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Cognition, economic decision-making, and physiological response to carbon dioxide

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Cognition, economic decision-making, and physiological response to carbon dioxide

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ABSTRACT

This study examines the isolated effect of carbon dioxide on cognition, economic decision-making, and the physiological response in healthy adults. The experiment took place in an air-tight respiration chamber controlling the environmental conditions. In a single-blind, within-subject study design, 20 healthy participants were exposed to artificially induced carbon dioxide concentrations of 3,000 ppm and 900 ppm in randomized order, with each exposure lasting for 8 h. A high ventilation rate and an air pollutant filter were used to keep concentrations of volatile organic compounds and fine particles equally low in both conditions. Cognition tests were conducted twice during the 8 h and physiological parameters were measured continuously over the 8 h. No evidence on a robust statistically significant effect of carbon dioxide on either cognitive or physiological outcome variables were found. These findings imply that the human body is able to deal with exposure to indoor carbon dioxide concentration of 3,000 ppm for a limited time without suffering significant cognitive decline, changes in decision-making or showing any physiological response.

1. Introduction

The indoor environmental quality in buildings plays an important role in influencing the cognitive performance and health of occupants [1,2]. Indoor air quality is an important aspect of the indoor environment, because it is influenced by the supply of fresh outside air via mechanical ventilation and natural ventilation [3]. Mounting evidence has shown that insufficient ventilation removing carbon dioxide and other air pollutants are associated with impaired cognitive performance and work performance in office workers [4,5]. Exposure to poor indoor air quality in classrooms has also negative effects on learning and academic achievement in school children [6,7]. A recent article by 43 experts emphasizes the importance of good indoor air quality for human health, productivity and learning [8].

However, buildings majorly contribute to greenhouse gas emissions, thus there is a need to provide energy efficient buildings [9]. On average, approximately half of a building's energy consumption is dedicated to heating, cooling, and ventilation [10]. This proportion varies depending on the climate and the building type. Increasing ventilation rates directly affects energy consumption, but also indirectly leads to higher energy demand for cooling and heating to maintain a stable indoor temperature during cold or hot weather [11–13]. Thus, building owners face a profound trade-off between providing healthy indoor air quality and improving the energy efficiency of buildings.

Modern demand-controlled ventilation systems use real-time measurements of carbon dioxide (CO_2) concentration levels to adjust the ventilation rate, providing good indoor air quality during high occupancy and reducing energy consumption during low occupancy [14,15]. CO_2 is a useful metric for estimating ventilation rates and modelling indoor air quality, because its concentration strongly correlates with human-emitted air pollutants (bioeffluents) and volatile organic compounds [16–18]. The negative effects of poor indoor air quality on cognition and health are often linked to bioeffluents and volatile organic compounds [4,19]. Thus, it has long been believed that, while CO_2 is a useful proxy for indoor air quality, its association with adverse cognitive and health outcomes is not of causal nature, but rather mediated by other air pollutants that increase in concentration with CO_2 indoors.

However, a number of papers have examined the isolated effect of CO_2 on cognitive parameters, showing mixed results [20–26]. These studies are quite heterogeneous in terms of participant population, exposure time, outcome measurement, and size of groups measured at

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the same time (see Supplementary Table S4 for an overview of previous literature on CO_2.). Additionally, only two studies have measured the effect of CO_2 exposure on cognitive and physiological responses simultaneously, reaching contradicting results about its influence on these outcomes [20,25]. The studies which found a strong negative effect of CO_2 did not measure any physiological parameters which could explain their results [21–23]. Although, there is evidence that elevated CO_2 concentrations can trigger adverse physiological reactions. It is assumed that elevated CO_2 levels lead to a change in breathing pattern, which could affect blood homeostasis and trigger heightened states of arousal or sleepiness [4,19,27]. However, it is unclear if changes in respiration are triggered by other air pollutants co-occurring with CO_2 [28]. Thus, measuring cognitive performance and physiological parameters provides valuable insights into the pathways of a possible impact of CO_2 on cognitive performance.

While current ASHRAE guidelines (American Society of Heating, Refrigerating and Air-Conditioning Engineers) see CO_2 solely as a proxy for indoor air quality, but not as an air pollutant itself, a position paper by ASHRAE recommends further research on the role of CO_2 itself on human health and cognition due to the mentioned inconsistency in previous studies [29,30]. The position paper emphasizes the need to examine the role of CO_2 on cognition and health with a focus on the physiological mechanism and its impact on blood chemistry and respiration. Such studies become particularly relevant considering that peak CO_2 concentrations commonly reach levels above 2,500 ppm, exceeding recommended threshold levels, sometimes despite the presence of mechanical ventilation [6,29].

Understanding the role of CO_2 in human cognitive performance and health also helps determine the importance of air cleaning devices. Since demand-controlled ventilation systems use CO_2 levels to adjust ventilation rates, removing CO_2 from the air should be done carefully and only when necessary, to avoid unintended effects such as increased concentrations of other air pollutants [30]. Air filtration and purification systems remove airborne pathogens and particles, but gaseous substances are not removed by this process. Therefore, in such a case, CO_2 might not be an accurate measure of air quality anymore [8]. Using filtration systems can reduce energy consumption from ventilation systems [31]. However, identifying CO_2 as an air pollutant would have consequences for determining the optimal combination of filtration and ventilation systems to provide healthy indoor air while maximizing energy efficiency.

To address this urgent gap in the understanding of CO_2 on human cognition and health, this study examines the isolated effect of CO_2 on a broad set of outcomes in a tightly controlled environment. Using an interdisciplinary approach, we investigated the effect of an 8-h exposure to a CO_2 level of 3,000 ppm induced from a liquid CO_2 bottle, as compared to a CO_2 level of 900 ppm, on the cognitive performance, economic decision-making, and physiological response of healthy adults. Ventilation rates were maintained at a high level ($>$ 500 l/min) and an air cleaner was used to ensure low levels of volatile organic compounds, bioeffluents and other air pollutants in both conditions, attributing any observed effects to CO_2. Various physiological parameters were continuously measured during exposure to associate any effects with potential physiological reactions, including changes in blood CO_2 concentration and respiration. The experiment was conducted in an airtight respiration chamber, commonly used in metabolic research [32].

We hypothesize that an elevated ambient CO_2 level leads to lower cognitive performance. Cognition is measured using a neuropsychological test battery to test the domains of attention, psychomotor control, executive function, and memory. We also investigated the impact on individuals' risk and time preferences by applying multiple price lists, a tool commonly used in economics literature, to analyse the effect of CO_2 on economic decision-making [33,34]. It is assumed that elevated CO_2 levels lead to changes in risk-taking and time preferences. Risk and time preferences have been found to predict economic decision-making in a wide variety of settings and are often found to correlate with cognition [35,36]. Moreover, any effect on cognitive performance or economic decision-making is assumed to be mediated by a physiological reaction, such as a higher heart rate, higher blood pressure, higher physical activity level, or elevated oxygen consumption. It is further hypothesized that the respiration rate will decrease as a response to the higher CO_2 concentration and this is associated with a higher blood CO_2 concentration, as suggested by earlier research [27,28]. This finding would indicate that elevated levels of CO_2 lead to a respiratory acidosis due to altered breathing patterns. Given the large number of hypotheses tested in the empirical analysis, we draw inferences based on *p*-values corrected for multiple hypothesis testing.

2. Methods

2.1. Experimental setup

This study was conducted on a cohort of 20 healthy individuals between November 2021 and July 2022. A sample size of 20 participants was chosen based on a power calculation using an effect size of 1, as suggested by previous studies on the impact of CO_2 on cognitive performance [4]. Participants were exposed to CO_2 levels of 3,000 ppm (High-CO_2) and 900 ppm (Low-CO_2) during an 8-h stay in a respiration chamber at the Metabolic Research Laboratories at Maastricht University. A CO_2 concentration of 3,000 ppm is commonly found in indoor spaces despite mechanical ventilation and has also been used in previous laboratory studies [6,19,20,25]. A level of 900 ppm is below the threshold for good indoor air quality, as suggested by common building guidelines [29,37].

The chamber (14 m^3) is equipped with a desk, sink, and deep-freeze toilet. It is airtight, creating negative pressure to allow precise measurements of CO_2 and oxygen levels, suitable for indirect calorimetry to determine metabolic rate. Fresh air is drawn from the building roof and circulated through the chamber. The concentrations of CO_2 and oxygen of the inflow and outflow air are measured minute-by-minute using paramagnetic oxygen analysers and infrared CO_2 analysers. Each gas sample is measured with two separate analysers to improve reliability. A detailed description of the chamber setup can be found in previous work [32].

Only one participant at a time was measured in the chamber, as behaviour and perception can be influenced when occupants are measured in groups [38]. We used a cross-over design where participants were exposed to both CO_2 conditions, with a break of four to six weeks between the two test days. The order of the test conditions was randomized. Among the 20 participants in this within-subject design, 10 were first exposed to the High-CO2 condition on their initial testing day and then to the Low-CO2 condition on their second testing day. The remaining 10 participants experienced the conditions in the reverse order, starting with the Low-CO2 condition on their first day, followed by the High-CO2 condition on their second day. Upon study inclusion, each participant was randomly assigned to one of the two starting conditions to ensure that the order of exposure was randomized throughout the participant inclusion process. Participants were unaware of the condition.

The ventilation rate was set in both conditions at a high level ($>$ 500 l/min) to minimize the concentrations of volatile organic compounds and fine particulate matter in the chamber. Thereby, the concentration of total volatile organic compounds was kept constant across both conditions. Previous work shows that increasing ventilation rate successfully reduces total volatile organic compounds concentration [21]. Additionally, a particle and volatile organic compounds filter (Molekule Air Mini+, Molekule, Florida, USA) was installed. Remaining fine particular matter ($PM_{2.5}$) and total volatile organic compounds were measured every 5 min using a commercially available monitor (Foobot SAT, Airboxlab SA, Luxembourg) to confirm low and

stable volatile organic compounds concentrations across the exposure conditions. The used monitor has been validated and compared to other low-cost sensors [39]. No standardized hygiene practices for participants were enforced.

In the Low-CO_2 condition, the ventilation rate of > 500 l/min led to a steady-state CO_2 concentration of 900 ppm. The same ventilation rate was kept in the High-CO_2 condition. For this condition, after participants entered the chamber, CO_2 was induced via a gas bottle until it reached a stable level of 3,000 ppm, which took an average of 11 min. After the 3,000 ppm concentration was reached, the infusion of additional CO_2 was reduced to a level sufficient to maintain the steady-state concentration of 3,000 ppm for the remainder of the test day. Inducing the CO_2 before participants entered the chamber would have resulted in an outflow of CO_2 when the door was opened due to the under-pressure condition inside the chamber. Therefore, in the Low-CO_2 condition, the 900 ppm CO_2 concentration represents participant-induced CO_2, while the High-CO_2 condition consisted of 3,000 ppm CO_2 from a mixture of exhaled and artificially added CO_2. Indoor temperature and relative humidity were maintained at 21° Celsius and 32%, respectively.

2.2. Recruitment of participants

Inclusion criteria were (1) having an office job that includes mentally demanding tasks, (2) being between 25 and 50 years old, (3) being generally healthy with no intake of any medication (except for contraceptives), and (4) not smoking. Individuals with any of the following characteristics were excluded: (1) being unemployed at the time of testing, (2) having a disorder or disease, including Parkinson's diseases, Attention Deficit Hyperactivity Disorder, Alzheimer's diseases, diabetes, cardiovascular disorders, respiratory impairments, or hypertension; (3) participating into professional sports or exercising more than five times a week for more than two hours; (4) working in shift work; (5) being colour-blind, or (6) being pregnant. Participants received a lump-sum compensation of €170.

The final sample included eleven female and nine male participants, with an average age of 31 years, ranging from 25 to 46. The average Body Mass Index (BMI) was 23, with the lowest at 20 and the highest at 27. The average height was 174 cm (minimum of 156 cm and maximum of 191 cm) and the average weight was 69 kg (minimum of 51 kg and maximum of 92 kg). From a socioeconomic perspective, participants were quite similar: All had a university degree, and the majority (N = 17) had a monthly gross income between €1,000 and €5,000, while two participants earned between €5,000 and €7,500, and one participant earning more than €10,000 in gross monthly salary.

This study received Medical Ethical Approval from the Clinical Trial Center Maastricht (CTCM) of the Academic Hospital Maastricht before any data collection began, adhering to the Declaration of Helsinki. Participants signed an informed consent form before starting the study and were informed of their rights, including their right to withdraw from the study at any point without the obligation to provide reasons. The approval is registered under the nation-wide Dutch number *NL77015.068.21*, internal CTCM number *METC21-033*.

2.3. Outcome variables

Cognitive tests: The Cambridge Neuropsychological Test Automated Battery (CANTAB) was used to assess participants cognitive functioning. Participants completed the test on a tablet computer with a touch screen. The CANTAB tests have been validated against other neuropsychological test batteries [40]. Four domains were measured: Attention, psychomotor control, memory, and executive function. For attention and psychomotor control, the Reaction Time Task and Motor Screening Task were used. The Reaction Time Task measures the speed of movement and mental response in milliseconds when a stimulus is presented. The Motor Screening Task assesses movement latency in milliseconds when a stimulus is presented. The Delayed Matching to Sample and Paired Associate Learning tests were used to measure memory. Delayed Matching to Sample measures visual matching ability and short-term visual recognition memory as a percentage of correct choices. Paired Associate Learning assesses visual memory and learning as the number of correct responses. To measure executive function, the Multitasking Test, One Touch Stocking of Cambridge, Stop Signal Task, and Spatial Working Memory were used. The Multitasking Test measures the ability to manage conflicting information as the time (in milliseconds) that a participant needs to give the correct response when two contradicting stimuli are presented. One Touch Stocking of Cambridge assesses spatial planning and working memory as the number of problems solved on the first attempt. Stop Signal Task measures impulse control as the time (in milliseconds) it takes for participants to inhibit a reaction when the test initially asks for a reaction. Last, Spatial Working Memory measures strategy and working memory errors as the number of incorrect revisions from finding a specific figure among several covered fields. A detailed description of the CANTAB tests can be found on the CANTAB website [41]. To ensure a balanced loading of the different cognitive domains, the same order of testing was applied during the test days: Start with the Reaction Time Task, then Paired Associate Learning, Stop Signal Task, and Spatial Working Memory, followed by a 10-min break. After the break, the testing continued with Motor Screening Task, One Touch Stocking of Cambridge, Delayed Matching to Sample, and Multitasking Test. The eight tests, including, the 10-min break, took approximately 60 min. The CANTAB tests were conducted twice during a test day, first in the morning after 30 min of exposure and then in the afternoon after 330 min of exposure.

Economic decision-making: In addition to general cognition, we tested how varying CO_2 levels affect economic risk and time preferences, specifically risk aversion (hereafter called "risk preferences") and the level of impatience when delaying a financial payment (hereafter called "time preferences"). To elicit these preferences, we employed multiple price lists (MPLs), following the methods by Holt and Laury [34] for risk preferences and by Coller and Williams [33] for time preferences. We used six multiple price lists in total, each comprising ten choices between two neutrally labelled options, A and B. These choices were involving either lotteries for risk preferences or intertemporal prospects for time preferences, defined over monetary payoffs. Supplementary Tables S1 and S2 provide summaries of all MPLs used in this experiment.

To elicit risk preferences, participants repeatedly chose between lotteries with differing levels of risk in MPL1.1, MPL1.2, MPL2.1 and MPL2.2. To assess time preferences, participants repeatedly chose between varying monetary payoffs at different points in time in MPL3.1 and MPL3.2. The order of displayed choices within each multiple price lists were randomized, while the sequence between the six multiple price lists remained fixed. To incentivize participants to reveal their true preferences, they were informed beforehand that at the end of each test day, one of the 60 presented choices would be randomly drawn, and they would receive the corresponding payments in cash at the end of the test day. If the randomly selected decision involved a choice between lotteries (risk preferences), a coin was flipped to determine the outcome of the chosen lottery. For an intertemporal choice (time preferences), participants would either receive payment immediately, or one month later, depending on their choice.

Physiological outcomes: To assess the physiological responses and thus the potential mechanism by which exposure to elevated CO_2 may impair cognitive performance, several outcome parameters were measured on a minute-by-minute basis throughout each 8-h test day. Blood CO_2 concentration was measured continuously with a transcutaneous monitor (SenTec, Therwil, Switzerland), which was also used in a previous study [27]. For this reason, a non-invasive sensor was attached to the forehead. The software V-STATS was used to derive the data (version 5.01, SenTec AG, Switzerland). Due to occasionally, brief measurement errors, the blood CO_2 concentration data was cleaned

in two steps. First, the monitor also measured the saturation level of oxygen, which, given the respiration chamber's condition (sea level atmospheric pressure and no exercising), were expec should stay above 95 percent [42]. Thus, minute-by-minute values of the partial pressure of CO_2 were excluded if the saturation level of oxygen during the particular minute fell below 95 percent, indicating a likely measurement error. Second, remaining blood CO_2 concentration values below 30 mmHg or above 50 mmHg were removed as outliers, as partial pressure values for blood CO_2 are expected to fall within this range [43]. This resulted in removing 10.4% of the minute values for blood CO_2. Additionally, heart rate and respiration rate were measured using the Polar H10 belt (H10, polar, USA, RR interval accuracy 99.6% [44]), which was attached around the thorax. The mobile application Polar SDK developer kit for Android was used to extract raw ECG data, while the Kubios software (Biosignal Analysis and Medical Image Group, Department of Physics, University of Kuopio, Kuopio, Finland, [45]) was used to calculate heart rate and respiration rate. Physical activity levels were measured using the three-axis activity monitor ActiGraph (ActiGraph GT3X) with a sampling frequency of 30 Hz. The ActiGraph was placed on the right side of the hip. The Vector Magnitude counts per minute were derived from the raw data. Oxygen consumption was continuously measured in the respiration chamber using indirect calorimetry equipment (Omnical, Maastricht Instruments, Maastricht, NL), which measures oxygen consumption over time [32]. Lastly, blood pressure was automatically measured every 15 min starting at each full hour, using the Mobil-O-Graph device (I.E.M. GmbH, Stolberg, Germany).

2.4. Experimental protocol

The detailed test protocol is shown in Fig. 1. Participants were continuously exposed to the testing conditions for 8 h, from 09:00 h until 17:00 h. The chamber is equipped with a desk, sink and toilet, allowing participants to remain in the chamber throughout the 8 h, ensuring consistent environmental conditions. They were allowed to eat their own breakfast while in the room. Additionally, participants were either provided with lunch or brought their own. The breakfast and lunch they ate during the first test day was documented to ensured that participants ate the same breakfast and lunch during the second test day. Food intake time was not standardized. Participants were provided with decaffeinated coffee if they requested coffee (they were not informed that coffee was caffeine-free). Between the cognition tests, participants were free to spend their time with either reading or desk-based work, but they were not allowed to watch TV or sleep. They were instructed to behave as they would during a normal workday. To reduce any interference from a learning effect, participants practised the cognition test once during the screening session prior to the first test day. Additionally, the statistical analysis described in Section 2.5 includes a test day fixed effect and morning fixed effect to control for any variation in test score due to initial exposure to the testing condition and any possible learning effect during the testing day. To further reduce a possible bias from a learning effect, the exposure of CO_2-condition has been equally randomized among the 20 participants, as described in Section 2.1.

2.5. Statistical analysis

Cognitive and physiological responses: We started the analysis by estimating the linear fixed-effect regression model described in Eq. (1) to evaluate the impact of elevated CO_2 level on the cognitive and physiological responses of participants:

$$Y_{itd} = \eta + \delta High\mathrm{CO2}_{id} + \lambda_t + \theta_i + \gamma_d + \epsilon_{itd} \quad (1)$$

Where Y_{itd} is the outcome variable measured for participant i at the time of the day t at test day d. $High\mathrm{CO2}_{id}$ is a binary variable that takes the value of *one* if participant i is exposed to the High-CO_2 condition (3,000 ppm) on test day d and *zero* otherwise. λ_t represents a set of binary variables capturing the exact time of the day at which certain outcome variables are measured. The cognitive tests (CANTAB) were measured twice a day, in the morning and afternoon, while the physiological parameters were continuously measured during the test day. We aggregated the physiological parameters to hourly averages. Therefore, we defined two different sets of dummy variables included in λ_t: For the cognitive outcome variables, we included one binary variable $Morning_t$, taking the value of *one* if the test was taken in the morning session and *zero* otherwise. For the physiological parameters, we included eight binary variables $Hour_t$ each representing one hour of the test day. In addition, we included an individual fixed effect θ_i to restrict the analysis to within-participant comparisons, and test day fixed effect γ_d to account for potential learning effects and familiarization with the testing environment when measuring cognitive performance on the second test day for each participant i. Lastly, Eq. (1) includes the constant η and error term ϵ_{itd}.

With this model, the parameter of interest δ measures the impact of each participant's exposure to 3,000 ppm CO_2 concentration on test day d for the outcome variable Y_{itd}, in comparison to the same participant being exposed to 900 ppm CO_2 concentration on the other test day. Given the random assignment of participants for both conditions and test days, δ allows for a causal interpretation. Finally, given the low number of clusters in our study (N = 20), which potentially violates the large-sample assumptions of analytical standard errors, we base our inference of standard errors on wild bootstrap clusters, as recommended in previous literature [46]. We applied 1,000 bootstrap replications clustered at the participant level to estimate the variance–covariance matrix. Using bootstrapped standard errors to derive significance does not require normal distribution of the outcome variable [47]. Given the relatively large number of hypotheses tested (8 tests for CANTAB and 7 tests for the physiological outcomes), we added adjusted p-values based on the method by Hommel to take the multiplicity of tests into account [48]. We provide the bootstrapped standard errors as well as the p-values based on multiple hypothesis testing with the estimated coefficients in the results table below.

Furthermore, we enhanced the baseline model from Eq. (1) to allow the treatment effect δ_t to vary over the day. We estimated the following regression model, adding an interaction term to Eq. (1) by interacting the treatment parameter $High\mathrm{CO2}_{id}$ with the time-of-the-day dummy variables λ_t.

$$Y_{itd} = \alpha + \delta_1 High\mathrm{CO2}_{id} + \delta_2(High\mathrm{CO2}_{id} \times \lambda_t) + \lambda_t + \gamma_d + \theta_i + \epsilon_{itd} \quad (2)$$

In Eq. (2), δ_1 represents the difference in outcome variables between High- and Low-CO_2 conditions at reference time t_0 (afternoon testing for CANTAB, and first test day hour for physiological parameters), and δ_2 represents the same difference, but measured during other times of the day in relation to t_0. Therefore, the analysis allows to draw conclusions on whether the effect of CO_2 exposure on outcome variables is time-variant, such as testing a dose–response gradient and how it influences the outcome variables.

Economic decision-making: To analyse the impact of increased CO_2 on economic risk and time preferences, we used a maximum likelihood model [35,49,50] to estimate preference parameters of a discounted expected utility model, similar to a previous study [49]. Utility over monetary gains is modelled assuming constant relative risk aversion (CRRA):

$$u(x) = \frac{x^{1-\alpha}}{1-\alpha} \quad (3)$$

where x denotes monetary gains, and α is the parameter of relative risk aversion, describing the curvature of the utility function; $\alpha = 0$ implies risk neutrality, $\alpha > 0$ risk aversion, and $\alpha < 0$ implies risk-seeking behaviour. For $\alpha > 0$, the larger α, the larger risk aversion.

Time in testing condition (min)	Time of day (hh:mm)	Testing steps and cognition tests	Physiological continuous measurements	
0	09:00	Chamber door closed	Blood CO2 level, heart rate, respiration rate, physical activity level, oxygen consumption	Systolic and diastolic blood pressure (measured every 15 minutes starting with the full hour)
30	09:30	CANTAB test (60 Min)		
60	10:00			
90	10:30			
120	11:00	Multiple price lists (15 Min)		
150	11:30			
180	12:00			
210	12:30			
240	13:00			
270	13:30			
300	14:00			
330	14:30	CANTAB test (60 Min)		
360	15:00			
390	15:30			
420	16:00	Multiple price lists (15 Min)		
450	16:30			
480	17:00	Leaving the chamber		

Fig. 1. Experimental protocol.

Secondly, intertemporal choices as a measure of time preferences are modelled using a simple expected discounted utility model:

$$U(x_t, \dots, x_t) = E_t[u(x_t) + \sum_{k=1}^{T-t} \frac{1}{(1+\rho)_k} u(x_{t+k})] \quad (4)$$

Here, ρ is the discount factor. The larger the value of ρ, the more the future is discounted, leading to a lower willingness to wait for the future payment. As a result, individuals become more impatient.

Participants repeatedly choose between two options, labelled A and B. We denote the expected discounted utility of options A and B as U^A and U^B, respectively. Our model allows for two types of decision errors to be as flexible as possible regarding the parametric assumptions. Specifically, decision noise is accounted for by a tremble error (κ) and a Fechner error (μ) [35,51]. The tremble error measures decision errors due to choice randomization, that is individuals may randomly choose between A and B with some probability κ. The Fechner error term accounts for errors in evaluating the expected utility of lotteries: options A and B are assessed based on their expected utility plus a random element ϵ, such that an individual chooses option B if $U^B + \epsilon^B > U^A + \epsilon^A$. Overall, the probability of choosing option B is given by:

$$P(B) = (1-\kappa)F(\frac{U^B - U^A}{\mu}) + \frac{\kappa}{2} \quad (5)$$

where F is the cumulative distribution function of $(\epsilon^A - \epsilon^B)$, which follows a standard logistic distribution. For $\kappa \to 0$, the tremble error has no effect on choice, and for $\kappa \to 1$, the choice approaches uniform randomization. For $\mu \to 0$, the decision becomes deterministic (conditional on not choosing at random due to the tremble error), and for $\mu \to \infty$, choice approaches uniform randomization. We estimate the preference parameters (α, ρ) and error parameters (κ, μ) of the model with maximum likelihood, using binary choice data from the multiple price lists. Parameters are estimated jointly for all participants as linear functions of the treatment dummy $HighCO_2$ and the interaction of $HighCO_2$ with a *Morning* dummy. Given that multiple price lists are asked two times per test day, once after 120 min of exposure and once after 420 min of exposure, we added a *Morning* fixed effect, equals one if the multiple price lists were answered after 120 min of exposure time. Binary controls such as sex and whether it is the first test day were added. The estimated coefficient of the treatment dummy thus indicates how much the estimated parameters differ across treatments.

3. Results

The results are presented in two parts. In the first part, we provide evidence supporting the validity of our experimental setting by showing that CO_2 concentration differed across the two test days, while other parameters remained constant. In addition to objective measures of indoor environmental quality, we also considered participants' subjective perceptions of the indoor environment between the two test days. We then proceed to the main part of the results, where we present the findings regarding the impact of increased CO_2 concentration on participant's cognitive performance, economic decision-making, and physiological responses.

3.1. Descriptive statistics of environmental conditions

Table 1 shows a comparison of environmental conditions between both testing conditions. In panel A, we show objective measures on the environmental conditions inside the respiration chamber for the two different CO_2 levels. The last column shows the resulting *p*-values, based on a simple *t*-test of equal means with the null hypothesis of no difference between 900 ppm CO_2 (Low-CO_2) and 3,000 ppm CO_2 (High-CO_2). The targeted average CO_2 concentration was achieved for both conditions, with an average CO_2 concentration of 918 ppm for the Low-CO_2 condition (122 ppm standard deviation) and 3011 ppm for the High-CO_2 condition (139 ppm standard deviation). In the Low-CO_2 condition, the ventilation rate was slightly higher (543 l/min) as compared to the High-CO_2 condition (525 l/min). However, the average concentrations of total volatile organic compounds did not

Table 1
Comparison of environmental conditions.

	Low-CO_2		High-CO_2		
	Mean	SD	Mean	SD	P-value
Panel A: Indoor environmental quality					
Carbon dioxide (CO_2) (ppm)	918	122	3011	139	0.000
Ventilation rate (l/min)	543	28	525	12	0.000
Total volatile organic compounds (ppb)	519	365	574	317	0.156
Temperature (°C)	21	0.15	21	0.16	0.144
Relative humidity (%)	32	6	32	6	0.525
Fine particles $PM_{2.5}$ (in counts/L)	0.000	0.000	0.001	0.045	0.317
Panel B: Perception of environment					
Air quality	2.7	1.4	2.4	1.2	0.457
Temperature	3.0	1.4	3.6	1.5	0.213
Light	2.8	1.4	2.8	1.3	0.867
Noise	4.6	1.2	4.3	1.5	0.522

Note: The table shows the mean and standard deviation (SD) of objectively measured and perceived indoor environmental quality during the test day with low (900 ppm) and high (3,000 ppm) CO_2 levels. Panel A contains environmental conditions continuously measured inside the respiration chamber. Panel B shows measures reflecting participants' perceived indoor conditions collected via a questionnaire for which participants reported their satisfaction with the air quality, temperature, lighting and noise based on a scale ranging from "1 - Extremely Satisfied" to "7 - Extremely Dissatisfied". Column 1 and 3 show the average value, and column 2 and 4 the standard deviation. The last column shows the resulting p-value from a simple t-test of equal means (H_0 = no difference between High- and Low-CO_2 condition).

differ significantly between the Low- and High-CO_2 conditions. Additionally, temperature, relative humidity and fine particular matter ($PM_{2.5}$) concentrations were not significantly different between the two conditions.

In addition to the comparison of the objective measures of indoor environmental conditions, we also collected information on participants' subjective perception of indoor environmental quality, based on a survey that participants had to complete shortly before leaving the respiration chamber (at the end of each test day). We used an adapted version of the Center for the Built Environment (CBE) survey [52], asking participants how satisfied they were with the temperature, air quality, lighting conditions, and noise level. The satisfaction level with each item was reported based on a 7-point Likert scale ranging from "1 - Extremely satisfied" to "7 - Extremely dissatisfied". Panel B in Table 1 shows the mean comparisons for these variables. There were no statistically significant differences ($p > 0.05$), which indicates that participants did not perceive indoor environmental quality differently in the Low-CO_2 or High-CO_2 condition. This confirms that participants were unaware of the testing condition. The analysis reveals no differences in objective or subjective measures of indoor environmental quality, except for the concentration of CO_2. This validates the experimental setting, thereby allowing us to attribute the outcome measures causally to CO_2 exposure.

3.2. Cognitive responses

Our main findings focus on the impact of exposure to 3,000 ppm CO_2 on cognitive performance and economic decision-making, starting with the effect on general cognitive abilities, as assessed by the Cambridge Neuropsychological Automated Test Battery (CANTAB). We provide the estimated treatment effects based on the fixed effects regression described in Eq. (1) in Table 2. The treatment coefficient $HighCO_2$ is defined as a dummy variable which is either 1 if the corresponding cognition test was done under the 3,000 ppm CO_2 exposure, or zero if it was conducted in the 900 ppm CO_2 condition. The regression results allow for direct inferences regarding the average difference in outcome variables between both testing conditions. In addition, the results of the interacted regression described in Eq. (2) in Table 2 assess the heterogeneity over the course of the day, describing a possible dose–response relationship of the effect of CO_2 on cognitive performance.

Focusing on the first model specification (without interaction terms), we did not find any statistically significant effect of elevated CO_2 concentrations on the cognitive domains of psychomotor control and attention, executive function, and the Paired Associate Learning task among the memory tasks. We document a statistically significant effect (at the 5%-level) for the Delayed Matching to Sample task, suggesting that exposure to 3,000 ppm improves participants' share of correct choices by 3.55%-points. However, based on the corrected p-values for multiple hypotheses testing, the effect becomes insignificant ($p = 0.2$).

For the second model specification, which includes an interaction term with the time of the day (*Morning* dummy), we observe a similar effect pattern. Only the Paired Associate Learning task, which measures memory, is affected at the 1% significance level in the High-CO_2 condition. This indicates that participants made, on average, one and a half more correct choices when asked to memorize the presented figure. Additionally, there is also a significant time effect at a 5% level, which offsets the positive effect of exposure to a 3,000 ppm CO_2 concentration. The results suggest that participants exposed for 30 min to the higher CO_2 concentration made, on average, two times fewer correct choices compared to when they were exposed to 3,000 ppm CO_2 for 330 min. However, these coefficients are also statistically insignificant once corrected for multiple hypothesis testing ($p = 0.056$ and $p = 0.184$, respectively). Overall, we document that statistically significant effects disappear once we correct for multiple hypotheses testing. The results in Table 2 do not provide robust evidence that exposure to a CO_2 concentration of 3,000 ppm (compared to 900 ppm) influences cognitive performance, at least as measured by the CANTAB tests.

3.3. Economic decision-making

We estimated the effects of CO_2 on risk and time preferences, using structural maximum likelihood estimations, similar to previous studies [35,49,50]. The estimated results for economic decision-making are shown in Table 3. Both parameters of relative risk aversion α and the monthly discount rate ρ are jointly estimated as linear functions of the treatment dummy while controlling for sex, time of day, and test day. Larger levels of α and ρ indicate higher levels of risk aversion and time discounting, respectively. The results show that neither risk nor time preferences are significantly affected by the higher CO_2 concentrations. To control for decision noise, we included a Fechner error and tremble error in the structural estimations. The tremble error captures random decision-making among individuals answering the multiple price lists, and the Fechner error captures errors in evaluating the expected utility of lotteries. Both errors are not significantly affected by the levels of CO_2 exposure. In summary, we conclude that exposure to CO_2 levels of 3,000 ppm does not have a detectable effect on individuals' risk and time preferences and decision errors.

Table 2
Elevated indoor CO_2 and CANTAB test scores.

	Panel A: Attention & psychomotor control				Panel B: Memory			
	Reaction Time Task		Motor Screening Task		Delayed Matching to Sample		Paired Associate Learning	
High CO_2	3.587	2.025	0.493	4.445	3.550*	4.050	0.500	1.550**
	(4.622)	(6.064)	(12.651)	(16.93)	(1.518)	(2.432)	(0.288)	(0.552)
	[0.871]	[0.798]	[0.968]	[0.798]	[0.200]	[0.501]	[0.483]	[0.056]
High CO_2 x Morning		3.125		−7.905		−1.000		−2.100*
		(8.910)		(7.905)		(3.405)		(0.915)
		[0.960]		[0.960]		[0.960]		[0.184]
Fixed effects								
First test day	Y	Y	Y	Y	Y	Y	Y	Y
Morning	Y	Y	Y	Y	Y	Y	Y	Y
Participant	Y	Y	Y	Y	Y	Y	Y	Y
Observations	80	80	80	80	80	80	80	80
R^2	0.897	0.897	0.625	0.625	0.483	0.484	0.705	0.737
Adj. R^2	0.858	0.855	0.480	0.471	0.284	0.272	0.591	0.628
	Panel C: Executive function							
	Multitasking Test		One-Touch Stocking of Cambridge		Stop Signaling Task		Spatial Working Memory	
High CO_2	−11.037	−9.650	0.450	0.350	6.239	6.437	−0.400	−1,000
	(8.516)	(13.517)	(0.233)	(0.239)	(4.140)	(4.073)	(0.677)	(0.845)
	[0.715]	[0.798]	[0.311]	[0.593]	[0.570]	[0.488]	[0.968]	[0.798]
High CO_2 x Morning		−2.775		0.200		−0.396		1.200
		(14.408)		(0.358)		(8.019)		(1.035)
		[0.960]		[0.960]		[0.960]		[0.960]
Fixed effects								
First test day	Y	Y	Y	Y	Y	Y	Y	Y
Morning	Y	Y	Y	Y	Y	Y	Y	Y
Participant	Y	Y	Y	Y	Y	Y	Y	Y
Observations	80	80	80	80	80	80	80	80
R^2	0.842	0.842	0.712	0.713	0.564	0.564	0.820	0.823
Adj. R^2	0.781	0.778	0.601	0.596	0.396	0.385	0.750	0.751

Note: The table shows the results of the regression analysis as presented in Section 2.5 with regards to the cognitive performance of participants in the Cambridge Neuropsychological Test Automated Battery (CANTAB) tests. For each outcome variable, we show two columns, with the first column containing the estimated treatment parameter δ based on Eq. (1), and column 2 showing δ_1 and δ_2 based on Eq. (2). Fixed effects on whether participants conduct the tests on their first test day independent of the CO_2 condition, if they conduct the test in the morning after 30 min of exposure, and participant fixed effect has been added. See Section 2.3 for a detailed description of the outcome variables. Bootstrapped standard errors based on wild bootstrap clusters with 1,000 replications are shown in (parentheses). Significance levels before multiple hypothesis testing are indicated as *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$. In addition, p-values resulting from multiple hypotheses testing, based on the method by Hommel [48] are in [brackets].

Table 3
Elevated indoor CO_2 and economic decision-making.

	Risk aversion α	Discounting ρ	Fechner error μ	Tremble error κ
High CO_2	0.000	0.005	0.116	−0.090
	(0.050)	(0.015)	(0.12)	(0.063)
	[0.998]	[0.998]	[0.984]	[0.616]
High CO_2 x Morning	0.022	0.009	−0.093	−0.030
	(0.061)	(0.010)	(0.144)	(0.093)
	[0.752]	[0.752]	[0.752]	[0.752]
Fixed effects				
First test day	Y	Y	Y	Y
Morning	Y	Y	Y	Y
Sex	Y	Y	Y	Y
Observations	4800	4800	4800	4800
Log likelihood	−1910	−1910	−1910	−1910

Note: The maximum likelihood estimation includes fixed effects controls for the time of the day when the multiple price lists were conducted (120 min and 420 min into the test day), for the sex of the participant, and whether it was the first test day for the participant. Standard errors clustered at the subject level are in (parentheses). Significance levels before multiple hypothesis testing are indicated as *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$. In addition, p-values resulting from multiple hypotheses testing based on the method by Hommel [48] are in [brackets].

3.4. Physiological responses

As a next step, we evaluated the physiological responses to exposure to CO_2 concentration of 3,000 ppm versus 900 ppm. The boxplots in Fig. 2 provide the unconditional distribution of the physiological parameters in each testing condition, and the results of the regression analysis in Table 4. Similar to the regression analysis conducted for the CANTAB tests, we first examined the effect of elevated CO_2 concentration on the hourly average level of the corresponding physiological parameter. In this analysis, we controlled for the hour of the test day, fixed effects for each participant, and included a dummy variable for the first test day. Next, we conducted a second analysis based on Eq. (2), where we interacted the CO_2 dummy coefficient with the dummy variables for each hour that participants were in the testing condition to examine a dose–response relationship.

The boxplots in Fig. 2 indicate similar distributions between the two testing conditions. This is confirmed by the regression analysis in Table 4. We do not find any significant difference in participants' physiological responses to Low-CO_2 versus High-CO_2 conditions for most of the outcomes, in both model specifications. Solely for physical activity level, the regression reveals a statistically significant increase

Table 4
Elevated indoor CO_2 and physiological response.

	Blood CO_2		Heart rate		Respiration rate		Systole blood pressure		Diastole blood pressure		Physical activity		Oxygen consumption	
High CO_2	−0.628	−0.379	0.637	1.151	−0.007	0.002	1.071	1.382	1.482	0.498	12.379	3.284	6.087	9.935
	(0.586)	(0.719)	(2.226)	(2.548)	(0.011)	(0.012)	(1.552)	(2.519)	(1.017)	(1.306)	(7.925)	(9.805)	(7.167)	(8.700)
	[0.647]	[0.817]	[0.677]	[0.817]	[0.677]	[0.817]	[0.677]	[0.817]	[0.530]	[0.817]	[0.424]	[0.817]	[0.677]	[0.817]
High CO_2 x Hour 2		−0.189		−0.486		−0.013		−2.653		0.299		21.363*		3.404
		(0.288)		(1.117)		(0.008)		(3.143)		(1.672)		(9.151)		(6.272)
		[0.864]		[0.864]		[0.752]		[0.864]		[0.864]		[0.287]		[0.864]
High CO_2 x Hour 3		−0.442		−1.898		−0.007		3.486		−0.187		8.884		−0.6814
		(0.374)		(1.958)		(0.010)		(2.953)		(1.621)		(11.058)		(9.395)
		[0.824]		[0.824]		[0.824]		[0.733]		[0.895]		[0.895]		[0.895]
High CO_2 x Hour 4		−0.466		−1.062		−0.003		−1.947		0.473		−4.414		−5.584
		(0.395)		(2.248)		(0.009)		(2.903)		(1.841)		(9.473)		(7.622)
		[0.839]		[0.839]		[0.839]		[0.839]		[0.839]		[0.839]		[0.839]
High CO_2 x Hour 5		−0.365		0.523		−0.008		−0.255		1.130		18.072		−5.404
		(0.436)		(2.019)		(0.006)		(3.239)		(1.671)		(15.324)		(8.468)
		[0.925]		[0.925]		[0.856]		[0.925]		[0.925]		[0.925]		[0.925]
High CO_2 x Hour 6		−0.469		0.611		−0.008		−1.511		2.317		21.034		−3.222
		(0.371)		(2.423)		(0.006)		(2.766)		(2.616)		(11.179)		(8.947)
		[0.750]		[0.750]		[0.619]		[0.750]		[0.750]		[0.426]		[0.750]
High CO_2 x Hour 7		−0.105		−1.464		−0.017		4.632		3.759		17.817		−10.479
		(0.423)		(2.263)		(0.009)		(3.294)		(2.086)		(14.248)		(11.642)
		[0.845]		[0.845]		[0.262]		[0.621]		[0.419]		[0.713]		[0.844]
High CO_2 x Hour 8		0.052		−0.331		−0.016		−4.491		−0.012		−9.999		−2.684
		(0.592)		(2.260)		(0.009)		(3.740)		(3.282)		(14.788)		(10.398)
		[0.997]		[0.997]		[0.425]		[0.997]		[0.997]		[0.997]		[0.997]
Fixed effects														
First test day	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Hour into test day	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Participant	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	311	311	288	288	288	288	295	295	295	295	312	312	288	288
R^2	0.745	0.746	0.816	0.817	0.759	0.762	0.657	0.670	0.603	0.609	0.456	0.471	0.844	0.845
Adj. R^2	0.720	0.714	0.796	0.792	0.732	0.729	0.620	0.626	0.561	0.556	0.402	0.404	0.828	0.825

Note: The table shows the results of the regression analysis as presented in Section 2.5 with regards to the physiological response. For each outcome variable, we show two columns, with the first column containing the estimated treatment parameter δ based on Eq. (1), and column 2 showing δ^1 and δ^2 based on Eq. (2). The dependent variable for each physiological parameter is aggregated on an hourly average. Fixed effects on whether participants were in their first test day, the hour into exposure, and participant fixed effect has been added. See Section 2.3 for a detailed description of the outcome variables. Bootstrapped standard errors based on wild bootstrap clusters with 1,000 replications are shown in (parentheses). Significance levels before multiple hypothesis testing are indicated as $***$ $p < 0.001$; $**$ $p < 0.01$; $*$ $p < 0.05$. In addition, p-values resulting from multiple hypotheses testing based on the method by Hommel [48] are in [brackets].

in physical activity after two hours of exposure to 3,000 ppm CO_2 concentration ($p < 0.05$). However, after conducting multiple hypothesis testing, this effect becomes insignificant ($p = 0.287$).

3.5. Physiological response during cognition tests

Furthermore, we examined the physiological response during the time that the individual CANTAB Cognition tests were conducted. We used a similar regression model, as described in Eq. (1) and Eq. (2), which includes an interaction effect between the $High$CO2 dummy and the $Morning$ dummy variable. The dummy is equals *one* if the CANTAB test was answered in the morning, 30 min into exposure, and **zero** if it was answered after 330 min of exposure. The dependent variables in these regressions are the average blood CO_2 concentration, average heart rate and average respiration rate during the time of the individual CANTAB tests. These physiological parameters were chosen because the human body is able to rapidly change its heart rate and respiration rate, which also impacts the blood CO_2 concentration. The individual CANTAB tests took between 1 min for the Motor Screening Task and 12 min for the One-Touch Stockings of Cambridge Task. Thus, changes in these outcomes could be expected within the short time the individual CANTAB tests were taken. In addition to a fixed effect for the first test day of the participant and a fixed effect for the participant, a fixed effect for the specific CANTAB test was also included. This approach controls for variation between testing time, participant, and individual CANTAB tests.

Table 5 shows the results of this analysis. We observe that, similar to the previous analysis, elevated CO_2 levels do not trigger any physiological response, even if cognitive load is imposed through the cognition tests. However, for the model including the interaction effect, an elevated CO_2 concentration of 3,000 ppm during the morning session of the CANTAB test (after 30 min of exposure) is significantly associated with a higher respiration rate ($p < 0.05$), compared to the afternoon session (after 330 min of exposure). This statistical significance remains after conducting multiple hypothesis testing ($p = 0.038$ for the adjusted p-value). However, the magnitude of the effect is small: The coefficient indicates an increase in the respiration rate of 0.017 Hz, which is approximately one additional breath per minute.

4. Discussion

Magnitude and significance: Overall, the results show that there is no effect of CO_2 concentrations of 3,000 ppm (compared to 900 ppm) on cognitive performance and physiological outcomes. Although this study uses a similar sample size compared to previous studies (see Supplementary Table S4 for an overview), the question remains about whether the estimated effects are indeed zero or if the sample size of 20 participants is simply too small to estimate the effects precisely enough to reject the null hypothesis. We addressed this question from two angles: First, we calculated relative effects, where we express the effects as changes in standard deviations of the underlying distribution of the outcome variable. This approach provides insights into the magnitude of the effects, that is whether the estimated effects are meaningful, independently of statistical significance. For instance, if the relative effects are very small, i.e., the High-CO_2 condition hardly changes the outcome variable, statistical significance is less relevant because the magnitude of the effect would be negligible. Second, we ran a post-hoc power analysis to calculate the required sample size to examine how many participants we actually would need in order to be able to estimate statistically significant effects in case the CO_2 concentration truly affects the outcome variable. Supplementary Table S3 provides the results of both analyses.

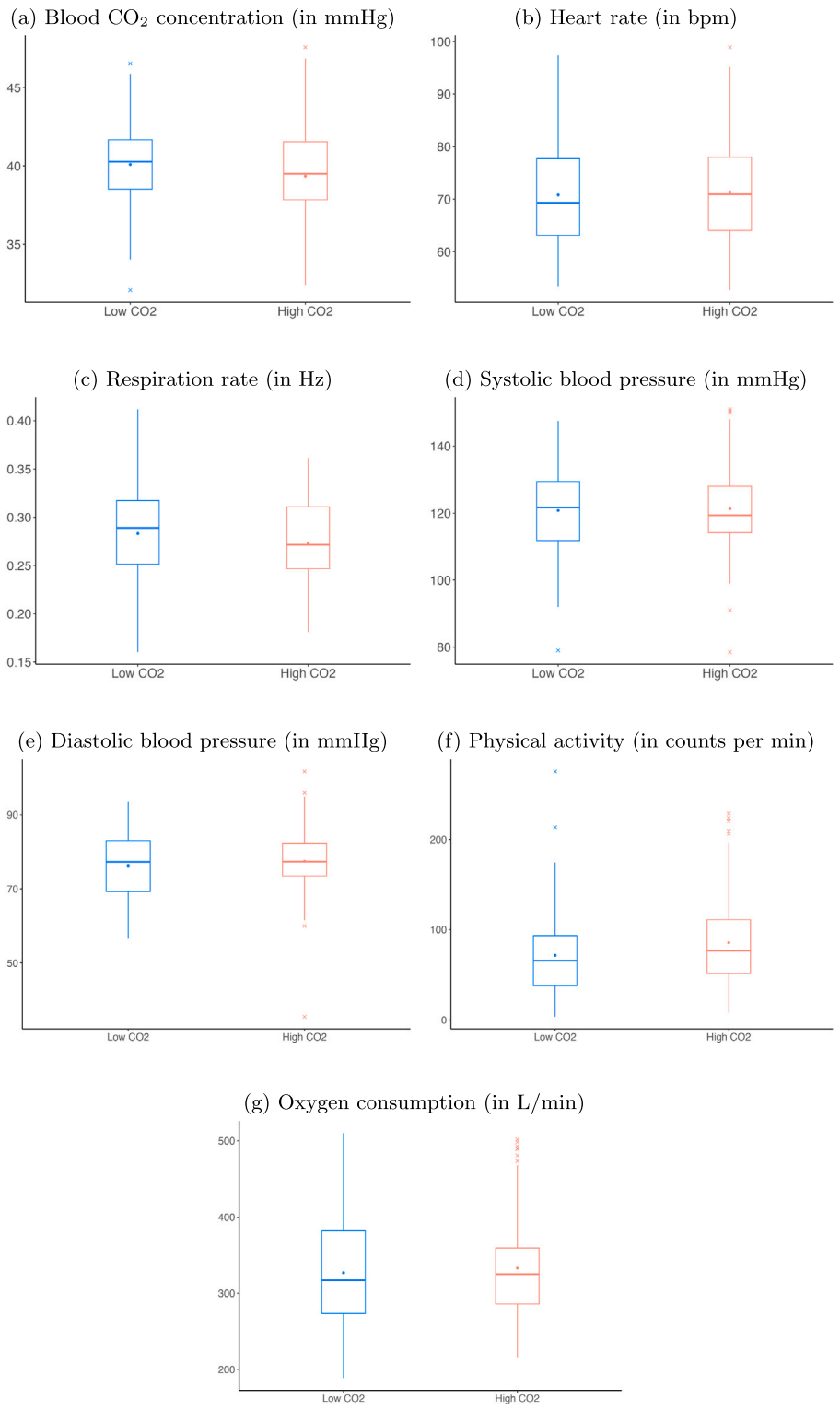

Fig. 2. Physiological response between CO_2 conditions. Note: In the boxplot diagrams, the thick line in the middle is the median and the point is the average value of each corresponding outcome. The upper and lower edges of the box are the upper and lower quartiles. Values that are more than 1.5 times the interquartile range away from the box are considered to be outliers and shown as crosses (x). The whiskers that extend from the box show the minimum and maximum of the remaining, non-outlier values. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

For the vast majority of outcome variables, the relative effect of elevated CO_2 levels is weak to very weak, with a change of 0.2 standard deviation or less. This suggests that the magnitude of most parameters is negligible, even if they were statistical significance. Only two parameters appear to be meaningful, showing relative effect sizes of 0.41 and 0.79 standard deviations for the CANTAB's Delayed Matching to Sample task and tremble error for time preferences, respectively. However, a power calculation based on the calculated effect sizes suggests a sample size of 22 participants for the CANTAB test and 13 participants for the economic decision-making test, which is very close to and below our actual sample of 20 participants. This indicates that our inference tests are reliable and sufficient to draw conclusions about the

Table 5
Physiological response during cognition tests.

	Blood CO_2		Heart rate		Respiration rate	
	(1)	(2)	(3)	(4)	(5)	(6)
High CO_2	−0.468	−0.596	0.056	−0.398	−0.010	−0.019
	(0.533)	(0.515)	(2.225)	(2.662)	(0.012)	(0.011)
	[0.980]	[0.860]	[0.980]	[0.980]	[0.980]	[0.652]
High CO_2 x Morning		0.256		0.909		0.017 *
		(0.414)		(2.337)		(0.007)
		[0.697]		[0.697]		[0.038]
Fixed effects						
First test day	Y	Y	Y	Y	Y	Y
Morning	Y	Y	Y	Y	Y	Y
Participant	Y	Y	Y	Y	Y	Y
CANTAB test	Y	Y	Y	Y	Y	Y
Observations	619	619	571	571	571	571
R^2	0.744	0.766	0.758	0.809	0.579	0.632
Adj. R^2	0.731	0.752	0.745	0.797	0.556	0.609

Note: The table shows the results of the regression analysis with the dependent variable as the average level of blood CO_2 concentration, heart rate, and respiration rate during the time each individual CANTAB cognition test has been conducted. Fixed effects on whether participants conduct the tests on their first test day, morning fixed effect, participant fixed effect, and individual CANTAB test fixed effect have been added. Bootstrapped standard errors based on wild bootstrap clusters with 1,000 replications are shown in (parentheses). Significance levels before multiple hypothesis testing are indicated as *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$. In addition, p-values resulting from multiple hypotheses testing based on the method by Hommel [48] are in [brackets].

statistical significance of this meaningful effect. Given that we find only a few significant effects based on the bootstrapped (analytical) standard errors and no statistical significance based on the multiple hypotheses tests, we conclude that the effects are statistically insignificant and, therefore, zero.

Link to previous literature: To our knowledge, this study is the first to exposed adults individually and uninterrupted to elevated CO_2 concentrations in an air tight respiration chamber for as long as 8 h. Most previous studies used exposure times of up to 255 min in either climate chambers or office rooms [4]. Previous work suggests that the exposure time plays an important role in moderating the effect of CO_2, assuming that humans can withstand high concentrations of CO_2 for a certain time period [53,54]. Only one previous study exposed adults for 8 h in groups to different air quality conditions in an office room [21]. However, behaviour and perception can be influenced if occupants are measured in groups [38].

Our results contrast with three studies that measured complex decision-making using the Strategic Management Simulator, documenting a negative effect of CO_2 concentration on cognitive decision making [21–23]. However, one such study, which included "astronaut-like" subjects, found that the negative effect was either mitigated or even reversed at higher CO_2 concentrations [23]. This study did not conduct multiple hypotheses testing to account for the multitude of hypotheses tested. A fourth study did not find any effect of CO_2 on complex decision-making using the Strategic Management Simulator test [24]. Among previous work, the study by Allen et al. (2016) [21] is the most similar to our setup, focusing on office workers who were exposed to elevated CO_2 concentrations for 8 h, while measuring the concentration of volatile organic compounds to ensure low levels of these air pollutants. However, this study was conducted in an ordinary office room and no physiological parameters were measured — factors that may explain the decline in complex decision-making abilities. Nevertheless, time pressure and task complexity can be important moderators of the effect of CO_2 and indoor air quality in general on cognitive performance [53,55,56]. It is reasonable to assume that the CANTAB tests used in our study do not provide a high level of complexity. Furthermore no tasks uses limited time to increase mental load, except for CANTAB's tests on attention and psychomotor control. Thus, our results should be compared carefully to previous studies using the Strategic Management Simulator or tests which induce time pressure.

Nevertheless, our finding that CO_2 has no significantly negative effect on human cognition is in agreement with a series of other previous studies [25,26]. These two studies used climate chambers and exposed their population for a short period of time (255 and 150 min, respectively). Although, volatile organic compound concentration was not measured during the testing to validate whether the concentrations of air pollutants have been successfully reduced. Our study extends this previous work by prolonging the exposure time to 8 h and measuring basic cognitive domains twice during this time. While these tests are only of diagnostic nature for cognitive performance and are thus not fully comparable with office work, they show that basic cognitive functions such as attention, psychomotor control, memory and executive functions are not negatively impacted by an elevated level of 3,000 ppm CO_2.

Unique to this study, we broadened the cognition analysis, including multiple price lists from the economic literature to examine the potential effect of CO_2 on economic decision-making in terms of risk-taking and time discounting for monetary payouts. We found no effect on risk and time preferences. Previous literature suggested a potentially negative effect as lower cognitive abilities lead to more random decision-making when answering multiple price lists [51]. The multiple price lists used in our study do not induce time pressure to respond, or require complex thinking — both of which could influence the impact of CO_2. However, the simplicity and transparency of multiple price lists are strengths, as they help to truthfully reveal individual preferences [57]. Additionally, while we used common reward amounts, most studies using multiple price lists included a student population, for whom the offered rewards can be much more substantial, compared to our participants. In contrast, the maximum reward and spread offered was less than 2% of their salary[1]. Therefore, it remains uncertain whether higher rewards can induce enough stress to trigger an effect of CO_2 on economic decision-making. Nonetheless, our results are consistent, showing no effect on neither cognitive performance measured with the CANTAB test, nor for economic decision-making.

Regarding the physiological response to CO_2 exposure, heart rate and blood pressure did not show any elevated levels, which would hint towards a physiological stress response. Previous studies that measured a variety of physiological parameters found a significantly higher heart rate at 2,700 ppm and 3,000 ppm CO_2, but no difference in heart

[1] The highest amount offered in our multiple price lists was €44 and the largest spread €42.60. Considering that 17 of the 20 participants earned on average €3,000, this amount would account for 1.5% and 1.4% of their salary, respectively.

rate at 5,000 ppm CO_2 compared to a concentration of 500 ppm CO_2 [19,20,26]. However, while various parameters were measured to record the physiological response to elevated CO_2 concentrations, no multiple hypotheses testing was conducted in these studies to adjust the *p*-values.

This study is the first study that specifically examined the physiological stress response during the time the cognition test was administered, to derive a possible performance-induced effect of CO_2. Past studies suggest that the cognitive load might play a mediating role in the effect of CO_2, and more generally, indoor air quality on cognition [4,5,55]. However, we did not find any significant change in heart rate or blood CO_2 levels during the time of testing, which would indicate a moderating role of cognitive load. Nevertheless, we found a robust and significant increase in respiration rate if the CANTAB tests were conducted in the morning during the elevated CO_2 condition. Such an increase could reveal a compensatory mechanism against the elevated CO_2 concentration during cognitive load, although its magnitude was rather small with an increase of just one breath per minute, and it occurred independent of any significant change in heart rate.

Furthermore, our findings do not support the hypothesis that an indoor CO_2 concentration of 3,000 ppm induces a respiratory acidosis. Neither the respiration rate nor the blood CO_2 partial pressure were significantly affected throughout the test day. Only one prior study found higher blood CO_2 concentrations after four hours of exposure to up to 5,000 ppm CO_2 [27]. However, the CO_2 concentration in that study was achieved by reducing the ventilation rate, leading to a 2.2-fold increase in volatile organic compounds concentration in the room. The authors attribute the elevation in blood CO_2 to the increased CO_2 level in the room, but did not elaborate on whether such a relationship could be mediated by the other air pollutants in the room which might had an impairing effect on the lungs [28,58].

Previous literature assumes that air pollutants could cause changes in the breathing pattern, which in turn leads to a build-up of CO_2 in the blood due to an insufficient removal through exhalation [28,59]. Moreover, Snow and co-authors [20] argue that the higher heart rate for an exposure level of 2,700 ppm could be indicative of an increase in circulation to maintain CO_2 levels in the blood. However, they documented no effect on respiration rate and emphasized that no blood-gas analysis was conducted to examine this hypothesis. Since we isolated the effect of CO_2 in our study setup, we cannot confirm that a respiratory acidosis is related to a CO_2 concentration of 3,000 ppm and associated with a change in respiration rate. However, we did not measure tidal volume which could be affected independently of the respiration rate. Importantly, our study does not aim to examine the claim stated in previous literature that air pollutants beyond CO_2 affect the breathing pattern of individuals [28,59].

Furthermore, two studies found an increase in end-tidal CO_2 in exhaled air but were not able to examine the physiological reasoning for this observation [19,26]. Increased exhalation of CO_2 can be a sign of increased cellular CO_2 production or CO_2 build-up in the blood due to increased metabolic rate. To maintain a stable pH-level, the body increases the respiration rate or tidal volume to remove excess CO_2 from the lungs [60]. However, we could not find any significant effect on oxygen consumption as a measure of metabolic rate and also no significantly higher physical activity level in the High-CO_2 condition, which would increase the energy expenditure and metabolic rate. Therefore, while we did not measure end-tidal CO_2 or tidal volume, our analysis cannot confirm that elevated CO_2 levels affect human metabolic rate, as suggested by a previous study [59].

Limitations and future recommendations: We used a validated respiration chamber and measured total volatile organic compounds continuously to ensure that our method of isolating the effect of CO_2 was successful. However, we simulated only two conditions: High- and Low-CO_2 with 3,000 ppm and 900 ppm concentration levels. In reality, CO_2 levels might be much higher. It has been shown that peak CO_2 levels in primary schools can easily exceed 3,000 ppm even in the presence of mechanical ventilation and effects of exposure to CO_2 might be non-linear [6,61]. In addition, the study population was an average age of 25 to 46 years and had no health-related complaints. Thus, our study does not answer how CO_2 concentrations might affect individuals with respiratory restrictions, such as chronic obstructive pulmonary disease and asthma, metabolic syndrome, or mental disorders such as depression and anxiety disorder. Future studies should investigate the effects of CO_2 on health and cognition of children and elderly people. Furthermore, we used diagnostic cognitive tasks, while our study provides input on the effect of CO_2 on general cognitive performance, thus it does not provide evidence on the effect of office work. However, it is reasonable to assume that office-related tasks rarely require maximum effort or time pressure to conduct, which is similar to the cognitive tests used in this study.

5. Conclusion

This study used a validated respiration chamber in a cross-over, single-blind experimental design to assess the impact of chemically pure CO_2 levels on cognitive performance and physiological response in 20 healthy adults. The analysis revealed that a CO_2 concentration of 3,000 ppm compared to 900 ppm does not trigger any significant cognitive decline or any physiological response. Only respiration rate was marginally elevated during time the cognition tests were conducted, which could hint towards an adaptive mechanism to resist elevated CO_2 levels. However, respiration rate and blood CO_2 concentration (among other physiological parameters), which would indicate an impact on bodily homeostasis, were unaffected by CO_2 during the course of the day. As such, these results suggest that for healthy individuals, no negative effect of a CO_2 concentration of 3,000 ppm compared to 900 ppm on cognition and health can be expected — at least for a relatively short exposure duration of one day. These results extend the findings of existing studies, which provide equivocal findings on the influence of short-term exposure to elevated CO_2 concentrations on cognition and health.

The results are of practical relevance, because CO_2 is used as a metric for indoor air quality. Modern control-demand ventilation systems use CO_2 to adjust ventilation rates based on occupancy rate and thereby reducing a building's energy consumption. Air filtering systems cannot remove CO_2, therefore, it is important to determine if CO_2 itself should be considered an air pollutant to optimize cognitive performance of groups such as office workers and school children. However, the results presented in this paper suggest that this may not be the case. Finding no physiological reaction supports the assumption that CO_2 at the examined level of 3,000 ppm does not affect humans during an uninterrupted exposure time of eight hours. Therefore, this study provides important implications for designing indoor spaces with good air quality and developing effective ventilation strategies to optimize occupants' cognitive performance.

CRediT authorship contribution statement

Stefan Flagner: Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Thomas Meissner:** Writing – original draft, Formal analysis. **Steffen Künn:** Writing – original draft, Supervision, Methodology, Formal analysis. **Piet Eichholtz:** Writing – review & editing. **Nils Kok:** Writing – review & editing. **Rick Kramer:** Writing – review & editing. **Wouter van Marken-Lichtenbelt:** Writing – review & editing. **Cynthia Ly:** Writing – review & editing, Data curation. **Guy Plasqui:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary tables

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References

[1] C. Wang, F. Zhang, J. Wang, J.K. Doyle, P.A. Hancock, C.M. Mak, S. Liu, How indoor environmental quality affects occupants' cognitive functions: A systematic review, Build. Environ. 193 (2021) 107647.
[2] I. Mujan, A.S. Anđelković, V. Munćan, M. Kljajić, D. Ružić, Influence of indoor environmental quality on human health and productivity - A review, J. Clean. Prod. 217 (2019) 646–657.
[3] S.J. Cao, D.H. Zhu, Y.B. Yang, Associated relationship between ventilation rates and indoor air quality, Rsc Advances 6 (112) (2016) 111427–111435.
[4] B. Du, M.C. Tandoc, M.L. Mack, J.A. Siegel, Indoor CO2 concentrations and cognitive function: A critical review, Indoor Air 30 (2020) 1067–1082.
[5] P. Wargocki, D.P. Wyon, Ten questions concerning thermal and indoor air quality effects on the performance of office work and schoolwork, Build. Environ. 112 (2017) 359–366.
[6] W. Fisk, The ventilation problem in schools: literature review, Indoor Air 27 (2017) 1039–1051.
[7] P. Wargocki, J.A. Porras-Salazar, S. Contreras-Espinoza, W. Bahnfleth, The relationships between classroom air quality and children's performance in school, Build. Environ. 173 (2020) 106749.
[8] L. Morawska, J. Allen, W. Bahnfleth, B. Bennett, P.M. Bluyssen, A. Boerstra, G. Buonanno, J. Cao, S.J. Dancer, A. Floto, et al., Mandating indoor air quality for public buildings, Science 383 (6690) (2024) 1418–1420.
[9] P. Eichholtz, N. Kok, J.M. Quigley, Doing well by doing good? Green office buildings, Amer. Econ. Rev. 100 (2010) 2492–2509.
[10] P. MacNaughton, J. Pegues, U. Satish, S. Santanam, J. Spengler, J. Allen, Economic, environmental and health implications of enhanced ventilation in office buildings, Int. J. Environ. Res. Public Health 12 (11) (2015) 14709–14722.
[11] H.R. Santos, V.M. Leal, Energy vs. ventilation rate in buildings: A comprehensive scenario-based assessment in the European context, Energy Build. 54 (2012) 111–121.
[12] P. Das, Z. Chalabi, B. Jones, J. Milner, C. Shrubsole, M. Davies, I. Hamilton, I. Ridley, P. Wilkinson, Multi-objective methods for determining optimal ventilation rates in dwellings, Build. Environ. 66 (2013) 72–81.
[13] D. Rim, S. Schiavon, W.W. Nazaroff, Energy and cost associated with ventilating office buildings in a tropical climate, PLoS One 10 (3) (2015) e0122310.
[14] S.J. Emmerich, A. Persily, Literature review on CO2 based demand controlled ventilation, ASHRAE Trans. 103 (2) (1997) 229–243.
[15] S. Haddad, A. Synnefa, M.Á.P. Marcos, R. Paolini, S. Delrue, D. Prasad, M. Santamouris, On the potential of demand-controlled ventilation system to enhance indoor air quality and thermal condition in Australian school classrooms, Energy Build. 238 (2021) 110838.
[16] A.K. Persily, Evaluating Building IAQ and Ventilation with Indoor Carbon Dioxide, American Society of Heating, Refrigerating and Air-Conditioning Engineers, 1997.
[17] L. Chatzidiakou, D. Mumovic, A. Summerfield, Is CO2 a good proxy for indoor air quality in classrooms? Part 1: The interrelationships between thermal conditions, CO2 levels, ventilation rates and selected indoor pollutants, Build. Serv. Eng. Res. Technol. 36 (2015) 129–161.
[18] X. Tang, P.K. Misztal, W.W. Nazaroff, A.H. Goldstein, Volatile organic compound emissions from humans indoors, Environ. Sci. Technol. 50 (23) (2016) 12686–12694.
[19] X. Zhang, P. Wargocki, Z. Lian, Physiological responses during exposure to carbon dioxide and bioeffluents at levels typically occurring indoors, Indoor Air 27 (2017) 65–77.
[20] S. Snow, A.S. Boyson, K.H.W. Paas, H. Gough, M.F. King, J. Barlow, C.J. Noakes, Exploring the physiological, neurophysiological and cognitive performance effects of elevated carbon dioxide concentrations indoors, Build. Environ. 156 (2019) 243–252.
[21] J.G. Allen, P. MacNaughton, U. Satish, S. Santanam, J. Vallarino, J.D. Spengler, Associations of cognitive function scores with carbon dioxide, ventilation, and volatile organic compound exposures in office workers: a controlled exposure study of green and conventional office environments, Environ. Health Perspect. 124 (2016) 805–812.
[22] U. Satish, M.J. Mendell, K. Shekhar, T. Hotchi, D. Sullivan, S. Streufert, W.J. Fisk, Is CO2 an indoor pollutant? Direct effects of low-to-moderate CO2 concentrations on human decision-making performance, Environ. Health Perspect. 120 (2012) 1671–1677.
[23] R.R. Scully, M. Basner, J. Nasrini, C. wing Lam, E. Hermosillo, R.C. Gur, T. Moore, D.J. Alexander, U. Satish, V.E. Ryder, Effects of acute exposures to carbon dioxide on decision making and cognition in astronaut-like subjects, Npj Microgravity 5 (2019) 1–15.
[24] C.D. Rodeheffer, S. Chabal, J.M. Clarke, D.M. Fothergill, Acute exposure to low-to-moderate carbon dioxide levels and submariner decision making, Aerosp. Med. Hum. Perform. 89 (2018) 520–525.
[25] X. Zhang, P. Wargocki, Z. Lian, C. Thyregod, Effects of exposure to carbon dioxide and bioeffluents on perceived air quality, self-assessed acute health symptoms, and cognitive performance, Indoor Air 27 (2017) 47–64.
[26] X. Zhang, P. Wargocki, Z. Lian, Human responses to carbon dioxide, a follow-up study at recommended exposure limits in non-industrial environments, Build. Environ. 100 (2016) 162–171.
[27] T. Vehviläinen, H. Lindholm, H. Rintamäki, R. Pääkkönen, A. Hirvonen, O. Niemi, J. Vinha, High indoor CO2 concentrations in an office environment increases the transcutaneous CO2 level and sleepiness during cognitive work, J. Occup. Environ. Hyg. 13 (2016) 19–29.
[28] S. Shriram, K. Ramamurthy, S. Ramakrishnan, Effect of occupant-induced indoor CO2 concentration and bioeffluents on human physiology using a spirometric test, Build. Environ. 149 (2019) 58–67.
[29] A. Ashrae, Standard 62.1-2019, Ventilation for Acceptable Indoor Air Quality, American Society of Heating, Refrigerating, and Air-Conditioning Engineers, Atlanta, GA, USA, 2019.
[30] ASHRAE, ASHRAE position document on indoor carbon dioxide, 2022, Available from: https://www.ashrae.org/file%20library/about/position%20documents/pd_indoorcarbondioxide_2022.pdf.
[31] E. Belias, D. Licina, Outdoor PM2. 5 air filtration: optimising indoor air quality and energy, Build. Cities 3 (1) (2022) 186–203.
[32] P.F. Schoffelen, K.R. Westerterp, W.H. Saris, F. Ten Hoor, A dual-respiration chamber system with automated calibration, J. Appl. Physiol. 83 (6) (1997) 2064–2072.
[33] M. Coller, M.B. Williams, Eliciting individual discount rates, Exp. Econ. 2 (1999) 107–127.
[34] C.A. Holt, S.K. Laury, Risk aversion and incentive effects, Amer. Econ. Rev. 92 (2002) 1644–1655.
[35] T. Meissner, X. Gassmann, C. Faure, J. Schleich, Individual characteristics associated with risk and time preferences: A multi country representative survey, J. Risk Uncertain. 66 (1) (2023) 77–107.
[36] O. Andersson, H.J. Holm, J.R. Tyran, E. Wengström, Risk aversion relates to cognitive ability: Preferences or noise? J. Eur. Econom. Assoc. 14 (2016) 1129–1154.
[37] DIN, EN, 13779: 2007-09, 2007. Lüftung von Nichtwohngebäuden: Allgemeine Grundlagen und Anforderungen für Lüftungs-und Klimaanlagen und Raumkühlsysteme. Deutsches Institut für Normung eV (DIN), Beuth, Berlin, 2007.
[38] M. Schweiker, A. Wagner, The effect of occupancy on perceived control, neutral temperature, and behavioral patterns, Energy Build. 117 (2016) 246–259.
[39] H. Zheng, V. Krishnan, S. Walker, M. Loomans, W. Zeiler, Laboratory evaluation of low-cost air quality monitors and single sensors for monitoring typical indoor emission events in Dutch daycare centers, Environ. Int. 166 (2022) 107372.
[40] P.J. Smith, A.C. Need, E.T. Cirulli, O.C. Falek, D.K. Attix, A comparison of the Cambridge Automated Neuropsychological Test Battery (CANTAB) with "traditional" neuropsychological testing instruments, J. Clin. Exp. Neuropsychol. 35 (2013) 319–328.
[41] Cambridge Cognition Ltd, CANTAB Cognitive assessment software, Available from: https://www.cambridgecognition.com/cantab/cognitive-tests/.
[42] B. Ceylan, L. Khorshid, Ü.Y. Güneş, A. Zaybak, Evaluation of oxygen saturation values in different body positions in healthy individuals, J. Clin. Nurs. 25 (2016) 1095–1100.
[43] Z. Messina, H. Patrick, Partial Pressure of Carbon Dioxide, StatPearls Publishing, Treasure Island (FL), 2022.
[44] R. Gilgen-Ammann, T. Schweizer, T. Wyss, RR interval signal quality of a heart rate monitor and an ECG holter at rest and during exercise, Eur. J. Appl. Physiol. 119 (2019) 1525–1532.
[45] M.P. Tarvainen, J.P. Niskanen, J.A. Lipponen, P.O. Ranta-aho, P.A. Karjalainen, Kubios HRV – Heart rate variability analysis software, Comput. Methods Programs Biomed. 113 (2014) 210–220.

[46] A.C. Cameron, J.B. Gelbach, D.L. Miller, Bootstrap-based improvements for inference with clustered errors, Rev. Econ. Stat. 90 (2008) 414–427.
[47] T. Hesterberg, Bootstrap, Wiley Interdiscip. Rev. Comput. Stat. 3 (6) (2011) 497–526.
[48] G. Hommel, A stagewise rejective multiple test procedure based on a modified Bonferroni test, Biometrika 75 (1988) 383–386.
[49] S. Andersen, G.W. Harrison, M.I. Lau, E.E. Rutström, Eliciting risk and time preferences, Econometrica 76 (2008) 583–618.
[50] G.W. Harrison, Risk Aversion in Experiments, Emerald Group Publishing, 2008.
[51] O. Andersson, H.J. Holm, J.R. Tyran, E. Wengström, Robust inference in risk elicitation tasks, J. Risk Uncertain. 61 (2020) 195–209.
[52] C. Huizenga, S. Abbaszadeh, L. Zagreus, E.A. Arens, Air Quality and Thermal Comfort in Office Buildings: Results of a Large Indoor Environmental Quality Survey, UC Berkeley: Center for the Built Environment, 2006.
[53] L. Kajtár, L. Herczeg, Influence of carbon-dioxide concentration on human well-being and intensity of mental work, QJ Hung. Meteorol. Serv. 116 (2012) 145–169.
[54] E. Bloch-Salisbury, R. Lansing, S.A. Shea, Acute changes in carbon dioxide levels alter the electroencephalogram without affecting cognitive function, Psychophysiology 37 (4) (2000) 418–426.
[55] S. Künn, J. Palacios, N. Pestel, Indoor air quality and strategic decision making, Manage. Sci. (2023).
[56] J.G. Allen, P. MacNaughton, J.G. Cedeno-Laurent, X. Cao, S. Flanigan, J. Vallarino, F. Rueda, D. Donnelly-McLay, J.D. Spengler, Airplane pilot flight performance on 21 maneuvers in a flight simulator under varying carbon dioxide concentrations, J. Expo. Sci. Environ. Epidemiol. 29 (2019) 457–468.
[57] S. Andersen, G.W. Harrison, M.I. Lau, E.E. Rutström, Elicitation using multiple price list formats, Exp. Econ. 9 (2006) 383–405.
[58] B. Danuser, Candidate physiological measures of annoyance from airborne chemicals, Chem. Senses 26 (2001) 333–337.
[59] Z.S. Bakó-Biró, P. Wargocki, D.P. Wyon, P.O. Fanger, Poor indoor air quality slows down metabolic rate of office workers, Proc. Indoor Air 1 (2005) 76–80.
[60] C.A.D. Negro, G.D. Funk, J.L. Feldman, Breathing matters, Nature Rev. Neurosci. 19 (2018) 351–367.
[61] P. Eichholtz, N. Kok, X. Sun, The effect of post-COVID-19 ventilation measures on indoor air quality in primary schools, PNAS Nexus 3 (1) (2024) pgad429.