

Article

Impact of Indoor Environmental Quality on Students' Attention and Relaxation Levels During Lecture-Based Instruction

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Abstract

Human cognitive performance is influenced by external factors, including indoor environmental quality (IEQ). Understanding how these factors affect stress, attention, and relaxation is essential in environments such as workplaces and educational institutions, where cognitive function directly impacts performance. This study examines the effects of IEQ on students' attention and relaxation levels during various lecture periods, focusing on design major students. Three key IEQ parameters (air temperature, relative humidity, and natural lighting) were evaluated for their effects on cognitive states using electroencephalogram (EEG) measurements in a controlled setting. Participants wore non-invasive, portable EEG devices to monitor neurophysiological activity across two sessions, each involving four scenarios: (i) baseline, (ii) increased natural light exposure, (iii) elevated relative humidity, and (iv) increased air temperature. EEG-derived metrics of attention and relaxation were analyzed alongside environmental data, including temperature, humidity, lighting conditions, carbon dioxide (CO₂) concentration, total volatile organic compounds (TVOC), and particulate matter (PM), to identify potential correlations. Results showed that natural light exposure improved relaxation but reduced attention, suggesting a restorative effect on stress that may also introduce distractions. Attention peaked under moderately warm, dry conditions (25–26 °C and 16–19% relative humidity), correlating positively with temperature (Pearson correlation coefficient, $r = 0.32$) and negatively with humidity ($r = -0.50$). Conversely, relaxation was highest under cooler, more humid conditions (23–24 °C and 24–26% relative humidity). Attention was negatively correlated with CO₂ ($r = -0.47$) and PM_{2.5} ($r = -0.46$), suggesting that poor air quality impairs alertness. Relaxation showed weaker but positive correlations with PM_{2.5} ($r = 0.38$), PM_{1.0} ($r = 0.35$), and CO₂ ($r = 0.32$). Ultrafine particles (PM_{0.3}, PM_{0.5}) and TVOC had minimal association with cognitive states. Overall, this study underscores the importance of optimizing indoor environments in educational settings to enhance academic performance and supports the development of evidence-based design standards to foster healthy, effective learning environments.

Keywords: indoor environmental quality; portable electroencephalogram devices; educational environments; attention; relaxation

1. Introduction

Indoor Environmental Quality (IEQ) in educational facilities is increasingly recognized as a critical determinant of students' cognitive and emotional development [1]. Classrooms



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serve not only as spaces for instruction but also as ecological contexts that profoundly influence health, well-being, and academic outcomes. A well-designed learning environment encompasses physical, psychological, and ergonomic elements that collectively foster concentration, motivation, and intellectual engagement. Among these, IEQ emerges as a cornerstone, influencing how students process, retain, and apply knowledge [2].

IEQ parameters such as air quality, lighting conditions, acoustics, and thermal comfort have been shown to affect both physiological and psychological states, which in turn modulate cognitive performance [3]. Poor IEQ has been linked to increased absenteeism, fatigue, and impaired learning efficiency, especially in environments that are poorly ventilated, inadequately illuminated, or thermally uncomfortable [4]. Consequently, understanding the multidimensional role of IEQ in educational settings is crucial for optimizing learning spaces in a way that supports sustainable student performance and health [5]. Learning is a complex process influenced by a constellation of factors encompassing pedagogical, social, individual, and environmental domains [6]. Social dimensions, particularly peer and teacher relationships, contribute to emotional safety, motivation, and collaborative learning environments [7]. Individual-level factors, such as students' ability to regulate stress and sustain intrinsic motivation, also play a critical role in shaping cognitive engagement and learning persistence [8]. However, these domains do not operate in isolation; they are often modulated by the physical characteristics of the learning environment, such as temperature, lighting, and humidity.

In a learning environment, understanding the impact of IEQ factors encompassing thermal conditions, lighting quality, acoustic performance, air quality, and even sensory access to natural views is critical. Each of these parameters contributes uniquely to students' cognitive states and comfort levels. For instance, research by Lee et al. [9] found strong correlations between various IEQ parameters and academic task performance, with particular emphasis on visual and acoustic conditions. Similarly, the study by Choi et al. [2] showed that student satisfaction with IEQ strongly predicted perceived learning and course satisfaction, emphasizing the holistic impact of the physical environment. Additionally, hygrothermal conditions in indoor environments have received prominent attention. According to the American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE) Standard 55 [10], optimal air temperature could range within 21–28 °C. A more specific range can be determined from the standard but depends on other factors, including metabolic rate, clothing insulation, humidity and air speed. Regarding relative humidity, the standard does not specify a lower humidity limit but notes that non-thermal comfort factors such as skin drying, irritation of mucus membranes, dry eyes, and static electricity may place limits on acceptability of very low humidity environments. Finally, ASHRAE Standard 62.1 [11] recommends that relative humidity in occupied spaces be controlled to less than 65% to reduce the likelihood of conditions that can lead to microbial growth.

Exposure to temperatures outside the optimal range has been found to decrease attention span and memory retention, while increasing stress markers [12,13]. Humidity levels also play a crucial role in influencing learning efficacy. Extremes in humidity can lead to respiratory discomfort and hinder voice projection, both of which negatively affect learning and engagement [14]. Lighting and views of nature are similarly impactful. Suboptimal lighting conditions can increase visual strain and cognitive fatigue, whereas blue-spectrum lighting with high correlated color temperature enhances alertness and cognitive engagement [3]. Studies also show that exposure to daylight and natural scenes supports mood stabilization and mental restoration [15,16].

Ventilation and indoor air quality (IAQ) are among the most rigorously documented components of IEQ. The United States Environmental Protection Agency (US EPA) [17] has established the National Ambient Air Quality Standards (NAAQS) for six primary pollutants,

including carbon monoxide, lead, nitrogen dioxide, ozone, particulate matter (PM), and sulfur dioxide, which pose risk to both public health and the environment [18]. Additionally, exposure to pollutants such as carbon dioxide (CO₂), often used as a proxy for ventilation efficiency, has been linked to adverse health outcomes and impaired cognitive function. CO₂ concentrations exceeding 1000 parts per million (ppm) are commonly associated with symptoms of sick building syndrome and reduced office work productivity [19]. Large-scale studies have further linked poor IAQ to decrease cognitive performance and increased absenteeism [20]. In educational settings, students exposed to classrooms with CO₂ levels above 1000 ppm exhibited lower task efficiency and higher stress levels, emphasizing the need for continuous air quality monitoring and real-time IAQ optimization [21]. Hutter et al. [22] have shown that short-term exposure to elevated CO₂ levels (as high as 3300 ppm averaged over an hour) can impair cognitive performance in children aged 6 to 8. Similarly, Satish et al. [23] showed that adult participants in an office-like environment experienced measured declines in cognitive function when CO₂ concentration raised from 600 ppm to 1000 ppm and 2500 ppm during three separate 2.5 h sessions. Other studies have demonstrated that cognitive and physiological responses to pollutants such as PM₁, PM_{2.5}, and CO₂, including changes in brain activity measured by electroencephalogram (EEG) devices, can be used to accurately estimate inhaled pollutants concentrations [24–26]. These findings highlight a measurable link between air pollution, cognitive function, and the human body's physiological response to indoor air contaminants.

Stress and attention are central components of cognitive performance, each modulated by the quality of the indoor environment. The inverse relationship between attention and relaxation observed in cognitive performance studies can be understood as both physiological and task dependent [27,28]. Attention typically reflects a heightened state of cognitive engagement, requiring mental effort, alertness, and often activation of stress-related physiological systems to sustain focus [29]. In contrast, relaxation is associated with reduced arousal and a shift toward mental rest or recovery, which may be more prominent in comfortable or low-demand environments [30]. These two states are naturally opposed, as the activation required for focused task performance tends to suppress the brain activity associated with relaxation. Moreover, tasks shape this relationship: during cognitively demanding activities, attention levels rise while relaxation decreases; conversely, in non-task or comfortable conditions, relaxation is more likely to dominate. This cognitive trade-off is therefore shaped by both environmental inputs and internal task requirements, making it a meaningful indicator when evaluating the impact of IEQ on mental states. In educational settings, elevated stress levels can impair executive function, reduce working memory capacity, and hinder attentional control, leading therefore to disengagement and suboptimal academic outcomes [8]. In recent years, EEG monitoring has emerged as a valuable tool in assessing cognitive states in educational and environmental psychology research. EEG measures electrical activity in the brain, offering real-time, non-invasive insights into students' mental states under varying environmental conditions. Research using EEG monitoring has provided new insights into these dynamics by identifying characteristic brainwave patterns associated with different mental states. Specific brain wave patterns have been linked to distinct cognitive processes: alpha and theta waves are typically associated with attention and sustained engagement, while elevated beta activity often reflects heightened stress and mental workload [3,29,30]. Unlike self-reported assessments, EEG provides continuous, objective data that can detect subtle variations in cognitive engagement and stress that may be imperceptible to participants themselves.

Numerous studies converge on the finding that IEQ influences both subjective comfort and objective cognitive performance in students. Key cognitive functions, such as attention, memory, and task execution, have been shown to decline under poor environ-

mental conditions [2,9]. The use of EEG technology has provided more nuanced insights into these relationships. A study by Guan et al. [31] found that EEG signatures such as elevated theta activity in the frontal cortex are indicative of improved comfort and attentional states in thermally and acoustically optimized environments. Additionally, the review by Zhang et al. [3] confirmed that lighting configurations with high illuminance and blue-enriched spectra increase beta and gamma EEG activity, correlating with elevated alertness and working memory function. EEG signals have also been shown to be sensitive to ambient CO₂ levels [32], with the power of EEG spectra being elevated at low frequency [33]. These physiological signatures provide strong, objective indicators that IEQ interventions, when precisely targeted, can enhance mental engagement and stress resilience in learning contexts.

While previous studies have linked IEQ factors, such as air quality, lighting conditions, and temperature to learning outcomes, they often rely on subjective reports based on questionnaires or generalized performance tests that do not capture students' engagement during real-world lectures on topics related to their majors. Furthermore, these approaches fail to reflect real-time physiological responses that more accurately represent how students truly experience their environment. This study addresses this research gap by using portable, non-invasive EEG devices to measure the effects of air temperature, relative humidity, and natural light exposure on students' attention and relaxation levels monitored during different lectures. These lectures focused on design-related topics intended to promote active participation and sustained attention among students majoring in design. Additionally, IAQ parameters including CO₂, total volatile organic compounds (TVOC), and PM across a size range of 0.3 µm to 10.0 µm were monitored to explore correlations between environmental conditions and cognitive performance indicators, namely attention and relaxation levels. The main contribution of this study lies in introducing EEG based evaluation method that complements traditional IEQ assessments by capturing objective, moment-by-moment cognitive responses in actual learning environments. Unlike self-reported methods, this approach offers a direct, physiological measure of how IEQ affects student engagement, making it a novel and human-centered tool for evidence-based classroom design. By focusing on adjustable classroom factors, the findings aim to inform strategies for improving student well-being and learning conditions.

In summary, this study aims to:

- Investigate how specific IEQ parameters, including air temperature, relative humidity, and natural lighting, affect students' cognitive states, specifically attention and relaxation levels, as measured by portable, non-invasive EEG headsets during different lectures.
- Identify statistical correlations between neurophysiological indicators of cognitive performance (attention and relaxation levels) and IEQ factors, including air temperature and relative humidity, CO₂, TVOC, and PM, monitored during the same lectures.
- Design evidence-based strategies for educational settings aimed at improving students' academic performance by analyzing how the assessed IEQ factors influence attention and engagement in lectures.

This paper is structured as follows. Section 2 outlines the methodology used in the analysis, including the data collection and the description of the monitoring devices. Section 3 presents the results regarding the effect of the monitored IEQ factors on the cognitive performance indicators examined in this study. Finally, Section 4 summarizes the findings and presents our conclusions.

2. Materials and Methods

The study was conducted in a controlled test room (described in Section 2.1) within the Department of Architecture, Design and Urbanism. It consisted of two experimental sessions, each lasting two hours and fifteen minutes. In each session, six students from the same academic department participated in four distinct environmental scenarios, specifically designed to isolate the effects of selected IEQ factors on participants' attention and relaxation levels during different lectures. In total, 12 different participants (four women and two men per session) were involved in the study. While the authors acknowledge the limitations of the sample size, the investigation's findings yielded intriguing and thought-provoking results that could serve as a foundation for future papers expanding the research methodology employed in this project. Additionally, it is important to note that several prior EEG-based studies have employed similar number of participant cohorts while still yielding valuable insights to the literature (see Tables 3–6 in LaRocco et al. [34]). For example, similar sample sizes were used in EEG-based studies such as Bashivan [35] (16 participants), Hoffmann [36] (19 participants) and Rohit et al. [37] (23 participants). Consequently, the present analysis contributes as a pilot study to evaluate the feasibility of EEG-based measurements using non-invasive, wearable devices in real-world educational environments, with the goal of expanding the sample size in future work.

During each session, all six participants wore EEG devices (described in Section 2.2) throughout the four scenarios. It is important to note that all participants were students of Architecture or Interior Design and thus shared a background in design and familiarity with lecture-based learning environment. The mean age and standard deviation of the participant was 21.0 ± 3.0 years.

The experimental setup consisted of two sessions, each lasting two hours and fifteen minutes, with four different scenarios per session. Each scenario, which lasted 30 min, was divided into three sequential phases: (i) completion of pre-questionnaires assessing participants' perceptions of indoor environmental conditions, (ii) participation in a 10 min lecture on a sustainable design-related topic intended to promote active engagement and enhance attention, and (iii) completion of post-questionnaires evaluating participants' subjective experience of the environment. A five-minute break was scheduled between scenarios, during which students were asked to wait outside the test room. This interval served to minimize participant fatigue and drowsiness and allowed the research team sufficient time to implement the environmental changes required for the subsequent scenario. The methodological framework of each session is illustrated schematically in Figure 1, and the different scenarios are described as follows:

- **Scenario 1 (Baseline):** This scenario served as the control condition against which all subsequent environmental interventions were evaluated. During this phase, the window shades remained closed, and no modifications were made to the air temperature and relative humidity within the test room. These environmental conditions were primarily influenced by the presence of occupants in the room.
- **Scenario 2 (Natural Light Exposure):** This scenario introduced natural light as the first environmental intervention. The window shades were fully opened, allowing daylight to enter the room and offering participants a direct view of a main street and nearby trees. This scenario was conducted during daylight hours in two time slots, namely from 13:50 to 14:20 and from 15:50 to 16:20, during the winter season on the East Coast of the United States.
- **Scenario 3 (Increased Humidity):** This scenario examined the impact of elevated relative humidity on cognitive performance. A humidifier was employed to manually raise the humidity level within the test room beyond baseline conditions.

- **Scenario 4 (Elevated Temperature):** This scenario investigated the influence of increased air temperature on cognitive performance. Two heaters were used to raise the room temperature, creating a warmer environment compared to the baseline.

It is important to note that Session 2 was conducted 30 min after the conclusion of Session 1, during which time the door of the test room was intentionally left open to facilitate a reduction in air temperature and partially restore the initial environmental conditions. Although this interval was insufficient to fully replicate the hygrothermal conditions present at the start of Session 1, the differing starting conditions at the onset of Session 2 offered complementary and valuable insights into participants' attention and relaxation levels under varying environmental scenarios.

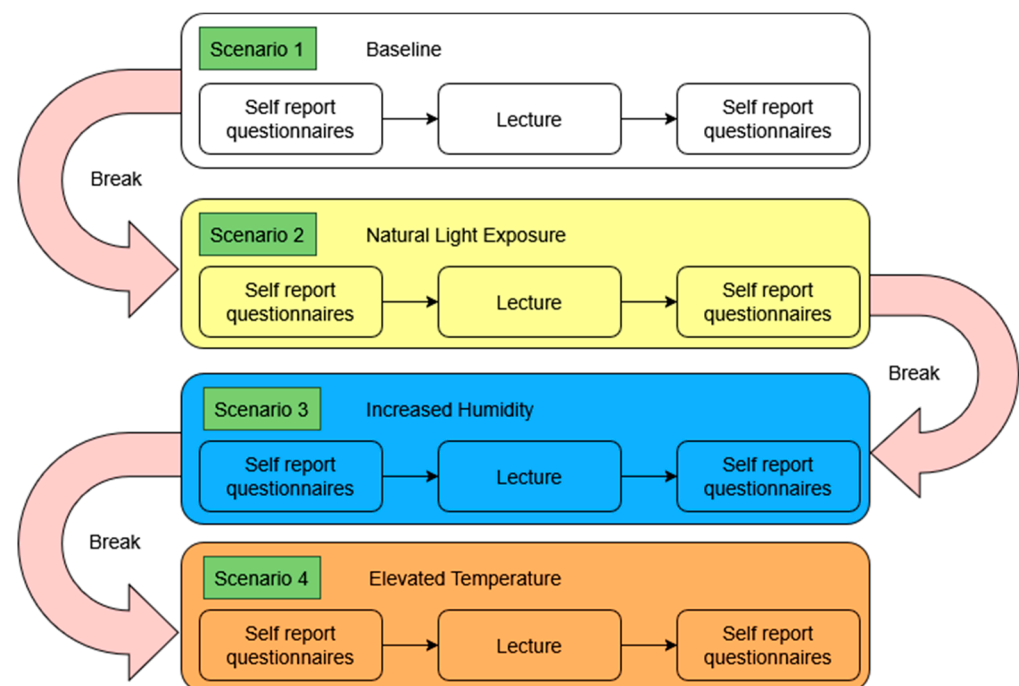


Figure 1. Schematic representation of the methodology followed during each session.

2.1. Experimental Setup

The experimental sessions were conducted in a test room, as illustrated in Figure 2a,b. Various environmental parameters were continuously monitored using several data loggers: four sensors recorded air temperature, relative humidity, and CO₂ concentrations; one sensor monitored TVOC; one sensor measured PM levels; and a spectrometer tracked lighting conditions, including illuminance and color temperature. Lighting in the test room was provided by ceiling-mounted fluorescent fixtures (4100 K color temperature) and natural daylight, which was present only during the scenarios in which the window shades were opened. Sensor placement followed a strategic configuration to enable a comprehensive spatial assessment of indoor environmental conditions, as depicted in Figure 2a. It is important to note that participants occupied the same location throughout the four scenarios in each session (see Figure 2b) to minimize the impact of potential spatial variations in indoor environmental conditions within the test room, which could introduce confounding factors when evaluating the correlations between students' attention and relaxation levels and the assessed IEQ factors.

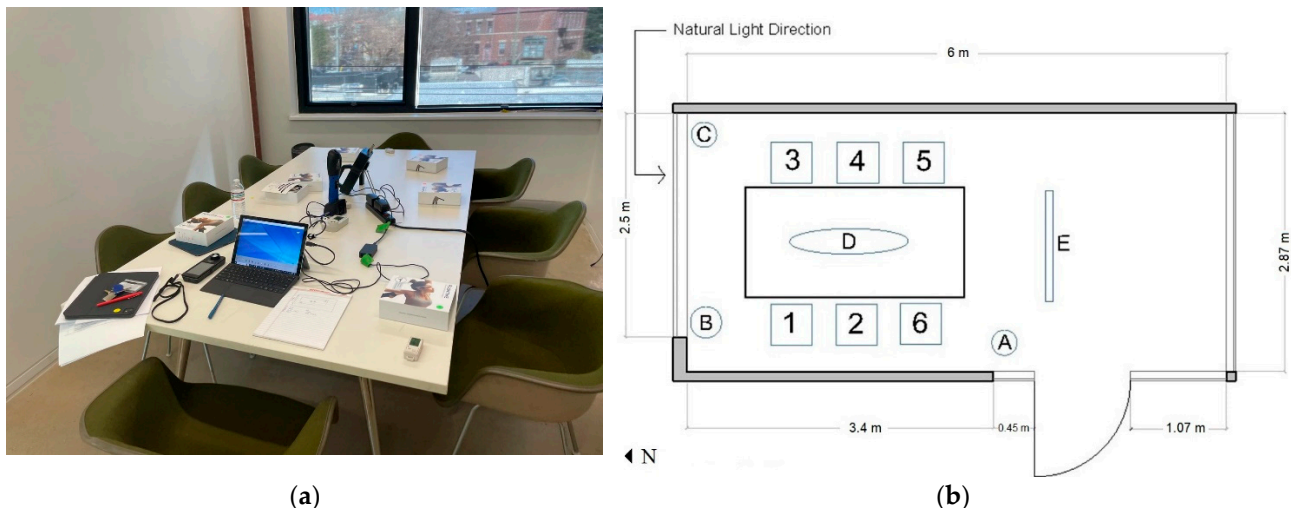


Figure 2. (a) Test room. (b) Configuration of the test room during the sessions. Heaters are labeled as A and C, while B represents the humidifier. The location of the IEQ sensors and the TV for lectures are indicated by D and E, respectively, and the numbers 1 to 6 correspond to the participants.

Environmental data were logged at 15 s intervals to capture variations in IEQ, with the exception of lighting. In that case, a single measurement, taken at the same height of seated participants, was performed in each environmental scenario. This approach was adopted following prior experimental verification that lighting conditions remained stable throughout the 10 min lecture periods. All sensors were mounted at 0.6 m above the floor level in accordance with ASHRAE Standard 55 [10], ensuring that measurements reflected conditions experienced by seated occupants. The metabolic rate of the participants was estimated at 1.0 MET, corresponding to a seated, quite activity, as per ASHRAE Standard 55 [10]. Other factors influencing thermal comfort, such as clothing insulation, were assessed through the pre-questionnaires administered at the beginning of each experimental scenario. However, these factors were not included in the current analysis, as thermal comfort assessment was not the primary research objective. Nonetheless, the authors acknowledge the potential for future studies to incorporate subjective responses from the pre- and post-questionnaires, enabling comparisons between quantitative data from environmental and EEG sensors and self-reported perceptions from students. Moreover, future work may consider introducing a coefficient similar to the Turhan and Özbey coefficients [38,39] to quantify the influence of mood states on thermal sensation and cognitive performance. Lastly, the linear slot diffusers in the test room were closed to isolate the space from the centralized chilled beam heating, ventilation, and air conditioning (HVAC) system. Additionally, the windows were non-operable. As a result, air speed around occupants, another factor influencing thermal comfort, remained negligible. All instrumentation and equipment utilized in this study are listed in Table 1.

Table 1. Monitoring devices and equipment utilized in the study.

Brand and Model	Manufacturer	IEQ and EEG Factors
HOBO® MX1101	Onset Computer Corporation (Bourne, MA, USA)	Temperature
HOBO® MX1101	Onset Computer Corporation (Bourne, MA, USA)	Relative Humidity
HOBO® MX1102A	Onset Computer Corporation (Bourne, MA, USA)	CO ₂
GrayWolf® DirectSense II	GrayWolf Sensing Solutions (Shelton, CT, USA)	TVOC
GrayWolf® PC-3500	GrayWolf Sensing Solutions (Shelton, CT, USA)	PM

Table 1. *Cont.*

Brand and Model	Manufacturer	IEQ and EEG Factors
SEKONIC® C-700	Sekonic Corporation (North White Plains, NY, USA)	Illuminance and Color Temperature
Flowtime® FT01-YHG001	Enter Technology Co., Ltd. (Hong Kong Island, Hong Kong SAR)	Attention and Relaxation
Honeywell® HEV620B	Honeywell (Charlotte, NC, USA)	Humidifier
Holmes® HCH4953	The Holmes Group, Inc. (Milford, MA, USA)	Heater

2.2. Data Collection of Attention and Relaxation Levels

The Flowtime Biosensing Headband [40] was selected for this study due to its practicality, affordability, and suitability for real-time cognitive and affective monitoring in applied environmental research contexts. This device, which has been employed in different research works [41–43], represents an ideal alternative for measuring EEG data in real-world situations, such as the learning environment replicated in this study, due to its non-invasive design. It consists of a wireless headband with dedicated sensors that gather cognitive and physiological responses at a logging rate of 1.6 Hz, including heart rate, heart rate variability, and brainwave activity across five frequency bands: alpha, beta, theta, delta, and gamma wave. The EEG data is transmitted via Bluetooth to a paired mobile device (tablet or smartphone) running the Flowtime application (version 5.0.9), enabling real-time monitoring and download of raw data. Notably, the Flowtime device also generates two metrics associated with the overall engagement of students during the lectures: attention and relaxation. These two metrics, which range on a scale from 0 to 100, are derived by the EEG device using algorithms that analyzed the relative contribution of the different brainwave frequencies at a given time to infer participants' cognitive engagement during the lectures. The specific brain wave patterns have been linked to distinct cognitive processes: alpha and theta waves are typically associated with attention and sustained engagement, while elevated beta activity often reflects heightened stress and mental workload [3,29,30]. Unlike self-reported assessments, EEG provides continuous, objective data that can detect subtle variations in cognitive engagement and stress that may be imperceptible to participants themselves.

Although raw brainwave signals were also collected for consistency checks and validation, this study focused on the derived performance indicators (attention and relaxation levels) due to their close association with brainwave activity. It is important to note that individual EEG device calibration, in accordance with the guidelines provided by the manufacturer, was also conducted during the first phase of each experimental scenario.

Unlike complex multi-electrode EEG systems, Flowtime's single-sensor design minimizes setup complexity and participant discomfort. Furthermore, it provides direct metrics such as attention and relaxation levels, which facilitated the evaluation of participants' cognitive performance in relation to the designed environmental interventions. Following a rigorous data screening and cleaning process to eliminate artifacts, noise, and inconsistencies, the dataset was refined to ensure reliability and consistency for subsequent analysis. Although none of the participants had prior hands-on experience with EEG devices, all demonstrated familiarity with the lecture content presented during the two experimental sessions, thereby minimizing variability due to subject-matter unfamiliarity. Finally, prior to data collection in each experimental session, participants received a standardized briefing from the research team before putting on an EEG headset, which continuously captured neural activity throughout the session.

3. Results

This section presents the numerical results of the investigation. The first part discusses the recorded values of the IEQ factors examined in this study, including air temperature, relative humidity, CO₂ concentration, TVOC levels, PM, and lighting conditions. Subsequently, the impact of IEQ on cognitive performance is analyzed in detail, with a focus on attention and relaxation levels. The analysis includes assessing correlations between IEQ parameters and cognitive performance indicators, as well as comparing attention and relaxation scores in each scenario relative to the baseline. Finally, to simplify notation when discussing the numerical results, the different scenarios and sessions are defined as “SX^(y)”, where X = 1, 2, 3, or 4 corresponds to the four scenarios, and y = 1 or 2 denotes the two sessions.

3.1. Environmental Monitoring

Figure 3 illustrates the evolution of the IEQ factors analyzed over the monitored period. In all graphs, the gray shaded regions denote the 10 min lecture periods during which the EEG devices were connected for each scenario. The corresponding mean and standard deviation of the IEQ factors during these lecture periods are summarized in Tables A1 and A2 in Appendix A.

Air temperature and relative humidity, shown in Figure 3a, exhibited consistent trends in response to the environmental interventions implemented across the different scenarios. The temperature in the test room steadily increased due to the presence of participants (six students and two investigators) in each scenario, with a more pronounced rise observed in S4⁽¹⁾ and S4⁽²⁾ as a result of the heater being activated. The opening of the door between scenarios and sessions also influenced the temperature, contributing to a slight decrease, most notably between sessions. It is important to note that during S1⁽²⁾ and S2⁽²⁾, the door was intentionally kept open to help restore baseline environmental conditions, and the monitored data reflected a corresponding minor decrease in temperature. In Session 1, S1⁽¹⁾ recorded the lowest mean temperature at 22.90 °C, while S4⁽¹⁾ recorded the highest at 25.69 °C. In Session 2, S3⁽²⁾ showed the lowest mean temperature at 25.42 °C, and S4⁽²⁾ the highest at 26.52 °C. Finally, the value outside the test room remained approximately constant during both sessions, at 22.72 ± 0.02 °C.

Relative humidity, also depicted in Figure 3a, showed greater variability compared to temperature. In each scenario of Session 1, the presence of occupants in the test room contributed to an increase in relative humidity, which then decreased briefly by opening the door between scenarios. The elevated relative humidity observed in S3⁽¹⁾ and S3⁽²⁾ was attributed to the activation of the humidifier. Conversely, the sharp decrease observed in S4⁽¹⁾ and S4⁽²⁾ was associated with the increase in air temperature due to heater use, reflecting the inverse relationship between air temperature and relative humidity, as warmer air can retain more moisture. The pronounced decrease observed around 15:25 was linked to the door being opened between sessions. Additionally, the decrease in relative humidity observed during S1⁽²⁾ and S2⁽²⁾ was consistent with the door being intentionally kept open to help restore baseline environmental conditions. In Session 1, S4⁽¹⁾ recorded the lowest mean relative humidity at 21.93%, while S3⁽¹⁾ recorded the highest at 25.43%. In Session 2, S1⁽²⁾ showed the lowest mean relative humidity at 17.37%, and S4⁽²⁾ the highest at 22.02%. Finally, the value outside the test room remained approximately constant during both sessions, at $17.26 \pm 0.19\%$.

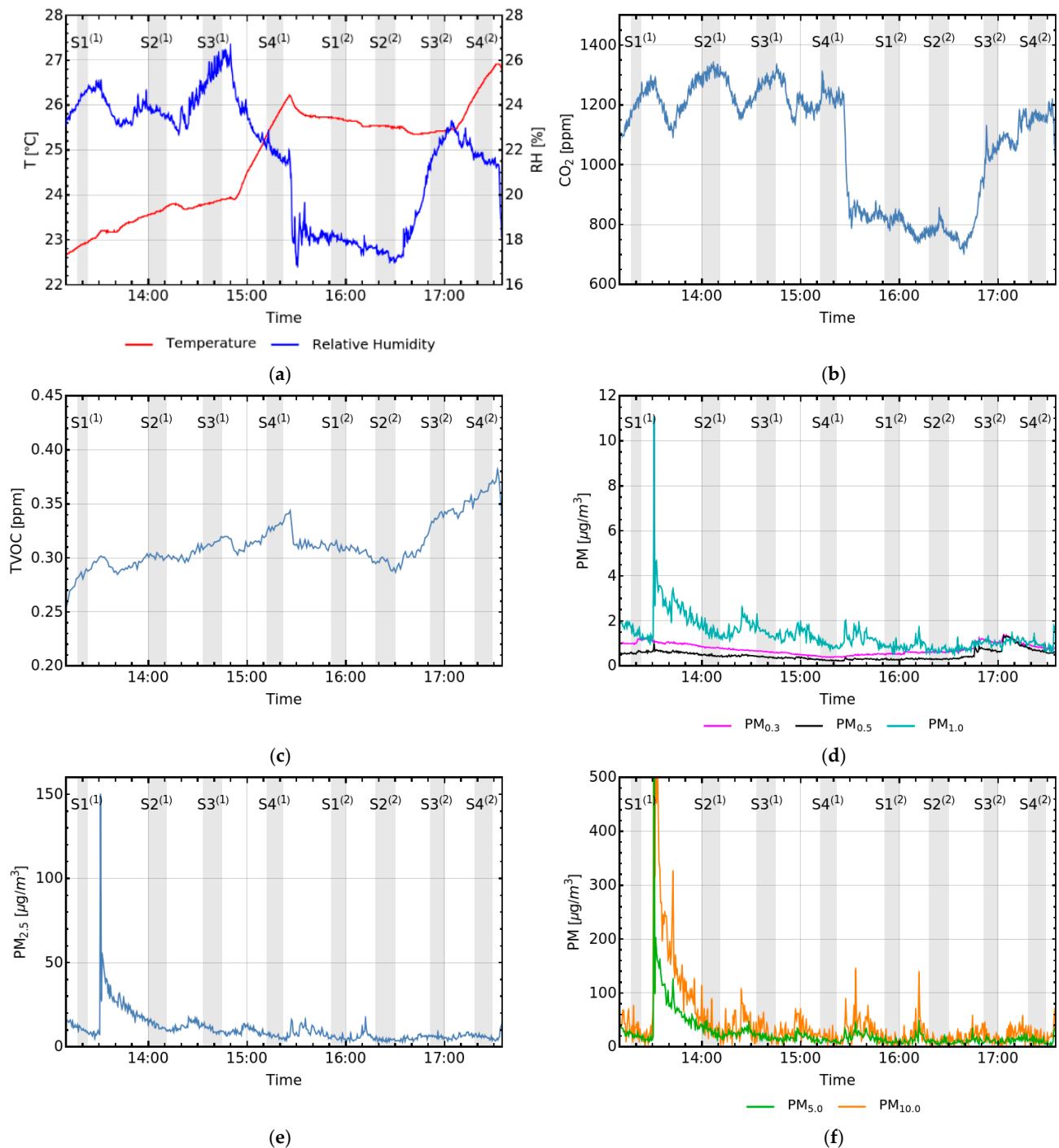


Figure 3. IEQ factors analyzed during the monitoring campaign: (a) temperature and relative humidity, (b) CO_2 concentration, (c) TVOC, and (d–f) PM levels. The gray shaded regions denote the 10 min lecture periods across the two experimental sessions.

Figure 3b illustrates the CO_2 concentration within the test room, which exhibited consistent trends throughout the monitored period, primarily influenced by occupant presence and whether the door was open or closed. In each scenario of Session 1, participants in the experiment contributed to a steady increase in CO_2 levels, which subsequently decreased briefly by opening the door between scenarios. The pronounced decrease observed around 15:25 was attributed to the door being opened between sessions. Additionally, the lower CO_2 concentrations recorded during $\text{S1}^{(2)}$ and $\text{S2}^{(2)}$, compared to those in Session 1, were consistent with the door being intentionally kept open to help restore baseline environ-

mental conditions. A marked increase in CO₂ concentration was observed around 16:40, corresponding to the door being closed for the final two scenarios of Session 2. The mean CO₂ concentrations during the four scenarios in Session 1 were relatively consistent, at approximately 1257 ppm. In contrast, greater variability was noted in Session 2, where S1⁽²⁾ recorded the lowest mean concentration at 789 ppm, while S4⁽²⁾ the highest at 1156 ppm. Finally, the 1000 ppm upper limit, commonly associated with sick building syndrome and reduced office work performance [19], was exceeded in all scenarios except for S1⁽²⁾ and S2⁽²⁾. This outcome is consistent with the effect of the open door, which facilitated ventilation and contributed to lower CO₂ levels during those scenarios. For comparison, the value outside the test room remained approximately constant during both sessions, at 533 ± 100 ppm.

TVOC levels monitored in the test room, as shown in Figure 3c, were influenced by both occupant presence and door status, either open or closed. During Session 1, TVOC concentration increased continuously, except for a brief time when the door was opened between scenarios, reaching a maximum at the end of S4⁽¹⁾. The door opening around 15:25 between sessions corresponded with a marked decrease in TVOC concentration. Furthermore, the decreases observed during S1⁽²⁾ and S2⁽²⁾ align with the door being intentionally kept open to facilitate the restoration of baseline environmental conditions. In Session 1, the lowest mean TVOC concentration was recorded during S1⁽¹⁾ at 0.285 ppm, while the highest was observed in S4⁽¹⁾ at 0.329 ppm. In Session 2, S1⁽²⁾ showed the lowest mean concentration at 0.295 ppm, and S4⁽²⁾ the highest at 0.361 ppm.

PM concentrations, shown in Figure 3d,f for the various particle sizes, followed similar trends throughout the experiment. Except for the smallest particles analyzed, PM_{0.3} and PM_{0.5}, whose concentrations remained approximately constant, all PM levels began at elevated values in each scenario and gradually decreased toward the end. This trend is attributed to the movement of investigators within the test room as they prepared the environment (e.g., distributing questionnaires, adjusting the screen, or installing the heater and humidifiers) for the subsequent scenario, which then proceeded without disruption. Notably, pronounced peaks in PM_{1.0}, PM_{2.5}, PM_{5.0}, and PM_{10.0} concentrations were observed around 13:30, corresponding to the opening of the window shades in preparation for S2⁽¹⁾. This peak was likely caused by the release of accumulated PM (e.g., dust) from the shades into the ambient air upon opening. Interestingly, a similar spike in PM concentration was not observed when the shades were opened again before S2⁽²⁾. This suggests that most of the accumulated dust had already been released during the initial opening of the shades prior to S2⁽¹⁾ and subsequently deposited on surfaces within the test room.

The average concentrations of PM_{0.3}, PM_{0.5} and PM_{1.0} during the four 10 min lectures in Session 1 were 0.74 µg/m³, 0.44 µg/m³, and 1.36 µg/m³, respectively. In the same session, PM_{2.5}, PM_{5.0}, and PM_{10.0} recorded average values of 9.99 µg/m³, 20.23 µg/m³, and 29.47 µg/m³, respectively. By comparison, Session 2 recorded average concentrations of 0.79 µg/m³, 0.51 µg/m³, and 0.90 µg/m³ for PM_{0.3}, PM_{0.5} and PM_{1.0}, and 5.55 µg/m³, 10.73 µg/m³, and 13.92 µg/m³ for PM_{2.5}, PM_{5.0} and PM_{10.0}, respectively. Overall, the concentrations of the smallest particles (0.3 µm to 1.0 µm) remained approximately constant between the two experimental sessions. In contrast, PM levels for particles ranging from 2.5 µm to 10.0 µm were significantly lower in Session 2 due to the higher deposition rates associated with larger particles. This observation aligns with experimental findings on PM deposition rates reported by Hussein et al. [44] and Faubel et al. [45].

Lighting conditions, including illuminance and color temperature, were measured at the beginning of each scenario. This approach was adopted following prior experimental verification that lighting conditions remained stable throughout each scenario. In Session 1, the lighting conditions in S1⁽¹⁾ were 605 lx for illuminance and 3948 K for color temperature.

In S2⁽¹⁾, both illuminance and color temperature increased to 715 lx and 4622 K, respectively, due to the opening of the window shades. In S3⁽¹⁾, the lighting conditions returned to values similar to those in S1⁽¹⁾, as the window shades were closed again. S4⁽¹⁾ exhibited identical lighting conditions to S3⁽¹⁾, reflecting the continued closure of the window shades.

Session 2 followed similar trends for lighting conditions. In S1⁽²⁾ and S2⁽²⁾, the illuminance levels were 488 lx and 534 lx, while the corresponding color temperatures were 3884 K and 4294 K. These variations are attributed to the closing and opening of the window shades during each scenario, respectively. In S3⁽²⁾, the lighting conditions again returned to levels comparable to those in S1⁽²⁾ due to the re-closure of the shades. Finally, the lighting conditions in S4⁽²⁾ mirrored those of S3⁽²⁾, as the window shades remained closed.

3.2. Impact of Indoor Environmental Quality on Cognitive Performance

Table 2 summarizes the mean and standard deviation of the cognitive performance indicators measured during the 10 min lecture in each scenario across the two sessions. The EEG device reported attention and relaxation on a scale from 0 to 100 and also recorded brainwave data across five frequency bands (alpha, beta, theta, delta, and gamma wave). Although raw brainwave signals were also collected to assess consistency and validate results, this analysis focuses on the derived performance indicators provided by the EEG device, namely, attention and relaxation, due to their close association with brainwave activity.

Table 2. Mean and standard deviation of the cognitive performance indicators during the 10 min lecture across the two experimental sessions.

EEG Data (Session 1)	S1 ⁽¹⁾	S2 ⁽¹⁾	S3 ⁽¹⁾	S4 ⁽¹⁾
Attention	71.69 ± 6.95	59.53 ± 10.44	58.94 ± 8.33	68.75 ± 6.53
Relaxation	38.82 ± 5.21	45.90 ± 9.07	48.85 ± 7.07	42.22 ± 4.62
EEG Data (Session 2)	S1 ⁽²⁾	S2 ⁽²⁾	S3 ⁽²⁾	S4 ⁽²⁾
Attention	75.61 ± 5.32	70.70 ± 5.19	66.20 ± 4.38	67.31 ± 8.65
Relaxation	38.30 ± 4.29	42.06 ± 4.40	42.10 ± 4.26	41.09 ± 6.75

The baseline scenario recorded the highest attention scores in both sessions, with means of 71.69 in S1⁽¹⁾ and 75.61 in S1⁽²⁾. In Session 1, attention levels in S2⁽¹⁾ and S3⁽¹⁾ were similar, at 59.53 and 58.94, respectively, while S4⁽¹⁾ showed a comparatively higher score of 68.75. A different trend emerged in Session 2, where the second-highest attention level, 70.70, was recorded in S2⁽²⁾, while S3⁽²⁾ and S4⁽²⁾ reported comparable values of 66.20 and 67.31, respectively.

Relaxation levels exhibited an inverse pattern relative to attention, reinforcing the expected cognitive activation mechanism. The lowest relaxation values were observed in the baseline scenario across both sessions, with values of 38.82 in S1⁽¹⁾ and 38.30 in S1⁽²⁾. In Session 1, S2⁽¹⁾ and S3⁽¹⁾ had higher relaxation scores, 45.90 and 48.85, respectively, corresponding with lower attention levels. In Session 2, the relaxation levels were more uniform across all scenarios, ranging narrowly between 38 and 42. The pattern in relaxation levels varied with the measured attention values accordingly, consistent with the inverse relationship between these two outputs derived from the EEG device.

To further explore variations in cognitive performance across scenarios relative to the baseline, Figure 4 illustrates the probability density functions (PDFs) of attention and relaxation levels for each scenario across both sessions. These PDFs provide insights into the distributional characteristics of the EEG-derived metrics and complement the mean and standard deviation values reported in Table 2.

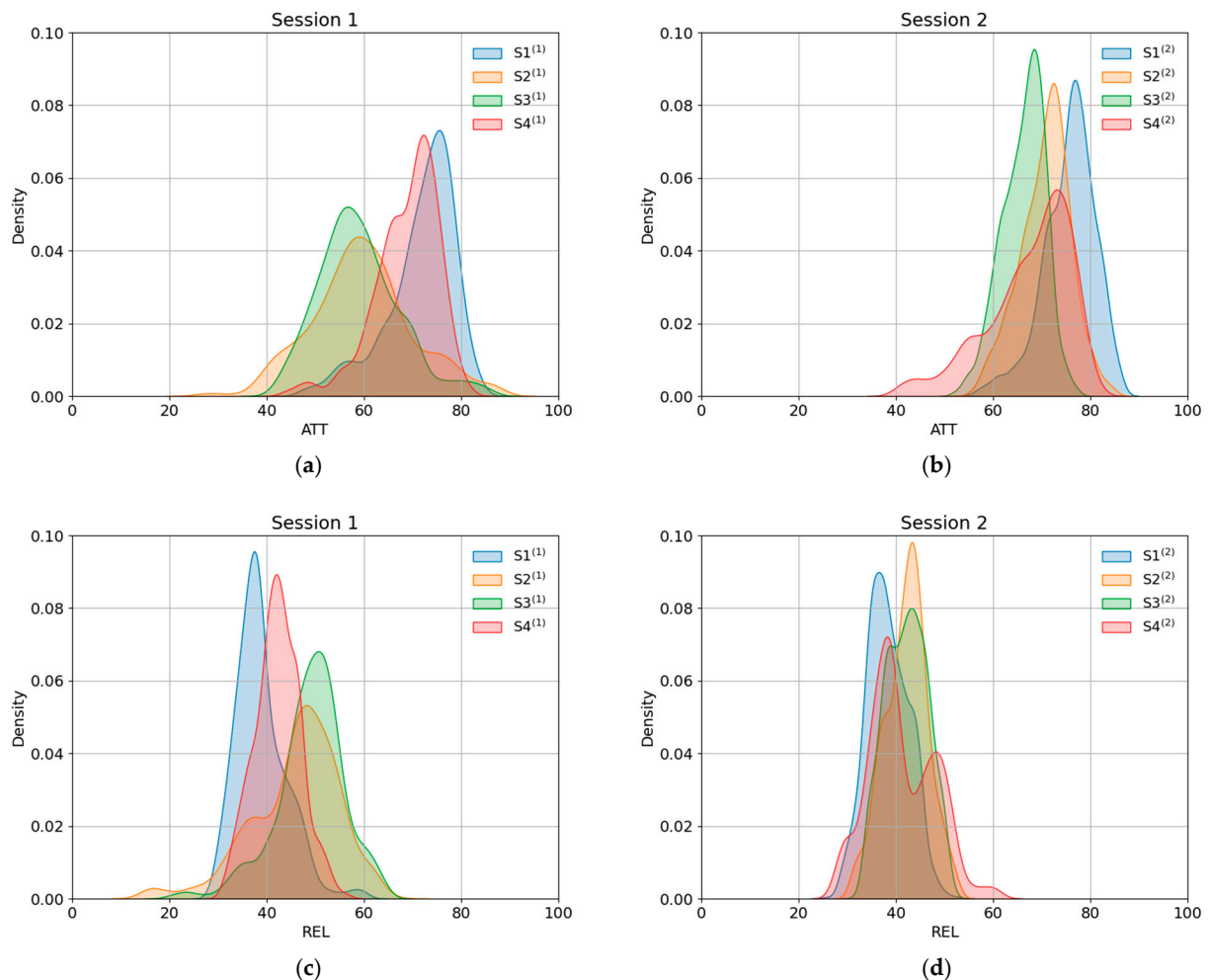


Figure 4. Probability density functions for attention (ATT) (a,b) and relaxation (REL) (c,d) in the 10 min lectures across Session 1 and Session 2.

The attention PDFs for Session 1, shown in Figure 4a, indicate that the highest attention levels were recorded in $S1^{(1)}$, followed by $S4^{(1)}$. These two scenarios also displayed narrower distributions compared to the other scenarios, indicating lower variability, which aligns with their means and standard deviations reported in Table 2. In contrast, the attention PDFs for $S2^{(1)}$ and $S3^{(1)}$ exhibited lower mean values and broader distributions, reflecting greater variability and reduced attention relative to the baseline scenario.

In Session 2, depicted in Figure 4b, the attention PDFs were generally more concentrated toward higher values compared to those in Session 1, indicating an overall improvement in attention. Again, the baseline scenario, $S1^{(2)}$, exhibited the highest attention levels. Additionally, the distributions were narrower across all scenarios with the exception of $S4^{(2)}$, which exhibited a broader distribution, indicating more disperse attention levels.

The relaxation PDFs for Session 1, depicted in Figure 4c, revealed that the lowest relaxation levels were recorded in $S1^{(1)}$, followed by $S4^{(1)}$. These two scenarios also had narrower distributions compared to the other scenarios, consistent with the results in Table 2. Moreover, $S3^{(1)}$ exhibited the highest relaxation levels with a broader distribution, indicating higher variability in relaxation, closely followed by $S2^{(1)}$, which also demonstrated a similarly wide relaxation PDF. In Session 2, depicted in Figure 4d, relaxation levels appeared more uniform across all scenarios, with $S3^{(2)}$ and $S2^{(2)}$ showing slightly higher relaxation means compared to $S1^{(2)}$ and $S4^{(2)}$.

Overall, the data in Table 2 and Figure 4 suggest that in Session 1, both the absence of exterior views and an increase in air temperature (in that order) were associated with enhanced attention, as reflected in the highest attention scores observed in S1⁽¹⁾, followed by S4⁽⁴⁾. In contrast, Session 2 showed more uniform attention levels across all scenarios, with mean values higher than those observed in Session 1. A key distinction between the two sessions is that all scenarios in Session 2 featured higher overall temperatures. These findings therefore suggest that increased air temperature has a more pronounced positive effect on attention than the absence of exterior views.

3.2.1. Correlation Matrix Analysis

The correlation matrix quantifies the strength and direction of linear relationships between pairs of variables. Each element in the matrix represents the Pearson correlation coefficient between a pair of variables x and y , as given by the following expression [46]:

$$r = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2 \sum_{i=1}^n (y_i - \bar{y})^2}}, \quad (1)$$

where $\bar{x}$ and $\bar{y}$ are the means of the variables, and n is the total number of data points. Correlation values near +1 or −1 indicate a strong positive or negative linear relationship, respectively, while values close to zero suggest weak or no linear dependence. Mathematically, the correlation matrix is symmetric and positive semi-definite, with unit values on the diagonal. These properties ensure that the matrix has nonnegative eigenvalues, and the symmetry implies that the correlation between variables x and y is equal to that between y and x . Additionally, strong positive correlations suggest redundancy or mutual reinforcement, while negative correlations may indicate inverse relationships or potential suppressor effects in multivariate models. It is important to note that, while the general principle remains that the absolute value of a correlation coefficient closer to 1 indicates a stronger relationship, the specific thresholds for interpreting weak, moderate, and strong correlations can differ across sources and fields. In the present study, we adopted the extended reference values provided by Cohen [47,48], which define small effects at $r = 0.10$, medium effects at $r = 0.30$, and large effects at $r = 0.50$. However, subsequent work by Gignac and Szodorai [49] recommended using $r = 0.10$, $r = 0.20$, and $r = 0.30$ to represent relatively small, typical, and relatively large effects. This indicates that Cohen's guidelines might be too stringent in some fields, but can be understood as a more conservative approach, as it sets a higher threshold for interpreting the strength of correlations. For example, a correlation of $r = 0.30$ would be classified as strong according to Gignac and Szodorai, but only medium according to Cohen. Therefore, adopting Cohen's benchmarks results in a more conservative interpretation, as outcomes based on correlation coefficients appear less strong compared to interpretations using Gignac and Szodorai's criteria.

The correlation matrix analysis enables the detection of co-variation patterns among the examined variables. By providing a comprehensive overview of inter-variable relationships, the correlation matrix supports the identification of statistical dependencies and potential causal relationships, which are critical for the interpretation of complex systems, as in the present study. Therefore, Figure 5 presents the correlation matrix derived from the complete dataset, encompassing cognitive performance indicators (attention and relaxation) and IEQ factors, recorded during all 10 min lecture periods across both experimental sessions, resulting in a dataset of 7719 data points. It is important to note that lighting conditions were not included in the correlation analysis, as they remained stable throughout the 10 min lectures periods in both sessions (see Tables A1 and A2 in Appendix A). Their inclusion would have led to minimal or null correlations with the other variables due to the limited variability.

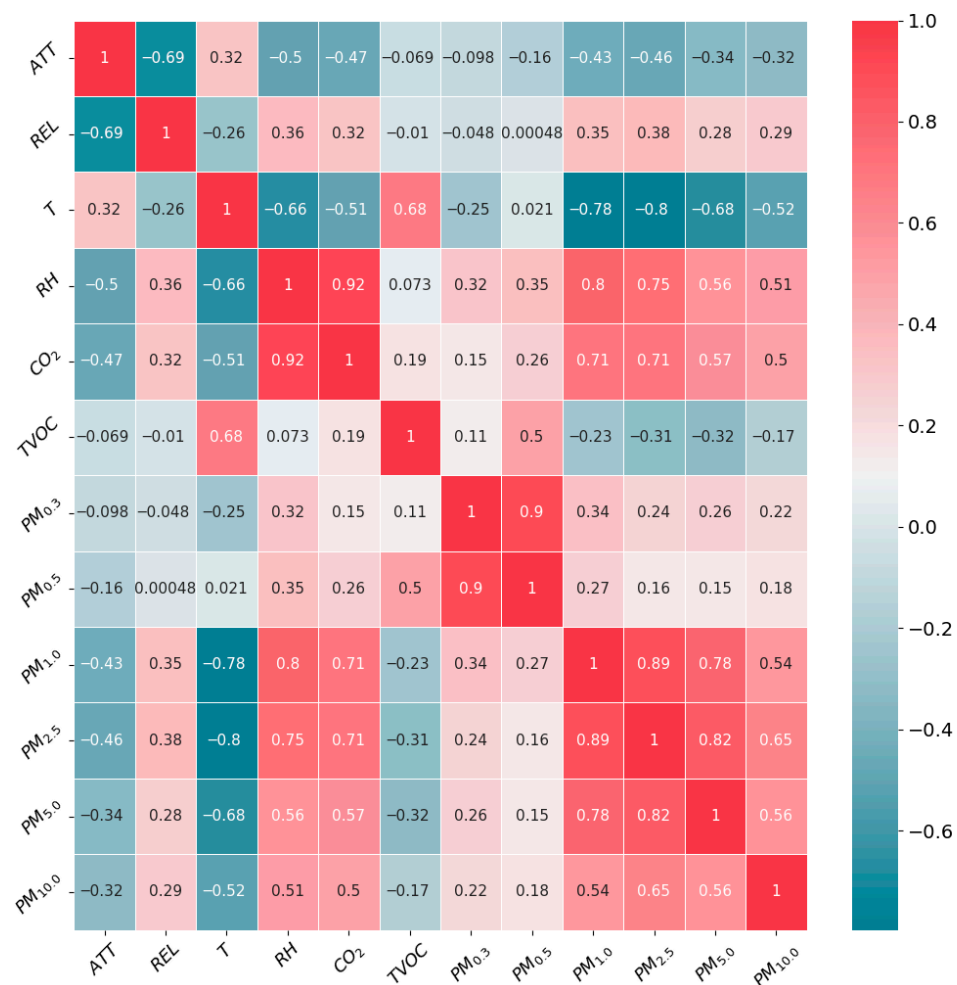


Figure 5. Pearson correlation matrix of cognitive performance metrics (attention and relaxation) and IEQ factors, based on data from all 10 min lectures across the two experimental sessions.

The correlation matrix offers a comprehensive overview of the linear associations among environmental conditions, particulate concentrations, and cognitive performance indicators, specifically attention and relaxation levels. Notably, these two cognitive states were strongly negatively correlated ($r = -0.69$), reflecting their functional opposition, as heightened attention typically entails reduced relaxation, and vice versa.

Attention levels exhibited moderate to strong negative correlations with several IEQ parameters. Specifically, relative humidity showed the strongest negative association with attention ($r = -0.50$), followed by CO₂ concentration ($r = -0.47$) and PM_{2.5} ($r = -0.46$). These findings suggest that elevated humidity and airborne pollutants are consistently associated with reduced cognitive alertness and focus. Regarding CO₂ levels, concentrations above 1000 ppm are commonly associated with sick building syndrome and reduced office work performance [19]. In contrast, temperature was positively correlated with attention ($r = 0.32$), indicating that slightly warmer conditions, without compromising thermal comfort, may support improved cognitive performance.

Complementing this, relaxation showed a mirror-like pattern but with generally weaker correlations. It was positively correlated with relative humidity ($r = 0.36$), PM_{2.5} ($r = 0.38$), PM_{1.0} ($r = 0.35$), and CO₂ ($r = 0.32$), suggesting that the same environmental conditions that impair attention may promote a relaxed state. Meanwhile, temperature was negatively correlated with relaxation ($r = -0.26$), further supporting the notion of a cognitive trade-off modulated by thermal cues. Notably, ultrafine particulates (PM_{0.3},

PM_{0.5}) and TVOCs showed negligible correlations with relaxation, indicating minimal impact under the tested indoor conditions.

The interrelationships among environmental variables were equally significant. Temperature and relative humidity were strongly negatively correlated ($r = -0.66$), reflecting the thermodynamic relationship whereby warmer air can retain more moisture, thus reducing relative humidity under constant absolute humidity. Furthermore, relative humidity exhibited strong positive correlations with both CO₂ concentration ($r = 0.92$) and PM levels (e.g., PM_{1.0}, $r = 0.80$). These patterns are consistent with the environmental conditions observed in the test room and are typically attributable to limited ventilation, which permits the accumulation of both moisture and airborne pollutants. Additionally, human occupancy contributes to both increased humidity (via respiration and perspiration) and elevated CO₂ and particulate emissions.

The high degree of correlation among independent environmental variables poses a significant challenge for statistical modeling, as it complicates the interpretation of individual contributions to cognitive outcomes. In particular, it reduces the precision of regression coefficient estimates and can obscure causal inference, making it difficult to isolate the effect of any single environmental parameter. Finally, high correlations among PM of different sizes (e.g., PM_{1.0}, PM_{2.5}, PM_{5.0}, and PM_{10.0}) were expected, given their common sources (e.g., human activity or resuspension of settled dust) and the shared physical processes governing their indoor dispersion. These strong internal correlations among PM size fractions suggest that broad particulate pollution events (e.g., opening window shades prior to session S2⁽¹⁾), rather than isolated surges in one PM fraction, shaped the IAQ dynamics.

3.2.2. Impact of Hygrothermal Conditions on Attention and Relaxation Levels

Kernel Density Estimate (KDE) contour plots were used to visualize the joint distribution of cognitive performance indicators, namely attention and relaxation levels, with hygrothermal parameters across all 10 min lecture periods for both sessions.

In the analysis of temperature and attention scores, depicted in Figure 6a, Session 2 demonstrated a concentrated peak of high attention levels (70–80) around 25–26 °C range, whereas Session 1 exhibited a broader, more diffuse attention distribution centered around 23–24 °C. The elevated temperature in Session 2, conducted after Session 1, can be attributed to the cumulative thermal load resulting from both occupant heat generation and the operation of electric heaters during later segments, specifically in S4^(1,2). Additionally, the tighter clustering of attention scores observed in Session 2 suggests that moderately warmer indoor temperatures may enhance attentional performance, aligning with the positive temperature-attention correlation identified in the correlation matrix. Moreover, the narrower density peak implies greater consistency in attentional responses under these thermally optimized conditions.

In contrast, the KDE analysis of relative humidity and attention levels, shown in Figure 6b, revealed an inverse relationship. In Session 2, higher attention scores clustered within a low humidity band, particularly 16–19%, while Session 1, characterized by higher humidity (22–26%), showed a broader, less focused distribution of attention scores. These observations reinforce the negative correlation between relative humidity and attention and support the notion that low to moderate humidity levels may be more conducive to focused cognitive engagement, at least under controlled indoor conditions. This pattern also aligns with thermodynamic expectations, as the higher air temperature in Session 2 corresponded with reduced relative humidity values due to increased moisture-holding capacity of warmer air.

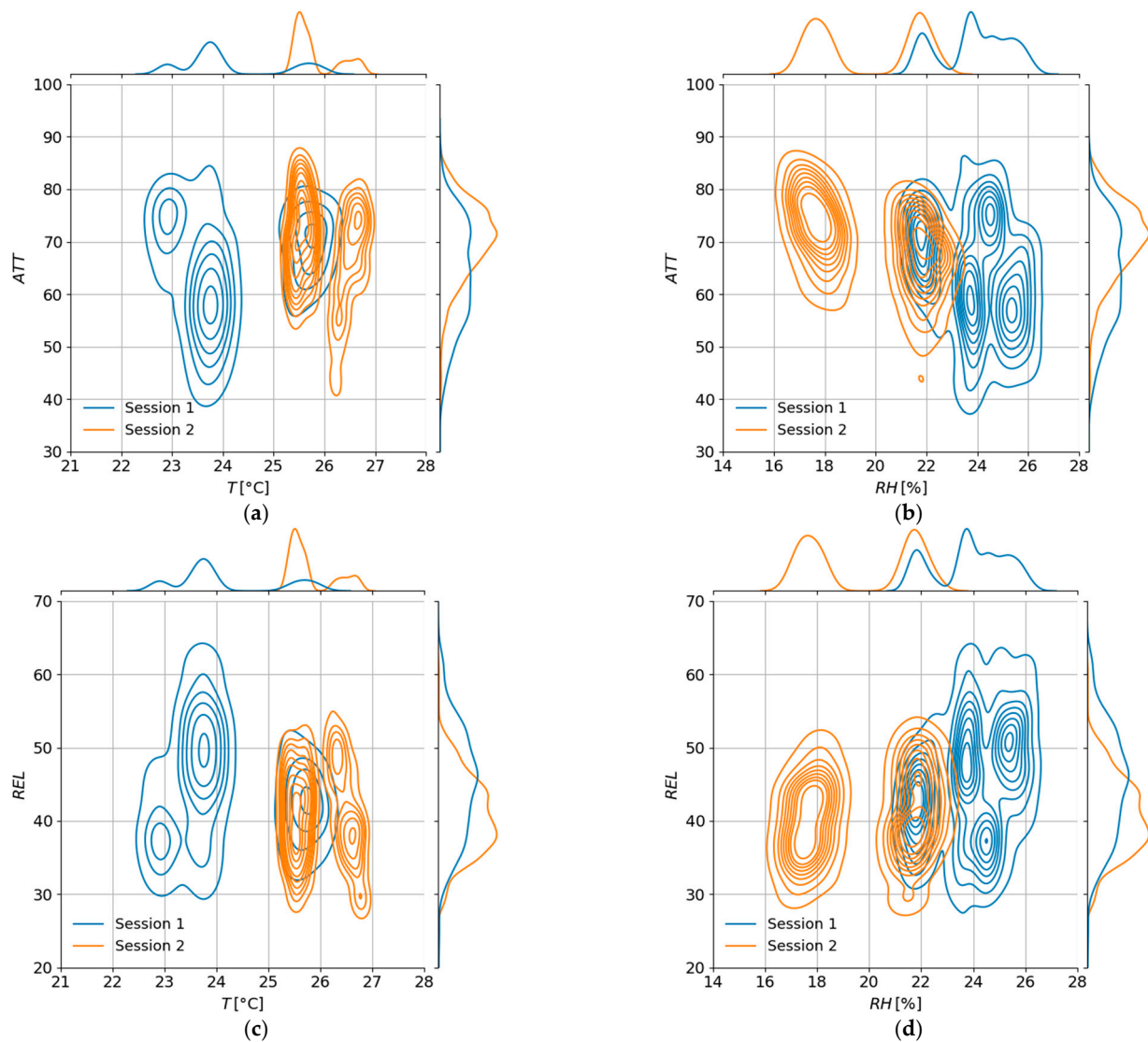


Figure 6. KDE contour plots of attention levels (ATT) over all 10 min lecture periods with temperature (a) and relative humidity (b) distributions for both sessions. Similar results for relaxation levels (REL) are depicted in (c) and (d), respectively.

Figure 6c presents the KDE distribution of temperature and relaxation. In contrast to attention, Session 1 exhibited higher and more stable relaxation scores, peaking around 50, whereas Session 2, despite warmer conditions, showed a tighter and slightly lower relaxation levels clustered around 40. This indicates that cooler environments may promote greater relaxation, whereas increased warmth, although beneficial for attention, may suppress relaxed cognitive states. This also complements the observed negative correlation between relaxation and temperature.

The KDE analysis of relative humidity and relaxation levels, shown in Figure 6d, revealed that in Session 1, relaxation scores were highest at higher relative humidity values, namely 24–26%, whereas lower relative humidity conditions in Session 2 at around 16–21% corresponded to lower relaxation scores. This supports the positive correlation between relative humidity and relaxation and again reflects the cognitive divergence between relaxation and attention. The environmental profiles that favor relaxation (cooler and more humid) contrast with those that favor attention (warmer and drier), further illustrating the differential sensitivity of cognitive states to IEQ.

4. Discussion

The findings of this study highlight the role of IEQ in shaping cognitive performance, particularly attention and relaxation levels, during lectures in educational settings. By systematically varying air temperature, relative humidity, and lighting conditions over various lecture periods, this investigation identified associations between environmental parameters and cognitive responses using correlation matrix and KDE analysis. Notably, hygrothermal conditions and IAQ parameters exhibited strong associations with cognitive performance, whereas variations in lighting, specifically the presence of natural light and exterior views, had a less pronounced effect under the tested conditions.

The KDE analyses revealed that the relationship between hygrothermal conditions and cognitive performance is both nonlinear and dependent on the specific cognitive domain being assessed. Attention levels were highest under moderately warm and dry conditions, particularly within the 25–26 °C temperature range and at relative humidity levels between 16 and 19%, conditions which were more characteristic of Session 2. These results were consistent with the positive temperature–attention ($r = 0.32$) and negative humidity–attention ($r = -0.50$) correlations observed in the correlation matrix, suggesting that such thermal environments may facilitate cognitive alertness and sustained attention.

In contrast, relaxation levels displayed an inverse pattern, with peak scores occurring at cooler temperatures around 23–24 °C and higher humidity levels between 24 and 26%, as observed primarily in Session 1. This divergence indicates that the environmental conditions promoting relaxation differ markedly from those that support attention focus. Specifically, while warmer and drier environments appear to enhance attention, cooler and more humid conditions may be more conducive to eliciting a relaxed cognitive state.

These findings align with previous research suggesting that slightly elevated but comfortable temperatures can support cognitive functioning by promoting thermal comfort and minimizing physiological distractions. It is noteworthy that in Session 2, which experienced a cumulative warming effect, attention distributions became more concentrated at higher levels, indicating a possible optimal thermal range for cognitive engagement in classroom-like settings. Regarding the relationship between humidity levels and cognitive performance, the results are consistent with psychophysiological literature indicating that excessive humidity can induce discomfort, and reduced alertness, thereby impairing cognitive performance.

It is important to note that, although not focused on educational settings, a recent meta-analysis by Porras-Salazar et al. [50], which reanalyzed the widely cited study by Seppänen et al. [51] on the relationship between air temperature and office work performance, found no significant association between temperature and work performance. This was true for both the typical temperature range observed in office buildings (20–30 °C) and a wider range (18–34 °C), despite Seppänen et al. having reported peak office work productivity at around 22 °C. Although this may appear contradictory to our findings, it is important to consider the differing experimental contexts (office work performance in Porras-Salazar et al. versus academic performance in the present study), which could lead to different outcomes regarding temperature-performance relationships. Moreover, as emphasized by Porras-Salazar et al., the absence of a statistically significant relationship does not imply that temperature has no effect on work performance, but rather the need for further research. Therefore, the current study aims to contribute to this ongoing investigation by exploring the effects of air temperature and relative humidity on students' attention and relaxation levels, both of which are potential proxies for academic performance.

Regarding the lighting conditions, illuminance and color temperature varied across scenarios due to window shade manipulation, which allowed natural light and exterior views during the experimental sessions. In Session 1, the absence of exterior views and an

increase in air temperature were associated with enhanced attention. In contrast, Session 2 showed more uniform attention levels across all scenarios, with mean values higher than those observed in Session 1. A key distinction between the two sessions is that all scenarios in Session 2 featured higher overall temperatures. These findings therefore suggest that increased air temperature has a more pronounced positive effect on attention than the absence of exterior views. It is important to note that lighting conditions were excluded from the correlation matrix and KDE analysis due to limited variability in illuminance and color temperature across the experimental sessions. However, subtle improvements in natural light exposure (e.g., during open-shade conditions) may interact with other IEQ factors, highlighting an area that warrants further investigation.

The relationship between IEQ parameters and cognitive performance indicators was also assessed using correlation matrix analysis. Specifically, attention exhibited moderate negative correlations with CO₂ concentration ($r = -0.47$) and PM_{2.5} ($r = -0.46$). These findings suggest that elevated concentrations of airborne pollutants are consistently associated with reduced cognitive alertness and focus. Complementing this, relaxation showed a mirror-like pattern but with generally weaker correlations. It was positively correlated with PM_{2.5} ($r = 0.38$), PM_{1.0} ($r = 0.35$), and CO₂ ($r = 0.32$), suggesting that the same environmental conditions that impair attention may promote a relaxed state. Notably, ultrafine particulates (PM_{0.3}, PM_{0.5}) and TVOCs showed negligible correlations with cognitive performance indicators, indicating minimal impact under the tested indoor conditions.

The findings of this study demonstrate that multiple IEQ factors can significantly affect cognitive performance, with implications for both attentional engagement and relaxation. In particular, the interaction between air temperature and relative humidity plays a key role, as different cognitive domains show varied sensitivity to hygrothermal conditions. These results suggest the potential to tailor indoor environments to specific cognitive demands, especially in educational and workplace settings where mental states may shift throughout the day. This study also supports the hypothesis that optimizing thermal conditions (specifically, maintaining moderate warmth) alongside low humidity and minimal pollutant levels, can enhance cognitive functioning. These outcomes reinforce the importance of integrated IEQ management strategies that address ventilation, thermal comfort, humidity control, and pollutant reduction, not only to protect physical health but also to support cognitive performance and psychological well-being.

While this study provides valuable insights, some limitations should be acknowledged. A larger sample size would offer greater statistical power. Additionally, the EEG device used in this study is portable, lightweight, and comfortable for participants. However, it employs a single-channel design, which limits the spatial resolution and depth of brainwave analysis. In contrast, multi-electrode EEG systems offer more comprehensive spatial coverage and the ability to capture complex neural dynamics across brain regions. While such systems can enhance the richness of cognitive data, they are often more intrusive and less feasible for studies prioritizing participant comfort. Moreover, their use in real-world educational settings is often impractical due to the typical setup, which requires physical connections to a laptop or dedicated processing device. In contrast, non-invasive, wireless EEG devices such as the Flowtime headband, although offering lower spatial resolution, are better suited for evaluating cognitive performance in real-world scenarios.

Furthermore, this study was conducted during the winter season, which may have influenced the range and variability of IEQ factors, particularly air temperature and relative humidity. Additionally, clothing insulation worn by the participants, closely linked to the season, also affects thermal sensation. While clothing insulation was assessed through the pre-questionnaires administered at the beginning of each experimental scenario, it was not included in the current analysis, as thermal comfort assessment was not the

primary research objective. Nonetheless, the authors acknowledge the potential for future studies to incorporate subjective responses from the pre- and post-questionnaires, enabling comparisons between quantitative data from environmental and EEG sensors and self-reported perceptions from students. Repeating the experiment across the other three seasons would strengthen the validity and generalizability of the results.

Additionally, we acknowledge the differing initial hygrothermal conditions between sessions. Session 2 was conducted 30 min after the conclusion of Session 1, and during that time the door of the test room was intentionally left open to facilitate a reduction in air temperature and partially restore the initial environmental conditions. Although this interval was insufficient to fully replicate the hygrothermal conditions present at the start of Session 1 (due to residual heat), the differing starting conditions at the onset of Session 2 offered complementary and valuable insights into participants' attention and relaxation levels under varying environmental scenarios. This allowed for the exploration of a broader range of temperature and relative humidity conditions and their effects on students' attention and relaxation levels during the experimental sessions.

5. Conclusions

This study demonstrates that IEQ parameters, particularly air temperature, relative humidity, and air quality, can significantly improve student well-being and academic performance. Attention levels improved under moderately warm (25–26 °C), dry (16–19%) conditions, while relaxation was higher in cooler, more humid environments. Airborne pollutants such as CO₂ and PM_{2.5} showed negative correlations with attention, reinforcing the cognitive relevance of IAQ. In contrast, lighting conditions, especially natural light and exterior views, had a less pronounced effect under the tested settings.

These findings offer practical insights for designing healthier, more cognitively supportive classrooms. Maintaining stable, slightly warm thermal conditions, controlling humidity, and ensuring good ventilation can enhance student focus and well-being. Specifically, the methodology employed in this investigation can be replicated in various classroom settings or configurations to identify optimal IEQ parameters, such as air temperature or relative humidity, that support students' attention levels during lectures. The findings can inform environmental management strategies (e.g., precise control of temperature and humidity) to enhance academic performance in educational settings, rather than relying solely on subjective assessments. This study underscores the critical importance of environmental optimization in educational settings and highlights the need for evidence-based design standards to foster healthy, effective learning environments.

Future research should build on these findings by employing larger, more diverse sample sizes, utilizing multi-channel EEG systems to provide deeper insights while balancing usability constraints, examining additional IEQ variables such as acoustic factors or dynamic lighting in varied educational contexts, and repeating the experiment in other seasons to enhance the applicability of the results.

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Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

IEQ	Indoor Environmental Quality
EEG	Electroencephalogram
CO ₂	Carbon Dioxide
TVOC	Total Volatile Organic Compounds
PM	Particulate Matter
ASHRAE	American Society of Heating, Refrigerating, and Air-Conditioning Engineers
IAQ	Indoor Air Quality
US EPA	United States Environmental Protection Agency
NAAQS	National Ambient Air Quality Standards
HVAC	Heating, Ventilation, and Air Conditioning
PDF	Probability Density Function
KDE	Kernel Density Estimate

Appendix A

Tables A1 and A2 summarize the numerical results for the IEQ factors analyzed during the monitoring campaign. Specifically, the mean and standard deviation values recorded during the 10 min lectures in each scenario are reported for air temperature, relative humidity, CO₂ concentration, TVOC levels, PM, and lighting conditions, including illuminance and color temperature. It is important to note that only one measurement of lighting conditions was performed during each lecture, following experimental verification that these conditions remained stable throughout the 10 min lecture periods.

Table A1. Mean and standard deviation of the IEQ factors measured during the 10 min lecture in each scenario of Session 1.

IEQ Factor	S1 ⁽¹⁾	S2 ⁽¹⁾	S3 ⁽¹⁾	S4 ⁽¹⁾
T [°C]	22.90 ± 0.03	23.64 ± 0.05	23.84 ± 0.04	25.69 ± 0.19
RH [%]	24.44 ± 0.19	23.71 ± 0.13	25.43 ± 0.42	21.93 ± 0.32
CO ₂ [ppm]	1203 ± 20	1310 ± 16	1279 ± 17	1236 ± 23
TVOC [ppm]	0.285 ± 0.003	0.302 ± 0.002	0.313 ± 0.003	0.329 ± 0.003
PM _{0.3} [µg/m ³]	1.09 ± 0.09	0.83 ± 0.02	0.64 ± 0.03	0.41 ± 0.01
PM _{0.5} [µg/m ³]	0.60 ± 0.05	0.48 ± 0.03	0.40 ± 0.02	0.26 ± 0.02
PM _{1.0} [µg/m ³]	1.47 ± 0.17	1.54 ± 0.21	1.49 ± 0.23	0.93 ± 0.10

Table A1. Cont.

IEQ Factor	S1 ⁽¹⁾	S2 ⁽¹⁾	S3 ⁽¹⁾	S4 ⁽¹⁾
PM _{2.5} [µg/m ³]	10.34 ± 1.14	12.73 ± 1.97	10.45 ± 1.71	6.42 ± 1.09
PM _{5.0} [µg/m ³]	20.91 ± 2.96	29.88 ± 8.32	18.23 ± 4.41	11.89 ± 2.91
PM _{10.0} [µg/m ³]	32.09 ± 17.05	39.20 ± 18.43	28.78 ± 16.13	17.79 ± 9.29
Illuminance [lx]	605	715	587	587
Color temp. [K]	3948	4622	3949	3949

Table A2. Mean and standard deviation of the IEQ factors measured during the 10 min lecture in each scenario of Session 2.

IEQ Factor	S1 ⁽²⁾	S2 ⁽²⁾	S3 ⁽²⁾	S4 ⁽²⁾
T [°C]	25.54 ± 0.02	25.70 ± 0.02	25.42 ± 0.01	26.52 ± 0.17
RH [%]	17.37 ± 0.18	18.09 ± 0.11	22.02 ± 0.37	21.64 ± 0.16
CO ₂ [ppm]	789 ± 20	820 ± 15	1037 ± 36	1156 ± 15
TVOC [ppm]	0.295 ± 0.004	0.311 ± 0.003	0.337 ± 0.004	0.361 ± 0.005
PM _{0.3} [µg/m ³]	0.63 ± 0.02	0.55 ± 0.02	1.10 ± 0.04	0.87 ± 0.05
PM _{0.5} [µg/m ³]	0.31 ± 0.01	0.30 ± 0.02	0.71 ± 0.04	0.71 ± 0.05
PM _{1.0} [µg/m ³]	0.72 ± 0.10	0.85 ± 0.13	1.05 ± 0.11	0.99 ± 0.14
PM _{2.5} [µg/m ³]	4.35 ± 0.85	5.48 ± 1.09	6.23 ± 0.95	6.14 ± 1.07
PM _{5.0} [µg/m ³]	9.70 ± 3.91	9.42 ± 3.62	11.93 ± 3.58	11.87 ± 3.93
PM _{10.0} [µg/m ³]	10.21 ± 6.77	10.41 ± 8.81	17.00 ± 9.48	18.06 ± 11.43
Illuminance [lx]	488	534	456	456
Color temp. [K]	3884	4294	3895	3895

References

- Wargocki, P.; Wyon, D.P. Ten Questions Concerning Thermal and Indoor Air Quality Effects on the Performance of Office Work and Schoolwork. *Build. Environ.* **2017**, *112*, 359–366. [\[CrossRef\]](#)
- Choi, S.; Guerin, D.; Kim, H.-Y.; Brigham, J.K.; Bauer, T. Indoor Environmental Quality of Classrooms and Student Outcomes: A Path Analysis Approach. *J. Learn. Spaces* **2014**, *2*, 14.
- Zhang, N.; Liu, C.; Li, J.; Hou, K.; Shi, J.; Gao, W. A Comprehensive Review of Research on Indoor Cognitive Performance Using Electroencephalogram Technology. *Build. Environ.* **2024**, *257*, 111555. [\[CrossRef\]](#)
- Toyinbo, O. Indoor Environmental Quality, Pupils' Health, and Academic Performance—A Literature Review. *Buildings* **2023**, *13*, 2172. [\[CrossRef\]](#)
- Palacios Temprano, J.; Eichholtz, P.; Willeboordse, M.; Kok, N. Indoor Environmental Quality and Learning Outcomes: Protocol on Large-Scale Sensor Deployment in Schools. *BMJ Open* **2020**, *10*, e031233. [\[CrossRef\]](#)
- Vermunt, J. The Power of Teaching-Learning Environments to Influence Student Learning. *Br. J. Educ. Psychol.* **2007**. [\[CrossRef\]](#)
- Wentzel, K.R. Social Relationships and Motivation in Middle School: The Role of Parents, Teachers, and Peers. *J. Educ. Psychol.* **1998**, *90*, 202–209. [\[CrossRef\]](#)
- Ryan, R.M.; Deci, E.L. Self-Determination Theory and the Facilitation of Intrinsic Motivation, Social Development, and Well-Being. *Am. Psychol.* **2000**, *55*, 68–78. [\[CrossRef\]](#)
- Lee, M.C.; Mui, K.W.; Wong, L.T.; Chan, W.Y.; Lee, E.W.M.; Cheung, C.T. Student Learning Performance and Indoor Environmental Quality (IEQ) in Air-Conditioned University Teaching Rooms. *Build. Environ.* **2012**, *49*, 238–244. [\[CrossRef\]](#)
- ANSI/ASHRAE Standard 55; Thermal Environmental Conditions for Human Occupancy. ASHRAE: Peachtree Corners, GA, USA, 2023. Available online: <https://www.ashrae.org/technical-resources/bookstore/standard-55-thermal-environmental-conditions-for-human-occupancy> (accessed on 1 April 2025).
- ANSI/ASHRAE Standard 62.1-2022; Ventilation and Acceptable Indoor Air Quality. ASHRAE: Peachtree Corners, GA, USA, 2022. Available online: https://store.accuristech.com/ashrae/standards/ashrae-62-1-2022?product_id=2501063#jumps (accessed on 1 April 2025).
- Hancock, P.A.; Warm, J.S. A Dynamic Model of Stress and Sustained Attention. *Hum. Perf. Extrem. Environ.* **2003**, *7*, 15–28. [\[CrossRef\]](#)
- Wang, D.; Xu, Y.; Liu, Y.; Wang, Y.; Jiang, J.; Wang, X.; Liu, J. Experimental Investigation of the Effect of Indoor Air Temperature on Students' Learning Performance under the Summer Conditions in China. *Build. Environ.* **2018**, *140*, 140–152. [\[CrossRef\]](#)

14. Wolkoff, P. Indoor Air Humidity, Air Quality, and Health—An Overview. *Int. J. Hyg. Environ. Health* **2018**, *221*, 376–390. [CrossRef]
15. Li, D.; Sullivan, W.C. Impact of Views to School Landscapes on Recovery from Stress and Mental Fatigue. *Landsc. Urban Plan.* **2016**, *148*, 149–158. [CrossRef]
16. Ulrich, R.S.; Simons, R.F.; Losito, B.D.; Fiorito, E.; Miles, M.A.; Zelson, M. Stress Recovery During Exposure to Natural and Urban Environments. *J. Environ. Psychol.* **1991**, *11*, 201–230. [CrossRef]
17. U.S. Environmental Protection Agency | US EPA. Available online: <https://www.epa.gov/> (accessed on 13 May 2025).
18. NAAQS Table | US EPA. Available online: <https://www.epa.gov/criteria-air-pollutants/naaqs-table> (accessed on 13 May 2025).
19. ASHRAE Position Document on Indoor Carbon Dioxide. 2025. Available online: <https://www.ashrae.org/file%20library/about/position%20documents/pd-on-indoor-carbon-dioxide-english.pdf> (accessed on 13 May 2025).
20. Durán, N.; Eichholtz, P.; Kok, N.; Palacios, J. Indoor Air Quality and Student Performance: Evidence from a Large Scale Field Study in Primary Schools. MIT Center for Real Estate Research Paper No. 22/13. 2022. Available online: <https://ssrn.com/abstract=4296077> (accessed on 1 April 2025).
21. Lee, S.C.; Chang, M. Indoor and Outdoor Air Quality Investigation at Schools in Hong Kong. *Chemosphere* **2000**, *41*, 109–113. [CrossRef]
22. Hutter, H.P.; Haluza, D.; Piegler, K.; Hohenblum, P.; Fröhlich, M.; Scharf, S.; Uhl, M.; Damberger, B.; Tappler, P.; Kundi, M.; et al. Semivolatile Compounds in Schools and Their Influence on Cognitive Performance of Children. *Int. J. Occup. Med. Environ. Health* **2013**, *26*, 628–635. [CrossRef]
23. Satish, U.; Mendell, M.J.; Shekhar, K.; Hotchi, T.; Sullivan, D.; Streufert, S.; Fisk, W.J. Is CO₂ an Indoor Pollutant? Direct Effects of Low-to-Moderate CO₂ Concentrations on Human Decision-Making Performance. *Environ. Health Perspect.* **2012**, *120*, 1671–1677. [CrossRef]
24. Talebi, S.; Lary, D.J.; Wijeratne, L.O.H.; Fernando, B.; Lary, T.; Lary, M.; Sadler, J.; Sridhar, A.; Waczak, J.; Aker, A.; et al. Decoding Physical and Cognitive Impacts of Particulate Matter Concentrations at Ultra-Fine Scales. *Sensors* **2022**, *22*, 4240. [CrossRef]
25. Ruwali, S.; Talebi, S.; Fernando, A.; Wijeratne, L.O.H.; Waczak, J.; Dewage, P.M.H.; Lary, D.J.; Sadler, J.; Lary, T.; Lary, M.; et al. Quantifying Inhaled Concentrations of Particulate Matter, Carbon Dioxide, Nitrogen Dioxide, and Nitric Oxide Using Observed Biometric Responses with Machine Learning. *BioMedInformatics* **2024**, *4*, 1019–1046. [CrossRef]
26. Ruwali, S.; Prothero, J.; Bhatt, T.; Talebi, S.; Fernando, A.; Wijeratne, L.; Waczak, J.; Dewage, P.M.H.; Lary, T.; Lary, M.; et al. Improvement in the Estimation of Inhaled Concentrations of Carbon Dioxide, Nitrogen Dioxide, and Nitric Oxide Using Physiological Responses and Power Spectral Density from an Astrapi Spectrum Analyzer. *Air* **2025**, *3*, 11. [CrossRef]
27. Watzl, S. What Attention Is. The Priority Structure Account. *WIREs Cogn. Sci.* **2023**, *14*, e1632. [CrossRef] [PubMed]
28. Herman, J.A. The Concept of Relaxation. *J. Holist. Nurs.* **1985**, *3*, 15–18. [CrossRef]
29. Antonenko, P.; Paas, F.; Grabner, R.; van Gog, T. Using Electroencephalography to Measure Cognitive Load. *Educ. Psychol. Rev.* **2010**, *22*, 425–438. [CrossRef]
30. Ismail, L.E.; Karwowski, W. Applications of EEG Indices for the Quantification of Human Cognitive Performance: A Systematic Review and Bibliometric Analysis. *PLoS ONE* **2020**, *15*, e0242857. [CrossRef]
31. Guan, H.; Hu, S.; Lu, M.; He, M.; Zhang, X.; Liu, G. Analysis of Human Electroencephalogram Features in Different Indoor Environments. *Build. Environ.* **2020**, *186*, 107328. [CrossRef]
32. Jin, R.N.; Inada, H.; Négyesi, J.; Ito, D.; Nagatomi, R. Carbon Dioxide Effects on Daytime Sleepiness and EEG Signal: A Combinational Approach Using Classical Frequentist and Bayesian Analyses. *Indoor Air* **2022**, *32*, e13055. [CrossRef]
33. Xu, F.; Uh, J.; Brier, M.R.; Hart, J.; Yezhuvath, U.S.; Gu, H.; Yang, Y.; Lu, H. The Influence of Carbon Dioxide on Brain Activity and Metabolism in Conscious Humans. *J. Cereb. Blood Flow Metab.* **2011**, *31*, 58–67. [CrossRef]
34. LaRocco, J.; Le, M.D.; Paeng, D.-G. A Systemic Review of Available Low-Cost EEG Headsets Used for Drowsiness Detection. *Front. Neuroinform.* **2020**, *14*, 553352. [CrossRef]
35. Bashivan, P.; Rish, I.; Heisig, S. Mental State Recognition via Wearable EEG. *arXiv* **2016**, arXiv:1602.00985.
36. Hoffmann, A. *The Iterative Development and Evaluation of the Gamified Stress Management App “Stress-Mentor”*; Technical University of Kaiserslautern: Kaiserslautern, Germany, 2020.
37. Rohit, F.; Kulathumani, V.; Kavi, R.; Elwarfalli, I.; Kecojevic, V.; Nimbarte, A. Real-time Drowsiness Detection Using Wearable, Lightweight Brain Sensing Headbands. *IET Intell. Transp. Syst.* **2017**, *11*, 255–263. [CrossRef]
38. Turhan, C.; Özbey, M.F.; Çeter, A.E.; Akkurt, G.G. A Novel Data-Driven Model for the Effect of Mood State on Thermal Sensation. *Buildings* **2023**, *13*, 1662. [CrossRef]
39. Yerlikaya-Özkurt, F.; Özbey, M.F.; Turhan, C. Modeling the Mood State on Thermal Sensation with a Data Mining Algorithm and Testing the Accuracy of Mood State Correction Factor. *New Ideas Psychol.* **2025**, *76*, 101124. [CrossRef]
40. Flowtime Biosensing Meditation Headband. Available online: <https://www.meetflowtime.com/products/flowtime-biosensing-meditation-headband> (accessed on 11 May 2025).

41. Barakat, A.; Ayad, H.; El-Sayad, Z. An Integrated Approach To User-Centered Design: Mobile Brain/Heart Imaging in Virtual Reality. *WIT Trans. Built Environ.* **2022**, *210*, 201–214. [[CrossRef](#)]
42. Ni, T.; Sun, Z.; Han, M.; Lan, G.; Xie, Y.; Li, Z.; Gu, T.; Xu, W. Towards Battery-Free Wireless Sensing via Radio-Frequency Energy Harvesting. In Proceedings of the Twenty-fifth International Symposium on Theory, Algorithmic Foundations, and Protocol Design for Mobile Networks and Mobile Computing, Athens, Greece, 14–17 October 2024.
43. Lin, R.R.; Hu, B.A.; Ke, K.Y.; Wu, W.; Zhang, K. Cell Space: Augmented Awareness of Intercorporeality. *Proc. ACM Comput. Graph. Interact. Tech.* **2024**, *7*, 1–10. [[CrossRef](#)]
44. Hussein, T.; Kubincová, L.; Džumbová, L.; Hruška, A.; Dohányosová, P.; Hemerka, J.; Smolík, J. Deposition of Aerosol Particles on Rough Surfaces inside a Test Chamber. *Build. Environ.* **2009**, *44*, 2056–2063. [[CrossRef](#)]
45. Faubel, C.; Martinez-Molina, A.; Suk, J.Y. Calculation of CO₂ Generation and Required Fresh Air Rates in a High-Intensity Physical Athletic Facility. *J. Build. Eng.* **2024**, *82*, 108289. [[CrossRef](#)]
46. Benesty, J.; Chen, J.; Huang, Y.; Cohen, I. Pearson Correlation Coefficient. *Springer Top. Signal Process.* **2009**, *2*, 1–4. [[CrossRef](#)]
47. Cohen, J. *Statistical Power Analysis for the Behavioral Sciences*; Routledge: New York, NY, USA, 2013; ISBN 9781134742707.
48. Cohen, J. A Power Primer. *Psychol. Bull.* **1992**, *112*, 155–159. [[CrossRef](#)]
49. Gignac, G.E.; Szodorai, E.T. Effect Size Guidelines for Individual Differences Researchers. *Pers. Individ. Dif.* **2016**, *102*, 74–78. [[CrossRef](#)]
50. Porras-Salazar, J.A.; Schiavon, S.; Wargocki, P.; Cheung, T.; Tham, K.W. Meta-Analysis of 35 Studies Examining the Effect of Indoor Temperature on Office Work Performance. *Build. Environ.* **2021**, *203*, 108037. [[CrossRef](#)]
51. Seppänen, O.; Fisk, W.J.; Lei, Q.H. Effect of Temperature on Task Performance in Office Environment. In Proceedings of the 5th International Conference on Cold Climate Heating, Ventilating and Air Conditioning, Moscow, Russia, 21–24 May 2006.

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