentiation is critical because the influence of indoor environmental quality (IEQ) on performance may vary markedly across different cognitive tasks. For example, evidence suggests that simpler tasks might be less affected by environmental factors such as noise and temperature compared to more complex tasks (Hancock & Vasmatzidis, 2003; van Kempen et al., 2010)

For the indoor air quality, both CO_2 and body odor are two popular chemicals which are the metabolic products exist in the indoor environment. Increased CO_2 levels within buildings have been linked to a higher incidence of acute health symptoms (Apte, 2000; Erdmann et al., 2002) and adverse impacts on mental capabilities (Bloch-Salisbury et al., 2000; Scully et al., 2019; Twardella et al., 2012a). Elevated levels of CO_2 have been linked to reductions in human performance, notably in a variety of cognitive assessments. Research focusing on how CO_2 affects cognitive abilities in indoor environments suggests that even at levels below 5000 parts per million (ppm), the exposure can lead to immediate health concerns such as headaches, lethargy, and irritation of the eyes, nasal passages, and respiratory system (Daisey et al., 2003; Scully et al., 2019). These symptoms have been found to lessen as CO_2 concentrations decrease, even at levels under 800 ppm. Thus, CO_2's role extends beyond a simple indicator of IAQ to that of a direct contaminant. This distinction highlights CO_2 not just as a measure of pollutant exposure and ventilation efficiency but as a contributing factor to health and cognitive issues. CO_2 concentrations indoors are typically detrimental to the work performance and health of occupants, with levels under 1000 ppm considered safe, whereas concentrations of 2000 ppm or more are deemed unsanitary. The American Conference of Governmental Industrial Hygienists (ACGIH) has established a threshold of 5000 ppm CO_2 as the maximum allowable occupational exposure over an 8-hour time-weighted average, aimed at preventing serious health issues such as narcosis, enhanced respiratory activity, and asphyxiation (Assessment, 2009b). For the in-car environment, research by Fruin et al. (2011) into air quality within aircraft cabins during flight revealed that CO_2 levels could surpass 2500 ppm within 15–20 minutes in stationary vehicles with two occupants under recirculated air conditions, yet stayed below 800 ppm in vehicles in motion with outside air. In vehicles, CO_2 levels tend to rise due to occupants' exhalation, especially when heating, ventilation, and air conditioning (HVAC) systems are set to recirculate air. In such scenarios, CO_2 concentrations can easily exceed 3000 ppm in fully occupied vehicles with closed windows (Hudda & Fruin, 2018; Shu et al., 2015). However, for moving vehicles with even slightly opened windows, CO_2 accumulation is generally minimal, illustrating the effectiveness of natural ventilation in maintaining air quality.

Beyond CO_2, the process of metabolism in humans also produces distinctive body odors. These odors serve not only as personal identifiers but are comprised of a diverse array of volatile organic compounds (VOCs) spanning various chemical categories (Gallagher et al., 2008). The spectrum of chemical emissions from human sources, including CO_2, VOCs, and bioaerosols, is intrinsically linked to metabolic activities (Pandey & Kim, 2011; J. Wang et al., 2014). Such emissions, originating from both human breath and skin, play a role in altering the chemical composition of indoor environments, thereby exacerbating issues related to indoor air quality.

The thermal environment, defined as the indoor conditions that influence heat transfer, directly impacts an individual's thermal perception and consequently their overall thermal comfort. This comfort is subjectively assessed based on the ambient thermal conditions (ANSI/ASHRAE, 2017). Lighting significantly impacts human circadian rhythms and cognitive performance, primarily through its intensity, color, and distribution (Keis et al., 2014a). It serves as a powerful zeitgeber, synchronizing endogenous circadian rhythms with the external environment and is key in enhancing visual comfort and cognitive functions (Ochoa & Capeluto, 2006; Shieh & Lin, 2000; Zhou & Rau, 2018). Natural daylight, combining direct and indirect sunlight, is optimal for color rendering and matches the human visual system closely (D. H. W. Li, 2010).

2.2. Cognition

Cognitive capabilities comprise essential brain-based abilities that facilitate the execution of activities ranging from the simplest to the most complex tasks (Angevaren et al., 2008). These capabilities encompass learning, memory, reasoning, and problem-solving, each crucial for absorbing new information (Staal, 2004). Studies in neuroscience have established that cognitive performance correlates with activities in specific brain areas, highlighting their fundamental role in cognitive processes (Hampson et al., 2006; Stevens, 2009). This research focusing on car-cabin environments primarily investigates cognitive capabilities like attention, perception, memory, and advanced cognitive skills.

Attention is the mental faculty that allows individuals to focus on specific information elements while disregarding others (M. Eysenck, 2012). It is classified into sustained attention, which pertains to maintaining focus over prolonged periods (Barkley, 19970101; Hancock, 2013; Sarter et al., 2001a), selective attention, which involves filtering out distractions(Corbetta et al., 1991; Duncan, 1984; Fockert et al., 2001; Green & Bavelier, 2003), and divided attention, which deals with handling multiple tasks at once (Castel & Craik, 2003; McDowd & Craik, 1988; Somberg & Salthouse, 1982). Tools such as the Continuous Performance Task (CPT) (Shalev et al., 2011), reaction time assessments (Saltzman & Garner, 1948), Stroop tasks (C. M. MacLeod, 1992), the attention network test (J. W. MacLeod et al., 2010), and the dot-probe task (Fockert et al., 2001) are utilized to evaluate attention. Attention's capacity is limited; multitasking is challenging unless the task is well practiced, allowing for automatic processing (Cowan, 2001).

Perception involves the cognitive processes that detect, organize, identify, and interpret sensory inputs to make sense of the environment (Schacter et al., 2019). It serves as a crucial link to our surroundings, fundamental to daily activities. While some studies separate perception from cognition (Montemayor & Haladjian, 2017; Tacca, 2011), it is generally seen as a part of cognition, significantly influenced by an individual's expectations and prior knowledge (Coren, 2012; Matlin, 2009).

Memory is the cognitive function that encodes, stores, retrieves, and acquires knowledge when needed (Tse et al., 2007). It forms a vital part of our cognitive framework, critical for personal identity, learning, and the continuity of consciousness (M. W. Eysenck & Brysbaert, 2018a; Hancock, 2015). It includes explicit memory, involving conscious recall, and implicit memory, which functions without conscious knowledge (Roediger III et al., 2017).

Higher order cognition encompasses a complex and varied range of mental processes including reasoning, conceptualization, critical thinking, decision-making, and creativity. This level of cognition facilitates the understanding and execution of the necessary steps for problem-solving, exploring new learning areas, and engaging in creative thought (Akella, 2019). Central themes in higher order cognition research include executive functions, reasoning, planning, and problem-solving. Executive functions represent a group of intricate cognitive processes that assist individuals in managing their thoughts, skills, behaviors, and actions to achieve specific goals (Friedman et al., 2006). Essential executive functions include cognitive inhibition, cognitive flexibility, and emotional control, while advanced activities like reasoning, planning, problem-solving, and decision-making involve multiple underlying processes operating concurrently (Chan et al., 2008; Diamond, 2013). Reasoning is the process through which problems are resolved by forming logical connections among different elements of the problem (Zimmerman, 2000), serving as a fundamental component of intelligent thought. Planning involves setting and achieving goals through the formulation of strategies and selection of actions based on expected outcomes (Hayes-Roth & Hayes-Roth, 1979), playing a crucial role in attention shifting, decision-making, self-regulation, and monitoring. Problem-solving is a critical skill that encompasses the creation and selection of solutions, relying on mental strategies and heuristics, and is influenced by physical health (Diamond, 2013). Research has shown that indoor environmental conditions such as lighting, noise, and temperature can significantly impact problem-solving abilities (Hygge & Knez, 2001b; Knez, 1995; Knez & Kers, 2000a).

2.3. Driving and associated secondary task

Driving performance involves a driver's capability to operate a vehicle safely and efficiently, requiring skills such as effective vehicle control, quick decision-making, and responsive actions to various driving situations (Savino, 2009). Impairments in cognitive functions can lead to a decline in these abilities, which can be objectively measured through metrics related to the vehicle's operation and the driving environment. The change in driving performance can be detected through various metrics related to the vehicle and the environment. To measure driving performance, driving speed and speed variability (Baron & Kalsher, 1998, 1998; Ott et al., 2008), distance from the vehicle in front (Baron & Kalsher, 1998, 1998), lateral position within the lane (Caberletti et al., 2010; Ott et al., 2008), measuring break reaction time (Raudenbush et al., 2009) have been used. This research used the speed variability and lateral position within the lane to measure the driving performance.

N-back task is one of the most common tasks involving working memory to impose an additional mental workload for the cognition assessment (Mehler et al., 2012). It is wide used as the secondary task during driving task. In the n-back task, participants listened to single-digit numbers and responded verbally with the number presented in n-positions before (n-back) the current number, right after it is read.

2.4. Effects of IEQ on cognition

2.4.1. Evidence in buildings

Indoor air quality, a pivotal facet of IEQ, exerts a significant influence on cognitive performance, as highlighted by research demonstrating the substantial impact of indoor air pollutant levels on cognitive functions (J. Chen & Schwartz, 2009; Chiu et al., 2013; Cleary et al., 2018a; Kicinski, Vermeir, Van Larebeke, Den Hond, Schoeters, Bruckers, Sioen, Bijnens, Roels, & Baeyens, 2015). Research consistently highlights the substantial impact of indoor air pollutants on cognitive functions such as attention (J. Chen & Schwartz, 2009), perception (Coley et al., 2007a), and memory (Ailshire & Crimmins, 2014a).

Elevated indoor pollutant levels are linked to a noticeable decline in cognitive abilities, underscoring the importance of monitoring and enhancing air quality. Prior studies have shown that exposure to increased CO_2 can impair essential cognitive functions, including attention, decision-making, and perception (Norbäck et al., 2013; Scully et al., 2019). For instance, Satish et al. (2012) demonstrated that decision-making capabilities were compromised at CO_2 concentrations of 1000 ppm and 2500 ppm compared to 600 ppm, with 22 participants exposed to three different CO_2 levels for 2.5 hours from a controlled source. Their findings revealed a significant downturn in cognitive performance as CO_2 levels increased, particularly at 2500 ppm and in tasks requiring greater cognitive effort. Similarly, Allen et al. (2016) reported that cognitive performance in decision-making tasks diminished for 24 individuals in environments with raised CO_2 levels (550, 945, and 1400 ppm) over an eight-hour period, noting a 21% decrease in cognitive scores for every 400 ppm rise in CO_2 concentration. Scully et al. (2019) explored the impact of CO_2 on mental efficiency, physiological states, and perceived air quality across a range from 600 to 5000 ppm. This research noted an uptick in self-reported fatigue and a downturn in concentration abilities after 2 to 3 hours of exposure to CO_2 levels exceeding 1200 ppm. All these findings above underscore CO_2 not merely as a benign marker of potential air pollutants but as an active environmental stressor. Nevertheless, the evidence regarding CO_2's effect on attention spans is mixed. For instance, Twardella et al. (2012) observed that while high CO_2 concentrations in educational settings did not significantly impair students' overall attention span, there was a noticeable decrease in performance accuracy for tasks requiring focused attention, like character processing, suggesting that air quality can subtly influence cognitive functions.

Despite the limited research on the effects of body odor on the productivity of individuals in dense indoor settings, it is essential to understand their role in air pollution within enclosed spaces such as vehicle cabins, which is significantly influenced by the metabolic processes of occupants. While numerous studies have explored the emission of body odors and their influence on the perceived quality of air (Assessment, 2009a; Fanger, 1988; Kruza & Carslaw, 2019), only a handful have delved into the specific effects of body odors on immediate health symptoms and performance amidst exposure to other pollutants. A particular field study (Assessment, 2009a) investigating volatile body odor emissions from students in a classroom setting noted 12 organic compounds during lecture sessions. This study also highlighted periods of examinations as times when students exhibited heightened stress compared to during lectures, resulting in a 43% increase in classroom CO_2 concentration under examination conditions (up to 700 ppm) compared to lecture environments. Gall et al. (2020) conducted a groundbreaking study on body odor emissions, focusing specifically on the rates of isoprene emission during stress versus relaxation. Their findings suggest that stress conditions lead to a significant increase in isoprene emissions. Cecchetto et al. (2019) provided insights into the influence of body odor on decision-making, demonstrating that body odors could subtly sway moral judgments by intensifying the emotional experience during the decision-making process, even when the odors are not consciously detected.

Research has demonstrated that thermal conditions significantly affect cognitive functions, such as attention, memory, and high-order cognitive skills, though results vary. For instance, one study found that 117 high-school students performed worse on attention tests under uncomfortable thermal conditions (Mazon, 2014). Another experiment showed optimal test results at 26 ℃ when students could adjust their own fan, unlike at 23 ℃ or 29 ℃ (Schiavon et al., 2017a). Additionally, rapid temperature increases from 22 °C were linked to improved concentration in one study (F. Zhang & Dear, 2017), while another reported better attention at 16 °C compared to higher temperatures of 26 °C and 36 °C (Hu & Maeda, 2020). However, tests like the cursor positioning and star count showed no significant differences in attention across various temperatures (Tanabe & Nishihara, 2004). Optimal memory performance was recorded between 22 °C and 26 °C (Cui et al., 2013a). Even in extreme conditions of 43.3/27.8 °C (dry/wet bulb), university students' short-term memory did not significantly differ from performance in a comfortable 26.7/17.2 °C environment (Wing & Touchstone, 1965). However, at very high temperatures of 48.9/31.1 °C, memory recall declined. Memory performance was stable between 16.7 °C and 32.2 °C but deteriorated above 32.2 °C to 35 °C. No significant correlations were found between thermal conditions and memory in studies across six temperature cycles (F. Zhang & Dear, 2017). These observations underscore the complexity of how thermal environments affect cognitive functions, suggesting a need for further study to clarify these relationships. Thermal comfort significantly affects higher cognitive functions, with warmer temperatures associated with quicker reaction times. Working memory, evaluated using a forward digit span test, deteriorated in cooler (21.7 °C) and warmer conditions (28.6 °C) compared to a neutral temperature (25.2 °C) (X. Wang et al., 2019). Participants performed tasks faster at 32 °C than at lower temperatures (27, 24, and 19 °C) (Lan et al., 2009a), possibly due to a desire to complete tasks quickly in uncomfortable conditions or increased metabolic activation (Hancock, 1993). Another study noted faster task execution as temperatures rose (Holland et al., 1985), though the optimal processing speed was observed at 26 °C (Schiavon et al., 2017a), indicating that 26 °C might be ideal for cognitive performance.

The influence of indoor lighting on cognitive performance is substantial, as noted by Wang et al. (2021). Properly configured lighting setups are known to boost focus, visual perception, and memory retention (El-Nasr et al., 2009; Huang et al., 2015a; Mohebian et al., 2018a; Mott et al., 2012a), whereas poor lighting conditions are linked to decreased cognitive abilities (Keis et al., 2014b; Kretschmer et al., 2012a). This underscores the importance of developing precise lighting strategies. Recent studies have shown that the spectrum, timing, and duration of light exposure can affect alertness and mood, leading to the development of new metrics based on radiometric quantities (Bansal et al., 2017; H. Li et al., 2017; Price et al., 2019). The impact of lighting on attention varies, with some studies indicating gender differences and interactions with environmental conditions. For example, a correlated color temperature of 4,300K improved sustained attention in undergraduates (Huang et al., 2015b), and changes in illuminance influenced attention differently depending on room temperature (Mohebian et al., 2018b). Dynamic lighting adjustments have been shown to enhance performance in visual tasks (El-Nasr et al., 2009), yet some studies found no significant effects of lighting on children's concentration or night shift workers' attention (Mott et al., 2012b). Memory performance can also be influenced by light, with specific color temperatures affecting mood and cognitive tasks (Knez, 1995; Knez & Enmarker, 1998). While cool-white lighting may impair long-term memory recall compared to warm-white, the effects of blue-enriched lighting on memory tasks in students showed no significant impact

(Keis et al., 2014a). Additionally, interactions between light and other environmental factors like noise were generally not significant, except for gender-specific effects on mood and memory under different light conditions (Knez, 1995). In problem-solving tasks, the color temperature of lighting can play a role, with "warm" white light (3,000K) being conducive to better performance. Moreover, people generally find high-frequency lighting more pleasant, potentially enhancing their problem-solving abilities (Knez, 2014).

Temperature and lighting might have interactive effects of human's perception, namely "hue-heat hypothesis." It suggests that color perception can affect thermal comfort and sensations. This suggests that lighting with varied color temperatures might evoke sensations of warmth or coolness that diverge from the actual temperature, thereby affecting the perceived environment. This hypothesis has attracted considerable interest due to its implications in environmental psychology and design. This hypothesis has been substantiated through various studies (Berry, 1961; Fanger et al., 1977; Huebner et al., 2016; Toftum et al., 2018; Winzen et al., 2014), highlighting the potential of color to impact our sensation of temperature. This enhancement is attributed to its positive effects on drivers' perceptions, notably in terms of the perceived spaciousness of the interior and their capacity to regulate the environment within the vehicle. The interplay between light color and thermal sensation introduces a layer of complexity in understanding how the physical driving environment affects drivers' comfort, emotional state, and performance. Research efforts in this domain have sought to ascertain whether specific wavelengths of light or color can induce feelings of warmth or coolness in individuals. A key investigation by Fanger and colleagues (1977), involving a small cohort of 16 individuals, revealed only a slight variance in thermal sensation—specifically, a 0.48 °C difference—when contrasting environments illuminated by blue versus red light. This finding highlights the subtle yet measurable impact that lighting color can have on human thermal perception. Similarly, an investigation conducted within an aircraft cabin by Winzen et al. (2014) found that yellow light created a sensation of warmth compared to blue light, impacting the perception of indoor temperature. Huebner et al. (2016) observed considerable differences in thermal perception across a range of correlated color temperatures (CCT) from 2700 K to 6500 K, particularly noting that individuals tended to wear more clothing under cooler lighting conditions. Toftum et al. (2018) pinpointed that the influence of correlated color temperature (CCT) on thermal sensation becomes significant in thermally neutral environments but diminishes when individuals are already feeling slightly warm or cool. This phenomenon is attributed to the predominant role of the body's heat balance in dictating thermal responses under such conditions. These intricate interactions between light and thermal environments underscore the complexity of the physical driving environment's effects on driver comfort, emotional well-being, and performance.

2.4.2. Evidence in car cabins

The impact of the vehicle cabin environment on cognitive abilities can detrimentally affect the driving performance. Consequently, creating a comfortable interior environment within the vehicle cabin has garnered attention, particularly in the realm of luxury vehicles. Research indicates that driving performance is intricately linked to various factors within the vehicle cabin, such as air quality, thermal conditions, lighting, and acoustics (Chowdhury, 2015; Morris & Pilcher, 2016; van Huysduynen et al., 2017; C. Wang et al., 2024). The degradation of a driver's cognitive functions can precipitate a drop in driving performance. This decline can be quantitatively assessed using several vehicles and environmental metrics. Key performance indicators include driving speed and its variability, the following distance to the vehicle ahead, the vehicle's lateral positioning within its lane, and the driver's brake reaction time. These metrics have been adopted in the research by Baron and Kalsher (1998), Beh and Hirst (1999), Caberletti et al. (2010), Ott et al.(2008), and Raudenbush et al. (2009) offering a framework to evaluate driving performance objectively.

Research has demonstrated the significant role that air quality inside vehicles plays in affecting driver performance. A study by Raudenbush et al. (2009) examined the effects of exposing drivers to three different olfactory conditions: peppermint, cinnamon, and a control group with no odor. The findings revealed that exposure to cinnamon and peppermint scents resulted in heightened alertness levels, a reduction in the perceived effort and time required to perform driving tasks, and less frustration with the driving process. In a parallel investigation, Baron & Kalsher (1998) evaluated how a pleasant scent environment impacts drivers' cognitive abilities, alertness, mood, and perceived task load. This study found notable improvements in both the drivers' performance and their state of alertness. These investigations collectively highlight the potential of utilizing specific scents within the vehicle environment to positively influence driver alertness and overall performance.

Thermal environment within the vehicle cabin plays a significant role in the effect on driving and cognitive performance. Nazi et al. (2015) conducted an analysis comparing driving performance across three distinct temperature settings to assess the influence of thermal comfort. Their research identified a notable impact of temperature on the variability of driving speed, highlighting temperature's significant role in driving performance dynamics. Further supporting this, Daanen et al. (2003) suggested that optimal driving performance might be achieved by maintaining a neutral temperature within the vehicle, pointing to the potential benefits of thermal regulation on driver efficiency. In a study analyzing traffic collision data, Hou et al. (2022) found a correlation between ambient temperatures and an increased likelihood of motor vehicle accidents in cities like New York and Chicago, potentially indicating the broader implications of temperature on road safety. Additionally, the interior lighting of a vehicle has been acknowledged as a factor that can affect driving performance, suggesting that both thermal and lighting conditions inside a vehicle play crucial roles in influencing driver behavior and safety.

Interior lighting serves to indirectly light the passenger area of a vehicle, playing a crucial role in enhancing both the subjective experience and objective visual capabilities of the occupants. The vehicles often incorporate interior ambient lighting as a means to enhance the driving experience and evoke a positive emotional response in the driver (Park et al., 2016). Studies (Caberletti et al., 2010; van Huysduynen et al., 2017) have shown that ambient lighting can positively affect users' experiences by being pleasant, informative, and/or alleviating boredom. This form of lighting is essential not just for improving the aesthetic and subjective impression of the vehicle's interior but also for boosting visual performance. Research by Caberletti et al. (2010) highlighted that interior lighting, even outside the direct line of sight, can significantly enhance perceptions of space, safety, functionality, and the quality of the vehicle's interior. Furthermore, Liu et al. (2021) found that the correlated color temperature of light could impact drivers' reaction times and pupil sizes, pointing to the tangible effects of lighting conditions on driver safety and performance. This body of research underlines the importance of developing optimized vehicle lighting systems that not only improve the driving experience but also potentially enhance driver safety and vehicle functionality, as evidenced by other studies (Kretschmer et al., 2012a; Lan et al., 2009b, 2011a; Mott et al., 2012a).

2.5. Multimodal physiological measurements for cognition and driving

The relationship between cognitive abilities and driving performance has been extensively studied, with neuroimaging technologies like EEG and fNIRS providing invaluable insights. EEG has emerged as a pivotal tool in the exploration and understanding of cognitive processes (Alsuradi et al., 2020; Kaur & Kaur, 2015; Niedermeyer & da Silva, 2005). This non-invasive technique records electrical activity in the brain, offering insights into neural dynamics across various cognitive states and functions. The application of EEG in cognitive science has significantly contributed to the understanding of the brain's operational mechanisms during different tasks, enabling researchers to examine the correlations between brain activity and cognitive performance more closely. EEG stands out for its exceptional temporal resolution, capturing the brain's electrical activity and changes in neural oscillations in real-time, making it ideal for investigating dynamic cognitive processes (Alsuradi et al., 2020; Niedermeyer & da Silva, 2005). Research employing EEG has significantly contributed to understanding the brain's operational mechanisms across different cognitive tasks, highlighting its versatility in cognitive research (M. X. Cohen, 2014). Simultaneously, fNIRS measures changes in cerebral blood flow and hemoglobin concentrations using near-infrared light, providing crucial insights into cortical hemodynamics and thus serving as a valuable adjunct to EEG in understanding cognitive processes (Yücel et al., 2021). fNIRS offers several advantages, including portability, and absence of electromyographic (EMG) and blink interference, while its signals are closely related to the blood oxygen level dependent (BOLD) signals from functional magnetic resonance imaging (fMRI), the gold standard in cerebral hemodynamics assessment (Huppert et al., 2006; Strangman et al., 2002). The integration of EEG and fNIRS provides deeper insights into the brain's neural dynamics associated with various cognitive functions, as evidenced by research from the studies (Aghajani et al., 2017; Ahn et al., 2016; He et al., 2019; Y. Liu et al., 2017; Unni et al., 2017). This underscores the complementary strengths of EEG and fNIRS in providing a comprehensive view of the brain's response to environmental and cognitive stimuli. The synergistic combination of EEG and (fNIRS has emerged as a notably advanced neuroimaging technique, surpassing the accuracy of each modality used independently.

EEG and fNIRS have been used to provide insights into how IEQ influence cognitive processes for a long time due to their portability and minimal setup requirement. The quality of indoor environments has a pronounced impact on cognitive function, affecting attention, memory, and decision-making processes. Factors such as air quality, lighting, and temperature have been extensively studied for their effects on cognitive performance, with emerging research employing EEG or fNIRS to investigate these relationships further (Lan et al., 2011a; J. Lee et al., 2022; M. Sharooni et al., 2023). In a study focusing on the effects of CO_2 on daytime sleepiness, Jin et al. (2022) found that EEG sensitivity was significantly altered by a brief exposure to high CO_2 levels (40,000 ppm), yet the duration of exposure had no impact. This led to the suggestion that EEG might not effectively detect sleepiness caused by CO_2 exposure due to its high sensitivity to environmental CO_2 concentrations. Conversely, employing EEG alongside other modalities has revealed the adverse effects of elevated CO_2 levels on cognitive functions such as working memory, mental workload, and visual concentration (J. Lee et al., 2022). Historically, despite evidence suggesting even low CO_2 concentrations can influence physiological responses, including EEG signals (Jacobson et al., 2019; R. J. Thomas, 2014), environmental CO_2 has not been widely acknowledged as a contributing factor to physiological artifacts in EEG studies (Xu et al., 2011). Another study identified by Snow et al. (2019) who reported a lack of significant correlation between EEG-detected brain activity, self-reported sleepiness, and CO_2 levels, despite observing a connection between sleep duration and EEG patterns. The study by M. Sharooni et al. (2023) demonstrated promising results in using fNIRS to recognize individual thermal sensations and comfort conditions, marking a significant advancement in environmental control strategies. By accurately interpreting brain signals related to thermal experiences, fNIRS offers an innovative, objective method to assess indoor thermal comfort.

This multimodal approach has been widely used in driving studies to detect changes in drivers' physical states across various driving tasks. Nguyen et al. (2017) explored the detection of driver drowsiness, a critical factor in automobile accidents, by integrating EEG and fNIRS technologies. Their findings revealed significant variations in oxyhemoglobin levels and beta band power within the frontal lobe when comparing awake to drowsy states. These changes serve as early drowsiness indicators, appearing before observable signs such as the first eye closure, offering a potential method for early detection of drowsiness. Otmani et al. (2005) investigated the effects of partial sleep deprivation and prolonged driving on driver alertness and performance. Their study found that sleep deprivation primarily influenced the drivers’ sleepiness levels (measured by the Karolinska Sleepiness Scale, KSS) without significantly affecting the (alpha+theta) spectral power in EEG recordings. However, extended driving durations impacted both sleepiness levels and EEG spectral power, indicating the combined effect of fatigue and driving duration on alertness and performance. Unni et al. (2017) focused on assessing cognitive working memory load during real-world driving scenarios using fNIRS. Their research accurately predicted changes in working memory load across participants, demonstrating the effectiveness of fNIRS in monitoring cognitive load in dynamic environments. In a driving context, Unni et al. (2017) demonstrated the efficacy of fNIRS in monitoring brain activation and accurately predicting working memory load, achieving a mean Pearson correlation of 0.61 between the induced and predicted loads. He et al. (2019). further explored the differentiation of cognitive task loads during simulated driving by analyzing EEG signals. Their study confirmed the ability to distinguish between varying levels of cognitive load and validated that a modified n-back task could effectively increase cognitive load, as indicated by changes in EEG power in the alpha band. These studies collectively highlight the critical impact of cognitive functions on driving performance and the potential of EEG and fNIRS technologies in enhancing our understanding of this relationship, offering pathways to improve driver safety through early detection and intervention strategies.

For the EEG features analysis, utilization of Power Spectral Density (PSD) analysis as a key to explore cognitive performance metrics. The PSD computation for each dataset was performed with the MNE software (Gramfort et al., 2013), adhering to protocols set forth by Gramfort et al. (2014). This procedure segmented brain activity into four principal frequency bands: delta (δ) (1–4 Hz), theta (θ) (4–8 Hz), alpha (α) (8–13 Hz), and beta (β) (13–30 Hz), using the Welch wavelet transform technique as specified by Al-Fahoum & Al-Fraihat (2014). Welch’s technique was instrumental in deriving the power within these bands, highlighting the total spectral power as well. The analysis gave particular attention to the theta band, recognized for its links to sleep necessity by the studies (Aeschbach et al., 1997; Buckelew et al., 2009; Cajochen et al., 1995), and the alpha band, associated with drowsiness as noted in studies (Kecklund & Åkerstedt, 1993; Simon et al., 2011) and cognitive functions such as memory performance (Klimesch, 1999). Furthermore, variations in mental workload were observed to affect theta and alpha bands as reported by Borghini et al. (2014), while changes in beta band activity were tied to arousal and stress levels (Kuo et al., 2016; J. Zhang et al., 2021). Delta band activity, relevant for its role in complex cognitive task engagement and sensory integration, was also examined (Dimitriadis et al., 2010). It may also play a role in processing complex tasks (Harmony, 2013), underscoring its significance in attention and response to olfactory stimuli. In addition to PSD values, ratio indices such as α/β, $(\theta+\alpha)/\beta$, θ/β, and $(\theta+\alpha)/(\beta+\alpha)$ were also calculated to enhance the differentiation between cognitive states. This approach was informed by studies (Eoh et al., 2005; Jap et al., 2009; Wen &

Aris, 2020) , which highlighted the value of these ratios in reflecting mental attentiveness and cognitive processing capacity. These indices were chosen for their reduced sensitivity to noise and increased specificity. The study of Hasegawa and Oguri (2006) shows distinct links between α (indicative of relaxation) and β (associated with stimulation) brain activities. It employs the α/β ratio to monitor ongoing shifts in mental attentiveness. The θ/β in EEG studies (Clarke et al., 2019), initially thought to represent arousal in Attention-Deficit/Hyperactivity Disorder (AD/HD), is now believed to indicate cognitive processing capacity. Furthermore, the EEG probes' regions of interest (ROI) were categorized into frontal, central, and parietal areas, as depicted in Figure 2 of Liang et al. (Liang et al., 2018). This segmentation allowed for a nuanced analysis of brain activity patterns across different regions, providing a comprehensive view of the cognitive effects associated with various driving conditions.

For the fNIRS features, hemoglobin oxygenation (HbO) and deoxygenation (HbR) statistics are frequently utilized as key features within the field and noted by von Lühmann et al. (von Lühmann et al., 2020; Yücel et al., 2021). The fNIRS features from various parameters, including the amplitude of HbO and HbR, the slope of these values, the temporal gap between their positive and negative peaks, and their maximum or minimum values recorded. The feature extraction was meticulously tailored to the regions of interest (ROI) within the brain and differentiated across various driving scenarios. Specifically, the brain ROIs were categorized into the prefrontal cortex (PFC), left prefrontal cortex (LPFC), and right prefrontal cortex (RPFC). This categorization allowed for a detailed analysis of cognitive load and brain activity patterns across different segments of the prefrontal cortex.

Chapter 3: Methods

This chapter provides a summary of the methods employed in all the investigations presented in Appendices A-E of this dissertation.

3.1. Systematic literature review regarding the effects of IEQ on cognition

To enhance comprehension of the relationship between IEQ and cognitive performance, we categorized IEQ factors into five primary categories: IAQ, thermal environment, noise, lighting, and non-light visual factors, which were then correlated with six cognitive functions: attention, perception, memory, language function, higher-order cognitive skills, and social cognition. It's important to note that this review did not encompass transient indoor environmental factors like music and natural soundscapes, despite acknowledging their potential cognitive benefits. This decision was based on the variable and often inconclusive evidence regarding their impact on cognitive functions (Hallam et al., 2002; Huang & Shih, 2011; Newbold et al., 2017; Proverbio et al., 2018; Thompson et al., 2012). Furthermore, the review excluded discussions on the influence of IEQ on the cognitive development of children (Dadvand et al., 2015). To thoroughly explore the impact of indoor environmental quality (IEQ) on cognitive performance, my research methodology involved a comprehensive search strategy and a two-pronged review approach. The initial phase comprised a broad search across several databases and sources, including Google Scholar, ScienceDirect, Springer, NCBI, ASHRAE, and proceedings from the Indoor Air and Healthy Buildings conferences. Subsequently, the analysis of the gathered literature was conducted using two distinct methods: a traditional manual review and a modern, data-driven text-mining review.

The manual review meticulously evaluated studies for their direct insights into the relationship between specific IEQ factors and cognitive functions, detailing the experimental designs, measurement tools, and key findings. Despite its labor-intensive nature, this method allowed for a detailed quantitative synthesis of research findings, following the precedents set by in review studies (Y. Li et al., 2007; Sundell et al., 2011). The literature was selected based on its explicit examination of the IEQ-cognition relationship, drawing from an array of scientific journals, conference proceedings, and relevant books, adhering to a set of predefined criteria. For the literature search, an initial scan utilized keywords associated with cognitive performance, such as "cognitive performance," "performance tasks," "cognitive function," "productivity," along with specific cognitive abilities like "attention," "perception," "memory," "language function," and "higher order cognitive skills." For IEQ factors, keywords included "IAQ," "ventilation," "thermal environment," "noise," "lighting," and "non-light visual factors." The selection of papers adhered to strict inclusion and exclusion criteria to ensure the relevance and quality of the included studies. Laboratory-based studies were required to be conducted in controlled environmental settings, while field studies needed detailed quantification of environmental factors. Exclusions were made for studies lacking quantitative IEQ measurements or those that did not assess cognitive performance under varying IEQ conditions with statistical analysis. The focus was narrowed to studies examining specific cognitive functions. Only performance tests that directly assessed these functions were considered, excluding those that combined multiple cognitive assessments without individual function scores. My review of indoor environmental quality (IEQ) and its impact on cognition revealed inconsistent findings, ranging from significant associations (both positive and negative) to no detectable link. Some studies showed mixed outcomes across different tests and participant groups. To quantify these relationships, we ranked the association between IEQ and cognitive performance on a scale from 0 to 2: "0" indicates no association, "1" represents mixed results, and “2” signifies a clear, significant association ($p < 0.05$). Cases without reported p-values were marked as “N/A,” providing a structured summary of the varying effects of IEQ on cognition.

Recognizing that many studies offer indirect insights into the IEQ-cognition nexus, a text-mining review was employed to uncover underlying associations within the vast body of literature. This innovative approach facilitated the extraction of nuanced information from thousands of studies, complementing the direct evidence gleaned from the manual review (J. Thomas et al., 2011). It is a specialized branch of data mining, is adept at processing both unstructured and semi-structured text data sources, turning them into analyzable datasets (Fan, n.d.). Recognized for its ability to uncover meaningful patterns and insights from naturally written documents (Tan, 1999). this approach proves indispensable for conducting comprehensive literature reviews, especially when dealing with voluminous data beyond manual analysis capabilities. Employing this technique allowed us to efficiently parse through unstructured texts, successfully condensing and visualizing critical insights. Initially, we pinpointed 8,133 studies linking IEQ and cognition through their abstracts or keywords, utilizing a specific search strategy on Scopus. Subsequently, we employed VOSviewer (van Eck & Waltman, 2009) to map out the relationships within our dataset, revealing key patterns between IEQ and cognition. This tool highlighted how certain concepts, like ventilation and indoor air quality, are interconnected. Additionally, it helped identify emerging research areas by analyzing trends in keyword occurrences over time.

3.2. Effects of CO_2 and body odor on driving and secondary task performance

3.2.1. Experiment design

3.2.1.1. Participants

We enrolled 25 students from Worcester Polytechnic Institute (WPI) through posters and emails, with the study's procedures, risks, and participant responsibilities detailed in an IRB-approved consent form, approved by WPI’s Institutional Review Board (IRB-19-0672). Prior to inclusion, candidates underwent a screening for simulator sickness—a condition affecting 2%-8% of individuals during simulations with extensive maneuvers (Akinwuntan et al., 2005)—using the Simulator Sickness Questionnaire (SSQ) (Kennedy et al., 1993), a standard tool for assessing susceptibility to simulator-induced discomfort (Balk et al., 2017). Due to symptoms of simulator sickness, four from the initial 29 were excluded, leaving 25 participants (15 males, 10 females, aged 18-22, mean age 19.88). A G*Power analysis (Faul et al., 2007) indicated a required sample of 19 (ANOVA: Repeated measures, within factors with effect size of 0.25 and power of 0.8) to adequately assess the effects of six CO_2 and body odor scenarios, considering this a study of six separate conditions.

3.2.1.2. Driving simulator and in-car environment setup

The experiment setup closely mimic conditions of a congested two-lane road, gathering detailed data on metrics like speed, acceleration, lane positioning, and steering behavior. The setup included a driving simulator featuring a control computer loaded with Carnetsoft’s software (Wim van Winsum, Groningen, the Netherlands), three projectors, a curved screen, Logitech G29 controls, an audio setup, and a simulated car interior. This system, powered by a computer with a GeForce GTX 770 GPU and an i7-9790 CPU running Windows 10 PRO with 32 GB RAM, projected a broad 210º view across three screens positioned around the driver (Figure 2) (C. Wang et al., 2024). The driving interface included a Logitech G29 steering wheel and pedals, providing realistic feedback and controls for the simulation. Additionally, a footswitch was integrated for cognitive task inputs, which will be detailed later. The simulator’s audio capabilities enhanced the realism with sounds of engine operations and tire movements.

Figure 2. Panorama of the driving simulator cabin (~ 2.94 m^3) and screen; The cabin was made of a metal frame, polyethylene boards, and clear acrylic plexiglass plastic boards. The seat was adjusted to make the participant's line of sight fall on the focal point on the apparent horizon line in the in-car environment displayed on this monitor

The experimental setup was equipped with a Fantech SH–56 CFM HRV for ventilation and a LEVOIT H13 air purifier to ensure air quality, maintaining cabin temperature and humidity at 24 ± 1 °C and 47 ± 2%, respectively. CO_2 concentrations within the car cabin were precisely regulated to 800, 1800, and 3500 ppm using a CO_2 meter, allowing for a detailed evaluation of its effects on driving performance and cognitive abilities. Additionally, the environment was altered with two body odor conditions by placing worn T-shirts within the cabin, a technique commonly used in olfactory research. Participants experienced one of the predetermined CO_2 levels during each session, with CO_2 measurements taken near the breathing zone using a CM-0001 CO_2 Sampling Data Logger (CO_2 METER), ensuring an accuracy of about ±30 ppm. The desired CO_2 levels were achieved by introducing CO_2 from an Airgas cylinder into the cabin, with natural exhalation accounting for the lowest CO_2 condition. This method of adjusting CO_2 for examining its influence on indoor environments aligns with established research protocols (Allen et al., 2016a; Satish et al., 2012a; X. Zhang et al., 2017a).

This investigation included two conditions regarding body odor within the vehicle: one with additional body odor not originating from the driver, and one without. Additional odor was introduced by placing six previously worn T-shirts in the vehicle, a method commonly adopted in olfactory studies (Haze et al., 2001; Munk et al., 2000; Rathinamoorthy & Thilagavathi, 2016). These T-shirts were provided by six healthy individuals (4 males, 2 females), aged 28 to 38 years (average age: 32.3 ± 4.5). Donors, confirmed as non-smokers without health conditions or medication that could alter olfactory perception, followed strict dietary and hygiene protocols to ensure odor consistency. Written consent was secured from each. They avoided alcohol, smoking, and specific foods, using fragrance-free body wash and towels laundered with unscented detergent for T-shirt pre-washing. The shirts, worn for over 12 hours post-shower, were collected over two days. Donors stored their T-shirts in odorless bags before lab submission, with all samples kept in a dark, dry place to avoid degradation.

In my research, we opted not to directly measure Volatile Organic Compounds (VOCs) within the car's interior during tests. Instead, my focus was on analyzing the chemical composition of body odor from worn T-shirts—one from a male and another from a female—without intending to link body odor levels to driving performance explicitly. Given the volatile nature of VOCs, we hypothesized their presence in the air, emanating from the T-shirts placed in the vehicle. For comparison, a clean shirt was also analyzed to serve as a control for baseline VOCs or similar compounds. Taking into account that body odor originates from various body regions (Natsch et al., 2006; Pandey & Kim, 2011), we prepared fabric samples from the chest, back, and armpit areas of the worn shirts and a clean shirt, each measuring 5 cm^2 and weighing between 440.7 and 472.8 mg. Using cotton samples from a clean shirt previously studied for VOCs on carpets (Katsoyiannis et al., 2008), we established a VOC baseline. Samples were individually extracted with methanol in glass bottles, then agitated on a shaker for 12 hours, and the solution was reduced to 1.5 ml for analysis by GC-MS (Agilent) using specific operational settings. VOC identification involved matching retention times with known standards and NIST spectral libraries. This methodology allowed us to select VOCs based on their presence in worn versus clean shirts, verifying each compound's profile against existing literature on skin volatiles.

Participants undertook a modified N-back task during the simulations to evaluate their working memory and cognitive abilities. These simulations were set on a digitally created two-lane road, each lane being 3.35 meters wide. The scenario featured a heavily trafficked highway demanding high-speed navigation, including frequent lane shifts, congestion, and the need for passing. Conducted under simulated daylight conditions free from weather-related visibility issues, such as fog or rain, each session was designed to last around 20 minutes.

The driving simulator was deployed to collect vehicle dynamics and positioning at 10 Hz, capturing key metrics such as speed, both forward and sideways, acceleration, steering behavior, and how much the vehicle strayed from its lane, as outlined in Appendix B (Appendix) Tables S1. Measures of sideways movement, lane positioning variance, and steering adjustments shed light on the driver's precision and identified common driving errors, especially regarding side control (Oron-Gilad et al., 2008). The deviation from the lane center and its variability, particularly measured while in the right lane to exclude the influence of overtaking, were analyzed to gauge lateral vehicle control. Steering variability also served as a gauge for the influence of environmental factors on driving (Thiffault & Bergeron, 2003).

3.2.1.3. Secondary task and questionnaires

The N-back task, essential for evaluating working memory and cognitive abilities during driving assessments, was adapted from a verbal variant detailed by Mehler et al. (2012). To circumvent potential interference from facial movements, not considered in my study, I employed a version similar to that by Solovey et al. (2014). In this adaptation, participants responded to numbers 0-9 shown on a screen at regular intervals while driving, identifying if the current number matched one shown N steps earlier, with "N" remaining fixed in a session to adjust task difficulty, as depicted in Figure 3 (C. Wang et al., 2024). The task, divided into 2-back, 1-back, and 0-back challenges, formed six sessions with tasks assigned randomly. Each session started with instructions, followed by the presentation of 16 numbers for response within set timeframes, concluding with a 140-second driving phase. Developed in Python, this program recorded each number's display time, session type, participant reaction time, and target status for analysis, treating missed targets as errors, thus measuring cognitive efficiency.

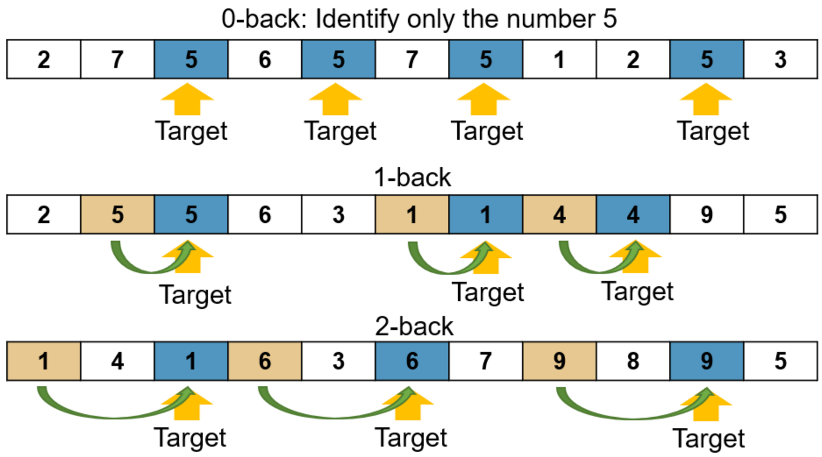


Figure 3. Example of N-back experimental paradigm to manipulate cognitive workload (C. Wang et al., 2024)

The study involved two questionnaires: a demographic one capturing age, gender, and driving history, and another assessing sleepiness, emotions, perceived air quality, and workload during tests. The Stanford Sleepiness Scale (SSS) (Hoddes et al., 1973) quantified alertness levels, the Self-Assessment Manikin (SAM) (Bradley & Lang, 1994) measured emotions across various scales, and the NASA-TLX evaluated workload across six dimensions (mental, physical, temporal demand, performance, effort, and frustration) (Hart, 2006), allowing participants to rate each on a scale of 1 to 7. Additionally, perceptions and acceptability of air quality were also assessed, reflecting participants' subjective evaluations.

3.2.1.4. EEG and fNIRS setup and data acquisition

Brain activity was captured using the g.Nautilus Research fNIRS-8 wireless headset and processed via the g.tec MATLAB-Simulink software, allowing for the simultaneous recording of EEG and fNIRS signals. The setup featured sixteen EEG channels and eight fNIRS channels, supported by low-power transmitters for EEG/fNIRS data. EEG electrode placement covered key brain regions including the frontal, central, and parietal areas, based on the International 10/10 system (Jasper, 1958), as displayed in Figure 5. The fNIRS optodes targeted the prefrontal cortex (PFC) with specific placements and utilized continuous-wave laser diodes at 760 nm and 850 nm for accurate brain activity measurement. The headset and optodes were affixed to the participant's head, with data relayed via Bluetooth to MATLAB for analysis, incorporating filters and settings to refine the data capture process, such as a 752 Hz sampling rate and specific bandpass and notch filters to enhance signal clarity. The system's design aimed to minimize motion artifacts and ensured snug cap fitting to reduce data distortion from movements or obstructions like hair.

This technology provided detailed monitoring of the PFC, critical for evaluating working memory. It combined EEG's broad coverage with fNIRS's focused analysis on the PFC, ensuring high-quality signals and efficient setup. The integration of EEG and fNIRS allowed for comprehensive brain activity analysis, with external markers synchronized for task initiation and completion signals, facilitating precise data collection throughout each n-back task session.

3.2.1.5. Procedure

Participants attended the lab four times (Figure 4) (C. Wang et al., 2024). The initial visit involved training on the driving simulator, an introduction to its controls, and a check for simulator sickness. Over the next three visits, they engaged in driving tasks under varying CO_2 conditions, with each visit consisting of two driving sessions—one with clean and the other with worn T-shirts in the cabin, presented in random order. The sequence of CO_2 exposure and T-shirt conditions was blinded, and the gap between visits averaged approximately one week (6.96 ± 2.87 days) with a minimum three-day break to ensure data reliability.

For the latter three visits, upon arrival, participants reported their sleep quality and sleepiness. Equipped with various sensors, they entered the simulator for an 18-minute driving task interspersed with six N-back tasks to vary cognitive demands. Following the drive, they exited to complete a survey on their current state and perceptions regarding air quality, which was deemed to be as effective as completing it inside the cabin. This interim allowed for the T-shirts to be exchanged. Participants then repeated the driving task under the same conditions. After completing all sessions, they received a debrief and compensation.

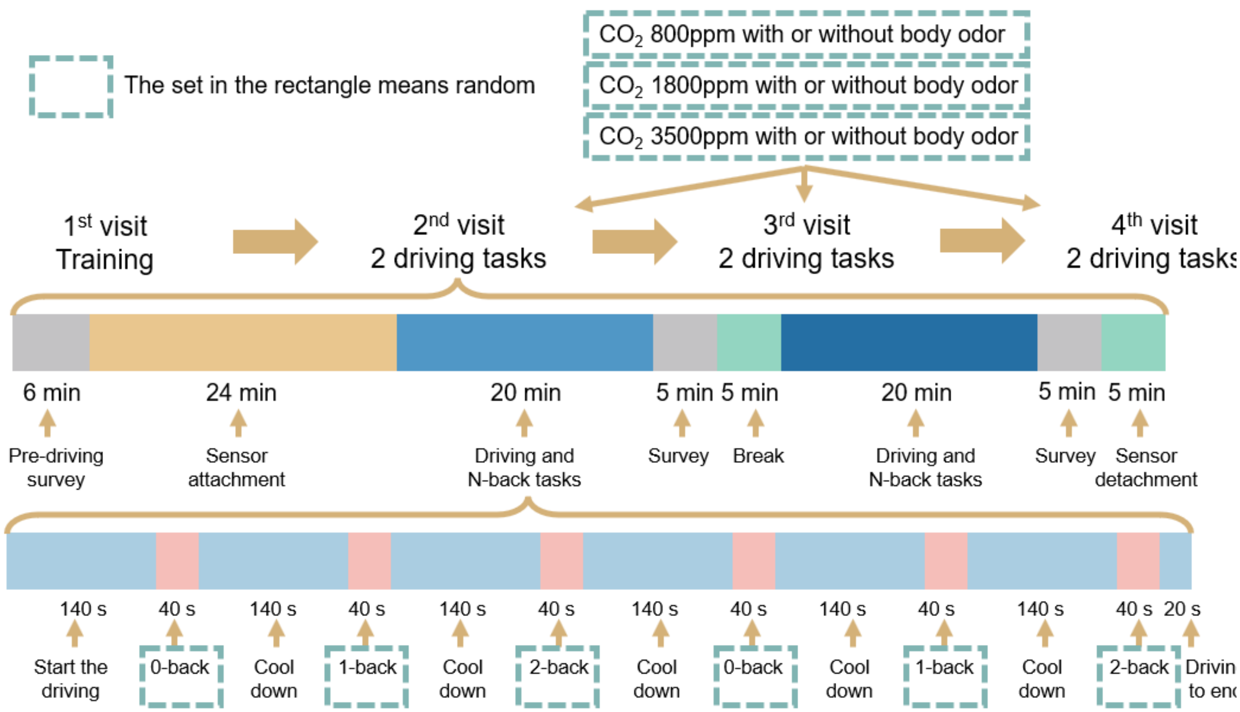


Figure 4. Experimental procedure (C. Wang et al., 2024)

3.2.2. Analysis of driving behaviors, secondary task performance, and survey responses

This research analyzed driving performance through metrics such as vehicle speed, acceleration, lane positioning, steering activity, and yaw rate, while cognitive effects of CO_2 and body odor were gauged using N-back task performance in terms of reaction times and accuracy. The variation in participants' sleepiness levels across driving tasks was determined by comparing pre- and post-task sleepiness survey scores. Emotional state, perceived air quality, and acceptance levels were evaluated through survey responses. Cognitive load during the tasks was measured using the NASA-TLX method (Hart, 2006), following the methodology of Al-Shargie et al. (2017).

To examine the influence of CO_2 levels or body odor on both driving and cognitive performance, we applied the Aligned Rank Transform (ART) two-way ANOVA with subsequent post-hoc tests, aligning with methods frequently used for analyzing group differences in studies (Durner, 2019; Elkin et al., 2021). Non-parametric data determined by the Shapiro-Wilk test were analyzed at a

0.05 significance threshold. This statistical analysis was performed using the R software (version 4.2.3) (R Core Team, 2013).

3.2.3. Physiological data analysis

3.2.3.1. Preprocessing

For EEG data preprocessing in this research, we utilized MNE-Python (Gramfort et al., 2013), following a detailed methodology (Gramfort et al., 2014). This process involved identifying defective EEG channels and replacing them through spherical spline interpolation (Perrin et al., 1989) based on nearby functional sensors. Data were simplified by resampling to 500 Hz and then averaged for reference. A third-order Butterworth filter limited frequencies between 0.5 Hz and 30 Hz to diminish high-frequency noise (Kar et al., 2010). Eye movement and blink-related artifacts were excluded, with Independent Component Analysis (ICA) aiding in physiological noise reduction (Delorme & Makeig, 2004).

fNIRS data were first converted from ".mat" to ".nirs" format using a converter for compatibility with Homer3 (Huppert et al., 2009), and then to ".snirf" for subsequent analyses. The Homer3 MATLAB toolbox was applied to correct motion and physiological artifacts and to process hemodynamic signals. We calculated relative changes in hemoglobin concentrations using the modified Beer-Lambert law (mBLL) and a differential path length factor (DPF) of 4 (Cope et al., 1988; Kocsis et al., 2006), with DPF of 4 (Scholkmann & Wolf, 2013), detailed in Appendix B Table 1. Channels showing abnormal signals were excluded after a visual check. We addressed motion artifacts through several methods, including channel rejection and wavelet transformation, and filtered physiological noise like respiratory and heart rate fluctuations. To minimize the influence of confounding variables like CO_2-induced vessel changes, we subtracted the global mean from the signal of interest, acknowledging physiological noise as a significant factor in fNIRS recordings.

The hemodynamic response function (HRF) was derived from the processed fNIRS data using the general linear model (GLM) approach which was favored for its capacity to better manage physiological noises by incorporating them as variables in the HRF calculation (Yücel et al., 2021). Brain activity was inferred from shifts in oxygenated (HbO) and deoxygenated hemoglobin (HbR), as well as total hemoglobin (HbT) levels, indicating changes in cerebral blood flow and oxygenation. Based on the seminal studies by Sitaram et al (2007) and Kwong et al. (1992), these shifts in hemoglobin concentrations served as the primary measures of brain activation in my analysis. Average HbO and HbR concentrations per channel, defined by specified Regions of Interest (ROIs) as illustrated in Figure 5, were systematically calculated for detailed evaluation.

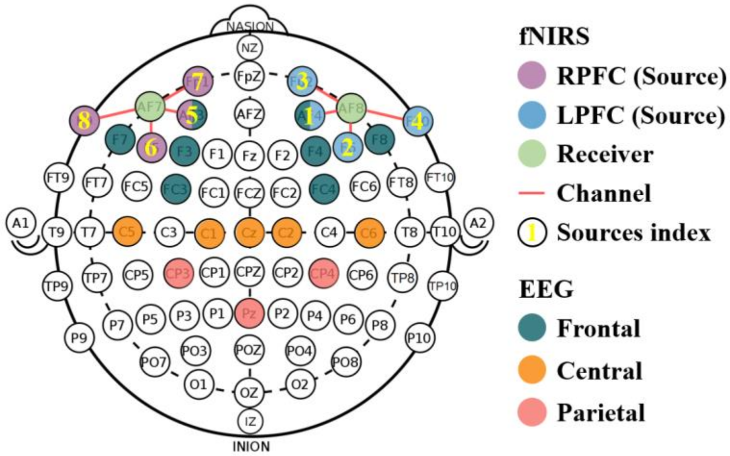


Figure 5. Graphical representation of the EEG/fNIRS probe array and optodes

3.2.3.1. Processing and analysis

For the 18-minute EEG recordings taken during each driving session, we processed the data to extract features indicative of brain activity under varied conditions, utilizing the MNE software (Gramfort et al., 2014). Power spectral density (PSD) analysis segmented into delta (δ), theta (θ), alpha (α), and beta (β) frequency bands was performed using Welch's wavelet transform method (Al-Fahoum & Al-Fraihat, 2014). This included a 2-second sliding window with overlapping halves to derive mean power values in the α band for EEG evaluation, employing a moving average to eliminate noise. Welch's method helped compute power across these bands and the total band power—the aggregate of powers across all bands. The selection of θ and α bands was based on their association with sleep need and alertness, respectively, in driving contexts (Aeschbach et al., 1997; Buckelew et al., 2009; Cajochen et al., 1995), while changes in β band power were linked to arousal and stress (Kuo et al., 2016; J. Zhang et al., 2021), and δ band activity related to attention and sensory processing (Dimitriadis et al., 2010). Additionally, ratio indices like α/β were included to refine analysis accuracy, offering insights into mental states of relaxation and stimulation, and indicating cognitive processing abilities as per recent findings (Clarke et al., 2019; Eoh et al., 2005; Jap et al., 2009; Wen & Aris, 2020). These indices, showing less susceptibility to noise, were analyzed across "frontal," "central," and "parietal" brain regions as defined in Liang et al. (2018).

I utilized measurements of oxygenated (HbO) and deoxygenated hemoglobin (HbR) as key indicators, following the approach in the previous studies (von Lühmann et al., 2020; Yücel et al., 2021). My focus was on the amplitude, slope, peak timing differences, and extreme values of HbO and HbR signals during N-back tasks. I also calculated their average amplitudes throughout each driving session as features, consistent with previous research methodologies. Similar to EEG data analysis, we extracted fNIRS features for specific regions of interest (ROIs) in the brain, including the prefrontal cortex (PFC), left prefrontal cortex (LPFC), and right prefrontal cortex (RPFC), based on Li et al. (2019). These features were analyzed at the channel level for each driving session to determine the impact of different driving conditions.

Six unique environmental settings were created for participants, combining varying CO2 concentrations with or without added body odor. Driving scenarios were split into "single-task," focusing exclusively on driving, and "dual-task," which added an N-back cognitive task. Each scenario was broken down into twelve sub-sessions, half dedicated to each task type, labeled from "1st sd" to "2nd sd" for single-task and "1st dd" to "2nd dd" for dual-task sessions. We analyzed the effect of CO_2 and odor on brain function by examining regional brain activity and at the probe level, utilizing EEG and fNIRS data outlined in the feature extraction methodology. Figure 6 visually summarizes how each environmental scenario impacted driving-related cognitive performance. We applied the Aligned Rank Transform (ART) two-way ANOVA with Bonferroni adjustment for further analysis (Durner, 2019; Elkin et al., 2021). This statistical approach, widely recognized for its efficacy in comparing multiple groups, revealed non-normal data distribution as per the Shapiro-Wilk test. We set the significance threshold at 0.05 for testing the hypotheses, performing the analysis using the R software (version 4.2.3) (R Core Team, 2013).

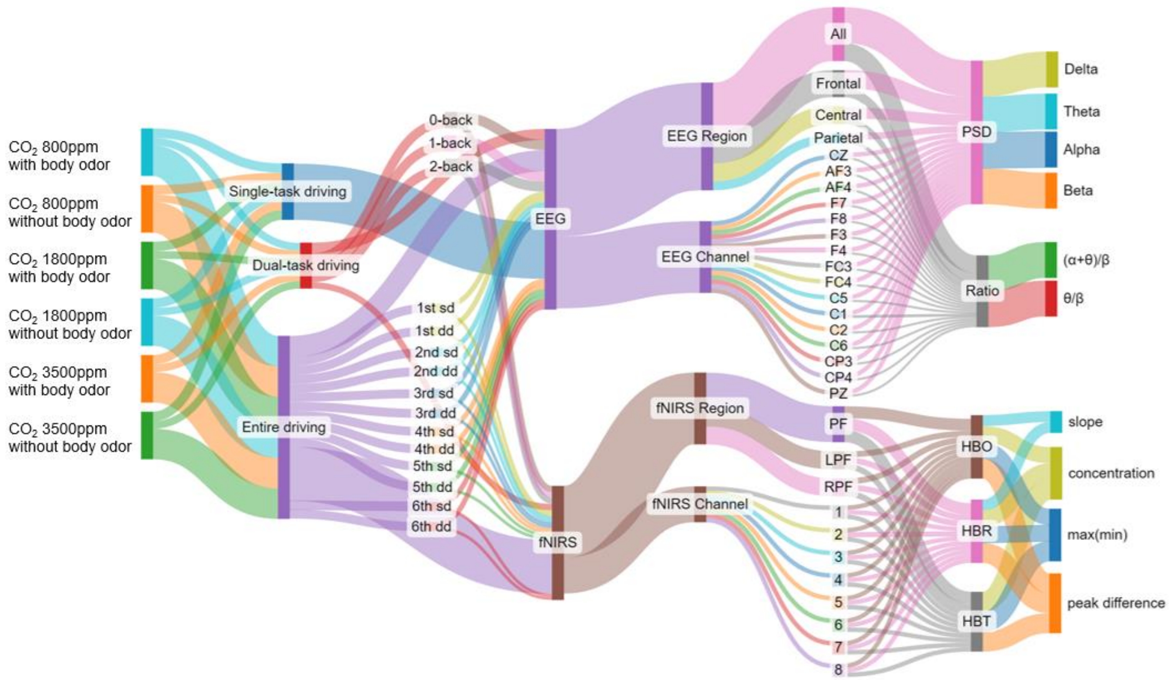


Figure 6. Integration figure of the features used in the ANOVA. “sd” refers to “single-task driving” and “dd” stands for “dual-task driving”. Trace the lines originating from left to right are the environmental conditions, task type, EEG and fNIRS brain regions and channels, features used to measure cognitive performance.

3.3. Effects of thermal environment and lighting on driving and secondary task performance

3.3.1. Experiment design

3.3.1.1. Participants

Seventy-two individuals (52 males, 20 females) aged between 18 and 32 years (average age 22.3 ± 1.69), holding valid driving licenses, were recruited from Worcester Polytechnic Institute (WPI) via email and poster advertisements. They all signed a consent form approved by WPI’s Institutional Review Board (IRB-22-0299), which detailed the study's procedures, risks, and participant obligations. Prior to their inclusion, candidates underwent a screening for simulator sickness, a condition that can affect 2% to 8% of individuals during simulations, especially in scenarios involving numerous turns and stops (Akinwuntan et al., 2005). The Simulator Sickness Questionnaire (SSQ) (Kennedy et al., 1993) a widely used tool comprising 16 items to gauge symptoms like headache, nausea, and blurred vision, was employed. Participants rated their symptoms shortly after the simulation. Due to simulator sickness, six out of an initial 78 were excluded, leaving seventy-two eligible participants for the study. A power analysis conducted with G*Power 3.1 (Faul et al., 2007), presented in Fig. S1 of the Appendix, helped determine a statistically significant sample size of 19 for analyzing four different lighting conditions at a single temperature, considering this as four separate trial conditions. This analysis aimed for an effect size of 0.25 and a power level of 0.8. Participants were advised to abstain from alcohol, nicotine, and caffeine both on the day of and the day before their session and to ensure they were well-rested. They received $15 per hour for their participation, with the possibility of earning up to an additional $15 as a performance incentive.

3.3.1.2. Driving simulator and in-car environment setup

The driving simulator setup was similar to the previous investigation on CO_2 and body odor. In this subsection, I only focus on the major differences and uniqueness in the experimental setup.

The Assetto Corsa video game (Simulazioni, 2014) was utilized to simulate driving conditions and assess performance. The simulated environment featured a nocturnal drive through the LA Grand Canyons, mimicking the actual terrain and roadways of the San Gabriel Mountains in California. The primary route extended over 42km, with the total distance reaching 47km when accounting for additional paths and detours. Conducted under night conditions devoid of any weather-related visibility issues, each trial spanned a minimum of 9 minutes on this consistent route. Drivers navigated this night-time course under uniform luminance conditions of 0.6 cd/m2 from the screen, optimizing visibility in the absence of natural light, in line with findings from Easa et al. (2010). regarding the diminished impact of ambient light during daytime.

The driving simulator was used to record vehicle position and movement at 10 Hz, tracking forward velocity (limited to 100 km/h or 62.1 mph), longitudinal and lateral acceleration, steering wheel angles, RPM, and yaw rate for performance assessment. I analyzed variations in speed and acceleration to identify driving impairments. The mean speed and its variability were also studied to understand vehicle behavior (Ting et al., 2008; X. Yan et al., 2014). Metrics like lateral velocity and steering were analyzed to determine driver precision and identify navigational errors, emphasizing lateral vehicle control as highlighted in earlier research (Oron-Gilad et al., 2008; Son et al., 2011; Thiffault & Bergeron, 2003).

In my study, cabin temperature and lighting were controlled variables, studied through a 3 x 4 factorial design to assess their effects on driving quality and satisfaction. Temperatures were set to 18 °C, 23 °C, and 28 °C using an HVAC system, based on ASHRAE 55 standards (Kelechava, 2024) which consider various factors like metabolic rate, clothing insulation, air speed, and humidity. Four lighting colors—red (Figure 7), blue, warm white, and cool white—were chosen, with LED strips placed in strategic cockpit locations identified by prior research (Caberletti et al., 2010; Schellinger et al., 2006), ensuring a brightness level of 1.5 lx at eye level to not affect vision contrast significantly (Park et al., 2016).

Figure 7. Simulated car-cabin lighting

Cabin environmental conditions such as temperature, humidity, VOCs, CO_2, PM2.5 levels, and lighting were constantly tracked. A ventilation rate of 18 ach, appropriate for speeds of 45-60 mph, kept CO_2 levels at approximately 800 ppm to avoid impairing cognitive abilities (Satish et al., 2012a). Tasks included primary driving responsibilities and a secondary N-back task to assess working memory during driving.

3.3.1.3. Secondary task and questionnaire

To simulate real-life driving situations that necessitate working memory and executive function, such as navigation and traffic monitoring, we also incorporate the N-back task used in the previous study in this project. But only 2-back was conducted by the drivers during the driving task. A 60-second driving interval followed each 2-back task. It logged number timings, session type, response times, and target accuracy, noting missed targets as incorrect. This data, crucial for assessing cognitive efficiency, was saved for analysis.

In this study, participants filled out two surveys. The initial survey collected basic demographic data including age, gender, and driving history. The second aimed at understanding participants' perceptions, focusing on aspects like lighting comfort vote (LCV), lighting brightness vote (LBV), lighting acceptance vote (LAV), thermal comfort vote (TCV), thermal sensation vote (TSV), and thermal acceptance vote (TAV) (Brambilla et al., 2020; Golasi et al., 2019; Winzen et al., 2014). Responses were recorded on a 7-point scale from -3 to +3 for both lighting and thermal conditions. Questions also included inquiries about sleep quality the night before and alertness levels before and after the drive, assessed by the Stanford Sleepiness Scale (SSS) using a scale from “very alert” to “very sleepy” (Hoddes et al., 1973). Emotional reactions to the driving environment were evaluated with the Self-Assessment Manikin (SAM) for valence, arousal, and dominance (Bradley & Lang, 1994). The NASA Task Load Index (NASA-TLX) was used to assess task workload, looking at stress, workload, and fatigue across six dimensions: mental and physical demand, temporal demand, performance, effort, and frustration, rated on a scale from 1 to 7 (Hart, 2006).

3.3.1.4. EEG and fNIRS setup and acquisition

I also measured brain activity by using the device in the previous project. The set up of g.Nautilus Research fNIRS-8 wireless headset and g.tec MATLAB-Simulink software were same to the parameters used in the previous study, allowing for the simultaneous recording of EEG and fNIRS signals.

3.3.1.5. Procedure

Participants attended a preliminary session for simulator sickness screening and familiarization with the driving simulator's operation and study protocols. After providing informed consent, they scheduled the main experimental session. In preparation for this session, they were advised to maintain normal eating and sleeping patterns and avoid medications, alcohol, or significant physical activity for 24 hours beforehand. The experiment employed a single-blind design, assigning participants to temperature settings via block randomization and organizing four driving tasks under different lighting conditions in a random sequence based on the Latin Square Design, as detailed in Figure 8. Each simulation lasted around 10 minutes, a duration consistent with similar studies (Jeihani et al., 2017; Saxby et al., 2007), incorporating a secondary 2-back cognitive task. Following each drive, participants filled out surveys on tablets set to dark mode to minimize light exposure from the screen. Lighting conditions were adjusted for the subsequent task immediately after survey completion, and cell phone and other electronic device use were strictly prohibited during the experiment to ensure undivided attention to the tasks.

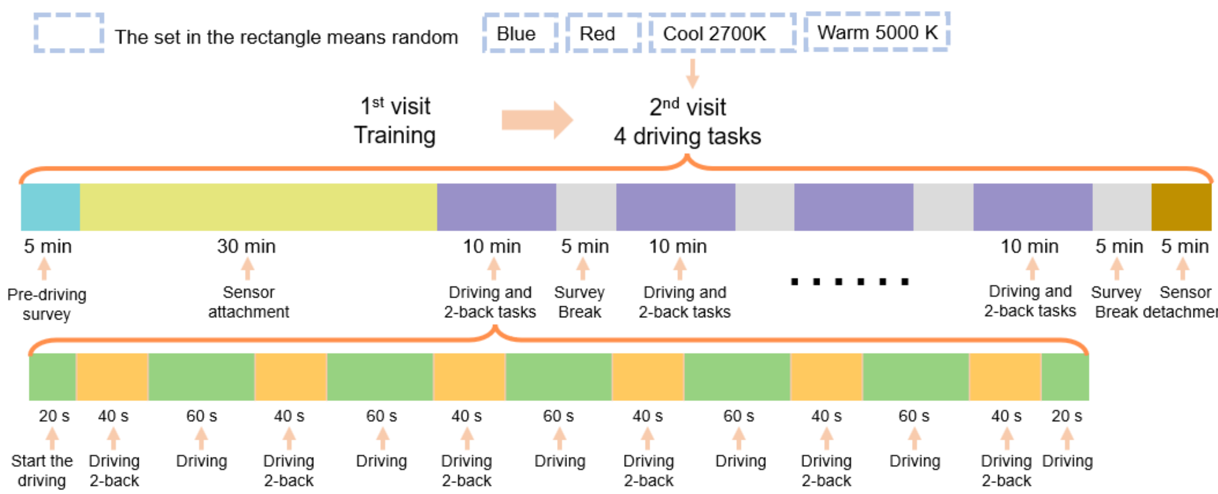


Figure 8. Experimental procedure

3.3.2. Analysis of driving behaviors, secondary task performance, and survey responses

My study aimed to analyze how temperature and light color affect driving performance and their subsequent effects on environmental satisfaction, secondary task performance, and physiological responses. I utilized a two-pronged analytical method for a thorough analysis.

A two-way ANOVA was initially conducted to assess the direct effects of temperature and light on driving metrics, providing a basic comparative analysis. However, ANOVA's limitations in fully characterizing driving behavior necessitated further examination through machine learning techniques, enhancing the ability to classify driving styles and predict performance variations. By integrating ANOVA with machine learning, I developed a sophisticated model to understand driving dynamics in varying environmental conditions. This combination allowed for a detailed exploration of how specific environmental factors like temperature and light influence driving behavior, leading to a more accurate prediction and analysis of their impact on real-world driving performance.

3.3.2.1. Two-way ANOVA

Statistical analyses were conducted to compare environmental satisfaction, driving actions, N-back task outcomes, workload, and survey feedback under different lighting and temperature settings. Key metrics for driving performance included speed (up to 100 km/h), longitudinal and lateral accelerations, steering dynamics, and yaw rate, with their averages and variability quantifying performance. Secondary task performance were gauged through reaction times and accuracy in 2-back tasks, with sleepiness levels derived from Stanford Sleepiness Scale (SSS) responses. Survey data provided insights into emotional state, environmental perception, and satisfaction. Cognitive load was measured using the NASA-TLX method, as established by Al-Shargie et al. (2017).

Statistical analyses were performed to evaluate survey feedback and driving metrics under varied lighting and thermal settings. Linear regression helped control individual variances, with residuals analyzed for objective comparison (Kliegl et al., 2011; Van Dongen et al., 2004). Normality was verified via the Shapiro-Wilk test. For skewed data, the Aligned Rank Transform (ART) ANOVA was used to detect group differences (Durner, 2019; Elkin et al., 2021), targeting variances in survey and driving data relative to temperature changes. The significance threshold was 0.05, with R software (version 4.2.3) (R Core Team, 2013) facilitating the analysis.

3.3.2.2. Driving style classification and prediction using ML

My study employed a machine learning process to investigate how temperature and light color within the car environment affect driving styles using a two steps approach. The first layer categorized driving styles from collected data, while the second layer recognized driving behaviors influenced by in-car temperature and light color.

In the first layer, I categorized driving styles using unsupervised learning algorithms and driving data, specifically speed, longitudinal acceleration, and lateral acceleration. I averaged these variables by each driving session of 288 tasks and adjusted for individual differences by including interaction terms with demographic and driving history data. This approach helped identify distinct driving styles, such as aggressive, moderate, and conservative (Chu et al., 2017; Deng et al., 2017; Palat et al., 2019; F. Yan et al., 2019), using K-Means clustering for its effectiveness in grouping data by feature similarities. The method relied on unsupervised learning to uncover natural patterns in the data, using scikit-learn for model application and Silhouette Coefficient (Luan et al., 2012) for evaluating clustering success, selecting a K-value over 0.5 to signify robust cluster differentiation.

In the second layer, the classification from Layer I was used to label data, integrating with in-car temperature and light color to train the classification model. The Random Forest (RF) method, known for its efficacy in data mining and classification, was selected. Leave-one-subject-out cross-validation evaluated the model's accuracy. I analyzed how temperature and light color affect driving, categorizing temperature into three levels and light color into four, to reflect actual driving conditions. This step allowed detailed examination of driving behaviors under varying environmental settings. Model performance was rigorously evaluated using metrics like confusion matrix, accuracy, precision, recall, and F-measure, helping to confirm the model's ability to accurately identify different driving styles influenced by temperature and light conditions.

3.3.3. Physiological data analysis

For EEG and fNIRS data preprocessing in this research, I adopted the same approach in the previous study to preprocess the raw data. For the processing, I employed a consistent methodology to extract features from preprocessed EEG and fNIRS physiological signals with the previous studies. I then applied a two-way Aligned Rank Transform (ART) ANOVA to analyze each feature across different conditions by temperature and lighting condition.

Chapter 4: Result and Discussion

This chapter discusses results and findings from the literature review work of Papers A.

4.1. A systematic literature review

4.1.1. Summary of the manual review

In a thorough review of major findings in 66 studies on the association of IEQ factors and cognition, the tabulated results of all the reviewed studies might not easily generate a clear "big picture. This is because many studies reported contradictory findings. Therefore, we calculated the percentage of studies that revealed statistically significant association (*with the assigned rating "2"*) between a particular IEQ factor and a cognitive function. Moreover, the percentage of studies showing both statistically significant association (*with the assigned rating "2"*), no statistical association (*with the assigned rating "0"*), mixed association (*with the assigned rating "1"*), and "N/A" to denote the significance level if a study did not report *p* values. Table 1 (C. Wang et al., 2021) list the percentage of studies reporting different levels of statistical significance studies on the association of IEQ factors and cognition. Table 1 demonstrates that the most studied cognitive functions are memory, high order cognitive skills, and attention, and that the most examined IEQ factors in the literature are thermal environment, noise, and IAQ. Overall, IEQ is associated with almost all cognitive functions to different extents except that few studies were reported on perception with a few exceptions. The results, including a classification of IEQ factors and cognitive functions, are summarized in Figure 1 of Appendix A

Table 1. Percentage of studies reporting different levels of statistical significance for the associations between IEQ and cognition provides a summary of the cognitive tasks evaluated, mapped to the respective cognitive functions. The results in Table 1 suggest extensive inconsistencies in the relevant literature, especially regarding the effects of IAQ or thermal environment on cognition. For example, 50% of the 16 reviewed studies indicated either a statistically significant association (*level "2"*) or a mixed association (*level "1"*) between thermal environment and memory, while only 20% of the studies confirmed a statistically significant association (*level "2"*). Where over five studies exist, significant links are noted: 50% for indoor air quality (IAQ) impacting higher cognitive skills, 71.4% for noise affecting memory, and 66.67% for noise influencing language function. However, minimal associations are observed between IAQ and memory, and the thermal environment's effect on attention, memory, and higher cognitive skills shows low percentages, highlighting inconsistencies, particularly in the thermal environment's impact on cognition. These disparities could stem from various factors, including experimental design and measurement techniques.

The table also averages the influence of IEQ elements across cognitive functions, showing noise affects cognition in 57% of the cases, much higher than IAQ or thermal elements (below 20%). This suggests noise more consistently affects cognitive performance, possibly due to its recent prevalence in modern environments. While memory and language are notably impacted, less than half of the studies show a clear effect of IAQ or thermal conditions on cognitive function, indicating a lack of consensus in the field.

Table 1. Percentage of studies reporting different levels of statistical significance for the associations between IEQ and cognition

	IAQ			Thermal environment			Noise			Lighting			Non-light visual factors			Row average	
	Perc. of sig. ⸸	*Perc. of mixed* ⸸	*# of studies*⸸	*Perc. of sig.*	*Perc. of mixed*	*# of studies*	*Perc. of sig.*	*Perc. of mixed*	*# of studies*	*Perc. of sig.*	*Perc. of mixed*	*# of studies*	*Perc. of sig.*	*Perc. of mixed*	*# of studies*	*Perc. of sig.*	*Perc. of sig. or mixed*
Attention	20%	20%	6	10%	30%	11	25%	25%	5	33%	34%	6	50%	50%	5	***28%***	***31%***
Perception	0	0	1	0	50%	3	NA	NA	0	0	67%	3	NA	NA	0	***25%***	***38%***
Memory	0	25%	8	14%	36%	16	71%	29%	8	29%	28%	7	0	100%	1	***23%***	***43%***
Language function	0	0	2	33%	0%	4	67%	33%	10	50%	0%	2	0	100%	1	***30%***	***26%***
Higher order cognitive skills	50%	33%	8	19%	50%	17	20%	40%	5	33%	0%	6	50%	0%	2	***34%***	***25%***
Column average	***14%***	***15%***		***15%***	***33%***		***57%***	***25%***		***29%***	***32%***		***25%***	***63%***			

⸸ "Perc. of sig.": the percentage of all reviewed studies in Appendix I Tables A2-A6 reporting a significant association only (with the rating "2"); "Perc. of mixed": the percentage of studies revealing a mixed association (with the assigned rating of "1"). The description of different rating levels can be found in Section 3.1. "# of studies": the total number of reviewed studies containing all ratings ("0", "1", "2", and "NA").

4.1.2. Keyword co-occurrence patterns

For the co-occurrence analysis, the result displayed by Figure 9 (C. Wang et al., 2021) illustrates the publication trends and knowledge frameworks based on keyword co-occurrence over various time frames, using the proximity of circles to indicate the frequency of keyword co-occurrence in the literature; closer circles signify higher co-occurrence rates. Utilizing a smart local moving algorithm optimized the keyword display within each circle (VOSviewer Manual, n.d.). Circle sizes depict the relative frequency of article citations per keyword, and color coding identifies thematic clusters, employing similarity visualization (VOS) (Eck et al., 2010). The initial related research dates back to 1932, with a notable surge in publications linking Indoor Environmental Quality (IEQ) and cognitive studies, reaching 684 publications in 2019, as detailed in Figure 8a. Subsequent figures, 8b through 8d, map out the conceptual linkages between IEQ and cognitive function across three distinct time spans: 1932–2010, 2011–2015, and 2016–2020, averaging around 3000 papers per interval. These diagrams, which build on a comprehensive manual review, highlight two prominent trends: thematic clusters in cognition and environment, differentiated by colors indicating various aspects like age, gender, and mental health conditions. These graphical representations, particularly in Figures 8b to 8d, trace the thematic shifts in research, marking the emergence of terms like “sound,” “light,” and “noise” in 2011–2015, and shifting focus towards “air pollution,” “temperature,” and “ventilation” after 2016. Concurrently, cognitive research broadened to include terms like “reading,” “social cognition,” and “language,” reflecting the field's evolving focus. Additionally, a recurring association of music with cognitive aspects underscores a consistent interdisciplinary interest across the analyzed periods.

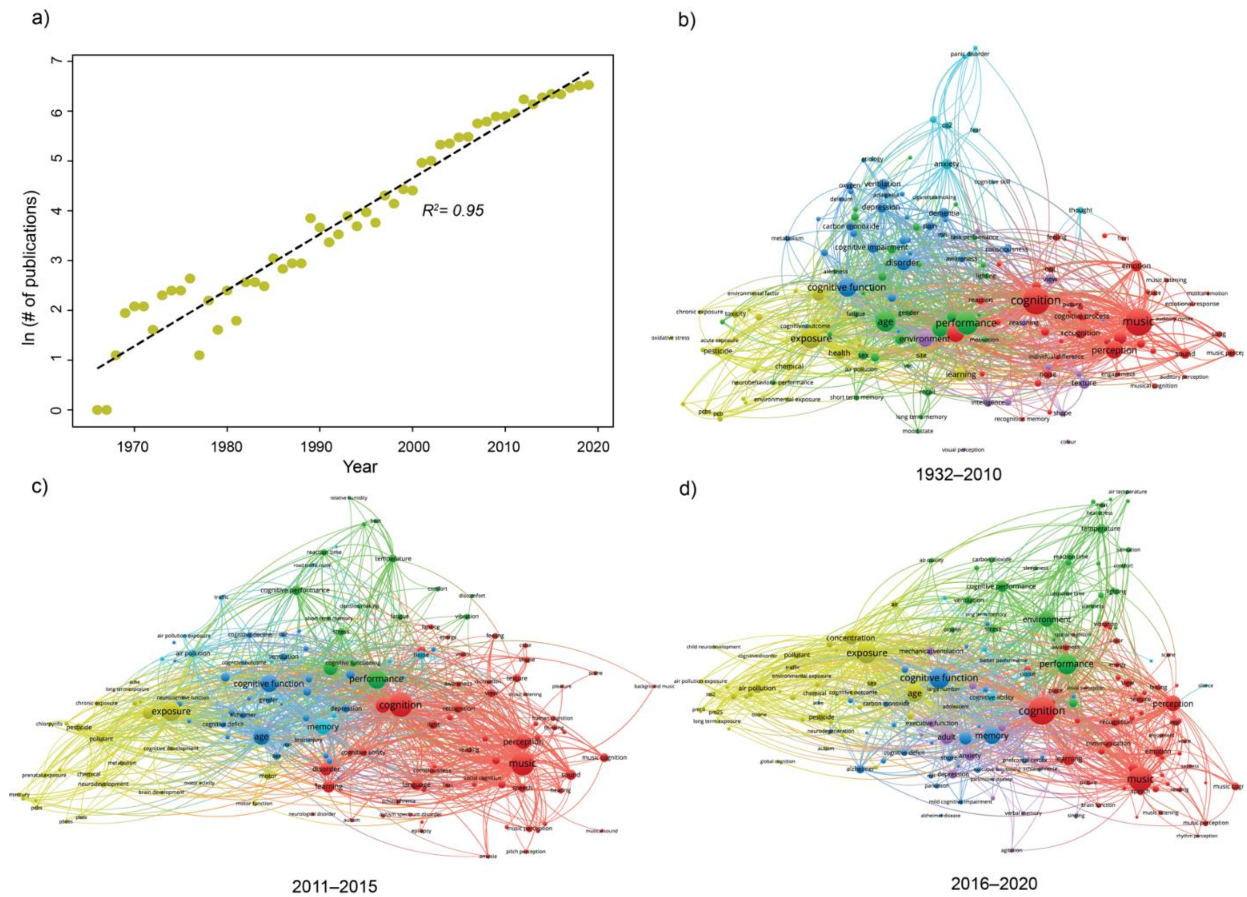


Figure 9. The number of publications and knowledge landscapes obtained from keyword co-occurrence analysis. a) The temporal number distribution of publications (The figure does not display the only paper published before 1958); b) keyword co-occurrence network with publications between 1932 and 2010 (n = 3421); c) keyword co-occurrence network with publications between 2011 and 2015 (n = 2464); d) keyword co-occurrence network with publications between 2016 and 2020 (n = 2956)

4.2. Air quality and driving study

This chapter discusses results from the experimental work of Papers B and C on the effect of CO_2 and body odor in the vehicle cabin on driving performance, cognitive performance, and physiological signal change.

4.2.1. Environmental measurement

Average CO_2 concentrations recorded were 786.42 ± 106.57 ppm (Mean ± SD) at low, 1815.00 ± 80.63 ppm at middle, and 3504.41 ± 149.39 at high levels. The study includes identifying volatile organic compounds (VOCs) from body odor in worn T-shirts, comparing these with clean ones, and found that worn T-shirts contained significantly higher levels of specific VOCs. Chemical analysis, restricted to two donors, identified unique body odor-related compounds in the worn shirts. A total of 26 distinct chemicals were detected in female donors' shirts and 19 in male donors', with 12 chemicals, like aldehydes and benzene, commonly present across both genders' samples, underscoring their association with body odor. For more information, please refer to my previous publication (C. Wang et al., 2024).

4.2.2. Driving performance

The study assessed the effects of varied CO_2 concentrations and body odor presence on driving dynamics, particularly speed and steering behaviors. It focused on variables like speed and acceleration averages and variations, lateral movements, steering actions, and yaw rates. Through two-way ANOVA, it explored the repercussions of differing CO_2 levels and body odor on these driving metrics. According to the data, changes in CO_2 or the presence of body odor didn't notably alter driving performance metrics. Results from the two-way ANOVA in Table 2 (C. Wang et al., 2024) indicated driving data metrics.

Specifically, average speeds were stable across CO_2 scenarios, showing minor fluctuations around 52 mph. Variability in speed also remained consistent, indicating unaffected driver speed control. Statistical analysis revealed no significant changes in speed due to CO_2 (mean speed: $F(2, 144) = 0.03$, $p > 0.05$; speed variation: $F(2, 144) = 0.41$, $p > 0.05$) or body odor effects. Similar stability was noted in acceleration metrics, with ANOVA findings indicating a lack of significant impact from CO_2 or body odor on both the average and variability of acceleration. Furthermore, the interaction between CO_2 levels and body odor showed no significant effect on the driving performance indices analyzed.

Lateral control, indicative of a driver's ability to maneuver the vehicle side-to-side on the road, was assessed through metrics like lateral acceleration, lane deviation, steering, and yaw rate. Observations revealed consistent lane deviations across CO_2 conditions—1.256 m, 1.217 m, and 1.184 m for low, medium, and high levels respectively (Appendix B Table 2). Statistical analysis showed no significant CO_2 effect on lane deviation's mean or variation. Body odor presence slightly altered the lane deviation mean from 1.172 m to 1.222 m, yet this was not statistically significant. Lateral acceleration showed a slight peak of 0.152 m^2/s at high CO_2 levels, but again, ANOVA confirmed no significant changes across different CO_2 environments. Similarly, the analyses for steering and yaw rate metrics indicated no substantial variations due to either CO_2 levels or body odor. The lack of significant findings from ANOVA for these lateral control measures implies no discernible interaction between CO_2 concentration and body odor affecting these specific driving performance aspects.

Table 2. Two-way Analyses of Variance of driving performance indices at different CO_2 levels and environments with or without body odor

	Parameters	Source	Sum of Squares	df	Mean Square	F	Sig. (*p*)	Partial Eta Squared
Speed (m/s)	Mean	CO_2	121.480	2	60.740	0.031	0.969	0.247
		Body odor	248.327	1	248.327	0.127	0.722	0.506
		CO_2 * Body odor	121.333	2	60.667	0.031	0.969	0.247
	S.D.	CO_2	1578.520	2	789.26	0.406	0.667	0.591
		Body odor	0.167	1	0.167	0.001	0.993	0.001
		CO_2 * Body odor	1090.773	2	545.387	0.281	0.755	0.409
Acceleration (m^2/s)	Mean	CO_2	2061.280	2	1030.640	0.533	0.588	0.522
		Body odor	504.167	1	504.167	0.260	0.611	0.128
		CO_2 * Body odor	1384.413	2	692.207	0.357	0.700	0.350
	S.D.	CO_2	2144.160	2	1072.080	0.553	0.576	0.823
		Body odor	144.060	1	144.060	0.074	0.786	0.055
		CO_2 * Body odor	317.213	2	158.607	0.081	0.922	0.122
Lane deviation (m)	Mean	CO_2	2142.720	2	1071.360	0.564	0.570	0.268
		Body odor	1980.167	1	1980.167	1.054	0.306	0.247
		CO_2 * Body odor	3886.573	2	1943.287	1.035	0.358	0.485
	S.D.	CO_2	766.240	2	383.120	0.198	0.821	0.303
		Body odor	190.407	1	190.407	0.098	0.754	0.075
		CO_2 * Body odor	1573.32	2	786.660	0.406	0.667	0.622
Steering (degree)	Mean	CO_2	4876.360	2	2438.18	1.273	0.283	0.724
		Body odor	1072.007	1	1072.007	0.552	0.457	0.159
		CO_2 * Body odor	789.88	2	394.940	0.203	0.817	0.117
	S.D.	CO_2	1088.920	2	544.460	0.349	0.706	0.432
		Body odor	988.167	1	988.167	0.690	0.407	0.392
		CO_2 * Body odor	443.560	2	221.780	0.144	0.866	0.176
Yaw rate (rad/s)	Mean	CO_2	5075.68	2	2537.84	1.326	0.269	0.836
		Body odor	117.927	1	117.927	0.061	0.806	0.020
		CO_2 * Body odor	879.613	2	439.807	0.226	0.798	0.145
	S.D.	CO_2	2708.040	2	1354.020	0.708	0.494	0.852
		Body odor	144.060	1	144.060	0.074	0.786	0.045
		CO_2 * Body odor	324.520	2	162.260	0.084	0.920	0.102
Lateral acceleration (m^2/s)	Mean	CO_2	3485.080	2	1742.540	0.909	0.405	0.752
		Body odor	636.540	1	636.540	0.329	0.567	0.137
		CO_2 * Body odor	513.760	2	256.880	0.132	0.877	0.111
	S.D.	CO_2	601.000	2	300.500	0.154	0.857	0.717
		Body odor	172.807	1	172.807	0.089	0.766	0.206
		CO_2 * Body odor	64.653	2	32.327	0.017	0.983	0.077

Note: * denotes p value less than 0.05, ** denotes p value less than 0.01

4.2.3. N-back task performance

Results from the two-way ANOVA indicated reaction time and response accuracy metrics. The response accuracy varying between 90.67% and 93.45%, was stable across CO_2 levels ($F(2, 144) = 1.29$, $p > 0.05$) (Table 3). Similarly, CO_2 concentration changes did not notably impact reaction times, which remained steady at about 0.58 to 0.59 seconds ($F(2, 144) = 2.88$, $p > 0.05$). Body odor's influence on reaction times was negligible ($F(1, 144) = 0.80$, $p > 0.05$). However, body odor presence reduced response accuracy from 93.17% to 91.102%, marking a significant change ($F(1, 144) = 9.21$, $p < 0.01$). No substantial interaction was observed between CO_2 levels and body odor for reaction time ($F(2, 144) = 2.43$, $p > 0.05$) or accuracy ($F(2, 144) = 0.23$, $p > 0.05$). The effect of CO_2 on reaction time exhibited a very large effect size (0.818), despite the *p*-value being slightly above 0.05. Although the results did not achieve statistical significance, the substantial effect size provides preliminary evidence of CO_2's impact. This suggests that the sample size may have been too small, which could be considered a limitation of our study.

Table 3. Two-way Analyses of Variance of response accuracy and reaction time of N-back tasks at different CO_2 levels and environments with or without body odor

Parameters	Source	Sum of Squares	df	Mean Square	F	Sig. (*p*)	Partial Eta Squared
Response accuracy (%)	CO_2	162608.1	2	81304.05	1.292	0.275	0.156
	Body odor	574058.8	1	574058.8	9.210	0.002**	0.552
	CO_2 * Body odor	303702.4	2	151851.2	2.427	0.089	0.292
Reaction time (s)	CO_2	388713	2	194356.5	2.880	0.057	0.818
	Body odor	54568.96	1	54568.96	0.804	0.370	0.115
	CO_2 * Body odor	31745.6	2	15872.8	0.234	0.792	0.067

Note: * denotes *p* value less than 0.05, ** denotes *p* value less than 0.01

4.2.4. Task Load Index, sleepiness, and emotion

NASA-TLX ratings from Appendix B (Appendix Tables S2 and S3) under varied CO_2 and body odor scenarios revealed minimal impact on task load, as determined by two-way ANOVA. Mental demand was consistent across CO_2 levels (low CO_2: 3.50, medium CO_2: 3.68, high CO_2: 3.46), with body odor effect insignificant (with odor: 3.59, without odor: 3.51). Medium CO_2 conditions experienced the highest temporal demand (2.72) and the lowest self-assessed performance (2.64), whereas body odor slightly lowered temporal demand (2.44) and improved performance (2.747). Frustration levels rose with increased CO_2 and presence of body odor, suggesting minor variances in certain subscales due to environmental factors. Varying CO_2 levels had no significant effect on drivers' mental demand ($F(2, 144) = 0.62$, $p > 0.05$, $\eta^2 = 0.28$). Likewise, the presence of body odor did not significantly alter mental demand ratings ($F(1, 144) = 0.67$, $p > 0.05$, $\eta^2 = 0.59$).

Sleepiness and emotional data from Appendix B (Appendix Table S7), post-analyzed through two-way ANOVA, showed negligible influence from CO_2 and body odor. Sleepiness levels, increasing slightly but insignificantly with CO_2, were insignificantly altered by body odor ($F(1, 144) = 0.17$, $p = 0.021$), maintaining stable emotional ratings of valence and dominance. Notably, body odor caused a slight and significant increase in negative arousal ($F(1, 144) = 4.70$, $p = 0.032$), pointing to discomfort. No significant CO_2 and body odor interaction on sleepiness or emotions was observed, indicating their limited effect on these aspects during driving.

4.2.5. EEG results

For the entire driving session, Table 4 shows two-way ART ANOVA findings for power spectral density (PSD) of brainwave bands and band power ratio indices impacted by CO_2 levels or body odor. The table focuses on significant findings from the in-car environment's effect on

PSD, highlighting only 2 out of 160 comparisons showing significant effects for band PSD, and 5 out of 160 comparisons for band ratios. Analysis of PSD during driving sessions across frontal, central, parietal regions, and a combined all categories revealed no significant changes due to CO_2 or body odor. However, a specific observation at the PZ channel indicated a significant increase in the δ band PSD with body odor presence ($F(1, 144) = 8.024$, $p = 0.005$). Analysis across brain regions (frontal, central, parietal, and combined all) during driving sessions found no substantial impact of CO_2 or body odor on band power ratio indices. However, focusing on specific EEG channels, AF3 and FC4 showed notable changes. At AF3, significant alterations were seen in the $\alpha+\theta/\beta$ and θ/β ratios due to CO_2 variations ($F(1, 144) = 5.235$, $p = 0.007$, and $F(1, 144) = 4.722$, $p = 0.011$, respectively). The $\alpha+\theta/\beta$ ratio at AF3 changed across CO_2 levels (800 ppm: 6.491, 1800 ppm: 8.388, 3500 ppm: 8.651 μV2/Hz). At FC4, significant CO_2-related differences appeared in θ/β and $\alpha+\theta/\beta$ ($F(2, 144) = 4.988$, $p = 0.008$, and $F(2, 144) = 4.712$, $p = 0.011$, respectively), with interactions between CO_2 and body odor also affecting the $\alpha+\theta/\beta$ ratio ($F(2, 144) = 5.271$, $p = 0.006$).

Table 4. Two-way ART ANOVA of EEG different frequency band PSD and ratio indices of bands PSD at different CO_2 levels and environments with or without body odor across the driving sessions

Driving session	**Source**	**Feature**	**Channel**	**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig. (*p*)**	**Partial Eta Squared**
Entire	Body odor	δ	PZ	8532.913	1	8532.913	8.024	0.005**	0.956
Single-task	Body odor	δ	C1	7871.268	1	7871.268	6.779	0.010*	0.597
Entire	CO_2	$(\alpha+\theta)/\beta$	AF3	14011.64	2	7005.819	5.235	0.007**	0.810
Entire	CO_2	θ/β	AF3	12694.13	2	6347.066	4.722	0.011*	0.801
Entire	CO_2	$(\alpha+\theta)/\beta$	FC4	12839.89	2	6419.944	4.988	0.008**	0.460
Entire	Interaction	$(\alpha+\theta)/\beta$	FC4	13133.45	2	6566.723	5.271	0.006**	0.471
Entire	CO_2	θ/β	FC4	11825.92	2	5912.96	4.712	0.011*	0.476
Single-task	CO_2	$(\alpha+\theta)/\beta$	AF3	12027.78	2	6013.89	4.754	0.010*	0.873

Note: "Interaction" denotes the interaction between the CO_2 and body odor. * denotes *p* value less than 0.05, ** denotes *p* value less than 0.01. This table only shows the significant results.

In the single-task driving analysis, CO_2 levels showed no significant impact on the PSD across all frequency bands within different ROIs. The presence of body odor similarly had no substantial effect on PSD values in these areas. From the Table 4, Channel C1, however, displayed a significant change in δ-band PSD with body odor ($F(1, 144) = 6.779$, $p = 0.010$). No significant changes were observed in band power ratio indices across the ROIs due to CO_2 or body odor. Nevertheless, channel AF3 exhibited a marked change in the $(\alpha+\theta)/\beta$ ratio due to varying CO_2 levels ($F(1, 144) = 4.754$, $p = 0.010$), indicating that CO^2 concentration had a significant effect.

In the dual-task driving sessions, which integrated different N-back task levels, the analyses of various brain regions and channels revealed no significant alteration in the power spectral density (PSD) bands or ratio indices due to CO_2 levels or body odor presence. This observation was further delineated through graphical representations in Figure 10 and Figure 11, showcasing the brain's topographical and heatmap analyses of EEG ratio indices under varying conditions, respectively. The 0-back task analysis pinpointed that body odor prominently influenced the ratio indices across different brain regions or channels, whereas CO_2 levels or their interaction with body odor displayed negligible effects. Similar observations were made during the 1-back task, where no notable changes in ratio indices due to CO_2 concentrations were detected across the brain's entirety. Body odor presence was consistently influential, affecting these ratios across different regions or channels during the 1-back task, without significant CO_2 and body odor interaction. In the 2-back task scenario, a nuanced examination of the environmental conditions' impact on the ratios, particularly for $(\alpha+\theta)/\beta$ and θ/β, showed distinct differences attributable to CO_2 levels, confirming their influence during this task complexity. The body odor's presence notably differentiated the ratios, underscoring a discernible impact during the 2-back task, yet without significant interplay with CO_2. This effect was particularly evident in the heatmap analysis, which underscored the ratio indices' changes due to body odor across specific channels.

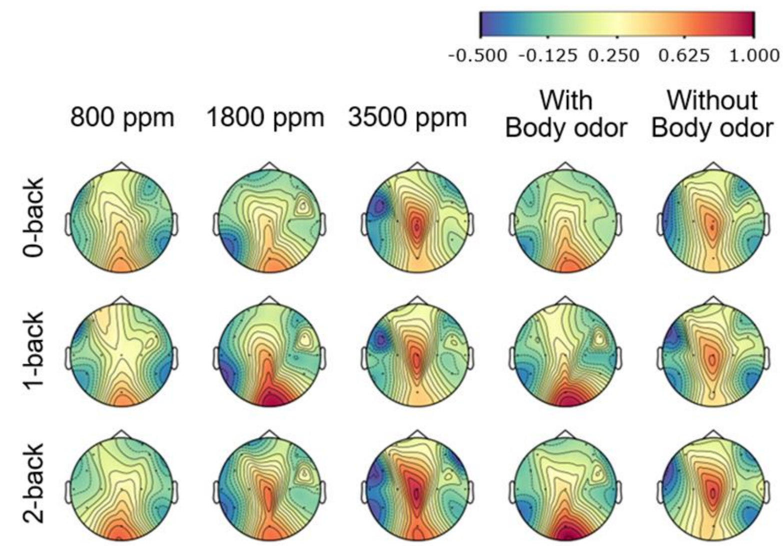


Figure 10. Brain topography of $(\alpha+\theta)/\beta$ during the dual-task session in various conditions

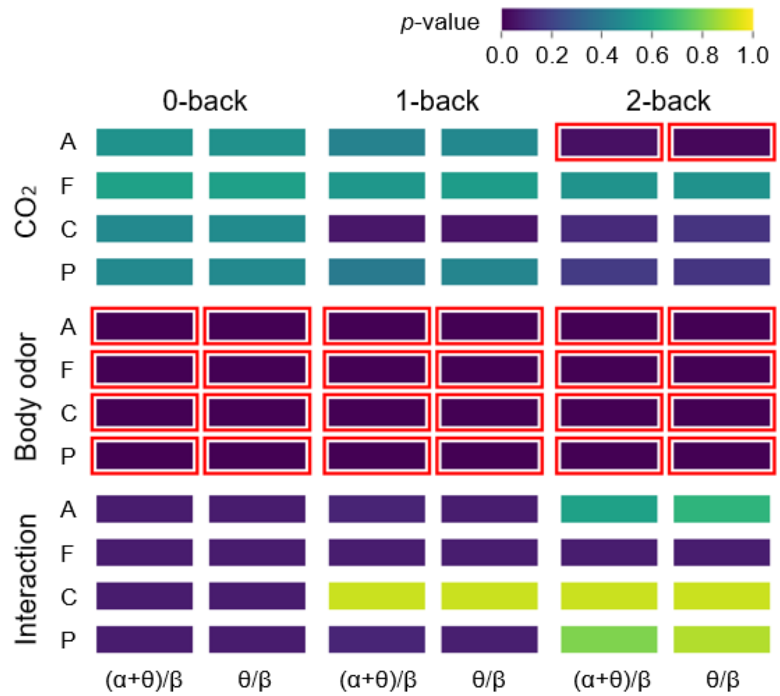


Figure 11. *p*-value heatmap of EEG ratio indices across various brain ROIs (all, frontal, parietal, occipital) during different N-back tasks under various conditions. Each column corresponds to a specific N-back task complexity (0-back, 1-back, 2-back from left to right). The x-axis labels represent the different EEG features assessed, while the y-axis labels denote the distinct ROIs. "Interaction" is the interactive effect between CO_2 and body odor. "A" denotes all regions of brain, "F" denotes frontal region of brain, "C" denotes central region of brain, and "P" denotes parietal region of brain. The color scale on the right denotes p-value ranges, with the red-framed boxes highlighting statistically significant changes where $p < 0.05$.

During various driving tasks, changes in EEG band power spectral density (PSD) and ratio indices were noted, particularly influenced by CO_2 levels or body odor presence. Notably, delta (δ) band alterations during different driving tasks suggest potential cognitive state modifications due to body odor. Shifts in theta (θ) and alpha (α) bands are recognized markers of sleepiness or alertness, reflecting cognitive state variations (Borghini et al., 2014; Buckelew et al., 2009; Klimesch, 1999). Additionally, beta (β) band elevation has been linked to increased stress or arousal levels (Kuo et al., 2016; J. Zhang et al., 2021). Zhang et al. (2021) reported significant EEG β power rise with increased CO_2, indicating altered cognitive states. In line with these, my study observed a θ power rise and β power decrease under high CO_2, resonating with Jin et al. (2022). This study further revealed the nuanced $(\alpha+\theta)/\beta$ ratio changes, suggesting these ratios may more accurately mirror cognitive state shifts during driving, influenced by environmental factors like CO_2. These findings underline the ratio indices' sensitivity in detecting cognitive adjustments, offering a refined lens to assess cognitive state changes, particularly in driving contexts influenced by varying CO_2 concentrations.

In different difficulty level N-back tasks, unlike integrated dual-task driving, body odor significantly influenced EEG ratio indices, specifically altering δ band's PSD in targeted channels. This effect was not observed in integrated dual-task sessions. δ band activity, critical for focused mental engagement, is thought to suppress external sensory distractions, aiding concentrated effort

(Dimitriadis et al., 2010), and possibly engages with complex cognitive tasks (Harmony, 2013). This points to the δ band's significance in attentional processes and its sensitivity to olfactory stimuli. The analysis showed that body odor presence led to changes in the $(\alpha+\theta)/\beta$ and θ/β ratios across certain N-back tasks, with a lower $(\alpha+\theta)/\beta$ ratio suggesting heightened alertness and a reduced θ/β ratio indicating improved attention. Additionally, we examined how CO_2 levels and body odor together influenced EEG signals during different driving tasks. There was no clear interactive effects emerged. During different N-back tasks, body odor significantly altered the $(\alpha+\theta)/\beta$ and θ/β ratios across various brain regions, pointing to nuanced effects of environmental factors on cognitive engagement during these tasks.

4.2.6. fNIRS results

The fNIRS data assessment focused on the behavior of HbO and HbR levels during various driving sessions, including single-task and dual-task scenarios. I conducted a two-way ART ANOVA to examine how CO_2 levels and body odor affected these hemodynamic responses. Across all examined ROIs and channels, the study found no significant alterations in HbO levels attributable to CO_2 or body odor. As a result, the specific ANOVA data is not included, given its lack of statistical significance. In the context of single-task driving, analysis showed that both CO_2 levels and body odor presence had no significant effect on the fNIRS measurements across any of the ROIs or channels. Table 5 detail the changes in brain activity through fNIRS measurements under different CO_2 concentrations and body odor conditions during the N-back tasks. In the 1-back task, the combined effects of CO_2 and body odor were significant on HbO at channel 6 and HbR at channel 7, with relevant mean values across CO2 levels showing distinct differences. These changes were statistically significant for both HbO at channel 6 ($F(1, 144) = 4.588$, $p = 0.012$) and HbR at channel 7 ($F(1, 144) = 5.435$, $p = 0.005$). During the 2-back task, HbT levels at channel 7 varied significantly with CO_2, marked by distinct mean HbT values at different CO_2 levels, demonstrating significant CO_2 influence ($F(2, 144) = 4.929$, $p = 0.009$). Although there were no remarkable differences in HbO or HbR levels across ROIs in all N-back tasks, the CO_2-related change in HbT at channel 7 indicates specific hemodynamic reactions to varying CO_2 levels. The fNIRS results did not show much variation between conditions, unlike the EEG data. Figure 12 displays the brain topography of HbO concentration during dual-task sessions under various conditions. The figure does not show significant differences in HbO concentration across most brain regions under different conditions during N-back tasks.

Table 5. Two-way ART ANOVA of fNIRS features at different CO_2 levels and environments with or without body odor during N-back tasks

Driving session	**Source**	**Value**	**Feature**	**Channel**	**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig. (*p*)**	**Partial Eta Squared**
1-back	Interaction	HbO	conc	6	14115.64	2	7057.82	4.588	0.012*	0.674
1-back	Interaction	HbR	conc	7	16613.04	2	8306.52	5.435	0.005**	0.789
2-back	CO_2	HbT	conc	7	14835.18	2	7417.591	4.929	0.009**	0.686

Note: "Interaction" denotes the interaction between the CO_2 and body odor. * denotes *p* value less than 0.05, ** denotes *p* value less than 0.01

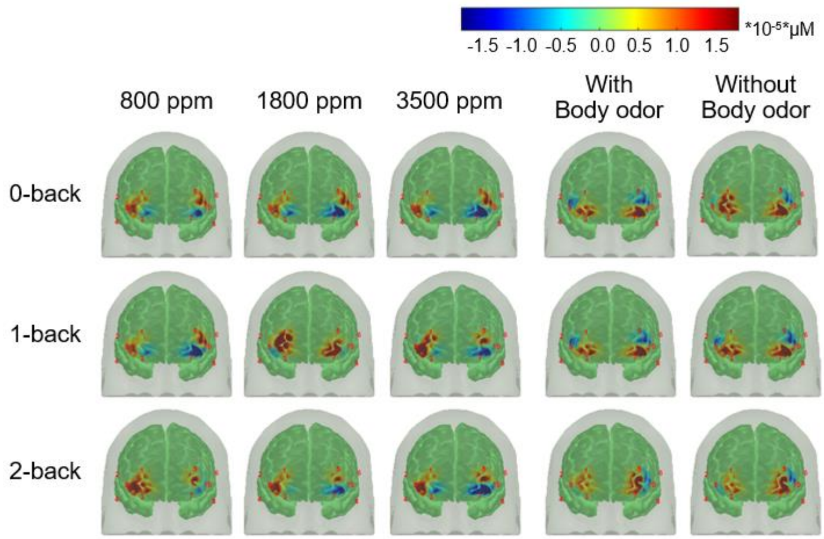


Figure 12. Brain topography of HbO concentration during dual-task session in various conditions

4.2.7. Limitation and recommendations

In this research, six driving-behavior parameters collected from a driving simulator were analyzed to evaluate driving performance. The study found mixed effects of increased CO_2 levels and body odor presence on driving skills. The rigor and validity of this investigation can be improved concerning the factors including sample size, driving environment complexity, CO_2 and body odor levels, exposure time, simulation-based experimental design, and the brain monitoring technology used. These factors are believed to contribute to the variability seen in the research findings.

The study estimated the required sample size assuming a significant effect size of 0.25 and plans to increase this size to enhance statistical validity in future research. The current research population was limited to young and inexperienced drivers, affecting performance diversity. Future research should include a wider age range to better gauge the effects of CO_2 and body odor on driving skills across different age groups.

While this study examined CO_2 and body odor's effects on driving, factors like Air Exchange Rate (AER) and vehicle interior chemicals might also play a role. Since body odor encompasses various compounds that could impact driving ability, these elements might interact with the investigated factors, affecting driving experience and proficiency. Therefore, exploring the combined influence of CO_2, body odor, AER, and other chemicals on driving performance is complex and merits further detailed study.

In my study, the highest CO_2 level tested was 3500 ppm, a concentration that may not have been high enough to significantly alter driving performance or brain activity detected through EEG and fNIRS within short exposure times. Literature suggests that driving duration influences performance (Antonson et al., 2009; Law et al., 2010; Thiffault & Bergeron, 2003; Ting et al., 2008), prompting a need to examine the effects of longer exposure to CO_2 and body odor on driving. Future research should investigate these factors over extended periods or at elevated CO_2 levels to discern their full impact. Over long driving sessions, subtle effects noted in brief exposures could become more pronounced or alter in nature. The CO_2 concentrations used here, though, mirror those found in real-world environments.

The current study's use of a driving simulator may not fully capture the nuances of real-world driving, potentially affecting the generality of the results. The freeway driving scenario employed was relatively straightforward and might not sufficiently challenge drivers of different skill levels. To enhance the assessment of CO_2 and body odor on driving performance, subsequent studies should consider more complex and realistic driving conditions.

In the research, post-driving surveys assessing sleepiness, emotions, perceived and accepted air quality, and workload were completed immediately after each driving session outside the cabin, coinciding with experimental setup changes. This timing raises the question of whether assessments made outside the vehicle truly reflect in-car experiences, introducing potential biases or inaccuracies that future research should address.

A significant methodological limitation was not using short separation channels in fNIRS data acquisition, essential for separating physiological signals from cerebral activity. This limitation, along with environmental influences, could confound fNIRS measurements. The employed fNIRS device missed capturing essential short-distance channel data, crucial for filtering out physiological noise (Yücel et al., 2021).

This study advances the understanding of how CO_2 and body odor impact neurophysiological responses during driving, paving the way for enhanced safety of driving and potentially other vehicle operating through the optimization of physical environment.

4.3. Effects of thermal environment and interior lighting

This chapter discusses results from the experimental work of Papers D on the effect of thermal environment, interior lighting conditions at night, and their interaction in the vehicle cabin on driving performance, secondary task performance, and environmental perception metrics.

4.3.1. Environmental perception

In this study, I explored how temperature settings (18 °C, 23 °C, 28 °C) and light colors (blue, red, warm white at 2700 K, and cool white at 5000 K) affect passenger satisfaction in a vehicle's interior. I assessed variables like comfort and acceptance related to lighting and temperature. Utilizing two-way ANOVA, the influence of these environmental elements on car cabin satisfaction was analyzed, with findings summarized in Table 6, showing satisfaction levels under different light and temperature scenarios. The analysis pinpointed that temperature notably alters thermal sensation, evidenced by significant differences ($F(2, 168) = 106.172$, $p < 0.01$) among the temperature conditions. The indoor temperature of 23 °C resulted in the highest comfort level. Both thermal comfort and acceptance significantly changed with temperature variations (thermal comfort: $F(2, 168) = 6.604$, $p < 0.01$, $\eta^2 = 0.711$; thermal acceptance: $F(2, 168) = 10.903$, $p < 0.01$; thermal sensation ($F(2, 57) = 106.172$, $p < 0.01$, $\eta^2 = 0.974$), with the proportion of variance explained by temperature in these measures being considerable. These effects demonstrate that temperature is a critical factor in both the physical and perceptual aspects of environmental comfort. The influence of lighting perception showed subtler differences, particularly in relation to temperature changes ($F(2, 168) = 3.912$, $p = 0.021$, $\eta^2 = 0.567$), indicating that variations in temperature can influence how bright a space is perceived to be by occupants. Analysis indicated minimal effects of lighting condition on perceptions of light comfort, brightness, and acceptance, as well as thermal attributes (light comfort: $F(3, 296) = 0.595$, $p = 0.619$; light brightness: $F(3, 296) = 0.863$, $p = 0.461$; light acceptance: $F(3, 296) = 0.445$, $p = 0.721$; thermal comfort: $F(3, 296) = 0.778$, $p = 0.507$; thermal sensation: $F(3, 296) = 0.687$, $p = 0.561$; thermal acceptance: $F(3, 296) = 0.104$, $p = 0.958$). Additionally, the interaction between temperature and light color was not found to be significant in any of the domains (all interaction *p*-values > 0.05). This suggests that the perception of light comfort, brightness, and acceptance is predominantly influenced by temperature rather than the color of light, and that the color of light does not modulate the effect of temperature on these perceptions.

Table 6. Two-way ART ANOVA of environment perception at different temperatures and lighting conditions

	Source	Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Light comfort	T	1070.771	2	535.385	0.074	0.928	0.021
	Light color	12771.03	3	4257.009	0.595	0.619	0.251
	T * Light color	36966.19	6	6161.031	0.871	0.517	0.728
Light brightness	T	54844.56	2	27422.28	3.912	0.021*	0.567
	Light color	18471.75	3	6157.25	0.863	0.461	0.191
	T * Light color	23379.81	6	3896.635	0.547	0.772	0.242
Light acceptance	T	17152	2	8576	1.202	0.302	0.278
	Light color	9554.75	3	3184.917	0.445	0.721	0.155
	T * Light color	34978.66	6	5829.777	0.824	0.552	0.567
Thermal comfort	T	90863.15	2	45431.57	6.604	<0.01**	0.711
	Light color	16680.69	3	5560.231	0.778	0.507	0.131

	T * Light color	20203.76	6	3367.293	0.472	0.829	0.158
Thermal sensation	T	864922.9	2	432461.5	106.172	<0.01**	0.974
	Light color	14749.86	3	4916.62	0.687	0.561	0.017
	T * Light color	8674.167	6	1445.694	0.201	0.976	0.010
Thermal acceptance	T	145485.8	2	72742.91	10.903	<0.01**	0.860
	Light color	2244.444	3	748.1481	0.104	0.958	0.013
	T * Light color	21509.86	6	3584.977	0.503	0.806	0.127

Note: * denotes p value less than 0.05, ** denotes p value less than 0.01

The research challenges the hue-heat hypothesis by showing that light color does not significantly affect thermal perception. The results in the Table 6 indicated that thermal sensation vote (TSV) was not significantly affected by the light color, which contradicts the conventional association of color temperature with thermal sensation (Chinazzo et al., 2021; Itten, 1997; Winzen et al., 2014). In the Table 1 of Appendix D, despite differing light conditions, light comfort vote (LCV) was consistent, but cool white light was preferred for brightness vote (LBV), with blue light leading in acceptance vote (LAV). These findings align with studies suggesting blue-enriched light improves thermal comfort (Bellia et al., 2021; Brambilla et al., 2020). Contrary to expectations,

The study's results also highlight the influence of experimental settings and the need for a more nuanced understanding of how light color and temperature interact to affect thermal perception. Despite existing theories, the findings suggest that ambient temperature and light color independently influence perception, necessitating further investigation into their specific effects during night driving.

The impact of temperature on visual perception, covering aspects like comfort, brightness, and acceptance, was found to be insignificant, reinforcing the notion that within a certain range, temperature does not alter visual perception significantly (H. Wang et al., 2018). The study underscores a complex relationship between thermal and lighting conditions, where temperature primarily influences comfort, challenging prior assumptions of direct correlations between light color and thermal sensation.

4.3.2. Driving performance

The study assessed the effects of temperature (18 °C, 23 °C, 28 °C) and light color (blue, red, warm white at 2700 K, cool white at 5000 K) on driving performance, analyzing speed, acceleration, rpm, steering, pitch, lateral acceleration, gas pedal usage, and roll. Descriptive and inferential statistics, presented in Tables 3 of Appendix D and Table 7, were used to evaluate these effects. Speed, acceleration, and rpm showed little change across temperatures, with speed averages near 68 m/s. Steering, lateral acceleration, gas pedal usage, and roll remained consistent across temperatures, indicating minor thermal impact on these metrics. However, pitch showed significant temperature sensitivity ($F(2, 288) = 5.099$, $p < 0.01$), suggesting temperature's influence on vehicle dynamics.

Temperature also affected speed variability ($F(2, 288) = 4.026$, $p = 0.019$) and gas pedal usage variance ($F(2, 288) = 3.395$, $p = 0.035$), pointing to altered driving behavior under different thermal conditions. Roll variability was significant with temperature ($F(2, 288) = 4.105$, $p = 0.018$), indicating its impact on vehicle control.

Light color slightly influenced driving speed, especially under red lighting, but did not significantly affect other performance metrics. No substantial interaction between temperature and light color on driving performance was found, highlighting their independent effects on driving dynamics.

Table 7. Two-way Analyses of Variance of driving performance indices at different temperatures and lighting conditions

	Parameters	Source	Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Speed (m/s)	Mean	T	14452.31	2	7226.156	1.009	0.366	0.502
		Light color	2681.25	3	893.75	0.124	0.649	0.093
		T * Light color	11647.31	6	1941.219	0.271	0.950	0.405
	S.D.	T	56148.4	2	28074.2	4.026	0.019*	0.635
		Light color	20536.72	3	6845.574	0.963	0.411	0.232
		T * Light color	11796.78	6	1966.131	0.275	0.948	0.133
Acceleration (m^2/s)	Mean	T	3293.943	2	1646.971	0.229	0.795	0.076
		Light color	29142.25	3	9714.083	1.370	0.252	0.673
		T * Light color	10849.15	6	1808.191	0.252	0.958	0.251
	S.D.	T	28798.08	2	14399.04	2.030	0.133	0.821
		Light color	1604.5	3	534.833	0.074	0.974	0.046
		T * Light color	4658.896	6	776.483	0.108	0.995	0.133
Rpm	Mean	T	214.146	2	107.073	0.015	0.985	0.011
		Light color	340.083	3	113.361	0.016	0.997	0.017
		T * Light color	19153.28	6	3192.214	0.448	0.846	0.972
	S.D.	T	32827.27	2	16413.64	2.321	0.100	0.326
		Light color	25878.58	3	8626.194	1.213	0.305	0.267
		T * Light color	42030.58	6	7005.096	0.994	0.430	0.417
Steering (degree)	Mean	T	19673.52	2	9836.76	1.393	0.250	0.294
		Light color	19562.9	3	6520.965	0.920	0.432	0.292
		T * Light color	27749.58	6	4624.929	0.657	0.684	0.414
	S.D.	T	7676.646	2	3838.323	0.543	0.582	0.268
		Light color	2182.583	3	727.528	0.103	0.958	0.076
		T * Light color	18801.87	6	3133.645	0.444	0.849	0.656
Pitch (rad/s)	Mean	T	70687.52	2	35343.76	5.099	<0.01**	0.472
		Light color	32404.69	3	10801.56	1.527	0.208	0.216
		T * Light color	46711.34	6	7785.223	1.108	0.358	0.312
	S.D.	T	26309.31	2	13154.66	1.862	0.157	0.574
		Light color	13782.36	3	4594.12	0.648	0.585	0.300
		T * Light color	5777.785	6	962.964	0.135	0.992	0.126
Lateral acceleration (m^2/s)	Mean	T	14674.08	2	7337.042	1.034	0.357	0.296
		Light color	12309.97	3	4103.324	0.575	0.632	0.248
		T * Light color	22664.41	6	3777.402	0.532	0.784	0.456
	S.D.	T	23736.9	2	11868.45	1.667	0.191	0.822
		Light color	658.472	3	219.491	0.030	0.993	0.023

		T * Light color	4496.326	6	749.388	0.104	0.996	0.156
Gas pedal	Mean	T	9601.583	2	4800.792	0.675	0.510	0.246
		Light color	6259.361	3	2086.454	0.292	0.831	0.160
		T * Light color	23179.2	6	3863.2	0.547	0.772	0.594
	S.D.	T	47689.15	2	23844.57	3.395	0.035*	0.867
		Light color	1395.806	3	465.269	0.065	0.978	0.025
		T * Light color	5906.882	6	984.480	0.137	0.991	0.107
Roll (rad/s)	Mean	T	30156.9	2	15078.45	2.126	0.121	0.425
		Light color	34853.53	3	11617.84	1.642	0.180	0.491
		T * Light color	5951.222	6	991.8704	0.138	0.991	0.084
	S.D.	T	57427.27	2	28713.64	4.105	0.018*	0.844
		Light color	3095.361	3	1031.787	0.143	0.934	0.045
		T * Light color	7523.222	6	1253.87	0.175	0.983	0.111

Note: * denotes *p* value less than 0.05, ** denotes *p* value less than 0.01

The study assessed how environmental factors like temperature and light color influence driving dynamics. Temperature changes showed a minor impact on driving parameters such as acceleration, rpm, and steering angle, which stayed consistent across temperatures. Significant changes in pitch and variations in speed, gas pedal usage, and roll under different temperatures indicate an influence on vehicle dynamics. This complements existing research that acknowledges temperature's effect on driving behaviors. The slight speed increased under red lighting, hinting at its potential impact on speed management. This finding dovetails with prior studies, like those by Caberletti et al. (2010), noting minimal effects of light conditions on driving. The anticipated interplay between temperature and light color did not significantly affect driving metrics, pointing to their independent roles in driver behavior.

4.3.3. N-back task performance

The study explored how ambient temperature and interior light color affect cognitive functions during driving, focusing on reaction time and response accuracy in N-back tasks. Data were gathered across three temperature settings (18 °C, 23 °C, and 28 °C) and four lighting conditions (blue, red, warm white—2700 K, and cool white —5000 K), as shown in Table 4 of Appendix D. Temperature had a significant effect on response accuracy ($F(2, 1728) = 3.886$, $p = 0.022$), with accuracy peaking at 23 °C (93.605%) and dropping significantly at 28 °C to 80.422%. This suggests that higher temperatures impair cognitive accuracy. Reaction times, however, showed little variation with temperature, indicating a consistency in cognitive processing speed across different thermal environments. The quickest average reaction time was recorded at 23 °C (0.661 s), but the variance was not statistically meaningful ($F(2, 1728) = 1.803$, $p = 0.167$). As for the impact of light color, blue lighting was associated with the highest response accuracy (93.673%), pointing to its beneficial effects on cognitive performance. In contrast, warm white light resulted in the lowest accuracy (90.934%), potentially hinting at increased cognitive load or distraction. Reaction times remained stable across different lighting scenarios, suggesting that cognitive speed is unaffected by changes in lighting color.

Table 8. Two-way Analyses of Variance of response accuracy and reaction time of N-back tasks at different temperatures and lighting conditions

Parameters	Source	Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Response accuracy (%)	T	53829.4	2	26914.7	3.886	0.022*	0.592
	Light color	17893.56	3	5964.519	0.846	0.470	0.197
	T * Light color	19218.7	6	3203.117	0.456	0.840	0.211
Reaction time (s)	T	25646.81	2	12823.41	1.803	0.167	0.799
	Light color	3225.389	3	1075.13	0.149	0.930	0.100
	T * Light color	3223.618	6	537.270	0.075	0.998	0.100

Note: * denotes p value less than 0.05, ** denotes p value less than 0.01

Our study probed the impacts of ambient temperature and light color on essential cognitive functions during driving, particularly focusing on response accuracy and reaction times in N-back tasks. Findings pointed to temperature's notable effect on response accuracy, with the highest accuracy at 23 °C, hinting at an optimal thermal range for cognitive tasks, consistent with prior research (Lan & Lian, 2009; Schiavon et al., 2017b; C. Wang et al., 2021). This underscores the need for optimal ambient conditions to boost cognitive functioning. Despite varying temperatures, reaction times exhibited stability, implying cognitive resilience to environmental fluctuations, likely due to the adaptive nature of cognitive processing. Light color influenced cognitive accuracy, yet its impact on reaction time was minimal, indicating consistent cognitive processing speeds across lighting conditions, resonating with earlier studies (Hawes et al., 2012a; Kretschmer et al., 2012a). Notably, higher CCT lights improved response accuracy, suggesting that specific light wavelengths might enhance brain activity. In contrast, lower CCT lights decreased accuracy, possibly inducing cognitive fatigue or distraction (Chellappa et al., 2011; Y. Li et al., 2021; Mehri et al., 2023), highlighting how light temperature can affect cognitive performance.

The investigation did not find significant interactions between temperature and light color on cognitive functions, indicating their independent influence without synergistic interactions, which differs from findings suggesting combined environmental effects on cognition (Seyedrezaei et al., 2023).

4.3.4. Task load index, comfort, sleepiness, and emotion

Appendix D Tables S2 and S3 detail how ambient temperature and light color affect drivers' task load perceptions, as gauged by the NASA-TXL index covering mental demand, physical demand, temporal demand, performance, effort, and frustration. A increase in mental demand ratings with temperature rise was noted, peaking at 28°C, indicating enhanced cognitive strain. A reduction in perceived performance effectiveness at this temperature suggests a negative impact on task execution. These findings highlight the complex relationship between environmental conditions and cognitive load, confirmed by significant changes in temporal demand and performance.

Lighting effects were nuanced, with red light slightly increasing mental demand and effort, while blue light maintained moderate task load levels. The analysis showed no significant interaction between temperature and light color on mental or physical demand, indicating their independent effects on perceived task load. Statistical analysis emphasized the temperature's influence on temporal demand and frustration ($p < 0.05$ for temporal demand; $p < 0.01$ for frustration). Significant temperature-related differences in performance ($p < 0.01$) further illustrate how environmental settings can impact perceived efficacy and cognitive load.

Appendix D Tables S4 and S5 present an analysis of how varying temperatures (18°C, 23°C, 28°C) and lighting (blue, red, warm white at 2700 K, cool white at 5000 K) impact participants' comfort, sweating levels, sleepiness, and emotions, showcasing the influence of these environmental factors on comfort and cognitive state. The study found that comfort levels were highest at a moderate temperature of 23°C, with significant temperature-related variations ($p < 0.05$) emphasizing temperature's strong influence on comfort. At 28°C, sweating increased notably ($M = 2.563$), with a significant temperature effect on sweating ($p < 0.01$). Sleepiness showed a slight increase at this temperature ($M = 3.052$), suggesting a potential trend for more sleepiness as temperatures rise, though not statistically significant ($p = 0.080$). Emotional state measures, covering valence, arousal, and dominance, remained steady across temperatures, indicating that emotional impacts may be subtle or complex. Regarding light color, its effect on comfort, sleepiness, and sweating was minimal, with no significant changes in emotional states across different lighting scenarios. This suggests that temperature has a more substantial effect on these aspects. Additionally, the interaction between temperature and light color showed no significant effect on comfort, sweating, sleepiness, or emotions ($p > 0.05$), pointing to temperature as the primary factor affecting perceived comfort rather than a combination of both environmental elements.

Statistical analyses revealed temperature's significant effect on temporal demand and frustration, highlighting its influence on perceived task urgency and emotional stress. The observed correlation between temperature and perceived performance underscores the need for optimal cabin conditions to enhance driver wellbeing and efficiency. Moderate temperatures, especially around 23°C, were preferred for comfort, aligning with prior research (Cui et al., 2013b; Nicol & Humphreys, 2002a; Z. Wang et al., 2018), while increased sweating at 28°C highlighted the thermal stress of warmer environments. The increasing sleepiness as temperature rising suggested complex thermal-cognitive interactions. Emotionally, the study found consistent states regardless of environmental changes, indicating a potential robustness of emotional responses to such conditions, or necessitating finer detection methods. Light color's impact on task load and comfort was intricate; red light slightly heightened mental effort, whereas blue light maintained a balanced task load. Importantly, no significant interaction between temperature and light color was found, pointing to their independent effects on the perceived load and cabin comfort.

4.3.5. In-car environment-based driving style recognition

K-means clustering was applied to driving data to identify two driving styles: aggressive and conservative. This classification of driving data clusters were depicted in Figure 13. Out of 72 participants who undertook 288 driving tasks, 281 data samples were usable after excluding 7 due to disqualification. This breakdown led to 147 samples categorized as aggressive and 134 as conservative. The clustering's effectiveness was assessed using the Silhouette Coefficient, which, at 0.55, surpassed the threshold of 0.5 (Dalmaijer et al., 2022), indicating distinct cluster separation. Subsequent analysis yielded the mean and standard deviations for each category, denoted as aggressive and conservative. A significant difference between these two groups with notable differences in speed, acceleration, and steering behaviors. Specifically, the aggressive group exhibited higher averages in these metrics, while the conservative group presented lower figures, reflecting their respective driving styles.

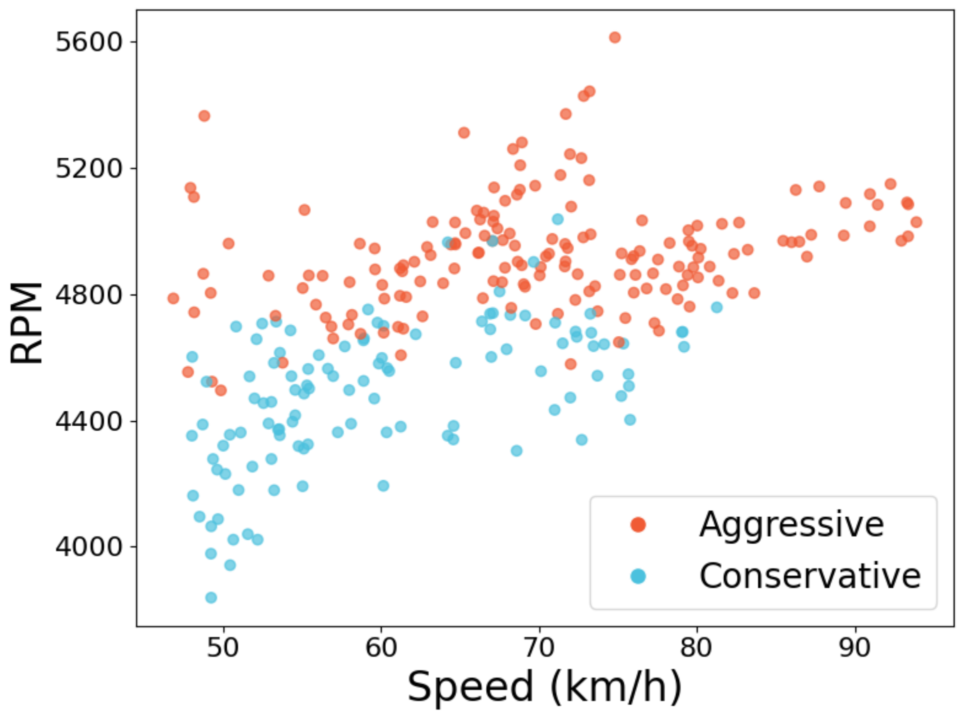


Figure 13. Results of K-means based on the driving data.

The Random Forest (RF) method, integrated with leave-one-subject-out cross-validation, focused on temperature and light color for driving style classification, yielded an overall accuracy of 72.9%. In this setup, the aggressive driving style had a precision of 69% and a recall of 43%, whereas the conservative driving style showed a precision of 73% and a recall of 89%. The F-measures stood at 53% for aggressive and 80% for conservative driving styles, indicating the model's better efficacy in predicting conservative behaviors. Feature importance analysis revealed contributions of 0.127 for both temperature and light color, with a predominant influence of their interaction at 0.746.

Aggressive drivers were identified by increased speed, acceleration, and steering activities, indicating a dynamic driving preference, while conservative drivers showed lower metrics in these areas, denoting caution. Driving skills, gauged by the mean and variability in performance metrics, inversely related to driving consistency, showing that aggressive drivers tend to have more variable driving skills (Lu, 2011; Martinussen et al., 2014). The results indicated that aggressive drivers had higher mean and variability in driving performance, suggesting a link between an aggressive driving style and increased variability in driving skills. This research aligns with prior findings (Martinussen et al., 2014; Reason et al., 1990; F. Yan et al., 2019; L. Yang et al., 2018), , highlighting the significant correlation between driver behaviors and their respective driving styles. Contrary to previous research that largely views driving style as an unchanging characteristic (S.-W. Chen et al., 2013; Shi et al., 2015), this investigation reveals a more complex reality. Within the participant group, 29 consistently adopted an aggressive driving style, 14 showed a flexible driving style alternating between conservative and aggressive, and 26 remained consistently conservative.

4.3.6. EEG measurements

Table 9 highlighted underscored the significant effects that temperature have on EEG signals.

The two-way Analysis of Variance (ANOVA) revealed significant alterations in EEG signal dynamics attributable to changes in different temperature conditions. For the entire driving task, in examining the entire brain region, the ANOVA results indicated the significant effects of temperature on the PSD of delta ($F = 6.817$, $p < 0.01$, $\eta^2 = 0.757$) and beta ($F = 7.890$, $p < 0.01$, $\eta^2 = 0.872$). When considering the band ratios, the results demonstrated a significant difference in the *α/β* ($F = 5.959$, $p < 0.01$, $\eta^2 = 0.785$) of the entire brain regions attributable to the temperature levels. This suggests that temperature significantly altered the mean value of the *α/β*. During dual-task driving sessions, notable changes were observed in the PSD of delta and beta band across all regions, with mean square F values suggesting substantial effects of temperature conditions ($F = 5.693$, $p = 0.004$, $\eta^2 = 0.875$). The temperature had a pronounced impact on δ and β bands, highlighting temperature's role in modulating cognitive load and attentional processes under different driving conditions. Similarly, the ANOVA test of single-task driving sessions within various ROI revealed significant effects of temperature on both the PSD of delta and beta and the band ratio *α/β*. In the study of Wang et al., (2023), they reported that the PSD of beta waves decreased with rising temperatures. As the ambient temperature increased, there was an elevation in the normalized power of theta and alpha activities, while vigilance and frontal EEG Asymmetry decreased.

Contrasting with temperature, I did not find the statistically significant influence exerted by light on the bands PSD or band ratios in any of the ROI across the various lighting conditions. This observation indicated the nuanced role of lighting in affecting brain activity, suggesting a secondary role of lighting conditions in modulating brain activity during driving tasks compared to temperature.

The two-way ANOVA results indicated no significant interaction effects between temperature and interior lighting conditions on the EEG signals for both single-task and dual-task driving sessions. This finding suggests that each environmental factor independently modulates brain activity without synergistic or compounded impacts.

Table 9. Two-way Analyses of Variance of EEG features at different temperatures and lighting conditions across the driving sessions

Driving session	**Source**	**Feature**	**ROI**	**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**	**Partial Eta Squared**
All	T	δ	All	93583.90	2	46791.95	6.817	0.001**	0.757
All	T	β	All	107463.31	2	53731.64	7.890	<0.001**	0.872
All	T	δ	Frontal	112122.52	2	56061.26	8.248	<0.001**	0.812
All	T	β	Frontal	109602.52	2	54801.26	8.071	<0.001**	0.870
All	T	δ	Central	69856.58	2	34928.29	5.024	0.007**	0.703
All	T	β	Central	84221.52	2	42110.76	6.108	0.002**	0.840
All	T	β	Parietal	121060.10	2	60530.04	8.947	<0.001**	0.833
All	T	*α/β*	All	82269.75	2	41134.88	5.959	0.003**	0.785
All	T	*α/β*	Frontal	76092.52	2	38046.26	5.492	0.005**	0.794
All	T	*α/β*	Parietal	100355.12	2	50177.57	7.362	0.001**	0.764
Dual-task	T	δ	All	66932.69	2	33466.34	4.807	0.009**	0.652

Dual-task	T	β	All	78661.58	2	39330.79	5.693	0.004**	0.875
Dual-task	T	δ	Frontal	70010.69	2	35005.34	5.039	0.007**	0.702
Dual-task	T	β	Frontal	82973.08	2	41486.54	6.029	0.003**	0.878
Dual-task	T	β	Parietal	91195.58	2	45597.79	6.633	0.002**	0.820
Dual-task	T	α/β	Parietal	70143.52	2	35071.76	5.054	0.007**	0.831
Single-task	T	δ	All	103851.51	2	51925.76	7.604	0.001**	0.803
Single-task	T	β	All	131626.63	2	65813.28	9.789	<0.001**	0.870
Single-task	T	δ	Frontal	131090.71	2	65545.34	9.740	<0.001**	0.841
Single-task	T	β	Frontal	137456.11	2	68728.04	10.275	<0.001**	0.882
Single-task	T	δ	Central	75657.52	2	37828.76	5.458	0.005**	0.762
Single-task	T	β	Central	105981.44	2	52990.70	7.776	0.001**	0.830
Single-task	T	δ	Parietal	149270.96	2	74635.45	11.211	<0.001**	0.855
Single-task	T	α/β	All	98118.75	2	49059.38	7.183	0.001**	0.764
Single-task	T	α/β	Frontal	100955.82	2	50477.89	7.403	0.001**	0.768
Single-task	T	α/β	Central	63758.77	2	31879.39	4.574	0.011**	0.472
Single-task	T	α/β	Parietal	103230.35	2	51615.13	7.615	0.001**	0.746
Single-task	T	$(\alpha+\theta)/\beta$	Parietal	74152.31	2	37076.31	5.366	0.005**	0.595

Note: * denotes p value less than 0.05, ** denotes p value less than 0.01

4.3.7. fNIRS measurement

Table 10 illustrates the analysis of variations in cortical brain activation across brain regions Prefrontal (PF), Lateral Prefrontal (LPF), and Right Prefrontal (RPF) under varying experimental conditions. In the dual-task session, a significant response to temperature was observed in the HBO concentration at all the prefrontal area. This finding is substantiated by statistical analysis, revealing significant variance ($F(2, 144) = 5.868$, $p = 0.003$). During the entire driving task, HBR concentration at all the prefrontal area exhibited significant variability in response to different temperature. The statistical analysis highlighted a notable effect of temperature on HbR concentration ($F(2, 144) = 5.926$, $p = 0.003$). There were no significant differences in HbO or HbR concentration found across the Prefrontal (PF), Lateral Prefrontal (LPF), and Right Prefrontal (RPF) regions due to the lighting condition change or the interaction between the two environment factors.

Table 10. Two-way Analyses of Variance of fNIRS features at different temperatures and lighting conditions by different regions, channels and value

Driving session	Source	Value	Feature	Region	Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
All	Temp	HBR	conc	all	81700.8	2	40850.4	5.926	0.003	0.572
All	Temp	HBR	conc	left	102813.9	2	51406.97	7.531	0.0007	0.661
Dual-task	Temp	HBO	conc	all	80948.9	2	40474.45	5.868	0.003	0.704
Dual-task	Temp	HBO	conc	left	68704.32	2	34352.16	4.953	0.008	0.604
Dual-task	Temp	HBO	conc	right	75329.08	2	37664.54	5.447	0.005	0.757
Dual-task	Temp	HBO	ppd	right	76890.79	2	38445.39	5.584	0.004	0.875

Note: * denotes p value less than 0.05, ** denotes p value less than 0.01. “All” represents the entire driving session. “Dual-task” represents the driving session with N-back tasks.

4.3.8. Limitation and recommendations

One notable limitation of the study is the relatively small sample size, which could diminish the statistical power of the findings. To address this, we plan to recruit more participants in future studies, thereby enhancing the research's robustness. Additionally, the methodology incorporated a mixed design by merging within-subjects and between-subjects designs. Employing a within-subjects design in human-factor experiments can help mitigate individual differences, enhancing the reliability of the results.

Furthermore, the investigation focused on driving performance within a simplified simulated driving task. Future research should extend to more complex driving scenarios, such as navigating multi-lane urban roads and making turns, to better understand the effects of ambient temperature on driving behavior under varied conditions.

The analysis did not account for light intensity, which is a significant oversight given its potential impact on the hue-heat effect. The literature suggests that both the intensity and the correlated color temperature (CCT) of light can influence perception (Baniya et al., 2018; Chao et al., 2020), which in turn can affect thermal sensation and comfort. Future investigations should include a comprehensive analysis of light intensity alongside CCT to better understand their combined effects on driver comfort and perception.

Finally, the demographic characteristics of the participant pool, including the predominance of younger drivers with limited driving experience and an unbalanced gender ratio, may have introduced bias into the findings. Since driving styles were classified based on task-specific rather than subject-specific data, the influence of participants' demographic traits on driving styles remains unexplored. Future research should aim to address these limitations by incorporating a more diverse participant group and examining the impact of demographic factors on driving behavior.

Chapter 5: Conclusions

This dissertation represents a comprehensive examination of the interplay between IEQ and cognitive performance, with a particular focus on driving behaviors and the physiological underpinnings that support or impair cognitive function. Throughout this research, a holistic approach was adopted to dissect the multifaceted aspects of IEQ, encompassing factors such as air quality, thermal environment, noise, lighting, and non-light visual factor, and their collective impact on cognitive functions including attention, perception, memory, language, and higher-order cognitive skills. Central to this research was the exploration of how specific environmental conditions within a vehicle's cabin, such as CO_2 levels and body odor, as well as ambient temperature and lighting condition, impact cognitive functioning and driving performance.

The literature review, serving as the foundation of this study, painted a broad picture of the current understanding in the field, emphasizing the notable emphasis on thermal environment and noise within IEQ research and their documented influences on cognitive tasks. The findings from the 66 studies indicate that while poor IEQ conditions are generally linked to reduced cognition, the effects of specific IEQ factors on different cognitive functions vary significantly. The subsequent empirical investigation extended these themes, delving into the specific impacts of CO_2 and body odor on drivers' cognitive and behavioral responses. Utilizing a high-fidelity driving simulator, the study investigated driving performance under varying environmental conditions, providing a rich dataset for analysis. Noteworthy in this exploration was the finding that while CO_2 levels and body odor independently influenced certain cognitive and driving performance metrics, their integrated effects, particularly over extended periods, were more pronounced and complex than initially anticipated. Body odor enhances response accuracy in the N-back task. Key findings from EEG presented that body odor significantly reduces $(\theta+\alpha)/\beta$ and θ/β ratios, indicating increased alertness and attention. However, it does not significantly impact fNIRS-measured hemodynamic responses. In contrast, CO_2 levels show no direct effect on EEG signal patterns and do not significantly affect fNIRS-measured hemodynamic responses either. Temperature has a notable impact, significantly influencing speed control, N-back task response accuracy, environment perception, dominance, and general comfort. It also affects EEG Delta band PSD, increasing it while decreasing Beta, which suggests a reduction in mental engagement during driving. Additionally, rising temperature significantly decreases fNIRS oxy-hemoglobin concentration during dual-task driving, indicating cognitive load challenges. Conversely, lighting conditions do not directly influence EEG and fNIRS signals, and no interaction between temperature and lighting was found during driving tasks. The study's examination of the hue-heat hypothesis in the context of night-time driving offered intriguing insights, challenging preconceived notions about the interplay between light color and thermal sensation. The results highlighted temperature as a more dominant factor influencing drivers' environmental satisfaction and cognitive performance. The investigation does not support the hue-heat hypothesis.

Looking forward, this dissertation sets the stage for a myriad of research opportunities. Future studies could explore these environmental-cognitive relationships in more diverse and real-world settings to capture the evolving nature of cognitive responses to environmental changes. Additionally, the impact of other IEQ factors, such as humidity, air velocity, and the presence of other volatile organic compounds, could be examined to provide a more holistic understanding of the indoor environmental conditions that optimize cognitive function and driving performance. The interdisciplinarity of this research, bridging environmental psychology, cognitive ergonomics, and automotive design. By emphasizing the critical role of ambient conditions in cognitive and behavioral outcomes, this study contributes valuable knowledge to the ongoing efforts to create safer, more comfortable, and cognitively supportive environments within the built environment.

In conclusion, this dissertation has illuminated the complex and multifaceted nature of the relationship between IEQ factors and cognitive performance, particularly within the context of driving. Through a rigorous and detailed investigation, it has provided valuable insights into how ambient temperature, air quality, and lighting conditions within a vehicle cabin can significantly influence cognitive functions and driving behavior. These findings not only contribute to the academic discourse on environmental psychology and cognitive ergonomics but also have practical implications for the design of vehicle interiors and the development of strategies to enhance driver comfort. As move forward, understanding and optimizing the in-car environmental conditions will be paramount in fostering enhanced cognitive performance, thereby paving the way for future research that continues to explore these vital interactions.

Appendix A

Paper A. How Indoor Environmental Quality Affects Occupants' Cognitive Functions: A Systematic Review

Chao Wang[1], Fan Zhang[2], Julian Wang[3], James K. Doyle[4], Peter A. Hancock[5], Cheuk Ming Mak[6], Shichao Liu[1*]

[1]*Department of Civil and Environmental Engineering, Worcester Polytechnic Institute, MA, USA*
[2]*School of Engineering and Built Environment, Griffith University, Gold Coast, Australia*
[3]*Department of Architectural Engineering, Pennsylvania State University, University Park, PA, USA*
[4]*Department of Social Science and Policy Studies, Worcester Polytechnic Institute, MA, USA*
[5]*Department of Psychology and Institute for Simulation and Training, University of Central Florida, Orlando, FL, USA*
[6]*Department of Building Services Engineering, The Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong*

* Shichao Liu (sliu8@wpi.edu)

Highlights

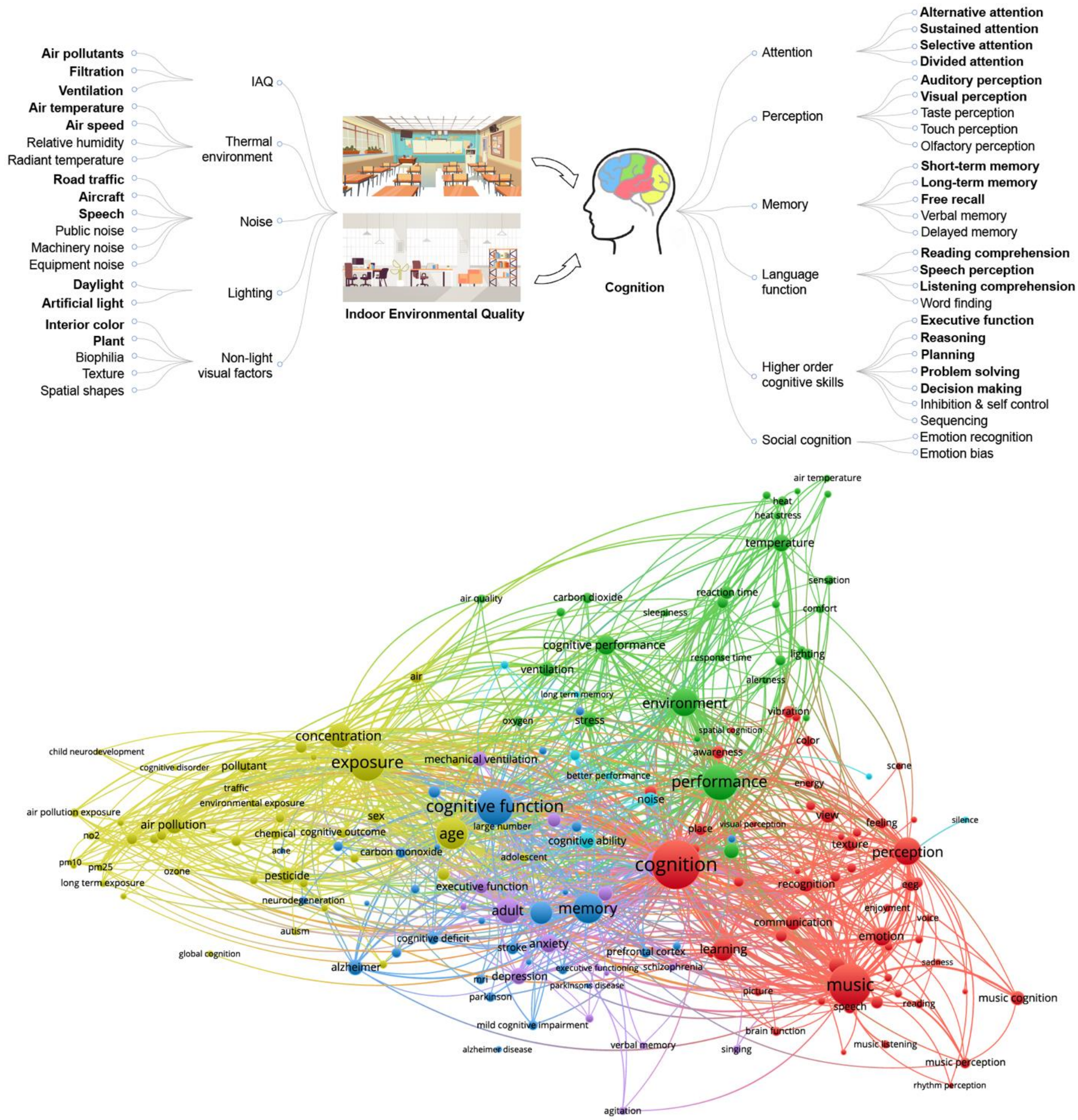
- Effects of IEQ factors on cognition are reviewed
- IEQ and cognition are but not always statistically associated
- Considerable conflicting results are identified among studies
- A specific IEQ factor may have varying effects on different cognitive functions

Abstract

Cognitive functions refer to the set of brain-based skills to execute tasks of various difficulty levels. As people spend substantial time indoors, the indoor environmental quality (IEQ) influences occupants' cognitive functions and consequently their learning and work performance. Previous studies have commonly examined the effects of IEQ on integrated learning or work performance, rather than specific cognitive skills. The present review decomposes IEQ into five factors—indoor air quality, the thermal environment, lighting, noise, and non-light visual factors. It divided cognition into five categories—attention, perception, memory, language function, and higher order cognitive skills—to better understand the relationship between IEQ and cognition. We conducted a detailed manual review of 66 focused studies and adopted co-occurrence analysis to generate landscapes of the associations between IEQ and cognition factors by analyzing keywords and abstracts of 8, 133 studies. Overall, results show that poor IEQ conditions are but not always associated with reduced cognition. However, the effects of a specific IEQ factor on different cognitive functions are quite distinct. Likewise, a specific cognitive function could be affected by different IEQ factors to varying degrees. Furthermore, the results suggest extensive inconsistencies in the relevant literature, especially regarding the effects of IAQ or thermal environment on cognition. Additionally, the keyword co-occurrence analysis identified more IEQ factors and cognitive functions emerging in the recent literature. Future studies are recommended to explore the factors causing the inconsistencies that we highlight here.

Keywords: *Environmental Design, Healthy Buildings, Occupant Satisfaction, Learning Performance, Productivity, Work Efficiency*

Graphical Abstract



Keyword co-occurrence of studies in the past five years (2016-2020)

Introduction

Cognitive functions refer to the set of brain-based skills to required execute tasks of various difficulty levels (Angevaren et al., 2008). They are associated intensively with the mechanisms of learning, remembering, reasoning, and problem-solving (Staal, 2004). Each function plays an essential role in processing new information. Research in neuroscience has been stated that cognitive performance is associated with the activities of specific brain centers. For instance, the activation of frontal and parietal areas is directly associated with sustained attention performance (Sarter et al., 2001b).

As people now spend a substantial amount of time indoors learning and/or working, particularly in the lockdown of the pandemic, IEQ could significantly affect occupants' cognitive functions and therefore their learning and work performance. Prior reviews have (Al Horr et al., 2016a; Fisk & Seppanen, 2007; Frontczak & Wargocki, 2011) classified IEQ factors into indoor air quality (IAQ), thermal environment, light, acoustic, office and layout, biophilia and views, look and feel, and location and amenities, to name a series of the major influences.

There is a substantial body of research showing that poor indoor air quality (Mendell & Heath, 2005b), ventilation (Allen et al., 2016b; Coley et al., 2007b), thermal conditions (Cui et al., 2013a; Lan et al., 2010), light (Hygge & Knez, 2001b), noise (Jahncke et al., 2011; Sundstrom et al., 1994), and room layout (Haynes, 2008) can profoundly degrade learning and work performance. Nevertheless, the findings of these studies, and other substantial ones on this topic (Choi et al., 2014; Haverinen-Shaughnessy & Shaughnessy, 2015; Servilha et al., 2014; Wargocki & Wyon, 2007), do not fundamentally differentiate between types of cognitive tasks. However, this is essential as the impacts of IEQ may vary significantly between cognitive tasks. For instance, previous research indicates that, compared with complex tasks, simple tasks, for example, might be less susceptible to environmental noise and heat (Hancock & Vasmatzidis, 2003; van Kempen et al., 2010). Obviously, different learning/work tasks rely upon different cognitive functions. For instance, the presidents or chief operating officers of large corporations might require stronger skills in decision making and planning, while customer service representatives, in a call center, who handle customer complaints should be able to excel at auditory perception and emotion recognition. Similarly, reasoning skills are more involved in the process of learning mathematics compared to foreign languages. It is difficult to associate IEQ and learning or work performance without specifying each of the cognitive activities involved.

In the contemporary indoor environment, success in learning and work is mainly determined by cognitive performance as opposed to physical performance (e.g., strength, endurance, balance). Understanding the influences of various IEQ factors on each cognitive function is the key to estimating how differently a chief officer could be susceptible to poor IEQ from the vulnerability of a service representative in a call center. Unlike previous reviews that examine learning/work performance as a whole (Al Horr et al., 2016b; Wargocki & Wyon, 2017), the present study focuses on specific cognitive functions that underpin various learning/work activities, it aims to provide a multidisciplinary and comprehensive survey of research associated with cognitive functions influenced by IEQ. Another motivation is the insufficiency of qualitative and/or quantitative summaries of massive numbers of studies (in the thousands) that may not directly focus on IEQ and cognition, but still shed light on the patterns of their relationship. To fill this gap, this review work applies keyword co-occurrence analysis to extract knowledge from thousands of identified and relevant published papers.

Categories of IEQ factors and Cognitive functions

In this work, we synthesized a large panoply of previous reported work and grouped IEQ factors into five categories (*IAQ, thermal environment, noise, lighting, and non-light visual factors*), we just posed these with five cognitive functions into the categories (*attention, perception, memory, language function, and higher order cognitive skills*). Social cognition has been identified but not discussed in this review due to limited number of studies identified. Indoor environmental factors that do not ubiquitously exist were not explicitly considered in this review. These include transients such as music and natural-based soundscapes. However, we acknowledge that these factors may serve to improve cognition (e.g., working memory (A. Wang et al., 2013), verbal memory (Kang & Williamson, 2014), spatial reasoning (Bell et al., 2016), speed of spatial processing (Angel et al., 2010)), albeit the literature is still rather equivocal concerning a number of their effects (Hallam et al., 2002; Huang & Shih, 2011; Newbold et al., 2017; Proverbio et al., 2018; Thompson et al., 2012). Additionally, this review does not consider the cognitive development of children that might be affected by IEQ (Dadvand et al., 2015). Figure 1 lists the main categories and subcategories of IEQ factors and cognitive functions identified in the literature. Next section provides an overview of the basic concepts of IEQ factors and cognitive functions.

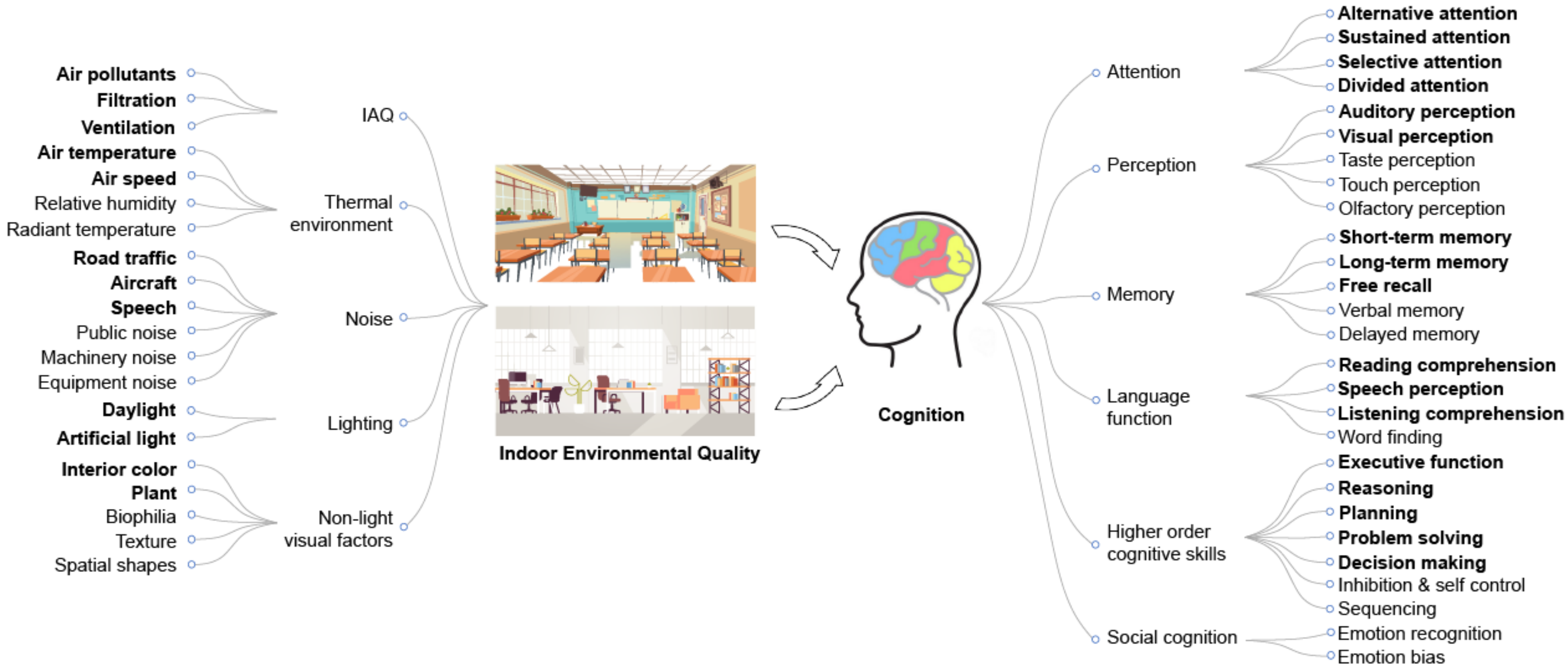


Figure 1. Summarized categories of IEQ and cognitive functions based on the literature; The factors in bold are explicitly studied in the literature concerning the IEQ-cognition-interaction.

Indoor Environmental Quality

Indoor air quality

Indoor air quality (IAQ) is a critical factor that affects both the health and productivity of space's occupants (Wargocki et al., 2002). Indoor air pollutants include carbon dioxide (CO_2) (Satish et al., 2012b), sulfur dioxide (SO_2) (Spengler et al., 1979), nitric oxide (NO) (S. C. Lee & Chang, 2000), nitrogen dioxide (NO_2) (Quackenboss et al., 1986), volatile organic compounds (VOCs) (Mølhave, 1991), semi-volatile organic compounds (SVOCs) (Weschler & Nazaroff, 2012), levels of particulate matter (PM) (Dennekamp et al., 2001), biological contaminants (Cabral, 2010; Europe, 1990) among many others. Practically, ventilation and indoor CO_2 concentration are used as an indicator or proxy for diverse levels of indoor air quality (Batterman & Peng, 1995; Chatzidiakou et al., 2015; Sherman & Wilson, 1986). A 1000 ppm increase in CO_2 concentration decreases 0.5-0.9% of annual average daily attendance, which is equivalent to a relative 10-20% increase in student absences (Shendell et al., 2003). Each of these pollutants can influence both acts of cognition as well as rates of learning.

Thermal environment

Thermal environment is the physical environment that can affect heat transfer in the indoor. It influences the thermal perception of an individual and through that, the thermal comfort of occupants. Thermal comfort is the subjective evaluation of a thermal environment (ANSI/ASHRAE, 2017) and is mainly influenced by four physical parameters (air temperature, mean radiant temperature, air velocity, and relative humidity). These physical values are concentrated with two personal variables (clothing insulation and activity level) (ANSI/ASHRAE, 2017). These go together with other factors such as gender (Karjalainen, 2012), age (Griefahn & Künemund, 2001; Indraganti et al., 2015), culture (Knez & Thorsson, 2006), exposure time (Nicol & Humphreys, 2002b), and physiological adaption (Luo et al., 2016). The complexity of these influencing factors results in various prediction models, including but not limited to predicted mean vote (PMV) – a predicted percentage dissatisfaction (PPD) model (Fanger, 1970), an adaptive thermal comfort model (de Dear & Brager, 2002; Nicol & Humphreys, 2002b), and the recent personal thermal comfort (J. Kim, Schiavon, et al., 2018; J. Kim, Zhou, et al., 2018; S. Liu et al., 2018, 2019) relying on machine learning principles. The thermal environment exerts fairly consistent and predictable effects on some elements of cognition, especially toward the outer bounds of tolerance (Hancock et al., 2007).

Noise

Indoor noise can come from sources inside the building or sources external to it. Internal sources can consist of conversations of occupants (Roelofsen, 2008), indoor operating equipment (Tsiou et al., 1998), and air distribution systems (Landsberger et al., 2008), while outdoor noise transmitted into indoor spaces can emanate from road traffic (Shield & Dockrell, 2004; Zhisheng et al., 2007), aircraft (Haines et al., 2002; Shield & Dockrell, 2004), outdoor construction (Zannin, 2007) and outdoor components of the heating, ventilation, and air conditioning (HVAC) (Guckelberger, 2000). Noise from traffic, aircraft, public, or equipment generates a complex sound assemblage that can negatively impact memory (Hygge & Knez, 2001b; Sörqvist, 2010; Stansfeld et al., 2005). Even speech from other classrooms in school can influence students' memory in adjacent classes (Ljung, 2009). Occupants' perceptions are affected by both energy intensity and distribution of acoustical stimuli (Ma et al., 2018).

Lighting

Lighting plays a critical role in synchronizing humans' endogenous and night pacemakers with the environment. As the most powerful zeitgeber synchronizing our endogenous circadian rhythm with the environment, light has been previously described as one of the agents involved in improving cognitive performance (Keis et al., 2014a). Light quality for visual comfort is primarily characterized by photometric variables (Ochoa & Capeluto, 2006; Shieh & Lin, 2000; Zhou & Rau, 2018), glare (Garciai & Wierwille, 1985; Osterhaus & Bailey, 1992; Rodriguez et al., 2016), and light color temperature (Mills et al., 2007; Mott et al., 2013). Literature regarding the effects of lighting on cognition has focused on photometric parameters (i.e., luminance, illuminance, color temperature, color rendering).

Artificial light is produced by electrical means such as lamps and light fixtures, while daylight is the combination of all direct or indirect sunlight. Daylight is considered as the best light source for color rendering and closely and unsurprisingly matches the human visual response (D. H. W. Li, 2010). It is a kind of trigger that motivates biological activities. Whenever possible, building design typically tries to use daylight as the source of illumination, because of its excellent color rendering provides higher satisfaction (Hua et al., 2011) and supports for stable circadian rhythms (S. Begemann et al., 1997). It also helps occupants to generate an active sense of pleasantness and brightness, which is positive for occupants' comfort and productivity (Atli et al., 2005; S. H. A. Begemann et al., 1997).

The enhancement of occupants' alertness and performance can be improved by light exposure through a "non-visual" photoreception system depending on melanopsin expressing retinal ganglion cells (mRGCs) (Daneault et al., 2018). It also has been reported in recent years that human alertness, cognitive performance, and mood can be affected by non-visual lighting effects related to spectrum distribution, timing, and exposure duration, in which certain new metrics have been developed based on radiometric quantities (Bansal et al., 2017; H. Li et al., 2017; Price et al., 2019).

Non-light visual factors

In addition to environment luminance, interior surface textures, spatial design, decoration, interior color, window views, biophilia, and many other non-light visual factors can influence cognition. The non-light visual factors in this review include interior color, spatial settings, closeness to natural views, and landscape. Satisfying non-light visual factors of the indoor environment positively affects occupants' cognitive function and overall performance. Humans have ingrained reactions to different colors, due to our essential relationship with nature. For example, the color green reminds us of an environment that makes us feel calm and harmonious (Ou et al., 2004). Also, indoor visual interests and opportunities for discovery provide intellectual and cognitive stimulation, which have been found to foster creative behaviors (McCoy & Evans, 2002). Such factors have been considered influential in restoring attentional resources, as we articulate further below.

Humans tend to seek connections with nature and other living things, as posited by the biophilia hypothesis (Wilson, 1984). Natural environments have, as we have noted a restorative effect on attention, according to the attention restoration theory (ART) (Kaplan, 1995). A view of natural elements is beneficial for high workability and job satisfaction (Lottrup et al., 2015). With respect to the visible features of outdoor or indoor space, landscapes with natural features have a positive effect on cognition and performance. High school landscapes that lack natural features have been shown to reduce standardized test scores (Matsuoka, 2010), while landscapes with greater tree coverage ratios show a higher percentage of proficiency or advancement in reading and mathematics (Kweon et al., 2017).

Cognitive functions

Cognitive functions can be summarized using a number of different taxonomies. Prior review work on cognition and human performance has classified cognitive functions into attention, memory, perceptual-motor performance, judgment, and decision making (Staal, 2004); while (Lan et al., 2009a) categorized it into perceptual functions, memory, thinking, and expressive functions. Another categorization approach to cognition consists of memory, attention, reasoning, visual perception, language function, problem-solving, and planning (M. W. Eysenck & Brysbaert, 2018b). Among the cognitive functions reported in the studies we have examined, attention, perception, memory, language function, and higher order cognitive skills are the most commonly studied when considering associations with IEQ. Each cognitive function can be further sub-divided as described in Figure 1. For instance, the higher order cognitive skills consist of problem solving, decision making, reasoning, and others (Blanchette & Richards, 2010). Other essential cognitions (e.g., social cognition) are also listed (in the unbolded text) but not studied in this current review.

Attention

Attention is an individual's ability to concentrate on a particular facet of information (M. Eysenck, 2012). Attentional processes can be further categorized as sustained attention (Barkley, 19970101; Hancock, 2013; Sarter et al., 2001a), selective attention (Corbetta et al., 1991; Duncan, 1984; Fockert et al., 2001; Green & Bavelier, 2003), and divided attention (Castel & Craik, 2003; McDowd & Craik, 1988; Somberg & Salthouse, 1982). Attentional performance can be assessed using the Continuous Performance Task (CPT) (Shalev et al., 2011), reaction time (Saltzman & Garner, 1948), Stroop tasks (C. M. MacLeod, 1992), the attention network test (J. W. MacLeod et al., 2010), and the dot-probe task (Fockert et al., 2001) among others. For instance, reaction time is the assessment of motor and mental response speeds, as well as measures of movement time (Lan et al., 2011b; Schiavon et al., 2017a). It is also an important performance measure of multiple cognitive functions beyond attention (Coley et al., 2007a), such as sensory memory (Alain et al., 1998).

Attention has a limited capacity. People cannot easily focus on more than one stimulus at a time, unless experience with the task that has enabled automatic processing (Cowan, 2001). Also, a person might possess an attentional bias that refers to the tendency of that individual to selectively attending to a certain category of stimuli in the environment while tending to overlook, ignore, or disregard other kinds of stimuli (*Neuroscience for Addiction Medicine*, 2016). Attentional bias can be influenced by emotion and mood (Baert et al., 2010; Becker & Leinenger, 2011), and these moderating effects may confound the association between IEQ and attention. Moreover, attention could be diverted from stimuli to be remembered by environmental proximal stimuli (e.g., conversation in an open-space)(Cowan et al., 2005), making it vulnerable to indoor environmental factors.

Perception

Perception refers to the set of cognitive processes to capture, organize, identify, and interpret the stimuli received by the sensory organs to understand the presented information in the environment (Schacter et al., 2019). It acts as an essential cognitive ability in our lives to connect us with the surrounding world. While some reports such as (Montemayor & Haladjian, 2017; Tacca, 2011) distinguish perception from cognition, numerous researchers regard perception as an aspect of overall cognition (Coren, 2012; Matlin, 2009). Perception is different from sensation. The sensation is the process of detecting our environment, while perception is the interpretation of what is sensed. Perception is more involved with top-down processing which itself is influenced by an individual's expectations and knowledge rather than simply by the stimulus itself (M. W. Eysenck & Brysbaert, 2018a).

Perception may be biased as a function of emotion (W. Liu et al., 2012), individual differences (such as different sensitivity to tone sequences (Postma-Nilsenová & Postma, 2013)), personal context (Schlee et al., 2007), beliefs, and expectations (Pronin, 2007) that might confound the influence of IEQ on perception. For instance, a person's perception of thermal comfort might be affected by the opinion of another person sharing the same office.

There are multiple modes of perception: auditory perception (Murch, 1973), visual perception (Cornsweet, 2012), speech perception (also a language function), taste perception (Hoegg et al., 2007), touch/haptic perception (Grunwald, 2008), and olfactory perception (Slotnick, 1990). Visual perception is the primary human sense that moderates surrounding information received by the eyes (Attneave, 1954). Ref (Runeson & Frykholm, 19820101) concludes that visual perception is efficient in getting information associated most especially with dynamic variations. Visual stimuli can be affected by people's motivational state (Balcetis & Dunning, 20061002). For instance, humans' motivation can influence the optical system to indicate the content of conscious perception. Speech perception has a more specific scope than general auditory perception, which refers solely to the ability to receive and interpret information received by the ear and interpreted by specific language cells in the brain.

Memory

Memory is a function that allows the brain to encode, store, acquire, and retrieve knowledge as needed (Tse et al., 2007). It is a crucial element of cognition that helps us identify who we are, gain new knowledge, and form a continuity of conscious experience (M. W. Eysenck & Brysbaert, 2018a; Hancock, 2015). Memory is a component of the information processing system with both explicit and implicit functions (M. W. Eysenck & Brysbaert, 2018a). Explicit memory refers to instances of conscious recollection, such as a response to a direct request for information about one's past. Implicit memory deals with cases when people are asked to perform some tasks without the use of declarative knowledge (Roediger III et al., 2017). The memory could be subdivided into as many as 256 different categories (Tulving, 2007), going from abnormal memory, through terms such as diencephalic memory, and on to rote memory and sensory memory, and finally to working memory (Roediger III et al., 2017). However, we mainly focus here on broad categories of short-term memory (STM) and long-term memory (LTM) (Cowan, 2008).

External stimuli can be converted to memorized information via roughly three steps (Shiffrin & Atkinson, 1969). First, human beings process stimuli through sensory memory that serves as a brief holding system for the information presented to various sensory systems (Gomes et al., 1999). Sensory memory is vital for the listener to integrate incoming acoustic information (Alain et al., 1998). Then, the working memory processor encodes the information, keeps it in mind temporarily, and meanwhile searches and activates data from previously-stored memories (Baddeley, 1966b).

Finally, the new information is integrated with and then stored in long-term memory (Baddeley, 1966a).

STM is versatile and supports reasoning and the guidance of decision-making behaviors (RepovŠ & Baddeley, 2006). When a person is distracted (e.g., by indoor noise or experiencing a cold draft near an exterior window), information can be rapidly lost from such informative storage. A more modern conceptualization of STM is working memory, which is a term for the type of memory holding information for short periods while being manipulated (Baddeley, 2002). Working memory involves the processing of information (such as solving simple arithmetic problems while also remembering given words during span tasks) as well as the executive control of attention. Besides, sensory memories, as a type of STM, are the brief holding system for the information presented to the various sensory systems. Information is thought to be held briefly in each system as it waits for further processing (Gomes et al., 1999). Sensory memory is, for example, a vital part of the listener to integrate incoming acoustic information (Alain et al., 1998).

LTM is a vast store of knowledge and a record of prior events. Long-term memory also possesses a lot of subtypes. Distinctions by type of material and mode of presentation include verbal memory, visual/spatial memory, and olfactory memory, together with procedural memory (also called kinesthetic or motor skill memory). Another set of distinctions, in terms of types of declarative (or explicit) memory, are episodic memory, autobiographical memory, and semantic memory (Roediger III et al., 2017). LTM has a much larger capacity and duration than STM. As such, LTM may be less susceptible to poor indoor environmental quality.

Language function

Language function involves a set of cognitive skills that enable an individual to effectively understand and generate language for effective interpersonal communication (Skehan, 1998). It can be divided into five components, semantics, phonology, morphology, syntax, and pragmatics (Franken & Weisglas-Kuperus, 2012). Language acquisition is the process by which humans perceive, comprehend, and acquire information from language (Chiswick & Miller, 1998). Some examples of language functions include word finding, language comprehension, repetition, expression, reading, and writing (Chiswick & Miller, 1998). Memory, attention, and individual differences are common factors that affect reading and writing abilities. As a function of language acquisition, speech perception is the process that employs sensory functions to hear, and then interpret and understand the sounds (Holt & Lotto, 2010; Pisoni & Remez, 2005).

Speech perception is an integrated result of the recipient's memory, attention, and both passive and active receipt of signals. The phenomena of short-term memory deficit are common for children who are poor readers (Brady et al., 1983). Speaker’s lip movements act as visual stimuli that affect the auditory perception of what is said. This process is most apparent when there is a combination of acoustic information and visual information for a bilabial utterance combined (Macdonald & McGurk, 1978). A perception study (Brady et al., 1983) proved that poor readers have a perceptual difficulty with speech perception due to the material-specific problem. Illusions can also be generated when aural perception becomes subordinate to what the listener believes they see in the expression of the speaker’s lips.

Higher Order Cognitive Skills

Higher order cognition is a multi-faceted and complex area of research that refers collectively to the mental processes of reasoning, conceptualization, critical thinking, decision making, and creativity. Higher order cognition involves the ability to understand and implement the steps necessary to solve problems, establish new areas of learning, and think creatively (Akella, 2019). Primary topics investigated in higher order cognition consists of executive function, reasoning, planning, and problem solving.

These executive functions are a set of complex cognitive processes that help people manage thought, skills, and necessary behavior, and action to achieve goals (Friedman et al., 2006). They are diverse, correlated, and overlapping. People need these functions to execute goal-oriented behaviors, such as managing time, focusing on a task, planning, and organizing. The basic executive functions can involve cognitive inhibition, cognitive flexibility, and emotional control, while reasoning, planning, problem-solving, and decision making remain higher-order executive functions with the requirement of several more fundamentally processes working at the same time to support them (Chan et al., 2008; Diamond, 2013).

Reasoning is regarded as the cognitive process that solves a problem by establishing logical relationships between different problem elements (Zimmerman, 2000). It is the central activity in intelligent thinking. General reasoning skills include inferential reasoning, deductive reasoning, analogical reasoning, conditional reasoning, and automated reasoning (Alexander et al., 1987). Reasoning ability can vary by gender, age, and are affected by the surrounding environments including IEQ (Knez, 1995; Piraksa et al., 2014; F. Zhang & Dear, 2017).

People use planning skills to set and achieve goals by developing plans and choosing the appropriate actions based on the anticipation of consequences (Hayes-Roth & Hayes-Roth, 1979). Planning is key in the ability to make shifts in attention. It is also a vital process for decision making, self-control, and self-monitoring. Age and gender can be related to differences in planning performance (Sorel & Pennequin, 2008). In one study younger adults usually made quicker and fewer inappropriate planning moves than older adults. And girls with the ages of 5 and 17 years have been documented to outperformed boys at the same age on certain measures of planning (Naglieri & Rojahn, 2001).

Problem solving is an integrated skill to generate and select solutions for problems. It is related to mental strategies and heuristics as well as physical health (Diamond, 2013). Previous research found that indoor environmental factors such as lighting, noise, or thermal environment have established effects on problem solving (Hygge & Knez, 2001b; Knez, 1995; Knez & Kers, 2000a). Other higher order cognitive skills could consist of judgment and decision making that is the cognitive ability to do a selection among several possible alternatives (Brun et al., 1997).

Methods

In order to establish systematic effects of IEQ on these orders of cognitive performance, we conducted a thorough search of the related scientific literature using two methods, a conventional manual review and keyword co-occurrence analysis. The conventional manual review focused on the most relevant studies about the explicit association between specific IEQ factors and cognitive functions. The experimental setup, assessment tools, and the major results were tabulated in detail after scrutinizing each study. Although arduous and time-consuming, the approach provides an avenue to meticulously analyze results and serves as one of the most commonly used methods in review studies (Y. Li et al., 2007; Sundell et al., 2011). There are thousands of studies in the literature involving IEQ and/or cognition that have only implicitly addressed these same associations. The information in these studies, though not providing direct evidence-informed decisions, can still shed much light on the association between IEQ and cognition. Such information can be revealed through the keyword co-occurrence analysis which we have provided here.

Conventional manual review

We searched and then gathered the most relevant studies that specifically and explicitly examined the relationship between IEQ and cognition. These were derived from multiple sources, including scientific journals, conference proceedings, and relevant books. The searched databases consisted of Google Scholar, ScienceDirect, Springer, National Center for Biotechnology Information (NCBI), the American Society of Heating, Refrigerating, and Air-conditioning Engineers (ASHRAE), and the Proceedings of Indoor Air and Healthy Buildings conferences.

Keywords

We first searched the following keywords, *cognitive performance, performance tasks, cognitive function, productivity, attention, perception, memory, language function, and higher order cognitive skills* for cognition, while using *IAQ, ventilation, thermal environment, noise, lighting, and non-light visual factors* for IEQ factors. We then conducted a follow-up round of searching for relevant studies by examining the reference lists of each of these collected studies.

Inclusion and exclusion criteria

We refined the papers selected based on the following rules. First, for laboratory studies, experiments had to have been conducted in well-controlled climate rooms or chambers; for field studies, environmental factors had to be clearly described and quantified. Studies without quantitative measurements of IEQ factors were excluded. Studies that did not carry out cognitive performance tests in different IEQ conditions or report performance test results with statistical analyses were excluded in the review. Third, we limited the search to concrete cognitive functions; namely, attention, perception, memory, language function, and higher order cognitive skills. Performance tests that could be mapped into these five cognitive functions were included here. Performance tests that did not fall into the above categories or integrated test kits combining various cognitive functions without reporting individual scores for each function were also excluded. Table A1 in Appendix I summarizes the cognitive tasks corresponding to different cognitive functions.

Levels of Association between IEQ and cognition

A preliminary review showed a number of conflicting results for the effects of IEQ factors on cognition. Some studies reported a statistically significant association (either positive or negative association); while some reported no clear association between the two. Yet others reported mixed results of positive associations, no associations and/or negative associations in different tests or participant categories. To demonstrate the overall quantitative relationship between IEQ factors and cognition, we, therefore, categorized levels of the statistical association between IEQ factors and cognition into three ordinal levels ranging between 0 and 2. Here, **"0"** refers to *no statistical association between IEQ and cognition*, meaning that the tested cognitive function was not significantly different between tested IEQ conditions ($p > 0.05$). A degraded **"1"** denoted *mixed association*, in which varying levels of statistical association were reported in different performance tests and/or participant groups; A score of **"2"** referred to *statistical associations*, where consistent positive or negative statistical association ($p < 0.05$) was reported between IEQ and cognition. We applied "N/A" to denote the significance level if a study did not report *p* values. An assigned score indicates an ordering of the association level.

Keyword Co-occurrence Analysis

As a particular form of data mining, text mining focuses on handling unstructured or semi-structured datasets, such as that represented by text documents (Fan, n.d.). It is a well-established practice that is commonly used to extract patterns and non-trivial knowledge from documents written in a natural language (Tan, 1999). In this review, keyword co-occurrence analysis was applied to assist in literature reviews in retrieving information from large-scale data that is usually too big to handle manually. Using the method, we were able to retrieve information from unstructured text and visualize distilled knowledge in a concise form (Ananiadou & McNaught, 2006). We first identified 8,133 studies that mentioned both IEQ and cognition in their abstracts and/or keywords using the following search logic on Scopus.

(cognition OR "cognitive function*)*
AND
("air pollution" OR "air filtration" OR ventilation OR Radon OR "particulate matter" OR PM10 OR PM2.5 OR "black carbon" OR aerosols OR voc OR "volatile organic compound" OR ozone OR O3 OR asbestos OR pollutant OR "carbon monoxide" OR "carbon dioxide" OR CO2 OR formaldehyde OR NO2 OR "nitrogen dioxide" OR pesticide OR moisture OR "indoor microorganism" OR "air odor" OR molds OR combustion OR "room temperature" OR "air temperature" OR "air speed" OR "air velocity" OR "relative humidity" OR "thermal comfort" OR "heat stress" OR "radiant temperature" OR "room NEAR/15 noise" OR "traffic noise" OR "airplane noise" OR "speech noise" OR "public noise" OR "machinery noise" OR "equipment noise" OR music OR lighting OR daylight OR "artificial light" OR "visual comfort" OR biophilia OR texture OR "spatial shapes" OR glare OR "room NEAR/15 plant" OR greenery OR glare OR "indoor layout" OR furniture OR furnishing OR "window view" OR "wall color" OR "interior design" OR "building material" OR vibration)

Then we applied the VOSviewer (visualization of similarities) (van Eck & Waltman, 2009) to construct bibliometric landscapes that extract a holistic relationship between IEQ and cognition from substantial bibliographical data (keywords and abstract). The tool provided the visualization of co-occurrences of scientific topics. For instance, ventilation is highly related to indoor air quality. Also, through co-occurrence keyword analysis of studies at different periods, we were able to identify emerging topics in the field.

Results

We synthesized the research findings on the influence of IEQ on attention, perception, memory, language function, and higher order cognitive skills using the conventional manual review of 66 studies and the co-occurrence analysis of keywords and abstracts of 8,133 studies. The experimental setups and major results of the reviewed studies are summarized in Appendix I Table A2-A6. Each of these tables summarizes the key findings between one specific cognitive function and IEQ factors. The table also includes sample size, environmental conditions, and metrics to evaluate cognitive functions. Please note some studies appear in multiple tables since they have investigated more than one cognitive function. This section summarizes the major findings of Appendix I Table A2-A6 and insights from the co-occurrence analysis.

Relationships identified with a conventional manual review

IEQ's Effects on Attention

The reviewed studies in Appendix I Table A2 revealed that most IEQ factors, when at disrupting levels of values, negatively influenced attention in general. However, there is also present evidence showing that some perceived adverse environments might even elevate attentional or concentration. For instance, several studies reported enhanced working attention (Hygge & Knez, 2001b) and concentration performance (F. Zhang & Dear, 2017) due to increased temperature and noise levels, respectively.

Indoor Air Quality

Air pollutants negatively impact the neurocognitive functions of occupants during work or learning processes. Increased levels of annual ozone and particulate matter was related to a decrease in cognitive performance (J.-C. Chen & Schwartz, 2009; Cleary et al., 2018b). An increase of 10 ppb in ozone concentration caused a 5.3 years' age-related decline in attentional performance (J.-C. Chen & Schwartz, 2009). Higher black carbon (BC) levels had a positive association with increased errors of commission and slower hit reaction time (HRT), as well as mean reaction time for all target responses (Chiu et al., 2013), but the absolute relationship between pollutant concentration and attention performance was not significant ($p > 0.05$). Traffic pollution exposure for adolescents showed an inverse association with their sustained attention and may therefore assumedly undermine neurobehavioral functions (Kicinski, Vermeir, Van Larebeke, Den Hond, Schoeters, Bruckers, Sioen, Bijnens, Roels, Baeyens, et al., 2015).

As an indicator of indoor air quality, CO_2 has recently been identified as an indoor pollutant due to its potential effect on cognitive function (Satish et al., 2012b). A field study in a primary school concluded that children showed significantly poorer concentrate levels on the courses when the level of CO_2 in classrooms was high (Coley et al., 2007b). The increased levels of CO_2 led to an approximately 5% decrement on attentional performance, as reported by the study. Nevertheless, other studies showed little influence of CO_2 level on attention (Twardella et al., 2012b; X. Zhang et al., 2017b) Elevated CO_2 concentration in the classrooms did not reduce students' global short-term attention, although a decrease in the secondary outcome accuracy (e.g. the total number of characters processed) was found for students exposed to poor air quality (Twardella et al., 2012b). Ref (X. Zhang et al., 2017b) argued that it might be the bio-effluents, rather than pure CO_2 level, that reduced cognitive performance. Another study employing physiological and neurophysiological monitoring also reported no effect of CO_2 on attention performance (Snow et al., 2019). A critical review of the area concluded that pure CO_2 only consistently affects high-level decision-making performance (Du et al., 2020).

Elevated indoor CO_2 concentration is primarily derived from insufficient ventilation. Previous studies have reported improvements in students' working memory and attention in primary school buildings at higher ventilation rates (Clements-Croome et al., 2008). Ref (Bakó-Biró et al., 2012) identified a 2.2% improvement in attentional performance during these higher ventilation rates.

Thermal Environment

Prior studies have shown that attention can be strongly influenced by the thermal environment, although the direction and magnitude of influence may not be always consistent. Under steady-state conditions, the attention index of 117 high-school students decreased when they were thermally uncomfortable (Mazon, 2014). Participants had the highest performance test score at 26 ℃ compared with at either 23 ℃ or 29 ℃ when a personally controlled fan was available to use (Schiavon et al., 2017a). Under thermal transients in Ref (F. Zhang & Dear, 2017), concentration performance was significantly and positively correlated with the rate of temperature increment ($p < 0.05$) in temperature cycles starting from 22 °C. This implies increased concentration performance when the temperature rises quickly. But a separate study (Hu & Maeda, 2020) indicated opposite results that subjects had a better attentional performance at 16 °C compared to results at 26 °C and 36 °C. Attention tested by using the cursor positioning test indicated no significant difference in the subjects' performance in three different thermal environments (Tanabe & Nishihara, 2004). There was also no significant difference of attention in a study (Maula et al., 2016) which used a star count test in two temperature conditions of 23 °C and 29 °C. Attention, as assessed by the Stroop test without feedback, was significantly different between 23 °C and 27 °C (Lan et al., n.d.). However, the difference was not significant when feedback was provided to the participants. These sorts of results confirm that at ambient temperature, close to setting, and individual capacities each exert impactful influences on outcome.

Noise

The influence of noise on attention is also complicated. High school students worked faster with high ventilation noise but only at the cost of less accuracy (Hygge & Knez, 2001b). The results supported a speed-accuracy trade-off hypothesis that decisions are made slowly with high accuracy or fast with a high error (Duckworth et al., 2018; Hockey, 1984; Mulligan & Hirshman, 1995), contingent upon acoustic surround. Age is a confounding factor when considering the influence of noise on attention. Elderly people may be more vulnerable to noise. Listening to speech with multi-talker babble noise, such as in a crowded office, reduces activation in the auditory cortex but increases memory and attention-related cortical areas (prefrontal and precuneus regions) for older people (Wong et al., 2009). However, noise exposure apparently has little significant influence on students' attention performance, at least to a reasonable threshold value (Lercher et al., 2003; Stansfeld et al., 2005).

Lighting

The literature has recorded controversial findings as to know if attention is affected by lighting. The correlated color temperature of 4,300 K resulted in the best-sustained attention performance for undergraduates using the Chu Attention Test. Also, sustained attention was more affected by lighting in females than male students (Huang et al., 2015b). Increasing illuminance from 200 lux to 1500 lux promoted attention when the room air temperature was 22 °C. But the opposite trend was found at 37 °C. This implies an interactive influence between thermal and visual comfort (Mohebian et al., 2018b). A dynamic lighting system that adjusted lighting color and brightness of computer screens significantly improved target spotting time in a computer game for both casual gamers and non-gamers (El-Nasr et al., 2009). However, the effects of lighting on attention have not been found in other studies. Neither light color temperature nor lighting intensity influenced the concentration of third-grade children (Mott et al., 2012b). For example, sustained attention was also independent of lighting conditions for older adults who were night shift workers (Kretschmer et al., 2012b).

Non-Light Visual Factors

Fisher et al. (Fisher et al., 2014) investigated how classroom decoration affected the ability of children to concentrate on lesson content. Children were more distracted by highly decorated environments, spent more time on the task, and gained less knowledge when compared with a relatively plainly decorated classroom. Colors can stimulate an individual's physiological and emotional responses for focal attention and thereby facilitate learning. Pale colors were rated more positively than vivid ones, due to feeling more calm and relaxed [109, 214]. Additionally, biophilic environments can promote the attention of occupants. Students' views of nature or buildings is another factor influencing attention. Both outdoor natural views (Tennessen & Cimprich, 1995) and indoor views of plants were reported to promote students' attention (Raanaas et al., 2011). In other words, indoor and outdoor visible greenery increases the ability to concentrate and reduces stress [217, 218]. Significantly better performance of participants' attention was reported when a window view is available than when it is unavailable (Ko et al., 2020).

IEQ's Effects on Perception

We summarized in Appendix I Table A3 the major findings as to how IEQ affects perception. Overall, the accumulated knowledge reports studies focusing on auditory perception and visual perception. Noise and poor lighting are common stressors for perception.

In a visual search task, participants showed a significantly different performance, normalized by mental workload, between warm and neutral conditions, and between warm and cool conditions (X. Wang et al., 2019). Survey results by Ref (Yun et al., 2008) demonstrated that façade design affected occupants' perceived control over their environments. Uncomfortable environments are through to generate perceptions of stress and negative attributions about performance (Loewen & Suedfeld, 1992).

Lee et al. (J.-H. Lee et al., 2014) examined the combined effects of color temperature and illuminance in the office on the visual perception of occupants. They concluded that the less than subjects were visually disturbed by light during tasks, the more visual comfort they felt. Lighting also affects the perception of facial surfaces (Hill & Bruce, 1996). Observers' ability to recognize and match faces and objects was higher for top lighting on the objects than bottom lighting. Berman's theory (S. Berman et al., 1990) states that elevated color temperature, associated with smaller pupil size can enhance visual acuity. In this same vein, the performance of a visual perception task on color recognition is higher with the lighting of higher color temperatures (Hawes et al., 2012b).

The negative effects of noise exposure on performance could be attributed, at least in part, to "learned helplessness", which is a syndrome of defeat typically resulting from exposure to uncontrollable circumstances (Hatfield et al., 2002). Occupants might perceive noise to be uncontrollable or have little perceived control. A socio-acoustic survey observing perceived control over aircraft noise correlated negatively with identified effects of noise (e.g., disturbances of reading and sleep). This supports the claim that "learned helplessness" contributes to the effects of noise exposure. In terms of specifics, the linear exposure-effect association was identified between exposure to chronic aircraft noise and impaired reading comprehension (Stansfeld et al., 2005).

IEQ's Effects on Memory

Appendix I Table A4 catalogs the major findings regarding the impairment of memory due to poor IEQ. Our review here demonstrated that short-term memory and working memory are most investigated by previous studies via recall tasks. Overall, results show that memory is generally associated with most IEQ factors.

Indoor Air Quality

The cross-sectional association between fine particulate concentration levels and cognitive function in older adults has identified that a higher air pollutant concentration leads to significantly reduced levels of working memory (Ailshire & Clarke, 2015; Ailshire & Crimmins, 2014b). The incident rate of errors on tests of working memory shows a ratio of 1.53 with a 10 μg/m^3 increase in $PM_{2.5}$ concentration (Ailshire & Clarke, 2015). Each 10 ppb increase in annual ozone was associated with decreased short-term memory, equivalent to 5.3 years of aging-related decline in cognitive performance (J.-C. Chen & Schwartz, 2009).

Students showed 8% higher picture memory with an increased room ventilation rate that was associated with lower CO_2 levels (Bakó-Biró et al., 2012). Strategic management simulations (Allen et al., 2016b; MacNaughton et al., 2017; Satish et al., 2012b) were applied to investigate how indoor CO_2 influenced cognitive performance, but its effects on memory were not reported as the tools were more predictive in domains such as strategy, information usage, and crisis response. However, the effects of elevated CO_2 concentrations on memory performance were not consistent in some other studies. Neither response time nor accuracy of a picture recognition task was significantly compromised at approximately 2,900 ppm when compared with 690 ppm (Coley et al., 2007a). A similar conclusion was reported for CO_2 at 2,700 ppm versus 700 ppm (Snow et al., 2019). Zhang et al. (X. Zhang et al., 2017b) also did not find any statistical significance in digit span memory scores under bioeffluents or pure CO_2. On the other hand, external oxygen administration was found to improve memory formation in the first place (Moss & Scholey, 1996; Scholey et al., 1999; Winder & Borrill, 1998). Inhalation of oxygen immediately before learning a word list increased the average number of words recalled some 10 minutes later (Moss & Scholey, 1996). Inhalation of 100% oxygen for a short time enhanced the memory for names and faces (Winder & Borrill, 1998). These findings, however, were not replicated by other studies that focused more on long-term memory (Andersson et al., 2002; Moss et al., 1998).

Thermal Environment

The reviewed studies on the effect of thermal environment on memory performance do not report consistent relationships between the two entities. The extended-U model suggests that memory performance will remain stable across a broad range but rapidly deteriorates at the thermal extremes [236, 237]. Students showed the best memory performance when the air temperature was between 22 °C and 26 °C (Cui et al., 2013a). Even while exposed to 43.3/27.8 °C (dry/wet bulb temperature), the short-memory performance for university students did not change significantly, as compared to a more comfortable condition of 26.7/17.2 °C (dry/wet bulb temperature) (Wing & Touchstone, 1965). Poorer short-memory by recalling word lists did occur at 48.9/31.1 °C (dry/wet bulb temperature). Similarly, the average recall performance did not drop significantly when the chamber air temperature was between 16.7 and 32.2 °C but did so between 32.2 to 35 °C as individuals began to approach integrable levels (Wing & Touchstone, 1965). Zhang and de Dear (F. Zhang & Dear, 2017) reported no significant correlation between thermal environment and memory performance in six temperature cycles. College students exposed to

25.5 °C, 28 °C and 33 °C did not demonstrate significant memory changes using a positioning test and letter search test (Tanabe & Nishihara, 2004). Neither working memory performance nor long-term memory performance was significantly impaired when the temperature, was raised from 23 °C to 29 °C (Maula et al., 2016).

Contradictory results were also reported in the literature regarding the influence of mild temperature on memory performance. Working memory measured via a forward digit span test dropped at slightly cooler (21.7 °C) and warmer conditions (28.6 °C) from the neutral condition (25.2 °C) (X. Wang et al., 2019). Nevertheless, significant reduction only occurred for the hard version of the task but not the easy one (F. Zhang et al., 2019), which suggests an interaction with task type. Regression analysis by Cui et al. (Cui et al., 2013a) showed that long-term memory performance peaked ($p < 0.01$) at 26 °C in the temperature range of 22 °C to 32 °C.

The influence on memory due to cooling might not be equivalent to that of heating. Elevated body core temperatures from 36.6-37.4 °C to 38.8-39.1 °C did not affect memory registration or the immediate ability to recall digit spans (Holland et al., 1985), but reduced body core temperatures from 36.7 °C to 34-35°C did induce a loss of approximately 70% of data that could normally be retained from a memory test (Coleshaw et al., 1983). In addition, memory performance in temperature cycles ranging between 21.3 and 31.2 °C was significantly higher than temperature cycles starting from a slightly higher temperature (23.0-31.5 °C) (F. Zhang & Dear, 2017). The performance of a digital span test increased by 2.8% when reducing the temperature from 27 °C to 23 °C (Lan et al., n.d.). However, this increase did not prove statistically significant.

Noise

Noise was reported as an environmental stressor that impacted memory in many studies [20, 72, 73, 242]. Noise hinders recall and recognition in student learning. Poor listening conditions due to background noise and/or long reverberation times, impair memory and learning, even if students could hear what was said by an instructor (Ljung, 2009). Traffic noise can also worsen performance in both a search task and a memory task (Hygge et al., 2003). Stansfeld et al. (Stansfeld et al., 2005) identified a linear association between exposure to chronic aircraft noise and impairment of recognition memory through the assessing 2,844 children aged 9 to 10 years. Both intentional and incidental memory were affected by chronic noise exposure, and school children who were chronically exposed to noise were found subsequently to be worse at recognition memory, as reported in Ref (Lercher et al., 2003).

Memory involved in complex tasks has proven to be more susceptible to noise compared to that of simple tasks [20, 244]. In addition to task complexity, one type of noise might be more harmful than another to memory, especially intermittent noise. Two experiments revealed that background speech was more detrimental to prose memory than aircraft noise [71, 245]. Furthermore, there might be interaction effects between noise and illumination on memory. Subjects' short-term and long-term memory recall was found to vary with combinations of ventilation noise and illuminance levels [12, 246]. Interactions were also found between noise and heat on the long-term recall of a text (Hygge & Knez, 2001b).

Lighting

Long-term memory was enhanced when individuals are exposed to a light color temperature that induced a less negative mood (Knez, 1995). The combination of color temperature and illuminance that best preserved a positive mood increased performance in free recall tasks. Cool-white lighting impaired the long-term memory recall of a novel text when compared to warm-white lighting (Knez & Hygge, 2002). However, the influence of blue-enriched classroom lighting on short-term encoding and retrieval of memories was not found for high school students (Keis et al., 2014a). No interactive effects on memory were reported between light and noise (Knez & Hygge, 2002), but interaction was found between gender and light color temperature on mood and long-term memory (Knez, 1995; Knez & Enmarker, 1998).

Non-light Visual Factors

Exposure to green space has beneficial effects on the development of working memory for primary school children (Dadvand et al., 2015) and thus access to these green spaces was associated with improved memory (McCormick, 2017). Ko et al. (Ko et al., 2020) reported that Window views influenced different memory associated with various levels of significance. The working memory test score of the participants in a room with a window view was 6% higher ($p < 0.009$) than that in a windowless room. However, no significant difference was identified for short-term memory by the study. Participants with a major depressive disorder performed better on memory span tests after walking through a green arboretum, relative to traffic-heavy streets lined with university and office buildings (M. G. Berman et al., 2012).

IEQ's Effects on Language Functions

Appendix I Table A5 catalogs the effects of IEQ on language functioning in terms of capacities, such as reading and writing. Ref (Marchand et al., 2014) investigated whether the combined environmental factors of light, sound, and temperature in a classroom affected student performance during listening and reading tasks. It was reported that indoor sound and temperature had a greater negative influence on students' listening and reading tasks when they were outside the comfort zone. However, the modeled association between reading test scores and ventilation rate did not show any statistical significance in another preliminary study (Shaughnessy et al., 2006). The conditions of artificial light were found to influence the students' reading performance (Mott et al., 2012b). It was revealed that "focus" lighting consisting of 1,000 lux illumination and 6500 K color temperature significantly increased students' oral reading fluency compared to a "normal" or baseline lighting condition (500 lux with 3,500 K).

Noise effects on recall and recognition are significant (Hygge, 2003). Item difficulty, position, and ability were not found to interact with these noise effects in the study. Neither did arousal, distraction, perceived effort, or perceived difficulty in reading and learning mediate the effects on recall and recognition. Anderson et al. (Anderson et al., 2010) showed that background noise usually disrupts neural timing and challenging listening conditions disrupted the inability of speech perception. Ref (Klatte, 2010) identified significant effects of reverberation on speech perception of spoken items in classrooms. Outside noise influences language fluency, which acts as the bridge between sound source and comprehension (Pikulski & Chard, 2005). Children's speech perception and listening comprehension can be significantly impaired by background speech (Klatte et al., 2010). Irrelevant speech has a significant influence on participants' reading comprehension (Sörqvist et al., 2010). Speech recognition was not only influenced by speech-to-noise ratios (SNRs), but also by thermal conditions as well (W. Yang & Moon, 2018). Moreover, Wong et al.

(Wong et al., 2009) reported that age confounds the relationship between noise exposure and speech perception. Compared to adults, children are more impaired by detrimental listening conditions. Older adults, who experience reduced activation in the auditory cortex, have increased activation in attention-related cortical areas. Age and hearing loss were both related to less release from the effort when increasing the intelligibility of speech in noise, as identified in the same study.

Non-light visual factors also affect language functions such as reading (AL-Ayash et al., 2016). The color in a private space affects students' learning, as well as physiological and emotional states. Vivid colors are beneficial for students' reading, while blue is better for relaxation and calmness.

IEQ's Effects on Higher Order Cognitive Skills

The listed studies in Appendix I Table A6 describe the association between indoor environmental factors and different forms of higher order cognitive skills. In general, poor IEQ conditions were reported to have negative effects on these higher order cognitive skills, but to varying degrees. However, some studies have found no significant association between IEQ factors and higher order cognitive skills.

Indoor Air Quality

Occupants' performance, which was assessed using, but the speed of addition, response time in a redirection task, and the error rate of tasks, was reduced when participants were exposed to an elevated level of CO_2 together with bio effluents (X. Zhang et al., 2017b). The adverse consequence due to high CO_2 levels includes the impairment of decision-making performance (Satish et al., 2012b). Also, the increased response time has been related to ozone exposure (J.-C. Chen & Schwartz, 2009). NO_x showed an association with a decline in the cognitive test scores for visuo-construction, which involves the ability to organize and manipulate spatial information (Schikowski et al., 2015). An epidemiologic study, using 789 elderly women who attended a medical examination in 2007-2009 supported the proposition that lower scores in reasoning were correlated to particulate air pollution (Tonne et al., 2014).

Thermal environment

Thermal comfort plays an important role in the higher order cognitive skills. A warm environment can be associated with reduced reaction time. Participants performed tasks more rapidly at 32 °C compared to other conditions (27, 24, and 19 °C) (Lan et al., 2009a). This phenomenon was explained by postulating that participants wanted to finish tasks quickly in the uncomfortable thermal environments, or that they were activated by elevated internal body temperature (Hancock, 1993). Another study also reported increased task speed as the temperature ascended (Holland et al., 1985). However, findings were not consistent overall in the literature. For example, a study found that compared to a cooler temperature of 23 °C or warmer temperature of 29 °C, subjects had the fastest processing speed at 26 °C (Schiavon et al., 2017a). This study suggested 26 °C as the optimum temperature for the optional cognitive performance. In another recent study (X. Wang et al., 2019), significant differences in participants' addition task performance were found for a "hard" mode but not for "easy" mode between slightly warm (PMV =1) and slightly cooler conditions (PMV = -1). In the study, the participants did not show a significant difference in response time on a choice reaction task for either "hard" or "easy" mode. Also, the participants' response time in two reaction tests ("hard" and "easy" modes) was insignificantly ($p > 0.05$) differentiated at three PMV conditions (-1, 0, and 1). However, the difference in response time was statistically significant ($p < 0.05$) for the Stroop task at the three PMV conditions. Ref (Lan et al., n.d.) stated that the subjects had neutral comfort at both 23°C and 27°C. But the reasoning performance, observed at 27°C, decreased by 11.2% compared to performance at 23°C. The study (Tanabe & Nishihara, 2004) indicated that only male subjects displayed significant differences in the four-choice test performance as the temperature increased from 28 °C to 33 °C, as well as the text typing test when the temperature increased from 25 °C to 28 °C or 33 °C.

Reasoning and planning skills were found to have a significant relationship with the thermal sensation vote (F. Zhang & Dear, 2017). The study reported that reasoning and planning performance was negatively correlated to TSV^2 and TSV respectively in the warmer temperature cycles starting from 24 °C. Planning skills were more sensitive to heat than reasoning in the rising temperature. That is, a higher rate of temperature increment had detrimental effects on planning, but not on reasoning performance.

Noise

Moderate noise enhances processing difficulties, such as the activation of abstract cognition and enhancing creative performance (Mehta et al., 2012). It was also found in the same study that mild noise could be a trigger for higher leave creativity, while loud noise reduces the extent of information processing, resulting in cognitive impairment. However, teacher-reported cognition functions of school children showed no significant effects of ambient noise levels upon executive function (Belojevic et al., 2012).

Lighting

No significant effect of lighting color temperature (3,000 K vs 4,000 K) was found on the performance of problem solving and judgment (Knez & Enmarker, 1998). However, another study concluded that “warm” white light (3,000 K) was optimal for problem solving (Knez, 1995). In addition, high-frequency lighting is perceived as more pleasant than low-frequency lighting and can then enhance problem solving performance (Knez, 2014).

Non-light visual factors

Mehta and Zhu (Mehta & Zhu, 2009) found that red backgrounds enhance motivation, whereas blue improves subjects’ creative ability. Blue light enhanced individuals’ purchase intentions toward products mainly bought for pleasure or enjoyment, indicating that blue lighting is a contributing factor in participants’ altered purchase intentions. In another study, participants’ planning skills did not significantly vary when a window view was present or not (Ko et al., 2020).

Summary of the conventional manual review

Appendix I Tables A2-A6 list the major findings of studies on the association of IEQ factors and cognition. While detailed and informative, the tabulated results of all the reviewed studies might not easily generate a clear “big picture”. This is because many studies have reported contradictory or mixed findings. Therefore, we calculated the percentage of studies that revealed statistically significant association (*with the assigned rating “2”*), and the percentage of studies showing mixed association (*with the assigned rating “1”*) between a particular IEQ factor and a cognitive function. For example, 36% of the 16 reviewed studies indicated a mixed association (*rating "1"*) between thermal environment and memory, while only 14% confirmed a statistically significant association (*rating "2"*). Please note that Table 1 does not distinguish between positive and negative associations. Even though the statistics is unable to quantify the effect size of each pair of an IEQ factor and cognitive function, the present approach in Table 1 can still shed lights on the amount of evidence n the topic and the intensity of research inconsistency across various disciplines that may not be easily obtained otherwise.

Table 1. Percentage of studies reporting different leveles of statistical significance for the associations between IEQ and cognition

	IAQ			**Thermal environment**			**Noise**			**Lighting**			**Non-light visual factors**			**Row average**	
	Perc. of sig. ⱡ	*Perc. of mixed* ⱡ	*# of studies*ⱡ	*Perc. of sig.*	*Perc. of mixed*	*# of studies*	*Perc. of sig.*	*Perc. of mixed*	*# of studies*	*Perc. of sig.*	*Perc. of mixed*	*# of studies*	*Perc. of sig.*	*Perc. of mixed*	*# of studies*	*Perc. of sig.*	*Perc. of sig. or mixed*
Attention	20%	20%	6	10%	30%	11	25%	25%	5	33%	34%	6	50%	50%	5	***28%***	***31%***
Perception	0	0	1	0	50%	3	NA	NA	0	0	67%	3	NA	NA	0	***25%***	***38%***
Memory	0	25%	8	14%	36%	16	71%	29%	8	29%	28%	7	0	100%	1	***23%***	***43%***
Language function	0	0	2	33%	0%	4	67%	33%	10	50%	0%	2	0	100%	1	***30%***	***26%***
Higher order cognitive skills	50%	33%	8	19%	50%	17	20%	40%	5	33%	0%	6	50%	0%	2	***34%***	***25%***
Column average	***14%***	***15%***		***15%***	***33%***		***57%***	***25%***		***29%***	***32%***		***25%***	***63%***			

ⱡ "Perc. of sig.": the percentage of all reviewed studies in Appendix I Tables A2-A6 reporting a significant association only (with the rating "2"); "Perc. of mixed": the percentage of studies revealing a mixed association (with the assigned rating of "1"). The description of different rating levels can be found in Section 3.1. "# of studies": the total number of reviewed studies containing all ratings ("0", "1", "2", and "NA").

Table 1 shows that the most examined IEQ factors in the literature are thermal environment, noise, and IAQ, while the most studied cognitive functions are memory, high order cognitive skills, and attention. The research on how IEQ influences perception is quite rare. Overall, for each pair of IEQ and cognition, a statistically significant association ($p < 0.05$) has been identified by a portion of studies in the literature.

To interpret the results from Table 1, the sample size (number of studies) in each cell and the percentage of significant association are both important, as a 100% statistical association reported in only one study may not carry weight. For pairs of IEQ and cognition with more than 5 studies, the percentage of studies reporting a significant association ($p < 0.05$) is 50% between IAQ and higher order cognitive skills, 67% between noise and language function, and 71% between noise and memory. In contrast, the percentages of studies showing a significant association is quite small (< 20%) between IAQ and memory (almost 0%), thermal environment and attention (10%), thermal environment and memory (14%), and thermal environment and higher order cognitive skills (19%).

Each row in Table 1 represents the influence of various IEQ variables on a specific cognitive function. Considering the aggregated effects of all IEQ factors on each cognitive function by averaging the percentages in a given row, approximately 34% of studies on average imply a significant association between IEQ and higher order cognitive skills, while the percentage drops to 30%, 28% and 23% for language functions, attention, and memory, respectively. However, 43% of studies suggest a mixed association between IEQ and memory, followed by 31% for attention, 26% for language function, and 25% for higher order cognitive skills. The small variations in those percentage values do not entitle differentiation between the most and least vulnerable cognitive functions to IEQ. One explanation for this may relate to the difficulty in isolating cognitive functions, particularly in realistic settings.

For each column of Table 1, the average percentage value over five rows of cognitive functions can help identify the influence of a particular IEQ factor on holistic cognitive functions. Approximately 57% of studies found that noise has a significant impact on cognition. Surprisingly, the percentage of studies reporting statistical significance for both IAQ and thermal environment are lower than 20% in terms of the effects on cognition. Even considering both the significant association and mixed association, the percentage is still less than 50%. The results thus suggest extensive inconsistencies in the relevant literature, especially regarding the effects of IAQ or thermal environment on cognition.

Keyword co-occurrence patterns identified by text mining

Figure 2 shows the number of publications and knowledge landscapes obtained from keyword co-occurrence analysis at different periods. The connection between two circles refers to co-occurrence instead of statistical association in the same document. A short distance between two keywords represents high co-occurrence. When two keywords are rarely mentioned together in the same document, the two circles containing them are therefore distanced. The number of keywords contained in circles was maximized using a smart local moving algorithm (*VOSviewer Manual*, n.d.). The size of each circle represents the percentage of the articles mentioning the corresponding keyword in the circle. The same circle color represents a clustered category using the mapping technique of visualization of similarities (VOS) (Eck et al., 2010).

The earliest study we found was published in 1932, and since then the number of publications involving both IEQ and cognition have been growing exponentially in the past few decades, as shown in Figure 2a. There were 684 papers published in 2019.

Figure 2b, 2c, and 2d show the relation landscape between IEQ factors and cognitive functions by extracting information from the keywords and abstracts of searched studies, including those reviewed in the manual review, published within the period of 1932 – 2010, 2011– 2015, and 2016 – 2020, respectively. During each period, there were approximately 3000 papers published on average. These results can significantly supplement the detailed manual review described in Appendix I Tables A2-A6 as well as Table 1. The co-occurrence networks in Figure 2b-2d reveal two essential patterns. First, the clustering can be summarized into three major topic themes, cognition (in blue, green, and red), environment (in yellow, aqua, and green), and mediating and confounding factors (in blue and purple) such as *"age", "gender" and "depression."* Second, the landscapes of keywords in Figure 2b-2d depict the evolution of the topics in terms of cognition and IEQ. To better quantify the results displayed in the figure, we summarized common topics sorted on the basis of occurrence frequency during different periods in Table 2 that constitutes a basis for Figure 2b-2d to further reveal the evolvement of the research field . Topics such as *"sound", "recognition", "light", "speech",* and *"noise"* emerged during 2011– 2015, while *"air pollution", "temperature",* and *"mechanical ventilation"* have been paid more attention since 2016. A similar patten has been also observed for cognition, such as new keywords of *"reading", "social cognition", and "language."* In addition to the two patterns, one can observe that music related variables frequently appear along with cognition in the literature during each period.

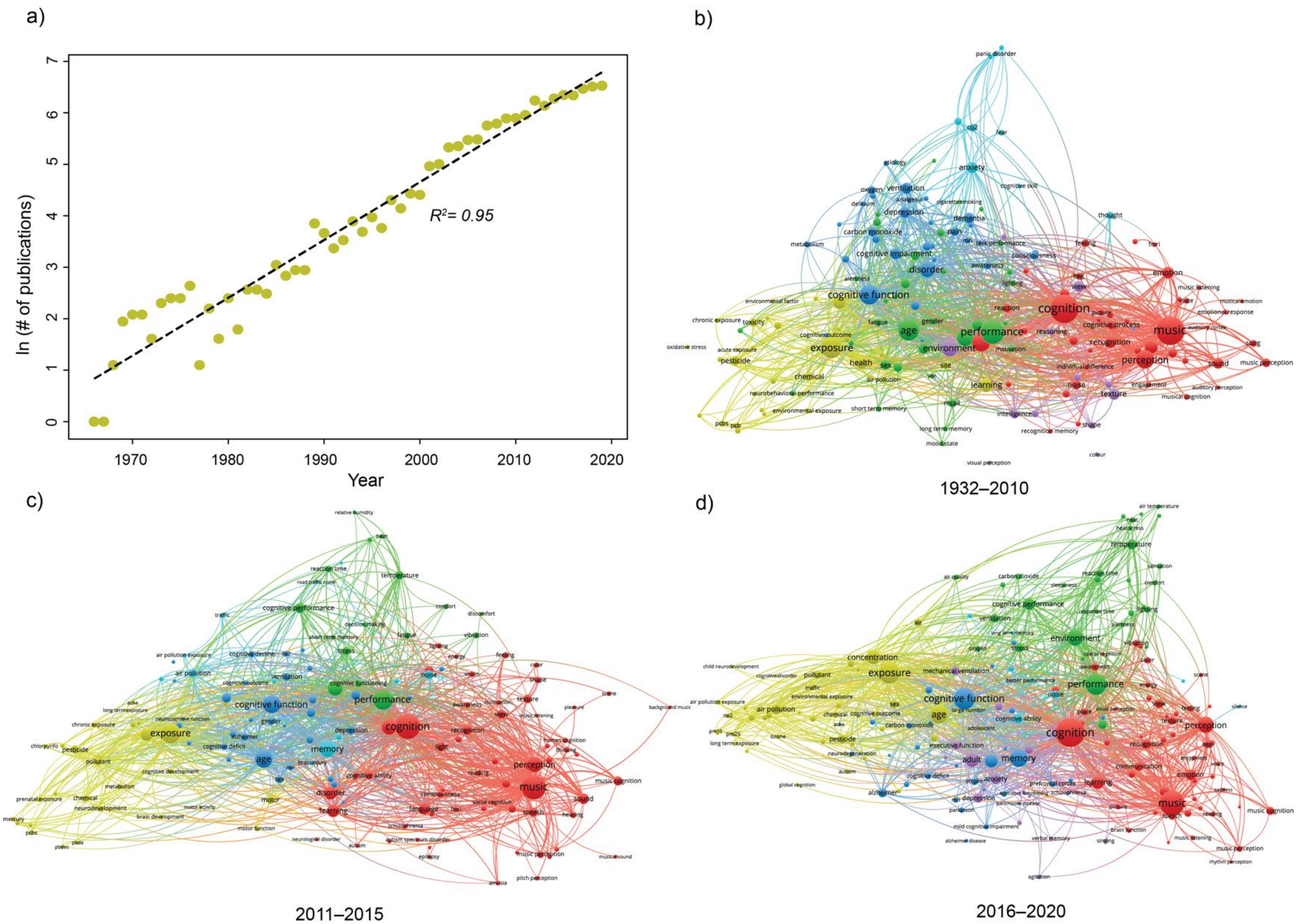


Figure 2. The number of publications and knowledge landscapes obtained from keyword co-occurrence analysis. a) The temporal number distribution of publications (The figure does not display the only paper published before 1958); b) keyword co-occurrence network with publications between 1932 and 2010 (n = 3421); c) keyword co-occurrence network with publications between 2011 and 2015 (n = 2464); d) keyword co-occurrence network with publications between 2016 and 2020 (n = 2956)

Table 2. Summary of the most frequently mentioned topics during different periods

Years 1932~2010		Years 2011~2015		Years 2016~2020	
Items	Occurrence	Items	Occurrence	Items	Occurrence
music	662	cognition	683	cognition	950
cognition	585	music	669	music	736
performance	416	exposure	432	cognitive function	547
exposure	384	performance	417	exposure	543
response	325	cognitive function	367	performance	482
cognitive function	314	age	326	age	397
perception	273	memory	310	memory	376
memory	272	response	309	attention	331
attention	239	perception	267	environment	320
environment	220	attention	257	perception	306
disorder	200	environment	257	concentration	236
language	150	disorder	186	disorder	203
concentration	145	concentration	165	learning	203
learning	142	emotion	153	language	184
emotion	115	language	145	cognitive performance	158
recognition	106	**sound**	121	emotion	145
ventilation	106	adult	113	adult	143
anxiety	103	cognitive performance	108	**air pollution**	132
cognitive impairment	103	cognitive impairment	102	anxiety	124
depression	103	**recognition**	100	**temperature**	112
texture	102	**light**	99	**cognitive ability**	110
music cognition	96	music cognition	92	depression	110
dementia	94	anxiety	89	pesticide	101
cognitive performance	93	**speech**	88	communication	100

rhythm	93	**noise**	87	view	99
mood	89	view	86	rhythm	98
sound	88	pesticide	84	mood	97
view	88	mood	83	**recognition**	95
carbon monoxide	77	**texture**	82	Alzheimer	93
pesticide	74	**communication**	79	**mechanical ventilation**	89

Note: The words in bold are emerging items comparing to the previous period.

Discussion

This review has focused on the association between IEQ factors and the five main categories of cognitive functioning. The reviewed literature consisted of a mixture of laboratory and field work, and both cross-sectional and longitudinal studies. Overall, there is a preponderance of the evidence that almost all IEQ factors, including indoor air quality, thermal environment, noise, lighting, and non-light visual factors could affect cognitive performance to varying degrees. Different IEQ factors can have distinct effects on a specific cognitive function. Likewise, a specific IEQ factor may also exert various impacts, if any, on different cognitive functions. We identify inconsistency, uncertainties, and confounding factors (such as age, sex, and emotion) in the reviewed studies, and point out limitations and future directions.

Inconsistency, uncertainties, and possible explanations

Appendix I Tables A2-A6 demonstrate inconsistency and uncertainties in reviewed studies. For instance, some experiments indicate that sustained attention is not impaired by aircraft noise (Stansfeld et al., 2005) or chronic noise exposure (Lercher et al., 2003), while others (Hygge et al., 2002; Smith & Miles, 1987) showed that noise does impair both attention and recall. Experimental studies of Ref (Allen et al., 2016b) and Ref (X. Zhang et al., 2017b) reported contradictory results regarding the effects of elevated CO_2 levels on cognitive performance. The research evidence on the effects of lighting on problem-solving is contradictory as well. Ref (Knez, 1995) reported the 'warm' white light source at 300 lx illuminance and the 'cool' white light source at 1,500 lx illuminance to be optimal for subjects' problem solving. However, no significant effect of lighting on problem-solving performance was found by another similar study (Knez & Enmarker, 1998).

We may distill a principled set of sources for the associated variations and inconsistencies that we have observed in the assemblage of data. In general, they relate to complexities in the environmental exposure, variation in the tasks undertaken as representative of both learning and work performance, significant differences between individuals who display that performance, and finally methodological barriers to a full and clear exposition of the relationships evaluated. The factors have been illustrated in Figure 3 for the purpose of ease of discourse. Much of the problem of inconsistency in results arises as a function of the interaction of these identified influences.

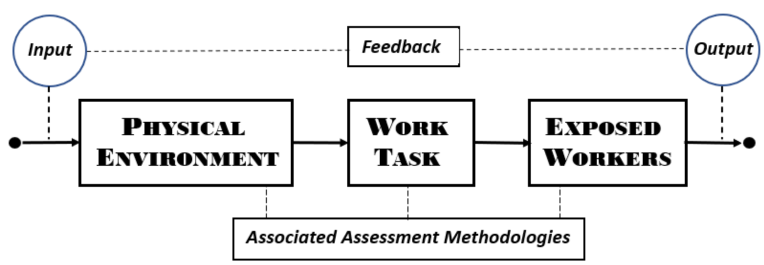


Figure 3. Potential sources of inconsistency and uncertainties related to environments, tasks, and exposed individuals.

From the input conditions composed of the physical environment through the specification of the work tasks involved and the variation of the individuals performing such tasks, we can identify numerous sources of potential inconsistency. Such sources of variability also emanate from the function of feedback loops involved in this process, as well as inherent characteristics and shortfalls in the methods employed to measure response in these varying and disparate sources of influence. The three majorly identified categories are the realms of quite disparate scientific disciplines with their own conventions and traditions. For instance, memory has been assessed by recall tests (Ailshire & Clarke, 2015), serial-digit learning tests (J.-C. Chen & Schwartz, 2009), picture recognition (Lan et al., 2009a), digit span tasks (Lan et al., 2011b; F. Zhang et al., 2017; F. Zhang & Dear, 2017), interviews through telephones (Ailshire & Crimmins, 2014b), electroencephalography (EEG) (Nayak et al., 2018), and functional magnetic resonance imaging (fMRI) (Wong et al., 2009). In a review, Zhang and colleagues (F. Zhang et al., 2019) summarized three common approaches to assess cognitive load/performance. These are primary tasks, subjective perception, and physiological responses (Hancock & Matthews, 2019). They pointed out that findings from these three approaches do not always agree with each other when applied concurrently. In itself, this can lead to conflicting results in Appendix I Tables A2-A6. Another source of inconsistencies can be exemplified by different ranges of values of the investigated IEQ factors. According to the extended-U model (Hancock, 1989; Hancock & Ganey, 2003), people can maintain a stable level of performance over a broad range of environmental stress levels. If the investigated experimental conditions are within this central plateau area, no performance change might be anticipated. It is, therefore, unlikely to find any significant relationship between the environmental factor and cognitive function. However, if the investigated range of environmental stress levels spans beyond this near-optimum range, a significant change of performance may be identified. For example, Ref (F. Zhang et al., 2017) did not find any significant difference in reasoning skills under two temperature conditions of 22 °C and 25 °C. However, a significant reduction in reasoning was found when the temperature was increased to 30 °C by another similar study (Lan et al., 2011b).

The effects of possible mediators, moderators, confounders, and covariates cannot be ignored as well, such as skill level, emotion, age, gender (Knez & Kers, 2000b), personal attitude, mood, past events (Torresin et al., 2018), and emotion. Previous studies have revealed that performers' skill levels significantly mediate the influences of environmental stress on cognitive function (Choi et al., 2014; Gaoua, 2010; Murphy et al., 2000). Performers with higher skill levels are less susceptible to performance decrements under environmental stress. In addition, emotion has a mediating effect on cognitive performance [173, 247]. For instance, cognitive performance was negatively affected by heat, partly because people were less motivated when feeling uncomfortable (Cui et al., 2013a). Age is also a confounding variable. Aging can degrade the sensory and processing functions (Murphy et al., 2000). Compared to young adults, older adults require a higher-level of illuminance or thermal comfort to maintain the same attention and perception performance [12, 212]. Age influences speech perception in noise conditions (Wong et al., 2009). Furthermore, the effects of participants' gender have become manifest in many associated aspects between IEQ and cognitive functions. For example, girls focused much more on a task than boys in experiments with uncomfortable conditions (Mazon, 2014; Ussher, 1992). Males showed better performance on an abstract cognitive task (Ussher, 1992) and performed significantly better than females in problem solving using an embedded figure task (Knez & Enmarker, 1998). We discussed in more detail the primary sources of inconsistency (illustrated in Figure 3) in Appendix II.

Limitations of the present review

We categorized IEQ factors and cognitive functions according to the terminology in the reviewed studies. Some performance tests require multiple cognitive functions and thus are difficult to map into the categories, such as addition, multiplication, and typing. Problem-solving skills involve both attention and memory. Furthermore, the present review does not include the entire spectrum of cognition, partially because there is little research identified regarding social cognition, visuospatial functions, or motor skills when considering the influence of IEQ factors. Also, many studies investigated more than one IEQ and/or cognitive factors, thus could carry more weights in the conclusions of the current analysis. Moreover, some keywords identified in the keyword co-occurrence analysis may not necessarily reflect the exact context of cognition. For instance, *"attention"* is often used in the phrase of "*pay attention to.*" Last, this review does not include studies in languages other than English.

Recommendation for future research

In addition to the substantial inconsistency in terms of the association between IEQ and cognition, existing literature lacks sufficient and granular evidence to present a comprehensive understanding of the underlying mechanism. First, most studies applied the cross-sectional approach. The consequences of long-term exposure to poor indoor environmental quality thus warrant further research. Second, most existing studies focus on static environments, while dynamic physical environments are rarely explored, especially when alliesthesia (Dear, 2011) is experienced by occupants. Any environmental stimulus that helps to offset the load on the thermo-regulatory system will be pleasantly perceived, and thus can potentially be used to preserve cognitive functions (F. Zhang et al., 2019). Future research could use physiopsychological sensors, such as electroencephalogram (EEG), functional magnetic resonance imaging (fMRI) as well as functional near-infrared spectroscopy (fNIRs) to respond to this challenge. Third, the inherent overlap between different cognitive functions, interaction effects of IEQ factors (Torresin et al., 2018), and mediating effects of other factors (e.g., emotion, age, and gender) imply that future research should further decompose each category of IEQ and cognition, by documenting values of all confounding or mediating variables. Otherwise, the true effects could be masked by these diverse influences.

In addition, the contribution of some factors remains missing in the literature, e.g. there is almost no research on how indoor microorganisms such as fungi or molds affect cognition. Research has also revealed that physical activity level could be associated with cognitive capabilities (Esteban-Cornejo et al., 2015). Would an office worker with a standing or treadmill desk have better cognitive function than his/her sedentary colleagues in the same office? More importantly, even though we may possess a number of dose-response nomograms for the association between IEQ and cognition, we still need to reference underlying theories and associated modeling and simulation to articulate and complete the panoply of empirical results that we do possess, and which have been discussed in this present review.

Albeit any researcher has the flexibility to decide their measurement approach for cognitive performance, it is always worth considering in the experimental design how to compare results with previous studies. Existing studies have been conducted mostly in isolated communities with significantly distinctive measurement protocols to quantify the indoor environment and/or cognition. Hence, the intrinsic complexity of the IEQ-cognition-causality warrants multidisciplinary endeavors in developing a unified framework or protocol to permit the synthesis of "localized" findings. Evidently, such endeavors might involve stakeholders in education research, social behavior, psychology, building science, and medical or health science.

Summary

This review has examined the effects of indoor environmental quality (IEQ) on cognition that are documented in a broad range of laboratory and field studies. In this work, IEQ in the literature consists of five major categories, i.e., indoor air quality, thermal environment, noise, lighting, and non-light visual factors. The reviewed cognitive functions consist of attention, perception, memory, language function, and higher order cognitive skills. Thermal environment and noise are the most studied IEQ factors, while memory and higher order cognitive skills are the most investigated cognitive functions in the literature based on the manual review.

In general, the reviewed studies demonstrate that poor IEQ is associated with reduced cognitive performance. However, the effects of a specific IEQ factor on different cognitive functions are disparate. Inconsistency and uncertainties have been found, possibly owning to distinct assessment approaches of cognition, different ranges of values of the investigated IEQ factors in the research design, and ignored confounding or mediating variables. Other variables associated with environments, tasks, and occupants could potentially contribute as well.

The keyword co-occurrence analysis of 8,133 studies can work alongside and supplement the conventional manual review to understand the complex network of IEQ and cognitive functions. The findings suggest an exponential growth of studies and emerging topics related to the association between IEQ factors and cognitive functions.

Future studies should improve the temporal granularity of the associations between IEQ and cognition, especially when advanced psychophysiological sensing is available. Also, further research needs to refine the categories of IEQ and cognition, take confounding or mediating factors into consideration, and further promote interdisciplinary collaboration.

Conflicts of interest

The authors declare no competing interests.

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Appendix I

Table A1. Tasks or methods to assess different cognitive functions

Cognitive function		Tasks
Attention	General attention*	Stroop task, Serial-digit learning test, d2-test, Corners' Continuous Performance test, Standard Toulouse Pieron questionnaire, Feature match test, Cursor positioning test, Visual search task, Memory-load search task, Curriculum-based measurement, Konzentrations-Leistungs test, Zahlen-Verbindungs test, Necker cube control Test, Symbol digit modalities test, Norwegian version of the reading span test, Double trouble test
	Sustained attention	Bourdon test, Toulouse-Pieron test, Psychomotor vigilance test, Chu attention test, Symbol-digit substitution test (SDST),
	Directed attention	Symbol digit modalities test (SDMT)
Perception	Acoustic perception	Questionnaire related to the environment
	Visual perception	Picture recognition test, Stroop test, Visual search test, Pairing test, Questionnaire related to visual annoyance, Color recognition tasks
Memory	General memory*	Picture recognition
	Short-term memory	Serial-digit learning test, Word recall test, Digit span tests, Code substitution and running memory test
	Long-term memory	Memory typing test, Text recalling test
	Working memory	Subtraction test, Memory span test, 2-Back test, 2-Digit visual addition/subtraction test, Forward digit span test, Computerized test, Visual learning test, Spatial span task, Code substitution, Digit span tests, Operation span task, N-back test, Token search test
	Episodic memory	Telephone interview, The Consortium to Establish a Registry for Alzheimer's Disease-Neuropsychological Assessment Battery, Child memory scale
Language function	Listening comprehension	Questionnaire related to instruction
	Reading comprehension	Proof-reading test, Suffolk reading scale, Oral reading fluency test, SAT comprehension test
	Speech comprehension	Speech test, fMRI test, Identification of words and sentence comprehension, Banford-Kowal-Bench test
Higher order cognitive skills	General higher order cognitive skills*	CNS Vital signs computerized cognitive test, Cognition test CERAD-Plus includes the Mini-Mental State Examination (MMSE), Addition tasks, Attention Deficit Disorder Questionnaire
	Reaction time†	Simple reaction time test, Redirection test, Four choice serial test, Stroop test, Visual signals choice test, Choice reaction time
	Reasoning	Alice Heim 4-I test, Logic problem test, Overlapping test, Grammatical reasoning, Verbal reasoning, Odd-One-Out task, Event sequence and graphic abstracting task
	Decision making	Computer-based test

	Problem solving	Embedded-figure task, She-polish test, Addition task,
	Planning	Spatial planning test, Spatial search task
	Creativity	Creative thinking test, Remote associates test, Idea-generation task

Note: Some instruments, such as the Stroop test, can assess more than one cognitive function.

* *A specific cognition was not explicitly described in the literature.*

† Reaction time is the time elapsed between the onset of a stimulus and a response to it (Colman, 2009). *It consists of simple reaction time, recognition reaction time, and cognitive reaction time. Since it could involve multiple cognitive skills, such as information processing, reasoning, and psychosensory* (Badau et al., 2018)*, we grouped reaction time together with higher order cognitive skills.*

Table A2. Summary of IEQ on attention

Reference	IEQ vs Cognition	Sample size & environmental conditions	Measures of cognitive functions	Major findings	Significance level⁺
(Coley et al., 2007a)	IAQ **vs** Attention	18 school children (age between 10 and 11). CO_2 concentration controlled by opening or closing the window to regulate the ventilation; the Mean CO_2 concentration is ranged from 690 ppm to 2909 ppm.	Cognitive Drug Researcher (CDR) computerized cognitive assessment system to measure the subjects' attention level	The increased levels of CO_2 led to a decrement in the power of attention of approximately 5% (p = 0.004).	2
(J.-C. Chen & Schwartz, 2009)	IAQ **vs** Attention	1764 adults (age around 37.5); Estimated exposure levels to PM_{10} and ozone-based on ambient concentrations in the EPA database.	Serial-digit learning test (SDLT) for testing attention. Symbol-digit substitution test (SDST) about coding ability measures an individual's sustained attention.	Increased ozone exposure was correlated with reduced performance in the SDLT test. Each 10-ppb increase in annual ozone was associated with an increased in SDST and SDLT scores by 0.16 and 0.56, which was equal to 3.5 and 5.3 years of aging-related decline in attention function.	N/A
(Twardella et al., 2012b)	IAQ **vs** Concentration	417 school students in total in 20 classrooms with mechanical ventilation systems; Median CO_2 concentration of 1045 ppm and 2115 ppm.	d2-test: a paper-and-pencil test with 14 rows of characters to distinguish; The total number of characters processed for handling speed and accuracy; The number of correctly marked target characters minus incorrectly marked distractor characters for concentration assessment.	No significant effect of experimental condition on concentration performance was found. No significant effect of experimental state or median CO_2 level on the "total number of characters processed" could be observed. The concentration performance was decreased by 1.11 points at 2115 ppm of CO_2 in comparison with 1045 ppm. Concentration performance, the total number of characters processed, and total errors changed less than 1.7%.	0
(Chiu et al., 2013)	IAQ **vs** Attention	174 children (46.5% males, age from 7 to 14). Estimate the children's lifetime exposure to black carbon.	Conners' Continuous Performance Test (CPT) for the task-based computerized assessment of attention disorders and neurological functioning.	Exposure to black carbon was associated with increased commission errors and slower hit reaction time (HRT). The associations between BC levels and attention parameters were significantly different (p < 0.05) between the middle two BC quartiles and the first BC quartile. But its association with omission errors was not statistically significant. Boys were more susceptible than	1

				girls to potential effects of traffic-related air pollution in some attention domains.	
(X. Zhang et al., 2017b)	IAQ **vs** Attention	25 students (40% males, age around 23). Five conditions mixed with three CO_2 levels (500 ppm, 1000 ppm, and 3000 ppm) and different bio-effluent concentrations.	d2 test: a paper-and-pencil test with 14 rows of characters needed to be distinguished.	No statistically significant effects on perceived air quality and attention performance were found by increasing CO_2 exposure; Exposure to bio-effluent reduced perceived air quality, increased the intensity of reported headache, fatigue, sleepiness, and difficulty in thinking, reduced speed of addition, and decreased the number of correct links made in the cue-utilization test.	0
(Snow et al., 2019)	IAQ **vs** Attention	31 participants were divided into four groups. CO_2 concentration in the study room was controlled at a normal condition (700 ppm) and a high condition (2700 ppm).	Shifting attention tasks and Stroop test were used for the attention test.	No effect of CO_2 on reaction times, complex attention, simple attention, sustained attention was found.	0
(Lan et al., 2009a)	Thermal environment **vs** Attention	24 participants (50% males, mean age 25 years). Four temperatures, 19℃, 24℃, 27℃, and 32℃ were considered in an air-conditioned office with eight fluorescent lamps.	Letter search tests, memory span tests, and picture recognition used in this study were all associated with subjects' attention performance.	No significant effect of temperature on the attention performance was observed in these three tests from both response time and results' accuracy.	0
(Lan et al., 2011b)	Thermal environment **vs** Attention	12 subjects (6 males, average age of 23 years) divided into two groups. One group was exposed to different temperatures in a sequence of 22-30-30-22 °C, while the other group 30-22-22-30 °C.	Computerized test: Stroop - a test of attentional vitality.	The Stroop test performance significantly (p = 0.01) decreased at 30 °C compared with 22 °C when feedback for the test was provided. The performance of the same test was not significantly different (p = 0.09) between the two temperatures without feedback provided.	1
(Schiavon et al., 2017a)	Thermal environment **vs** attention	56 subjects (28 males, average age of 24.7 years). The temperature changed in order at 26 ℃, then 29 ℃, then 23 ℃. The effect of elevated air movement with an occupant-controlled fan was investigated for 26 ℃ and 29 ℃.	Stroop test was used to measure the ability to switch attention in different tasks.	Using a fan did not significantly affect the performance of a Stroop test at 26 ℃ (p = 0.12) or 29 ℃ (p = 0.37).	0

(Lan et al., n.d.)	Thermal environment **vs** Attention	12 subjects (6 males, 18 to 30 years old) divided into two groups. They were exposed to the environment with different temperatures (23 °C and 27 °C).	Computerized test: Stroop - a test of attentional vitality.	The Stroop test performance significantly (p = 0.04) decreased at 27 °C compared with 23 °C when there was no feedback. The performance of the same test was not significantly different (p = 0.17) between the two temperatures with feedback provided.	1
(Hu & Maeda, 2020)	Thermal environment **vs** Sustain attention	10 students divided into two groups. They are exposed to six combinations of clothing and air temperature (16 °C, 26 °C, and 36 °C)	The Bourdon test was used to test the subjects' sustained attention.	From the result of the Bourdon test, no significant effects were observed on the change rate of performance from pre-test to post-test. However, the results indicated a higher relative speed (p < .05) and a higher relative overall performance (p < .05) of sustained attention at 16 °C than 26 °C for the 0.3 clo clothing condition. No significance was found for 0.9 clo regarding the two metrics.	1
(Mazon, 2014)	Thermal environment **vs** Attention	117 high school students (aged from 12 to 18 years). One experiment in summer (33.6 °C) and the other in autumn (20.3 °C).	Standard Toulouse Pieron questionnaire to measure the attention index.	The attention index decreased under thermally uncomfortable conditions. The younger the subjects were, the more reduction of the attention index was in thermal discomfort situations.	N/A
(F. Zhang et al., 2017)	Thermal environment **vs** Concentration	26 office workers (46% males, 73% between 31 and 50 years old, 29% under 30 years old); Temperature conditions: 22 ℃ and 25℃.	Feature match test to measure concentration.	The test scores for the concentration test were approximately 137 at 25℃ and 128 at 22℃. No statistical difference was found.	0
(F. Zhang & Dear, 2017)	Thermal environment **vs** Attention and concentration	56 subjects (28 males, mean age of 25 years). The chamber conditions were adjusted by the air volume system from 16℃ to 38 ℃. The room temperature was cycled at eight different conditions. Illumination was fixed at 500 lx and the background noise was 40 ± 5 dBA.	Attention: feature match test by comparing particular features of various shape images to one another and indicating whether the contents were identical. Concentration: rotations test.	Concentration performance was related to the rate of temperature change. Concentration performance was elevated when the temperature rose faster (Experiment 1 with cooler cycling conditions). Concentration performance had a nearly significant, positive linear relationship with centered air temperature (Experiment 2 with warmer cycling conditions, p=*0.070*).	0
(Maula et	Thermal environment **vs**	33 students (17 males, aged between 19 and 30 years).	Attention performance was measured by Star counting task and vigilance task.	There is no significant improvement in speed (p = 0.84) and accuracy (p = 0.67) of the Star counting task.	0

al., 2016)	Attention	The participants needed to finish the designed task in two temperature conditions (23 °C and 29 °C).		There is also no significant improvement shown in speed (p = 0.2) and accuracy (p = 0.82) of the vigilance task.	
(Tanabe & Nishihara, 2004)	Thermal environment **vs** Attention	20 males and 20 females at college-age experienced three operative temperatures: 25.5 °C, 28 °C, and 33 °C.	A cursor positioning test was used to measure attention performance.	No significant difference in positioning performance was found in three temperature conditions for both females and males.	0
(Mohebian et al., 2018b)	Thermal environment **vs** Attention	33 students (17 males, mean age of 22.1 ± 2.3 years for all participants); Temperatures: 22 and 37 ℃; Lighting levels: 200, 500, and 1500 lux with the same color temperature 4500 ℃.	Attention level was measured with Conners continuous performance test (CPT), while reaction time (RT) was measured by an RT meter. The attention rate was determined by measuring RT and calculating the number of errors.	For the same lighting condition, an increase in temperature caused an increase in commission error, omission error, response time, and correct response ($p < 0.05$)	2
(Lercher et al., 2003)	Noise **vs** Attention	123 primary school children (54% males; mean age of 9.7 years). The two noise levels: 46.1 Ldn and 62 Ldn (Ldn is a weighted, 24-hour average for community noise exposure).	Visual search task for attention test. Children circled the fish facing the opposite direction for 2 minutes.	No effects of chronic noise exposure on the attention performance test, $t(121) < 1.0$ ($M_{quiet} = 21.60$ *and* $M_{noisy} = 21.55$ *number of hits; maximum* $= 23$).	0
(Hygge & Knez, 2001b)	Noise **vs** Attention	128 high school students (50% male, 18 to 19 years). The experiment was run in an off-white chamber; Noise: 38 and 58 dBA; Temperature: 21 ℃ and 27 ℃; Illuminance: 300 and 1500 lx.	Memory-load search task: searched random capital letters and recorded the score of accuracy and speed.	The noise accelerated working attention but reduced accuracy (p = 0.035).	2
(Stansfeld et al., 2005)	Noise **vs** Sustained attention	2844 students (age from 9 to 10 years) from three countries. Aircraft and road traffic noises were recorded in the classroom and outdoors using microphones at the time of testing of cognitive functions.	Sustained attention was measured by adapting the Toulouse Pieron test for classroom use.	Neither aircraft noise nor road traffic noise affected sustained attention.	0

(Wong et al., 2009)	Noise **vs** Attention	24 adults (12 youngers with the mean age of 21.75, and 12 older with the mean age of 67.5); Signal-to-noise ratios (SNRs) of stimuli: -5 dB, 20 dB, and quiet condition. The three sets of stimuli were then normalized to 70 dBA.	Younger and older subjects identified single words in quiet and two noise conditions (SNR 20 and -5 dB). The cortical area for attention was measured by fMRI.	The fMRI results showed reduced activation in the auditory cortex but an increase in attention-related cortical areas (prefrontal and precuneus regions) in older subjects, especially in the SNR −5 condition.	N/A
(Hygge et al., 2002)	Noise **vs** Attention	326 children (mean age of 10.4 years) in four groups. Experimental groups were comprised of children exposed to aircraft noise. For the noise group, 65 children were in the old airport (noise changed from 59 to 55 dBA). 111 in the new airport (noise changed from 53 to 55 dBA). Control groups with little exposure to aircraft noise. 43 in the old-airport, no-noise group (noise changed from 68 to 54 dBA); 107 in the new-airport, no noise group (noise changed from 53 to 62 dBA).	Visual search and reaction time were used to test the general attention in this study. Visual search was performed by the embedded-figure tasks. The reaction was executed by pressing the button.	For the visual search task, there were no significant interactions involving chronic aircraft noise over time. For the reaction time, performance in acute noise or no noise condition did not qualify the interaction. The aircraft-noise group at the old airport was slower than its control group (p = 0.026). But at the new airport, the aircraft-noise group was slower than the no-aircraft-noise group (p = 0.039).	1
(Mott et al., 2012b)	Lighting **vs** Concentration	84 students (age from 7 to 8 years). Two lighting conditions: focus lighting (1000 lux, color temperature 6500 K), and normal lighting (500 lux, color temperature 3500 K).	d2 test was used for measuring processing speed, rule compliance, and concentration performance.	No lighting effects were found on either motivation or concentration.	0
(Kretschmer et al., 2012b)	Lighting **vs** Sustained attention	32 participants (16 males, age from 48 to 68 years). BL (Bright light) group (n = 16) and RL (Room light) group (n = 16) worked under standardized conditions over three consecutive simulated night shifts. RL group worked at 300 lux all nights, BL group was exposed to a 4-hour moving light (3000 lux) and 300 lux.	Psychomotor vigilance test (PVT) to test reaction time for sustained attention. Konzentrations-Leistungs-Test (KLT-R) for mental concentration.	Exposure to bright light at night reduced error rates for a concentration performance task. The mean relative frequency of false responses of the concentration performance task was significantly smaller under bright light than under room light (p < 0.05). However, the performance (e.g., reaction time) of a sustained attention task was not significantly affected by lighting conditions. (p = 0.25).	1

(Keis et al., 2014a)	Lighting **vs** Concentration	58 students (age under 18 years). Two light color temperatures, high (5500 K) vs low (3000 – 3500 K). Two luminance distributions, indirect lighting bounced back from the white ceiling creating large-area lighting source vs purely direct lighting.	d2 test for concentration; German Zahlen-Verbindungs-Test (ZVT) for speed of cognitive processing.	Students showed faster cognitive processing speed and better concentration with blue-enriched white lighting with a high color temperature (5500 K) ($p < 0.001$).	2
(Huang et al., 2015b)	Lighting **vs** Sustained attention	210 undergraduate students (50% males; age from 18 to 23 years). Three correlated color temperatures (CCT): 2700 K, 4300 K, and 6500 K while maintaining the same illuminance of 500 lux.	Chu Attention test for focused and sustained attention.	CCTs affected attention. In specific, the 4300 K condition resulted in significantly better focused and sustained attention (for males, $p = 0.302$. for females, $p = 0.049$).	1
(Mohebian et al., 2018b)	Lighting **vs** Attention	33 students (17 males, mean age of 22.1 ± 2.3 years). Temperatures: 22 and 37 ℃; lighting levels: 200, 500, and 1500 lux with the same color temperature 4500 ℃.	Attention level was measured with Conners continuous performance test (CPT), while reaction time (RT) was measured by an RT meter (not described in the original paper). The attention rate was determined by measuring RT and calculating the number of errors.	In the 22 ℃ environment, an increase in lighting levels caused a decrease in commission error, omission error, response time, but a decrease of correct response ($p < 0.05$). In the or 37 ℃ environment, an increase in lighting levels caused an increase in commission error, omission error, the response time ($p < 0.05$).	2
(Knez, 2014)	Lighting **vs** Attention	132 subjects aged from 18 to 44 (66 females, 66 males, the mean age is 26). Dimmable, electronic, high-frequency ballasts (32000 Hz), and conventional, magnetic, low-frequency ballasts (50 Hz) Three types of fluorescent tube: 3000K, 4000K, and 5500K.	Memory-loaded search task was used to test the subjects' attention performance.	No effect was found on attention performance by the lighting conditions.	0

(Tennessen & Cimprich, 1995)	Non-light visual factors **vs** Direct attention	72 undergraduate students (41.6% male, age from 18 to 25). Four groups in different dormitories with views ranging from natural to all buildings.	The capacity to direct attention was measured by the Necker Cube Control (NCPC) Test and Symbol Digit Modalities Test (SDMT) in a complex task. The Digit span test was a standardized clinical measure of attention in this study.	Subjects who had a natural view scored significantly better on the SDMT which was used for directed attention. The nature view group scored significantly higher in the SDMT ($p < 0.05$). In the NCPC test, the difference of attention score in various views was not significant. The Digit span test also did not indicate the significant difference in attention performance in different view conditions.	1
(Raanaas et al., 2011)	Non-light visual factors **vs** Attention	34 students (12 males, average age of 24 years). Participants were randomly assigned to one of two conditions: 1) an office setting with four indoor plants, both flowering and foliage, or 2) the same setting without plants.	Attention capacity was assessed three times by using a Norwegian version of the reading span test.	The study confirmed that natural elements can affect cognitive performance in an office work environment. However, the results varied from the repeated reading span test. The performance was similar in the first and second condition ($p = 0.98$). But a moderate difference in the different views happened in the third condition ($p = 0.08$).	1
(Fisher et al., 2014)	Non-light visual factors **vs** Focused attention	24 kindergarten students (12 boys and 12 girls, mean age of 5.37 years). Two conditions: 1) decorated classroom with science posters, maps, the children's own artwork as a visual distraction, and 2) sparse classroom condition with all materials irrelevant to ongoing instruction removed.	Frequency and duration of off-task behaviors of a child for attention.	Classroom visual environment can affect attention and thereby affect learning in kindergarten children. Children's learning gains were higher in the sparse-classroom condition. The overall percentage of instructional time spent off-task was significantly greater when children were in the decorated classroom (*M = 38.58%, SD = 10.49*) than when they were in the sparse classroom (*M = 28.42%, SD = 13.19*) ($p = 0.015$). Also, learning scores were higher in the sparse-classroom condition (M = 55%) than in the decorated-classroom condition (M = 42%) ($p = 0.011$).	2
(AL-Ayash et al., 2016)	Non-light visual factors **vs** Attention	24 students (45.8% male, age from 20 to 38 years). In a simulated study environment, the color of a Corflute panel on a wall in front of the subjects' desk was manipulated with six options (vivid red, vivid	The participants were asked to read a passage and then they answered seven multiple-choice questions. These tests were adopted from the SAT Comprehension Test website.	Pale yellow had positive effects on participants' attention on reading tasks and motivated them to study, while vivid yellow impaired participants' attention.	N/A

		blue, vivid yellow, pale red, pale blue, and pale yellow).			
(Ko et al., 2020)	Non-light visual factors **vs** Attention	86 participants (43 males, old than 18 years old). The office-like test room had two views which included one without window view and window view shaded by large overhangs and trees in from	The attention performance was tested by the Double Trouble test.	The participants' score of concentration tests were 5% higher in window condition than the windowless condition ($p = 0.03$)	2

ⱡ**Significance level labeled by authors** (0: no statistical association between cognition and tested IEQ ($p > 0.05$); 1: mixed statistical association for varying levels in different performance tests and/or participant groups; 2: the statistical significance of consistently positive or negative statistical association ($p < 0.05$) between cognition and tested IEQ; N/A: not labeled because no reported p-value from the study)

Table A3. Summary of IEQ on perception

Reference	IEQ vs Cognition	Sample size & environmental conditions	Measures of cognitive functions	Major findings	Significance level[‡]
(Coley et al., 2007a)	IAQ **vs** Visual perception	18 school children. CO_2 concentration controlled by opening or closing the window to regulate the ventilation; Mean CO_2 concentration from 690 ppm to 2909 ppm.	A picture recognition test was used to test the subjects' visual perception.	The increased levels of CO_2 led to a decrement of accuracy (p = 0.72) and an increasement of reaction time in the visual perception test (p = 0.15).	0
(Zhu et al., 2020)	Thermal environment **vs** Visual perception	32 students (16 males). The test room was controlled with four temperature conditions: 26 °C, 30 °C, 33 °C, and 37 °C and two relative humidity levels.	Stroop test was used to measure visual perception.	The Stroop test result showed the best performance (accuracy and speed) when the temperature was 30 °C. The performance was generally better at 50% than 70% of relative humidity.	N/A
(Lan & Lian, 2009)	Thermal environment **vs** Perception	21 participants (6 females, 15 males aged from 18 to 20 years old). They needed to finish tasks in three different indoor air temperatures (17 °C, 21 °C, and 28 °C)	A letter search was used to measure the subjects' visual search. The overlapping test was used to test the subjects' spatial orientation. The carryover effects were corrected for the measured performance.	The visual search performance had the highest correct ratio when the temperature was 17 °C (p = 0.06). But the response time was the shortest when the temperature was 21 °C (p = 0.46). The overlapping performance had the highest correct ratio (p = 0.15) and the shortest response time when the temperature is 21 °C (p = 0.09).	0
(X. Wang et al., 2019)	Thermal environment **vs** Visual perception	15 students (ages between 22 and 33). In the climate chamber, the temperature was set as slightly cool (21.7 °C), neutral (25.2 °C), and slightly warm (28.6 °C),	A visual search task was used to measure subjects' visual perception ability. It requires the subject to rapidly and accurately search for the target object.	The result table shows the subjects' visual perception were significantly different in the cool and warm condition ($p < 0.05$). But there was not too much difference for the subjects in neutral with the other two conditions.	1
(Hill & Bruce, 1996)	Lighting **vs** Visual perception	12 observers. Facial recognition with top lighting vs bottom lighting.	The accuracy of matching the view and the objects; Observers were presented with pairs of faces and had to decide if they were of the same or different people, that is, whether the faces were the same or different in shape.	Top-lit three-quarter and full-face was best for male items ($p < 0.05$). But no difference between the top and bottom lighting directions for profile views. There were no significant effects of light or view from any direction for female items.	1

(J. -H. Lee et al., 2014)	Lighting **vs** Visual perception	20 students (9 males, mean age of 25). Illuminance level: 500 lx and 750 lx; Light color temperature: 3000 K, 4000 K, and 6500 K.	Questionnaires for visual annoyance including annoyance with tasks, visual satisfaction with a light color, and visual distraction. Computer and paper-based reading tasks to identify letters 'eul' and 'reul' in the paragraphs.	Under 500 lx condition, subjects preferred the color of the 6500 K for better visual perception. Occupants preferred 500 lx under the 6500 K condition, and 500 lx and 750 lx under the 4,000 K condition, reporting better visual satisfaction when performing office tasks.	N/A
(Hawes et al., 2012b)	Lighting **vs** Visual perception	24 subjects (20 male and 4 female) mean age is 21.46 years. Four lighting condition was used in the test for different lighting condition. The average color temperature of them are traditional fluorescent lighting (3345 K), and three LED lighting (4175K, 5448K, and 6029K).	Color recognition tasks include the pseudoisochromatic plates and the Farnsworth-Munsell 100 color hue test. Visual acuity task was used for the subjects to read the entire chart.	In Color task 1, the results did not reveal a significant difference in correct response in four light condition (p = 0.89). The time needed to complete the Color task 2 is less as the color temperature increase (p = 0.02). But the error rates of the three conditions did not vary significantly (p = 0.29). For the visual acuity task, the error rates did not reveal a difference as a function of lighting condition (p = 0.38).	1

ⱡ**Significance level labeled by authors** (0: no statistical association between cognition and tested IEQ (p>0.05); 1: mixed statistical association for varying levels in different performance tests and/or participant groups; 2: the statistical significance of consistent positive or negative statistical association (p<0.05) between cognition and tested IEQ; N/A: not labeled because no reported p-value from the study)

Table A4. Summary of IEQ on memory

Reference	IEQ vs Cognition	Sample size & environmental conditions	Measures of cognitive functions	Major findings	Significance level[+]
(J.-C. Chen & Schwartz, 2009)	IAQ **vs** Short memory	1764 adults (average age of 37.5 years. Ambient PM_{10} and ozone concentration were retrieved from EPA Aerometric Information Retrieval system database.	A simple reaction time test (SRTT) measuring motor response speed to a visual stimulus; A symbol-digit substitution test (SDST) for coding ability; and a serial-digit learning test (SDLT) for attention and short-term memory.	Increased levels of estimated annual ozone exposure were correlated with reduced performance in the SDLT test. Each 10 ppb increase in annual ozone was associated with increased SDLT scores by 0.56.	N/A
(X. Zhang et al., 2017b)	IAQ **vs** Memory	25 students (40% males, age around 23). Five conditions mixed with three CO_2 levels (500 ppm, 1000 ppm, and 3000 ppm) and different bio-effluent concentrations.	Digit span memory test which needed subjects to recall and reproduce the string by sequence.	No statistically significant effects of CO_2 or bioeffluent concentrations on memory performance using the digit span test.	0
(Ailshire & Crimmins, 2014b)	IAQ **vs** Episodic memory	13996 old adults (44% males, the mean age of 64 years). Cross-sectional association between residential $PM_{2.5}$ concentration and cognitive functions.	Telephone interview for cognitive status. Two separate components of cognitive functions of episodic memory and mental status were measured in the experiment.	Older adults had a worse cognitive function in the area with higher $PM_{2.5}$. The episodic memory performance was decreased as the concentration of $PM_{2.5}$ rose. Part of the results were significant ($p < 0.05$).	1
(Tonne et al., 2014)	IAQ **vs** Short-term memory	10308 old adults (mean age 66 years). The annual average concentration of $PM_{2.5}$ and PM_{10} from 2003 to 2009.	Short-term verbal memory was measured by a 20-word free-recall test in which participants were presented a list of 20 1-or-2 syllable words at 2-second intervals and then were asked to recall them by writing (in any order, within 2 minutes).	All particle metrics were associated with lower scores of memory test performance during the 2007–2009. Higher $PM_{2.5}$ of 1.1 $\mu g/m^3$ was associated with a 0.03 5-year decline in standardized memory score and a 0.04 decline when participants remained in London between study waves. It did not support the hypothesis that traffic-related particles were more strongly associated with cognitive function than particles from all sources.	N/A

(Ailshire & Clarke, 2015)	IAQ **vs** Working memory	780 old adults (39% males, age above 55 years). Pollution levels for each respondent were calculated based on air monitoring data from Environmental Protection Agency's Air Quality System (AQS) monitoring sites within a 60-km radius of the respondent's tract centroid.	Cognitive function was assessed with a serial 3's subtraction test to measure working memory and recall of the date, day of the week, and name of the president and vice-president to measure orientation. It is an assessment abbreviated form of the Short Portable Mental Status Questionnaire (SPMSQ).	The subjects living in areas with greater exposure to $PM_{2.5}$ had an error rate of 1.5 times greater than those exposed to lower $PM_{2.5}$ concentration. The increase in $PM_{2.5}$ associated with increased incident rate ratios of errors.	N/A
(Snow et al., 2019)	IAQ **vs** Working memory	31 participants were divided into four groups. CO_2 concentration in the study room was controlled at a normal condition (700 ppm) and a high condition (2700 ppm).	Working memory test (third-party CNS software was used)	No effects of CO_2 on the working memory tests were reported.	0
(Coley et al., 2007a)	IAQ **vs** Memory	18 school children. CO_2 concentration controlled by opening or closing the window to regulate the ventilation; Mean CO_2 concentration from 690 ppm to 2909 ppm.	The picture recognition task was used to measure the subjects' memory performance.	No significant effects of CO_2 on memory performance in different CO_2 condition (p = 0.15 for reaction, p = 0.72 for accuracy).	0
(Schikowski et al., 2015)	IAQ **vs** Semantic memory and episodic memory	789 elderly women (age around 55 years). Assessment of exposure to $PM_{2.5}$ and nitrogen oxides.	A cognition test *The Consortium to Establish a Registry for Alzheimer's Disease* (CERAD)-Plus includes the Mini-Mental State Examination (MMSE).	Air-pollution was cross-sectionally associated with a lower cognitive function. NO_x showed an association with a decline in the CERAD total score.	N/A
(Hygge & Knez, 2001b)	Thermal environment **vs** Long-term recall and short-term recall	128 high school students (50% males, age of 18 to 19 years). The experiment was run in an off-white chamber, furnished as a neutral office. Low-frequency noise: 38 and 58 dBA; Temperature: 21 ℃ and 27 ℃; Illuminance: 300 and 1500 lx.	Long-term recall: read a seven pages text about the ancient culture and answered six knowledge questions and eighteen multiple-choice questions after 130 min. Short-term recall: write down all the words they recalled after three wordlists were presented on a PC-screen.	Interactions were found between noise and heat on the long-term recall of a text, and between noise and light on the free recall of emotionally toned words. Long-term recall: Performance was better in low noise environment 38 dBA than in high noise 58 dBA when the temperature was 27 ℃ (p = 0.016). Short-term recall: More words were remembered at 21 °C than 27 °C (p = 0.009).	2

(Wing & Touchstone, 1965)	Thermal environment **vs** Recall	18 male university students. Exposed for 1 hour in the chamber at dry bulb/wet bulb temperatures of 26.7/17.2 °C, 43.3/27.8 °C, and 48.9/31.1 °C.	Recall test of wordlists and digit-span tests for short-memory.	The average recall dropped significantly as environmental temperature increased. From the results of mean error rate, the recall decrement from 43.3/27.8 °C (dry/wet bulb) to 48.9/31.1 °C (dry/wet bulb) was statistically significant ($p < 0.05$), but the drop of the recall performance between 26.7/17.2 °C and 43.3/27.8 °C was not significant.	1
(Holland et al., 1985)	Thermal environment **vs** Long-term memory and short-term memory	20 subjects (50% males, age from 20 to 26 years). Core body temperature was raised to 38.80–39.05 °C within a few minutes by immersion in water at 41 °C.	Long-term memory was assessed by a test that needs the subjects to learn a passage of prose containing 20 facts in 3 min and then recall it 1 h later. Short-term memory was measured by the ability to repeat digit spans forward and backward.	A high core temperature did not affect the ability to learn new facts by the either free or cued recall. It also had no significant effect on short-term memory. However, the increase in core temperature was associated with a significant increase in the speed of the performance of the tests and with a significant decrease in alertness and an increase in irritability.	N/A
(Cui et al., 2013 a)	Thermal environment vs Long-term memory	36 students (50% males, the mean age of 23.3 years). Group A (20 subjects) was exposed to five air temperatures (22 °C, 24 °C, 26 °C, 29 °C, 32 °C), while Group B (16 subjects) was only exposed to 26℃.	Memory typing was used as simulated office work. According to the human cognitive process, memory typing belonged to a long-term memory task and needed a relatively high mental demand.	The optimum temperature range for the performance of memory typing in this study was between 22 ℃ and 26 ℃. The performance of memory typing was a little better at 26℃ compared to other conditions. The regression results showed that subjects had the optimum performance when the temperature was 25.8 °C. The performance at 26 °C was significantly higher than that of other temperatures ($p < 0.01$).	2
(Lan et al., 2009 a)	Thermal environment **vs** Working memory and learning memory	24 participants (50% males, mean age 25 years). Four temperatures, 19℃, 24℃, 27℃, and 32℃ were considered in an air-conditioned office with eight fluorescent lamps.	Picture recognition as the visual recognition memory and attention task; Memory span test for verbal working memory and attention; Symbol-digit modalities test for learning memory assessment.	No significant effect of temperature on the performance of the memory test which was observed within the short duration of experimental sessions in this study. In particular, there was no ideal temperature that produced the highest scores of all memory tests.	0
(Schiavon et al.,	Thermal environment **vs** Working memory	56 subjects (28 males, average age of 24.7 years); Temperature changed in order at 26 ℃, then 29 ℃, then 23 ℃. The effect of elevated air movement with an	2-Back(2B) was used to measure subjects' working memory.	Using a fan did not significantly affect the performance of a memory test at 26 ℃ (p = 0.49) or 29 ℃ (p = 0.23).	0

2017 a)		occupant-controlled fan was investigated for 26 ℃ and 29 ℃.			
(F. Zhang et al., 2017)	Thermal environment **vs** Memory	26 office workers (46% males, 73% between 31 and 50 years old, 29% under 30 years old). Temperature conditions: 22 ℃ and 25℃.	Digit span test was used for memory performance.	The test scores for the digit span test were approximately 7.2 at 25℃ and 7.4 at 22℃. No statistical difference was found ($p = 0.218$).	0
(Lan et al., 2011 b)	Thermal environment **vs** Working memory	12 subjects (6 males, average age 23 years) divided into two groups. One group was exposed to different temperatures in a sequence of 22-30-30-22 °C, while the other group 30-22-22-30 °C.	Digit span memory and visual learning memory tests were used to measure the subjects' memory performance.	There is no significant difference in digit span test ($p = 0.44$) or visual learning test ($p = 0.51$) in two temperature conditions.	0
(Cedeño Laurent et al., 2018)	Thermal environment **vs** Working memory	44 students (mean age was 20.2) were divided into two groups. They had cognitive tests in the AC ($n = 24$) and non-AC ($n = 20$) building before (mean temperature of 20.4 °C), during (mean the highest temperature of 33.4 °C), and after (mean the highest temperature of 28.1 °C) a heatwave.	2-digit visual addition/subtraction (ADD) test was used to measure working memory.	Students without AC showed a significant increase (13.3%, $p < 0.001$) in reaction time of the ADD test, and an insignificant reduction (-6.3%, $p = 0.08$) in throughput of the ADD test during heatwaves compared to the students with AC as the baseline.	1
(X. Wang et al., 2019)	Thermal environment **vs** Working memory	15 students (ages between 22 and 33). In the climate chamber, the temperature was set as slightly cool (21.7 °C), neutral (25.2 °C), and slightly warm (28.6 °C),	Forward digit span was adapted to test subjects working memory.	The result shows for the easy mode of digit span test, subjects have no significant difference in the three temperatures condition. But for the hard mode, they had a significant difference in slightly cool and warm condition ($p < 0.05$)	1
(Lan et al., n.d.)	Thermal environment **vs** Working memory	12 subjects (6 males, 18 to 30 years old) divided into two groups. They are exposed to different temperatures 23 °C and 27 °C.	Computerized test: Digit span	The performance of Digit Span was not significantly different ($p = 0.50$) between the two temperatures.	0
(Zhu et al., 2020)	Thermal environment **vs**	32 students (16 males). The test room was controlled with four temperature conditions:	Visual learning test	Visual learning test results indicated the best performance (accuracy and speed) when the temperature was 30 °C. The performance	N/A

	Working memory	26 °C, 30 °C, 33 °C, and 37 °C and two relative humidity levels.		was generally better at 50% than 70% of relative humidity.	
(F. Zhang & Dear, 2017)	Thermal environment **vs** Working memory	56 subjects (28 males, mean age of 25 years). The chamber conditions adjusted by the air volume system from 16 ℃ to 38 ℃. The room temperature was cycled at eight different conditions. Illumination was fixed at 500 lx and the background noise was 40 ± 5 dBA.	Memory skill: Digit Span and Spatial Span task.	In Experiment 1 (setpoint of 22 °C), the memory and air temperature were very nearly significant (p=0.066). In Experiment 2 (setpoint of 24 °C), no significant effect found between temperature and memory performance. For the Digit Span test in Experiment 1, performance scores in Condition 2 were significantly higher than they were in Condition 1 (P < 0.05). However, the results were not found for the spatial span test.	1
(Tanabe & Nishihara, 2004)	Thermal environment **vs** Working memory	20 males and 20 females at college-age experienced three operative temperatures: 25.5 °C, 28 °C, and 33 °C.	Running the memory test.	No significant difference in memory performance was found in three temperature conditions.	0
(Lan & Lian, 2009)	Thermal environment **vs** Working memory	21 participants (6 females, 15 males aged from 18 to 20 years old). They needed to finish tasks in three different indoor air temperatures (17 °C, 21 °C, and 28 °C)	Digit span was used to measure the subjects' working memory. The carryover effects were corrected for the measured performance.	The memory span performance declined as the temperature was increased. But the result was not significant (p = 0.79).	0
(Maula et al., 2016)	Thermal environment **vs** Memory	33 students (17 males, aged between 19 and 30 years). The participants needed to finish the designed tasks in two temperature conditions (23 °C and 29 °C).	The operation span task and N-back task were used for working memory. Long-term memory was evaluated through a task of memorizing facts about a specific new theme.	In the N-back task for working memory, the accuracy of the performance was decreased as the temperature was increased from 23 °C to 29 °C (p = 0.46), while the reaction time was significantly longer (p<0.001) at 29 °C. The accuracy of the long-term memory task was decreased at 29 °C compared to 23 °C (p = 0.28).	1
(Hygg	Noise **vs**	128 high school students (50% males, age of 18 to 19 years).	Long-term recall: read a seven pages text about the ancient	Interactions were found between noise and heat on the long-term recall of a text, and	1

e & Knez, 2001 b)	Long-term recall and short-term recall	The experiment was run in an off-white chamber, furnished as a neutral office. Low-frequency noise: 38 and 58 dBA; Temperature: 21 ℃ and 27 ℃; Illuminance: 300 and 1500 lx.	culture and answered six knowledge questions and eighteen multiple-choice questions after 130 min. Short-term recall: write down all the words they recalled after three wordlists were presented on a PC-screen.	between noise and light on the free recall of emotionally toned words. Long-term recall: Subjects performed better in the high illuminance 1500 lx than in 300 lx (p = 0.052). The performance was better in a low noise environment 38 dBA than in high noise 58 dBA when the temperature was 27 ℃ (p = 0.016). But the effect of noise was not significant when the temperature was 21 ℃.	
(Hygge et al., 2002)	Noise **vs** Long-term memory and Short-term memory	326 children (mean age of 10.4 years) in four groups. Experimental groups were comprised of children exposed to aircraft noise. For the noise group, 65 children were in the old airport (noise changed from 59 to 55 dBA). 111 in the new airport (noise changed from 53 to 55 dBA). Control groups with little exposure to aircraft noise. 43 in the old-airport, no-noise group (noise changed from 68 to 54 dBA); 107 in the new-airport, no noise group (noise changed from 53 to 62 dBA).	Long-term memory: read the text with noise and then recalled the text after one day in silence. Short-term memory: strings of consonants were presented per second over headphones. Then the children were asked to write down as many consonants as they could remember, in the correct position, starting at the end of the sequence.	After the opening of the new Munich International Airport and the termination of the old airport, long-term memory (p = 0. 015) and reading were impaired in the noise group at the new airport and were improved in the formerly noise-exposed group at the old airport. Short-term memory was also improved in the latter group after the old airport was closed (p = 0.092).	2
(Wong et al., 2009)	Noise **vs** Working memory	24 adults (12 youngers with the mean age of 21.75, and 12 older with the mean age of 67.5). Signal-to-noise ratios (SNRs) of stimuli: -5 dB, 20 dB, and quiet condition. The three sets of stimuli were then normalized to 70 dBA.	Younger and older subjects identified single words in quiet and two noise conditions (SNR 20 and -5 dB). The working memory was measured by fMRI.	The fMRI results showed reduced activation in the auditory cortex but an increase in working memory-related cortical areas (prefrontal and precuneus regions) in older subjects, especially in the SNR −5 condition.	N/A
(Hygge, 2003)	Noise **vs** Long-term recall	1358 children (age from 12 to 14 years). Ten noise experiments in the classrooms for recall and recognition. Single and combined noise sources (e.g., train noise, aircraft noise) were presented for 15 min at 55 or 66 dBA L_{eq}.	Three texts about ancient cultures were used as the source of six open-ended recall questions and twelve multiple-choice questions. The scoring system gave points to each item of information the child remembered.	There was a strong noise effect on recall (p < 0.01), and a smaller but significant effect on recognition (p = 0.011). Train noise and verbal noise did not affect recognition or recall. Some of the pairwise combinations of aircraft noise with train or road traffic interfered with recall and recognition.	2

(Lercher et al., 2003)	Noise **vs** Intentional, incidental, and recognition memory	123 primary school children (54% males; mean age of 9.7 years); The two noise levels: 46.1 Ldn and 62 Ldn (Ldn is a weighted, 24-hour average for community noise exposure).	Free recall and recognition for the puzzle diagrams assessed incidental memory. Children were asked to recognize the correct diagrams from a set with an equal number of correct and incorrect drawings.	Significant effects of chronic noise exposure on both intentional and incidental memory were reported. Intentional memory was significantly better in the low noise environment ($p < 0.02$). Incidental memory performance was degraded by chronic noise exposure ($p < 0.05$). Recognition memory was also worse for the chronically noise-exposed children ($p < 0.04$).	2
(Stansfeld et al., 2005)	Noise **vs** Episodic memory, working memory	2844 students (age from 9 to 10 years) from three countries Aircraft and road traffic noises were recorded in the classroom and outdoors at the time of testing cognitive functions using microphones.	Episodic memory (recognition and recall) was assessed by a task adapted from the child's memory scale. This task assessed time delayed cued recall and delayed recognition of two stories presented on a compact disc. The search and memory task was used to assess working memory and prospective memory.	A linear exposure-effect association was found between exposure to aircraft noise and impaired recognition memory in children (p=0.0141). Exposure to road traffic noise was linearly associated with increases in episodic memory (conceptual recall: p = 0.066; information recall: p = 0.0489).	2
(Ljung, 2009)	Noise and reverberation time **vs** Memory	Experiment 1: 28 university students (age from 19 to 35 years) in a sound-attenuated climate chamber; Noise condition: one lecture with a broadband noise with the spoken lecture with an S/N ratio of +5dBA; Control condition: spoken lecture with an S/N ratio of +29dBA without background noise. Experiment 2: 19 adolescents (2 males, age around 17 years). Short reverberation condition, 0.3 s in all octave bands from 125 Hz to 4 kHz; Long reverberation time, 1.84 s at 125 Hz, 1.46 s at 250 Hz, 0.94 s at 500 Hz, 0.77 s at 1 kHz, 0.78 s at 2 kHz and 0.68 s at 4 kHz.	Experiment 1: Hearing tests: participants were asked to repeat two lists of ten sentences in different noise conditions. Experiment 2: Participants listened to the 10 paragraphs and answered 20 questions by typing them on the computer keyboard to score their ability to hear the lecture on a 7-point scale.	The participants' memory performance was worse when the lecture was heard in the noise condition than in the control condition ($p < 0.05$). In the long reverberation time condition, participants' memory performance was worse than that in short reverberation time conditions ($p < 0.001$).	2
(Sörqvist, 2010)	Noise **vs** Speech	23 adolescents (9 males, age of 17 years). Experiment 1: sounds from different airborne aircraft were	The operation span task was used to assess the participants' working memory capacity. Prose memory was tested by two tasks	The significant difference in participants' scores on the prose memory task was found between the speech noise condition and silence condition and between speech noise	1

	prose memory	recorded outside using a stereophonic microphone and then were put together with computer software to create 10 sound sequences of aircraft at 55-60 dBA L_{eq}. Experiment 2: the speech was recorded in an echo-free room and then was played back to the participant at around 55-60 dBA L_{eq}.	which were combined by the reading phase and recall phase.	condition and aircraft noise condition ($p < 0.01$). However, the difference was insignificant between the aircraft noise condition and silence condition ($p = 0.24$). The speech was more detrimental to prose memory than is aircraft noise, and individual differences in working memory capacity contributed more to individual differences in susceptibility to the effects of aircraft noise on prose memory than to the effects of speech.	
(Hygge & Knez, 2001b)	Lighting **vs** Long-term recall and short-term recall	128 high school students (50% males, age of 18 to 19 years). The experiment was run in an off-white chamber, furnished as a neutral office. Low-frequency noise: 38 and 58 dBA; Temperature: 21 ℃ and 27 ℃; Illuminance: 300 and 1500 lx.	Long-term recall: read a seven pages text about the ancient culture and answered six knowledge questions and eighteen multiple-choice questions after 130 min. Short-term recall: write down all the words they recalled after three wordlists were presented on a PC-screen.	Interactions were found between noise and light on the free recall of emotionally toned words. Long-term recall: Subjects performed better in the high illuminance 1500 lx than in 300 lx ($p = 0.052$). Short-term recall: When the noise was 38 dBA, more words were remembered at 1500 lx than 300 lx ($p = 0.032$). However, the effect of illumination was insignificant when noise was 58 dBA.	1
(Knez, 1995)	Lighting **vs** Long-term memory	96 subjects (aged from 18 to 55 years). The first experiment was full factorial with two light color temperatures (3000 K vs 4000 K) and two illuminance levels (300 lx vs 1500 lx), while maintaining a high color rendering index (CRI) 95. The second experiment had the same set as the first one except for a low CRI 55.	Long-term recall and recognition task: seven pages of compressed test about an ancient culture as an encoding-retrieval task. In particular, read the text and answered six general knowledge questions and eighteen multiple-choice questions. Free recall task for memory performance: recall wordlists shown on a PC-screen.	In specific, a light color temperature that induced the least negative mood enhanced the performance in the long-term memory and problem-solving tasks in both genders ($p < 0.05$). Also, the combination of color temperature and illuminance that best preserved the positive mood in one gender enhanced this gender's performance in the problem-solving and free recall tasks.	2
(Kretschmer et al., 2012b)	Lighting **vs** Working memory	32 participants (16 males, age from 48 to 68 years). BL (Bright light) group (n = 16) and RL (Room light) group (n = 16) worked under standardized conditions over three consecutive simulated night shifts. RL group	One-digit numbers were presented for 1.5 s on a computer screen successively for 5 minutes per session. Subjects were instructed to conduct a task related to the numbers remembered.	Exposure to bright light at night reduced error rates of a working memory task. The mean number of correct responses was significantly higher under bright light than under room light ($p < 0.01$).	2

		worked at 300 lux all nights, and BL group was exposed to a 4-hour moving light (3000 lux) and 300 lux.			
(Knez & Enmarker, 1998)	Lighting **vs** Memory	40 subjects (50% males, age from 18 to 55 years). Two color temperatures, 3000 K and 4000 K at color rendering index (CRI) of 95, and illuminance level of 1500 lx.	For long-term recall, the subjects need to read the materials and then accomplish the recall and recognition task. For free recall, the subjects need to recall the words they read from the word list.	No significant effect of lighting on the performance of free recall, the long-term recall was obtained.	0
(Hawes et al., 2012 b)	Lighting **vs** Working memory	24 subjects (20 male and 4 female, mean age are 21.46 years). Four lighting condition was used in the test for different lighting condition. The average color temperature of them are traditional fluorescent lighting (3345 K), and three LED lighting (4175K, 5448K, and 6029K).	The verbal event planning task was used for challenging subjects' verbal working memory. The spatial map study task was used for challenges subjects' spatial working memory.	For both the verbal working memory and spatial working memory test, the accuracy of both tests did not vary significantly as a function of lighting condition ($p > 0.05$). But reaction time of these two tests became less as the increasing color temperature ($p < 0.01$).	1
(Knez, 2014)	Lighting **vs** Long-term memory and short-term memory	132 subjects aged from 18 to 44 (66 females, 66 males, the mean age is 26). Dimmable, electronic, high-frequency ballasts (32000 Hz), and conventional, magnetic, low-frequency ballasts (50 Hz) Three types of fluorescent tube: 3000K, 4000K, and 5500K.	The subjects were asked to finish the 24 questions for recalling the content in the materials read 130 minutes ago.	No effect was found on long-term memory or short-term memory performance by the lighting conditions.	0
(Keis et al., 2014 a)	Lighting **vs** Memory	58 students (age under 18 years). Two light color temperatures, high (5500 K) vs low (3000 – 3500 K); Two luminance distributions, indirect lighting bounced back from the white ceiling creating large-area lighting source vs purely direct lighting.	Visual and verbal memory test was used to test the memory retention.	No effects of blue-enriched white lighting on short-term encoding and retrieval of memories were found ($F(3,53) < 1$; $F(3,52) < 1$).	0

(Ko et al., 2020)	Non-light visual factors **vs** Working memory and short memory	86 participants (43 males, old than 18 years old). The office-like test room has two views which include one without window view and window view shaded by large overhangs and trees in from	Token Search test was used to test subjects' working-memory and Digit Span test was for short-term memory)	Working memory for window condition was 6% higher compared to windowless one (p = 0.009). But the short-term memory has no significant difference in the two conditions (p = 0.53).	1

ˡ**Significance level labeled by authors** (0: no statistical association between cognition and tested IEQ (p>0.05); 1: mixed statistical association for varying levels in different performance tests and/or participant groups; 2: the statistical significance of consistent positive or negative statistical association (p<0.05) between cognition and tested IEQ; N/A: not labeled because of no reported p-value from the study

Table A5. Summary of IEQ on language function

Reference	IEQ vs Cognition	Sample size & environmental conditions	Measures of cognitive functions	Major findings	Significance level[ǂ]
(X. Zhang et al., 2017b)	IAQ **vs** Reading comprehension	25 students (40% males, age around 23). Five conditions mixed with three CO_2 levels (500 ppm, 1000 ppm, and 3000 ppm) and different bio-effluent concentrations.	Proof-reading test which needed subjects to highlight the errors in the printed text.	There is no statistically significant effects of CO_2 or bioeffluent concentrations on proof-reading performance.	0
(Shaughnessy et al., 2006)	IAQ **vs** Reading	Students in 5th grade participate in the task. Monitoring the CO_2 concentration and ventilation rate in fifth-grade classrooms of 54 elementary schools.	The students are asked to take the tasks of math skills and reading skills.	The association observed using linear regression between ventilation rate and the reading score has no statistical significance (p = 0.56).	0
(Lan & Lian, 2009)	Thermal environment **vs** Reading comprehension	21 participants (6 females, 15 males aged from 18 to 20 years old) They needed to finish tasks in three different indoor air temperatures (17 °C, 21 °C, and 28 °C)	A verbal comprehension task was used to measure the subjects' reading comprehension. The carryover effects were corrected for the measured performance.	The reading comprehension performance had the highest correct ratio when the temperature was 21 °C (p = 0.63). But the response time was the shortest when the temperature was 28 °C (p = 0.16).	0
(Marchand et al., 2014)	Thermal environment **vs** Reading comprehension	158 undergraduate students (95 males, age from 17 to 49 years). Normal condition: 22.2 °C, 35 dBA and 500 lx; Discomfort condition: 26.7 °C, 60-65 dBA and 2500 lx.	The subjects read a test passage then took an assessment. The Sentence Verification Task (SVT) was used as the test for comprehension. It can be adapted to any reading assignment or oral presentation.	Students in the reading condition have reported no difference between conditions for the reading modality (p = 0.25).	0
(W. Yang & Moon, 2018)	Thermal environment **vs** Speech recognition	24 students (50% male, age from 19 to 27) The indoor environmental chamber with packaged air-conditioners (four thermal conditions with PMV -1.53, 0.03, 1.53, and 1.83), ventilation fan, humidifiers, dehumidifiers, lighting, and loudspeakers (for	Set the duration of exposure and various background noise. In the two different speech-noise-ratio recognition tests, participants need to take the 25-words speech test. This study recorded the normality of the subjective responses to the questionnaire.	Both speech-noise-ration and thermal comfort can affect speech recognition. But only PMV with SNR of 5 dB affects the speech recognition scores.	N/A

		fan and babbles sounds of 45 and 60 dBA).			
(Wittersehet al., 2004b)	Thermal environment **vs** Reading comprehension	30 subjects (16 males, aged from 18 to 29) were divided into six groups. The experimental room was set at 22 °C, 26 °C, and 30 °C in two noise conditions (35 dBA and 55dBA)	Proof-reading was used to measure subjects' reading comprehension	The proof-reading performance was decreased as the temperature was raised in the same noise condition ($p < 0.05$).	2
(Stansfeld et al., 2005)	Noise **vs** Reading comprehension	2844 students (age from 9 to 10 years) from three countries Aircraft and road traffic noises were recorded in the classroom and outdoors at the time of testing of cognitive functions using microphones.	Questions on perceived health, and perceptions of noise and annoyance; Questionnaire for the parents to complete including questions on the perceived health of their child. Reading comprehension with nationally standardized and normed tests—Suffolk reading scale, 10 CITO (Centraal Instituute Toets Ontwikkeling) readability index for elementary and special education, and the ECL-2.	A linear exposure-effect association was found between exposure to aircraft noise and impaired reading comprehension ($p = 0.0097$).	2
(Klatte et al., 2010)	Noise **vs** Listening comprehension and speech perception	94 adult students, children in elementary school, 108 first grade students, 149 third grade students participated in the experiment. For the speech perception, the experiment was conducted in two virtual classrooms with two reverberation time (RT) 0.47 and 1.1s. For the listening comprehension, the task was performed in the room with	The students need to listen to the instruction and take the test to indicate the misunderstanding of the content.	The background speech affects much more on listening comprehension ($p < 0.001$). The classroom noise influenced speech perception more than that by background speech ($p < 0.001$).	2

		classroom noise and with background speech.			
(W. Yang & Moon, 2018)	Noise **vs** Speech recognition	24 students (50% male, age from 19 to 27) The indoor environmental chamber with packaged air-conditioners (four thermal conditions with PMV -1.53, 0.03, 1.53, and 1.83), ventilation fan, humidifiers, dehumidifiers, lighting, and loudspeakers (for fan and babbles sounds of 45 and 60 dBA).	Set the duration of exposure and various background noise. In the two different speech-noise-ratio recognition tests, participants need to take the 25-words speech test. This study recorded the normality of the subjective responses to the questionnaire.	Both speech-noise-ration and thermal comfort can affect speech recognition. Speech recognition performance increased as the SNR increase.	N/A
(Witterseh et al., 2004b)	Noise **vs** Reading comprehension	30 subjects (16 males, aged from 18 to 29) were divided into six groups. The experiment room was set as 22 °C, 26 °C, and 30 °C in two noise condition (35 dBA and 55dBA)	Proof-reading was used to measure subjects reading comprehension.	For the same temperature condition, the proof-reading speed was increased in the noise condition ($p < 0.05$).	2
(Hygge et al., 2002)	Noise **vs** Speech perception	326 children (mean age of 10.4 years) in four groups. Experimental groups were comprised of children exposed to aircraft noise. For the noise group, 65 children were in the old airport (noise changed from 59 to 55 dBA). 111 in the new airport (noise changed from 53 to 55 dBA). Control groups with little exposure to aircraft noise. 43 in the old-airport, no-noise group (noise changed from 68 to 54 dBA); 107 in the new-airport, no noise group (noise changed from 53 to 62 dBA).	Speech perception: the children heard a story under different noise backgrounds (aircraft noise, road noise, and broadband noise) and used buttons to adjust the sound level of the story when it dropped randomly by 10 dBA. They were instructed to re-adjust the volume to the point where they could understand what was said if they concentrated.	Speech perception was improved between before switch and after the switch, but there was no differential improvement between groups. At the new airport, the onset of aircraft noise seemed to block improvement in auditory discrimination from Wave 1 to Wave 3, as evidenced by the group*wave interaction (p <0.001).	1

(Wong et al., 2009)	Noise **vs** Speech perception	24 adults (12 youngers with the mean age of 21.75, and 12 older with the mean age of 67.5); Signal-to-noise ratios (SNRs) of stimuli: -5 dB, 20 dB, and quiet condition. The three sets of stimuli were then normalized to 70 dBA.	Younger and older subjects identified single words in quiet and two noise conditions (SNR 20 and -5 dB). The speech perception was measured by fMRI to collect the information on cortical cerebral hemodynamics.	Increased cortical activities in general cognitive regions were positively correlated with behavioral performance in older listeners. ANOVA analysis showed a main effect of noise conditions on the accuracy of spoken word processing *(p* < 0.001*)*.	2
(Marchand et al., 2014)	Noise **vs** Reading comprehension	158 undergraduate students (95 males, age from 17 to 49 years). Normal condition: 22.2 °C, 35 dBA and 500 lx; Discomfort condition: 26.7 °C, 60-65 dBA and 2500 lx.	The subjects read a test passage then took an assessment. The Sentence Verification Task (SVT) was used as the test for comprehension. It can be adapted to any reading assignment or oral presentation.	Students outside the comfort zone reported were more negatively affected by the sound of the room. The sound had a more negative effect on their performance than those in the normal condition (p = 0.02).	2
(Klatte, 2010)	Noise and Reverberation **vs** Speech perception	487 students (first and second grade, 249 boys, mean age from 7 -8 years). The reverberation time of speech from 0.49 to 1.1 seconds, the ambient noise level from 22 – 29 LAeq in empty classrooms. The speech materials were presented with a signal level of 65 dBA.	Identification of single words and sentence comprehension for speech perception.	The students from school 8 in the control room had better improvement in word identification test (p < 0.01). In both school 1 and school 8, students had higher accuracy in the extra room than in the classroom. But the effect of the test room and the interaction did not reach significance (p = 0.09). No effect of reverberation time had been found on sentence comprehension.	1
(Anderson et al., 2010)	Noise **vs** Speech Perception	66 children (44 males, age from 8-14 years). Grouped based on the performance on the clinical measure of speech-in-noise (SIN) perception and reading. The experiments were performed in quiet and noise conditions (six-talker babble with the signal-to-noise ratio at 10 dB).	Speech understanding in noise was evaluated with the Hearing in Noise Test (HINT) used the Banford-Kowal-Bench (BKB) phonetically balanced sentences appropriate for children at the first-grade reading level and above. Subjects were divided into two groups: 1) top SIN group, >50th percentile in HINT-Front scores, and 2) bottom SIN group <50th percentile in HINT-Front scores.	Background noise delayed the response significantly (p < 0.001). In the quiet condition, two groups have the same neural response timing. In the noise condition, bottom groups exhibited greater neural delays relative to the top groups.	2

(Sörqvist et al., 2010)	Noise **vs** Reading comprehension	40 students (mean age of 23.7, 62.5 female). The irrelevant speech was recorded and played through headphones at approximately 70-75 dBA. The participants were asked to sit in the silent room with listening to the various speech fragments.	Participants need to read the first 5 short texts and answer the accompanying questions in 90 seconds. Then they need to select one from four words to make the sentence which missing one word coherent in the remaining 15 texts.	The irrelevant speech disrupted the reading comprehension ($p<0.05$). But it did not affect the time need to finish the task.	1
(Mott et al., 2012b)	Lighting **vs** Reading comprehension	84 students (age from 7 to 8 years); Two lighting conditions: focus lighting (1000 lux, color temperature 6500 K), and normal lighting (500 lux, color temperature 3500 K).	ORF was used to measure subjects' reading performance for the focus light set on that.	The focus light setting was an instructional technology that improved the reading performance of the participants ($p < 0.001$).	2
(Marchand et al., 2014)	Lighting **vs** perception and comprehension	158 undergraduate students (95 males, age from 17 to 49 years). Normal condition: 22.2 °C, 35 dBA and 500 lx; Discomfort condition: 26.7 °C, 60-65 dBA and 2500 lx.	The subjects read a test passage then took an assessment. The Sentence Verification Task (SVT) was used as the test for comprehension. It can be adapted to any reading assignment or oral presentation.	The light did not affect the participants' performance on their listening or reading.	0
(AL-Ayash et al., 2016)	Non-light visual factors **vs** Reading comprehension	24 students (45.8% male, age from 20 to 38 years). In a simulated study environment, the color of a Corflute panel on a wall in front of the subjects' desk was manipulated with six options (vivid red, vivid blue, vivid yellow, pale red, pale blue, and pale yellow).	The participants were asked to read a passage and then they answered seven multiple-choice questions. These tests were adopted from the SAT Comprehension Test website.	Reading comprehension scores were significantly higher in the vivid color conditions compared to the pale color conditions ($p = 0.022$). But the main effect of hue was not significant ($p = 0.676$).	1

ⱡ**Significance level labeled by authors** (0: no statistical association between cognition and tested IEQ ($p > 0.05$); 1: mixed statistical association for varying levels in different performance tests and/or participant groups; 2: the statistical significance of consistent positive or negative statistical association ($p < 0.05$) between cognition and tested IEQ; N/A: not labeled because no reported *p*-value from the study)

Table A6. Summary of IEQ on higher order cognitive skills

Reference	IEQ vs	Sample size & environmental conditions	Measures of cognitive functions	Major findings	Significance level⁽¹⁾
(Ko et al., 2020)	IAQ **vs** Reaction time (simple and choice)	18 school children (age between 10 and 11). CO_2 concentration controlled by opening or closing the window to regulate the ventilation; the Mean CO_2 concentration is ranged from 690 ppm to 2909 ppm.	Cognitive Drug Researcher (CDR) computerized cognitive assessment system to measure the subjects' attention level	The increased levels of CO_2 led to a decrement in the accuracy of choice reaction (p = 0.75) while with an increment in reaction time (p = 0.06). The simple reaction time was increased by the increase of CO_2 concentration (p = 0.02).	1
(J.-C. Chen & Schwartz, 2009)	IAQ **vs** Reaction time	1764 adults (age around 37.5). Estimated exposure levels to PM_{10} and ozone-based on ambient concentrations in the EPA database.	A simple reaction time test (SRTT) to measure visuomotor speed to a visual stimulus.	Increased ozone exposure was not correlated with reduced performance in the SRTT test.	0
(Tonn 4)	IAQ **vs** Reasoning	10308 old adults (mean age 66 years); The annual average concentration of $PM_{2.5}$ and PM_{10} from 2003 to 2009.	Alice Heim 4-I test to measure reasoning performance.	Low reasoning performance was associated with all particle metrics, especially for the years more distant in time.	N/A
(X. t al.,	IAQ **vs** Calculation and redirection test	25 students (40% males, age around 23). Five conditions mixed with three CO_2 levels (500 ppm, 1000 ppm, and 3000 ppm) and different bio-effluent concentrations.	The redirection test was used to record the response time and error rate. The task was to state whether the disk was in the same direction as the person's face in the image. Also, an additional test (arithmetical calculation) was applied to evaluate speed and error rates.	Exposures to bioeffluents with injected CO_2 at 3000 ppm reduced the speed of addition (for speed p = 0.023; for error rate p = 0.049), and the response time in a redirection task, and significantly affected speed (p=*0.023*) and error rates of the addition test (p = *0.049*).	2
(Sno 19)	IAQ **vs** Executive function and reaction time	31 participants were divided into four groups. CO_2 concentration in the study room was controlled as normal condition (700 ppm) and high condition (2700 ppm).	CNS Vital signs computerized cognitive test battery	For the executive function test, significant effects of condition with scores in the normal CO_2 concentration condition which was better the baseline (p = 0.01). But there was no effect on reaction time performance in different IAQ environment.	1

(Schikowski et al., 2015)	IAQ **vs** Visuo-construction	789 elderly women (age around 55 years). Assessment of exposure to $PM_{2.5}$ and nitrogen oxides.	Cognition test CERAD-Plus includes the Mini-Mental State Examination (MMSE).	Air-pollution was cross-sectionally associated with lower cognitive function. NO_x showed an association with a decline in the CERAD total score.	N/A
(Satish et al., 2012 b)	IAQ **vs** Decision making	22 students (10 males, age from 18-39 years). Median CO_2 concentration approximately 600, 1000, and 2500 ppm.	The computer-based test was used to measure decision-making performance.	Compare to 600 ppm of CO_2, moderate, and statistically significant decrements occurred in six of nine scales of decision-making performance as the increasing CO_2 concentration ($p < 0.001$). At 2500 ppm, large and statistically significant reductions occurred in seven scales of decision-making performance (raw score ratios, 0.06–0.56), but performance on the focused activity scale increased.	2
(Maddalena et al., 2014)	IAQ **vs** Decision making	32 adult subjects were divided into eight study groups. Four groups subjects participated in the chamber with varying VR (ventilation rate) per occupants (8.5 and 2.6 L/s per person). Other four groups participated in the study of varying VR per floor area (5.5 and 0.8 L/s-m^2)	Strategic management simulation (SMS) which is a web-based simulation was used to assess decision-making performance.	Decision-making performance decreased as the VR reduce in both experiments. From the performance metric tables, almost all the factors that contribute to decision-making were different significantly in various ventilation condition ($p < 0.05$)	2
(Hu & Maeda, 2020)	Thermal environment **vs** Calculation	10 students divided into two groups. They are exposed to six combinations of clothing and air temperature (16 °C, 26 °C, and 36 °C)	Calculation test which was based on the Uchida-Kraepelin test form was used	There were no significant differences were observed in the 5-minutes mean accuracy and 5-minutes overall performance. These results suggest that pre-test conditions significantly affected post-test conditions concerning speed but exerted no effect on accuracy and overall performance. The speed of the test indicated a significant difference ($p < .05$) between 26°C/0.3 clo and 36°C/0.3 clo at the fourth minute; however, no significant differences were observed between other clothing or temperature conditions. In particular, the	1

				most significant changes were observed at 26°C (e.g., the 1st minute vs the 2nd minute, $p < .01$, for 0.3 clo). During the first minute, accuracy ($p < .05$) and overall performance ($p < .05$) were higher at 26 °C than 36 °C for 0.9 clo.	
(Tanabe & Nishihara, 2004)	Thermal environment **vs** Addition and choice reaction test	20 males and 20 females at college age. They experienced three operative temperatures: 25.5 °C, 28 °C, and 33 °C.	Addition task, four-choice serial reaction time, and code substitution	No significant difference in performance was found in all tests between three conditions for females. For males, typing performance was significantly lower at 25 °C than the other two conditions ($p < 0.05$); The performance of the four-choice serial reaction time task was significantly lower at 33 °C than the other two conditions ($p < 0.05$).	1
(Schiavon et al., 2017a)	Thermal environment **vs** Choice and executive function	56 subjects (28 males, average age of 24.7 years). The temperature changed in order at 26 ℃, then 29 ℃, then 23 ℃. The effect of elevated air movement with an occupant-controlled fan was investigated for 26 ℃ and 29 ℃.	Choice reaction time with three choices to test the processing speed and alertness. Stroop test was used to measure inhibition.	In the same temperature condition, the use of a fan did not significantly affect the subjects' performance of a choice reaction at 26 ℃ ($p = 0.57$) or 29 ℃ ($p = 0.34$). Similar, using a fan did not significantly affect the performance of a Stroop test at 26 ℃ ($p = 0.12$) or 29 ℃ ($p = 0.37$).	0
(Mohebian et al., 2018b)	Thermal environment **vs** Reaction time (simple, selective, and diagnostic)	33 students (17 males, mean age of 22.1 ± 2.3 years). Temperatures: 22 and 37 ℃; lighting levels: 200, 500, and 1500 lux with the same color temperature 4500 ℃.	Reaction time (RT) was measured by an RT meter (Donder's device).	All types of reaction times in higher temperatures (37 ℃) have been significantly increased compared to those in lower temperature conditions (22 ℃) ($p < 0.05$).	2
(X. Wang et al., 2019)	Thermal environment **vs** Calculation and reaction	15 students (ages between 22 and 33). In the climate chamber, the temperature was set as slightly cool (21.7 °C), neutral (25.2 °C), and slightly warm (28.6 °C),	Choice reaction time with three choices to test the processing speed and alertness. A number addition task was used to test subjects' calculation ability.	The results table shows the reaction performance has no significant difference in either easy or hard mode. For the calculation ability, the subjects only had significantly different performances when they were in cool and warm conditions for the hard-mode test ($p < 0.05$).	1

(Lan a)	Thermal environment **vs** Conditional reasoning and Visual choice RT	24 participants (50% males, mean age 25 years). Four temperatures, 19 °C, 24 °C, 27 °C, and 32 °C were considered in an air-conditioned office with eight fluorescent lamps.	Visual choice reaction time to measure response speed and accuracy to visual signals. Stimuli consisting of arrow and triangle were displayed one at a time on the screen. A verbal deductive reasoning task was used for conditional reasoning tests. The spatial image was sued for measuring spatial reasoning.	Participants performed tasks most quickly at 32 °C and lowest at 19 °C. The variation of response time between 24 °C and 27 °C was smallest compared with other temperature pairs, and the response time of 27 °C was longer than that of 24 °C (p = 0.887). The large variance of accuracy and speed indicated that there were large individual differences in the performance of neurobehavioral tests. For reasoning test, there was no significant difference of accuracy (p = 0.25 and p = 0.274) and response time (p = 0.61 and p = 0.607) for subjects in both two tests.	0
(Hyg 2001b)	Thermal environment **vs** Problem solving	128 high school students (50% males, age of 18 to 19 years). The experiment was run in an off-white chamber, furnished as a neutral office; Low-frequency noise: 38 and 58 dBA; Temperature: 21 °C and 27 °C; Illuminance: 300 and 1500 lx.	An embedded-figure-task was used to assess problem-solving performance. The participants' task was to find out which one of the five solutions/figures was present in the 16 large targets.	No significant effects were obtained.	0
(Holland et al., 1985)	Thermal environment **vs** Reasoning	20 subjects (50% males, age from 20 to 26 years). Core body temperature was raised to 38.80–39.05 °C within a few minutes by immersion in water at 41 °C.	Subjects were given 16 simple logic problems. They were asked to decide whether the statement correctly described the sequence of the letters.	No significant difference in the performance of accuracy was found in different control experiments. But the speed of performance was increased as the temperature went up (p < 0.02).	1
(Cedeño Laurent et al., 2018)	Thermal environment **vs** Working memory	44 students (mean age was 20.2) were divided to two groups. They had cognitive tests in the AC ($n = 24$) and non-AC ($n = 20$) building before (mean temperature of 20.4 °C), during (mean the highest temperature of 33.4 °C), and after (mean the highest temperature of 28.1 °C) a heatwave.	The Stroop test was used for measuring subjects' inhibition performance.	Students in the non-AC buildings had an increase in reaction time (13.4%, p < 0.0001) and a significant reduction in throughput (9.9%, p < 0.0001) of Stroop test compared to the subjects in the AC buildings during heatwaves compared to the students with AC as the baseline.	2

(Zhu et al., 2020)	Thermal environment **vs** Reasoning, addition, multiplication, and redirection	32 students (16 males) The test room was controlled with four temperature conditions: 26 °C, 30 °C, 33 °C, and 37 °C and two relative humidity levels.	The overlapping test was used to measure spatial reasoning ability. Redirection was assessed by the spatial orientation test. Addition and multiplication tests were used to examine mental arithmetic ability.	The accuracy of the overlapping test was the highest when the temperature was 33 °C. But the speed was the lowest at the temperature. Accuracies and speeds of the addition and multiplication test were the highest and lowest respectively when the temperature was 30 °C. The speed performance of these four tests was generally better at 50% than 70% of relative humidity. But the difference in accuracy at the two humidity levels was minimized. No statistical significance was provided.	N/A
(Lan et al., 2011 b)	Thermal environment **vs** Reasoning, calculation, and text typing	12 subjects (6 males, average age of 23 years) divided into two groups. One group was exposed to different temperatures in a sequence of 22-30-30-22 °C, while the other group 30-22-22-30 °C.	Grammatical reasoning, number calculation, typing test were the test for measuring subjects' higher order cognitive skills.	The performance of reasoning (tasks on grammatical reasoning, calculation, and addition) almost significantly decreased at 30 °C compared with 22 °C. The grammatical reasoning performance reduced by 25% (p = 0.06) at 30 °C. Calculation speed decreased significantly as the temperature increased (p = 0.08). The subjects input more characters at 30 °C for the typing task (p = 0.75), but they also made more errors.	1
(Lan et al., n.d.)	Thermal environment **vs** Reasoning, number calculation, and typing performance	12 subjects (6 males, 18 to 30 years old) divided into two groups. They are exposed to different temperatures 23 °C and 27 °C.	Computerized tests of grammatical reasoning, number calculation, and typing performance.	The typing performance significantly (p < 0.001) decreased at 27 °C compared with 22 °C when there was no feedback. The performance of the same test was not significantly different (p = 0.68) between the two temperatures with feedback provided. Performance in other tests was not significantly different.	1
(F. Zhang et al., 2017)	Thermal environment **vs** Reasoning and planning	26 office workers (46% males, 73% between 31 and 50 years old, 29% under 30 years old). Temperature conditions: 22 ℃ and 25 ℃.	Reasoning skill was used to measure the subjects' verbal reasoning ability. The planning skill was used to test spatial planning performance. The two tests were conducted on the platform of CBS.	CBS test scores of the reasoning skill (p = 0.594) and planning skill (p = 0.114) were not significantly affected by temperature.	0

(F. Dear,	Thermal environment **vs** Reasoning and planning	56 subjects (28 males, mean age of 25 years). The chamber conditions adjusted by the air volume system from 16 °C to 38 °C. The room temperature was cycled at eight different conditions. Illumination was fixed at 500 lx and the background noise was 40 ± 5 dBA.	Reasoning skill: Odd-One-Out task; Grammatical reasoning task. Planning skill: spatial search; Hampshire tree task adopted from the Tower of London test.	No significant correlation was found between reasoning & planning performance and thermal comfort at a lower cooling setpoint of 22 °C. At a higher cooling setpoint of 24 °C, subjects' reasoning and planning performance showed a trend of decline at the higher heat intensity and longer heat exposure. Subjects' reasoning performance score was negatively associated with TSV^2 (TSV: thermal sensation vote), which predicted an optimal reasoning performance around a neutral thermal sensation. Planning performance had a highly significant negative linear relationship with TSV and air temperature (p<0.001).	1
(Witt 2004b)	Thermal environment **vs** Creative thinking	30 subjects (16 males, aged from 18 to 29) were divided into six groups. The experiment room was set as 22 °C, 26 °C, and 30 °C in two noise condition (35 dBA and 55dBA)	Writing words associated to the specific category was used to measure the subjects' creative thinking ability.	For creative thinking, its score of performance was insignificantly decreased as the temperature was increased in 55 dBA conditions, while the performance varied with temperature non-linearly at the 35dBA condition.	0
(Lan)9)	Thermal environment **vs** Reasoning, calculation, visual choice	21 participants (6 females, 15 males aged from 18 to 20 years old). They need to finish tasks in three different indoor air temperatures (17 °C, 21 °C, and 28 °C)	Event sequence, spatial image, and graphic abstracting were used to test the participants' reasoning skills. Number calculation was used for calculation ability. The visual choice test was another test for subjects' reaction time. The carryover effects were corrected for the measured performance.	The correct ratio of all the three tests for reasoning skill was varied at different temperature (event sequence p = 0.25, spatial image p = 0.62, graphic abstracting p = 0.27). The response time was also a function of temperature (event sequence p = 0.61, spatial image p = 0.33, graphic abstracting p = 0.02). For the calculation test, the subjects had the highest correct ratio (p = 0.95) and the shortest response time when the temperature was 17 °C (p = 0.19). The visual choice performance had the highest correct ratio when the temperature was 17 °C (p = 0.0005). But the response time was the shortest when the temperature	1

				was 21 °C (p = 0.17) as the temperature was increased.	
(Cui et al., 2013a)	Thermal environment **vs** Motivation	36 students (50% males, the mean age of 23.3 years). Group A (20 subjects) was exposed to five air temperatures (22 °C, 24 °C, 26 °C, 29 °C, 32 °C), while Group B (16 subjects) was only exposed to 26 ℃.	Self-reported motivation on a 7-point scale.	A warm discomfort environment harmed motivation. Warm discomfort environments were more harmful to motivation than cold discomfort environments. The improvement in thermal comfort level also made people more motivated (p < 0.047).	2
(Hyg 2001b)	Noise **vs** Problem solving	128 high school students (50% males, age of 18 to 19 years). The experiment was run in an off-white chamber, furnished as a neutral office; Low-frequency noise: 38 and 58 dBA; Temperature: 21 ℃ and 27 ℃; Illuminance: 300 and 1500 lx.	An embedded-figure-task was used to assess problem-solving performance. The participants' task was to find out which one of the five solutions/figures was present in the 16 large targets.	No significant effects were obtained.	0
(Meht 2)	Noise **vs** Creativity	65 undergraduate students (21 males) for Experiment 1 and 2; 95 students (35 males) for Experiment 3 and 4; 68 students (24 males) for Experiment 5. The high, moderate, and low-noise conditions: the noise level at 85 dB, 70 dB, and 50 dB, respectively. And one control condition that average ambient noise level for each session setting varied between 39 dB and 44 dB, with an overall average of 42 dB	The Remote Associates Test was used to assess creative performance. It was widely used to assess creative thinking in both psychology and marketing research. Idea-generation task: participants were asked to imagine themselves as a mattress manufacturer looking for creative ideas for a new kind of a mattress. Shoe-polish problem-solving task: subjects were asked to generate as many solutions as they could think of for the given problem.	A moderate (70 dB) versus low (50 dB) level of ambient noise enhanced performance on creative tasks. Respondents in the moderate-noise condition generated more correct answers than those in the low-noise, high noise, or control condition (p < 0.05). But the time spent in the test of high-noise condition (85 dB) was significantly less than that need in the other condition (p < 0.05).	1
(Belojevic et al., 2012)	Noise **vs** Executive function	311 children (146 boys, age of 7-11 years). Noise levels in front of children's schools were measured in three daytime intervals (9 to 11	Teachers rated children's cognitive functions on a five-item scale adapted from the Attention Deficit Disorder Questionnaire.	No significant relation was found between noise levels at school or home and executive function on the overall sample. Traffic noise at home was significantly associated with executive functions (EF) in	1

		a.m. 12 to 2 pm. 3 to 5 pm). 24-h noise exposure at children's residence was 71 dB on average. Day-time noise level at school: 76 dB and 75 dB for boys and girls respectively.		boys. Ambient noise from street traffic in a major urban center is related to deficits in EF for boys (p = 0.006) but not for girls when they are at home.	
(Hatfield et al., 2002)	Noise **vs** Perceived control	1015 residents (48.5% male). Aircraft noise was measured at numerous residential sites near flight paths in the vicinity of Sydney Airport.	A structured interview assessed aspects of physical and mental health, reactions to noise, attitudes to the noise source, sensitivity to noise, demographic variables, and noise-induced disturbance. Perceived control: each subject was asked "how much control do you personally have over the amount of aircraft noise you hear" based on a 7-point scale self-report (from no control to complete control).	Perceived control had a significant change from high compared to low noise areas ($p < 0.05$). Perceived control over aircraft noise correlated negatively with some effects of noise (e.g., disturbances of reading and sleep) but not others (e.g., depression and anxiety). Furthermore, these effects were better predicted by perceived control than by noise level.	2
(Witterseh et al., 2004b)	Noise **vs** Creative thinking	30 subjects (16 males, aged from 18 to 29) were divided into six groups. The experiment room was set as 22 °C, 26 °C, and 30 °C in two noise condition (35 dBA and 55dBA)	Creative thinking was set as the executive function to measure the subjects' performance.	At a certain temperature, creative thinking performance was decreased or increased with the noise level, but not significantly.	0
(Hygge & Knez, 2001b)	Lighting **vs** Problem-solving	128 high school students (50% males, age of 18 to 19 years). The experiment was run in an off-white chamber, furnished as a neutral office; Low-frequency noise: 38 and 58 dBA; Temperature: 21 ℃ and 27 ℃; Illuminance: 300 and 1500 lx.	An embedded-figure-task was used to assess problem-solving performance. The participants' task was to find out which one of the five solutions/figures was present in the 16 large targets.	No significant effects were obtained.	0
(Knez, 1995)	Lighting **vs** Problem-solving	96 subjects (aged from 18 to 55 years). The first experiment was full-factorial with two light color temperatures (3000 K vs 4000 K)	The embedded-figure-task used to measure problem-solving performance.	The 'warm' white light source at 300 lx illuminance and the 'cool' white light source at 1500 lx illuminance was optimal for subjects' problem-solving. Females had significantly better problem-solving	2

		and two illuminance levels (300 lx vs 1500 lx) while maintaining a high color rendering index (CRI) 95. The second experiment had the same set as the first one except for a low CRI 55.		performance in the warm than in the cool white light source ($p < 0.05$), while males had the opposite performance.	
(Knez & Enmarker, 1998)	Lighting **vs** Problem-solving motivation and judgment	40 subjects (50% males, age from 18 to 55 years). Two color temperatures, 3000 K and 4000 K at color rendering index (CRI) of 95, and illuminance level of 1500 lx.	The embedded-figure-task was used to measure problem-solving performance. Judgment performance was assessed on a 7-point scale based on a performance appraisal task that consisted neutral (balanced) information about a fictitious employee	No significant effect of lighting on the performance of cognitive tasks was found. Males performed significantly better than females. The results consolidated that males had better performance in an abstract cognitive task. The female rates were rated as significantly more motivated than the male.	0
(Tanabe & Nishihara, 2004)	Lighting **vs** Number addition	16 college-age males participated in two lighting conditions. 800 lx and 3 lx (temperature fixed at 23.6 °C and RH 37%).	Addition tasks were adopted.	No significant difference in performance was found between two lighting conditions.	0
(Mohebian et al., 2018 b)	Lighting **vs** Reaction time (simple, selective, and diagnostic)	33 students (17 males, mean age of 22.1 ± 2.3 years). Temperatures: 22 and 37 ℃; lighting levels: 200, 500, and 1500 lux with the same color temperature 4500 ℃.	Reaction time (RT) was measured by an RT meter (Donder's device).	The lighting level on all types of reaction time was statistically significant ($p < 0.001$).	2
(Knez, 2014)	Lighting **vs** Problem solving	132 subjects aged from 18 to 44 (66 females, 66 males, the mean age is 26). Dimmable, electronic, high-frequency ballasts (32000 Hz), and conventional, magnetic, low-frequency ballasts (50 Hz) Three types of fluorescent tube: 3000K, 4000K, and 5500K.	The embedded figure task	A significant improvement in problem solving performance when the lighting is high frequency ($p = 0.06$).	0

(Mehta & Zhu, 2009)	Non-light visual factors **vs** Creativity	208 and 118 participants for two studies on creativity. The color was manipulated through the background screen color. Hue (e.g., red versus blue) was adjusted, and chroma and value were kept constant.	A creative task where subjects were asked to generate as many creative uses for a brick as they could think of within 1 min. The Remote Associate's Test (RAT) was used to test creative thinking.	Red color enhanced performance on a detail-oriented task, whereas blue color enhanced performance on a creative task ($p < 0.03$).	2
(Ko et al., 2020)	Non-light visual factors **vs** Planning	86 participants (43 males, old than 18 years old). The office-like test room has two views which include one without window view and window view shaded by large overhangs and trees in from	Spatial planning was selected for measuring the participants' planning performance.	The planning test results did not show a significant difference between the two window conditions ($p = 0.53$).	0

ⱡ**Significance level labeled by authors** (0: no statistical association between cognition and tested IEQ ($p > 0.05$); 1: mixed statistical association for varying levels in different performance tests and/or participant groups; 2: the statistical significance of consistent positive or negative statistical association ($p < 0.05$) between cognition and tested IEQ; N/A: not labeled because no reported p-value from the study)

Appendix II

Sources of Potential Inconsistency

The first source of impact on associations between IEQ and cognition emanates from assessment of the physical environment itself. While much basic knowledge can be derived from the more pristine investigations of single factors (e.g., the effect of thermal state on sustained attention (Hancock, 1986), actual working conditions are always interactive in their constitution. Thus, temperature level is a ubiquitous presence, as is sound presence, air quality variation etc. The problem here is that the number of potential interactive states of the environment itself rapidly proliferate, and this effect occurs even independent of the essential dynamics of changing states over time. In some ways, inconsistency also emerges here from the disparate base disciplines that underlie measure in many of these areas. Some sources of influence (e.g., temperature, sound), rely on a foundation in physics, others (e.g., air pollutants) can be underwritten by studies of chemistry of particulate studies. More complex sources of influence, such as air exchange, as founded upon an extensive body of practical investigation that has traditionally drawn on an amalgam of disciplinary insights. What this means is that differing cadres of scientific investigators and their associated professional bodies, tend to adopt and prefer their own measurement techniques, developed assessment scales, and then associated applicable standards. None of these are either 'right' or 'wrong' per se, rather the inter-disciplinary cross-talk tends to inject degrees of uncertainty and confusion, most especially when linguistic terms common to each, are employed in diverse ways (and see (Hancock & Volante, 2020)).

It is across such disciplinary and divisional boundaries that we have to face the behemoth of interaction proliferation (Hancock & Pierce, 1985). It is by no means solely in the area of IEQ that proliferating interactions plague those who seek deterministic specification, especially using formal methods. The problem derives from the fact that as we add more and more factors, involved in the consideration of practical indoor environments, so the number of possible states increases almost exponentially. And, as we shall see, the effects of many of these factors on cognition is not a linear one, but rather exhibit non-linear effects with the degree of stress each particular factor exerts.

Were these effects all, we might be quite sanguine about some eventual resolution of the interaction problem, most especially because IEQ concerns are actually bounded within fairly narrow limits of the possible ranges of factors involved (e.g., we would not normally evaluate noise effects above 100 dB(A), since this would imply an unacceptable facility design in the first place). Yet now we have to consider problems and issue that emerge when we begin to consider the task, or range of tasks, that the exposed individual is performing in their workplace. As we have seen, these differing forms of task can themselves present very wide-ranging and disparate forms of cognitive demand. Where one profession features an emphasis on memory, another can be characterized by time-pressure decision-making, etc. Our knowledge of the discrete effects of individual sources of disturbance on specific facets of cognition (e.g., attention) has been improving across the decades. However, precisely how each of these elements of cognition then match to specific professional activities is much less well understood. The area of cognitive task analysis has wrestled with this difficult issue and has made some degree of progress. However, one particular hurdle in terms of clearer understanding, derives from the fact that many modern work situations either encourage or mandate that individual's multi-task in order to resolve the demands set before them. This creates the issue of stability in which, at one moment, a required task may feature important aspects of perception, while at the next, it emphasizes critical elements of decision-making. We can witness this in safety-critical professions such as air-traffic control in which it is vital that the controller sustain their situation awareness, yet at the same time they have to switch to decision-making in determining the advised path of an aircraft on their screen. These sequences of fluctuating cognitive demand profiles can be repeated many times per minute. These represent largely acute challenges, but human beings learn over time and become better, yet they are also fatigued across a work shift and so experienced degraded performance. Each of these acute and chronic sources of instability add to those already noted for establishing the precise nature of the IEQ experienced. They also lead us to the next source of inconsistency, namely the issue of individual differences.

There are few things that we can assert with certainty about human beings, but one of these is that they each vary across different dimensions. So, while we witness many remaining questions about the physical environment experienced, and the work task that is being performed, we also have an intrinsic source of variation embedded in the fact that there is wide variation amongst workers themselves. Evidently, some people have extensive experience at work, others are new hires. Often such experience co-varies with age, but not necessarily so. Men and women differ in their response to identified factors, and the workplace is now one where multiple gender identifications are becoming more prevalent. One most powerful influence in mediating someone's reaction to their workplace is the degree of autonomy that they can exert. If work occurs in an immalleable place of confinement, as many are now experiencing in 'lockdown' conditions (Hancock & Volante, 2020), then stress levels build and a general exhaustion syndrome can set in, regardless of the best intentions of workplace designers. If, however, some degree of freedom is given the individual, in terms of controlling their time or the configuration of the space around them, then at least some degree of that general stress is dissipated. In short, people bring a lifetime of experience into their job location and those influences interact with the task they are performing and some intimately affect the outcome of what they are required to do.

This triad of categories represent only those central features which make it problematic to find stable and deterministic patterns to describe the effect of IEQ on cognition. However, there are two other sources that we cannot pass over without some direct comment. As shown in Figure 3, these are connoted by the diversity of applicable measurement techniques, as well as the critical influence of feedback upon all of the noted effects. We deal with them in this order. It will have been noted that as our survey progresses from descriptions of the environment to descriptions of the task, to descriptions of the people involved, the measurement instrument co-vary accordingly. Physical values can be established by external and objective instruments such as those that assess sound pressure level, light level, dry bulb temperature, and the like. However, understanding work tasks means that we must be much more oriented toward cognitive assessment. Here, use of sophisticated techniques to assess brain state, such as EEG, fNIRS etc., are required since the complexity of the entity to be studied has now itself inflated by many orders of magnitude. True, these forms of assessment provide 'objective' evidence, but such evidence has to be interpreted in terms of performance accomplished. At the level of the individual worker, we see featured many more psychological forms of test and evaluation. These impose interrogatories upon the consciousness of the individual. And already we have to accept that what a person says is not necessarily related either to their momentary brain state, nor the instantaneous state of the indoor environment (and see (Hancock & Matthews, 2019)). In brief, these differing instruments tend to access different orders of information, and almost as critically, at differing temporal levels. Thus, while EEG has a time-base commonly measured in milliseconds, a psychological survey instrument might ask about feelings concerning a whole work shift or more. At the same time, those instruments recording IEQ might integrate over minutes, hours, or even days. These disparate time-bases ought to warn us that strong consistency should not be expected, even if the underlying relationship are coherent and discoverable. Precisely how we measure and when we measure tends to inject much variance into our possible understanding of underlying effects.

Finally, feedback impacts all of the factors that have been identified as under-writing the current confused state of experimental information relating IEQ to cognition. This is because awareness of circumstances acts immediately to change those circumstances. So, for example, someone rewarded for their past performance may rate current conditions as more productive and comfortable as a result of that approbation and not any manifest change in the environment. The brain too adjusts to reward and punishment, most especially with respect to its own internally generated feedback loops. As a result, trying to establish the specific effects of IEQ on cognition is like a grandiose signal to noise effort in which the experimentalist must seek to elevate the signal to trans-threshold levels while suppressing and trying to eliminate sources of obstructing noise. But all this is occurring in a flux of related and unrelated variation against which the embattled investigator must seek to fight. While we have pointed to a number of the major reasons why the picture lining IEQ to cognition remains an obscured one, these are by no means the only sources of variation which impinge on the process. As noted earlier, social cognitive influences can certainly play a role as can cultural, political, and informational impacts. In short, we have strong reason to believe that IEQ does exert significant impacts on cognition, but we have equally strong reasons to believe that providing a closed-end specification of such influences is liable to prove a difficult and arduous endeavor, and one that will take a significant interval of time to resolve.

Appendix B

Paper B. Air quality in the car: how CO_2 and body odor affect drivers' cognition and driving performance?

Chao Wang[1*], Yingzi Lin[2], Yevgeniy Ptukhin[3], Shichao Liu[1]

[1]Civil, Environmental, and Architectural Engineering, Worcester Polytechnic Institute, Worcester, MA, USA
[2]Intelligent Human Machine Systems Lab, Mechanical and Industrial Engineering Department, Northeastern University, Boston, MA, USA
[3]Accounting, Finance, Economics and Decision Science, Western Illinois University, Macomb, IL, USA

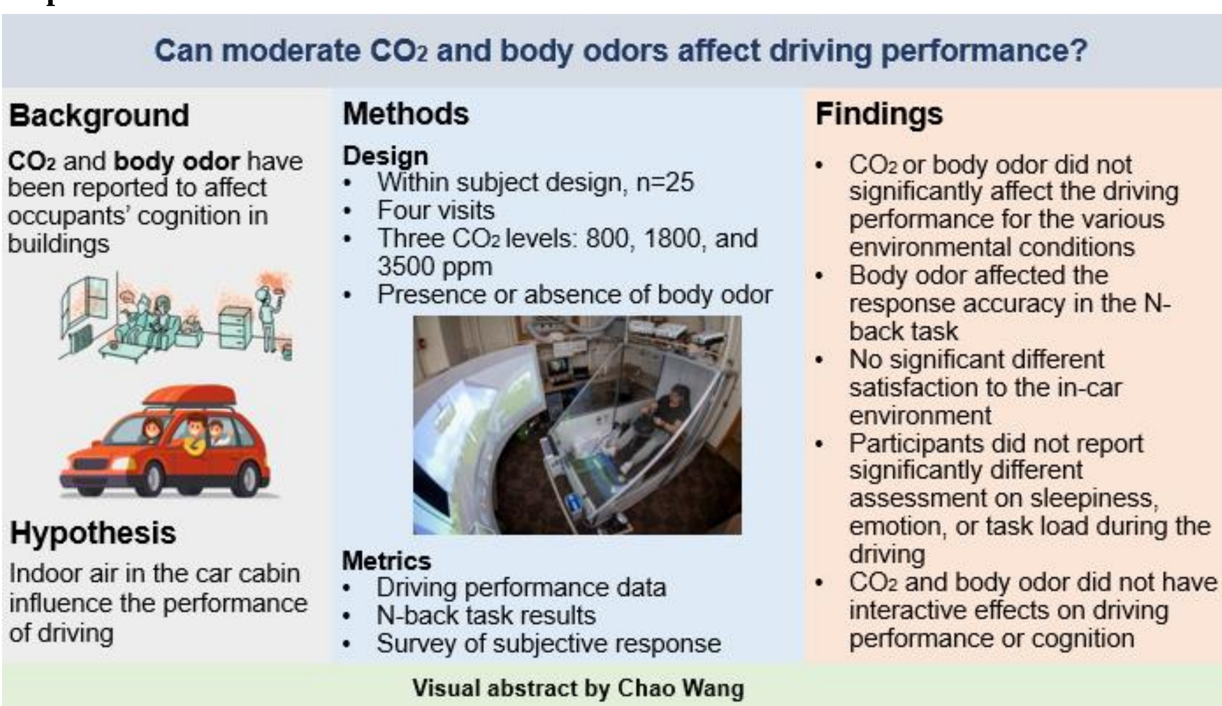
Keywords

Indoor air quality, VOCs, N-back, Task load, Interactive effects, Perceived air quality, Driver Cognition, Driving performance

Highlights

- Assessed driver cognition and driving performance under three CO_2 levels and two body odor conditions
- Analyzed VOCs present in the body odor from T-shirts of male and female donors
- CO_2 or body odor did not significantly impact driving performance in this study
- Body odor increased response accuracy of N-back tasks
- Moderating effects of task difficulty and exposure time impact cognition and driving performance

Graphical abstract



Abstract

Elevated indoor levels of CO_2 and the presence of body odor have been shown to have adverse effects on the cognitive function of building occupants. These factors may also contribute to impaired in-car driving performance, potentially posing a threat to transportation and public safety. To investigate the effects of CO_2 and body odor on driving performance, we enrolled 25 participants in highway driving tasks under three indoor CO_2 levels (800, 1800, and 3500 ppm) and two body odor conditions (presence and absence). CO_2 was injected in the cabin to increase CO_2 levels. In addition, we assessed working memory and reaction time using N-back tasks during driving. We found that driving speed, acceleration, and lateral control were not significantly affected by either CO_2 or body odor. We observed no significant differences in sleepiness or emotion under varying CO_2 or body odor conditions, except for a lower level of emotion valence with exposure to body odor. Task load was also not significantly impacted by CO_2 or body odor levels, except for a higher reported effort at 1800 ppm compared to 800 ppm CO_2. However, participants did demonstrate significantly higher accuracy with increased body odor exposure, suggesting a complex effect of volatile organic compounds on driver cognition. Our findings also revealed moderating effects of task difficulty of N-back tests and exposure duration on cognition and driving performance. This is one of the first few in-depth studies regarding environmental factors and their effect on drivers' cognition and driving performance, and these results provide valuable insights for car-cabin environmental design for air quality and driving safety.

Introduction

CO_2 and body odor

Elevated CO_2 in buildings was reported to increase the prevalence of acute health symptoms (Apte, 2000; Erdmann et al., 2002) and deteriorate cognitive function (Bloch-Salisbury et al., 2000; Scully et al., 2019; Twardella et al., 2012a; C. Wang et al., 2021). A relatively high exposure (even below 5000 ppm) can cause headaches, fatigue, eye, nose, and respiratory tract symptoms (Daisey et al., 2003; Scully et al., 2019). In addition, Satish et al. (2012) found decision-making performance declined at both 1000 ppm and 2500 ppm concentrations relative to 600 ppm. Additionally, Allen et al. (2019) stated that exposure to CO_2 at 700 and 1,500 ppm increased the odds of passing a flight maneuver significantly compared to exposure at 2,500 ppm. Scully et al. (2019) reported that exposure to CO_2 above 1,200 ppm increased self-reported exhaustion and decreased concentration ability after 2-3 hours of exposure.

In addition to indoor CO_2, body odor from occupants may also contribute to the impacted cognition. Human body odor is a unique identifying feature of an individual and contains numerous VOCs belonging to significant chemical classes (Gallagher et al., 2008). Cecchetto et al. (2019) concluded that body odor could effectively influence moral decision-making by changing the emotional experience during the process, even when the perceiver is unable to detect its presence. A field study found that 12 organic compounds increased during lecture periods, with students experiencing increased stress during examination periods due to elevated metabolism (Assessment, 2009a). Zhang et al. (2017) reported that exposure to 3000 ppm of exhaled CO_2 and accompanying body odor reduced mental performance, increased intensity of reported headache, and increased difficulty in thinking clearly compared to background exposure (500 ppm CO_2).

Ventilation in the car

Ventilation is a general strategy to dilute pollutants and improve air quality in the car cabin. The ventilation Air Exchange Rate (AER) in the vehicle cabin directly affects drivers' exposure to various air pollutants and air quality (Brodzik et al., 2014; Ott et al., 2008). A higher AER can decrease the air pollutants that originated in the vehicle but can also increase the air pollutants from outside (Shu et al., 2015). A low AER, on the other hand, can cause the accumulation of CO_2 and unpleasant body odor that result from occupants. Many studies have measured AER in regular passenger vehicles. Hudda et al. (2012) found that median of AER 6.0 h^{-1} under recirculation (RC) ventilation, which was approximately one order of magnitude lower than the 63 h^{-1} under outside air (OA) ventilation settings. Another study (Hudda & Fruin, 2018) found that AER ranged from 3 to 23 h^{-1} under RC and 45 to 104 h^{-1} under OA settings, at speeds ranging from 15 to 60 km/h. The statistical model built by Fruin et al. (2008) indicated a typical California passenger vehicle manufactured in 2010 would have an AER of 20 h^{-1} at a speed of 105 km/h, with ventilation maintained at 18 h^{-1} in the recirculation mode of the car.

Due to the variation in AER, the level of CO_2 that accumulates in a vehicle during driving varies greatly. In a study by Fruin et al. (2011) on the air quality in the vehicle cabin during cruising, it was found that CO_2 concentrations exceeded 2,500 ppm after 15-20 min in a stationary vehicle with two occupants using recirculation (RC) ventilation. However, CO_2 levels never exceeded 800 ppm while in motion under outside air (OA) conditions. CO_2 levels in the vehicle cabin tend to increase due to occupant exhalation when the HVAC air is recirculated. The CO_2 levels, particularly in the window-closed cabin, typically exceed 3000 ppm in the fully loaded condition (Hudda & Fruin, 2018; Shu et al., 2015).

Research motivation and objectives

Although many studies have investigated the impact of CO_2 and/or body odor on occupants' cognition and work performance in buildings, research into these environmental factors and their effect on drivers' cognition and driving performance, which is crucial for safe and effective driving performance in vehicles, seem to be missing in the literature study.

Driving performance refers to as an individual's ability to operate a vehicle safely and effectively, including controlling the vehicle, making quick decisions, and responding to various driving situations (Savino, 2009). Impairments in a driver's cognitive abilities can lead to a decline in driving performance, which can be measured through various metrics related to the vehicle and the environment, such as driving speed and variability, distance from the vehicle in front, lateral position within the lane, and brake reaction time. These metrics have been employed in studies by Baron and Kalsher (1998), Beh and Hirst (1999), Caberletti et al. (2010), Ott et al.(2008), and Raudenbush et al. (2009) to assess driving performance.

To date, studies examining the impact of moderate CO_2 concentrations and body odor on cognitive performance have mostly focused on indoor office environments and tasks lasting several hours. However, due to the potential for CO_2 accumulation and body odor emission in vehicles, there is a gap in knowledge regarding the effects of in-car air quality on driving and the cognitive abilities essential for safe driving. Thus, this study aims to explore the impact of in-car CO_2 and body odor on driving performance, filling the gap in knowledge in this understudied field.

Methodology

Participants and enrollment

Twenty-five student participants were recruited from Worcester Polytechnic Institute (WPI) via poster and email. The Institutional Review Board (IRB-19-0672) of WPI approved the experimental procedure, and all participants completed an IRB-approved consent form informing them of the procedures, risks, and responsibilities of the study.

The interested participants were screened for simulator sickness before the final selection. A very small percentage of individuals (2%–8%) may experience simulator sickness symptoms (a form of motion sickness) during the driving simulation, particularly when the simulation involves multiple curves and stops (Akinwuntan et al., 2005). We used the Simulator Sickness Questionnaire (SSQ) (Kennedy et al., 1993) to assess simulator sickness, as it is the widely used measure of simulator sickness symptoms to predict participant dropout (Balk et al., 2017). It comprises 16 items that address subjective feelings of headache, nausea, and blurred vision. Subjects rate their feeling from 0 (none) to 3 (severe) in three to five minutes after the simulated driving. We removed four participants (original sample size of 29 participants) with adverse physiological and psychological reactions to the driving simulator from the study due to the simulator sickness. Finally, twenty-five young drivers with valid licenses (fifteen males and ten females) within the ages of 18-22 years (*Mean* = 19.88, *S.D.* = 1.33) met the criteria and participated in the formal experiment. To determine the appropriate sample size for our study, we performed a power analysis using G*Power software 3.1 (Fig. S1) (Faul et al., 2007). Since each subject experienced all six combinations of the CO_2 and body odor conditions, we treated the study as having six distinct conditions for the purpose of the power analysis. The calculated sample size was 19 using "ANOVA: Repeated measures, within factors" with effect size of 0.25 and power of 0.8.

Participants were requested to avoid alcohol for 24 hours and to abstain from nicotine and caffeine for 3 hours before the simulated driving. They were also instructed to have enough sleep the night before the visit. The compensation was $15 per hour with a performance-based bonus of up to $15 to motivate participants to engage in the task.

Experiment set up and driving simulator

In this study, the driving simulator comprised several components, including a control computer with simulator software, three display projectors, a curvature screen, a Logitech G29 driving control set, an audio system, and a car cabin. The driving simulator software used in the study was provided by Carnetsoft (Wim van Winsum, Joeswerd 85, Groningen, 9746CR, the Netherlands). The control computer with a GeForce GTX 770 GPU, an i7-9790 CPU, Windows 10 PRO Operating System, and 32 GB RAM was connected to three display projectors. Moreover, the central screen was located 0.5 m in front of the cabin. The simulator provided images on a 210º horizontal field of view, with 70º for the forward view and 70º for each left and right out of the window views. A Logitech G29 steering wheel, shift gear, and pedal set, which included brake, clutch, and accelerator pedals, were used, along with force feedback steering (rotation -450 to +450º), and gear shifter. A foot-switch control pedal was installed to provide additional driver input for N-back tasks that will be described in Section 2.4. The simulator was also equipped with an audio system to mimic the sounds from car engines and tires.

Fig. 1. Panorama of the driving simulator cabin (~ 2.94 m^3) and screen; The cabin was made of a metal frame, polyethylene boards, and clear acrylic plexiglass plastic boards. The seat was adjusted to make the participant's line of sight fall on the focal point on the apparent horizon line in the in-car environment displayed on this monitor.

In-car environment

Ventilation, temperature, and humidity

A wall-mounted heat recovery ventilator (Fantech SH–56 CFM HRV) ventilated the experimental room with the simulator inside. Exhaust air from the car cabin was removed directly by the ventilator. In addition, the experimental room was purified with an air purifier (LEVOIT Air Purifiers for Home, H13) located near the air inlet of the car cabin. We controlled air temperature and relative humidity at 24 ± 1 °C and 47 ± 2% inside the car cabin, respectively.

CO_2

Subjects were randomly assigned to expose to one of the three CO_2 concentrations: 800, 1800, and 3500 ppm for each visit. The CO_2 concentrations were measured near the driver's breathing zone using an active meter (CM-0001 CO2 Sampling Data Logger, CO_2 METER) embedded with an air pump. The measurement accuracy is approximately ±30 ppm. The target CO_2 concentrations inside the cabin were achieved by delivering nearly CO_2 (99.9%) from a gas cylinder (Airgas, Food grade, CGA-320) into the driving simulator cabin. For the low CO_2 condition, the concentration in the cabin was around 800 ppm without adding any artificial CO_2 due to the presence of driver's exhalated CO_2. In the experiment, we injected CO_2 to raise indoor levels at 1800 ppm and 3500 ppm, which is the common approach in the literature (Allen et al., 2016a; Satish et al., 2012a; X. Zhang et al., 2017a).

Body odor

In this study, we considered two body odor conditions: presence and absence of extra body odor that was not emitted by the driver. The extra body odor was added to the car cabin by hanging six worn T-shirts in the car cabin during the driving session. This approach has been widely used in the literature for body odor research (Haze et al., 2001; Munk et al., 2000; Rathinamoorthy & Thilagavathi, 2016). Worn T-shirts were collected from six healthy odor donors (4 males, 2 females) aged between 28 and 38 years old (mean ± SD age: 32.3 ± 4.5 years old). Before collecting the body odor, the donors were screened to ensure they were non-smokers and did not have any health issues or undergo drug treatment known to affect their sense of smell. To maintain consistency, the donors adhered to specific guidelines that controlled their personal nutrition and hygiene practices during the collection session. Informed written consent was obtained from each donor. During the collection session, all individuals providing odor samples were required to comply with specific guidelines that controlled their personal nutrition (meaning they couldn't consume alcohol, smoke, or eat foods that altered their natural body odor) (Cecchetto et al., 2019) as well as their hygiene practices. All T-shirts were previously washed with an odorless detergent (All Mighty Pacs with stain lifters free clear Laundry Detergent). Donors wore T-shirts for more than 12 consecutive hours during the day, right after having taken a shower using fragrance-free body wash (Aveeno Skin Relief Fragrance-Free Moisturizing Body Wash) and having dried themselves with towels washed with the same odor-free detergent used to pre-wash the T-shirts. Donors collected their body odor on separate T-shirts for each collection day for two days. Odorless plastic bags were provided to each donor to store their T-shirts before bringing them to the lab the day after each collection period. All samples were then stored in a dry, light-free environment to prevent sample deterioration.

In this study, we did not measure VOCs directly from the air inside the cabin during the experiments. Instead, we examined the chemical makeup of body odor from two worn shirts (one from a male and one from a female) since the aim of the study was not to establish a relationship between the amount of body odor and driving performance. We assumed that the VOCs emitted from the worn shirts, which were hung in the car cabin, would have diffused into the air due to their volatile nature. To establish a control baseline, we also measured the potential body odor or similar VOCs on a clean shirt. As body odor can come from various parts of the body (Natsch et al., 2006; Pandey & Kim, 2011), we cut fabric samples from the chest, back, and armpit sections of two worn T-shirts (one male and one female) and two pieces from a laundered T-shirt. Each sample was a 5 cm × 5 cm square with a weight ranging from 440.7 to 472.8 mg (Mean = 459.2 mg, SD = 11.2 mg). We used the cotton fabrics from the laundered T-shirt to measure the baseline level of VOCs present on the fabric, which was employed in previous study on carpets (Katsoyiannis et al., 2008). Each cotton fabric sample was placed in a separate glass bottle, according to its corresponding body part from the worn or laundered T-shirts and extracted using 15 ml of methanol. We placed the glass bottles with the solvent inside on an Innova 2100 shaker (New Brunswick Scientific, Edison, N.J.) and shaken at 180 rpm for 12 hours. The extract was condensed to 1.5 ml using RapidVap® (Labconco, Missouri, USA). Then, we further analyzed the condensed extract by gas-chromatography/mass spectrometry (GC-MS) (Agilent, models 7890B and 5977B MSD) with a J&W HP-5MS 30 m × 0.25 mm × 0.25 μm column. The GC-MS was operated under the electron impact (EI) mode (70 eV). The oven temperature program was set as follows: 50 °C (3 min), 50–250 °C (8 °C/min), and 250 °C (3 min) with helium as carrier gas at a flowrate of 1.2 mL/min. Compound identification was achieved by comparing the retention time with chemical standards following NIST spectral libraries. We conducted a search of the literature to identify potential volatile compounds. Published literature on volatiles from the skin of other body sites (i.e., axilla, chest, and back) was also examined. The profile of each compound as the pure compound was checked by GC/MS to confirm consistency with the published literature. Exported VOCs were selected on the basis of existence identified by comparing the clean T-shirt samples with those worn T-shirts.

Driving and secondary tasks

Virtual Environment

The driving tasks were conducted in a virtual environment that depicted a two-lane highway with a lane width of 3.35 meters, as shown in Fig. 2. The highway was busy and required the participants to drive at high speeds, with multiple lane changes, traffic jams, and overtaking maneuvers. The driving scenario was set in daylight without weather disturbances such as fog, snow or rain. Each driving session lasted for at least 20 minutes and included traffic congestion in the first half, where drivers had to slow down to avoid collisions, followed by a return to normal speeds after the heavy traffic subsided.

Fig. 2. Freeway driving scenario

Driving performance

The driving simulator system was utilized to gather data on driving by recording the position and motion of the vehicle at a frequency of 10 Hz. The collected data, including forward velocity, acceleration, lateral velocity, lateral acceleration, lane deviation, steering, and yaw angle rate (Table S1 in Appendix), were analyzed to assess driving performance. Variations in vehicle velocity and acceleration were used as indicators of driving performance impairment. The mean and standard deviation of speed were also examined to evaluate vehicle dynamics. Lateral velocity, lateral acceleration, lane deviation, steering, and yaw rate provided insights into drivers' accuracy and potential errors when driving on the road, particularly in terms of lateral control (Oron-Gilad et al., 2008). Lane deviation represented the average distance of the vehicle from the center of the lane, while the standard deviation of lane deviation was computed only when the vehicle remained in the right lane to avoid overtaking effects. Steering was used to assess the lateral control of the vehicle, and its standard deviation was indicative factor of the impact of road environmental (Thiffault & Bergeron, 2003).

N-back task

The N-back task is a commonly used method for testing working memory and cognitive function in driving tests. It is documented in detail in (Mehler et al., 2012) which used the verbal version of the N-back task. Considering that facial muscle movements can interfere with bio-signals that are not analyzed in the current study, we used a modified version of the N-back task based on the one utilized in (Solovey et al., 2014) to avoid the artifact of the task paradigm.

During the task, participants are presented with a sequence of single-digit numbers from 0-9, displayed on the left corner of the middle screen, at two-second intervals while driving. They were required to determine whether each number was the same as the number that appeared N items before. The value of N is kept constant throughout one session as detailed further in the experimental procedure section, with higher values of N indicating a higher difficulty level. Figure 3. Example of N-back experimental paradigm to manipulate cognitive workload3 illustrates how the N-back task works for N values of 2, 1, and 0. Participants were instructed to react to new items that appeared two, one, or zero items back for the 2-back, 1-back, and 0-back sessions, respectively. Each driving task consists of six sessions equally divided into 2, 1, and 0-back tasks presented randomly. Each session begins with an instruction block followed by 16 randomly selected numbers, with each number displayed for 500 ms and participants given 1,500 ms to react. A 140 s driving block follows each N-back session.

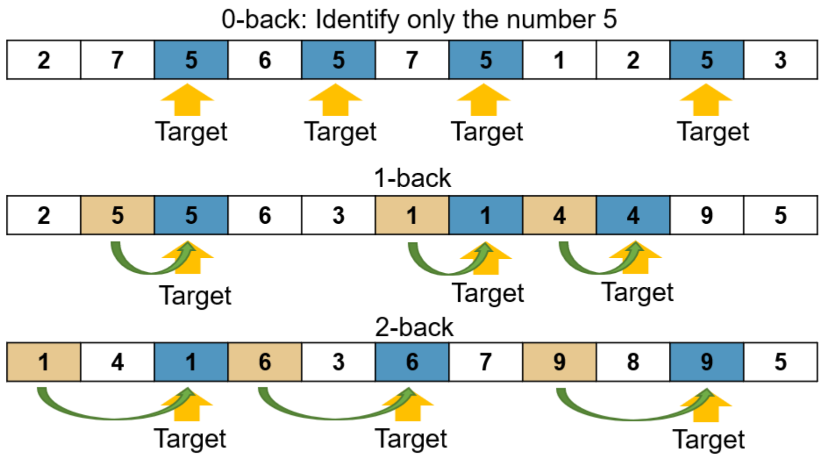


Fig. 3. Example of N-back experimental paradigm to manipulate cognitive workload

This task implementation program was created using Python. The time when each number appeared, the session type, the subject's response time, and whether the presented number was a target or not (in order to calculate response accuracy, %) were all recorded and saved as a text file for subsequent processing. The missed target was considered an incorrect response. This data reflected the efficiency of cognitive processing in each session.

Before and During experiments questionnaires

Participants in the study completed two questionnaires. The first was a brief demographic questionnaire that recorded age, sex, and driving experience. The second questionnaire was completed during the testing and contained items related to sleepiness, emotion, perceived air quality and air quality acceptance, and task workload. The sleepiness before and after driving were measured using the Stanford Sleepiness Scale (SSS), which is a 7-point Likert-type scale ranging from very alert to very sleepy (Hoddes et al., 1973). The Self-Assessment Manikin (SAM) procedure was used to measure participants' emotions, with scales ranging from -2 to 2 (Valence: unpleasant, unsatisfied, neutral, pleased, pleasant. Arousal: calm, dull, neutral, wide-awake, excited. Dominance: dependent, powerless, neutral, powerful, independent) (Bradley & Lang, 1994). Task workload was measured using the NASA Task Load Index (NASA-TLX) questionnaire, which measures different dimensions of stress, workload, and fatigue (Hart, 2006). The questionnaire is divided into six subscales, including mental demand (MD), physical demand (PD), temporal demand (TD), own performance (OP), effort (EF), and frustration (FR). Participants rated their performance on each of these subscales from 1 to 7. Furthermore, participants evaluated their perception, preference, perceived air quality, and air quality acceptance.

Procedure

Each participant visited the laboratory four times to complete the participation. During the first visit, participants took driving training, became familiar with simulator's operation, and completed simulator sickness screening (as shown Fig. 4). In the subsequent three visits, the participants finished driving tasks while exposed to one of the three CO_2 levels randomly. Each visit included two identical driving sessions, one with clean T-shirts while the other with worn T-shirts inside the driving cabin. The order of the two sessions were randomized. Subjects were blinded to randomized experimental conditions. Additionally, we controlled the interval (6.96 ± 2.87 days) between consecutive experimental visits to enhance the independence of observations. The minimum interval between two experimental visits was 3 days.

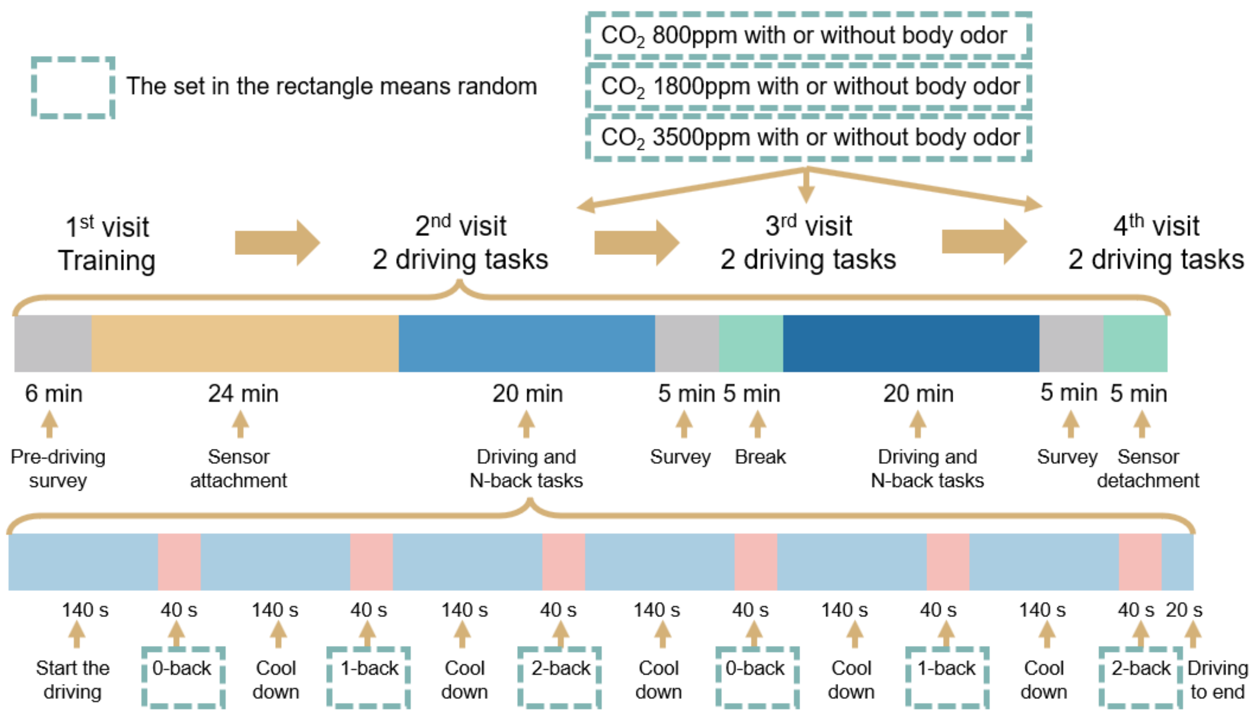


Fig. 2. Experimental procedure

Upon arrival at the laboratory for each visit of the last three, subjects took a survey about the sleeping quality of last night and sleepiness before entering the driving cabin. Then, they began the first driving task, which lasted approximately 18 minutes in the vehicle cabin. While driving, subjects completed six N-back tasks (two 0-back, two 1-back, and two 2-back) randomly, which induced different workload levels. Next, participants were asked to leave the car cabin and finish the physical and psychological state survey (sleepiness, task load, emotion, and perceived air quality and air quality acceptance) regarding the entire driving sessions. We did not expect that taking the survey outside the cabin immediately after driving would significantly change the participants' responses compared to taking the survey inside the cabin. This survey took about five minutes to complete while we swapped the T-shirts inside the cabin. Then they returned to the car cabin for another identical driving session. At the end of all visits, participants were debriefed and compensated.

Data Analysis

The study evaluated driving performance based on recorded vehicle velocity, acceleration, lane deviation, steering wheel movements, and yaw rate. We used reaction time and response accuracy for N-back tasks to measure the impact of CO_2 and body odor on cognitive performance during driving. Subjects' sleepiness level of each driving task was assessed by the difference of the surveys on sleepiness before (pre-test) and after (post-test) the test session. Further, we used the numerical responses in other surveys to assess emotion, and perceived air quality and air quality acceptance. In addition, we followed the approach in a previous study (Al-Shargie et al., 2017) to quantify cognitive load assessed by NASA-TLX.

The effect of CO_2 or body odor on driving performance, cognition with N-back tasks was statistically assessed using Aligned Rank Transform (ART) two-way ANOVA coupled with post-hoc analysis, a commonly employed method in the literature for assessing differences among three or more groups (Durner, 2019; Elkin et al., 2021). All datasets were not normally distributed by using the Shapiro-Wilk normality test. The significance level used for hypothesis testing was 0.05. The data analysis was conducted with R language software (version 4.2.3) (R Core Team, 2013).

Results

Environmental conditions

CO_2 concentration

On average, the measured CO_2 concentration (Fig. S2) was 786.42 ± 106.57 ppm (Mean ± SD) for the low level, 1815.00 ± 80.63 ppm for the middle level, and 3504.41 ± 149.39 ppm for the high level.

Body odor detection on T-shirts

We analyzed the VOC composition of worn T-shirts but did not quantitatively measure their concentration. The compounds extracted from the normal worn T-shirt samples of the upper body are listed in Table 1, and are significantly higher concentration compared to clean cotton samples. Please note that the chemical analysis was conducted with body odor from only two donors. Also, Table 1 displays the chemicals found exclusively in worn T-shirts and not in clean ones, indicating that these chemicals are specifically associated with body odor. In total, we have identified 26 chemicals in the fabric of the female odor donors' clothing and 19 chemicals in that of the male odor donors. There were 12 common chemical constituents found in all the worn fabric samples of male and female donors, including aldehydes and benzene.

The GC-MS spectrogram revealed a higher number of fatty acid groups in the isolates from the worn cotton swatch. Table 1 identifies the following important fatty acids and alcohols which are considered to be odor forming components. Benzene acetaldehyde, found in the female sample, is an aldehyde consisting of acetaldehyde bearing a methyl substituent, and has an odor reminiscent of lilac and hyacinth. Undecanoic acid, identified in the worn textile, is one of the odor-forming sources of sweet and butter-like odor (Shiratsuchi et al., 1995). 2-phenoxy-ethanol, found in the female samples, is a normal constituent of human sweat, blood, and breath, probably resulting from acetaldehyde by oxidation as well as direct injection (Mier et al., 2019). Octanol, 2-butyl and 1-Decanol, 2-hexyl were found in both female and male samples. They are primary alcohols that are colorless oily liquids with a sweet odor. Dodecanoic acid, detected in both female and male samples, is a saturated fatty acid with a 12-carbon atom chain and was identified in axillary sweat samples by Allison et al (Curran et al., 2005). Tetradecanol acid, found in all the samples, is a derivative of myristyl alcohol, as identified in worn textiles (Rathinamoorthy & Thilagavathi, 2016). Methyl esters of tridecanoic acid from male samples were identified as human skin emanations that attract mosquitoes (Verhulst et al., 2016). A saturated fatty acid of myristic acid, ethyl octadecyl ester of carbonic acid was found from female sample. It is a derivative of carbonic acids and has a pleasant smell.

The study also detected other significant odor-forming fatty acids and alcohols such as octanoic acid, hexanoic acid, nonanoic acid, benzene propanoic acid, tridecanoic acid, palmitoleic acid, 9-hexadecenoic acid, trans-13-octadecenoic acid, and n-Decanoic acid in the worn textile. These compounds were derivatives of specific odor components found in the human body such as octanoic acid, hexanoic acid, nonanoic acid, and tridecanoic acid (Ishino et al., 2010; C. Liu et al., 2013; Wachira et al., 2021).

Table 1. Detected chemicals in the body odor present only in the worn T-shirts

Sample location	Compound name	Present in the female sample	Present in the male sample	Property
Armpit, chest, and back	***Glycerin***	✓	✓	odorless
	2-propanol,1-(2-methoxypropoxy)		✓	ethereal odor
	Benzene acetaldehyde	✓		grassy odor
	Undecanoic acid	✓		waxy, creamy, cheese-like
	Cyclopentasiloxane, decamethyl		✓	
	Octanoic acid	✓		pungent odor
	Hexanoic acid	✓		fatty type odor and an cheesy type flavor
	2-phenoxy-ethanol	✓		odor forming compound
	1-Phenoxypropan-2-ol	✓		odorless
	Nonanoic acid	✓		unpleasant, rancid odor
	Benzene propanoic acid	✓		sweet, floral scent
	1-Octanol, 2-butyl	✓	✓	sweet odor
	1-Decanol, 2-hexyl	✓	✓	sweet odor
	Dodecanoic acid	✓	✓	sweet odor
	2-Tridecenoic acid	✓		odorless
	Tridecanoic acid	✓	✓	odorless
	E-9-tetradecenoic acid		✓	odorless
	Tetradecanoic acid	✓	✓	waxy, fatty or soapy odor
	Pentadecanoic acid	✓	✓	odorless
	Carbonic acid, ethyl octadecyl ester	✓		pleasant smell
	Tridecanoic acid, 4,8,12-trimethyl, methyl ester		✓	odor forming compound
	Palmitoleic acid	✓	✓	slightly waxy fatty
	Ascorbic acid, 2,6-dihexadecanoate		✓	odorless
	9-hexadecenoic acid	✓	✓	odorless
	Trans-13-octadecenoic acid	✓	✓	odorless
	Octadecanoic acid	✓	✓	odorless
	Glycerol 1-palmitate	✓	✓	odorless
Armpit	Z-8-Methyl-9-tetradecen	✓		odorless
	n-Decanoic acid	✓		odorless
	Naphthalene, 2-methoxy		✓	odorless
Back	(2-mercaptoethyl)guanidine	✓		odorless
	Undecanoic acid	✓		odorless
Chest	1, 2-pentanediol		✓	odorless

Note: Bold Italicize in the table are the chemicals found in both male and female samples.

Driving performance

This analysis aims to investigate the impact of varying CO_2 levels and body odor on drivers' speed control and lateral control. Several dependent variables, including the mean and standard deviation of speed, acceleration, lateral acceleration, lane deviation, steering, and yaw rate, were analyzed. A two-way ANOVA was conducted to assess the influence of CO_2 and body odor on these driving performance indices. Table 2 presents the means and standard deviations for these indices, while Table 3 displays the results of the two-way ANOVA examining the effects of CO_2 and body odor. In summary, our findings indicate that neither CO_2 levels nor body odor conditions significantly affected any of the analyzed driving performance indices.

The results indicate that the mean speeds were consistently maintained across different CO_2 conditions, with values of approximately 52.25 mph, 53.04 mph, and 52.77 mph, respectively. The standard deviation of speed exhibited uniformity across all conditions. Notably, the ANOVA showed no significant effects of CO_2 on either the mean ($F(2, 144) = 0.03$, $p > 0.05$, $\eta^2 = 0.25$) or standard deviation ($F(2, 144) = 0.41$, $p > 0.05$, $\eta^2 = 0.59$) of driving speed. Additionally, the presence of body odor did not result in any significant impact on either mean or standard deviation of driving speed. Mean speed were quite similar in environments both with and without body odor, with no significant differences observed ($F(1, 144) = 0.13$, $p > 0.05$, $\eta^2 = 0.51$). Similar patterns were observed for mean ($F(2, 144) = 0.53$, $p > 0.05$, $\eta^2 = 0.52$) and standard deviation ($F(2, 144) = 0.55$, $p > 0.05$, $\eta^2 = 0.82$) of acceleration remained stable across CO_2 levels. The ANOVA did not reveal any significant differences in these measures across difference CO_2 levels, and the presence of body odor also had no significant effect on the mean ($F(1, 144) = 0.53$, $p > 0.05$, $\eta^2 = 0.52$) or standard deviation ($F(1, 144) = 0.07$, $p > 0.05$, $\eta^2 = 0.82$) of acceleration. Furthermore, the two-way ANOVA results show there was no significant interaction between CO_2 and body odor on mean or standard deviation of speed or acceleration.

Lateral control refers to the driver's ability to steer the car in a lateral direction on the road. To evaluate lateral control performance, we used the mean and standard deviation of lateral acceleration, lane deviation, steering, and yaw rate. The average lane deviation shows a similar value, of 1.256 m, 1.217 m, and 1.184 m respectively in the low, medium, and high CO_2 level conditions. The ANOVA indicated no significant impact of CO_2 on the average ($F(2, 144) = 0.56$, $p > 0.05$, $\eta^2 = 0.27$) or standard deviation ($F(2, 144) = 0.20$, $p > 0.05$, $\eta^2 = 0.30$) of lane deviation. Moreover, the presence of body odor led to a slight increase in lane deviation average, from 1.172 m to 1.222 m. However, this change was not statistically significant, as indicated by the ANOVA ($F(1, 144) = 1.05$, $p > 0.05$, $\eta^2 = 0.25$). Participants had the largest lateral acceleration 0.152 m^2/s, when the CO_2 was at a high level. The ANOVA revealed that the average lateral acceleration remained consistent across the various CO_2 conditions, with no statistically significant differences observed ($F(2, 144) = 0.91$, $p > 0.05$, $\eta^2 = 0.75$). Furthermore, for other indices of later control, the ANOVA demonstrated no significant differences in the mean or standard deviation of steering and yaw rate across the different CO_2 levels or in the presences of the body odor. No interactions between CO2 and body odor on driving performance indices of lateral control were found.

Table 2. Descriptive Statistics for driving performance indices at different CO_2 levels and environments with or without body odor

Conditions	Parameters	M	SD	N
800 ppm CO_2	Speed (m/s)	24.671	5.439	50
	Acceleration (m^2/s)	0.063	0.727	50
	Lane deviation (m)	0.802	1.839	50

	Steering (degree)	-0.041	19.452	50
	Yaw rate (rad/s)	-0.0001	93.853	50
	Lateral acceleration (m^2/s)	-0.007	2.559	50
1800 ppm CO_2	Speed (m/s)	24.223	5.347	50
	Acceleration (m^2/s)	0.072	0.725	50
	Lane deviation (m)	0.774	1.847	50
	Steering (degree)	-0.062	17.886	50
	Yaw rate (rad/s)	-0.003	90.804	50
	Lateral acceleration (m^2/s)	-0.010	2.481	50
3500 ppm CO_2	Speed (m/s)	24.618	5.609	50
	Acceleration (m^2/s)	0.063	0.740	50
	Lane deviation (m)	0.587	1.836	50
	Steering (degree)	-0.049	18.235	50
	Yaw rate (rad/s)	-0.0003	94.807	50
	Lateral acceleration (m^2/s)	-0.008	2.548	50
With the body odor	Speed (m/s)	24.598	5.424	75
	Acceleration (m^2/s)	0.066	0.737	75
	Lane deviation (m)	0.739	1.814	75
	Steering (degree)	-0.072	18.669	75
	Yaw rate (rad/s)	-0.0004	86.729	75
	Lateral acceleration (m^2/s)	-0.011	2.547	75
Without the body odor	Speed (m/s)	24.410	5.506	75
	Acceleration (m^2/s)	0.066	0.725	75
	Lane deviation (m)	0.704	1.868	75
	Steering (degree)	-0.029	18.380	75
	Yaw rate (rad/s)	-0.0001	99.581	75
	Lateral acceleration (m^2/s)	-0.006	2.511	75
Total	Speed (m/s)	24.504	5.465	150
	Acceleration (m^2/s)	0.066	0.731	150
	Lane deviation (m)	0.721	1.841	150
	Steering (degree)	-0.051	18.524	150
	Yaw rate (rad/s)	-0.0003	93.155	150
	Lateral acceleration (m^2/s)	-0.009	2.529	150

Table 3. Two-way Analyses of Variance of driving performance indices at different CO_2 levels and environments with or without body odor

	Parameters	**Source**	**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**	**Partial Eta Squared**
Speed (m/s)	Mean	CO_2	121.480	2	60.740	0.031	0.969	0.247
		Body odor	248.327	1	248.327	0.127	0.722	0.506
		CO_2 * Body odor	121.333	2	60.667	0.031	0.969	0.247
	S.D.	CO_2	1578.520	2	789.26	0.406	0.667	0.591
		Body odor	0.167	1	0.167	0.001	0.993	0.001
		CO_2 * Body odor	1090.773	2	545.387	0.281	0.755	0.409
Acceleratio	Mean	CO_2	2061.280	2	1030.640	0.533	0.588	0.522
		Body odor	504.167	1	504.167	0.260	0.611	0.128

n (m^2/s)		CO_2 * Body odor	1384.413	2	692.207	0.357	0.700	0.350
	S.D.	CO_2	2144.160	2	1072.080	0.553	0.576	0.823
		Body odor	144.060	1	144.060	0.074	0.786	0.055
		CO_2 * Body odor	317.213	2	158.607	0.081	0.922	0.122
Lane deviation (m)	Mean	CO_2	2142.720	2	1071.360	0.564	0.570	0.268
		Body odor	1980.167	1	1980.167	1.054	0.306	0.247
		CO_2 * Body odor	3886.573	2	1943.287	1.035	0.358	0.485
	S.D.	CO_2	766.240	2	383.120	0.198	0.821	0.303
		Body odor	190.407	1	190.407	0.098	0.754	0.075
		CO_2 * Body odor	1573.32	2	786.660	0.406	0.667	0.622
Steering (degree)	Mean	CO_2	4876.360	2	2438.18	1.273	0.283	0.724
		Body odor	1072.007	1	1072.007	0.552	0.457	0.159
		CO_2 * Body odor	789.88	2	394.940	0.203	0.817	0.117
	S.D.	CO_2	1088.920	2	544.460	0.349	0.706	0.432
		Body odor	988.167	1	988.167	0.690	0.407	0.392
		CO_2 * Body odor	443.560	2	221.780	0.144	0.866	0.176
Yaw rate (rad/s)	Mean	CO_2	5075.68	2	2537.84	1.326	0.269	0.836
		Body odor	117.927	1	117.927	0.061	0.806	0.020
		CO_2 * Body odor	879.613	2	439.807	0.226	0.798	0.145
	S.D.	CO_2	2708.040	2	1354.020	0.708	0.494	0.852
		Body odor	144.060	1	144.060	0.074	0.786	0.045
		CO_2 * Body odor	324.520	2	162.260	0.084	0.920	0.102
Lateral acceleration (m^2/s)	Mean	CO_2	3485.080	2	1742.540	0.909	0.405	0.752
		Body odor	636.540	1	636.540	0.329	0.567	0.137
		CO_2 * Body odor	513.760	2	256.880	0.132	0.877	0.111
	S.D.	CO_2	601.000	2	300.500	0.154	0.857	0.717
		Body odor	172.807	1	172.807	0.089	0.766	0.206
		CO_2 * Body odor	64.653	2	32.327	0.017	0.983	0.077

Note: * denotes p value less than 0.05, ** denotes p value less than 0.01

	Parameters	Source	Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Speed (m/s)	Mean	CO_2	121.480	2	60.740	0.031	0.969	0.247
		Body odor	248.327	1	248.327	0.127	0.722	0.506
		CO_2 * Body odor	121.333	2	60.667	0.031	0.969	0.247
	S.D.	CO_2	1578.520	2	789.26	0.406	0.667	0.591
		Body odor	0.167	1	0.167	0.001	0.993	0.001
		CO_2 * Body odor	1090.773	2	545.387	0.281	0.755	0.409
Acceleration (m^2/s)	Mean	CO_2	2061.280	2	1030.640	0.533	0.588	0.522
		Body odor	504.167	1	504.167	0.260	0.611	0.128
		CO_2 * Body odor	1384.413	2	692.207	0.357	0.700	0.350
	S.D.	CO_2	2144.160	2	1072.080	0.553	0.576	0.823
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		CO_2 * Body odor	1573.32	2	786.660	0.406	0.667	0.622
Lateral acceleration (m^2/s)	Mean	CO_2	3485.080	2	1742.540	0.909	0.405	0.752
		Body odor	636.540	1	636.540	0.329	0.567	0.137
		CO_2 * Body odor	513.760	2	256.880	0.132	0.877	0.111
	S.D.	CO_2	601.000	2	300.500	0.154	0.857	0.717
		Body odor	172.807	1	172.807	0.089	0.766	0.206
		CO_2 * Body odor	64.653	2	32.327	0.017	0.983	0.077

N-back task performance

Table 4 and 5 display the results of the two-way ANOVA, utilized to explore the influences of CO_2 levels (800 ppm, 1800 ppm, and 3500 ppm) and the presence of body odor on response accuracy and reaction time in N-back tasks. The means and standard deviations for reaction time and response accuracy are presented in Table 4 below. Response accuracy ranged from 90.67% to 93.45% and exhibited no significant variation across CO_2 levels ($F(2, 144) = 1.29$, $p > 0.05$, $\eta^2 = 0.16$). Additionally, different CO_2 levels did not significantly affect drivers' reaction times in N-back tasks ($F(2, 144) = 2.88$, $p > 0.05$, $\eta^2 = 0.82$), with reaction times ranging from 0.58 to 0.59 seconds. Body odor did not have a significant effect on drivers' reaction time in N-back tasks ($F(1, 144) = 0.80$, $p > 0.05$, $\eta^2 = 0.11$). Reaction time remained consistent in the presence or absence of body odor. However, the presence of body odor significantly influenced response accuracy ($F(1, 144) = 9.21^{**}$, $p < 0.01$, $\eta^2 = 0.55$), as response accuracy of subjects decreased from 93.17% to 91.102%. Additionally, the two-way ANOVA results show there was no significant interaction between CO_2 and body odor on reaction time ($F(2, 144) = 2.43$, $p > 0.05$, $\eta^2 = 0.29$) or response accuracy ($F(2, 144) = 0.23$, $p > 0.05$, $\eta^2 = 0.07$).

Table 4. Descriptive Statistics for response accuracy and reaction time of N-back task at different CO_2 levels and environments with or without body odor

Conditions	Parameters	M	SD	N
800 ppm CO_2	Response accuracy (%)	93.451	9.989	50
	Reaction time (s)	0.591	0.137	50
1800 ppm CO_2	Response accuracy (%)	92.294	11.003	50
	Reaction time (s)	0.598	0.123	50
3500 ppm CO_2	Response accuracy (%)	90.667	12.231	50
	Reaction time (s)	0.596	0.122	50
With the body odor	Response accuracy (%)	93.137	10.463	75
	Reaction time (s)	0.592	0.126	75
Without the body odor	Response accuracy (%)	91.137	11.740	75
	Reaction time (s)	0.597	0.128	75
Total	Response accuracy (%)	92.137	11.159	150
	Reaction time (s)	0.594	0.127	150

Table 5. Two-way Analyses of Variance of response accuracy and reaction time of N-back tasks at different CO_2 levels and environments with or without body odor

Parameters	Source	Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Response accuracy (%)	CO_2	162608.1	2	81304.05	1.292	0.275	0.156
	Body odor	574058.8	1	574058.8	9.210	0.002**	0.552
	CO_2 * Body odor	303702.4	2	151851.2	2.427	0.089	0.292
Reaction time (s)	CO_2	388713	2	194356.5	2.880	0.057	0.818
	Body odor	54568.96	1	54568.96	0.804	0.370	0.115
	CO_2 * Body odor	31745.6	2	15872.8	0.234	0.792	0.067

Note: * denotes p value less than 0.05, ** denotes p value less than 0.01

Task Load Index

Table S2 and S3 present the results of the NASA-TLX subjective task load ratings across different CO_2 levels and the environments with or without body odor for six subscales. The two-way ANOVA results revealed that CO_2 levels or the presence of body odor had no significant impact on all subscales. For the mental demand subscale, participants rated their task load at an average of 3.50 for the low CO_2 condition, 3.68 for the medium CO_2 condition, and 3.46 for the high CO_2 condition. Different CO_2 levels did not significantly affect drivers' mental demand ($F(2, 144) = 0.62$, $p > 0.05$, $\eta^2 = 0.28$). The presence of body odor also did not lead to a significant difference in mental demand ratings ($F(1, 144) = 0.67$, $p > 0.05$, $\eta^2 = 0.59$), with average scores of 3.59 and 3.51 for conditions with and without body odor, respectively. Temporal demand ratings were highest (M = 2.72) and own performance ratings were lowest (M = 2.64) in the medium CO_2 condition. In the presence of body odor, temporal demand decreased (M = 2.44), and own performance ratings increased (M = 2.747). Additionally, participants reported increased frustration with higher CO_2 levels or the presence of body odor.

Overall, the study suggests that CO_2 levels and body odor have a limited impact on task load as assessed through the NASA-TLX subscales, with some variations in perceived effort and mental demand at different CO_2 levels.

Perceived air quality and air quality acceptance

Table S4 and S5 display the results of the two-way ANOVA, utilized to explore the influences of CO_2 levels (800 ppm, 1800 ppm, and 3500 ppm) and the presence of body odor on perceived air quality and air quality acceptance. The analysis revealed that drivers rated the air quality as low (M = 1.2) in the environment with a medium CO_2 level, and high (M = 1.84) when exposed to high levels of CO_2. However, there was no statistically significant difference in perceived air quality between the different CO_2 level conditions ($F(2, 144) = 0.66$, $p > 0.05$, $\eta^2 = 0.36$). Interestingly, when it comes to air quality acceptance, participants rated significantly higher acceptance of air quality in high CO_2 environments. Nevertheless, there was no significant difference in subjects' acceptance of air quality between the environments of different CO_2 levels ($F(2, 144) = 0.28$, $p > 0.05$, $\eta^2 = 0.08$). We also sought to understand how the presence of body odor influenced participants' perceptions. The results showed that the presence of body odor did not significantly affect participants' perception of air quality ($F(1, 144) = 0.52$, $p > 0.05$, $\eta^2 = 0.15$) or their air quality acceptance ($F(1, 144) = 2.15$, $p > 0.05$, $\eta^2 = 0.32$). Participants' ratings for perceived air quality and air quality acceptance were similar, whether body odor was present or absent. Additionally, there was no significant interaction between CO_2 levels and the presence of body odor on perceived air quality ($F(2, 144) = 0.91$, $p > 0.05$, $\eta^2 = 0.50$) or air quality acceptance ($F(2, 144) = 2.06$, $p > 0.05$, $\eta^2 = 0.60$).

These findings suggest that CO_2 levels played a more prominent role in influencing participants' perceptions of air quality, with higher CO_2 levels corresponding to higher perceived air quality acceptance. However, the presence of body odor did not significantly impact these perceptions.

Sleepiness and emotion

Table S6 and S7 present the results for changes in participants' sleepiness levels before and after driving across different CO_2 levels and the environments with or without body odor, as well as their emotional responses (valence, arousal, and dominance). A two-way ANOVA was conducted to assess the impact of CO_2 levels on sleepiness and emotions. Although the analysis did not reveal significant effects of CO_2 or body odor on participants' sleepiness differences before and after driving ($F(2, 144) = 0.78$, $p > 0.05$, $\eta^2 = 0.75$), it is noteworthy that the sleepiness difference appeared to increase with rising CO_2 concentrations, hinting at a potential adverse influence of higher CO_2 levels on sleepiness. The results indicated that the presence or absence of body odor did not significantly affect participants' sleepiness differences before and after driving ($F(1, 144) = 0.17$, $p > 0.05$, $\eta^2 = 0.09$). There was no significant interaction between CO_2 levels and the presence of body odor on sleepiness ($F(2, 144) = 0.17$, $p > 0.05$, $\eta^2 = 0.16$). Regarding emotional responses, participants consistently rated similar levels of positive valence, negative arousal, and positive dominance, regardless of the CO_2 levels. The analysis showed no significant impact of CO_2 on drivers' emotions. However, the presence of body odor did lead to significant higher negative arousal ratings ($F(1, 144) = 4.70$ $p = 0.032$, $\eta^2 = 0.96$), suggesting that participants experienced high levels of valence in the absence of body odor. Arousal level and dominance ratings were not significantly affected by the presence of body odor. Additionally, no interaction between CO_2 levels and the presence of body odor was found on the emotion.

In summary, these findings suggest that CO_2 levels may have a subtle but insignificant impact on sleepiness levels during driving, while body odor appears to have a modest influence on emotions, particularly negative arousal. Participants consistently rated similar levels of valence and dominance regardless of the experimental conditions.

Discussion

Moderating effects of N-back task difficulty on cognition and driving performance

This section presents a moderator analysis to investigate whether N-back task difficulty alters the relationship between CO_2 (or body odor) and cognition. Fig. 5 displays boxplots of response accuracy and reaction time for the 0-back, 1-back, and 2-back tasks under different CO_2 or body odor conditions. The results show that CO_2 had a significant impact on response accuracy only for 1-back or 0-back tasks. When the task (e.g., 2-back) was hard, CO_2 did not exert any impact on response accuracy or reaction time. The finding suggests moderating effects of task difficulties in the relationship between CO_2 exposure and cognition. Moreover, response accuracy was significantly different between the conditions with and without body odor, only for difficult tasks such as 2-back task. Table S8 and S9 describe the results of pairwise comparison at different N-back task difficulties in detail. Additionally, Table S10 and S11 describe the statistical analysis of the differences in driving performance while taking N-back tasks at various CO_2 or body odor levels. Nevertheless, no significant difference in pairwise comparisons was found for any driving performance variable. The only exception is mean lateral acceleration between the conditions with and without body odor while participants were taking 1 back tasks.

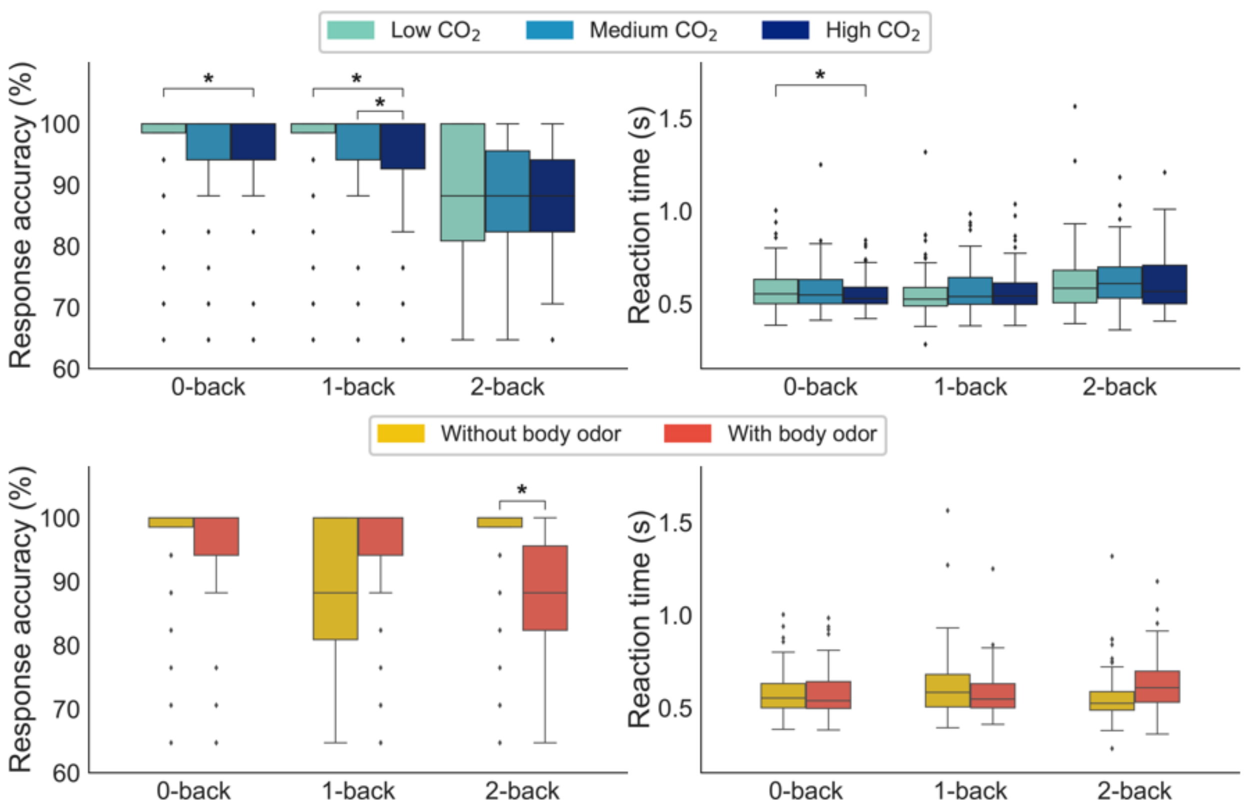


Fig. 5. Response accuracy and reaction time of various N-back tasks with different CO_2 levels and body odor conditions

Moderating effect of exposure time on driving performance

To account for the variability in the exposure duration to CO_2 and body odor on driving performance, we analyzed two different snippets of driving performance data with the same time window size of 3 min, one from 10 to 12 min and the other from 16 to 18 min. Since the sampling frequency was 10 Hz, a data size of even 3 min should still be sufficient for statistical analysis. Our hypothesis is that CO_2 or body odor could exert varying impact for long exposure time, such as 16 min as opposed to 10 min for discussion.

Fig. 6 illustrate that significant differences in driving performance, such as mean speed and acceleration, occurred during specific time windows. Specifically, there was a significant difference in mean speed between 800 ppm and 3500 ppm CO_2 from 16 to 18 min, but not in the time window between 10 and 12 min. A similar finding can be observed in Figure 9 for mean yaw rate, which was significantly different between the conditions with and without body odor in the time window of 16-18 min. As discussed in Table 2 and 3 that either CO_2 or body odor showed significant impact on driving throughout the entire driving session, the results in Fig. 6 suggest that CO_2 or body odor may have a significant impact in specific time windows, indicating the moderating effect of exposure duration. For instance, Table S6 of Appendix shows that the standard deviation values of driving speed were significantly different between 800 ppm and 1800 ppm when body odor was absent within the time window of 16 to 18 min.

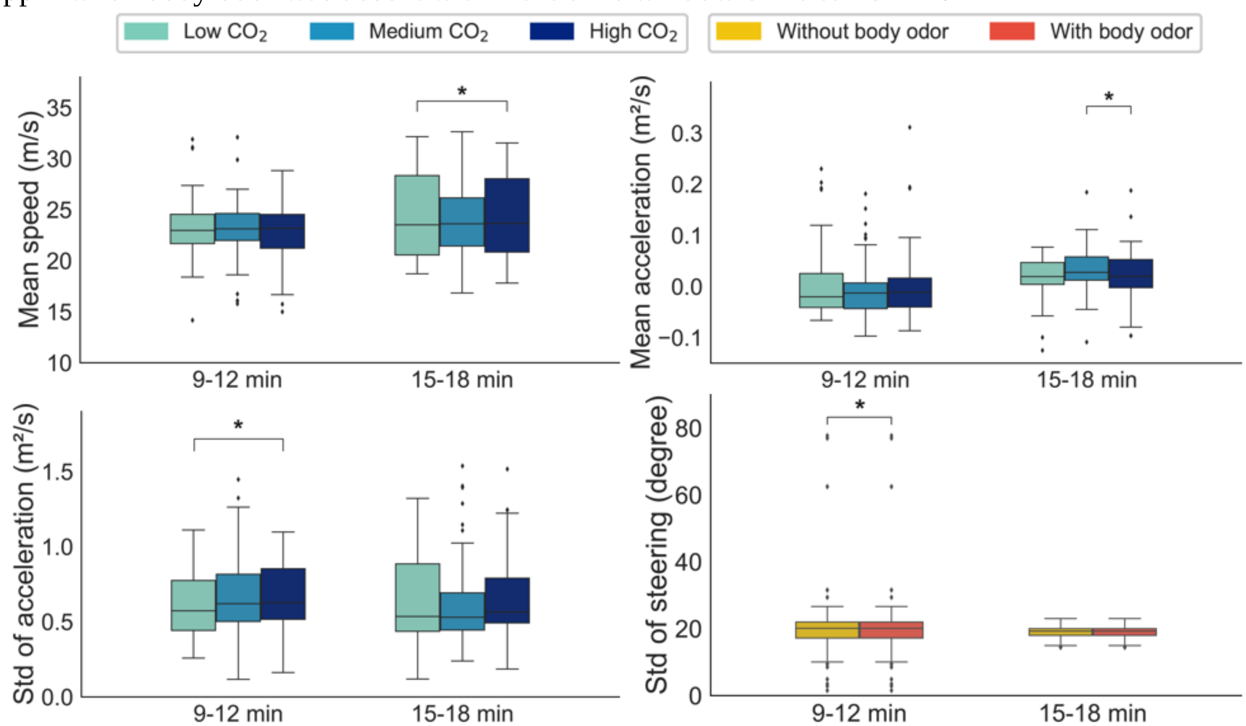


Fig. 6. Moderating effects of exposure duration on the relationship between CO_2 or body odor exposure and driving performance

Limitation and recommendations

In this study, we utilized six recorded variables by the driving simulator to assess driving performance. The results indicated that elevated CO_2 levels or the presence of body odor had mixed effects on driving performance. The mixed results could be attributed to sample size, the complexity of the driving environment, magnitude of CO_2 or body odor exposure and exposure duration, experimental setup using a simulator as well as the statistical analysis approach.

The sample size was estimated based on a relatively large effect size of 0.25. Further research would be conducted to augment the sample size to increase statistical power. In addition, the sample population in this study consisted solely of young and inexperienced individuals operating the simulators, which may have limited the variability in driving performance. Future studies could expand the population and consider age differentiation to better understand the impact of CO_2 and body odor on driving performance across a broader demographic.

We focused on the impact of CO_2 and body odor, but other variables, such as the Air Exchange Rate (AER) and chemicals from interior materials, may also influence driving performance. In addition, body odor comprises a vast spectrum of chemicals that could adversely influence driving. These additional elements could interact with the factors studied here, potentially contributing to overall driving experience and performance. Investigating the combined effects of CO_2, body odor, AER, and other chemicals represents an intricate endeavor that may warrant further dedicated investigations.

The highest CO_2 concentration examined in this study was 3500 ppm, which may not be sufficient to produce a perceptible impact on driving performance, particularly with respect to short exposure durations. Previous studies (Antonson et al., 2009; Law et al., 2010; Thiffault & Bergeron, 2003; Ting et al., 2008) reported the impact of driving time on driving performance, which suggests further studies on the influence of CO_2 and body odor exposure duration on driving performance. Future studies could explore longer exposure times and/or higher CO_2 concentrations to better assess their impact on driving performance. In situations involving prolonged driving periods, it is possible that the observed effects, though initially noticeable over shorter durations, may magnify or manifest differently as a result of extended exposure. However, it is important to note that the CO_2 levels we used in this study are relevant to real world settings.

This study utilized a simulated driving task on a simulator, which may not accurately represent real-world driving situations and may limit the ecological validity of the findings. The driving scenario on a freeway in this study was relatively easy, which may not effectively differentiate driving performance among drivers with varying levels of driving skill. Future researchers could consider using more complex but still realistic driving scenarios to assess the impact of CO2 and body odor more accurately on driving performance.

In this study, participants completed the surveys on sleepiness, emotion, perceived air quality and air quality acceptance, and task workload outside of the vehicle cabin immediately after the driving task, while the experimenter was preparing for the next experimental condition. Although we do not have strong reasons to believe their responses changed in such a short period, it is possible that their responses given outside of the cabin may not be fully representative of the in-car experience. Therefore, potential uncertainty might be introduced accordingly. Further studies might be needed to verify the potential bias and uncertainty caused by the protocol. Furthermore, it is noteworthy that the study did not regulate the exposure level of body odor, nor did it quantify the specific compounds of body odor in the air. Future studies could adopt a more precise approach to maintain the gaseous phase of body odor in the car cabin, allowing for a more comprehensive understanding of the impact of body odor on driving performance.

Summary

The presented study investigates the effects of CO_2 and body odor on drivers' driving performance and cognition using a high-fidelity driving simulator. The findings indicate that the effects of exposure to CO_2 levels of up to 3500 ppm and body odor vary to a large extent. The following particular findings can be summarized from this study:

- During the 18 min driving, CO_2 levels up to 3500 ppm and body odor from T-shirts did not show significant effects on driving speed, acceleration, or lateral control. However, analyzing specific time windows revealed significant differences in driving performance. For example, average values of driving speed were significantly different between 800 ppm and 3500 ppm during the time window of 16 to 18 min. The results imply potential moderating effects of exposure duration.

- Our analysis identified 26 chemicals in the fabric of female odor donors' clothing and 19 chemicals in male odor donors'.
- Participants reported significantly higher effort in the NASA-TXL test at 1800 ppm compared to 800 ppm. They were required to exert more effort while driving in an environment with higher CO_2 levels. Elevated CO_2 levels heightened the subjects' effort to complete the driving task.
- Accuracy in N-back tasks was significantly higher at 800 ppm compared to 3500 ppm, and the presence of additional body odor from worn T-shirts significantly increased accuracy. Cognitive task performance was influenced by varying CO2 levels and the presence of body odor.
- Interactive effects of CO_2 and body odor were not observed on driving performance and cognition.
- Both the difficulty of N-back tasks and exposure duration had moderating effects. The effects of CO_2 or body odor were significant only for certain N-back tasks or during a specific exposure duration.

Acknowledgements

We thank the participants for their participation in the experiment, and the research technician (Russell Lang) for their assistance. The research is supported by Worcester Polytechnic Institute.

Appendix

Dependent variables

Table S11. Summary of the tasks and surveys

Task/Survey	Major parameters	Purposes	Administration
Driving task	Forward velocity Acceleration Lateral velocity Lateral acceleration Lane deviation Steering Yaw rate	Evaluate the driving performance to observe compensatory behaviors under different environments	During driving
Secondary task (N-back task)	2-back 1-back 0-back	Simulate the non-driving behavior during the driving Measure drivers' working memory and attention	During driving
Emotion (Self-assessment manikin (SAM))	Valance Arousal Dominance	Measure the effect of environmental change on drivers' emotions, including valence, arousal, and dominance	After driving
Sleepiness	Stanford Sleepiness Scale	Measure the effect of cabin environmental change on drivers' sleepiness	After driving
In-car environment satisfaction	Air quality Acceptance of the air quality Thermal comfort Thermal sensation Thermal acceptance	Measure the change of drivers' satisfaction with different cabin environments	After driving
NASA-TLX workload	Mental demand Physical demand Temporal demand Own performance Effort Frustration	Evaluate and quantify the perceived workload of an individual or a team performing a specific task	After driving

G power software

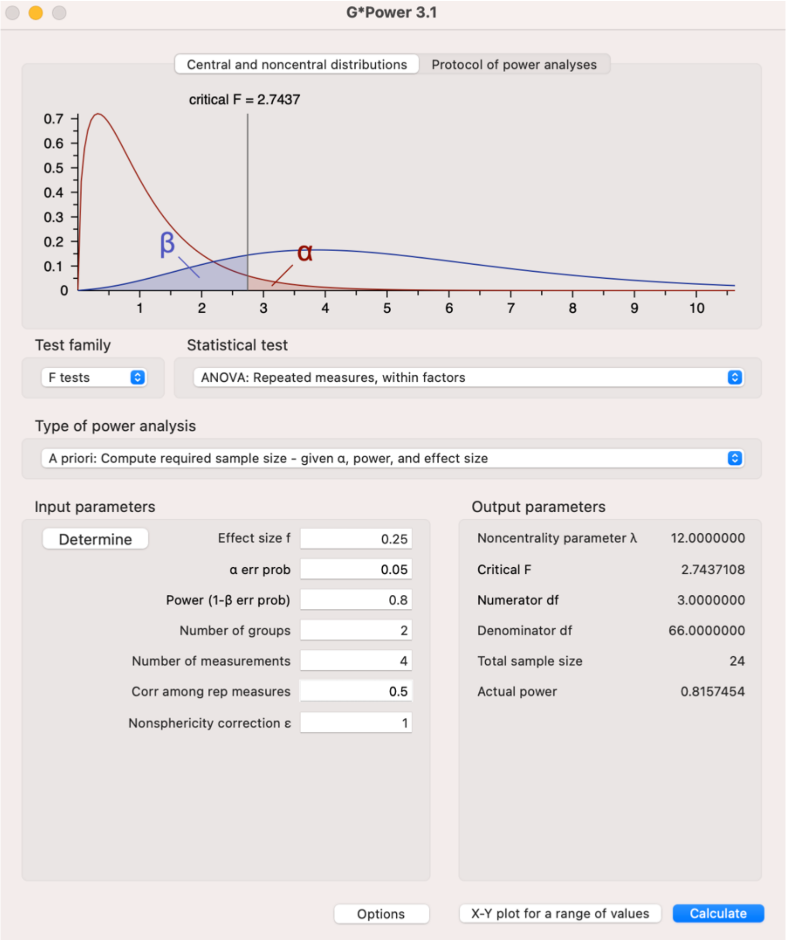


Fig. S1. Settings for power analysis in G*power

Questionnaire used in the study

a. Sleepiness

(Finish the question 1~2 before the experiment)

Q1: Sleeping quality before the experiment (very poor to excellent)

1 2 3 4 5 6 7 8 9 10

Q2: Rate the degree of sleepiness before the driving task (awake to asleep)

1 2 3 4 5 6 7

(Finish the remaining questions after the experiment)

Q3: Rate the degree of sleepiness after the driving task (awake to asleep)

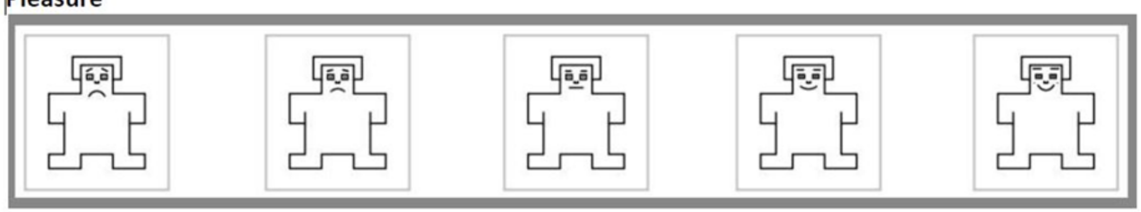
1 2 3 4 5 6 7

b. Emotion

Q4: Rate the valence (how negative or positive the emotion is) after the experiment (negative to positive)

-2 1 0 1 2

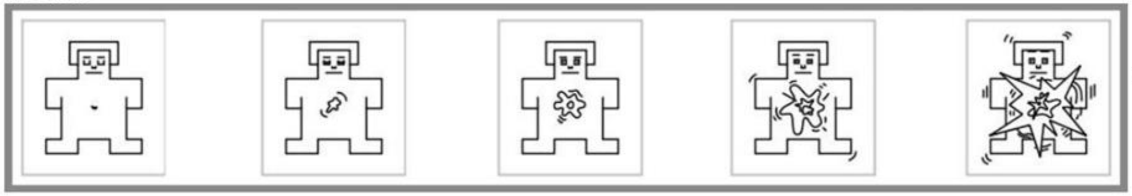
Pleasure



Q5: Rate the arousal (how excited or uninterested the emotion is) after the experiment (low to in high)

-2 1 0 1 2

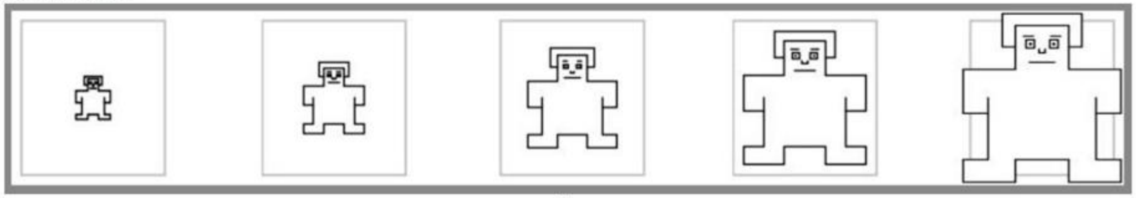
Arousal



Q6: Rate the feeling of dominance (the extent to which you feel you are in control of the situation) after the experiment (low to in high)

-2 1 0 1 2

Dominance



c. Physical symptoms

Q7: Rate the general comfort after the experiment (slight to severe)

1 2 3 4 5 6 7 8 9 10

Q8: Rate the feeling of nausea after the experiment (none to severe)

1 2 3 4 5 6 7 8 9 10

Q9: Rate the headache after the experiment (none to severe)

1 2 3 4 5 6 7 8 9 10

Q10: Do you have blurred vision (none to severe)

1 2 3 4 5 6 7 8 9 10

Q11: Are you sweating (slight to severe)

1 2 3 4 5 6 7 8 9 10

Q12: Do you feel faint (none to severe)

1 2 3 4 5 6 7 8 9 10

d. Perceived air quality and air quality acceptance

Q13: Rate your feeling of the air quality (worse to better)

-3 -2 -1 0 1 2 3

Q14: Rate your acceptance of the air quality (unacceptable to acceptable)

-3 -2 -1 0 1 2 3

e. Cognitive load

Q15: How mentally demanding was the task? (low to high)

1 2 3 4 5 6 7

Q16: How physically demanding was the task? (low to high)

1 2 3 4 5 6 7

Q17: How hurried or rushed was the pace of the task? (low to high)

1 2 3 4 5 6 7

Q18: How successful were you in accomplishing what you were asked to do? (perfect to failure)

1 2 3 4 5 6 7

Q19: How hard did you have to work to accomplish your level of performance? (low to high)

1 2 3 4 5 6 7

Q20: How insecure, discouraged, irritated, stressed, and annoyed were you? (low to high)

1 2 3 4 5 6 7

CO_2 concentration

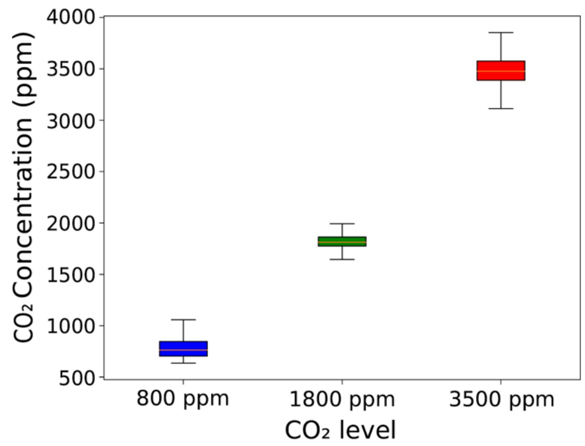


Fig. S2. CO_2 concentration (ppm) in the car cabin at three levels

Effect of CO_2 and body odor on the items in the survey

Table S2. Descriptive Statistics for task load index at different CO_2 levels and environments with or without body odor

Conditions	NASA-TXL task load (scale from 1 to 7)	M	SD	N
800 ppm CO_2	Mental demand	3.500	1.418	50
	Physical demand	1.900	0.839	50
	Temporal demand	2.380	1.308	50
	Own performance	2.840	1.235	50
	Effort	2.920	1.209	50
	Frustration	2.440	1.567	50
1800 ppm CO_2	Mental demand	3.680	1.421	50
	Physical demand	2.280	1.107	50
	Temporal demand	2.720	1.294	50
	Own performance	2.640	1.290	50
	Effort	3.300	1.216	50
	Frustration	2.680	1.491	50
3500 ppm CO_2	Mental demand	3.460	1.249	50
	Physical demand	2.000	0.881	50
	Temporal demand	2.360	1.045	50
	Own performance	2.780	1.036	50
	Effort	3.160	1.251	50
	Frustration	2.840	1.543	50
With the body odor	Mental demand	3.507	1.349	75
	Physical demand	2.080	1.010	75
	Temporal demand	2.533	1.288	75
	Own performance	2.760	1.228	75
	Effort	3.173	1.256	75
	Frustration	2.760	1.523	75
Without the body odor	Mental demand	3.587	1.376	75
	Physical demand	2.040	0.907	75
	Temporal demand	2.440	1.165	75
	Own performance	2.747	1.152	75
	Effort	3.080	1.205	75
	Frustration	2.547	1.545	75
Total	Mental demand	3.547	1.359	150
	Physical demand	2.060	0.957	150

	Temporal demand	2.487	1.225	150
	Own performance	2.753	1.187	150
	Effort	3.127	1.228	150
	Frustration	2.653	1.533	150

Table S3. Two-way Analyses of Variance of task load index at different CO_2 levels and environments with or without body odor

Parameters	Source	Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Mental demand	CO_2	2353.410	2	1176.705	0.622	0.539	0.276
	Body odor	5034.407	1	5034.407	0.670	0.104	0.591
	CO_2 * Body odor	1128.503	2	564.252	0.295	0.745	0.133
Physical demand	CO_2	3162.360	2	1581.180	0.852	0.429	0.271
	Body odor	5174.407	1	5174.407	2.787	0.097	0.444
	CO_2 * Body odor	3317.293	2	1658.647	0.904	0.407	0.285
Temporal demand	CO_2	339.040	2	169.520	0.088	0.915	0.074
	Body odor	110.940	1	110.940	0.058	0.811	0.024
	CO_2 * Body odor	4108.440	2	2054.220	1.118	0.330	0.901
Own performance	CO_2	1113.210	2	556.605	0.324	0.724	0.616
	Body odor	26.460	1	26.460	0.015	0.904	0.015
	CO_2 * Body odor	668.173	2	334.087	0.190	0.827	0.370
Effort	CO_2	1496.920	2	748.460	0.389	0.678	0.165
	Body odor	695.527	1	695.527	0.361	0.549	0.077
	CO_2 * Body odor	6855.893	2	3427.947	1.856	0.160	0.758
Frustration	CO_2	598.12	2	299.060	0.156	0.855	0.431
	Body odor	5.607	1	5.607	0.003	0.957	0.004
	CO_2 * Body odor	784.013	2	392.007	0.207	0.813	0.565

Note: * denotes p value less than 0.05, ** denotes p value less than 0.01

Table S4. Descriptive Statistics for perceived air quality and air quality acceptance at different CO_2 levels and environments with or without body odor

Conditions	Item (scale from 1 to 7)	M	SD	N
800 ppm CO_2	Perceived air quality	0.540	1.373	50
	Air quality acceptance	1.660	1.533	50

1800 ppm CO_2	Perceived air quality	0.120	1.507	50
	Air quality acceptance	1.200	1.702	50
3500 ppm CO_2	Perceived air quality	0.600	1.178	50
	Air quality acceptance	1.840	1.267	50
With the body odor	Perceived air quality	0.453	1.388	75
	Air quality acceptance	1.613	1.432	75
Without the body odor	Perceived air quality	0.387	1.355	75
	Air quality acceptance	1.520	1.622	75
Total	Perceived air quality	0.420	1.367	150
	Air quality acceptance	1.567	1.526	150

Table S5. Two-way Analyses of Variance of perceived air quality and air quality acceptance at different CO_2 levels and environments with or without body odor

Item	Source	Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Perceived air quality	CO_2	2512.210	2	1256.105	0.659	0.519	0.360
	Body odor	1008.807	1	1008.807	0.522	0.471	0.145
	CO_2 * Body odor	3452.040	2	1726.020	0.911	0.404	0.495
Air quality acceptance	CO_2	1061.320	2	530.660	0.277	0.759	0.083
	Body odor	4087.260	1	4087.260	2.151	0.145	0.321
	CO_2 * Body odor	7600.253	2	3800.127	2.064	0.131	0.596

Note: * denotes p value less than 0.05, ** denotes p value less than 0.01

Table S6. Descriptive Statistics for sleepiness and emotion at different CO_2 levels and environments with or without body odor

Conditions	M	SD	N
Difference in Sleepiness (pre and post driving) (scale from 1 to 7)			
800 ppm CO_2	2.920	1.441	50
1800 ppm CO_2	3.240	1.572	50
3500 ppm CO_2	3.140	1.629	50
With the body odor	3.093	1.604	75
Without the body odor	3.107	1.494	75
Total	3.100	1.545	150
Emotion (scale from -2 to 2)			

800 ppm CO_2	Valence	3.180	0.800	50
	Arousal	2.740	0.876	50
	Dominance	3.480	0.789	50
1800 ppm CO_2	Valence	3.200	0.728	50
	Arousal	2.560	0.812	50
	Dominance	3.460	0.676	50
3500 ppm CO_2	Valence	3.320	0.653	50
	Arousal	2.660	0.961	50
	Dominance	3.500	0.789	50
With the body odor	Valence	3.280	0.727	75
	Arousal	2.653	0.892	75
	Dominance	3.573	0.738	75
Without the body odor	Valence	3.187	0.730	75
	Arousal	2.653	0.878	75
	Dominance	3.387	0.751	75
Total	Valence	3.233	0.727	150
	Arousal	2.653	0.882	150
	Dominance	3.480	0.748	150

Table S7. Two-way Analyses of Variance of sleepiness and emotion at different CO_2 levels and environments with or without body odor

Parameters	Source	Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Difference in Sleepiness (pre and post driving) (scale from 1 to 7)							
Sleepiness	CO_2	2941.480	2	1470.740	0.775	0.463	0.750
	Body odor	331.527	1	331.527	0.172	0.679	0.0855
	CO_2 * Body odor	648.093	2	324.047	0.167	0.846	0.165
Emotion							
Valence	CO_2	139.080	2	69.540	0.039	0.962	0.018
	Body odor	7533.127	1	7533.127	4.699	0.032*	0.963
	CO_2 * Body odor	148.893	2	74.447	0.042	0.959	0.019
Arousal	CO_2	271.720	2	135.860	0.073	0.929	0.023
	Body odor	11633.610	1	11633.610	6.777	0.067	0.969

	CO_2 * Body odor	104.173	2	52.087	0.028	0.972	0.009
Dominance	CO_2	1126.210	2	563.105	0.327	0.721	0.567
	Body odor	41.607	1	41.607	0.023	0.878	0.021
	CO_2 * Body odor	819.893	2	409.947	0.232	0.793	0.412

Note: * denotes p value less than 0.05, ** denotes p value less than 0.01

Moderating effects of task difficulties

Table S8. Statistical results (mean, 95% CI, and Significance level) of response accuracy and reaction time of N-back task at different CO_2 levels considering the moderating effects of task difficulty

	N-back task	**800 ppm CO_2 (95% CIs)**	**1800 ppm CO_2 (95% CIs)**	**3500 ppm CO_2 (95% CIs)**	***p*-value (800 ppm vs. 1800 ppm)**	***p*-value (800 ppm vs. 3500 ppm)**	***p*-value (1800 ppm vs. 3500 ppm)**
Response accuracy	*2-back*	88.235 (86.059, 90.176)	88.235 (85.271, 89.317)	88.235 (84.082. 88.271)	0.516	0.165	0.453
	1-back	100 (94.084, 97.681)	100 (92.932, 97.068)	100 (89.923, 94.783)	0.597	0.022*	0.044*
	0-back	100 (94.712, 97.993)	100 (92.459, 96.717)	100 (90.966, 95.975)	0.216	0.049*	0.469
Reaction time	*2-back*	0.583 (0.586, 0.652)	0.609 (0.602, 0.654)	0.567 (0.585, 0.647)	0.091	0.992	0.246
	1-back	0.525 (0.533, 0.582)	0.539 (0.546, 0.594)	0.542 (0.547, 0.593)	0.312	0.196	0.758
	0-back	0.553 (0.556, 0.600)	0.547 (0.546, 0.592)	0.526 (0.538, 0.575)	0.633	0.031*	0.41

Note: Numbers in the table represent mean (95% CI) or significance level. * denotes p value less than 0.05, ** denotes p value less than 0.01

Table S9. Comparison of response accuracy and reaction time of N-back tasks between the conditions with and without body odor considering the moderating effects of task difficulty

	N-back task	**With the body odor (95% CIs)**	**Without the body odor (95% CIs)**	***p*-value (With vs. without body odor)**

Response accuracy	*2-back*	88.235 (86.945, 90.231)	88.235 (84.125, 87.483)	0.021*
	1-back	0.586 (0.602, 0.650)	0.582 (0.591, 0.641)	0.263
	0-back	100 (93.375, 96.664)	100 (91.991, 95.617)	0.242
Reaction time	*2-back*	0.539 (0.547, 0.584)	0.528 (0.545, 0.587)	0.815
	1-back	100 (94.267, 97.341)	100 (91.910, 95.698)	0.159
	0-back	0.540 (0.548, 0.585)	0.545 (0.553, 0.585)	0.269

Note: Numbers in the table represent mean (95% CI) or significance level. * denotes p value less than 0.05, ** denotes p value less than 0.01

Table S10. Statistical results (mean, 95% CI, and Significance level) of driving performance during N-back tasks at different CO_2 levels considering the moderating effects of task difficulty

		N-back task	**800 ppm CO_2 (95% CIs)**	**1800 ppm CO_2 (95% CIs)**	**3500 ppm CO_2 (95% CIs)**	***p*-value (800 ppm vs. 1800 ppm CO_2)**	***p*-value (800 ppm vs. 3500 ppm CO_2)**	***p*-value (1800 ppm vs. 3500 ppm CO_2)**
Speed (m/s)	Mean	*2-back*	20.195 (21.221, 23.440)	21.061 (21.391, 23.569)	20.968 (21.398, 23.427)	0.877	0.847	0.912
		1-back	21.910 (21.557, 23.928)	23.182 (22.470, 24.500)	20.968 (21.398, 23.427)	0.332	0.324	0.056
		0-back	21.012 (20.715, 23.092)	21.668 (21.113, 23.368)	21.636 (21.542, 23.681)	0.522	0.226	0.511
	S.D.	*2-back*	2.235 (2.327, 3.403)	2.118 (2.132, 2.894)	2.136 (2.351, 3.311)	0.778	0.405	0.421
		1-back	1.909 (2.264, 3.370)	1.975 (2.112, 3.007)	2.478 (2.617, 3.546)	0.975	0.075	0.061
		0-back	2.140 (2.322, 3.320)	2.146 (2.276, 3.095)	2.271 (2.360, 3.169)	0.910	0.997	0.869
Acceleration (m^2/s)	Mean	*2-back*	-0.006 (-0.060, 0.020)	0.014 (-0.004, 0.058)	-0.005 (-0.049, 0.031)	0.091	0.630	0.107
		1-back	-0.002 (-0.021, 0.060)	0.019 (-0.011, 0.056)	-0.035 (-0.090, -0.018)	0.366	0.075	0.103
		0-back	0.010 (-0.020, 0.045)	-0.011 (-0.029, 0.048)	0.018 (-0.020, 0.052)	0.899	0.762	0.557
	S.D.	*2-back*	0.503 (0.493, 0.658)	0.504 (0.469, 0.646)	0.511 (0.526, 0.700)	0.360	0.667	0.398
		1-back	0.462 (0.476, 0.647)	0.463 (0.486, 0.675)	0.589 (0.594, 0.767)	0.645	0.113	0.127
		0-back	0.534 (0.496, 0.656)	0.506 (0.508, 0.660)	0.550 (0.510, 0.646)	0.741	0.948	0.866
	Mean	*2-back*	0.156 (0.607, 1.271)	0.239 (0.833, 1.531)	0.164 (0.619, 1.268)	0.543	0.931	0.566

Lane deviation (m)		*1-back*	0.729 (1.016, 1.707)	0.469 (0.866, 1.533)	0.109 (0.584, 1.226)	0.384	0.221	0.117
		0-back	0.092 (0.536, 1.197)	0.126 (0.552, 1.225)	0.220 (0.729, 1.376)	0.888	0.490	0.429
	S.D.	*2-back*	0.714 (0.675, 0.899)	0.603 (0.630, 0.845)	0.714 (0.707, 0.952)	0.350	0.940	0.215
		1-back	0.809 (0.812, 1.095)	0.758 (0.734, 0.989)	0.825 (0.813, 1.081)	0.178	0.893	0.357
		0-back	0.663 (0.759, 1.025)	0.688 (0.721, 0.984)	0.730 (0.716, 0.978)	0.531	0.325	0.967
Steering (degree)	Mean	*2-back*	0.849 (0.496, 2.392)	1.031 (0.911, 3.103)	1.587 (1.210, 3.286)	0.726	0.375	0.596
		1-back	-0.037 (0.637, 4.609)	-0.542 (0.189, 2.063)	-0.401 (-0.457, 1.499)	0.344	0.058	0.397
		0-back	1.970 (1.072, 4.653)	0.617 (0.144, 2.125)	0.835 (0.362, 2.440)	0.112	0.081	0.934
	S.D.	*2-back*	11.772 (10.804, 14.909)	12.517 (11.414, 15.281)	13.336 (11.889, 15.633)	0.343	0.355	0.783
		1-back	9.213 (9.108, 15.762)	12.127 (10.355, 14.442)	9.062 (10.005, 14.450)	0.713	0.516	0.783
		0-back	13.272 (12.164, 25.640)	11.741 (10.787, 15.416)	12.063 (10.763, 14.914)	0.075	0.100	0.907
Yaw rate (rad/s)	Mean	*2-back*	0.003 (0.002, 0.014)	0.003 (0.004, 0.018)	0.008 (0.006, 0.019)	0.831	0.384	0.543
		1-back	-0.000 (0.003, 0.017)	-0.004 (-0.000, 0.011)	-0.003 (-0.004, 0.008)	0.405	0.090	0.403
		0-back	0.011 (0.008, 0.021)	0.003 (-0.001, 0.011)	0.002 (0.001, 0.014)	0.054	0.071	0.896
	S.D.	*2-back*	0.072 (0.067, 0.092)	0.080 (0.070, 0.094)	0.088 (0.074, 0.097)	0.419	0.355	0.710
		1-back	0.060 (0.056, 0.081)	0.076 (0.065, 0.089)	0.054 (0.060, 0.086)	0.500	0.606	0.829
		0-back	0.084 (0.075, 0.100)	0.071 (0.065, 0.088)	0.077 (0.067, 0.091)	0.054	0.244	0.580
Lateral acceleration (m^2/s)	Mean	*2-back*	0.024 (-0.020, 0.257)	0.013 (0.043, 0.394)	0.099 (0.053, 0.356)	0.929	0.547	0.536
		1-back	-0.037 (-0.002, 0.326)	-0.131 (-0.074, 0.196)	-0.106 (-0.152, 0.161)	0.529	0.123	0.487
		0-back	0.146 (0.085, 0.415)	-0.011 (-0.045, 0.242)	-0.042 (-0.029, 0.289)	0.177	0.155	0.975
	S.D.	*2-back*	1.395 (1.507, 2.108)	1.736 (1.519, 2.072)	1.840 (1.612, 2.104)	0.566	0.379	0.534
		1-back	1.243 (1.232, 1.855)	1.498 (1.469, 2.067)	1.121 (1.023, 2.017)	0.264	0.449	0.775
		0-back	2.063 (1.663, 2.257)	1.397 (1.447, 2.038)	1.623 (1.493, 2.067)	0.091	0.153	0.554

Note: Numbers in the table represent mean (95% CI) or significance level. * denotes p value less than 0.05, ** denotes p value less than 0.01

Table S11. Comparison of driving performance during N-back tasks between the conditions with and without body odor considering the moderating effects of task difficulty

		N-back task	**With the body odor (95% CIs)**	**Without the body odor (95% CIs)**	***p*-value (With vs. without body odor)**
Speed (m/s)	Mean	*2-back*	20.686 (21.809, 23.609)	22.745 (21.270, 22.942)	0.205
		1-back	22.086 (22.113, 23.851)	22.685 (22.087, 24.056)	0.809

		0-back	21.141 (21.452, 23.417)	21.618 (21.221, 22.918)	0.798
	S.D.	*2-back*	2.209 (2.448, 3.237)	2.010 (2.260, 3.001)	0.194
		1-back	2.106 (2.373, 3.042)	2.118 (2.476, 3.387)	0.965
		0-back	2.243 (2.344, 3.090)	2.155 (2.457, 3.138)	0.578
Acceleration (m^2/s)	Mean	*2-back*	0.002 (-0.034, 0.033)	-0.007 (-0.028, 0.027)	0.553
		1-back	0.001 (-0.021, 0.041)	-0.010 (-0.047, 0.012)	0.233
		0-back	-0.005 (-0.025, 0.032）	0.024 (-0.007, 0.051)	0.455
	S.D.	*2-back*	0.530 (0.521, 0.648)	0.540 (0.516, 0.632)	0.558
		1-back	0.563 (0.528, 0.643)	0.482 (0.545, 0.715)	0.653
		0-back	0.530 (0.521, 0.648)	0.540 (0.516, 0.632)	0.558
Lane deviation (m)	Mean	*2-back*	0.225 (0.812, 1.352)	0.134 (0.686, 1.236)	0.468
		1-back	0.362 (0.787, 1.305)	0.369 (0.981, 1.549)	0.300
		0-back	0.188 (0.720, 1.257)	0.059 (0.615, 1.151)	0.725
	S.D.	*2-back*	0.608 (0.686, 0.877)	0.745 (0.697, 0.878)	0.516
		1-back	0.869 (0.897, 1.114)	0.649 (0.727, 0.945)	0.280
		0-back	0.757 (0.781, 0.993)	0.627 (0.733, 0.948)	0.933
Steering (degree)	Mean	*2-back*	1.331 (1.230, 2.995)	0.788 (0.900, 2.474)	0.396
		1-back	0.647 (0.800, 3.520)	-0.765 (-0.151, 1.524)	0.131
		0-back	0.787 (0.429, 2.479)	1.710 (1.011, 3.279)	0.459
	S.D.	*2-back*	12.059 (11.350, 14.502)	13.809 (12.122, 15.313)	0.546
		1-back	11.719 (11.185, 15.936)	7.564 (9.372, 12.921)	0.089
		0-back	14.154 (12.337, 17.750)	11.553 (10.695, 19.007)	0.310
Yaw rate (rad/s)	Mean	*2-back*	0.007 (0.006, 0.018)	0.003 (0.002, 0.014)	0.364
		1-back	0.002 (0.004, 0.014)	-0.005 (-0.002, 0.008)	0.079
		0-back	0.003 (0.002, 0.015)	0.009 (0.004, 0.014)	0.520
	S.D.	*2-back*	0.076 (0.071, 0.090)	0.089 (0.074, 0.094)	0.732
		1-back	0.072 (0.069, 0.089)	0.047 (0.057, 0.077)	0.066
		0-back	0.086 (0.075, 0.094)	0.070 (0.068, 0.087)	0.206
Lateral acceleration (m^2/s)	Mean	*2-back*	0.096 (0.092, 0.363)	0.054 (0.016, 0.250)	0.409
		1-back	-0.019 (0.049, 0.308)	-0.174 (-0.143, 0.089)	0.026*
		0-back	0.005 (0.035, 0.310)	0.095 (0.030, 0.262)	0.458
	S.D.	*2-back*	1.540 (1.599, 2.066)	1.730 (1.595, 2.021)	0.850
		1-back	1.526 (1.556, 2.064)	0.992 (1.292, 1.779)	0.113

0-back	1.966 (1.704, 2.181)	1.316 (1.476, 1.950)	0.115

Note: Numbers in the table represent mean (95% CI) or significance level. * denotes p value less than 0.05, ** denotes p value less than 0.01

Moderating effect of exposure duration on driving performance

Table S12. *p* values of pairwise comparison of driving performance among different CO_2 levels at a certain body odor condition considering the moderating effects of exposure duration

	CO_2 level		**800 ppm vs. 1800 ppm**	**800 ppm vs. 3500 ppm**	**1800 ppm vs. 3500 ppm**
Speed (m/s)	10-12 minutes	Mean	0.612	0.197	0.443
		Std	0.973	0.257	0.619
	16-18 minutes	Mean	0.95	0.045*	0.126
		Std	0.484	0.29	0.188
Acceleration (m^2/s)	10-12 minutes	Mean	0.996	0.851	0.866
		Std	0.08	0.007*	0.825
	16-18 minutes	Mean	0.056	0.471	0.017*
		Std	0.244	0.758	0.333
Lane deviation (m)	10-12 minutes	Mean	0.768	0.521	0.357
		Std	0.299	0.466	0.449
	16-18 minutes	Mean	0.245	0.836	0.299
		Std	0.599	0.843	0.843
Steering (degree)	10-12 minutes	Mean	0.49	0.229	0.783
		Std	0.112	0.188	0.073
	16-18 minutes	Mean	0.592	0.544	0.881
		Std	0.178	0.388	0.851
Yaw rate (rad/s)	10-12 minutes	Mean	0.377	0.858	0.703
		Std	0.295	0.382	0.996
	16-18 minutes	Mean	0.935	0.521	0.836
		Std	0.606	0.64	0.754
Lateral acceleration (m^2/s)	10-12 minutes	Mean	0.308	0.342	0.599
		Std	0.382	0.282	0.942
	16-18 minutes	Mean	0.904	0.739	0.904
		Std	0.342	0.942	0.696

Table S13. *p* values of pairwise comparison of driving performance between the conditions with and without body odor at a certain CO_2 level considering the moderating effects of exposure duration

	Body odor		
Speed (m/s)	10-12 minutes	Mean	0.684
		Std	0.506
	16-18 minutes	Mean	0.803
		Std	0.389
Acceleration (m^2/s)	10-12 minutes	Mean	0.256
		Std	0.898
	16-18 minutes	Mean	0.143
		Std	0.364
Lane deviation (m)	10-12 minutes	Mean	0.337
		Std	0.163
	16-18 minutes	Mean	0.895
		Std	0.565
Steering (degree)	10-12 minutes	Mean	0.916
		Std	0.044*
	16-18 minutes	Mean	0.526
		Std	0.378
Yaw rate (rad/s)	10-12 minutes	Mean	0.219
		Std	0.154
	16-18 minutes	Mean	0.316
		Std	0.101
Lateral acceleration (m^2/s)	10-12 minutes	Mean	0.834
		Std	0.296
	16-18 minutes	Mean	0.064
		Std	0.135

Appendix C

Paper C. The influence of in-car air quality on drivers' brain states with hybrid fNIRS and EEG

Chao Wang[1], Yuanyuan Gao[2], Xiaojun Cheng[3], Xiaosu Hu[4], Erin T. Solovey[5], Yingzi Lin[6], Shichao Liu[1, *]

[1]Civil, Environmental, and Architectural Engineering, Worcester Polytechnic Institute, Worcester, MA, USA
[2]Center for Interdisciplinary Brain Sciences Research, Department of Psychiatry and Behavioral Sciences, School of Medicine, Stanford University, Stanford, CA, USA
[3]Neurophotonics Center, Department of Biomedical Engineering, Boston University, MA, USA
[4]Department of Psychology, University of Michigan, Ann Arbor, MI, USA
[5]Computer Science, Worcester Polytechnic Institute, Worcester, MA, USA
[6]Intelligent Human Machine Systems Lab, Mechanical and Industrial Engineering Department, Northeastern University, Boston, MA, USA

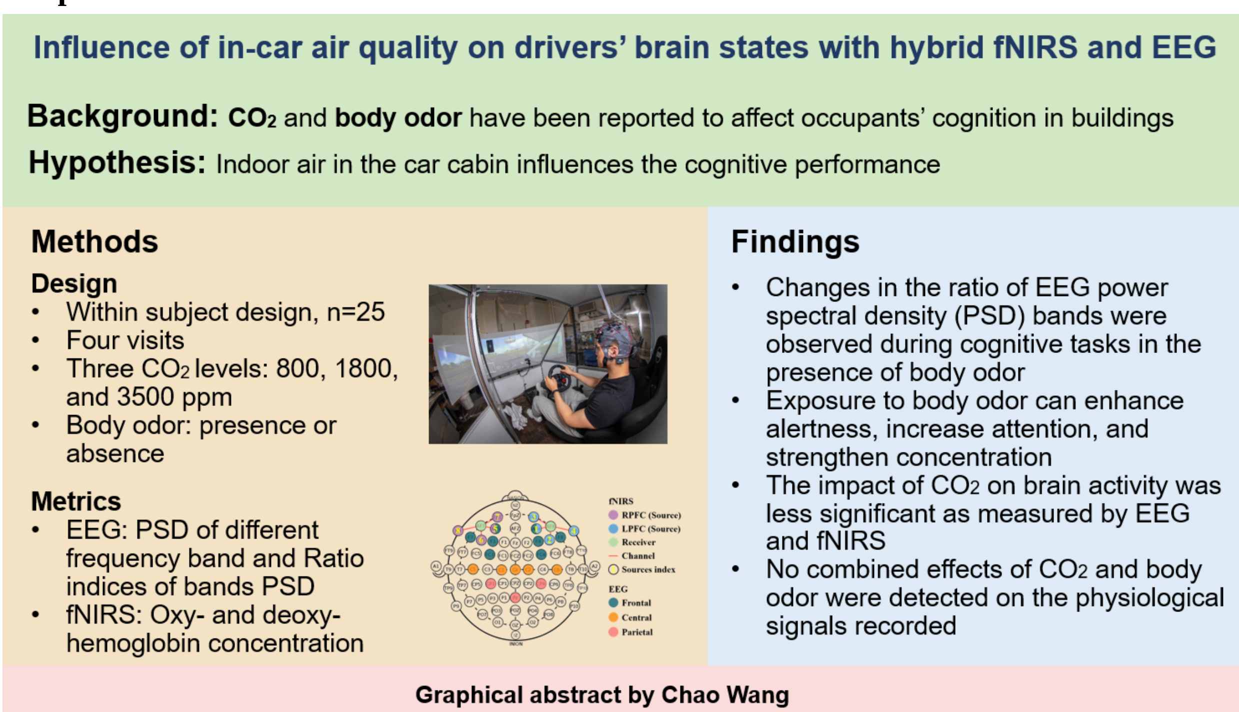
Keywords

Multimodal neuroimaging, Driving and cognition task, Carbon dioxide, Body odor, Driver Cognition, Brain function

Highlights

- Investigated the effects of CO_2 and body odor on drivers' brain states during driving
- Enrolled 25 participants in simulated highway driving under varying conditions
- Altered EEG ratio indices of bands PSD during N-back task due to body odor
- Body odor heightened alertness, boosted attention, and improved concentration
- Measured less pronounced impact of CO_2 on brain activity by EEG and fNIRS

Graphical abstract



Abstract

This study investigates the effects of in-car carbon dioxide (CO_2) levels and body odor on cognitive performance during driving using advanced neuroimaging techniques. Prior literature on building environments suggested that occupant-induced CO_2 and body odor can negatively impact cognitive abilities, especially when building ventilation is limited. Various indoor environmental factors may hinder cognition and therefore driving performance, thereby raising concerns for transportation safety. In our study, we investigated the influence of elevated CO_2 and body odor on driving capabilities. We enrolled 25 participants in simulated highway driving scenarios for a two-factor experimental setup, varying the indoor CO_2 concentrations across three levels (800, 1800, and 3500 ppm) and two levels of body odor. CO_2 concentrations in the cabin were increased by introducing pure CO_2. Electroencephalography (EEG) and functional Near-Infrared Spectroscopy (fNIRS) were applied to monitor brain activities during driving. The EEG data features included Power Spectral Density (PSD) in delta, theta, alpha, and beta bands, and various ratio indices, while fNIRS data focused on the metrics of oxyhemoglobin (HbO) and deoxyhemoglobin (HbR). The findings indicated that body odor significantly impacts EEG band PSD ratios, especially during N-back tasks. Specifically, the ratio index $(\alpha+\theta)/\beta$ was lower in the condition with body odor, indicating increased alertness. Concurrently, exposure to body odor reduced the θ/β ratio, which was associated with an increase in stimulus-driven attention and an enhanced ability of the subjects to concentrate. In contrast, CO_2 levels exhibited a nuanced influence on cognitive functions, with no direct impact on EEG band PSD or ratio indices observed. This suggests a complex or trivial relationship between CO_2 exposure and cognitive responses that our neuroimaging modalities could not directly unravel. Moreover, fNIRS data did not indicate significant hemodynamic response changes attributable to CO_2 or body odor, pointing to the specificity of EEG findings in detecting cognitive state shifts. The study contributes to our understanding of how CO_2 and body odor affect cognitive performance during driving, with implications for improving driving safety and designing better in-car environments.

Introduction

Carbon dioxide (CO_2) is a prevalent chemical which is an odorless, tasteless, and colorless gas in the indoor environment that affects occupants' physiological conditions (Guais et al., 2011; C. Wang et al., 2021). Elevated CO_2 in buildings, often due to poor ventilation, was reported to increase the prevalence of acute health symptoms and impairs occupants' work performance (Apte, 2000; Daisey et al., 2003; Erdmann et al., 2002). Furthermore, previous studies reported that exposure to high CO_2 level condition deteriorated cognitive functions like attention, decision-making, and perception, which are critical cognitions to driving, especially to the emergency response in complex traffic (Bloch-Salisbury et al., 2000; Norbäck et al., 2013; Scully et al., 2019; Twardella et al., 2012a). Satish et al. (2012) found decision-making performance declined at both 1000 ppm and 2500 ppm concentrations relative to 600 ppm. Additionally, Allen et al. (2019) stated that exposure to CO_2 at 700 and 1,500 ppm increased the odds of passing a flight maneuver significantly compared to exposure at 2,500 ppm. In the field study conducted in a primary school, Coley et al. (2007) reported the children showed significantly poorer concentration levels on the courses when the level of CO_2 in classrooms was high. However, many studies also suggested that elevated CO_2 concentration in classrooms did not impact students' attention performance significantly, suggesting the inconsistency of the literature on this topic. The study of Twardella et al. , (2012) claimed that the elevated CO_2 concentration in classrooms did not reduce students' global short-term attention. Additionally, another study using physiological and neurophysiological monitoring reported no effect of CO_2 on attention performance (Snow et al., 2019).

Beyond the direct impact of CO_2, human body odor, a complex mix of chemicals released through breath and skin, contributes to indoor air quality, and potentially affects cognition. These emissions, which include CO_2, volatile organic compounds (VOCs), and bioaerosols, are byproducts of human metabolism (Gallagher et al., 2008; Pandey & Kim, 2011; J. Wang et al., 2014). In fact, rather than elevated CO_2 levels, Zhang et al. (2017) argued that the body odor reduced cognitive performance. Exposure to 3000 ppm of exhaled CO_2 and accompanying body odor reduced mental performance, increased diastolic blood pressure, and increased stress markers (salivary α- amylase) compared to 500 ppm. Cecchetto et al. (2019) obtained the result that the body odors could effectively influence moral decision-making by increasing the emotional experience during the process even when the perceiver cannot detect the presence of body odors.

The vehicle cabin, a confined space akin to indoor settings of buildings, can play a pivotal role in influencing cognitive performance during driving. Such performance is modulated by various factors including air quality, thermal conditions, acoustics, and lighting. These elements collectively impact cognitive load and the driver's physical state (Chowdhury, 2015; Morris & Pilcher, 2016; van Huysduynen et al., 2017). Nazi et al. (2015) reported a significant temperature effect on speed variability by comparing the subjects' driving performance at three different temperatures. Helen et al. (1999) found a substantial increase in response time to peripheral signals under high-demand conditions with high-intensity music. Previous studies also suggested that air quality in the vehicle has widespread effects on driving performance. Raudenbush et al. (2009) conducted a study on the influence of three odor conditions on driving performance and revealed that both cinnamon and peppermint administration led to increased ratings of alertness, decreased temporal demand, and decreased frustration over the driving scenario. Complementing this, Baron and Kalsher (1998) evaluated cognitive performance, wakefulness, mood, and workload under conditions with a pleasing fragrance, noting a substantial enhancement in driving performance and alertness.

The integration of Electroencephalography (EEG) and functional Near-Infrared Spectroscopy (fNIRS) is promising as powerful neuroimaging technique that is more accurate than the individual modalities alone, offering researchers valuable insights into the neural dynamics underlying specific cognitive functions (Aghajani et al., 2017; Ahn et al., 2016; He et al., 2019; Y. Liu et al., 2017; Unni et al., 2017). EEG is a non-invasive method that records electrical activity in the brain, capturing real-time changes in neural oscillations (Alsuradi et al., 2020). Its high temporal resolution makes it particularly well-suited for studying dynamic cognitive processes. Recently, Snow et al. (Snow et al., 2019) exposed gaps in linking EEG signals to subjective sleepiness and CO_2 levels, with no significant correlation found between self-reported sleepiness and CO_2 exposure, despite a notable relationship between sleep duration and EEG patterns. In another study by using the EEG to measure the effect of CO_2 on daytime sleepiness, Jin et al., (2022) stated that EEG was significantly affected by a short exposure to the high condition (40,000 ppm) but not exposure time. They suggested that EEG may not be suitable to detect objective sleepiness induced by CO_2 exposure because the EEG signal was highly sensitive to environmental CO_2 concentration. In contrast, the combined use of EEG and other modalities has elucidated the detrimental impacts of increased CO_2 on cognitive functions like working memory, mental workload, and visual concentration (J. Lee et al., 2022). The environmental CO_2 has been rarely considered a source of the factors causing physiological artifacts in most previous studies (Xu et al., 2011), even though the low concentration of CO_2 could affect the physiological parameters, including EEG signals

(Jacobson et al., 2019; R. J. Thomas, 2014). Concurrently, fNIRS gauges alterations in cerebral blood flow (CBF) and associated hemoglobin concentrations by utilizing near-infrared light sources and detectors on the scalp (Yücel et al., 2021). Its capacity to furnish insights into cortical hemodynamics makes fNIRS a valuable complement to EEG, enhancing the overall comprehension of cognitive processes. Notably, fNIRS is akin to EEG in terms of portability. Furthermore, it lacks electromyographic (EMG) and blink artifacts, and its signal closely aligns with the blood oxygen level dependent (BOLD) signal derived from functional magnetic resonance imaging (fMRI), a recognized standard for assessing cerebral hemodynamics (Huppert et al., 2006; Strangman et al., 2002). Unni et al. (2017) utilized fNIRS in a driving study to measure brain activation and predict working memory load, demonstrating a mean Pearson correlation of 0.61 between induced and predicted load.

Although many studies have investigated the impact of moderate CO_2 and/or body odor on occupants' cognition and work performance in buildings, research into these environmental factors and their effect on drivers' cognition performance, which is crucial for safe and effective driving performance in vehicles, seem to be missing in the literature study. Furthermore, findings from previous studies about the impact of IEQ factors on working or cognitive performance have often shown inconsistencies due to methodological variability, sample diversity, environmental complexity, and measurement limitations.

The aim of this study was, first, to explore the impact of in-car CO_2 and body odor on cognitive performance during driving, filling the gap in knowledge in this understudied field. Cognitive performance during the driving refers to as an individual's ability to operate a vehicle safely and effectively, including controlling the vehicle, making quick decisions, and responding to various driving situations (Savino, 2009). Impairments in a driver's cognitive abilities can lead to a decline in driving performance, which can be measured through various metrics related to the cognitive performance. The environment of the vehicle cabin has the potential to influence the driving performance because of both the cognitive load during driving and the driver's physical state. A comfortable vehicle internal environment of the vehicle cabin has come into the focus of discussion. While previous research has focused on drowsiness and sleepiness related to CO_2 or body odor, this study extends to examine the effects of these factors on both cognitive performance and physiological state. The secondary objective is to conduct EEG and fNIRS-based measurement to discern the impact of CO_2 or body odor on cognitive performance, facilitating accurate assessment in a simulated vehicle cabin setting. The neuroimaging techniques are instrumental in advancing driving studies, offering nuanced insights into cognitive demands such as attention, decision-making, and memory, thus contributing to driver safety and intelligent transportation system design. Moreover, EEG and fNIRS have been pivotal in indoor environment studies, illuminating the effects of environmental factors on cognitive performance. They have enabled researchers to elucidate the intricate relationship between environmental factors, such as air quality and thermal comfort, and cognitive functions. By extracting EEG and fNIRS features from comprehensive signal datasets, this study considers the confounding effects of CO_2 on brain responses to the environment, enhancing the understanding of its impact on cognitive performance in the vehicle. The outcome could have significant practical implications, such as improving driving safety. Moreover, such an outcome would necessitate the inclusion of the air quality condition as an environmental factor in drivers' cognitive performance.

Methodology

Participants

Our study at Worcester Polytechnic Institute (WPI) enrolled twenty-five student participants, recruited through posters and email. The Institutional Review Board (IRB-19-0672) at WPI approved the experimental protocol, and participants gave informed consent after being briefed on the study's procedures, risks, and responsibilities.

To mitigate simulator sickness, which affects 2% – 8% of individuals in driving simulations (Akinwuntan et al., 2005), we screened candidates using the Simulator Sickness Questionnaire (SSQ) (Kennedy et al., 1993). This questionnaire assesses symptoms like headache, nausea, and blurred vision, and is recognized for predicting simulator sickness and participant attrition (Balk et al., 2017). Post-simulation, participants rated their symptoms on a scale from 0 (none) to 3 (severe). Four out of the initial 29 candidates were excluded due to significant simulator sickness responses. The final sample comprised 25 licensed drivers (15 males, 10 females), aged between 18 and 22 years (Mean ± SD: 19.88 ± 1.33). A power analysis using G*Power 3.1 (Faul et al., 2007) determined the optimal sample size for the six CO_2 and body odor conditions as 19, based on an ANOVA for repeated measures, with an effect size of 0.25 and a power of 0.8. Participants were instructed to avoid alcohol for 24 hours, and nicotine and caffeine for 3 hours before the sessions, as well as to get sufficient sleep the previous night. Compensation was set at $15 per hour, with an additional performance-based bonus of up to $15, to encourage focused participation in the study.

Experimental setup

Driving simulator

The investigation encompassed the utilization of an advanced driving simulator, comprising several key components. The setup included a control computer with Carnetsoft simulator software (Wim van Winsum, Joeswerd 85, Groningen, 9746CR, the Netherlands), three display projectors, a curved screen, a Logitech G29 driving control system, an audio setup, and a car cabin mock-up. The control computer, essential for the simulation, was equipped with a GeForce GTX 770 GPU, an i7-9790 CPU, Windows 10 PRO, and 32 GB RAM, ensuring smooth operation and graphics rendering. The central screen, positioned 0.5 meters from the cabin, provided a 210º horizontal field of view. This was split into a 70º forward view and 70º for each side window, creating a realistic driving experience. The Logitech G29 setup, including a steering wheel, gear shifter, and pedals (brake, clutch, accelerator), featured force feedback and a rotation range of -450 to +450º, offering an interactive and responsive driving interface. A foot-switch control pedal was also included to facilitate additional inputs for N-back tasks, as detailed in Section 2.4. To enhance the simulation's realism, an integrated audio system replicated sounds like car engines and tire movements, immersing participants in the driving environment. This comprehensive simulator setup was instrumental in accurately replicating driving conditions for the study.

In-car environment

The experimental room, containing the driving simulator, was fitted with a wall-mounted heat recovery ventilator (Fantech SH–56 CFM HRV) for air circulation, extracting exhaust air from the car cabin. An air purifier (LEVOIT Air Purifiers for Home, H13) was strategically positioned close to the air inlet of the car cabin. Room temperature was kept at 24 ± 1 °C, and relative humidity at 47 ± 2%, ensuring stable environmental conditions for reliable experimental outcomes.

In the previous studies, CO_2 concentration tends to increase in the vehicle cabin due to occupant exhalation when the HVAC air is in recirculation mode (Hudda & Fruin, 2018; Shu et al., 2015). CO_2 levels below 1000 ppm can be regarded as harmless, while 2000 ppm and above are hygienically unacceptable (Apte, 2000). But the CO_2 levels, particularly in the window-closed cabin, typically exceed 3,000 ppm in the fully loaded condition (Hudda & Fruin, 2018; Shu et al., 2015). In our study, we used three distinct CO_2 concentrations (800, 1800, and 3500 ppm) and participants were assigned randomly to experience one of them during each session. A specialized active meter (CM-0001 CO_2 Sampling Data Logger, CO_2 METER, accuracy ±30 ppm) equipped with an integrated air pump was employed to measure CO_2 concentrations in close proximity to the driver's breathing area. For varying CO_2 concentrations, pure CO_2 gas (99.9%) was introduced from a gas cylinder (Airgas, Food grade, CGA-320) into the cabin, ensuring the targeted CO_2 levels were reached. Notably, in the case of simulating low CO_2 concentrations, the cabin's existing CO_2 content hovered around 800 ppm without the introduction of any supplementary artificial CO_2 due to the presence of CO_2 exhaled by the participating driver.

We investigated the effects of body odor presence and absence, not originating from the driver, on driving performance. Instead of injecting body odor gases, we changed the body odor levels by introducing extra T-shirts by body odor donors. Only two conditions (with extra body odor vs without extra body odor) were considered in this study due to the complexity of controlling body odor at a fixed level. To introduce an extra body odor into the car cabin, six previously worn T-shirts were placed within the vehicle during the driving session. This method was well documented in body odor research (Haze et al., 2001; Munk et al., 2000; Rathinamoorthy & Thilagavathi, 2016). Specifically, six T-shirts, previously worn by healthy, non-smoking individuals (4 males, 2 females, aged 28–38 years; Mean ± SD: 32.3 ± 4.5 years), were placed in the vehicle during driving sessions. These donors were provided informed consent for participation. Throughout the collection period, individuals providing odor samples rigorously adhered to guidelines regulating personal nutrition, prohibiting the consumption of alcohol, smoking that could alter their natural body odor (Cecchetto et al., 2019), while also observing specific hygiene practices. Prior to use, all T-shirts underwent thorough washing with an unscented detergent (All Mighty Pacs with stain lifters free clear Laundry Detergent). Following a shower with fragrance-free body wash (Aveeno Skin Relief Fragrance-Free Moisturizing Body Wash), donors wore the T-shirts for 12 consecutive hours. The collection occurred over two days, with each donor using separate T-shirts. The T-shirts were stored in odorless plastic bags and subsequently in a dry, light-free environment to prevent degradation. For a detailed analysis of the chemical composition of the body odor samples from these T-shirts, refer to Wang et al. (2024).

Virtual environment and secondary tasks

The virtual driving experiments were conducted in a simulated two-lane highway environment, with each lane measuring 3.35 meters in width. The simulation required participants to perform high-speed driving tasks, including multiple lane changes, response to traffic congestion, and overtaking maneuvers. Set in daylight conditions without weather disturbances (e.g., fog, snow, or rain), each session lasted at least 20 minutes. It began with a traffic congestion phase, necessitating reduced speeds to avoid collisions, followed by a return to normal driving speeds post-congestion.

The N-back task, a standard tool for evaluating working memory in driving contexts, was adapted from the verbal variant described comprehensively by Mehler et al. (2012), and inspired by the version used by Solovey et al. (2014). Our adaptation was designed to avoid potential confounds with unanalyzed bio-signals due to facial muscle movements.

In our version, participants were presented with single-digit numbers (0-9) at two-second intervals on the central screen's upper-left corner during driving. The task required identifying whether the current number matched the one shown N positions earlier. The value of N remained constant within each session and varied in complexity, as discussed in the experimental procedure section. Figure 1 illustrates the task dynamics for N values of 0, 1, and 2. Each session comprised six segments, with an equal distribution of randomly selected 0-back, 1-back, and 2-back tasks. Every session began with an instructional phase, followed by a sequence of 16 random numbers. Each number appeared for 500 milliseconds, and participants had 1,500 milliseconds to respond. A 140-second driving block succeeded each N-back segment.

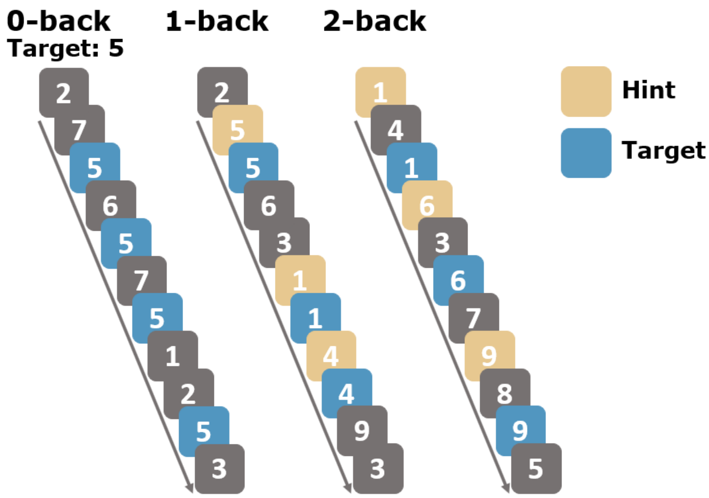
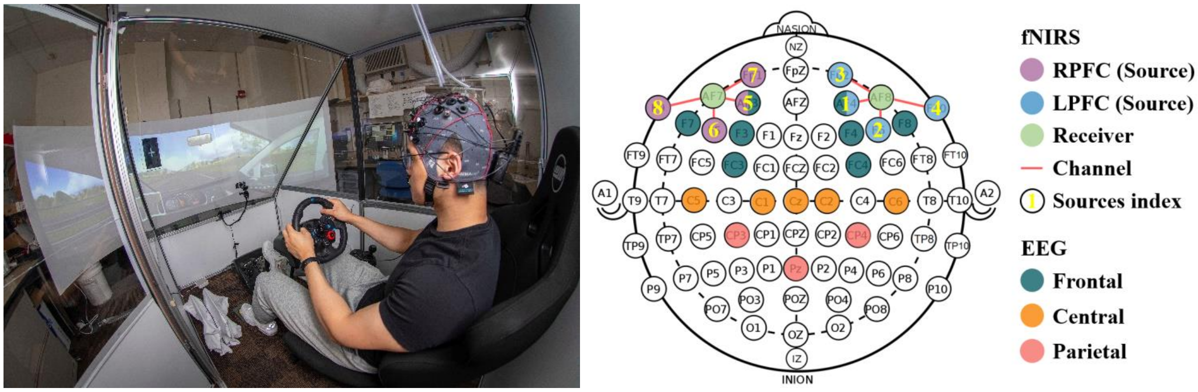


Fig. 1. Example of N-back experimental paradigm to manipulate cognitive workload

EEG and fNIRS setup and acquisition

Data acquisition of brain activity was conducted using the g.Nautilus Research fNIRS-8 wireless headset (Figure 2a) and the g.tec MATLAB-Simulink software (g.tec medical engineering GmbH, Austria). This setup enabled the simultaneous collection of both EEG and fNIRS data. The study utilized sixteen wet EEG channels and eight fNIRS channels from the headset, augmented by EEG/fNIRS low-power transmitters. The EEG electrodes placement encompassed CZ, AF3, AF4, F7, F8, F3, F4, FC3, FC4, C5, C1, C2, C6, CP3, CP4, and PZ, with earlobe electrodes serving as reference nodes. This arrangement targeted the frontal, central, and parietal regions, adhering to the International 10-10 system landmarks (Jurcak et al., 2007). Figure 2b illustrates the configuration of the probe array and electrodes placed on the scalp. The fNIRS optodes, comprising 8 sources and 2 detectors, were positioned at FP1, AF3, F5, F9, FP2, AF4, F6, and F10, focusing on the prefrontal cortex (PFC), integral to working memory load detection. The system utilized continuous-wave laser diodes at 760 nm and 850 nm wavelengths, with a 3 cm source-detector separation. To mitigate motion artifacts, the cap was securely positioned on participants' heads. Our setup offered comprehensive frontal lobe coverage via fNIRS and full-head coverage with EEG. The placement of fNIRS optodes on the forehead not only enhanced signal quality but also streamlined preparation.



(a) (b)

Fig. 2. a) Driving simulator and EEG/fNIRS cap. b) Graphical representation of the EEG/fNIRS probe array and optodes

The g.Nautilus Research Headset and optodes connector box were mounted on the subject's head for concurrent EEG and fNIRS data capture. Data collection and monitoring were conducted using MATLAB, with Bluetooth transmission to the g.tec MATLAB-Simulink software. This platform enabled synchronous EEG and fNIRS data acquisition and facilitated adjustment of sampling frequency, bandpass, and notch filters. Settings included a 752 Hz sampling frequency, a 5-60 Hz bandpass filter, and a 58-62 Hz notch filter. EEG data were quantified in microvolts and fNIRS data as raw optical density.

Task commencement and conclusion in each N-back task block were marked by a trigger sent through the serial port to both the fNIRS and EEG systems on Channel 54, configured to receive external markers.

Procedure

In this study, each participant undertook a total of four laboratory visits as part of their participation. The initial visit focused on essential preparations and familiarization, including becoming acclimated to the simulator's operation, and underwent a screening process for simulator sickness, as illustrated in Figure 3. The following three formal visits constituted the main experimental phase, where participants were engaged in driving tasks under randomly assigned CO_2 concentrations, spanning three different levels. During each of these visits, participants underwent two driving sessions. Each session involved random exposure to either clean or body odor-infused T-shirts. The order and nature of these conditions were unknown to the participants, safeguarding the study's integrity.

At the beginning of the formal visit, participants completed a pre-session survey evaluating their sleep quality from the previous night and current sleepiness levels. For more information about the survey, please refer to our previous publication (C. Wang et al., 2024). They were then equipped with physiological sensors before entering the driving simulator. Each driving session lasted approximately 20 minutes, during which participants completed six N-back tasks (two each of 0-back, 1-back, and 2-back), randomly ordered to vary cognitive workload. Post-driving, participants exited the simulator to complete a survey assessing their physical and psychological state. This interval also allowed for the replacement of T-shirts in the simulator. Participants then repeated the same driving task under different environmental conditions. After completing all visits, participants received a debriefing and compensation for their participation in the study.

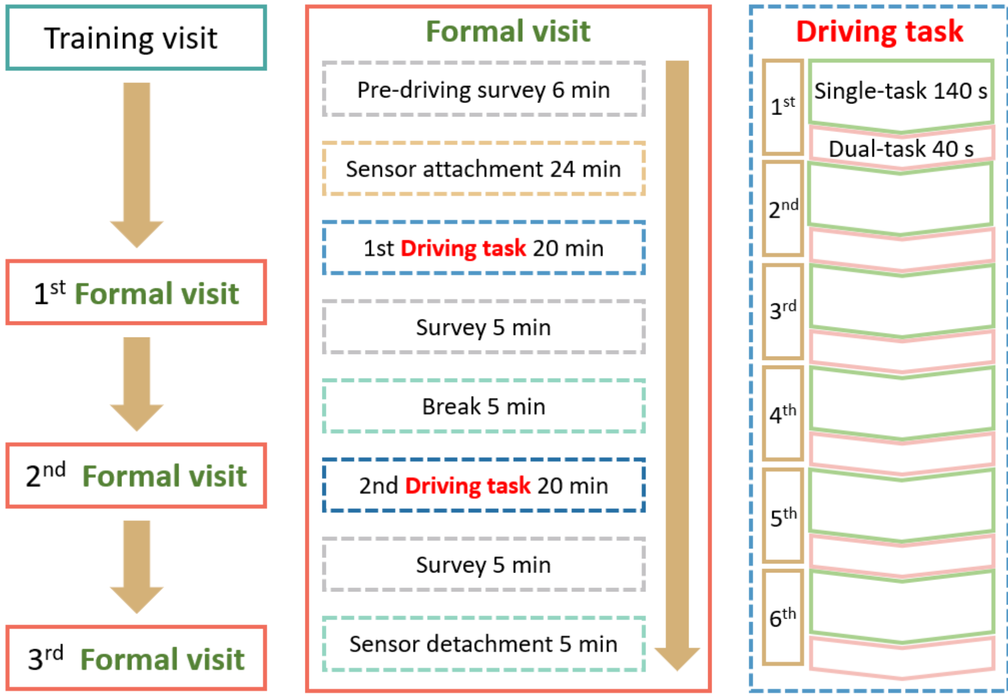


Fig. 3. Experimental procedure. The left column outlines one training visit followed by three formal visits. The middle column details the process involved in a single formal visit. The right column depicts the driving sub-sessions included within a single driving session.

Data processing

Data preprocessing

In this study, we employed the MNE-Python (Gramfort et al., 2013) for processing raw EEG data, adhering to a systematic approach (Gramfort et al., 2014). This included identifying and removing bad EEG channels, followed by their reconstruction through the spherical spline interpolation method (Perrin et al., 1989), using data from adjacent good sensors. The EEG data were resampled to 500 Hz for simplicity and re-referenced to the average reference. To reduce high-frequency physiological noise, we applied a third-order Butterworth filter for bandpass filtering between 0.5 Hz and 30 Hz (Kar et al., 2010). Eye-movement artifacts and the channels affected by eye-blink were removed, and Independent Component Analysis (ICA) was utilized to decompose the EEG data and mitigate physiological effects (Delorme & Makeig, 2004).

For fNIRS data preprocessing, initially, we used the data converter (C. Wang, 2024) to transform the time-series raw data in ".mat" format file to ".nirs" format file which can be read by the popular used software Homer3 (Huppert et al., 2009). The data were then transformed into ".snirf" files for further processing. We used Homer package (Homer3), a MATLAB-based toolbox to correct motion artifacts, physiological noise, and analyze captured hemodynamic data. We adopted the modified Beer-Lambert's law (mBLL) to relative concentrations of oxygenated hemoglobin (HbO) and de-oxygenated hemoglobin (HbR) from the light intensities of the eight detectors (Cope et al., 1988; Kocsis et al., 2006), with DPF of 4 (Scholkmann & Wolf, 2013). Table 1 lists the parameters of each algorithm. After visual inspection to remove abnormal noise, weak, deviating, or excessively noisy signal channels were pruned. Motion artifacts were corrected using channel rejection, motion detection, wavelet transformation, Savitzky-Golay spline interpolation, and band-pass Butterworth filter. Physiological noise, such as respiration, and cardiac activities, was addressed using a bandpass filter. Confounding effects, like vessel changes due to CO_2, were mitigated by subtracting the global signal average from the interested signal. Physiological noise was identified as the noise significantly impacts the recorded fNIRS data (Yücel et al., 2021).

We used a general linear model (GLM) to extract the hemodynamic response function (HRF) from the preprocessed fNIRS signals, considering its advantages over block averaging. GLM accounted for potential physiological noise as one of the regressors in calculating HRF, with options for specifying temporal basis functions, regression of short separation channels, drift order, and motion artifact correction (Yücel et al., 2021). It elucidated the HRF across all channels under various experimental conditions by incorporating specific weights for each computational component—physiological, functional, and drift order—determined via a linear combination of N normalized Gaussian functions. Cerebral activation is characterized by changes in HbO, HbR, and total hemoglobin (HbT) concentrations, correlating with variations in cerebral oxygenation and blood flow. Consequently, alterations in HbO, HbR, and HbT concentrations were the primary indicators of cerebral activation in our analyses, drawing on the foundational work by Sitaram et al (2007) and Kwong et al. (1992). We computed average HbO, HbR values for each channel, delineated based on the Regions of Interest (ROIs) as shown in Figure 2b, for in-depth analysis.

Table 1. User parameter settings for every HOMER3 function used in the processing stream.

Name	Function	Parameters and Values
Channel rejection	hmrR_PruneChannels	dRange: (0.2, 1.8) SNRthresh = 1 Sdrange: (0.0, 45.0)
Motion detection	hmrR_MotionArtifactByChannel	tMotion = 0.5 Sec tMask = 1.0 Sec SDEVThresh = 15 AMPthresh = 0.2
Wavelet	hmrR_MotionCorrectWavelet	iqr = 1
SplineSG	hmrR_MotionCorrectSplineSG	p = 0.99 FrameSize_Sec = 10
Bandpass filter	hmrR_BandpassFilt	hpf = 0 Hz lpf = 0.5 Hz
OD change	hmrR_OD2Conc	dod = 1.0 probe = 1.0 ppf = 1.0
GLM	hmrR_GLM	Trangt: (-5, 45) Sec glmSolveMethod = 1 idxBasis = 1 paramsBasis: [1 1] rhoSD_ssThresh = 0 flagNuisanceRMethod = 1 driftOrder = 3.0

Feature Extraction

EEG data spanning an 18-minute duration were used to extract the features across each driving session under various driving conditions. A power spectral density (PSD) was computed for each trial using the MNE package (Gramfort et al., 2014). To calculate the PSD, we considered four spectral band ranges: delta (δ) (1–4 Hz), theta (θ) (4–8 Hz), alpha (α) (8–13 Hz), and beta (β) (13-30 Hz), using welch wavelet transform (WT) (Al-Fahoum & Al-Fraihat, 2014). Using a time-sliding window of 2 s and half window size overlapping, the mean power values of α frequency band signals were extracted and used as features for EEG assessment. We used the moving average due to its ability in removing spurious artifacts in continuous signals. Using Welch's method, each of the band powers for δ, θ, α, and β, as well as total band power, which is defined as the sum of all band powers were calculated. The θ was selected because an increase in the frequency range of θ band has been put forward as a sign of sleep need (Aeschbach et al., 1997; Buckelew et al., 2009; Cajochen et al., 1995). For α band, an increase in α content has been found to be a robust indicator of sleepiness in a driving setting (Kecklund & Åkerstedt, 1993; Simon et al., 2011) and memory performance (Klimesch, 1999). Borghini et al. (2014) stated that an increase in θ band and a decrease in α band occurred in high mental workload. Furthermore, an increase in relative β band has been associated with arousal and stress (Kuo et al., 2016; J. Zhang et al., 2021). The δ band is linked to cortical deafferentation during mental tasks, reducing sensory interference with concentration (Dimitriadis et al., 2010). It may also play a role in processing complex tasks (Harmony, 2013), underscoring its significance in attention and response to olfactory stimuli. Except the RPL of different frequency bands, we also incorporated the ratio indices of (θ+α)/β and θ/β as the features. Given the tendency of basic indices to present conflicting outcomes, ratio indices were calculated to enhance the discernibility of differences The results from studies by Jap et al. (2009) and Eoh et al. (2005) indicated that (θ+α)/β was a more reliable fatigue indicator. The θ/β in EEG studies (Clarke et al., 2019), initially thought to represent arousal in Attention-Deficit/Hyperactivity Disorder (AD/HD), is now believed to indicate cognitive processing capacity. The declined value of θ/β ratio reflects an increase of stimulus-driven attention and the subjects have stronger capability to concentrate (T.-S. Wang et al., 2024). Furthermore, these ratio indices were less sensitive to noise and have relatively higher sensitivity. The ROI of all EEG probes were divided as "frontal", "central", and "parietal" area as show in the Figure 2 (Liang et al., 2018).

The statistics of HbO and HbR are commonly used as features in fNIRS studies (von Lühmann et al., 2020; Yücel et al., 2021). The fNIRS features we focused on included the amplitude of HbO and HbR, the slope of these signals, the temporal difference between their peaks, and their maximal or minimal values observed during the N-back tasks. Additionally, we computed the average amplitude of HbO and HbR concentration throughout the entire driving session to serve as features, aligning with methodologies from prior studies (von Lühmann et al., 2020). Mirroring the analytical techniques applied in EEG signal analysis, we derived features based on specified ROI and across various driving sessions. The brain ROIs were categorized into the prefrontal cortex (PFC), left prefrontal cortex (LPFC), and right prefrontal cortex (RPFC), following the classification by Li et al. (2019). The study using fNIRS during driving simulations highlighted hemispheric differences in spatial attention (Oka et al., 2015). It suggested that the left hemisphere directs attention more strongly to the right side than the right hemisphere does to the left. Another research (Henson et al., 1999) has focused on episodic memory retrieval and the role of the RPFC proposed that the RPFC activation during memory retrieval tasks might reflect the degree of retrieval effort, being more active when retrieval is difficult. Furthermore, we assessed the features *at the level of individual channels across different driving sessions to examine the effects of varied conditions.*

Statistical analysis

The study evaluated the influence of various in-car environmental factors on brain activity, with particular focus on EEG and fNIRS signals, as illustrated in Figure 4. Participants were subjected to six distinct in-car conditions of various levels of CO_2 concentration and the presence or absence of additional body odor. The driving sessions were categorized based on the inclusion of an additional cognitive task into two types: “single-task driving,” where the subject was solely focused on driving, and “dual-task driving,” which involved performing an N-back task concurrently with driving. Within these categories, a task was further subdivided into twelve sub-sessions: six dedicated to single-task and six to dual-task activities. These sub-sessions were designated as “1st sd”, “2nd sd”, and so on for single-task driving, and “1st dd”, “2nd dd”, etc., for dual-task driving. To discern the impact of CO_2 levels and body odor on cognitive functions during these tasks, we conducted a comparative analysis across different ROIs in the brain with multiple probes or optodes, as well as at the individual level. The features derived from the EEG and fNIRS signals, which are detailed in the feature extraction section of this paper, were integral to this comparison. The corresponding effects of each environmental condition on cognitive performance during driving are depicted and summarized in Figure 4.

The effect of CO_2 or body odor on EEG and fNIRS signal was statistically assessed using two-way Aligned Rank Transform (ART) Analysis of Variance (ANOVA) coupled with Bonferroni correction and post-hoc analysis, a commonly employed method in the literature for assessing differences among three or more groups (Durner, 2019; Elkin et al., 2021). All datasets were not normally distributed by using the Shapiro-Wilk normality test. The significance level used for hypothesis testing was 0.05. The data analysis was conducted with R language software (version 4.2.3) (R Core Team, 2013).

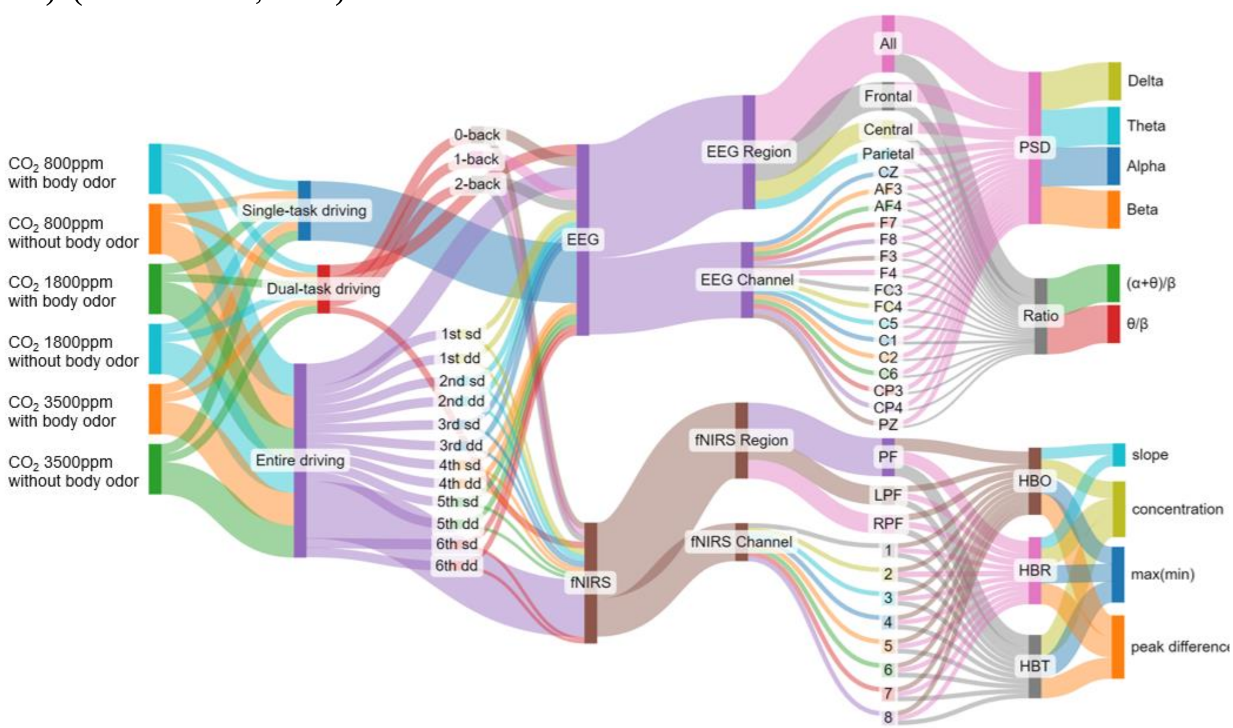


Fig. 4. Integration figure of the features used in the ANOVA. “sd” refers to “single-task driving” and “dd” stands for “dual-task driving”. Trace the lines originating from left to right are the environmental conditions, task type, EEG and fNIRS brain regions and channels, features used to measure cognitive performance.

Results

Environmental conditions

On average, the measured CO_2 concentration was 786.42 ± 106.57 ppm (Mean ± SD) for the low level, 1815.00 ± 80.63 ppm for the middle level, and 3504.41 ± 149.39 ppm for the high level (Figure S2 in the appendix). We also analyzed the VOC composition of worn T-shirts but did not quantitatively measure their concentration. For more information, please refer to our previous publication (C. Wang et al., 2024).

EEG measurements

The analysis of EEG focused on drivers’ PSD across spectral bands and the ratio indices in different ROI during assorted driving sessions as the entire driving session, single-task driving, dual-task driving, and various difficulty level N-back tasks. The ART two-way ART ANOVA evaluated the impact of CO_2 and body odor on these EEG features.

PSD of different frequency band

Table S1 (in the appendix) outlines the mean and standard deviation values for PSD of different bands which were significantly affected by the CO_2 level or body odor, and Table 2 details the corresponding results of the two-way ART ANOVA, which investigates the effects of CO_2 or body odor. In these tables, we included only the ANOVA results that demonstrated a significant influence of the in-car environment on the PSD of various frequency bands. This selective inclusion is due to the fact that, out of 160 total comparisons, 158 did not show a significant effect of the in-car environment on PSD of different frequency bands.

Entire driving session

For the entire driving session, in examining various ROI — namely, the frontal, central, and parietal regions, as well as an aggregate ‘all’ category, the ANOVA results indicated that no significant effects of CO_2 and body odor on the PSD of different bands. But the results presented when considering from the channel instead of the brain regions, channel PZ showed a notable difference in δ due to the presence of body odor ($F_{(1, 144)} = 8.024$, $p = 0.005$, $\eta^2 = 0.956$), with δ PSD values averaging 9.951 $\mu V^2/Hz$ with body odor and 8.425 $\mu V^2/Hz$ without it.

Table 2. Two-way ART ANOVA of EEG PSD of different frequency band at different CO_2 levels and environments with or without body odor across the driving sessions

Driving session	**Source**	**Feature**	**Channels**	**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig. (*p*)**	**Partial Eta Squared**
Entire	Body odor	δ	PZ	8532.913	1	8532.913	8.024	0.005**	0.956
Single-task	Body odor	δ	C1	7871.268	1	7871.268	6.779	0.010*	0.597

Note: * denotes *p* value less than 0.05, ** denotes *p* value less than 0.01

Single-task driving session

During the single-task driving session, in examining various ROI the ANOVA revealed no significant effects of CO_2 on the absolute value of the PSD across four frequency bands. Similarly, the presence of body odor did not exert a statistically significant influence on the PSD of different bands in any of the ROI across the various driving conditions. In addition, in the Table 3, Channel C1 showed a notable difference in PSD of δ due to the presence of body odor ($F_{(1, 144)} = 6.779$, $p = 0.010$, $\eta^2 = 0.597$), with values averaging 8.829 $\mu V^2/Hz$ with body odor and 4.077 $\mu V^2/Hz$ without it.

Dual-task driving session

For the integrated dual-task driving session which merge the various N-back tasks sessions, either in examining various ROI or channels, neither bands' PSD nor ratios was significantly affected due to the CO_2 or the presence of the body odor.

We also explore the influence of varying CO_2 levels and the presence of body odor on EEG PSD of different bands during N-back tasks of varying difficulty. Table S2 outlines the mean and standard deviation values for these indices which were significant effected by the CO_2 or body odor in different N-back tasks, and Table 3 details the results of the two-way ART ANOVA, which explores the effects of CO_2 or body odor. While we did not find significant differences in the various frequency band PSD due to CO_2 or body odor across different ROIs, a different pattern emerged when examining individual channels.

During the 0-back task, the δ band PSD was significantly affected by body odor on channels FC3 ($F_{(1, 144)} = 8.997$, $p = 0.003$, $\eta^2 = 0.618$), FC4 ($F_{(1, 144)} = 6.686$, $p = 0.011$, $\eta^2 = 0.577$), and PZ ($F_{(1, 144)} = 11.415$, $p = 0.001$, $\eta^2 = 0.569$). For example, in the environment with the body odor, the mean PSD of δ at FC3 increased to 2.828 $\mu V^2/Hz$ compared to 1.686 μV2/Hz without it.

During 1-back task, some channels show the significant differences of δ due to the body odor. Table 5 shows that the PSD of δ in channel PZ decreased significantly ($F_{(1, 144)} = 17.050$, $p < 0.001$, $\eta^2 = 0.547$) from 3.825 $\mu V^2/Hz$ in the environment with the body odor to 1.340 $\mu V^2/Hz$ (Table S2) in the environment without the body odor. Another θ band in the same channel, the PSD were also significantly different ($F_{(1, 144)} = 12.178$, $p < 0.001$, $\eta^2 = 0.495$) due to the body odor and decreased from 0.588 with the presence of body odor to 0.236 $\mu V^2/Hz$ without body odor.

For the 2-back task, significant effects from body odor were found on δ at channels FC4 ($F_{(1, 144)} = 6.824$, $p = 0.011$, $\eta^2 = .486$) and C1 ($F_{(1, 144)} = 8.865$, $p = .010$, $\eta^2 = .408$). For instance, the mean δ value at FC4 was 1.652 $\mu V^2/Hz$ at 800 ppm CO_2 and 3.770 at 3500 ppm CO_2. With body odor, the mean δ value increased to 2.990 $\mu V^2/Hz$ compared to 1.415 $\mu V^2/Hz$ without it. No significant effects were found from the PSD of bands due to CO_2, body odor, or their interaction by regions.

Table 3. Two-way Analyses of Variance of EEG PSD of different frequency band at different CO_2 levels and environments with or without body odor during N-back tasks

Driving session	Source	Feature	Channel	Sum of Squares	df	Mean Square	F	Sig. (*p*)	Partial Eta Squared
0-back	Body odor	δ	FC3	5091.064	1	5091.064	8.997	0.003**	0.618

0-back	Body odor	δ	FC4	4127.213	1	4127.213	6.686	0.011*	0.577
0-back	Body odor	δ	PZ	5657.301	1	5657.301	11.415	0.001**	0.569
1-back	Body odor	δ	PZ	8575.42	1	8575.42	17.050	<0.001**	0.547
1-back	Body odor	δ	C1	3986.482	1	3986.482	6.704	0.011*	0.596
1-back	Body odor	θ	PZ	6787.995	1	6787.995	12.178	<0.001**	0.495
2-back	Body odor	δ	FC4	4162.529	1	4162.529	6.824	0.011*	0.486
2-back	Body odor	δ	C1	3681.853	1	3681.853	8.865	0.010*	0.408

Note: * denotes *p* value less than 0.05, ** denotes p value less than 0.01

Ratio indices of bands PSD

Entire driving session

Table S3 outlines the mean and standard deviation values for band power ratios indices which were significantly affected by the CO_2 level or body odor, and Table 4 details the corresponding results of the two-way ART ANOVA, which investigates the effects of CO_2 or body odor. Similar to the results of band PSD, we included only the ANOVA results that demonstrated a significant influence of the in-car environment on the ratio indices (5 out of 160 total comparisons).

For the entire driving session, in examining various ROI — namely, the frontal, central, and parietal regions, as well as an aggregate ‘all’ category, the ANOVA results indicated that no significant effects of CO_2 and body odor on the band power ratios indices. But the results presented when considering from the channel instead of the brain regions, channel AF3 demonstrated a significant difference in the α+θ/β ($F_{(1, 144)}$ = 5.235, p = 0.007, η^2 = 0.810) and θ/β ($F_{(1, 144)}$ = 4.722, p = 0.011, η^2 = 0.801), attributable to CO_2 levels. This suggests that CO_2 concentration significantly altered the mean value of the (α+θ)/β of channel AF3, with observed values approximately being 6.491 μV2/Hz, 8.388 μV2/Hz, and 8.651 μV2/Hz under CO_2 levels of 800 ppm, 1800 ppm, and 3500 ppm, respectively. Channel FC4 also exhibited significant differences due to CO_2 levels in both the θ/β ($F_{(2, 144)}$ = 4.988, p = 0.008, η^2 = 0.460) and (α+θ)/β ($F_{(2, 144)}$ = 4.712, p = 0.011, η^2 = 0.476) during the entire driving session. The interaction between the CO_2 and body odor also led to the significant difference of the (α+θ)/β ($F_{(2, 144)}$ = 5.271, p = 0.006, η^2 = 0.471) at Channel FC4.

Table 4. Two-way ART ANOVA of ratio indices of bands PSD at different CO_2 levels and environments with or without body odor across the driving sessions

Driving session	Source	Feature	Channel	Sum of Squares	df	Mean Square	F	Sig. (*p*)	Partial Eta Squared
Entire	CO_2	(α+θ)/β	AF3	14011.64	2	7005.819	5.235	0.007**	0.810
Entire	CO_2	θ/β	AF3	12694.13	2	6347.066	4.722	0.011*	0.801
Entire	CO_2	(α+θ)/β	FC4	12839.89	2	6419.944	4.988	0.008**	0.460
Entire	Interaction	(α+θ)/β	FC4	13133.45	2	6566.723	5.271	0.006**	0.471
Entire	CO_2	θ/β	FC4	11825.92	2	5912.96	4.712	0.011*	0.476
Single-task	CO_2	(α+θ)/β	AF3	12027.78	2	6013.89	4.754	0.010*	0.873

Note: “Interaction” denotes the interaction between the CO_2 and body odor. * denotes *p* value less than 0.05, ** denotes *p* value less than 0.01

Single-task driving session

During the single-task driving session, examining various ROI the ANOVA revealed no significant effects of CO_2 on the band power ratio indices. Similarly, the presence of body odor did not exert a statistically significant influence on the ratio indices of bands PSD in any of the ROI across the various driving conditions. Ratios as θ/β and (α+θ)/β, also did not show significant differences attributable to either the presence of body odor or the interactive effect of CO_2 and body odor by examining different ROI. However, in examining various channel, specifically, channel AF3 demonstrated a significant difference in the (α+θ)/β ratio, attributable to CO_2 levels ($F_{(1, 144)} = 4.754$, $p = 0.010$, $\eta^2 = 0.873$). This suggests that CO_2 concentration significantly altered the mean value of the (α+θ)/β ratio of channel AF3, with observed values approximately being 6.528, 8.325, and 8.232 $\mu V^2/Hz$ under different CO_2 conditions of 800 ppm, 1800 ppm and 3500 ppm, respectively.

Dual-task driving session

For the integrated dual-task driving session, either in examining various ROI or channels, neither bands' PSD nor ratios was significantly affected due to the CO_2 or the presence of the body odor.

We also explore the influence of varying CO_2 levels and the presence of body odor on ratio indices of bands PSD during N-back tasks of varying difficulty. Figure 5 shows the brain topography of ratio index (α+θ)/β during the dural-task session in various conditions. Figures 6 and 7 display heatmaps showing the p-value of EEG ratio indices across various brain ROIs and channels during different N-back tasks under assorted conditions.

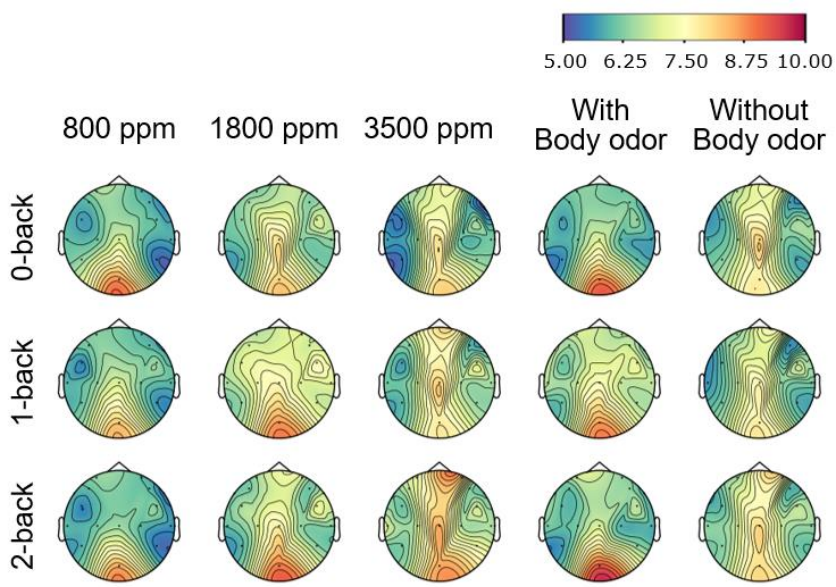


Fig. 5. Brain topography of (α+θ)/β during the dural-task session in various conditions

During the 0-back task, the results in Figure 6 and 7 indicated the body odor led to significant difference to the ratios in different ROI or channels. But it was hard to find the effect due to the CO_2 or the interaction between the CO_2 and body odor.

During 1-back task, the results we got were similar to the results during the 0-back task. The ANOVA did not reveal the significant differences by ratio indices in these measures across *different CO_2 levels of the all brain during 1-back task. In Figure 7, the ratios between the bands exhibited uniformity across different N-back tasks by channels. The channel CP3 indicated the difference due to the CO_2 during the 1-back task by the (α+θ)/β and θ/β. But the body odor led to significant differences to the ratios include (α+θ)/β and θ/β during the 1-back in different regions or channels. Furthermore, the two-way ART ANOVA results show there was no significant interaction between CO_2 and body odor on band ratios compared by regions or individual channels during 1-back task.*

For the 2-back task, when we compared the results between the different environments conditions by the ratios in regions or channels (Figure 6 and 7), the ANOVA revealed the only significant differences by (α+θ)/β and θ/β in these measures across different CO_2 levels of the all brain during 2-back task. In different conditions with or without the presence of body odor, the ratios (α+θ)/β and θ/β indicated the great difference during the 2-back task. The interaction between the CO_2 and body odor had no effect on the ratios from EEG signals. In the Figure 6, we can also find the significant difference of the ratios (α+θ)/β and θ/β due to the body odor at the channels corresponding to the regions.

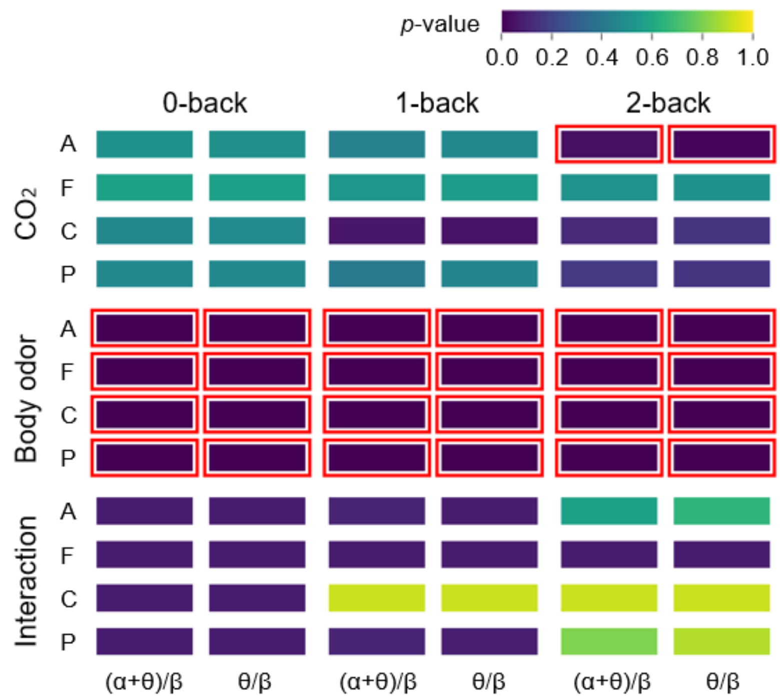


Fig. 6. *p*-value heatmap of EEG ratio indices across various brain ROIs during different N-back tasks under various conditions. Each column corresponds to a specific N-back task complexity (0-back, 1-back, 2-back from left to right). The x-axis labels represent the different EEG features assessed, while the y-axis labels denote the distinct ROIs. "Interaction" is the interactive effect between CO_2 and body odor. "A" denotes all regions of brain, "F" denotes frontal region of brain, "C" denotes central region of brain, and "P" denotes parietal region of brain. The color scale on the right denotes p-value ranges, with the red-framed boxes highlighting statistically significant changes where $p < 0.05$.

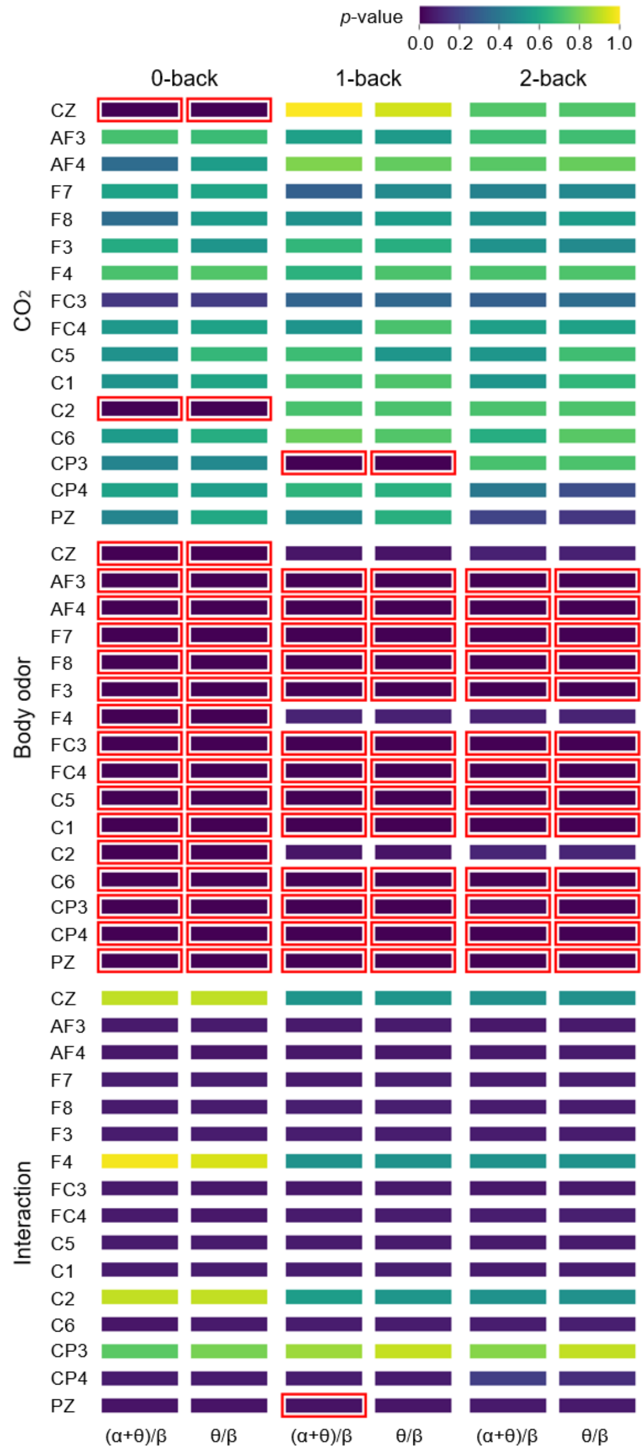


Fig. 7. *p*-value heatmap of EEG ratio indices across various channels during different N-back tasks under various conditions. Each column corresponds to a specific N-back task complexity (0-back, 1-back, 2-back from left to right). The x-axis labels represent the different EEG features assessed, while the y-axis labels denote the distinct ROIs. “Interaction” is the interactive effect between CO_2 and body odor. The color scale on the right denotes p-value ranges, with the red-framed boxes highlighting statistically significant changes where $p < 0.05$.

fNIRS measurement

Entire driving session

The analysis of fNIRS data concentrated on the dynamics of HbO and HbR across various ROI during distinct driving sessions, including single-task, dual-task, and the entire driving session. A two-way ART ANOVA was employed to assess the effects of CO_2 concentration, body odor and their interaction on these fNIRS measurement. Despite the comprehensive analysis across different ROIs and channels for each driving session, our findings indicated that neither the CO_2 levels nor the presence of body odor significantly influenced the statistics of HbO and HbR. Therefore, the detailed ANOVA results are not presented due to insignificance.

For the single-task driving session, either in examining various ROI or channels, neither fNIRS feature was significantly affected due to the CO_2 or the presence of the body odor.

Dual-task driving session

Table S4 and Table 5 illustrate the variations in cortical brain activation across fNIRS ROIs under varying experimental conditions, namely different CO_2 levels and the presence or absence of body odor. In the 0-back task, a significant response to CO_2 levels was observed in the beta of HBR at channel 3. The mean values were -2.127e-6 µM at 800 ppm, 9.930e-7 µM at 1800 ppm, and 6.134e-6 µM at 3500 ppm CO_2. This finding is substantiated by statistical analysis, revealing significant variance ($F_{(1, 144)}$ = 4.545, p = 0.012, η^2 = 0.670). In the 1-back task, the interaction of CO_2 levels and body odor significantly influenced both HbO concentrations at channel 6 and HbR concentrations at channel 7. The mean HbO values were 7.137e-6, 9.054e-6, and -1.716e-6 µM, while HbR means were -2.395e-6, 2.406e-6, and 2.177e-6 µM across the three CO_2 conditions. The statistical analysis showed significant effects for HbO concentration at channel 6 ($F_{(1, 144)}$ = 4.588, p = 0.012, η^2 = 0.674) and for HbR concentration at channel 7 ($F_{(1, 144)}$ = 5.435, p = 0.005, η^2 = 0.789). During the 2-back task, HbT concentration at channel 7 exhibited significant variability in response to CO2 levels, with mean values of -9.356e-6 µM at 800 ppm, 1.612e-6 µM at 1800 ppm, and 7.929e-6 µM at 3500 ppm CO_2. The statistical analysis highlighted a notable effect of CO_2 on HbT concentration ($F_{(2, 144)}$ = 4.929, p = 0.009, η^2 = 0.686). It's important to note that while no significant differences in HbO or HbR concentration were found across the ROI during the 2-back task, the distinct impact of CO_2 on HbT concentration underscores the varied hemodynamic responses under these experimental conditions.

Table 5. Two-way ART ANOVA of fNIRS features at different CO_2 levels and environments with or without body odor during N-back tasks

Driving session	**Source**	**Value**	**Feature**	**Channel**	**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig. (*p*)**	**Partial Eta Squared**
1-back	Interaction	HbO	conc	6	14115.64	2	7057.82	4.588	0.012*	0.674
1-back	Interaction	HbR	conc	7	16613.04	2	8306.52	5.435	0.005**	0.789
2-back	CO_2	HbT	conc	7	14835.18	2	7417.591	4.929	0.009**	0.686

Note: "Interaction" denotes the interaction between the CO_2 and body odor. * denotes p value less than 0.05, ** denotes p value less than 0.01

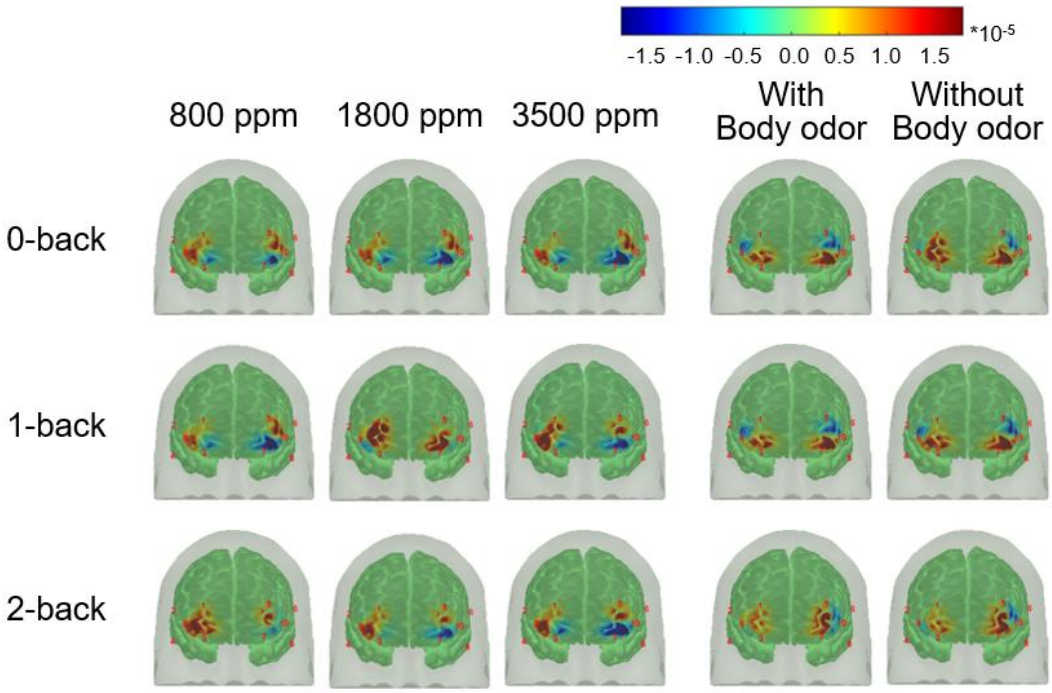


Fig. 8. Brain topography of HbO concentration during dual-task session in various conditions

Discussion

Effect of CO_2 and body odor

Our study marks a significant foray into the combined use of EEG and fNIRS to examine the effects of CO_2 levels and body odor on brain activity during driving. This innovative, multimodal neuroimaging method offers a nuanced view of how environmental factors interact with cognitive states. While the fNIRS measurements revealed subtle differences across various CO_2 and body odor conditions, the EEG data suggested more pronounced changes in band PSD or ratio indices during different driving sessions, thereby providing insights into the brain's response to environmental changes.

Across the different driving task sessions, EEG band PSD and ratios indices at some channels were affected by CO_2 or the presence of body odor. Specifically, the observed alterations in the δ and across entire or single-task driving session highlight the potential shifts in cognitive states due to the body odor. Alterations in specific EEG frequency bands, such as θ and α waves, are widely accepted recognized indicators as one of the valid indicators of objective sleepiness, relaxed states, or wakefulness (Borghini et al., 2014; Buckelew et al., 2009; Klimesch, 1999). Furthermore, an increase in relative β band power has been associated with arousal and stress (Kuo et al., 2016; J. Zhang et al., 2021). In previous study, Snow et al. (2018) used EEG to assess sleepiness and suggested increased susceptibility to CO_2 at ~2700 ppm in sleep-deprived individuals. However, they found no significant EEG changes between normal and high CO_2 conditions using repeated measures ANOVA. Conversely, Zhang et al. (2021) observed that higher CO_2 levels (around 5000 ppm) significantly increased EEG relative β power, along with changes in breathing wave amplitude and heart rate variability during Multi-Attribute Task Battery tasks. Our findings of decreased β power and increased θ power in high CO_2 conditions align with these studies (Jin et al., 2022). The variation in $(\alpha+\theta)/\beta$ ratios, with higher values potentially indicating a more relaxed or drowsy state (Angelidis et al., 2016), and lower values suggesting increased alertness, adds more evidence to our understanding of cognitive states during driving. The ratios increase the power than the using of the bands PSD. Interestingly, our findings showed more pronounced changes in ratio indices than in PSD values at some channels, indicating that ratios might be more sensitive indicators of cognitive state changes due to the CO_2 level.

Compared to the results from dual-task driving session and driving during various N-back tasks, the EEG ratio indices were significantly affected by body odor condition (presence vs. absence of body odor) during the specific N-back task but not the aggregated dual-task driving. Body odor's impact was particularly evident in the N-back task sessions, altering the PSD of the δ band across specific channels. The δ band in the regions are mental tasks are associated with functional cortical deafferentation, or inhibition of the sensory afferences that interfere with internal concentration (Dimitriadis et al., 2010). Besides, δ waves may be involved in certain cognitive processes, such as understanding complex tasks or problems, though this is less well understood and an area of ongoing research (Harmony, 2013). This finding underscores the role of δ band in attention performance and suggests a sensory-specific response to olfactory stimuli. For the ratio indices, $(\alpha+\theta)/\beta$ and θ/β established the significant difference of different brain regions across the specific N-back tasks due to the body odor. The ratio index $(\alpha+\theta)/\beta$ was lower in the condition with body odor, indicating increased alertness. Concurrently, with body odor, a lower θ/β ratio was associated with an increase in stimulus-driven attention and an enhanced ability of the subjects to concentrate. We also analyze potential interactive effects between CO_2 and body odor on EEG signal change during the various driving session. There was no significant difference generated due to the interaction during the N-back tasks.

During the driving sub-sessions, we could find the ratio indices $(\alpha+\theta)/\beta$ and θ/β were significantly affected by the body odor and even the interaction between CO_2 and body odor across most of the brain regions. The different driving task sessions had no significant difference while the driving sub-sessions had.

Although our ANOVA results did not indicate significant differences in band ratios arising from the various CO_2 levels, brain topography data (Figure 9) during dual-task sessions revealed discernible differences between low and higher CO_2 conditions. Post-hoc analyses supported the subtle but existing effect of CO_2 on cognitive state during driving with addition cognition task. Earlier research has shown that high CO_2 levels decrease γ, β, and α brainwave powers (Driver et al., 2016; Hall et al., 2011) while increasing δ and θ wave powers (D. Wang et al., 2015; Xu et al., 2011), possibly indicating the physiological impact of hypercapnia, hypoxia, or increased sympathetic nerve activity. It's also important to consider that these EEG alterations could be influenced by heightened sympathetic nerve activity.

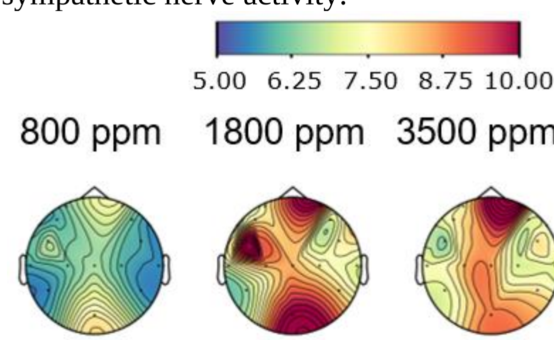


Fig. 9. EEG brain topography of $(\alpha+\theta)/\beta$ of entire driving session in different CO_2 levels

In contrast to the EEG findings, the fNIRS data failed to demonstrate distinct differences across the conditions. This discrepancy may stem from the inherent difficulties associated with identifying subtle variations in hemodynamic responses, or it could be related to fNIRS's particular sensitivity to various cognitive and environmental factors. Further investigation is needed to elucidate these aspects.

Effects of N-back task difficulty

The results section 3.2.1.4, 3.2.2.4, and 3.3.2 presents the analysis to investigate whether N-back task difficulty alters the relationship between CO_2 (or body odor) and brain signal measurement. Figure 5 displays the p-value of band ratios for the 0-back, 1-back, and 2-back tasks under different CO_2 or body odor conditions. The results show that body odor had a significant impact on the band ratios indices for 0-back, 1-back, or 2-back tasks, particular the 0-back. Nevertheless, no significant difference in ANOVA was found for any EEG signal due to the N-back task difficulty. The finding suggests there were no effects of task difficulties in the relationship between CO_2 exposure and brain activity measured from the EEG. Moreover, band ratio indices were significantly different between the conditions with and without body odor, for distinct difficulty level N-back tasks. In the study conducted by Wang et al (2024), it only show that CO_2 had a significant impact on response accuracy only for 1-back or 0-back tasks. When the task (e.g., 2-back) was hard, CO_2 did not exert any impact on response accuracy or reaction time.

We found the features of fNIRS measurement have significant differences due to the CO_2 or body odor at a few channels during different levels of the N-back task. In previous studies fNIRS can show the workload due to the different N-back tasks (write more things here and the citation). But the ANOVA test with using the fNIRS signal features did not find significant difference due to the N-back task difficulty level. The potential reason is the cognition on driving mitigate the workload of N-back tasks measured by the fNIRS.

Time course of EEG and fNIRS

We did the comparison by using ANOVA tests to exam the effects of CO_2 levels, body odor, and the interaction between them on ratio indices of bands PSD, and haemoglobin concentration across the driving sub-sessions. The results can be insightful to understand the effect of exposure time.

Figure 10 displays the p-values heat map from ANOVA tests examining the effects of CO_2 levels, body odor, and the interaction between them on EEG ratio indices by ROI across the separated driving sub-sessions. These differences were predominantly influenced by body odor across various regions during distinct driving sub-sessions. Furthermore, the interaction between CO_2 levels and body odor resulted in notably difference on the ratios of $(\alpha+\theta)/\beta$ and θ/β. However, CO_2 levels alone did not significantly influence these ratios. In addition, a channel-based comparison, as detailed in the Figure S3 had the similar results. This variability in response to environmental factors underscores the sensitivity of EEG measures to external environmental stimuli, particularly during complex tasks like driving with another secondary task.

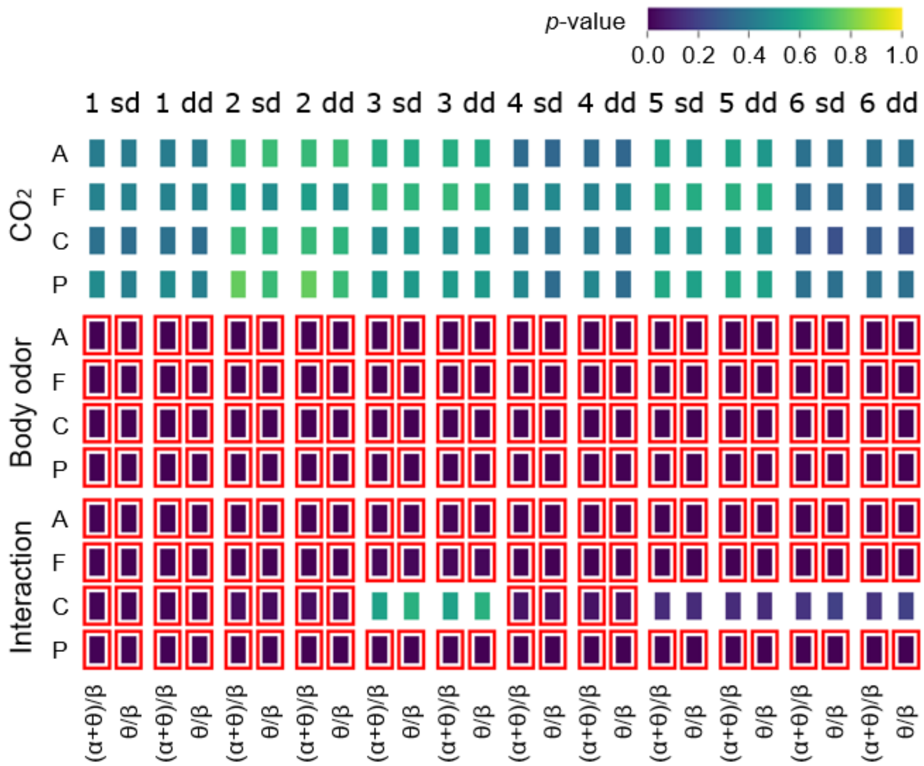


Fig. 10. *p*-value heatmap of EEG ratio indices alterations across various brain regions of interest (ROIs) during separated driving sub-sessions under conditions of CO_2 (top panel), presence of body odor (middle panel), and their interaction (bottom panel). “Interaction” is the interactive effect between CO_2 and body odor. “A” denotes all regions of brain, “F” denotes frontal region of brain, “C” denotes central region of brain, and “P” denotes parietal region of brain. Each column corresponds to a separated driving sub-session. The x-axis labels represent the different EEG ratio indices assessed, while the y-axis labels denote the distinct ROIs. The color scale on the right denotes p-value ranges, with the red-framed boxes highlighting statistically significant changes where $p < 0.05$.

Figure S4 (in the appendix) displays the p-values heat map from ANOVA tests examining the effects of CO_2 levels, body odor, and the interaction between them on fNIRS features by ROI and channels across the driving sub-sessions. The analysis emphasized the influence of the exposure time as the factor on cerebral hemodynamic. The results about differentiating the effect of the time-on-task indicate the CO_2 had effect on the HbR concentration as the exposure time increasing. The observed variations in HbO, HbR, and HbT concentrations across driving sub-sessions and brain regions highlight the intricate relationship between physiological processes and environmental stimuli.

The ANOVA test which compares the features in driving sub-sessions found no significant difference. In the study (C. Wang et al., 2024), there was a significant difference in mean speed between 800 ppm and 3500 ppm CO_2 from 15 to 18 min, but not in the time window between 9 and 12 min. The results are corresponding found from the fNIRS signal which had the most different in the post separated driving subsections.

Limitation and recommendation

In this research, we employed EEG and fNIRS to investigate the impact of elevated CO_2 levels and body odor on brain activity. Our findings revealed variable effects, highlighting the complex interplay between environmental factors and neurophysiological responses. The heterogeneity in results may stem from several factors, including the limited sample size, the specific devices utilized for brain signal acquisition, variations in the intensity and duration of CO_2 and body odor exposure, and the use of a driving simulator in the experimental design. These elements collectively contribute to the observed variability in the study's outcomes.

The participants primarily comprised young, inexperienced individuals, potentially limiting the variability in driving performance observed. Notably, a learning effect was evident. It presents a limitation and an area for future research, particularly in understanding age-related differences in sensitivity to environmental factors. The younger individuals might better compensate for potential sleepiness or cognitive declines associated with poor air quality, indicating a need to increase the sample size to enhance statistical power and include a more diverse demographic, considering age differences to gain a comprehensive understanding of the impacts of CO_2 and body odor.

Another limitation was the omission of short separation channels in the fNIRS data collection, which are crucial for distinguishing physiological factors from brain activities. The environmental factors might have confounded the EEG and fNIRS signals. The fNIRS device used did not capture signals from these short separation channels, which are known to collect physiological noise (Yücel et al., 2021). Furthermore, it is crucial to acknowledge potential data inaccuracies stemming from subject movement or hair interference with electrodes.

The highest CO_2 concentration tested was 3500 ppm, potentially insufficient to significantly affect brain activity measured by EEG or fNIRS, especially during short exposure periods. Previous research (Jap et al., 2009; Thiffault & Bergeron, 2003; Ting et al., 2008) has highlighted the influence of exposure duration on driving performance and brain activity. Another study found the EEG was significantly affected by a short exposure to the 40,000 ppm CO_2 concentration condition (Jin et al., 2022). The CO_2 level used in their study was 10 times than the highest one we used. Future studies could explore longer exposure times and/or higher CO_2 concentrations to better assess their impact on driving performance. However, it is important to note that the CO_2 levels we used in this study are relevant to real world settings. Consequently, future studies should consider longer exposure durations and higher CO_2 concentrations, while ensuring relevance to real-world settings.

The study's use of a simulated driving task might limit ecological validity, as the relatively straightforward freeway scenario may not effectively distinguish between drivers of varying skill levels. Future research could employ more complex, yet realistic, driving scenarios to assess the impacts of CO2 and body odor more accurately.

Additionally, this study did not regulate the body odor exposure level or identify specific body odor compounds. Subsequent research could adopt a more controlled approach, maintaining consistent body odor levels in the cabin, to thoroughly investigate its effects on driving performance.

Lastly, this study contributes to understanding the effects of CO_2 and body odor on EEG and fNIRS measurement during driving, using various theoretical and methodological approaches. We found that body odor influenced EEG band ratios, laying groundwork for future research aimed at developing technological interventions in construction safety. These findings underscore the potential of using neurophysiological data in construction safety to evaluate mental effort and risk compensation among workers.

Conclusions

Our study conducted an exploration into the impact of environmental factors within a vehicle cabin—specifically, varying levels of CO_2 and the presence of body odor—on drivers' physiological states. Using advanced neuroimaging techniques, such as EEG and fNIRS, we were able to capture the brain's nuanced response to these varying environmental conditions.

The investigation revealed that the presence of body odor significantly influenced EEG band ratios indices, the indication of electrical activity changes in the brain that can reflect alterations in cognitive states during driving. This effect underscores the potent impact of body odor on cognitive processes essential for safe driving. Specifically, we found that the ratio index $(\alpha+\theta)/\beta$ was lower in the condition with body odor, indicating increased alertness. Concurrently, a lower θ/β ratio with body odor was associated with increased stimulus-driven attention and an enhanced ability of the subjects to concentrate, which are crucial for driving safety. Contrastingly, CO_2 levels did not demonstrate a direct influence on EEG band PSD or ratio indices, suggesting a more complex interaction with cognitive functions that may not directly translate to altered brain states detectable through our neuroimaging modalities. The notable changes in EEG signal patterns in response to body odor point to potential shifts in mental states, even if not directly correlated with performance outcomes in the driving tasks. It also suggests that even subtle changes in environmental air quality can have cognitive implications, which are crucial for tasks requiring high levels of concentration and decision-making during driving. However, fNIRS data displayed a different picture. The fNIRS measurements did not show a significant impact of CO_2 or body odor on hemodynamic responses, suggesting that these environmental factors do not notably affect blood flow changes associated with brain activity.

In summary, our research highlights that body odor within a vehicle cabin can significantly impact cognitive states as detected by EEG, whereas CO_2 levels do not show a direct effect through the neuroimaging techniques employed. These insights contribute to the broader understanding of how in-vehicle environmental quality can influence driver safety, emphasizing the importance of considering air quality in the design of vehicle cabins. Future studies should aim to explore the implications of these findings across a wider demographic to fully grasp the potential safety implications for all drivers.

Declaration of competing interest

The authors report no potential conflicts of interest.

Acknowledgements

We thank the participants for their participation in the experiment, and the research technician (Russell Lang) for their assistance. The research is supported by Worcester Polytechnic Institute.

Appendix

G power software

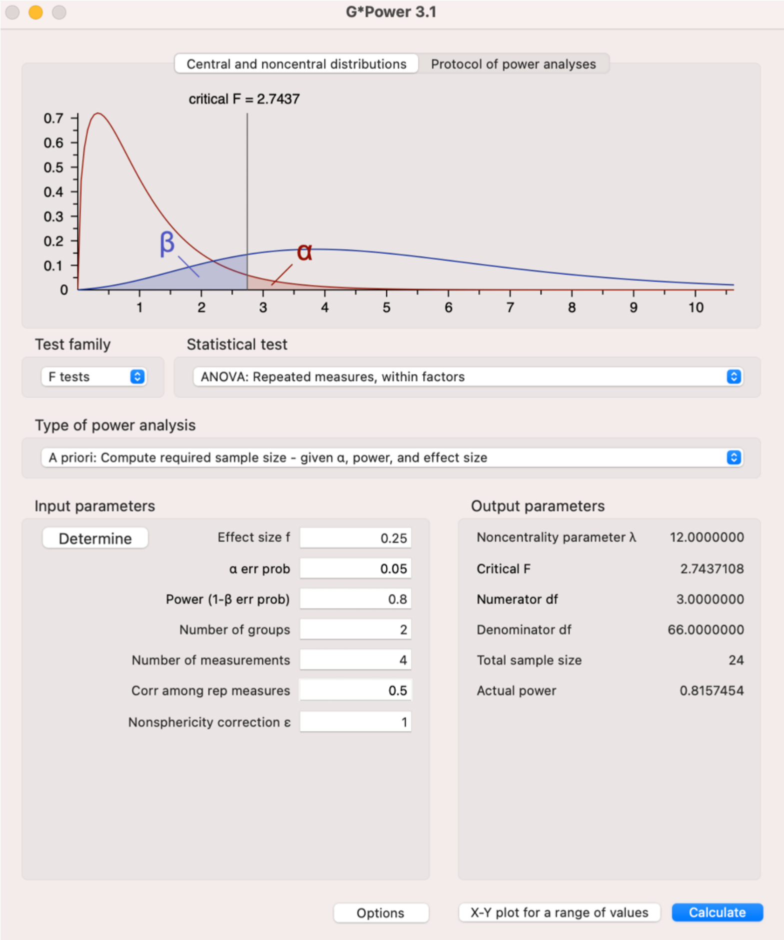


Fig. S1. Settings for power analysis in G*power

CO_2 concentration

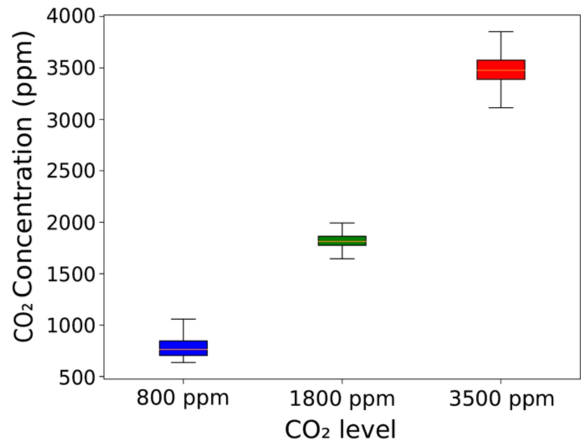


Fig. S2. CO_2 concentration (ppm) in the car cabin at three levels

EEG measurements

Table S1. Descriptive statistics for EEG PSD of different frequency band under different CO_2 levels and environments with or without body odor during the entire driving session

Driving session	Feature	Channel	Conditions	M ($\mu V^2/Hz$)	SD	N
Entire	δ	PZ	800 ppm CO_2	6.132	12.484	46
			1800 ppm CO_2	10.704	31.016	43
			3500 ppm CO_2	10.476	23.553	40
			With the body odor	9.591	16.562	64
			Without the body odor	8.425	28.589	65
			Total	9.003	23.324	129
Single-task	δ	C1	800 ppm CO_2	5.888	13.652	45
			1800 ppm CO_2	5.405	10.323	42
			3500 ppm CO_2	8.219	13.189	38
			With the body odor	8.829	15.281	62
			Without the body odor	4.077	8.265	63
			Total	6.434	12.439	125

Note: "M" denotes mean, "SD" denotes standard deviation, "N" denotes the total number of driving sessions in a certain condition.

Table S2. Descriptive Statistics for EEG PSD of different frequency band at different CO2 levels and environments with or without body odor during N-back tasks

Driving session	Feature	Region	Conditions	M($\mu V^2/Hz$)	SD	N
0-back	δ	FC3	800 ppm CO_2	1.479	3.329	39
			1800 ppm CO_2	2.040	1.038	30
			3500 ppm CO_2	3.447	9.749	29
			With the body odor	2.828	7.765	47
			Without the body odor	1.686	4.057	51
			Total	2.233	6.116	98
0-back	δ	FC4	800 ppm CO_2	1.103	2.803	39
			1800 ppm CO_2	0.803	1.511	30
			3500 ppm CO_2	2.737	6.027	29
			With the body odor	2.015	4.918	47
			Without the body odor	1.015	2.489	51
			Total	1.495	3.862	98
0-back	δ	PZ	800 ppm CO_2	1.908	5.325	39
			1800 ppm CO_2	0.989	2.680	30
			3500 ppm CO_2	3.529	9.803	29
			With the body odor	3.113	8.303	47
			Without the body odor	1.179	4.029	51
			Total	2.106	6.481	98
1-back	δ	PZ	800 ppm CO_2	2.110	5.640	39
			1800 ppm CO_2	0.851	2.039	30
			3500 ppm CO_2	4.838	12.368	29
			With the body odor	3.825	10.273	47
			Without the body odor	1.340	4.131	51
			Total	2.532	7.772	98
1-back	δ	C1	800 ppm CO_2	3.281	11.890	39
			1800 ppm CO_2	1.856	4.095	30
			3500 ppm CO_2	5.457	10.744	29
			With the body odor	3.525	8.473	47
			Without the body odor	3.455	10.938	51

			Total	3.489	9.783	98
1-back	θ	PZ	800 ppm CO_2	0.359	0.905	39
			1800 ppm CO_2	0.160	0.420	30
			3500 ppm CO_2	0.721	1.792	29
			With the body odor	0.588	1.500	47
			Without the body odor	0.236	0.707	51
			Total	0.405	1.162	98
2-back	δ	FC4	800 ppm CO_2	1.652	4.620	39
			1800 ppm CO_2	1.297	2.905	30
			3500 ppm CO_2	3.770	8.768	29
			With the body odor	2.990	7.560	47
			Without the body odor	1.415	3.540	51
			Total	2.170	5.848	98
2-back	δ	C1	800 ppm CO_2	2.972	10.097	39
			1800 ppm CO_2	2.672	6.909	30
			3500 ppm CO_2	7.130	18.349	29
			With the body odor	5.074	14.701	47
			Without the body odor	3.223	10.038	51
			Total	4.111	12.462	98

Note: “M” denotes mean, “SD” denotes standard deviation, “N” denotes the total number of driving sessions in a certain condition.

Table S3. Descriptive Statistics for ratio indices of bands PSD under different CO_2 levels and environments with or without body odor across the driving sessions

Driving session	**Feature**	**Channel**	**Conditions**	**M ($\mu V^2/Hz$)**	**SD**	**N**
Entire	(α+θ)/β	AF3	800 ppm CO_2	6.491	3.143	46
			1800 ppm CO_2	8.388	3.926	43
			3500 ppm CO_2	8.651	3.706	40
			With the body odor	7.884	3.870	64
			Without the body odor	7.704	3.548	65
			Total	7.793	3.698	129
Entire	θ/β	AF3	800 ppm CO_2	4.306	2.599	46
			1800 ppm CO_2	5.623	3.283	43
			3500 ppm CO_2	5.964	3.232	40

			With the body odor	5.321	3.205	64
			Without the body odor	5.197	3.019	65
			Total	5.259	3.101	129
Entire	(α+θ)/β	FC4	800 ppm CO_2	6.577	4.854	46
			1800 ppm CO_2	10.648	11.011	43
			3500 ppm CO_2	6.341	3.934	40
			With the body odor	7.411	5.747	64
			Without the body odor	8.304	8.972	65
			Total	7.861	7.530	129
Entire	θ/β	FC4	800 ppm CO_2	4.674	4.231	46
			1800 ppm CO_2	8.194	9.821	43
			3500 ppm CO_2	4.416	3.311	40
			With the body odor	5.324	5.088	64
			Without the body odor	6.203	7.915	65
			Total	5.767	6.653	129
Single-task	(α+θ)/β	AF3	800 ppm CO_2	6.528	3.058	45
			1800 ppm CO_2	8.325	3.997	42
			3500 ppm CO_2	8.232	3.260	38
			With the body odor	7.572	3.622	62
			Without the body odor	7.726	3.472	63
			Total	7.650	3.533	125

Note: "M" denotes mean, "SD" denotes standard deviation, "N" denotes the total number of driving sessions in a certain condition.

fNIRS measurement

Table S4. Descriptive statistics for fNIRS features at different CO_2 levels and environments with or without body odor during N-back tasks

Driving session	Source	Feature	Channel	Conditions	M (μM)	SD	N
1-back	CO_2&Body odor	HBO concentration	6	800 ppm CO_2	7.137e-6	2.913e-5	45
				1800 ppm CO_2	9.054e-6	2.771e-5	45
				3500 ppm CO_2	-1.716e-6	4.703e-5	48
				With the body odor	3.102e-6	3.100e-5	68

				Without the body odor	6.218e-6	4.055e-5	70
				Total	4.683e-6	3.606e-5	138
1-back	CO_2&Body odor	HBR concentration	7	800 ppm CO_2	-2.395e-6	2.617e-5	45
				1800 ppm CO_2	2.406e-6	3.266e-5	45
				3500 ppm CO_2	2.177e-6	2.585e-5	48
				With the body odor	3.151e-6	2.244e-5	68
				Without the body odor	1.194e-6	3.305e-5	70
				Total	7.607e-7	2.823e-5	138
2-back	CO_2	HBT concentration	7	800 ppm CO_2	-9.356e-6	3.642e-5	45
				1800 ppm CO_2	1.612e-6	3.604e-5	45
				3500 ppm CO_2	7.929e-6	5.226e-5	48
				With the body odor	5.549e-6	3.495e-5	68
				Without the body odor	4.395e-6	5.068e-5	70
				Total	4.964e-6	4.349e-5	138

Note: “M” denotes mean, “SD” denotes standard deviation, “N” denotes the total number of driving sessions in a certain condition

Time course of EEG and fNIRS

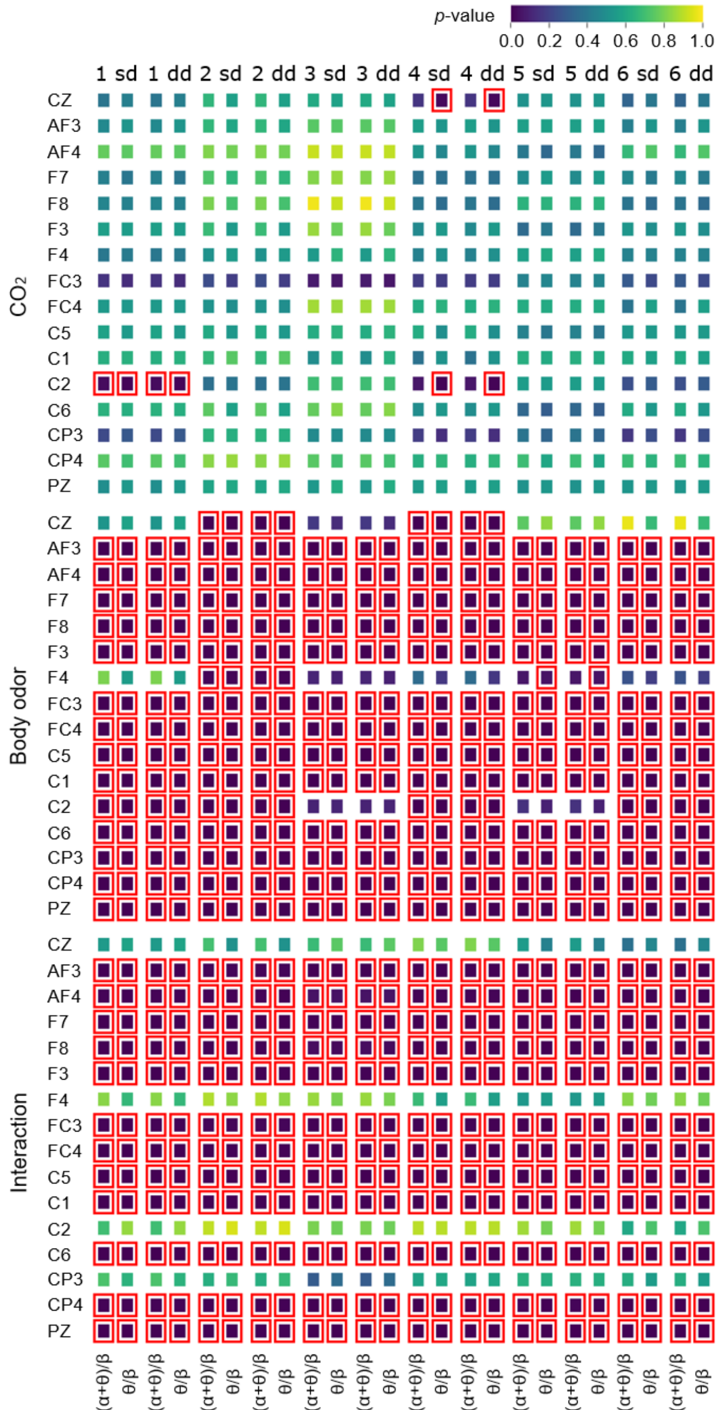


Fig. S3. *p*-value heatmap of EEG ratio indices alterations across various channels during separated driving sub-sessions under conditions of CO_2 (top panel), presence of body odor (middle panel), and their interaction (bottom panel). "Interaction" is the interactive effect between CO_2 and body odor. Each column corresponds to a separated driving sub-session. The x-axis labels represent the different EEG ratio indices assessed, while the y-axis labels denote the distinct channels. The color scale on the right denotes p-value ranges, with the red-framed boxes highlighting statistically significant changes where $p < 0.05$.

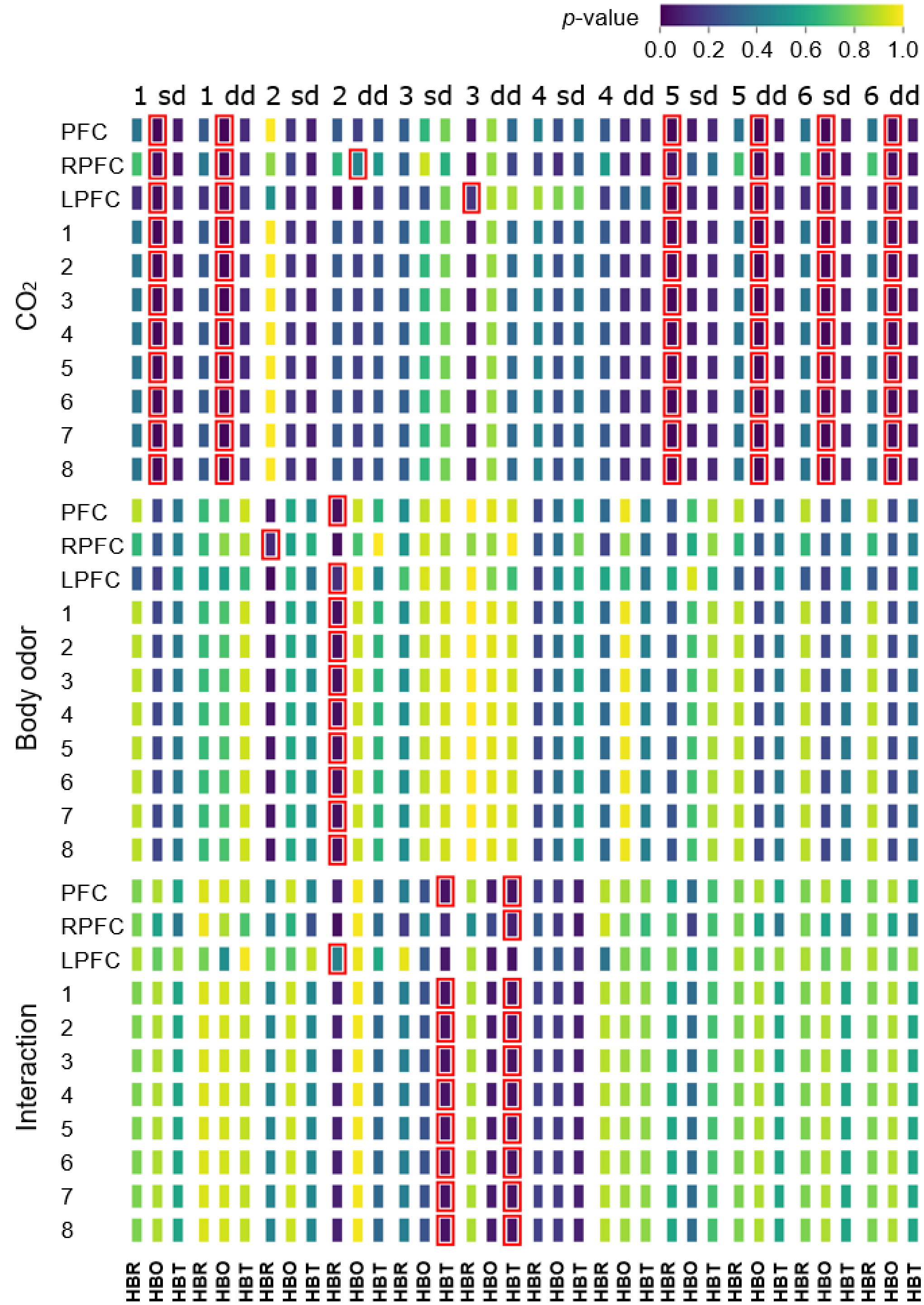


Fig. S4. *p*-value heatmap of fNIRS hemoglobin concentration across various channels during separated driving sub-sessions under conditions of CO_2 (top panel), presence of body odor (middle panel), and their interaction (bottom panel). "Interaction" is the interactive effect between CO_2 and body odor. Each column corresponds to a separated driving sub-session. The x-axis labels represent the different EEG ratio indices assessed, while the y-axis labels denote the distinct channels. The color scale on the right denotes p-value ranges, with the red-framed boxes highlighting statistically significant changes where $p < 0.05$.

Appendix D

Paper D. Interactive effects of interior ambient light and temperature on thermal comfort and driving performance

Chao Wang[1*], John Elson[2], Yingzi Lin[3], Shichao Liu[1]

[1]*Civil, Environmental, and Architectural Engineering, Worcester Polytechnic Institute, Worcester, MA, USA*
[2]*The Ford Motor Company, MI, USA*
[3]*Intelligent Human Machine Systems Lab, Mechanical and Industrial Engineering Department, Northeastern University, Boston, MA, USA*

Keywords

Hue-heat hypothesis, Thermal environment, Lighting, Interactive effects, Thermal comfort, Driving and cognitive performance, Driving style recognition

Highlights

- Evaluated effects of three temperature settings and four interior lighting on drivers' cognitive and driving performance
- Measured drivers' working memory and reaction time through N-back tasks during driving
- Introduced a two-layer driving style recognition and predication by incorporating in-car temperature and light color condition
- Identified significance in influences of temperature on driving performance and environment perception during night driving
- Found no interactive effect between temperature and light color on night driving performance

Abstract

Interior ambient lighting has been applied in high-end vehicles to improve driving experience and emotion, owing to a favorable impact on drivers' perceptions of interior spaciousness and ability to control the vehicle interior environment. This study investigates the effects of interior ambient lighting and temperature on driving experience, focusing on their impact on drivers' perceptions of comfort, emotion, and performance. While the influence of these factors is well-documented in building environments, their interactive effects in the context of driving remain underexplored. Drawing on the hue-heat hypothesis—which suggests colors can influence temperature perception—this research explores how different lighting temperatures might affect drivers' thermal sensation and, by extension, their overall driving experience. We recruited and randomly assigned seventy-two licensed drivers without susceptibility to simulator sickness to one of three groups, each exposed to different temperatures (18°C, 23°C, and 28°C) representing slightly cool, neutral, and slightly warm environments, respectively. Participants undertook repeated driving tasks in a high-fidelity simulator under varying interior lighting conditions (red, blue, warm white at 2700 K, and cool white at 5000 K). Performance was assessed alongside secondary tasks to simulate real-world driving distractions. Post-task surveys gauged sleepiness, environmental satisfaction, task load, and emotional state. Additionally, the study introduces an innovative two-layer driving style recognition model that leverages in-car temperature and light color to predict driving behavior more accurately. The results highlight the significant role of temperature in influencing driving dynamics and environmental perception. Light color also affects thermal perception and comfort, albeit to a lesser extent. No definitive interactive effect between temperature and light color on driving performance metrics was observed. However, the

combined influence of temperature and lighting conditions significantly impacts driving style, suggesting a nuanced interplay of environmental factors in driving scenarios. This research underscores the importance of ambient environmental conditions in vehicle cabin design, with implications for enhancing driver comfort and efficiency. By providing insights into the psychological and physiological impacts of lighting and temperature, the study offers a valuable foundation for future automotive designs aimed at creating more comfortable and optimized driving environments.

Introduction

There has been extensive research exploring the "hue-heat hypothesis" in experimental psychology, applied psychology, and psychological ergonomics regarding the potential impact of colors on thermal comfort and sensation (Berry, 1961; Fanger et al., 1977; Huebner et al., 2016; Toftum et al., 2018; Winzen et al., 2014). These studies aimed to identify whether light or color with specific wavelengths can make a person feel warmer or cooler. Fanger et al. performed surveys on 16 subjects and found a temperature sensation difference of only 0.48 °C depending on whether a room was illuminated by blue or red light (Fanger et al., 1977). A study conducted in an aircraft cabin (Winzen et al., 2014) found that the color of lighting influenced the perception of indoor temperature, with yellow light making the room feel warmer than blue light. Huebner et al. stated that thermal perception varied significantly for correlated color temperature (CCT) values between 2700 K and 6500 K with warming and cooling cycles applied between 20 °C to 24 °C (Huebner et al., 2016). They also found that people wore more clothes under cold light than warm light. But conflicting results were reported in other studies. Toftum et al. identified that CCT influenced thermal sensation only in thermally neutral conditions but not when subjects felt slightly cool or warm, possibly because the body heat balance dominated the thermal response in those situations (Toftum et al., 2018). Some other studies primarily examined non-visual impacts of light on human circadian rhythms (Brainard et al., 2001) or solely on the effects of electric light color on physiological responses, measuring skin and core body temperatures without gathering subjective responses (te Kulve et al., 2016). Such interaction between light and thermal environment complicates the influence of the physical driving environment on drivers' comfort, emotion, and driving performance. Though existing research has reported their interactions in buildings, very few studies have been conducted to investigate the interactive effects on driving.

The vehicle cabin environment can impact driving performance because of the cognitive load during driving and the driver's physical state. Luxury vehicles have utilized interior ambient lighting to enhance the driving experience and emotional response (Park et al., 2016). Previous studies found that driving performance is closely related to several vehicle cabin factors, including thermal environment, lighting, acoustic, and air quality (Chowdhury, 2015; Morris & Pilcher, 2016; van Huysduynen et al., 2017; C. Wang et al., 2024). For instance, the correlated color temperature of light can affect reaction times and pupil sizes (Y. Liu et al., 2021). Research has indicated that temperature may significantly affect driving performance, which may be enhanced by maintaining a thermoneutral temperature within a vehicle (Daanen et al., 2003). Using traffic collision data, Hou et al. (2022) discovered that ambient temperatures were correlated with an increased risk of motor vehicle crashes in New York and Chicago. Further, driving performance can be influenced by the interior light of a car. The study demonstrated that interior ambient lighting, even in the driver's peripheral vision, can positively impact their perception of space, safety, functionality, and interior quality (Caberletti et al., 2010). Nazi et al. compared the subjects' driving performance at three different temperatures to evaluate the impact of thermal comfort (Chowdhury, 2015). They found a significant effect of temperature on speed variability. The results of the studies (Caberletti et al., 2010; van Huysduynen et al., 2017) indicated that ambient light had pleasant, informative and/or counteracting boredom on humans' experience. Interior lighting provides indirect illumination of the passenger compartment in the vehicle. It is significant because it offers an improved subjective impression and objective visual performance. It is unknown whether the hue-heat hypothesis still holds for driving. And if yes, to the extent drivers' visual and thermal comfort, emotion, and driving performance are affected by such interaction are rarely studied.

Although there has been some exploration of these interactions in buildings (Hygge & Knez, 2001a; Wu et al., 2020), the relationship between light and the thermal environment on drivers' performance in addition to thermal and light comfort remains relatively unexplored in the context of driving. Moreover, the outcomes in prior research on the impact of light color on environment satisfaction had conflict. To address the existing knowledge gap, we conducted the study in a simulated vehicle cabin mock-up to examine the interplay between light and temperature on drivers' visual and thermal comfort, as well as driving performance. In the realm of electric vehicles (EVs), energy efficiency is of paramount concern, with heating and cooling systems accounting for approximately 18% and 14% of the battery's energy capacity, respectively (Doyle & Muneer, 2019). Our study posits that optimizing light settings to broaden the range of thermally comfortable in-car temperatures could significantly lower the energy demands of these systems. This approach not only promises to enhance energy efficiency but also reduces the overall energy consumption of EVs, aligning with broader efforts to develop sustainable energy-saving practices for both industrial applications and daily life. The implications of achieving such energy savings are vast and varied, extending beyond vehicle manufacturing to potentially influence sectors such as aviation. By incorporating colored lighting as a factor in energy conservation strategies, we could significantly reduce operational costs and environmental impacts across multiple industries. Moreover, this research underscores the necessity of integrating lighting considerations into models of drivers' thermal comfort, thereby enriching our understanding of environmental factors' roles in vehicular settings.

Methodology

Participants

We recruited seventy-two participants, including fifty-two males, aged 18 to 32 years (Mean ± SD: 22.3 ± 1.69), with valid driving licenses from Worcester Polytechnic Institute (WPI) through email and poster advertisements. All participants completed a WPI's Institutional Review Board (IRB-22-0299)-approved consent form informing them of the procedures, risks, and responsibilities of the study. The interested participants were screened for simulator sickness before the final selection. A very small percentage of individuals (2% – 8%) may experience simulator sickness symptoms (a form of motion sickness) during the driving simulation, particularly when the simulation involves multiple curves and stops (Akinwuntan et al., 2005). We used the Simulator Sickness Questionnaire (SSQ) (Kennedy et al., 1993) which is widely adopted to measure the simulator sickness symptoms. It comprises 16 items that address subjective feelings of headache, nausea, and blurred vision. Subjects rated their feeling from 0 (none) to 3 (severe) in three to five minutes after the simulated driving. We removed six participants (original sample size of 78 participants) with adverse physiological and psychological reactions to the driving simulator from the study due to the simulator sickness. Finally, seventy-two young drivers met the criteria and participated in the formal experiment. To determine the appropriate sample size for our study, we performed a power analysis using G*Power software 3.1 (Fig. S1 in Appendix) (Faul et al., 2007). Since each subject experienced all four combinations of light conditions in one temperature, we treated the study as having four distinct conditions for the purpose of the power analysis. The calculated sample size was 19 using “ANOVA: Repeated measures, within factors” with effect size of 0.25 and power of 0.8.

Participants were instructed to refrain from consuming alcohol, nicotine, and caffeine on the day of the test and the preceding. They were also instructed to have enough sleep the night before the visit. The compensation was $15 per hour with a performance-based bonus of up to $15 to motivate participants to engage in the task.

Driving simulator and virtual scenario

We positioned the driving simulator within an environmental chamber designed to simulate a typical sedan car cabin, with a projection system that offers a 210° horizontal field of view, 70° for the forward view, and 70° each for the left and right window views. The simulator was operated using a Logitech G29, equipped with a force feedback steering wheel system that creates a lifelike sensation of steering, as well as a pedal set with brake and accelerator pedal. A foot-switch control pedal was installed to provide additional driver input for N-back tasks that will be described in Section 2.5.3. To create an immersive experience, we equipped an audio system to generate the sounds from car engines and traffic. The control computer with a GeForce GTX 770 GPU, an i7-9790 CPU, Windows 10 PRO Operating System, and 32 GB RAM was connected to three display projectors. We adjusted the driver’s seat to direct the driver’s focus toward the horizon line of the projected driving scenario.

We employed the Assetto Corsa videogame (Simulazioni, 2014) to execute driving scenarios and tasks. This software enabled monitoring of various vehicle dynamics and driving performance parameters. The driving tasks were conducted in a virtual environment that depicted a night desert view drive in LA Grand Canyons, based on real roads in California, which wind through the San Gabriel Mountain range, high above Los Angeles. Consisting of tight bends, parking areas, numerous junctions, turnouts, picnic areas, and fast sweepers are perfect for cruising or driving. Roads are fully signed and include real world distance signs, speed & warning signs, markings, guard rails, jersey barricades and multiple dynamic parked vehicles. The Main Version has a 42km main loop, and totals 47km with the additional small side roads and turnings. The driving scenario was set at night without weather disturbances such as fog, snow or rain. Each driving session lasted for at least 9 minutes with the same driving route. All the drivers executed the driving task in a basic night driving scenario (Figure 1) with an adjusted luminance level of 0.6 cd/m^2 from the projector screen for all experimental conditions since interior ambient lighting was deemed less effective during the day (Easa et al., 2010).

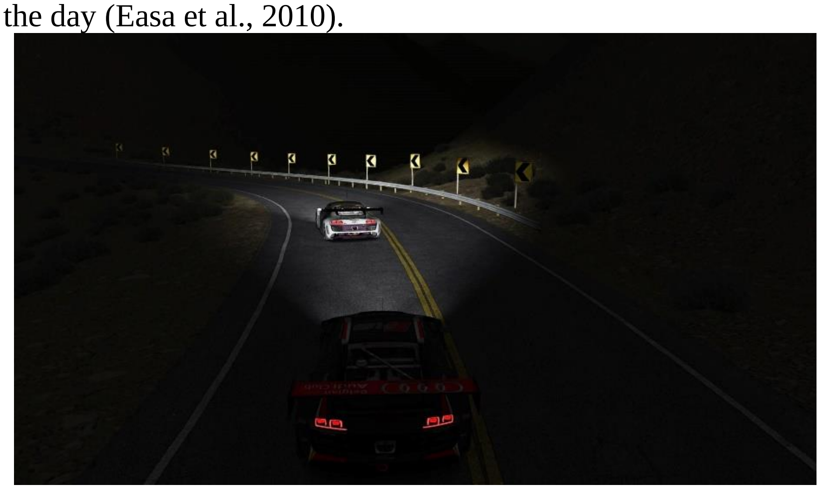


Fig. 1. Night Grand Canyon driving scenario

Vehicle cabin environment

We regulated the temperature and lighting condition as the environmental factors in the driving cabin and used a 3 x 4 factorial design to investigate the impact of environment on both driving performance and satisfaction. The temperature was maintained at 18 °C, 23 °C, or 28 °C by a centralized HVAC system, corresponding to slightly cold, neutral, and slightly warm conditions, respectively. The predicted mean vote (PMV) calculation specified in ASHRAE 55 (ANSI/ASHRAE, 2017) was used to determine the temperature based on driving conditions (1.5 met for driving, 0.39 clo), air speed (0.1 m/s), and relative humidity (50%). We examined four distinct interior lighting conditions: red, blue, warm white (2700 K), and cool white (5000 K) in this study. The LED strip lights were installed in four specific areas within the cockpit, the right door trim, foot space, center console, and left door trim. These were the best locations determined by previous research on this topic, as cited in references (Caberletti et al., 2010; Schellinger et al., 2006). The brightness of all four conditions in the driving cabin was maintained at around 1.5 lx at the driver's eye level. This level of illumination is unlikely to have a significant impact on contrast vision (Park et al., 2016).

The indoor conditions of the car cabin, including temperature, humidity, VOCs, lighting, color temperature (for passengers), CO_2, and PM2.5, were monitored. The ventilation rate of the car cabin was regulated to 18 air changes per hour (ach) when the car was traveling at speeds between 45-60 mph with a common AC recirculation setting (Hudda & Fruin, 2018). This ventilation rate maintained the CO_2 level at around 800 ppm, minimizing the potential negative impact of CO_2 accumulation on cognitive function (Satish et al., 2012a). The heat recovery ventilator (HRV) with a MERV 14 air filter was used to provide ventilation for the cabin.

Driving performance and secondary tasks

We employed the driving simulator system to collect driving data by continuously recording the vehicle's position and motion at a frequency of 10 Hz. The gathered data, encompassing metrics such as forward velocity (capped at 100 km/h or 62.1 mph), longitudinal acceleration, lateral acceleration, steering wheel movements (measured in degrees), revolutions per minute (RPM), and yaw angle rate (detailed in Table S1 in the Appendix), underwent analysis to evaluate driving performance. Fluctuations in vehicle velocity and acceleration served as indicators of potential impairments in driving performance. Additionally, we examined the mean and standard deviation of speed to gain insights into vehicle dynamics (Ting et al., 2008; X. Yan et al., 2014). The parameters of lateral velocity, lateral acceleration, steering, and yaw rate provided valuable information regarding the accuracy of drivers and potential errors made during road navigation, with a particular focus on lateral control, as suggested by the previous studies (Oron-Gilad et al., 2008; Son et al., 2011; Thiffault & Bergeron, 2003).

To simulate real-life driving situations that necessitate working memory and executive function, such as navigation and traffic monitoring, the participants were tasked with performing the N-back task. This method is extensively employed to evaluate working memory and cognitive function within driving test contexts (Kirchner, 1958; Mehler et al., 2012). However, it's worth noting that facial muscle movements can potentially interfere with certain bio-signals if we use the verbal version, which were not under consideration in the present study. To mitigate this potential artifact, we employed a modified version of the N-back task, as described in (Solovey et al., 2014). In our study, we only used the 2-back task as illustrated in Figure 4. During the task, participants were presented with a sequence of single-digit numbers from 0 to 9, displayed on the left corner of the center screen at two-second intervals. They were tasked to respond to new item that was same as the number appeared two items back in the sequence. Each driving task consisted of six sessions, evenly distributed between 2-back. Each session commenced with an instructional block, followed by the presentation of 16 randomly selected numbers. Each number was displayed for 500 ms, and participants had 1,500 ms to respond. After each 2-back task, there was a 60-second driving block. The task was implemented using Python, and it recorded the timing of each number presentation, the session type, the subject's response time, and whether the presented number was a target or not (used to calculate response accuracy %). A missed target was considered an incorrect response. This data was used to assess the efficiency of cognitive processing during each session and was saved as a text file for subsequent analysis.

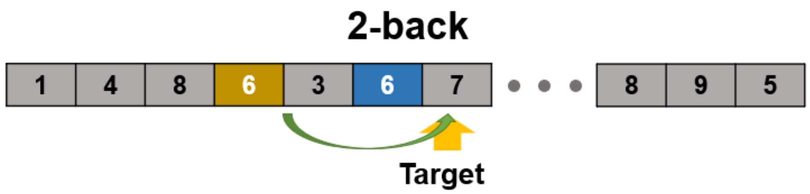


Fig. 4. 2-back task paradigm

Questionnaires

Participants were required to complete two questionnaires in the study. The first questionnaire collected demographic information, such as age, sex, and driving experience. The second questionnaire aimed to capture participants' subjective assessments questionnaire covered various aspects, including lighting comfort vote (LCV), lighting brightness vote (LBV), lighting acceptance vote (LAV), thermal comfort vote (TCV), thermal sensation vote (TSV), and thermal acceptance vote (TAV) (Brambilla et al., 2020; Golasi et al., 2019; Winzen et al., 2014). Responses for light and thermal environment variables were gathered using a 7-point Likert scale that ranged from -3 to 3. The questionnaire also had the question about the drivers' sleep quality of the last night and sleepiness levels before and after driving by using the Stanford Sleepiness Scale (SSS), which employs a 7-point Likert-type scale, spanning from "very alert" to "very sleepy" (Hoddes et al., 1973). To measure participants' emotional response to the environment, we used the self-assessment manikin (SAM) procedure to measure valence and arousal, which provides scales for valence unpleasant to pleasant), arousal (calm to excited), and dominance (dependent to independent) (Bradley & Lang, 1994). Task workload was measured using the NASA Task Load Index (NASA-TLX) questionnaire, which examines various dimensions of stress, workload, and fatigue (Hart, 2006). This questionnaire is composed of six subscales: mental demand, physical demand, temporal demand, own performance, effort, and frustration. Participants rated their experiences on each of these subscales on a scale from 1 to 7.

Procedure

Each participant was scheduled for two visits: one for screening and training, and another for the formal test. All enrolled participants underwent a screening for simulator sickness during a training session prior to the formal experiment. This session also allowed them to become familiar with the experimental procedure and the basic operation of the driving simulator. Following this, participants provided informed consent and scheduled their formal experiment.

For their second visit, participants were instructed to have regular meals, adequate sleep, and to refrain from taking medication, consuming alcohol, or engaging in excessive exercise for 24 hours prior to the test. The experiment was conducted using a single-blind design. Participants were assigned to a temperature condition through block randomization and completed four driving sessions in a randomized order of light conditions, utilizing the Latin Square Design.

Figure 5 depicts the detailed procedure of the formal experiment. Each simulated driving session had a duration of approximately 10 min which is a common driving duration in other studies with the use of driving simulator (Jeihani et al., 2017; Saxby et al., 2007). Participants were also tasked with completing a secondary N-back task (Solovey et al., 2014) during the driving sessions. Upon completing each driving task under specific light and temperature conditions, they needed to complete the survey on a provided tablet featuring a dark mode background, minimizing exposure to excessive light from the device. The next lighting condition was promptly implemented after the participant finished the survey. The use of cell phones was strictly prohibited during the experiment. The lighting condition was adjusted immediately after the participant finished the surveys.

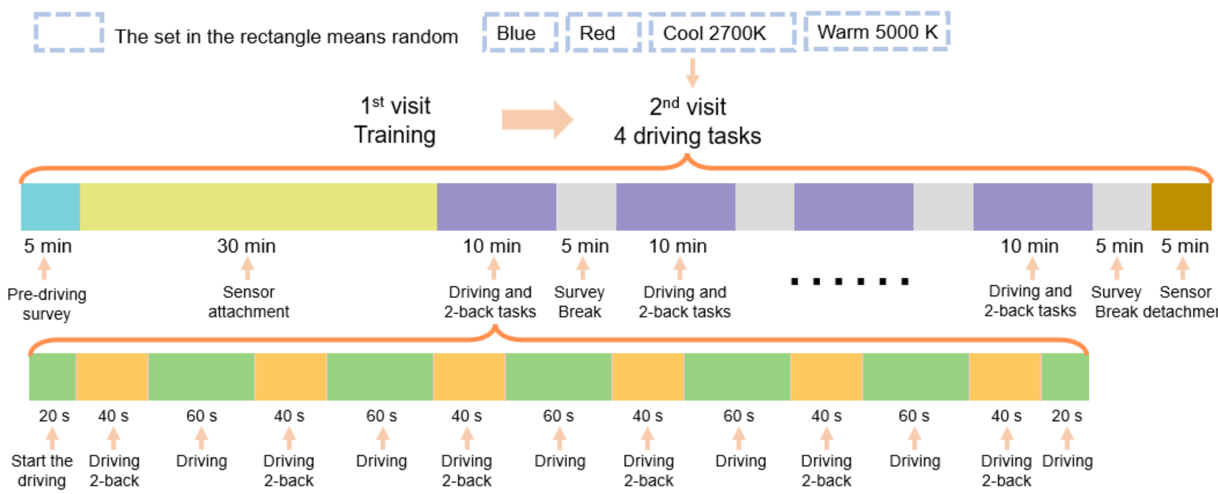


Fig. 5. Experimental procedure

Data Analysis

The primary goal of our research was to dissect the impacts of environmental factors—temperature and light color—on driving performance, while also assessing their secondary effects on environmental satisfaction, cognitive functioning, and physiological states. Our methodology integrated two complementary analytical strategies to furnish a comprehensive understanding of these dynamics.

Initially, we applied a two-way Analysis of Variance (ANOVA) to examine the direct influences of varying temperature and light condition on a series of performance metrics. This statistical method facilitated a foundational comparison, yet its capacity to encapsulate driving behavior through singular indices proved limited. Specifically, ANOVA alone could not yield a detailed model for driving style classification without expert input, based on video analysis of driving sessions. To address these limitations and capture the complexity of driving behaviors under different environmental stimuli, we incorporated machine learning techniques. This dual approach enabled the development of a nuanced classification model for driving styles and a predictive framework capable of accounting for the inherent variability in human performance. This machine learning approach complements traditional statistical methods, offering a data-driven framework to uncover complex patterns and relationships within multidimensional datasets.

Through this synergistic application of ANOVA and machine learning algorithms, our study not only identifies and quantifies the specific effects of temperature and lighting condition on driving performance but also enhances our predictive understanding of their combined impact in real-world conditions.

Statistical analysis

We employed statistical tests to evaluate differences in metrics including environmental satisfaction, driving behavior data, N-back task performance, task load, and survey results across various light conditions and thermal environments. The indicators used to assess driving performance were forward speed (maximum speed was limited to 100 km/h), longitudinal acceleration, lateral acceleration, steering wheel movements (measured in degrees), and yaw rate. We used the mean and standard deviation of these four parameters as the index to measure the driving performance. These indicators are widely recognized in the field of driving performance. To evaluate the effect of temperature and lighting conditions on cognitive performance while driving, we used the reaction time and response accuracy of the 2-back tasks in different environments. The response accuracy was computed as the percentage of incorrect or non-response. We determined the level of sleepiness in participants by averaging their responses to all the questions in the SSS. Additionally, we used numerical responses from other surveys to evaluate emotions, perception, preferences, and overall satisfaction with the in-car environment. To quantify cognitive load assessed by NASA-TLX, we followed the methodology outlined in a prior study by Al-Shargie et al (2017) and used the NASA-TLX approach.

There were twelve different vehicle cabin environments, each characterized by three levels of temperature and four different lighting conditions. To minimize the individual differences and variations among sessions, we analyze only the difference in response between identical in-car environments. i.e., the difference in performance between the blue and red lighting condition in both aggregate thermal environments. To compare the impact of a single factor on driving performance, all the data was grouped based on the same parametric condition. For example, the data collected at 23°C consisted of measurements taken under four different lighting colors. All data was analyzed using the R language software. We utilized statistical tests to determine the pairwise differences in driving performance and subjective responses between any two conditions of lighting or temperature. We checked data normality using the Shapiro-Wilk normality test.

To compare subjective survey responses and driving performance across different light conditions and thermal environments, we conducted statistical tests. First, we adapted the linear regression model to mitigate the individual difference. The residuals from the linear regression models were used for comparison without the effect from the individual factors (Kliegl et al., 2011; Van Dongen et al., 2004). Then, we assessed data normality using the Shapiro-Wilk normality test. For non-normally distributed data, we applied the Aligned Rank Transform (ART) nonparametric two-way ANOVA test, a commonly employed method in the literature for assessing differences among three or more groups (Durner, 2019; Elkin et al., 2021). We used the same approach to investigate differences in subjective survey responses and driving performance associated with temperature. The significance level for these statistical tests was set at 0.05. All data analysis was performed using R language software (version 4.2.3) (R Core Team, 2013).

Driving style recognition

To elucidate the complex interplay between environmental factors—namely temperature and light color—and driving performance, we proposed a two-layer in car temperature and light color-based driving style recognition method. Layer I used driving data to classify driving style. Layer

II dealt with driving behavior recognition based on in-car temperature and light color. Our methodology adopts a machine learning framework, structured around data preparation, feature engineering, model selection, and evaluation.

Layer I: driving style classification based on driving data

In Layer I, driving style was classified based on driving data and the unsupervised learning algorithm. The three key variables as speed, longitudinal acceleration, and lateral acceleration of the 288 driving tasks were averaged and mitigated for the individual difference. We introduced an interaction term to capture the synergistic effects of individual difference by incorporating covariates such as drivers' sex, age, driving frequency and years of driving experience, to furnish a comprehensive set of predictors for driving performance. The evolution from raw data to insightful features led us to the phase of performance label generation. We devised a method to classify driving styles into various tiers. In addition, previous studies have suggested that based on the driving behavior data, driving style can be classified into various types such as aggressive type, moderate type, and conservative type (Chu et al., 2017; Deng et al., 2017; Palat et al., 2019; F. Yan et al., 2019). Among the models considered, K-Means clustering stood out for its efficiency in identifying inherent data groupings based on feature similarity. Model selection focused on unsupervised learning techniques due to the exploratory nature of our study and the initial absence of predefined labels. This choice allowed us to discern natural clusters within the dataset, offering a fresh perspective on the data structure. The model implementation and evaluation stage saw the deployment of selected unsupervised learning models via the scikit-learn library in Python. We assessed model efficacy and determined the cluster count through Silhouette Coefficient (Luan et al., 2012). K that met the criterion which more than 0.5 is chosen to ensure that the clusters provided meaningful insights into driving performance dynamics. Then, the variables were scaled and clustered by K-means clustering method to two clusters of base driving features,

Layer II: driving behavior classification based on in-car temperature and light color

In Layer II, the classification results of Layer I as labels, combined with temperature and light color data as features, were applied as inputs to train the classifier model. Random Forest (RF) approach which is a typical non-parametric method for data mining and classification was utilized as a classifier, and a leave-one-subject-out cross validation was applied for evaluation. Then, the insights and interpretation stage involved mapping the derived clusters back to our original research questions regarding temperature, light color, and their collective impact on driving performance. This involved categorizing temperature into three distinct classes to mirror the varied thermal environments encountered during driving sessions. Similarly, light color was segmented into four classes to reflect the spectrum of lighting conditions. This classification facilitated a nuanced analysis of driving behavior under different environmental conditions. We employ a comprehensive evaluation strategy that includes the use of a confusion matrix, overall accuracy, precision, recall, and F-measure metrics for each classified group. These evaluation measures allow us to rigorously assess the performance of our classification models, ensuring that they can reliably distinguish between aggressive and conservative driving behaviors based on in-car environmental factors such as temperature and light color.

Results

This study aimed at analyzing the effects of four different lighting colors and three temperature conditions on the driving experience in the driving cabin environment. The results here present the drivers' driving performance, n-back task performance, satisfaction to the environment, emotion, and task load when they were exposed to different lighting and temperature conditions.

Statistical analysis results

Environment satisfaction

This section delves into the impact of varying temperatures (18 °C, 23 °C, 28 °C) and light colors (blue, red, warm white at 2700 K, and cool white at 5000 K) on occupants' satisfaction within the car environment, examining parameters such as light comfort, brightness, acceptance, and thermal comfort, sensation, and acceptance. Through a detailed analysis using two-way ANOVA, we uncover how these environmental factors influence the overall in-car experience. Table 2 presents the ANOVA results for drivers' satisfaction with light and temperature, as well as their two-way interaction across four different conditions.

Further analysis revealed that thermal sensation was particularly sensitive to changes in temperature, with a significant variance observed across different temperature settings ($F(2, 432461.5) = 106.172$, $p < 0.01$), highlighting how temperature adjustments can dramatically affect occupants' sensation levels. For instance, occupants expressed distinct preferences for thermal comfort at the moderate temperature of 23 °C, which was reflected in higher satisfaction scores. This preference underscores the significance of maintaining an optimal temperature to enhance the in-car experience. Specifically, thermal comfort and thermal acceptance exhibited significant variations with temperature changes ($F(2, 45431.57) = 6.604$, $p < 0.01$ for thermal comfort; $F(2, 72742.91) = 10.903$, $p < 0.01$ for thermal acceptance), reinforcing the critical role of thermal conditions in the in-car environment. In contrast, the impact of light brightness on satisfaction was more nuanced, with a notable difference observed across temperatures ($F(2, 27422.28) = 3.912$, $p = 0.021$), suggesting that how occupants perceive light brightness can vary with the interior temperature, potentially affecting their overall satisfaction.

Conversely, light color did not play a role in shaping the in-car environment, albeit to a lesser extent than temperature. In terms of the independent effects of light, the ANOVA results reveal no significant differences in perceived light comfort ($F(3,4257.009) = 0.595$, $p = 0.619$), light brightness ($F(3,6157.25) = 0.863$, $p = 0.461$), light acceptance ($F(3,3184.917) = 0.445$, $p = 0.721$), thermal comfort ($F(3,5560.231) = 0.778$, $p = 0.507$), thermal sensation ($F(3,4916.62) = 0.687$, $p = 0.561$), and thermal acceptance ($F(3,748.148) = 0.104$, $p = 0.958$).

Our findings indicate a nuanced interaction between the chosen temperatures and light colors on the perceived satisfaction levels.

Table 1. Descriptive Statistics for in-car environment satisfaction indices at different temperatures and light colors

Conditions	Parameters	M	SD	N
18 °C	Light comfort	1.105	1.617	96
	Light brightness	-1.227	1.302	96
	Light acceptance	1.270	1.496	96
	Thermal comfort	0.234	1.858	96
	Thermal sensation	-1.271	1.020	96
	Thermal acceptance	0.840	1.757	96
23 °C	Light comfort	1.305	1.568	96
	Light brightness	-0.378	1.693	96
	Light acceptance	1.651	1.323	96
	Thermal comfort	1.331	1.463	96
	Thermal sensation	0.188	1.223	96

	Thermal acceptance	1.797	1.237	96
28 °C	Light comfort	1.276	1.518	96
	Light brightness	-0.989	1.470	96
	Light acceptance	1.555	1.442	96
	Thermal comfort	0.639	1.808	96
	Thermal sensation	1.099	0.917	96
	Thermal acceptance	0.845	1.709	96
Blue	Light comfort	1.397	1.581	72
	Light brightness	-0.921	1.570	72
	Light acceptance	1.593	1.413	72
	Thermal comfort	0.804	1.784	72
	Thermal sensation	-0.090	1.463	72
	Thermal acceptance	1.111	1.765	72
Red	Light comfort	1.204	1.570	72
	Light brightness	-1.026	1.598	72
	Light acceptance	1.483	1.359	72
	Thermal comfort	0.631	1.720	72
	Thermal sensation	-0.0375	1.381	72
	Thermal acceptance	1.156	1.591	72
Warm white (2700 K)	Light comfort	1.106	1.541	72
	Light brightness	-0.815	1.455	72
	Light acceptance	1.333	1.537	72
	Thermal comfort	0.583	1.891	72
	Thermal sensation	0.011	1.497	72
	Thermal acceptance	1.117	1.649	72
Cool white (5000 K)	Light comfort	1.208	1.588	72
	Light brightness	-0.696	1.523	72
	Light acceptance	1.558	1.405	72
	Thermal comfort	0.926	1.702	72
	Thermal sensation	0.138	1.323	72
	Thermal acceptance	1.258	1.590	72
Total	Light comfort	1.229	1.565	288
	Light brightness	-0.865	1.534	288
	Light acceptance	1.492	1.426	288
	Thermal comfort	0.736	1.772	288
	Thermal sensation	0.005	1.413	288
	Thermal acceptance	1.160	1.642	288

Table 2. Two-way Analyses of Variance of environment satisfaction at different temperatures and light colors

	Source	**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**	**Partial Eta Squared**
Light comfort	T	1070.771	2	535.385	0.074	0.928	0.021
	Light color	12771.03	3	4257.009	0.595	0.619	0.251
	T * Light color	36966.19	6	6161.031	0.871	0.517	0.728
Light brightness	T	54844.56	2	27422.28	3.912	0.021*	0.567
	Light color	18471.75	3	6157.25	0.863	0.461	0.191

	T * Light color	23379.81	6	3896.635	0.547	0.772	0.242
Light acceptance	T	17152	2	8576	1.202	0.302	0.278
	Light color	9554.75	3	3184.917	0.445	0.721	0.155
	T * Light color	34978.66	6	5829.777	0.824	0.552	0.567
Thermal comfort	T	90863.15	2	45431.57	6.604	<0.01**	0.711
	Light color	16680.69	3	5560.231	0.778	0.507	0.131
	T * Light color	20203.76	6	3367.293	0.472	0.829	0.158
Thermal sensation	T	864922.9	2	432461.5	106.172	<0.01**	0.974
	Light color	14749.86	3	4916.62	0.687	0.561	0.017
	T * Light color	8674.167	6	1445.694	0.201	0.976	0.010
Thermal acceptance	T	145485.8	2	72742.91	10.903	<0.01**	0.860
	Light color	2244.444	3	748.1481	0.104	0.958	0.013
	T * Light color	21509.86	6	3584.977	0.503	0.806	0.127

Note: * denotes p value less than 0.05, ** denotes p value less than 0.01

Driving performance

This study explored the influence of environmental variables, specifically temperature and light color, on various driving performance metrics. Our analysis methodically examined parameters such as speed, acceleration, rpm, steering, pitch, lateral acceleration, gas pedal usage, and roll across different temperature settings (18 °C, 23 °C, and 28 °C) and light colors (blue, red, warm white (2700 K), and cool white (5000 K). Table 1 delineates the descriptive statistics for these driving performance indices, offering a comprehensive view of the mean (M) and standard deviation (SD), while Table 2 displays the results of the two-way ANOVA conducted to discern the effects of temperature and light color on the aforementioned driving performance indices. examining the effects of temperature and light color. Descriptive statistics showcased mean and standard deviation values for each condition, offering a comprehensive overview of driving dynamics across varying environmental settings.

Temperature variations appeared to have a minimal impact on the majority of driving performance indices, with speed, acceleration, and rpm maintaining relative stability across the three tested temperatures. For instance, the speed average slightly fluctuated around the 68 m/s mark, with minimal differences in acceleration and rpm. The analysis of mean steering, lateral acceleration, gas pedal usage, and roll also exhibited consistent patterns across different temperatures, indicating that temperature alone does not significantly alter these driving metrics. A particularly compelling discovery emerged in the analysis of pitch (rad/s) mean values, where a significant temperature effect was observed ($F(2, 288) = 5.099$, $p < 0.01$, $\eta2 = 0.472$), highlighting a profound impact of thermal conditions on vehicle dynamics and potentially driver's control stability. Conversely, the statistical analysis, detailed in Table 3, unveils several noteworthy findings. The speed standard deviation (S.D.) significantly varied with temperature ($F(2, 288) = 4.026$, $p = 0.019$, $\eta2 = 0.635$), indicating a discernible impact of thermal conditions on driving speed variability among drivers. Similarly, gas pedal usage's standard deviation demonstrated significant variability with temperature ($F(2, 288) = 3.395$, $p = 0.035$, $\eta2 = 0.867$), suggesting that drivers' acceleration behavior is sensitive to ambient temperature changes. Additionally, roll (rad/s) standard deviation showed a significant temperature effect ($F(2, 288) = 4.105$, $p = 0.018$, $\eta2 = 0.844$), underscoring the nuanced ways in which temperature can influence vehicular control and orientation.

However, when examining light color effects, subtle yet noteworthy distinctions emerged. The transition between blue, red, warm white, and cool white lighting conditions demonstrated slight variances in driving speed, with red light conditions marginally increasing the mean speed to 68.423 m/s. This change, though minor, suggests light color may subtly influence driver speed control. Similarly, acceleration, steering, pitch, lateral acceleration and gas pedal usage under ANOVA analysis largely showed no significant differences attributable to light color.

However, no significant interactions between temperature and light color were found for driving performance indices, indicating that these factors independently influence driving performance without synergistic effects and the combined influence of these environmental factors on driving performance indices might be minimal.

Table 3. Descriptive Statistics for driving performance indices at different temperatures and light colors

Conditions	**Parameters**	**M**	**SD**	**N**
18 °C	Speed (m/s)	68.114	17.715	96
	Acceleration (m^2/s)	0.0034	0.022	96
	Rpm	4837.593	974.330	96
	Steering (degree)	-0.0010	0.068	96
	Pitch (rad/s)	-0.0032	0.067	96
	Lateral acceleration (m^2/s)	0.0048	0.185	96
	Gas pedal	0.328	0.237	96
	Roll (rad/s)	0.00024	0.061	96
23 °C	Speed (m/s)	68.180	19.243	96
	Acceleration (m^2/s)	0.0031	0.024	96
	Rpm	4830.871	978.639	96
	Steering (degree)	-0.0009	0.065	96
	Pitch (rad/s)	-0.0038	0.065	96
	Lateral acceleration (m^2/s)	0.0043	0.191	96
	Gas pedal	0.325	0.250	96
	Roll (rad/s)	0.00018	0.060	96
28 °C	Speed (m/s)	68.084	18.934	96
	Acceleration (m^2/s)	0.0032	0.023	96
	Rpm	4821.092	1008.59	96
	Steering (degree)	-0.0009	0.069	96
	Pitch (rad/s)	-0.0025	0.066	96
	Lateral acceleration (m^2/s)	0.0040	0.191	96
	Gas pedal	0.329	0.233	96
	Roll (rad/s)	6.25e-5	0.0611	96
Blue	Speed (m/s)	68.299	18.480	72
	Acceleration (m^2/s)	0.0033	0.023	72
	Rpm	4826.937	976.711	72
	Steering (degree)	-0.0010	0.068	72
	Pitch (rad/s)	-0.0033	0.065	72
	Lateral acceleration (m^2/s)	0.0050	0.191	72
	Gas pedal	0.330	0.242	72
	Roll (rad/s)	0.00031	0.0603	72
Red	Speed (m/s)	68.423	17.882	72

	Acceleration (m^2/s)	0.0034	0.023	72
	Rpm	4827.78	958.379	72
	Steering (degree)	-0.0008	0.068	72
	Pitch (rad/s)	-0.0036	0.066	72
	Lateral acceleration (m^2/s)	0.0040	0.187	72
	Gas pedal	0.319	0.238	72
	Roll (rad/s)	0.00013	0.0605	72
Warm white (2700 K)	Speed (m/s)	68.197	19.202	72
	Acceleration (m^2/s)	0.0031	0.023	72
	Rpm	4841.255	1002.822	72
	Steering (degree)	-0.0011	0.067	72
	Pitch (rad/s)	-0.0034	0.066	72
	Lateral acceleration (m^2/s)	0.0048	0.188	72
	Gas pedal	0.332	0.242	72
	Roll (rad/s)	0.00011	0.0605	72
Cool white (5000 K)	Speed (m/s)	67.586	18.960	72
	Acceleration (m^2/s)	0.0032	0.023	72
	Rpm	4823.435	1010.833	72
	Steering (degree)	-0.0009	0.068	72
	Pitch (rad/s)	-0.0023	0.066	72
	Lateral acceleration (m^2/s)	0.0037	0.189	72
	Gas pedal	0.329	0.238	72
	Roll (rad/s)	9.72e-5	0.0614	72
Total	Speed (m/s)	68.126	18.631	288
	Acceleration (m^2/s)	0.0033	0.023	288
	Rpm	4829.852	987.186	288
	Steering (degree)	-0.0010	0.067	288
	Pitch (rad/s)	-0.0031	0.066	288
	Lateral acceleration (m^2/s)	0.0044	0.189	288
	Gas pedal	0.327	0.240	288
	Roll (rad/s)	0.00016	0.0607	288

Table 4. Two-way Analyses of Variance of driving performance indices at different temperatures and lighting conditions

	Parameters	**Source**	**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**	**Partial Eta Squared**
Speed (m/s)	Mean	T	14452.31	2	7226.156	1.009	0.366	0.502
		Light color	2681.25	3	893.75	0.124	0.649	0.093
		T * Light color	11647.31	6	1941.219	0.271	0.950	0.405
	S.D.	T	56148.4	2	28074.2	4.026	0.019*	0.635
		Light color	20536.72	3	6845.574	0.963	0.411	0.232
		T * Light color	11796.78	6	1966.131	0.275	0.948	0.133
Acceleratio	Mean	T	3293.943	2	1646.971	0.229	0.795	0.076
		Light color	29142.25	3	9714.083	1.370	0.252	0.673
		T * Light color	10849.15	6	1808.191	0.252	0.958	0.251

n (m^2/s)	S.D.	T	28798.08	2	14399.04	2.030	0.133	0.821
		Light color	1604.5	3	534.833	0.074	0.974	0.046
		T * Light color	4658.896	6	776.483	0.108	0.995	0.133
Rpm	Mean	T	214.146	2	107.073	0.015	0.985	0.011
		Light color	340.083	3	113.361	0.016	0.997	0.017
		T * Light color	19153.28	6	3192.214	0.448	0.846	0.972
	S.D.	T	32827.27	2	16413.64	2.321	0.100	0.326
		Light color	25878.58	3	8626.194	1.213	0.305	0.267
		T * Light color	42030.58	6	7005.096	0.994	0.430	0.417
Steering (degree)	Mean	T	19673.52	2	9836.76	1.393	0.250	0.294
		Light color	19562.9	3	6520.965	0.920	0.432	0.292
		T * Light color	27749.58	6	4624.929	0.657	0.684	0.414
	S.D.	T	7676.646	2	3838.323	0.543	0.582	0.268
		Light color	2182.583	3	727.528	0.103	0.958	0.076
		T * Light color	18801.87	6	3133.645	0.444	0.849	0.656
Pitch (rad/s)	Mean	T	70687.52	2	35343.76	5.099	<0.01**	0.472
		Light color	32404.69	3	10801.56	1.527	0.208	0.216
		T * Light color	46711.34	6	7785.223	1.108	0.358	0.312
	S.D.	T	26309.31	2	13154.66	1.862	0.157	0.574
		Light color	13782.36	3	4594.12	0.648	0.585	0.300
		T * Light color	5777.785	6	962.964	0.135	0.992	0.126
Lateral acceleration (m^2/s)	Mean	T	14674.08	2	7337.042	1.034	0.357	0.296
		Light color	12309.97	3	4103.324	0.575	0.632	0.248
		T * Light color	22664.41	6	3777.402	0.532	0.784	0.456
	S.D.	T	23736.9	2	11868.45	1.667	0.191	0.822
		Light color	658.472	3	219.491	0.030	0.993	0.023
		T * Light color	4496.326	6	749.388	0.104	0.996	0.156
Gas pedal	Mean	T	9601.583	2	4800.792	0.675	0.510	0.246
		Light color	6259.361	3	2086.454	0.292	0.831	0.160
		T * Light color	23179.2	6	3863.2	0.547	0.772	0.594
	S.D.	T	47689.15	2	23844.57	3.395	0.035*	0.867
		Light color	1395.806	3	465.269	0.065	0.978	0.025
		T * Light color	5906.882	6	984.480	0.137	0.991	0.107
Roll (rad/s)	Mean	T	30156.9	2	15078.45	2.126	0.121	0.425
		Light color	34853.53	3	11617.84	1.642	0.180	0.491
		T * Light color	5951.222	6	991.8704	0.138	0.991	0.084
	S.D.	T	57427.27	2	28713.64	4.105	0.018*	0.844
		Light color	3095.361	3	1031.787	0.143	0.934	0.045
		T * Light color	7523.222	6	1253.87	0.175	0.983	0.111

*** Significant at the 0.05 level, ** Significant at the 0.01 level.**

N-back tasks

Our investigation delved into the effects of ambient temperature and light color on driving performance, with a particular focus on the nuances of response accuracy and reaction time during N-back tasks. This assessment aimed to unearth the subtleties of environmental impacts on cognitive functions critical for driving. The descriptive statistics outlined in Table 4 offer insight into these cognitive metrics across three temperature ranges (18 °C, 23 °C, and 28 °C) and four distinct light environments (blue, red, warm white [2700 K], and cool white [5000 K]), providing a comprehensive dataset for analysis.

Notably, response accuracy exhibited a significant variance with temperature changes ($F(2, 1728) = 3.886$, $p = 0.022$), underscoring the potential impact of thermal conditions on cognitive performance. Specifically, the highest response accuracy was observed at 23 °C (93.605%), marginally higher than at 18 °C (93.518%), while a notable decrease to 80.422% was recorded at 28 °C, suggesting a detrimental effect of higher temperatures on cognitive accuracy. In contrast, reaction times across different temperatures conditions remained relatively consistent, with minor fluctuations indicating a robustness in cognitive speed irrespective of environmental changes. The reaction times were slightly quicker at 23 °C (0.661 s) compared to 18 °C (0.673 s) and 28 °C (0.655 s), although these differences were not statistically significant ($F(2, 1728) = 1.803$, $p = 0.167$).

The influence of light color on cognitive performance during driving tasks also warrants attention. Blue light conditions yielded the highest response accuracy (93.673%), suggesting an environment conducive to optimal cognitive engagement. Conversely, warm white light (2700 K) led to the lowest accuracy levels (90.934%), indicating potential cognitive strain or distraction in such lighting conditions. Reaction times varied minimally across light conditions, reinforcing the notion of stable cognitive processing speeds under varying visual stimuli.

Table 4. Descriptive Statistics for response accuracy and reaction time of N-back task at different temperatures and lighting conditions

Conditions	**Parameters**	**M**	**SD**	**N**
18 °C	Response accuracy (%)	93.518	13.493	576
	Reaction time (s)	0.673	0.147	576
23 °C	Response accuracy (%)	93.605	12.515	576
	Reaction time (s)	0.661	0.149	576
28 °C	Response accuracy (%)	80.422	16.312	576
	Reaction time (s)	0.655	0.167	576
Blue	Response accuracy (%)	93.673	12.430	432
	Reaction time (s)	0.657	0.153	432
Red	Response accuracy (%)	92.631	13.399	432
	Reaction time (s)	0.666	0.155	432
Warm white (2700 K)	Response accuracy (%)	90.934	17.240	432
	Reaction time (s)	0.669	0.159	432
Cool white (5000 K)	Response accuracy (%)	92.824	13.432	432
	Reaction time (s)	0.660	0.153	432
Total	Response accuracy (%)	92.515	14.267	1728
	Reaction time (s)	0.663	0.155	1728

Table 5. Two-way Analyses of Variance of response accuracy and reaction time of N-back tasks at different temperatures and lighting conditions

Parameters	**Source**	**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**	**Partial Eta Squared**

Response accuracy (%)	T	53829.4	2	26914.7	3.886	0.022*	0.592
	Light color	17893.56	3	5964.519	0.846	0.470	0.197
	T * Light color	19218.7	6	3203.117	0.456	0.840	0.211
Reaction time (s)	T	25646.81	2	12823.41	1.803	0.167	0.799
	Light color	3225.389	3	1075.13	0.149	0.930	0.100
	T * Light color	3223.618	6	537.270	0.075	0.998	0.100

Note: * denotes p value less than 0.05, ** denotes p value less than 0.01

Task load index

Tables S2 and S3 (in the appendix) elucidate the impact of ambient temperature and light color on drivers' perceived task load, as measured by the NASA-TXL index across six distinct domains: mental demand, physical demand, temporal demand, own performance, effort, and frustration. These dimensions were quantitatively assessed under three temperature settings (18°C, 23°C, and 28°C) and four lighting conditions (blue, red, warm white at 2700 K, and cool white at 5000 K), generating a comprehensive dataset of subjective task load ratings.

In the context of temperature, a noticeable escalation in mental demand ratings was observed as the ambient temperature increased, peaking at 28°C with an average rating of 4.521, indicative of heightened cognitive strain. Conversely, own performance ratings exhibited a slight decline at 28°C, suggesting a perceived decrement in task efficacy under higher temperatures. This trend underscores the nuanced interplay between environmental conditions and cognitive load, further substantiated by the statistical significance of these variations in the temporal demand and own performance domains, as evidenced by the two-way ANOVA outcomes presented in Table S3.

The lighting condition analysis revealed a more complex interaction, with no single light color consistently exacerbating or alleviating the perceived task load across all metrics. However, the red lighting condition appeared to marginally elevate mental demand ($M = 4.208$) and effort ratings ($M = 4.153$), whereas blue light was associated with intermediate levels of task load across the evaluated domains. Notably, the interaction between temperature and light color did not significantly alter the mental or physical demand, as the statistical analysis indicated a lack of significant interaction effects, thereby suggesting that each factor independently influences the driver's task load perception.

The variance analysis highlighted specific areas of statistical significance, particularly in the temporal demand and frustration domains, where temperature exerted a pronounced effect ($p < 0.05$ for temporal demand; $p < 0.01$ for frustration). This implies that environmental temperature plays a crucial role in modulating both the urgency with which tasks are perceived and the level of frustration experienced by drivers. Own performance also emerged as a critical area of impact, with a significant difference observed across temperature conditions ($p < 0.01$), reinforcing the notion that environmental factors can substantially affect perceived task efficacy and cognitive load.

General comfort, sleepiness, and emotion

Tables S4 and S5 delve into the multifaceted dimensions of participants' experiences, including general comfort, sweating, sleepiness before and after driving, and emotional states (valence, arousal, dominance), across different ambient temperatures (18°C, 23°C, 28°C) and lighting conditions (blue, red, warm white at 2700 K, cool white at 5000 K). This comprehensive dataset offers insights into how such environmental variables can influence human comfort and cognitive states.

The analysis of general comfort reveals a discernible variation across temperatures, with participants reporting the highest comfort levels at 23°C (M = 7.010), highlighting a preference for moderate ambient conditions. This preference is statistically supported by a significant temperature effect in the two-way ANOVA ($p < 0.05$), indicating a robust influence of ambient temperature on perceived comfort. Sweating rates significantly increased with temperature at 28°C (M = 2.563), reflecting the physiological response to higher ambient temperatures. This finding is corroborated by the statistical analysis, which shows a highly significant effect of temperature on sweating ($p < 0.01$), underscoring the direct impact of environmental heat on the body's thermoregulatory processes. Differences in sleepiness before and after driving were subtly influenced by temperature, with the highest increase observed at 28°C (M = 3.052). However, this effect narrowly missed statistical significance ($p = 0.080$), suggesting a trend towards greater sleepiness at higher temperatures that warrants further investigation. The emotional responses of participants, quantified as valence, arousal, and dominance, showed no significant changes across different temperatures, demonstrating a remarkable consistency in emotional states despite varying environmental conditions. This stability suggests that the emotional impact of these environmental variables is either negligible or complex, requiring more nuanced measures to detect.

Light color, however, did not significantly affect general comfort, sleepiness, and sweating. The emotional responses of participants, quantified as valence, arousal, and dominance, showed no significant changes across different light colors. The results suggested that temperature is a more critical determinant in modulating this aspect of cognitive state.

However, when examining the interaction effect between temperature and light color on the general comfort, sweating, sleepiness, and emotional response, the analysis did not indicate a statistically significant impact ($p > 0.05$), suggesting that the perceived comfort is more directly attributable to temperature alone, rather than its interaction with light color.

In-car environment-based driving style recognition

Driving behaviour data-based classification

K-means was used to classify driving behaviors based on driving data and performing the clustering. Two driving style groups (aggressive and unaggressive) were obtained via the locations of the initial clustering centers (see Fig. 6). It was observed that each of the final clustering centers followed a similar compass point (or direction) to its corresponding initial center, respectively. 72 participants completed 288 driving tasks and hence 281 samples of driving data were acquired. 7 data samples were disregarded due to qualification. The 3-dimension feature vectors of the driving data divided the 281 to 147 and 134 for aggressive and conservative respectively. The Silhouette Coefficient was utilized to determine the quantification of the clusters number, which was 0.55 more than the criterion of 0.5, which signifies a good separation between clusters. Therefore, the two clusters maintain the names of their corresponding driving behavior groups.

The mean values and standard deviations of the driving data for each group were calculated and the two groups were referred to as the aggressive group and conservative group. The analysis of variance (ANOVA) indicated that there was significant difference of the driving data among two groups of different driving styles. The aggressive group demonstrated higher mean values in speed, acceleration, and steering, whereas the conservative group showed lower values in these variables.

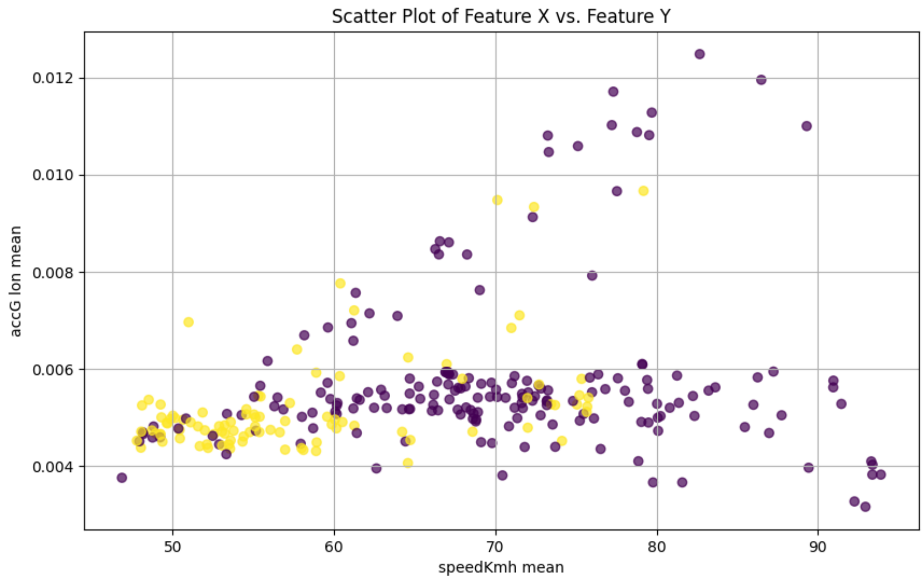


Fig. 6. Results of K-means based on the driving data.

In-car environment-based driving style classification

The results of RF approach combined with the leave-one-subject-out cross validation was adopted for temperature and light color-based classification reported the classification achieved an overall accuracy of 72.9%. Precision and recall for the aggressive group were 69% and 43%, respectively, and for the conservative group, 73% and 89%, respectively. The F-measures were 53% for the aggressive group and 80% for the conservative group, indicating a stronger predictive power for identifying conservative driving behaviors. The feature importance of temperature, light color, and interaction between two factors were 0.127, 0.127, and 0.746, respectively.

Discussion

The current study explored the interactive effects of temperature and light color on driving performance, cognitive tasks, and subjective perceptions of the indoor environment. This exploration was facilitated through an experimental study conducted within a hybrid experimental setting that integrated a driving simulator into a climate chamber, allowing for precise control over temperature and light color. The findings reveal that ambient temperature impacts driving performance and satisfaction with the environment compared to the effects of light color. Specifically, the study found no significant evidence to suggest that changes in driving performance, cognitive task performance, or environmental satisfaction could be attributed to variations in light color. Additionally, the study employed a two-layer driving behavior recognition system, which demonstrated proficiency in identifying types of driving behaviors based solely on data related to the in-car environment. This model underscores the potential for using environmental data to independently assess driving behavior.

Effect of temperature, lighting condition, and interaction

Effect of light on thermal perception

The investigation revealed that light color did not significantly influence participants' perceptions of thermal comfort, sensation, and acceptance, which diverges from the expected outcomes based on the hue-heat hypothesis. Despite this, our study uncovered nuanced variations in drivers' perceptions under different lighting conditions during night driving. Specifically, the analysis of LCV suggested uniform comfort across the examined lighting conditions, whereas the LBV highlighted a preference for the brightness of cool white lighting. Interestingly, drivers showed a significant preference for the blue lighting condition in terms of LAV, surpassing the acceptance levels for cool white lighting.

The findings further indicated that drivers experienced the greatest TCV under cool white lighting, significantly more so than under warm white lighting. This preference for cool white and blue lighting conditions aligns with recent research suggesting enhanced thermal comfort in blue-enriched spectrum light (Bellia et al., 2021; Brambilla et al., 2020). Contrary to our expectations, the TSV values revealed that lighting conditions did not exert a significant influence on participants' thermal sensations. Interestingly, participants reported feeling warmer under red lighting conditions, consistent with the intuitive association of red hues with warmth. However, perceptions of cabin temperature were warmer in cool white light than in warm light, leading to an unexpected phenomenon where cool white light induced warmer sensations and warm white light cooler sensations. This observation stands in contrast to the hue-heat hypothesis and further challenges the warm-cool categorization, suggesting that these principles may not directly apply or may require reevaluation in the context of driving under artificial lighting conditions (Chinazzo et al., 2021; Itten, 1997; Winzen et al., 2014). Such findings indicate a complex interplay between perceived color temperature and thermal sensation. The preference for blue lighting in both visual and thermal contexts, as reflected by TAV scores, suggests a nuanced perception where subjects find blue hues more satisfactory in warm environments. This preference challenges the hue-heat hypothesis, which posits a direct correlation between color temperature and thermal perception and suggests the need for further exploration into the interaction between color perception and thermal comfort.

Our results diverge from literature suggesting colored stimuli significantly influence thermal perception according to the hue-heat hypothesis. The lack of significant effects observed in our study may be attributed to the limited exposure time to visual and thermal stimuli, preventing full adaptation, and the unique context of night driving, which limits "complete body" immersion in colored light environments. This discrepancy highlights the potential influence of experimental setup on perceived thermal responses, as demonstrated by studies like (Martini et al., 2013), where skin color changes due to colored light exposure affected pain perception. Moreover, our findings suggest no consistent effects of light color on thermal sensation and comfort across different ambient temperatures, indicating that other factors may play a more pivotal role in influencing these perceptions in night driving scenarios. This insight calls for further research into the complex interplay between light color, thermal perception, and environmental context to fully understand the mechanisms at play.

Effect of temperature on light perception

The investigation into the effects of temperature on visual perception, focusing on light comfort, brightness, and acceptance, revealed that temperature did not significantly influence the visual perception. This finding is consistent across general evaluations of light, indicating that temperature levels, similar to those in prior studies (e.g., 23°C to 29°C)(H. Wang et al., 2018), were not a significant factor in visual perception responses. Despite varying the type and intensity of thermal stimuli, as seen in prior research where significant effects were noted, our findings remained nonsignificant. This suggests that the specific thermal conditions chosen, including the most uncomfortable cool condition, did not alter the general perception of light in the ways anticipated.

Interestingly, the highest LCV was observed during neutral temperature conditions, indicating a thermally comfortable state enhances light comfort. This observation is in line with previous research, suggesting a complex relationship between thermal comfort and light perception that extends beyond neutral lighting conditions (Chinazzo et al., 2018; te Kulve et al., 2018). Temperature effects were distinctly noted in the LBV, where participants perceived light as significantly brighter in cooler conditions compared to warmer ones. This shift in brightness perception suggests that ambient temperature influences visual sensitivity to light brightness. Moreover, LAV varied with temperature, with cooler conditions leading to lower acceptance than neutral and warm conditions, highlighting how ambient temperature can shape preferences for light environments.

Contrary to our initial hypotheses, the interaction between light color and temperature did not significantly alter satisfaction indices, suggesting a dominant role of temperature in determining occupants' comfort and satisfaction. The ANOVA analysis supported this, showing no significant interaction effects between light and temperature on variables such as light comfort, brightness, acceptance, and thermal metrics. This discrepancy might stem from the limited exposure time to the thermal conditions in our study, preventing full thermal adaptation, or the predominance of visual stimuli in the night-time driving overshadowing any potential temperature effects on color perception. Moreover, our study found a weak correlation between thermal and light comfort ratings, indicating that thermal comfort is not directly modifiable through changes in light comfort. This stands in contrast to previous findings and challenges the notion that improving light comfort can mitigate thermal discomfort (te Kulve et al., 2018).

Driving performance

The investigation into the influence of environmental variables, specifically temperature and light color, on driving performance reveals nuanced insights into the dynamics of driver-vehicle-environment interaction.

The analysis of how temperature and light color affect driving performance reveals that temperature has a minimal impact on most driving performance indices such as acceleration, rpm, and steering angle, which maintained relative stability across the tested temperatures. This indicates that drivers' ability to control acceleration, and engine output is not significantly influenced by mild temperature changes. However, the significant effect of temperature on the pitch's mean values and the standard deviations for speed, gas pedal usage, and roll suggests that temperature variations affect vehicle dynamics in a simulator. Our findings align with prior research indicating temperature's significant role in influencing vehicle control metrics such as speed variability, gas pedal usage, and roll (Chowdhury, 2015; Daanen et al., 2003). These findings are particularly important for understanding how thermal comfort in different driving environments may subtly influence driving behavior.

Interestingly, the study also highlights that light color has a more nuanced effect on driving performance. While the overall impact of light color on driving metrics was found to be minimal, the slight increase in mean speed under red light conditions suggests that light color may influence drivers' speed perception or control. These outcomes align with previous studies investigating the effect of ambient light on driving performance, such as (Caberletti et al., 2010), which found no significant impact of ambient light scenarios on drivers.

However, contrary to the anticipated synergistic effects of temperature and light color, the lack of significant interaction between temperature and light color on driving performance indices in this study suggests that these environmental factors independently contribute to driver behavior.

Therefore, further investigation is necessary to determine whether there is an interactive effect of temperature and light conditions inside the car on driving performance.

The observation that temperature and light color independently affect driving performance without synergistic effects has several implications. While driving performance remains largely consistent across different temperatures and light colors, certain conditions such as temperature can influence the variability in speed control among drivers. The absence of a significant interaction between temperature and light color challenges the notion of their combined effect on cognition tasks, prompting a reevaluation of environmental control strategies within vehicular design. This directs future research towards isolating these variables in real-world settings to ascertain their individual and collective impacts more comprehensively.

N-back task

This detailed exploration into the effects of ambient temperature and light color on cognitive functions essential for driving reveals critical insights, specifically focusing on response accuracy and reaction times during N-back tasks. The findings reveal a significant impact of temperature on response accuracy, with optimal performance observed at 23 °C. This suggests a potential thermal optimum for cognitive tasks, aligning with previous research indicating that moderate environmental temperatures can facilitate cognitive performance (Lan & Lian, 2009; Schiavon et al., 2017b; C. Wang et al., 2021). It also emphasizes the importance of maintaining optimal ambient conditions for enhancing cognitive function. Interestingly, reaction times remained relatively stable across varying temperatures, suggesting a degree of robustness in cognitive processing speed against the subtle temperature changes. This resilience might be attributed to the adaptive capabilities of cognitive processes, which can maintain speed of response despite minor environmental stressors.

While light color appears to influence cognitive accuracy and reaction time, the effects are less pronounced, suggesting that cognitive speed remains constant across different lighting conditions. The results were aligned with the findings from the previous studies (Hawes et al., 2012a; Kretschmer et al., 2012a). However, the high CCT light conditions enhancing response accuracy were also notable. This finding supports the hypothesis that certain wavelengths of light can stimulate brain activity more effectively, possibly by influencing circadian rhythms and alertness levels. Conversely, the reduced accuracy observed under low CCT light conditions could reflect the potential for certain light temperatures to induce cognitive fatigue or distraction, thereby impacting performance (Chellappa et al., 2011; Y. Li et al., 2021; Mehri et al., 2023). These findings contribute to a deeper understanding of how subtle environmental variations can influence the complex dynamics of cognitive performance in driving contexts.

Despite these individual effects, our analysis did not reveal significant interaction effects between temperature and light color on cognitive performance, suggesting that each factor independently influences cognitive functions without synergistic or antagonistic interactions. This observation conflicted to the previous finding that the interaction between the temperature and light color affect the cognition task (Seyedrezaei et al., 2023).

Physiological and psychological response

The exploration of task load, general comfort, sleepiness, and emotion within the vehicle cabin environment, as influenced by ambient temperatures and light color, yields significant insights into the holistic driver experience. The gradations in six dimensions of task load, perceived comfort, physiological responses (sweating), cognitive states (sleepiness before and after driving), and emotional responses (valence, arousal, dominance) under varying temperatures and lighting conditions underscore the intricate dynamics at play between environmental factors and human responses.

The findings indicated the statistical significance in the domains of temporal demand, and frustration, particularly influenced by temperature, underscores the critical role of environmental conditions in shaping drivers' task urgency perceptions and frustration levels. The significant impact of temperature on own performance further emphasizes the importance of optimizing cabin conditions to support driver wellbeing and task efficiency. The analysis delineates a clear preference for moderate ambient temperatures aligned with previous study (Cui et al., 2013b; Nicol & Humphreys, 2002a; Z. Wang et al., 2018), with the highest levels of general comfort reported at 23°C. This finding highlights the pivotal role of temperature in optimizing comfort within the vehicle cabin. The significant increase in sweating rates at higher temperatures (28°C) not only corroborates the physiological burden imposed by warmer conditions but also underscores the importance of maintaining a balanced thermal environment for enhanced comfort and physiological well-being. Interestingly, while sleepiness levels showed a trend towards an increase with rising temperatures, the absence of statistical significance suggests a complex relationship between thermal conditions and cognitive fatigue that warrants further investigation. This observation invites a deeper examination of the mechanisms through which temperature influences alertness and cognitive performance during driving. The stability of emotional responses across varying temperatures and lighting conditions is an intriguing aspect of our findings. The lack of significant changes in valence, arousal, and dominance suggests that emotional states may be more resilient to environmental variations than previously thought, or that the emotional impacts of these factors are nuanced and require more sophisticated measures to detect.

The interplay between light color and task load, general comfort, and sleepiness presents a complex picture, with no single lighting condition consistently intensifying or mitigating the perceived load across all metrics. However, red hue light marginally increased mental demand and effort, while blue light appeared to maintain intermediate task load levels. Notably, the absence of significant interaction effects between temperature and light color suggests an independent influence of these environmental factors on perceived task load.

The absence of a statistically significant interaction effect between temperature and light color on task load, general comfort, sweating, sleepiness, and emotional responses suggests that the perceived comfort and cognitive states within the vehicle cabin are primarily influenced by temperature within out test parameters and duration.

Driving style classification based on in-car environment

In this study we introduced a driving style recognition schema based on a combination of driving behavior data with in-car temperature and light color. The classification of driving data into aggressive and conservative styles via K-means clustering, and subsequent training of the RF model with in-car environmental features, underscores the potential of environmental conditions to influence driving behavior. The achieved classification accuracy of 73.0% and balanced F-measures between driving styles affirm the model's capability to discern driving patterns based on in-car conditions.

The analysis revealed that aggressive driving is characterized by higher speed, acceleration, and steering wheel activity, aligning with a preference for dynamic driving. Conversely, conservative driving is marked by lower values in these variables, indicating a cautious approach. The concept of driving skill is defined by a driver's proficiency in vehicle control, often assessed through the mean and standard deviation of driving performance data. This metric inversely correlates with driving skill stability (Lu, 2011; Martinussen et al., 2014). Our analysis reveals that mean and standard deviations across nearly all measured driving parameters were higher for the Aggressive group compared to the Conservative group. This pattern suggests a potential correlation between driving style and skill variability: the more aggressive the driving style, the greater the fluctuations in driving skills. This research aligns with prior findings (Martinussen et al., 2014; Reason et al., 1990; F. Yan et al., 2019; L. Yang et al., 2018), underscoring the strong link between drivers' behavioral patterns and their driving styles. While earlier studies have predominantly characterized driving style as a static trait, resistant to change (S.-W. Chen et al., 2013; Shi et al., 2015), our findings present a more nuanced picture. Among our participants, 29 exhibited a consistently aggressive driving style throughout the study, 14 displayed variability in their driving style, oscillating between conservative and aggressive, and 26 consistently demonstrated a conservative driving style. This dichotomy not only reflects a driver's inherent style but also suggests that in-car environmental conditions can induce variations in driving behavior. The observation that driving styles fluctuated among participants during the study indicates the dynamic nature of driving behavior, potentially influenced by the in-car environment.

The F-measures showed that this classifier was approximately equally sensitive to the two driving styles and the classification performance was balanced. These results suggested a close relationship between in-car environment and driving style and demonstrated the feasibility of driving style recognition and prediction using in-car temperature and light color data. The findings elucidate the hierarchy of impact among the studied factors: temperature emerges as the most critical, followed by the interaction between variables, with light color being identified as the least influential. This hierarchy not only clarifies the relative importance of each factor but also guides future research and practical applications in enhancing driving optimization and behavior prediction. Furthermore, the methodology for recognizing driving behavior based on in-car temperature and light color holds significant promise for the development of more nuanced driving assistance systems. By accurately determining a driver's behavioral group, these systems can tailor their responses to individual drivers more effectively. By predicting driving styles through the features of the in-car environment, this research extends beyond conventional focuses such as indoor air quality or thermal comfort prediction. It emphasizes the critical role of temperature and the significant yet lesser impact of light color on driving style, suggesting that these factors, especially temperature, have the potential to modulate driving behaviors. Such insights are invaluable, opening new avenues for research aimed at optimizing in-car conditions to foster safer driving practices.

Effect of thermal sensitivity on driving performance and environmental satisfaction

Our analysis further segmented participants based on their thermal sensitivity, distinguishing between those sensitive to cold and those who are not. 36% of participants were identified being particularly sensitive to cold temperatures. This subgroup exhibited the influence of cold sensitivity on their driving performance, with low cold sensitivity individuals exhibiting experiencing more substantial impacts on their driving capabilities compared to their counterparts with higher sensitivity to cold. Similarly, the study participants were categorized based on their heat sensitivity. 46% of the sample reported high sensitivity to heat, indicating a substantial portion of individuals potentially affected by warmer temperatures. Those with elevated heat sensitivity demonstrated more significant alterations in driving performance in response to temperature variations. While thermal sensitivity is a factor that mildly influences the thermal effects of lighting, its interaction with the thermal impacts of lighting appeared to be minimal. Specifically, our findings did not reveal any significant interaction effects between temperature and lighting on driving performance across the different groups, segmented by their sensitivity to either coldness or warmth.

Limitation and recommendations

One notable limitation of our study is the relatively small sample size, which could diminish the statistical power of our findings. To address this, we aim to recruit more participants in future studies, thereby enhancing our research's robustness. Additionally, our methodology incorporated a mixed design by merging within-subjects and between-subjects designs. Employing a within-subjects design in human-factor experiments can help mitigate individual differences, enhancing the reliability of our results.

Furthermore, our investigation focused on driving performance within a simplified simulated driving task. Future research should extend to more complex driving scenarios, such as navigating multi-lane urban roads and making turns, to better understand the effects of ambient temperature on driving behavior under varied conditions.

The role of clothing was also not extensively explored in our study. Considering that a 0.39 clo ensemble is more suitable for hotter environments, this factor might have influenced the observed lack of significant difference in thermal comfort across conditions. Future work will delve into the impact of insulation levels in both neutral and hot environments to further elucidate this aspect.

The manual adjustment of the air conditioning system introduced potential variability and inaccuracies in temperature control. Moreover, while relative humidity levels were broadly consistent, they were not perfectly regulated. Future studies should consider employing a broader range of temperature settings with finer increments, such as 5°C, to achieve higher precision in environmental control.

Our analysis did not account for light intensity, which is a significant oversight given its potential impact on the hue-heat effect. The literature suggests that both the intensity and the correlated color temperature (CCT) of light can influence perception (Baniya et al., 2018; Chao et al., 2020), which in turn can affect thermal sensation and comfort. Future investigations should include a comprehensive analysis of light intensity alongside CCT to better understand their combined effects on driver comfort and perception.

Finally, the demographic characteristics of our participant pool, including the predominance of younger drivers with limited driving experience and an unbalanced gender ratio, may have introduced bias into our findings. Since driving styles were classified based on task-specific rather than subject-specific data, the influence of participants' demographic traits on driving styles remains unexplored. Future research should aim to address these limitations by incorporating a more diverse participant group and examining the impact of demographic factors on driving behavior.

In summary, while our study has provided valuable insights into the relationship between in-car environmental conditions and driving styles, several limitations highlight the need for further research. By addressing these gaps, future work can build on our findings to develop a more comprehensive understanding of how ambient conditions influence driving behavior.

Conclusions

Our investigation into the effects of in-car environmental factors—specifically temperature, lighting conditions, and the interaction between these two factors—on driving performance, cognitive function, and subjective comfort, has elucidated nuanced insights with considerable implications for the hue-heat hypothesis during night-time driving. The findings underscore a significant impact of temperature on driving performance, perception of light brightness and thermal perception, with lighting condition also playing a role in modulating light perception.

Notably, the anticipated interactive effect between temperature and light color on driving performance was not observed, indicating that these factors independently influence the driver's experience. Although prior literature (Gagge et al., 1967; Velt & Daanen, 2017) suggests potential correlations between thermal sensation value and color sensation value, our findings did not corroborate these associations under varied lighting and temperature conditions. This discrepancy indicates a pressing need for further research into this interaction, taking into account potential confounding factors not considered in previous studies.

Furthermore, we utilized a two-layer driving style recognition model to predict driving styles by incorporating in-car temperature and lighting conditions. These results underline the importance of optimizing vehicle interiors, particularly in terms of temperature and lighting conditions, to enhance driver alertness and cognitive performance. Our research suggests that optimizing ambient conditions could not only improve driver comfort but also potentially reduce energy consumption in electric vehicles.

However, the study also recognizes limitations, including the use of a controlled laboratory setting and a homogeneous participant pool, which may limit the generalizability of the results. Future research should aim to explore these dynamics in more diverse and real-world scenarios to validate our findings and further investigate how ambient conditions can be leveraged to improve driving safety and efficiency.

This research offers valuable insights into the environmental determinants of cognitive performance and driving performance, providing significant implications for vehicle design and the development of guidelines to enhance driver comfort and optimization. Our findings advocate for the inclusion of environmental condition optimization as a critical component in the design of future vehicles and driving interfaces.

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Appendix

Dependent variables

Table S12. Summary of the tasks and surveys

Task/Survey	Major parameters	Purposes	Administration
Driving task	Forward velocity Acceleration Lateral velocity Lateral acceleration Lane deviation Steering Yaw rate	Evaluate the driving performance to observe compensatory behaviors under different environments	During driving
Secondary task (N-back task)	2-back	Simulate the non-driving behavior during the driving Measure drivers' working memory and attention	During driving
Emotion (Self-assessment manikin (SAM))	Valance Arousal Dominance	Measure the effect of environmental change on drivers' emotions, including valence, arousal, and dominance	After driving
Sleepiness	Stanford Sleepiness Scale	Measure the effect of cabin environmental change on drivers' sleepiness	After driving
In-car environment satisfaction	Light comfort Light brightness Light acceptance Thermal comfort Thermal sensation Thermal acceptance	Measure the change of drivers' satisfaction with different cabin environments	After driving
NASA-TLX workload	Mental demand Physical demand Temporal demand Own performance Effort Frustration	Evaluate and quantify the perceived workload of an individual or a team performing a specific task	After driving

G power software

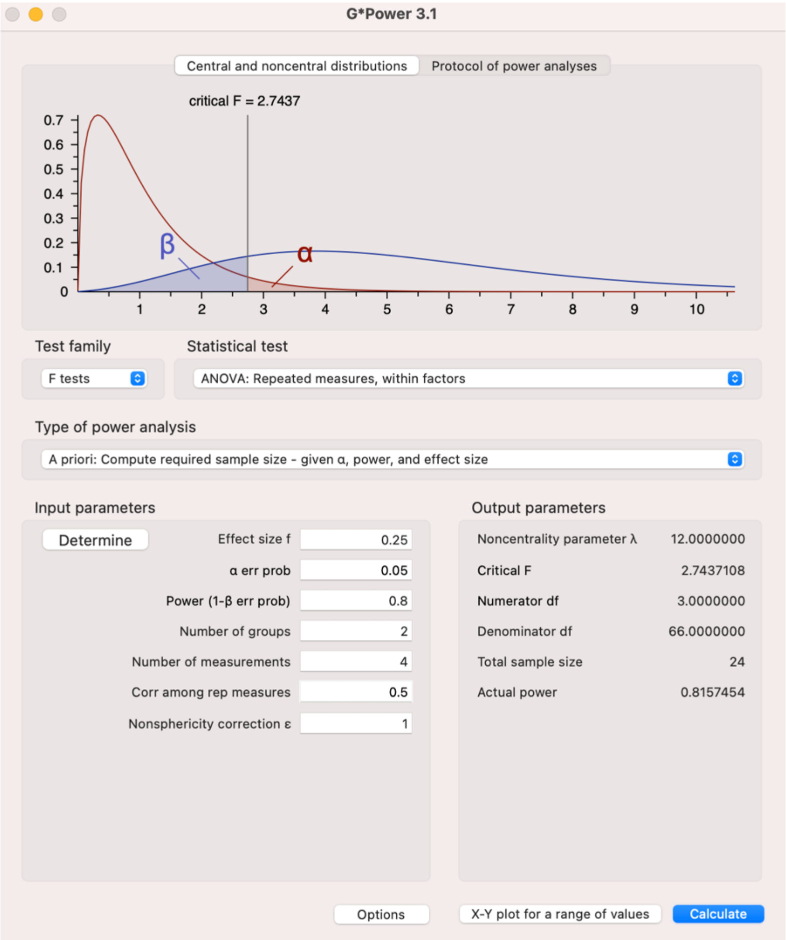


Fig. S1. Settings for power analysis in G*power

Questionnaire used in the study

a. Sleepiness

(Finish the question 1~2 before the experiment)

Q1: Sleeping quality before the experiment (very poor to excellent)

1 2 3 4 5 6 7 8 9 10

Q2: Rate the degree of sleepiness before the driving task (awake to asleep)

1 2 3 4 5 6 7

(Finish the remaining questions after the experiment)

Q3: Rate the degree of sleepiness after the driving task (awake to asleep)

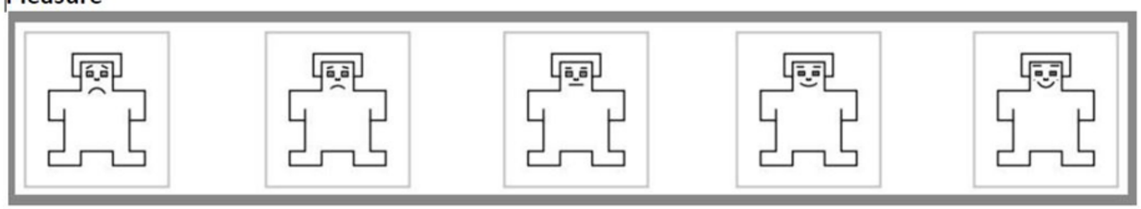
1 2 3 4 5 6 7

b. Emotion

Q4: Rate the valence (how negative or positive the emotion is) after the experiment (negative to positive)

-2 1 0 1 2

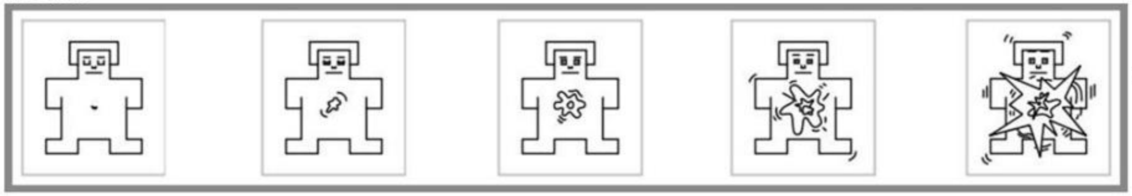
Pleasure



Q5: Rate the arousal (how excited or uninterested the emotion is) after the experiment (low to in high)

-2 1 0 1 2

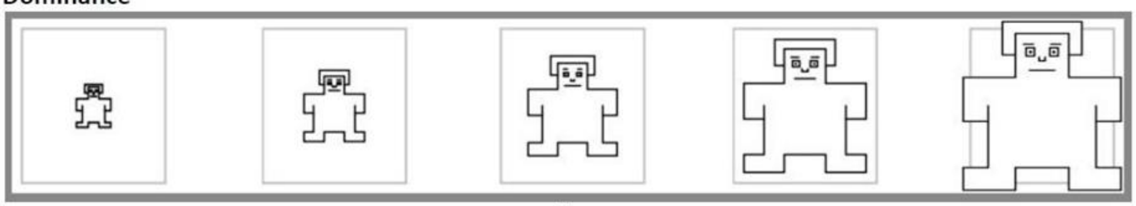
Arousal



Q6: Rate the feeling of dominance (the extent to which you feel you are in control of the situation) after the experiment (low to in high)

-2 1 0 1 2

Dominance



c. **Physical symptoms**

Q7: Rate the general comfort after the experiment (slight to severe)

1 2 3 4 5 6 7 8 9 10

Q8: Rate the feeling of nausea after the experiment (none to severe)

1 2 3 4 5 6 7 8 9 10

Q9: Rate the headache after the experiment (none to severe)

1 2 3 4 5 6 7 8 9 10

Q10: Do you have blurred vision (none to severe)

1 2 3 4 5 6 7 8 9 10

Q11: Are you sweating (slight to severe)

1 2 3 4 5 6 7 8 9 10

Q12: Do you feel faint (none to severe)

1 2 3 4 5 6 7 8 9 10

d. Perceived air quality and air quality acceptance

Q13: Rate your feeling of the air quality (worse to better)

-3 -2 -1 0 1 2 3

Q14: Rate your acceptance of the air quality (unacceptable to acceptable)

-3 -2 -1 0 1 2 3

e. Cognitive load

Q15: How mentally demanding was the task? (low to high)

1 2 3 4 5 6 7

Q16: How physically demanding was the task? (low to high)

1 2 3 4 5 6 7

Q17: How hurried or rushed was the pace of the task? (low to high)

1 2 3 4 5 6 7

Q18: How successful were you in accomplishing what you were asked to do? (perfect to failure)

1 2 3 4 5 6 7

Q19: How hard did you have to work to accomplish your level of performance? (low to high)

1 2 3 4 5 6 7

Q20: How insecure, discouraged, irritated, stressed, and annoyed were you? (low to high)

1 2 3 4 5 6 7

Effect of temperature and light color on the task load in the survey

Table S2. Descriptive Statistics for task load index at different temperature and light color

Conditions	NASA-TXL task load (scale from 1 to 7)	M	SD	N
18 °C	Mental demand	4.031	1.410	96
	Physical demand	2.25	1.257	96
	Temporal demand	3.281	1.429	96
	Own performance	5.063	1.221	96
	Effort	4.042	1.313	96
	Frustration	2.906	1.550	96
23 °C	Mental demand	3.990	1.559	96
	Physical demand	2.677	1.447	96
	Temporal demand	3.083	1.587	96
	Own performance	5.063	1.280	96
	Effort	3.906	1.543	96
	Frustration	2.969	1.657	96
	Mental demand	4.521	1.248	96

28 °C	Physical demand	2.604	1.476	96
	Temporal demand	3.615	1.417	96
	Own performance	4.708	1.151	96
	Effort	4.490	1.133	96
	Frustration	3.542	1.673	96
Blue	Mental demand	4.139	1.377	72
	Physical demand	2.556	1.500	72
	Temporal demand	3.333	1.592	72
	Own performance	4.972	1.198	72
	Effort	4.097	1.406	72
	Frustration	2.931	1.523	72
Red	Mental demand	4.208	1.383	72
	Physical demand	2.319	1.161	72
	Temporal demand	3.194	1.498	72
	Own performance	5.083	1.264	72
	Effort	4.153	1.329	72
	Frustration	3.083	1.726	72
Warm white (2700 K)	Mental demand	4.208	1.394	72
	Physical demand	2.528	1.353	72
	Temporal demand	3.389	1.439	72
	Own performance	4.861	1.225	72
	Effort	4.097	1.386	72
	Frustration	3.361	1.586	72
Cool white (5000 K)	Mental demand	4.167	1.574	72
	Physical demand	2.639	1.577	72
	Temporal demand	3.389	1.449	72
	Own performance	4.861	1.225	72
	Effort	4.236	1.337	72
	Frustration	3.181	1.747	72
Total	Mental demand	4.181	1.427	288
	Physical demand	2.510	1.404	288
	Temporal demand	3.326	1.490	288
	Own performance	4.944	1.226	288
	Effort	4.146	1.359	288
	Frustration	3.139	1.647	288

Table S3. Two-way Analyses of Variance of task load index at different temperature and light color

Parameters	Source	Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Mental demand	T	33041.52	2	16520.76	2.330	0.099	0.341
	Light color	2744.028	3	914.6759	0.127	0.944	0.028
	T * Light color	61060.01	6	10176.67	0.193	0.193	0.630
Physical demand	T	12939.94	2	6469.969	0.908	0.405	0.340
	Light color	9010.694	3	3003.565	0.420	0.739	0.237
	T * Light color	16097.17	6	2682.862	0.377	0.894	0.423
Temporal demand	T	43835.9	2	21917.95	3.108	0.046*	0.538
	Light color	8350.556	3	2783.519	0.388	0.762	0.102
	T * Light color	29301.25	6	4883.542	0.688	0.660	0.360
Own performance	T	88107.15	2	44053.57	6.403	<0.01**	0.611
	Light color	9123.361	3	3041.12	0.424	0.736	0.063
	T * Light color	46931.15	6	7821.858	1.112	0.356	0.326
Effort	T	46185.58	2	23092.79	3.279	0.039*	0.605
	Light color	4193.611	3	1397.87	0.194	0.900	0.055
	T * Light color	25914.99	6	4319.166	0.607	0.725	0.340
Frustration	T	71977.75	2	35988.88	5.183	<0.01**	0.692
	Light color	20857.78	3	6952.593	0.975	0.405	0.200
	T * Light color	11198.78	6	1866.464	0.260	0.955	0.108

Note: * denotes p value less than 0.05, ** denotes p value less than 0.01

Table S4. Descriptive Statistics for sleepiness and emotion at different temperature and light color

Conditions	M	SD	N
General comfort			
18 °C	5.917	2.055	96
23 °C	7.010	2.179	96
28 °C	6.313	2.455	96
Blue	6.389	2.504	72
Red	6.375	2.229	72
Warm white (2700 K)	6.319	2.219	72

Cool white (5000 K)		6.569	2.168	72
Total		6.413	2.274	288
Difference in Sleepiness (pre and post driving) (scale from 1 to 7)				
18 °C		2.365	1.274	96
23 °C		2.958	1.406	96
28 °C		3.052	1.605	96
Blue		2.889	1.459	72
Red		2.847	1.450	72
Warm white (2700 K)		2.833	1.434	72
Cool white (5000 K)		2.597	1.517	72
Total		2.792	1.462	288
Sweating				
18 °C		1.198	0.626	96
23 °C		1.635	0.964	96
28 °C		2.563	1.811	96
Blue		1.875	1.644	72
Red		1.722	1.201	72
Warm white (2700 K)		1.764	1.295	72
Cool white (5000 K)		1.833	1.278	72
Total		1.799	1.359	288
Emotion (scale from -2 to 2)				
18 °C	Valence	3.073	0.798	96
	Arousal	3.167	0.706	96
	Dominance	3.396	0.624	96
23 °C	Valence	3.25	0.883	96
	Arousal	3.083	0.914	96
	Dominance	3.427	0.830	96
28 °C	Valence	3.219	0.810	96
	Arousal	3.052	0.671	96
	Dominance	3.656	0.708	96
Blue	Valence	3.208	0.887	72
	Arousal	3.083	0.783	72
	Dominance	3.583	0.727	72
Red	Valence	3.25	0.801	72

	Arousal	3.083	0.783	72
	Dominance	3.417	0.746	72
Warm white (2700 K)	Valence	3.083	0.852	72
	Arousal	3.069	0.757	72
	Dominance	3.458	0.768	72
Cool white (5000 K)	Valence	3.181	0.793	72
	Arousal	3.167	0.769	72
	Dominance	3.514	0.692	72
Total	Valence	3.181	0.832	288
	Arousal	3.101	0.770	288
	Dominance	3.493	0.732	288

Table S5. Two-way Analyses of Variance of sleepiness and emotion at different temperature and light color

Parameters	Source	Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
General comfort							
General comfort	T	62798.81	2	31399.41	4.498	0.012*	0.764
	Light color	3093.472	3	1031.157	0.143	0.934	0.038
	T * Light color	16320.66	6	2720.11	0.381	0.891	0.199
Difference in Sleepiness (pre and post driving) (scale from 1 to 7)							
Sleepiness	T	36060.27	2	18030.14	2.547	0.080	0.462
	Light color	21384.53	3	7218.176	1.000	0.393	0.274
	T * Light color	20620.74	6	3436.791	0.482	0.821	0.264
Sweating							
Sweating	T	293436.1	2	146718	24.314	<0.01**	0.917
	Light color	10506.83	3	3502.275	0.502	0.681	0.033
	T * Light color	16073.53	6	2678.922	0.383	0.890	0.050
Emotion							
Valence	T	13267.75	2	6633.875	0.2942	0.391	0.292
	Light color	12799.61	3	4266.537	0.605	0.612	0.282
	T * Light color	19367.55	6	3227.925	0.459	0.839	0.426
Arousal	T	23357.26	2	11678.63	1.649	0.194	0.472
	Light color	4810.139	3	1603.38	0.224	0.879	0.097
	T * Light color	21288.62	6	3548.103	0.501	0.807	0.430

Dominance	T	87891.52	2	43945.76	6.405	<0.01**	0.710
	Light color	15805.19	3	5268.398	0.739	0.529	0.128
	T * Light color	20175.5	6	3362.583	0.474	0.827	0.163

Note: * denotes p value less than 0.05, ** denotes p value less than 0.01

Effect of temperature and light color on skin temperature

Table S4. Descriptive Statistics for perceived air quality and air quality acceptance at different temperature and light color

Conditions	**Item (scale from 1 to 7)**	**M**	**SD**	**N**
18 °C	D	29.312	2.922	96
	K	31.743	5.309	96
	O	30.302	1.397	96
	Q	27.856	2.171	96
	Integrated			96
23 °C	D	32.167	1.453	96
	K	33.708	1.124	96
	O	33.158	1.776	96
	Q	30.597	1.105	96
	Integrated			96
28 °C	D	34.437	0.930	96
	K	35.350	0.693	96
	O	34.426	0.950	96
	Q	32.835	0.766	96
	Integrated			96
Blue	D	31.910	2.925	72
	K	33.753	1.720	72
	O	32.546	2.276	72
	Q	32.389	2.568	72
	Integrated			72
Red	D	32.021	2.885	72
	K	33.072	6.309	72
	O	32.644	2.153	72
	Q	30.441	2.542	72
	Integrated			72
Warm white (2700 K)	D	31.950	2.839	72

	K	33.786	1.733	72
	O	32.662	2.227	72
	Q	30.422	2.589	72
	Integrated			72
Cool white (5000 K)	D	32.005	2.881	72
	K	33.783	1.737	72
	O	32.662	2.306	72
	Q	30.463	2.404	72
	Integrated			72
Total	D	31.972	2.868	288
	K	33.601	3.487	288
	O	32.629	2.230	288
	Q	30.429	2.514	288
	Integrated			288

Table S5. Two-way Analyses of Variance of perceived air quality and air quality acceptance at different temperature and light color

Item	Source	Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
D	T	1391762	2	695880.8	320.835	<0.01**	0.997
	Light color	1817.167	3	605.722	0.086	0.968	0.001
	T * Light color	2654.674	6	442.446	0.063	0.999	0.002
K	T	1058694	2	529346.8	175.834	<0.01**	0.986
	Light color	8660.528	3	2886.843	0.452	0.716	0.008
	T * Light color	5930.889	6	988.4815	0.152	0.989	0.006
O	T	1217928	2	608963.9	217.909	<0.01**	0.991
	Light color	595.25	3	198.417	0.028	0.994	0.001
	T * Light color	10179.98	6	1696.663	0.237	0.964	0.008
Q	T	1577577	2	788788.6	0.	<0.01**	0.
	Light color	631.4167	3	210.4722	0.	0.	0.
	T * Light color	5488.257	6	914.7095	0.	0.	0.
Integrated	T		2		0.	<0.01**	0.
	Light color		3		0.	0.	0.
	T * Light color		6		0.	0.	0.

Note: * denotes p value less than 0.05, ** denotes p value less than 0.01

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