International Journal of Innovative Research and Scientific Studies, 8(5) 2025, pages: 2237-2250

IJIRSS
International Journal of Innovative Research & Scientific Studies

ISSN: 2617-6548

URL: www.ijirss.com

Maintaining cognitive integrity: An analysis of thermal stress in high-stakes clean room environments

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Abstract

Rising heat waves and elevated indoor temperatures raise concerns about the resilience of cognitive functions to minor shifts in microclimate, which is significant because individuals spend up to 90% of their time indoors. Previous research indicates that moderate warming and increased CO_2 levels can impair reaction speed, accuracy, and executive control, although the effects vary depending on temperature ranges and methodologies. However, the combined impact of heat, CO_2, and humidity within the typical 22–30 °C range remains insufficiently characterized. This study addresses the broader issue of how moderate heat stress and concurrent changes in air quality influence specific cognitive domains in healthy young adults. In a pilot crossover study, 10 participants completed two sessions: a thermoneutral condition (23–24.8 °C) and an elevated heat-stress condition (>27 to approximately 30 °C) with continuous monitoring of temperature, humidity, CO_2, particulate matter, noise, and eTVOC. Cognitive performance was assessed using standardized CogniFit tests. The findings demonstrate that higher temperatures are associated with increases in group scores for reasoning, coordination, perception, and memory, whereas attention appears most vulnerable, showing mixed or decreased responses. Domain-specific correlations were identified: humidity significantly degrades perception ($r = -0.66$), temperature moderately supports coordination ($r = 0.34$), and attention exhibits a negative association with temperature ($r = -0.19$). These results refine the common assumption of a uniform decline under moderate warming, revealing that effects are heterogeneous and domain-dependent, with attention being the most sensitive indicator. In a broader context, the findings support adaptive microclimate management targeting temperature and humidity according to current cognitive tasks and demonstrate the applicability of an IoT-integrated platform (e.g., Home Assistant with automated ventilation at $CO_2 > 1000$ ppm) for research and practical applications. Ultimately, this pilot study lays the groundwork for deploying real-world systems with online analytics and adaptive algorithms.

Keywords: Clean room, Cognitive performance, Environmental monitoring, Indoor air quality, Machine learning, Smart environment, Thermal stress.

DOI: 10.53894/ijirss.v8i5.9444
Funding: This work is supported by the Science Committee of the Ministry of Science and Higher Education of the Republic of Kazakhstan (Grant number: BR24993051).
History: Received: 8 July 2025 / **Revised:** 13 August 2025 / **Accepted:** 13 August 2025 / **Published:** 22 August 2025

Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: All authors contributed equally to the conception and design of the study. All authors have read and agreed to the published version of the manuscript.
Transparency: The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.
Publisher: Innovative Research Publishing

1. Introduction

Global climate change is increasingly characterized by frequent and intense heat waves that not only alter outdoor conditions but also raise temperatures inside buildings that are not always designed to mitigate thermal stress. Because people reportedly spend up to 90% of their time indoors, it is critical to understand how even small shifts in indoor environmental conditions especially temperature affect cognitive functions and performance-related outcomes [1, 2]. While most thermal-comfort research has traditionally focused on subjective well-being and physiological comfort, emerging studies show that even moderate indoor temperature increases can disrupt complex cognitive processes despite occupants reporting acceptable comfort levels [2, 3]. Moderate indoor warming from conventionally neutral set-points to warmer conditions has been linked to diminished cognitive performance, manifested as slower reaction times, lower accuracy, and reduced executive control [4].

A comparison of university students living in air-conditioned versus non-air-conditioned dormitories during a heat wave found that at an indoor temperature of approximately 26.3 °C, the lack of air conditioning prolonged reaction time by roughly 13% and lowered task accuracy. Standardized protocols, including the Stroop color test and two-digit arithmetic tasks, were used to capture changes in inhibitory control and working memory [4]. Tropically acclimatized participants exhibit an inverted U-shaped performance–temperature curve: peak cognitive efficiency occurs around 26 °C, with performance declining at temperatures below or above that point [5]. However, in settings where occupants are not acclimatized or where modern climate control is lacking, moderate indoor heating is more likely to impair cognitive functions and overall productivity [6, 7].

At the cellular level, heat exposure triggers the release of stress hormones and inflammatory mediators that can alter neuronal function and synaptic connectivity. Research indicates that even mild elevations in core temperature can disrupt neurovascular coupling and reduce cerebral blood flow in key brain regions responsible for executive functions and memory, such as the medial prefrontal cortex and hippocampus [8]. Functional MRI studies likewise reveal temperature-induced alterations in brain connectivity: under thermal stress, connectivity patterns within the default-mode network and between the posterior cingulate cortex and frontal areas are reduced, leading to less efficient neural communication underlying attention, working memory, and decision-making [4, 8]. Moreover, moderate heat stress appears to affect cognitive domains differentially. Passive hyperthermia studies show that tasks requiring high inhibitory control and mental arithmetic are more sensitive to heat stress than simpler tasks like typing or calculator use likely due to greater metabolic demands and neuronal activation needed for executive functioning. Moderate indoor heating also negatively influences sleep quality, which can further jeopardize cognition through sleep deprivation and fragmented sleep architecture. Elevated nighttime temperatures during heat waves have been linked to shorter sleep duration and poorer sleep quality, ultimately contributing to daytime cognitive deficits such as reduced alertness and slower reactions. Collectively, these mechanisms suggest that moderate indoor warming can impair cognition via a combination of physiological strain, neurovascular insufficiency, and secondary effects mediated by disrupted sleep and hormonal imbalance [4].

Indoor CO_2 concentration serves as an indirect indicator of ventilation quality and, by extension, the presence of other indoor pollutants. Studies consistently show that elevated CO_2 levels impair cognitive functions independently of temperature. Under laboratory conditions where CO_2 is varied from well-ventilated (~600 ppm) to up to 1800 ppm, declines in cognitive performance typically appear in tasks requiring memory, attention, and executive function [9]. Elevated CO_2 appears to diminish cognition by lowering cerebral oxygen saturation and increasing drowsiness, particularly during tasks that demand sustained attention [4, 9].

Existing research largely targets extreme thermal-stress parameters, making it difficult to generalize findings to the moderate 22–30 °C range typical of most indoor environments in workplaces and educational facilities [10, 11]. In Addition, studies on the combined effects of thermal load, elevated CO_2, and high humidity are often fragmented and use diverse methodologies, complicating cross-study comparisons and the development of a unified model [9].

2. Literature Review

Modern research on the impact of indoor air quality on brain function is gaining increasing relevance due to growing urbanization and the development of energy-efficient building technologies, which sometimes lead to reduced air exchange rates in enclosed spaces [12]. Carbon dioxide (CO_2) is traditionally used as a marker of ventilation and is considered one of the key parameters of public health in indoor environments, as its concentration is directly linked to the accumulation of bioeffluents and other pollutants, such as volatile organic compounds (VOCs) and airborne biological agents [11, 12]. Numerous studies have shown that even at CO_2 levels previously considered safe (around 600–800 ppm), cognitive performance can be affected, particularly during complex tasks that require high executive functioning and rapid responses [12].

Special attention is paid to the combined influence of multiple air quality parameters, temperature, oxygen levels, CO_2 concentration, VOCs, and particulate matter on cognitive performance, as many studies demonstrate that deterioration in one factor can be amplified by the impairment of others, creating a synergistic effect [13, 14]. For example, research conducted in office settings has shown that reduced ventilation not only increases CO_2 levels but also elevates VOC concentrations, which together negatively affect strategic thinking, reaction speed, and calculation accuracy [12, 13].

The methodological foundation of studies examining the impact of CO_2 and air quality on cognitive performance encompasses a wide range of experimental designs. Many investigations have employed randomized crossover trials with double-blind control, allowing researchers to minimize the influence of subjective factors and inter-individual variability. For example, a clinical study conducted in climate-controlled chambers with schoolchildren included three ventilation conditions with varying CO_2 levels. Cognitive performance was assessed using digital test batteries (CANTAB), while sleep quality was measured through actigraphy and questionnaires, enabling the identification of potential delayed effects of air quality on cognitive functioning [15].

During the implementation of COVID-19 safety measures, a sharp increase in CO_2 concentrations was observed in classrooms, with average levels reaching 2380 ppm and peak values exceeding 4400 ppm. Such high CO_2 levels indicate insufficient ventilation in conditions where natural airflow was limited due to epidemiological restrictions, negatively affecting students' overall well-being and concentration. Although direct measurements of cognitive impairments in these settings are often inconclusive due to the influence of other factors (such as temperature and thermal discomfort), studies have reported a correlation between deteriorating perception of the indoor climate, reduced overall comfort ratings, and a potential decline in cognitive performance [16].

A linear relationship has been observed between rising CO_2 concentrations and declining cognitive performance, with an increase of 400 ppm potentially associated with a 21% decrease in cognitive scores [1, 2]. Moreover, studies employing natural experiment models, such as analyses of chess tournament data, have demonstrated that deteriorating air quality, particularly elevated levels of fine particulate matter, negatively affects players' decision-making abilities under stressful and time-constrained conditions. This indirectly supports the detrimental impact of poor air quality on cognitive functioning [17].

The human body's ability to maintain thermal homeostasis is significantly challenged when exposed to the combined effects of high temperature, elevated humidity, and climate-related changes driven by CO_2. Physiological studies have shown that these combined stressors lead to substantial alterations in cardiovascular and thermoregulatory responses. Experimental research involving elderly individuals, particularly those with pre-existing cardiovascular conditions, has demonstrated that exposure to high temperatures combined with poor indoor air quality, as indicated by elevated CO_2 levels, can result in a marked increase in heart rate and a concurrent decrease in mean arterial pressure. These changes are likely associated with vasodilation and impaired heat dissipation, which, in turn, elevate the risk of heat-induced cardiovascular events [18].

The physiological strain induced by combined heat and humidity is exacerbated by the duration and intensity of exposure, as demonstrated by studies conducted in enclosed environments such as underground shelter chambers. Under conditions where both temperature and humidity rise simultaneously, subjects exhibit increased thermal discomfort, elevated skin temperature, and higher respiratory rates, symptoms indicative of progressive heat stress [19]. Notably, even slight elevations in CO_2 concentration, although often secondary to the effects of heat and humidity, can contribute to a perceptible decline in air quality and intensify discomfort by altering breathing patterns [18, 19]. These physiological responses are particularly dangerous for vulnerable populations, such as the elderly, outdoor workers, and individuals living in poorly ventilated urban or enclosed spaces where the mitigating effects of air conditioning or natural ventilation may be limited [18].

In addition to cardiovascular strain, the synergistic impact of these factors can impair cognitive functions and reduce overall work performance. Elevated core body temperature combined with high humidity hinders the body's ability to cool through evaporation, leading to a rapid rise in internal temperature and resulting in fatigue or diminished cognitive capacity [20, 21]. Prolonged exposure to such extreme conditions is projected to cause substantial labor productivity losses in regions already experiencing high ambient temperatures and rapid population growth, particularly in developing urban centers at lower latitudes [22].

The performance of complex cognitive tasks, such as working memory tests and tasks involving executive functions, reaches its optimum at an ambient temperature of approximately 22 °C. In an experiment involving young men, the highest levels of accuracy and reaction speed were observed at this temperature, whereas both heating to 30 °C and cooling to 18 °C led to significant performance declines. These findings support the existence of a narrow optimal temperature range for peak cognitive functioning [1].

Changes in indoor air temperature trigger corresponding shifts in physiological indicators such as heart rate variability (HRV), autonomic nervous system markers, and respiratory rate [1]. When temperatures rise above the optimal range, physiological stress increases, as reflected in altered HRV metrics, indicating that the body is under greater strain and, as a result, cognitive efficiency declines [1, 23]. Similarly, temperatures falling below the optimal range also place additional stress on the body, negatively affecting working memory performance and task accuracy [1].

Techniques used in green office environments, where air parameters are strictly controlled, demonstrate that not only air cleanliness but also the optimization of temperature, humidity, and lighting levels contribute to improved cognitive performance among workers [24, 25]. In this context, it can be assumed that cleanrooms, as specialized working environments that maintain not only sterility but also optimal thermal conditions, can support maximum cognitive efficiency by reducing stressors that impact the central nervous system [1, 25]. Maintaining optimal temperature conditions in cleanrooms may be critically important not only for upholding technologically advanced production standards but also for ensuring the safety and effectiveness of operators and specialists performing tasks that require high levels of attention and rapid decision-making [1].

Given the importance of controlling background variables, it is essential to emphasize the need for a comprehensive approach to data analysis. In addition to the technical maintenance of a stable experimental environment, it is critically important to consider individual characteristics of participants, including age, education level, socio-cultural factors, and other demographic variables. As demonstrated in several studies, these variables can significantly influence the interpretation of cognitive test results. Therefore, to ensure an accurate assessment of experimental outcomes, it is necessary to apply multivariate statistical analysis that accounts for both external and internal factors [26, 27]. Such an approach allows researchers to differentiate the true effects of experimental manipulation from variability caused by individual characteristics of the subjects [26, 28].

Studies conducted in cleanroom settings demonstrate a high degree of reproducibility of results, which is a compelling argument in favor of using such environments to assess subtle cognitive effects. When background variables are tightly controlled, researchers achieve a substantial proportion of explained variance, allowing confident conclusions regarding the impact of specific environmental factors on cognitive performance [12].

Recent advances in machine learning and the processing of physiological signals such as electroencephalography (EEG), heart rate monitoring, heart rate variability (HRV), and facial thermal infrared imaging have opened new possibilities for building effective systems to analyze cognitive responses to thermal stress. Several studies show that cognitive load, reflecting mental performance and fatigue, is strongly correlated with sensitive physiological markers detectable through multisensory systems [29, 30].

Techniques such as k-nearest neighbors (kNN), decision trees (e.g., C5/C4.5), and the naive Bayes classifier have proven effective in analyzing cognitive states, especially when using high-level, manually engineered features extracted from EEG and HRV signals. These algorithms enable real-time classification of data along a predefined scale (e.g., low/high cognitive load), which is particularly useful for monitoring operator states under thermal stress conditions [31].

One of the key directions in this field is the application of convolutional neural networks (CNNs) for automatic feature extraction from spectrograms of breathing patterns and thermal facial images, eliminating the need for manual feature selection. Studies analyzing respiratory signals using two-dimensional spectrograms, such as the respiratory variability spectrogram (RVS) and CNNs, have shown high accuracy in classifying stress levels [32].

Research on elevated temperature settings in office environments has demonstrated that applying machine learning algorithms to EEG and HRV data enables an objective assessment of workers' cognitive states. Signal preprocessing using Butterworth filtering, segmentation, and discrete wavelet transform for energy feature extraction has shown high sensitivity to changes in cognitive load under heat stress conditions [30].

Applications for real-time mental stress detection using smartphone-based photoplethysmography and thermal imaging have demonstrated significant improvements in recognition accuracy when employing multisensory approaches. In these studies, low-level features such as interbeat intervals and temperature variability in the nasal region are processed using neural networks and k-nearest neighbor algorithms to classify stress states in real time. These findings highlight the importance of integrating data from multiple sensors to enhance the reliability of detecting cognitive changes under thermal exposure [32].

In the context of firefighting and extreme work environments, models based on heart rate variability (HRV) have been developed to distinguish between mental, physical, and combined stress within short time windows (up to one minute). Experimental data collected during firefighter training exercises show that algorithms such as decision trees and support vector machines (SVMs) can achieve up to 88% accuracy in detecting cognitive (psychosocial) stress, which also arises under heat load conditions [33].

Electronic skin systems and wearable technologies, such as CARES, integrate multisensory data, including physiological and biochemical indicators for continuous monitoring of stress and anxiety levels. In these systems, machine learning is applied not only for the classification of stress states but also for the quantitative assessment of anxiety levels, enabling adaptive control and alert systems in response to thermal stress [34].

Comprehensive analyses of cognitive load using multisensory data, including EEG, heart rate monitoring, galvanic skin response, and thermal characteristics, have been conducted using multi-task learning approaches. These methods allow the incorporation of individual psychological traits, such as personality factors and subjective workload assessments, thereby significantly enhancing the accuracy and validity of cognitive state classification under heat stress conditions [35]. Physiological signals collected in real-world environments are often affected by noise, motion artifacts, and external interferences. Robust preprocessing, filtering, and segmentation techniques are necessary to minimize errors introduced by these factors [30, 35].

Experimental studies conducted in controlled laboratory environments must be adapted for real-world applications. In this context, it is essential to develop systems based on machine learning that can operate in real time while accounting for dynamic environmental changes and variable thermal conditions [33]. Future directions include the development of more resilient systems that integrate multi-task learning, explainable models, and adaptive algorithms capable of continuous selflearning from incoming data. Additionally, the creation of large open-access databases of physiological signals recorded under thermal stress conditions would enhance the generalizability and accuracy of such models [30, 36].

Despite progress, a gap remains: findings for the moderate thermal range of 22–30 °C and the combined effects of temperature, CO_2, and humidity are fragmented and methodologically heterogeneous, hindering generalization to work and educational spaces. Against this background, the study formulates the research question of how moderate heat stress and accompanying CO_2/humidity changes affect short-term memory, attention, and reaction time in healthy young adults within a controlled laboratory environment. Methodologically, a within-subjects crossover with two sessions (thermoneutral 23–24.8 °C and elevated heat stress >27 to ~30 °C) ensures direct comparability of conditions. The architecture includes continuous multimodal IEQ monitoring (temperature, relative humidity, CO_2, PM_{10}/$PM_{2.5}$, noise, eTVOC) with presence verification, acquisition via Wi-Fi/Zigbee, and centralization in Home Assistant with threshold-based automation (ventilation at CO_2 > 1000 ppm), enabling closed-loop control and full data traceability. Cognitive assessment relies on standardized CogniFit tasks by domain (attention, memory, reasoning, coordination, perception) with key metrics including reaction latency, and post-hoc alignment of IEQ time series with behavioral metrics by timestamps. The analytical pipeline envisages the use of machine learning (scikit-learn, TensorFlow) to examine nonlinear interactions between environmental covariates and cognitive indicators on a time-synchronized dataset. Together, the platform and protocol establish a reproducible basis for task-oriented microclimate management and for future randomized exposures under laboratory conditions.

3. Materials and Methods

3.1. Architecture of the System

This research introduces a hierarchically structured architecture synthesizing high-fidelity environmental sensing with standardized cognitive assessment through synergistic hardware-software integration. The sensing stratum incorporates heterogeneous devices, Qingping Air Quality Monitors and Aqara Multi-Sensors performing continuous metrological surveillance of critical parameters: particulate matter mass concentrations (PM_{10}, $PM_{2.5}$), carbon dioxide (CO_2) levels, total volatile organic compound (TVOC) density, ambient temperature, relative humidity, and broadband acoustic noise. This instrumentation suite further augments data collection by embedding passive infrared occupancy detection, enabling verification of participant presence during experimental protocols. Data acquisition leverages dual-communication paradigms Wi-Fi for high-bandwidth Qingping telemetry and Zigbee for low-power Aqara mesh networking, optimizing both energy efficiency and transmission reliability across distributed node deployments.

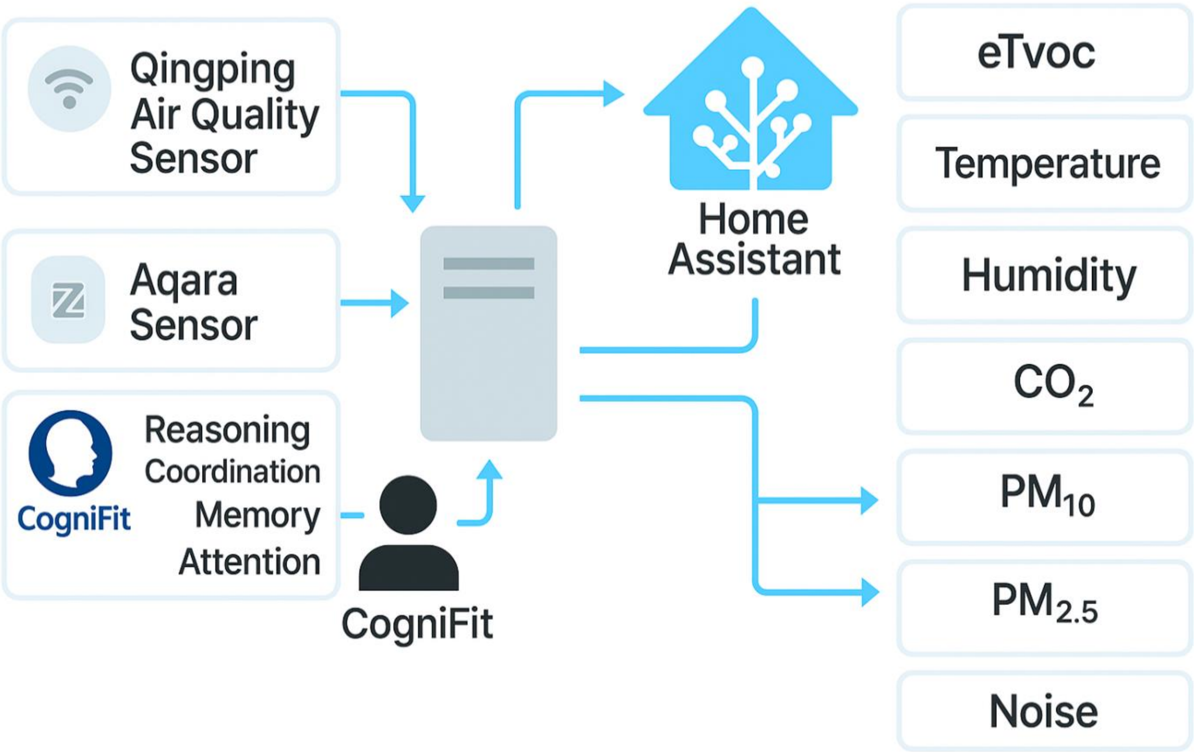

Figure 1.
Architecture of an intelligent laboratory environment for air quality monitoring and human cognitive function assessment.

Centralized computational orchestration occurs via the Home Assistant platform hosted on a dedicated local server. Ingesting heterogeneous real-time data streams, this control layer executes deterministic timestamp synchronization, automates temporal indexing into structured databases, and implements threshold-driven actuation protocols. Exemplary interventions include autonomous ventilation triggering upon CO_2 concentration excursions beyond 1000 ppm or particulate matter ($PM_{2.5}$) exceedances of WHO Tier-1 guidelines, demonstrating closed-loop responsiveness while maintaining interoperability with HVAC subsystems through standardized APIs.

Cognitive performance quantification utilizes the validated CogniFit assessment ecosystem, administering psychometrically calibrated mobile-based neuropsychological tasks. Participants engage with standardized batteries measuring executive domains, including sustained attention, working memory capacity, visuospatial reasoning, sensorimotor coordination, and perceptual acuity. Primary metrics encompass reaction latency, error rate quantification, task completion efficiency, and intra-individual variability. Temporal alignment between cognitive assessments and environmental time-series, achieved through manual post-hoc timestamp reconciliation, ensures millisecond-accurate correlation integrity for subsequent analyses.

Advanced analytical processing employs Python-based machine learning frameworks (Scikit-learn, TensorFlow) operating on temporally fused datasets. This methodology facilitates the identification of non-linear covariate interactions and exposure-response threshold phenomena, revealing how multivariate environmental states collectively influence cognitive biomarkers. Gradient-boosted regression and convolutional neural network architectures, trained on epoch-partitioned data, enable predictive modeling of individual neurocognitive susceptibility during dynamic microclimate perturbations such as CO_2-induced attentional decrements or thermo-hygrometric fluctuation impacts on mnemonic consolidation.

Converging distributed environmental sensing networks, automated cyber-physical control systems, and ecologically validated neurocognitive metrics, this integrated architecture establishes a robust methodological paradigm for longitudinal observational studies and randomized environmental exposure trials. The platform, characterized by extensible modularity and IoT-native scalability, advances causal inference capabilities regarding ambient parameter influences on human cognitive throughput within occupationally relevant built environments. Future implementations may incorporate physiological sensing modalities or expand actuator integration depth, further bridging environmental science with neuroergonomic optimization.

3.2. Experiment Description

This pilot study employed a within-subjects experimental design to examine the effects of thermal stress on cognitive performance. Ten adult participants (n = 10; 3 female, 7 male) completed two controlled testing sessions under distinct thermal conditions.

Table 1.
Cognitive test results and accompanying laboratory environmental parameters.

Name	Reasoning	Imagination	Memory	Perception	Attention	eTvoc	Temp	Humidity	CO2	PM10	PM2.5	Noise
ID 1	723	544	493	28.7	481	0	23.3	53	868	95	89	84
ID 2	567	403	304	42.7	584	54	24.2	46	872	118	109	59
ID 3	614	876	335	44.2	606	55	24	47	798	62	59	59
ID 4	687	354	598	52.3	556	96	25	46	848	127	113	58
ID 5	770	707	609	70.6	750	62	24	45	854	117	113	63
ID 6	133	238	229	41.0	367	46	24.6	47	814	169	163	62
ID 7	517	571	444	46.1	461	53	24.5	49	846	154	146	58
ID 8	587	403	304	42.1	585	56	24.2	46	837	113	107	59
ID 9	652	451	502	52.9	611	55	24.0	46	748	111	105	58
ID 10	387	410	563	44.5	537	50	24.2	46	816	118	113	59
ID 11	610	690	397	45.6	637	110	26.7	44	804	9	13	56
ID 12	570	556	627	56.4	584	118	29	49	808	9	9	55
ID 13	650	540	359	44.3	336	130	29.9	44	868	14	13	55
ID 14	472	314	529	58.4	262	84	27.2	44	921	6	6	53
ID 15	780	717	673	75.2	757	105	28.2	40	816	8	7	53
ID 16	390	451	644	47.9	234	124	29.2	44	801	13	10	56
ID 17	185	521	574	60.5	373	87	27.2	44	887	8	8	70
ID 18	611	556	299	42.2	584	66	26.7	46	866	22	19	56
ID 19	654	607	217	56.6	455	110	26.2	44	804	8	8	56
ID 20	442	412	562	46.5	434	64	29	46	805	22	19	56

The first session (Experiment 1) was conducted under thermoneutral conditions (23–24.8°C), with indoor air quality parameters maintained within optimal ranges (moderate CO_2 levels, low particulate matter). Participants performed a standardized computerized test battery assessing five cognitive domains: reasoning, sensorimotor coordination, memory, perception, and attention.

During the second session (Experiment 2), participants were exposed to elevated thermal stress (ambient temperatures >27°C, peaking at approximately 30°C) accompanied by increased eTVOC and CO_2 concentrations. Identical cognitive assessments ensured direct comparability of outcomes.

Continuous monitoring of environmental parameters (temperature, humidity, CO_2, PM_{10}, $PM_{2.5}$, noise, eTVOC) validated experimental conditions across both sessions. The dataset enables rigorous comparative analysis of cognitive metrics under thermal comfort versus stress paradigms.

This experimental framework provides preliminary insights into the detrimental effects of elevated ambient temperatures and concomitant air quality factors on multi-domain cognitive functioning. The repeated-measures design under controlled conditions enhances the internal validity of the findings.

4. Results and Discussion

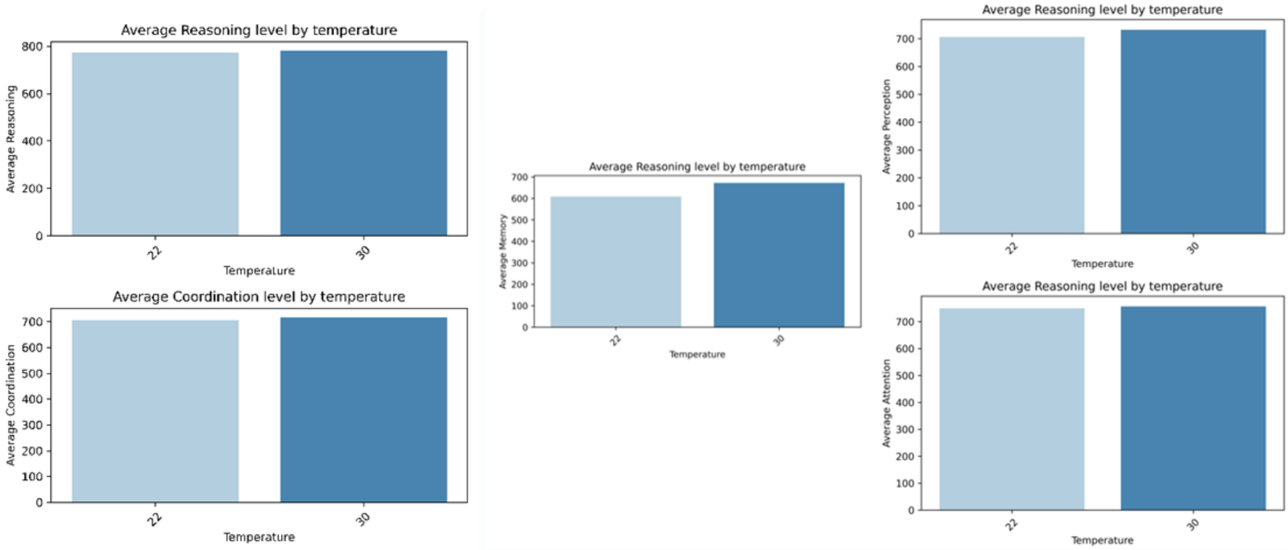

Figure 2.
Average cognitive scores under thermoneutral and elevated temperatures.

Figure 2 displays a set of five bar charts, each depicting the mean value of an individual cognitive metric under two temperature regimes: 22 °C (light-blue bars) and above 30 °C (dark-blue bars). The charts are arranged in a matrix: the upper-left panel shows memory ("Average Memory"), where the bar for 30 °C is roughly 40 points higher than for 22 °C (≈ 650 vs. ≈ 610), marking the largest increase across all metrics. To its right is perception ("Average Perception"): the higher temperature yields an average of about 730 units compared with roughly 700 at 22 °C, an uplift of approximately 4%. Below that, on the right, lies attention ("Average Attention"); although the difference is smaller (≈ 760 vs. ≈ 750), the upward trend persists. A second panel set completes the figure with two additional charts: at the top, reasoning ("Average Reasoning") rises from approximately 770 to approximately 780 units, and beneath it, coordination ("Average Coordination") increases from approximately 700 to approximately 715 units. In every case, the dark-blue bars (t > 30 °C) either equal or slightly surpass the light-blue bars, indicating a consistent positive effect of the elevated temperature on key cognitive functions. The most pronounced gains occur in memory and perception, while attention shows the smallest improvement.

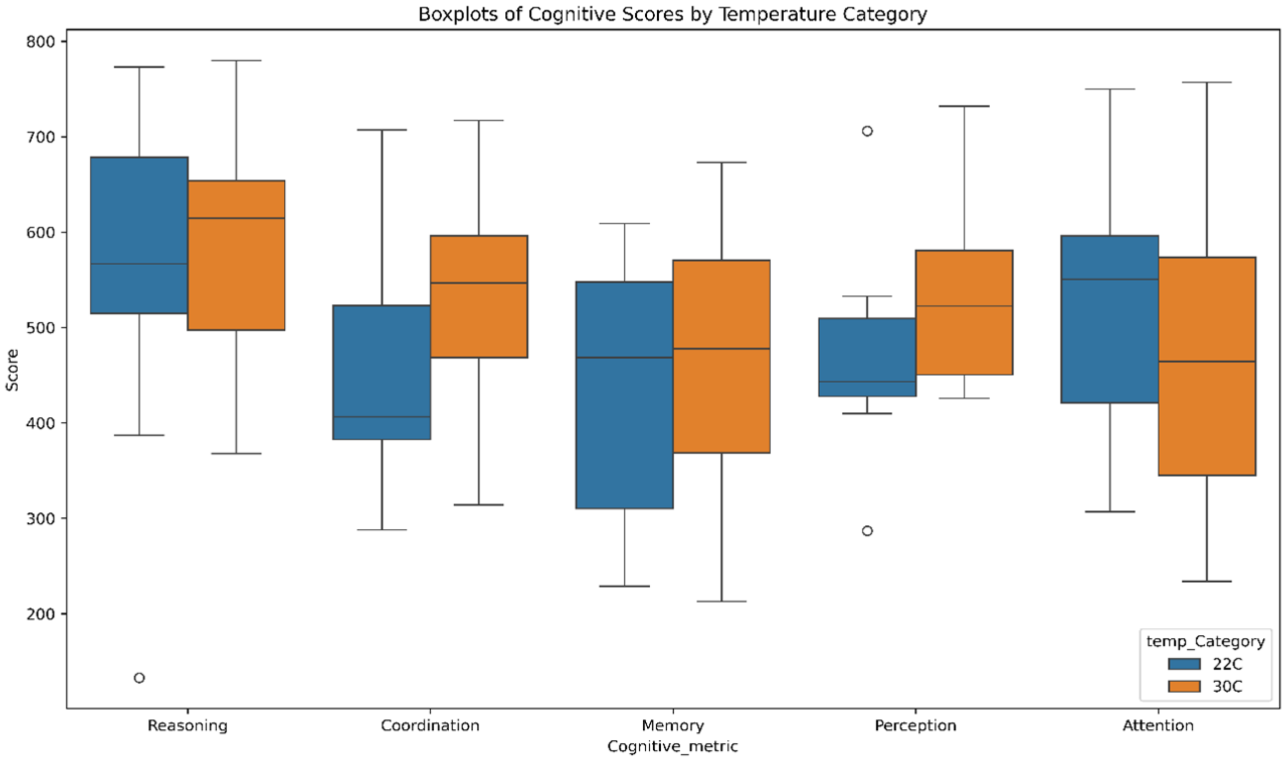

Figure 3.
Distributions of cognitive scores by temperature condition.

Figure 2 employs box-and-whisker plots to visualize not only mean values but also the full score distribution for each of the five cognitive metrics under two thermal regimes. For reasoning, the median shifts noticeably upward from roughly 550 points at 22 °C to about 620 points above 30 °C while the interquartile range (IQR) widens and the upper whisker extends toward 780 points, indicating a subset of participants who perform exceptionally well in hotter conditions. Coordination shows a similar pattern: the median climbs from the 420–430 range to nearly 500 points, and its IQR stretches to span approximately 470–600 points; elongated whiskers confirm the surge in dispersion.

The gain for memory is more moderate: its median rises from approximately 470 to 520 points, yet the score spread increases markedly the upper whisker approaching 710 points and the lower dipping toward 310, underscoring heterogeneous individual responses. Perception likewise benefits from heat: the median advances to roughly 540 points compared to approximately 490 points at 22°C, and an extended upper whisker (approximately 730 points) highlights outliers with very high results; a single low outlier in the cooler group (~280 points) further illustrates personal variability.

A distinctive exception is attention: its median at temperatures above 30 °C alters only slightly and appears marginally below that of the cooler group (≈ 470 vs. ≈ 580 points) while the range expands considerably, especially downward to about 190 points. Overall, the warmer environment leads to greater variability across participants, with clear upward median shifts in reasoning, coordination, memory, and perception, whereas attention emerges as the most sensitive and inconsistent metric. Collectively, these patterns point to a differentiated yet predominantly advantageous influence of elevated temperature on cognitive performance.

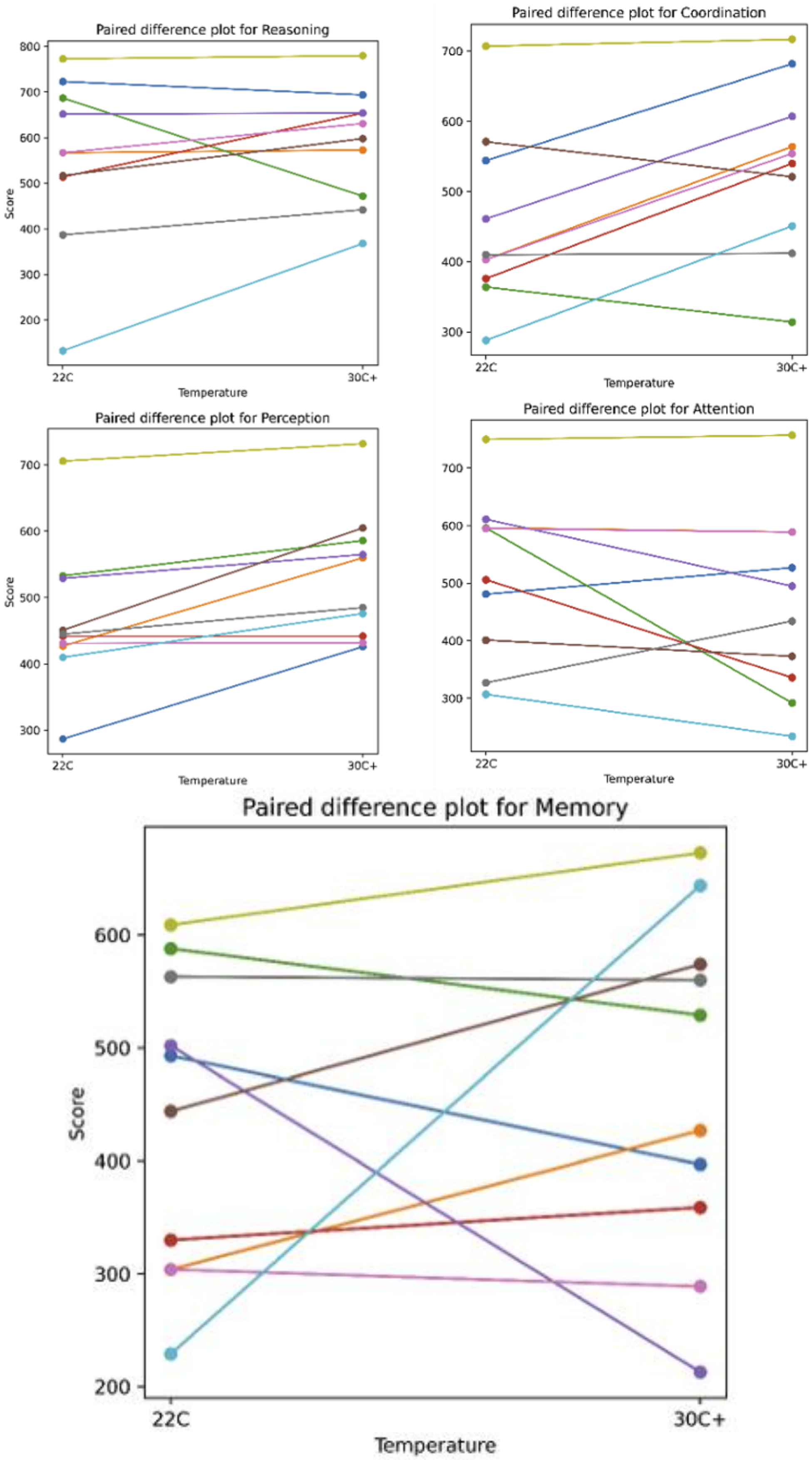

Figure 4.
Distributions of cognitive scores by temperature condition.

Figure 4 presents paired line plots illustrating the individual trajectories of cognitive performance for each participant when transitioning from 22°C to temperatures above 30°C across four cognitive domains: reasoning, coordination, perception, and attention. Each colored line corresponds to a single participant, making it possible to trace personal changes and heterogeneity in response to thermal variation. In the reasoning panel (top left), most lines slope upward, indicating that the majority of participants experienced an improvement in logical thinking under elevated temperatures. Individual gains vary widely: some participants demonstrate a pronounced increase of more than 200 points, while a small number show a minor decline, resulting in an overall upward group trend.

The coordination plot (top right) reflects a similarly positive pattern. Many lines ascend from approximately 300–600 points at 22°C to higher scores at 30°C+, with several participants showing marked improvements. Only a few downward-sloping lines indicate that the positive effect is not entirely universal but remains dominant across the sample. The perception panel (bottom left) exhibits predominantly rising lines as well. Even though some increments are moderate, the cumulative picture suggests that higher temperatures tend to enhance sensory processing and perception scores. A few trajectories remain nearly horizontal, implying that certain individuals were minimally affected by thermal changes.

In contrast, the attention plot (bottom right) shows a more heterogeneous pattern. Several lines slope downward, revealing that some participants' attention scores decreased in hotter conditions, whereas others maintained stable performance or slightly improved. This variability aligns with the earlier statistical and box-plot observations that attention is the most sensitive and inconsistent cognitive domain in response to thermal shifts.

Overall, Figure 4 highlights that the transition to higher temperatures produced mostly positive individual trends in reasoning, coordination, and perception, while attention exhibited mixed responses. These individualized line plots provide a detailed view of participant-level dynamics and confirm that the group's general trajectory under heat exposure remains predominantly upward, with isolated cases of performance decline.

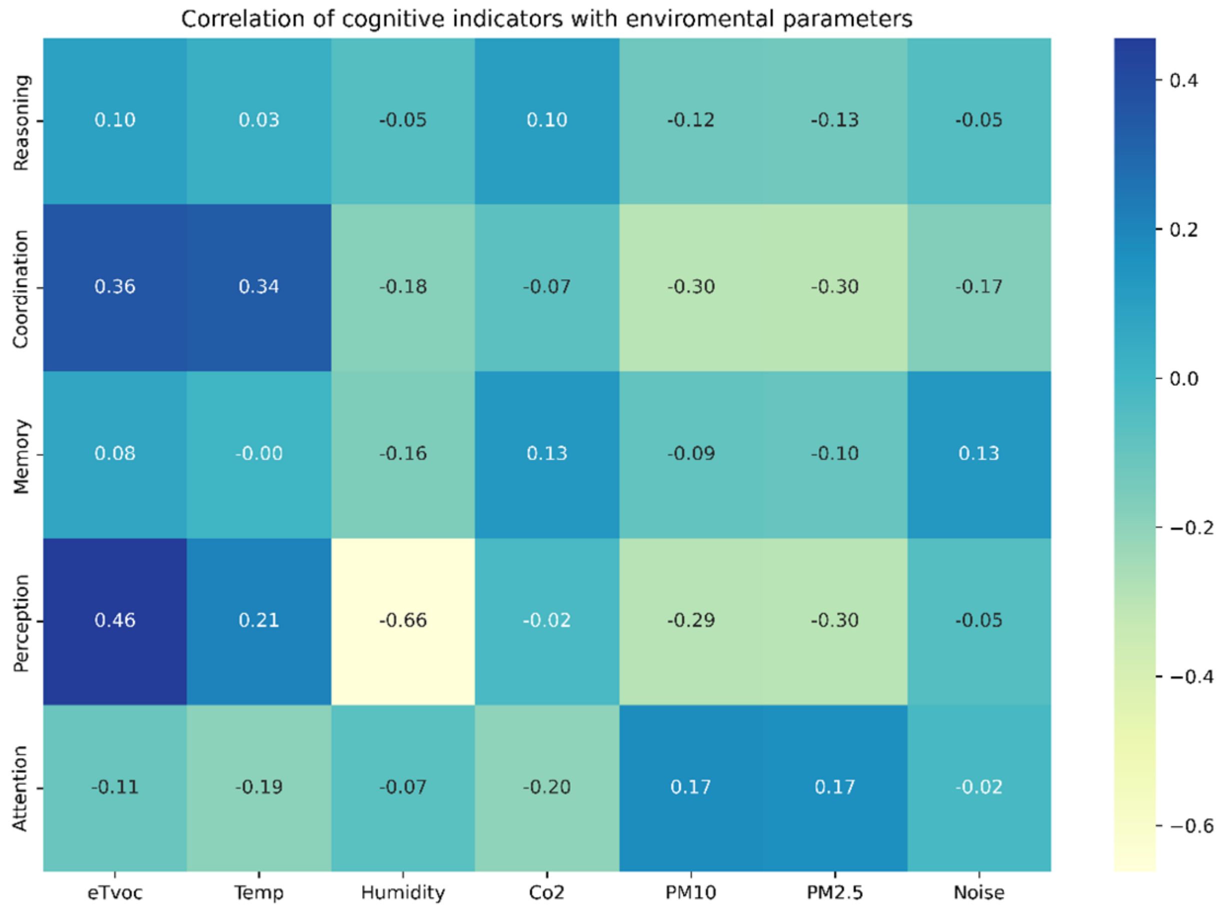

Figure 5.
Matrix of Pearson correlations: environmental parameters vs. cognitive outcomes.

Figure 5 presents a heatmap illustrating the correlations between five cognitive indicators (rows) and six microclimatic variables (columns). The color scale ranges from dark blue (positive coefficients) to pale yellow (negative), facilitating a quick assessment of both the direction and magnitude of relationships. Perception exhibits the largest absolute coefficient: the bright-yellow cell for *Perception–Humidity* shows r = –0.66, indicating that higher humidity significantly reduces sensory processing accuracy. Additionally, perception correlates negatively with PM10 and PM2.5 (both approximately 0.30), highlighting its sensitivity to aerosol pollution. Its modest positive correlation with temperature (r = 0.21) suggests a slight beneficial thermal effect.

Coordination shows a dual moderate association with temperature (r = 0.34) and eTVOC (r = 0.36), dark-blue cells in the "Temp" and "eTVOC" columns implying that slight warming and higher volatile organic compounds coincide with better motor coordination. In contrast, PM fractions (≈ –0.30) and noise (r = –0.17) relate negatively to coordination. For reasoning, correlations are generally weak: the largest value is with temperature ($r = 0.03$), essentially neutral; small negatives with particulate matter ($r \approx -0.12 \ldots -0.13$) suggest only slight suppression of reasoning as PM rises.

Memory shows a mixed profile: a small positive association with CO_2 ($r = 0.13$) and with eTVOC/temperature ($r = 0.08/0.00$) is paired with negatives for humidity ($r = -0.16$) and PM indicators ($r \approx -0.09 \ldots -0.10$), implying that excess moisture and particles modestly depress memory, while warming has virtually no effect. Attention is the most variable metric: negative r with temperature (–0.19) and eTVOC (–0.11) point to reduced concentration under heat and higher VOCs; by contrast, modest positives with PM10 and PM2.5 (both 0.17) look paradoxical and may reflect compensatory behaviors or sample specifics.

Overall, the matrix indicates that temperature tends to support coordination and, to a lesser extent, reasoning and perception, but may impair attention; humidity is strongly detrimental to perception; and PM generally exerts negative pressure on most functions except attention, where the relationship reverses slightly. These patterns highlight domain-specific sensitivity to microclimate and the need for integrated environmental control when evaluating performance and well-being.

There are multiple hypotheses that may explain the observed domain-specific effects of temperature. One posits differential reactivity of neural circuits depending on the functional specialization of brain regions: for example, networks responsible for logical relations and planning may temporarily benefit from a moderate temperature increase via enhanced synaptic transmission, whereas networks organizing attentional processes are less flexible and more sensitive to excitatory shifts [37]. In addition, physiological mechanisms such as changes in heart rate variability and the sympathetic–parasympathetic balance may act as important mediators of temperature's influence on cognition, as they differentially modulate activity in prefrontal structures involved in complex cognitive control. This framework helps explain why some cognitive tasks improve with slight warming while others deteriorate, a pattern supported by both experimental and theoretical work [38, 39].

Research findings suggest that maintaining a moderately warm microclimate (around 21–22 °C) can facilitate improvements in logical reasoning, coordination, memory, and perception, especially relevant for classrooms and offices where high cognitive efficiency is required. Conversely, given attention's vulnerability to even small temperature fluctuations, it is advisable to develop innovative climate-control systems that can dynamically adjust temperature in line with current cognitive demands and provide periodic opportunities to restore concentration [39]. Such measures may include adaptive ventilation, the use of personal temperature regulators, and the organization of breaks to reset attentional focus.

Many laboratory studies are conducted with student samples under controlled conditions, which may not fully capture the nuances of adult workers' performance in real office environments. There is also variability in how cognition is measured: some studies focus on reaction time, others on accuracy, complicating direct comparisons and the establishment of a universal temperature–performance relationship. Accordingly, future research should account for interindividual differences in adaptive capacity and consider concomitant factors such as physical activity levels, stress, and overall physiological readiness [37].

5. Conclusion

The pilot study (n=10) conducted in a controlled laboratory setting demonstrated that moderate heat stress, defined as an increase in temperature from approximately 23–24.8 °C to over 27–30 °C and associated changes in indoor air quality parameters, differentially impact cognitive functions in young healthy participants. The most vulnerable domain was attention, which showed a negative association with temperature ($r = -0.19$). Conversely, coordination improved moderately with warming ($r = 0.34$). Perception was significantly impaired by higher humidity levels ($r = -0.66$). Short-term memory and reaction time exhibited mixed and statistically unstable associations within laboratory temperature ranges. Fluctuations in CO_2 and other indoor environmental quality (IEQ) factors such as particulate matter (PM) and total volatile organic compounds (eTVOC) did not show associations as consistent as those observed for temperature and humidity. These findings refine the prevailing notion of a universal decline in cognitive efficiency under moderate warming, indicating that effects are domain-specific. Consequently, microclimate management should be task-oriented, implementing cooler and drier environments for attention-critical tasks and tolerable moderate warming for tasks relying on coordination and sensory processing. The use of Internet of Things (IoT) integration, such as automated ventilation for closed-loop control, can optimize indoor conditions. Limitations of this pilot study include a small sample size and short exposure durations, which warrant confirmation in larger cohorts with extended protocols. Future research should consider stratification by individual factors such as sex, chronotype, and heat tolerance, as well as include physiological mediators like heart-rate variability to clarify causal mechanisms and enhance the generalizability of results to real educational and office settings.

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