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Abstract

There is currently no robust method to evaluate how built environment design affects our emotion. Understanding emotion is significant, as it influences cognitive processes, behaviour, and wellbeing, and is linked to the functioning of physiological systems. As mental health problems are becoming more prevalent, and exposure to indoor environments is increasing, it is important we develop rigorous methods to understand whether design elements in our environment affect emotion. This study examines whether the scale of interior built environments modulate neural networks involved in emotion regulation. Using a cave automatic virtual environment and controlling for indoor environmental quality, 66 adults (31 female, aged 18-55) were exposed to context-neutral enclosed indoor room scenes to understand whether built environment scale affected self-report, autonomic nervous system, and central nervous system correlates of emotion. Our results revealed enlarged scale increased electroencephalography (EEG) power in the beta bandwidth. Frontal midline low gamma and high gamma power were also found to increase with enlarged scale, but contrary to our hypothesis, scale did not modulate frontal midline power or lateralization in the theta or alpha bandwidths. We did not detect an effect of scale on autonomic indicators or self-reported emotion. However, we did find increased range in skin conductance response and heart rate variability to the built environment conditions. This study provides a rigorous empirical framework for assessing the environmental impact of a design characteristic on human emotion and suggests that measures of high frequency oscillations may provide a useful marker of the response to built environment.

Significance statement

Our empirical study provides a technique and approach for assessing the impact of built environment design on emotion. Using virtual reality, we assessed autonomic nervous system, EEG correlates and self-report of emotion to built environments that vary in scale. Although we did not detect autonomic and EEG markers linked to emotional processing, we found evidence that enlarged scale of the built environment modulates high-frequency oscillatory activity, which may have further implications for attention and cognitive performance. This novel approach for measuring neural correlates and physiological indicators controlled the exposure through a cave automatic virtual environment, while monitoring indoor environmental quality. This research and technique enhance our understanding of how to predict, design, and optimize interior spaces for optimal mental health.

1.0 Introduction

There is currently no robust method to evaluate how building design affects our emotion. Emotion is recognized to play an important role in our mental and physical health (Damasio, 1998; Lopez, Denny, & Fagundes, 2018). Accordingly, understanding if the buildings we inhabit effect our emotions is critical. Through building design, we may be able to mediate health outcomes, leading to major health and economic benefits for society (Hoisington et al., 2019).

Environmental enrichment studies in animal models have suggested that features of the physical enclosure, including size of the environment (Barker, George, Howarth, & Whittaker, 2017), impact cellular, molecular and behavioral outcomes (Nithianantharajah & Hannan, 2006; van den Bosch et al., 2018). Despite this, there have been few human studies investigating interior environments as a component of environmental enrichment (McDonald, Hayward, Rosbergen, Jeffers, & Corbett, 2018). Following work indicating the role of environmental enrichment on brain structure, function and behaviour, we investigated the built environment as one of the enrichment modulating factors; specifically, the scale of enclosure.

Scale has strong theoretical underpinnings in social and architectural history (Alexander, Ishikawa, & Silverstein, 1977; Raskin, 1954). The concept of understanding whether room or enclosure scale affects behaviour patterns is not new, with work undertaken in both animal and human studies (Wolfe, 1975). However, commonly research does not distinguish between the concept of physical and social environment. In human studies, “proxemics”, or the behaviour and interaction of space and people, is often studied (Evans, Schroeder, & Lepore, 1996). Similarly, in animal models the concept of “housing density” is explored

(Whittaker, Howarth, & Hickman, 2012). This makes it difficult to determine whether the scale of the physical environment makes a difference, or whether differences result from affordances the scale produces for social interactions.

Emerging empirical studies exploring design characteristics of interior built environments have approached the question using experimental designs where design aesthetics comprise a complex array of features and characteristics (Coburn et al., 2020; Vartanian et al., 2015). However, across this emerging research field, questions exist as to the validity of the experimental design approach and reporting parameters to ensure reproducibility (Bower, 2019).

In this study, we investigated whether the scale of an interior room would result in modulation of autonomic, EEG and self-report indicators of emotion. We defined emotion as a response to an environmental event involving multiple systems of cognitive, autonomic, and behavioural response (Hagemann, Waldstein, & Thayer, 2003; Levenson, 1988; Thayer & Lane, 2000). Here, we tested whether there was a change in participants' autonomic nervous system response through electrocardiography (ECG), skin conductance response (SCR) and respiration measures; alongside recording central nervous system response with electroencephalography (EEG). Self-reported emotion was assessed using the self-assessment manikin, based on the affective dimensional model classification of emotion. Demographic and personality data were also collected to investigate whether individual factors influenced responses to built environment scale, as existing studies show personality dimensions, such as neuroticism, can affect how individuals interpret and respond to the environment (LeBlanc, Ducharme, Pasto, & Thompson, 2003).

To reduce the complexity of building design, the study used a Cave Automatic Virtual Environment (CAVE), to create an environmentally controlled, cost-effective simulation, and providing greater sensorimotor integration than virtual reality (VR) headsets (Bohil, Alicea, & Biocca, 2011; Kalantari, Rounds, Kan, Tripathi, & Cruz-Garza, 2021; Sanchez-Vives & Slater, 2005). Scene neutrality was carefully considered through non-context specific visual cues in the form of a closed door and a chair to help participants determine height, width, and surface depth (Brouwer, van Ee, & Schwarzbach, 2005).

As this field of research is early in development, in conjunction with our *a priori* hypotheses, we opted to perform exploratory analyses across the remaining EEG power spectra regions of interest (ROIs) and of the overall power spectral density. This approach was selected as we were interested in understanding whether the built environment may affect other cognitive functions such as perception, attention, and memory which have been associated with higher frequency oscillatory activity. Neural oscillations in the gamma frequency range have been associated with visual tasks such as perception (Keil, Müller, Ray, Gruber, & Elbert, 1999), attention (Müller, Gruber, & Keil, 2000), and memory (Tallon-Baudry, Bertrand, Peronnet, & Pernier, 1998). We expected changes to scale would result in increased frontal midline power and frontal hemispheric lateralization in the theta and alpha bandwidths, due to their association with emotion (Aftanas & Golocheikine, 2001; Coan & Allen, 2004; Davidson, 2004). We also hypothesized scale conditions would increase baseline autonomic measures, and self-report may not reflect underlying autonomic or EEG modulations.

2.0 Materials and Methods

To investigate our research questions, we examined if there are detectable differences in autonomic, EEG, and self-report indices of emotion when changing the design characteristic of scale within a virtual built environment. Using EEG, we investigated frontal midline power and lateralization in the alpha and theta bandwidths. In addition to our primary hypothesis-driven analyses, we conducted exploratory data driven analysis of low and high gamma, and overall power spectral density across electrodes. The study was approved by the Deakin University Human Research Ethics Committee and carried in accordance with relevant guidelines and regulations. On completion of the study participants were offered a $20.00 gift voucher as reimbursement for their time. An overview of the experimental design and setup is illustrated in Figure 1.

2.1 Participants

The sample size for this study was determined by an *a priori* power analysis using G*Power 3.1.9.3 (Faul, Erdfelder, Lang, & Buchner, 2007). Due to the limited robust studies conducted, a small to moderate effect size was selected (f=.15) with 1 group and 5 measurements, a power of .95, a correlation amongst repeated measures of 0.6, and non-sphericity correction of 1. This indicated a total sample size of 68 participants would be required.

The study took place over a consecutive five-week period at Deakin University Waurn Ponds campus, Geelong, Victoria, Australia. We recruited 66 adults (31 women, mean age = 34.9 ± 11.3 years, 4 participants left-handed) aged between 18-55 years old; with no prior training or work experience in built environment design; and with no prior diagnosed psychiatric, neurological, or neurodevelopmental conditions. A healthy adult sample was selected due to the experimental nature of the study and to reduce confounding variables. All participants were able to speak and read English and had normal or corrected-to-normal vision. 12 different languages were spoken at home by participants and 14 countries were identified as the location participants spent the most time growing up in.

2.2 Procedure

Participants were individually tested, and each session ran for approximately 90-minutes. On arrival, participants completed a secure web-based survey (Qualtrics), which took between 15-30 minutes. The survey included 13 questions regarding socio-demographic background, experience, and expertise for both VR and computer gaming. This was followed by a personality test using the abbreviated

International Personality Inventory Pool (IPIP-NEO-120) (Johnson, 2014). The open-source test included 24 questions across the five-factor-model domains of openness, conscientiousness, extroversion, agreeableness and neuroticism (OCEAN) (McCrae & John, 1992). Once the participant completed the self-report survey, the researcher explained the equipment to be used and demonstrated how this would be fitted. To reduce external factors that could influence physiological measures, we asked whether participants had eaten prior to the experiment and prompted the opportunity to use the bathroom before the experiment to avoid bladder discomfort (Quintana & Heathers, 2014).

Before fitting electrophysiological equipment, skin surfaces on hand and wrist sites which would be in contact with ECG electrodes and the skin conductance response cradle were cleaned to remove any residues. This was done by using a cotton tip to rub the skin surface with an abrasive gel (Weaver and Company NuPrep) and cleaning the surface of any residue with an alcohol wipe. Three ECG electrodes were placed on the hand and wrists. The positive electrode was located on the left wrist and the negative electrode was placed on the right wrist. The reference was placed on the knuckle of the middle finger on the left-hand side. For SCR, finger electrodes were placed underneath the middle and index finger on the left hand and secured with a Velcro strap. A respiratory belt transducer was positioned on the sternum and secured firmly around the chest. A 10-minute, three-lead ECG recording (PowerLab, LabChart Pro 8.1.16) was performed. Circuit zero was applied before the first recording and a subject zero was undertaken between each condition recording. A sampling rate of 1000 Hz and notch filter of 50 Hz was used.

We used a 64-channel cap (Philips Hydrocel Geodesic Sensor Net 64-channel HCGSN) for acquiring EEG data. Net Station 5 Geodesic EEG software, version 5.4.2 (Electrical Geodesics Inc) was used to record EEG data. The cap was positioned on the head after being soaked in an electrolyte solution. Data were acquired at a sampling rate of 1000 Hz, with Cz as the online reference. The Cz electrode was not included in our analysis, however, for the purposes of visualization, we have interpolated the Cz site for figures. A continuous recording was created for each participant and the EEG trace was manually time stamped by the researcher at the start and end of each 2-minute scene exposure. The majority of impedances were kept under 50 kΩ with an average value of 25.2 kΩ (SD = 7.75).

Participants were then led into the VR lab containing the CAVE. Participants were assisted to step into the CAVE and take a seat while the researcher carefully took the cords leading from the attached EEG, ECG and SCR sensors to connect to the monitoring equipment behind the participant. A pair of stereoscopic glasses to view the CAVE projection were then carefully fitted on top of the EEG cap. These remained on throughout the experiment. Impedances were checked and adjusted when necessary to ensure the quality of electrode-to-scalp contact.

Participants were seated for the duration of the experiment and instructed to pay attention to the scene they were presented. We elected to run a static resting state study where participants sat immersed in the space, rather than setting a task involving movement through thresholds, as this has been thought to affect cognition and memory (Pettijohn & Radvansky, 2016). By sitting, any height differences were also minimized between participants, and this also helped to minimize any movement-related artefacts in the electrophysiological measures. Each participant was exposed to an eyes-open resting state, followed by four built environment scenes in randomized order, displayed for two minutes each. At the end of each scene the virtual environment was returned to the resting state scene and the participant was asked to complete a short self-report survey using a 5-point visual Self-Assessment Manikin. This process was repeated five times, with a total duration of approximately 15-20 minutes.

We measured indoor environmental quality (IEQ) variables within the CAVE throughout the study. These measures were analysed to ensure any fluctuations to these properties linked to data which may influence emotion and neurophysiological response were minimized. To reduce the chance of negative influence all data were collected over a consecutive period in spring to reduce heat/cool load on the building triggering changes in the heating, ventilation, and air conditioning system.

2.3 Equipment and Stimuli

2.3.1 Cave Automatic Virtual Environment. The CAVE consisted of three walls (3m wide x 2.4m high) and a floor (2.4m wide x 3m long), each with Barco Galaxy NW-12 stereoscopic projectors. The projectors connect to a series of image generators (computers) each consisting of Nvidia Quadro P6000 graphic cards. The graphic cards are synced using Quadro Sync II cards at 120 Hz (60 Hz per eye) to frame lock the projectors to ensure rendered images are displayed at the same time. The CAVE uses an optical-based tracking system consisting of eight cameras that tracks active LED markers located on the stereoscopic glasses to track user movements. The tracking system operates at 240 Hz with sub millimeter accuracy and connects back to a Virtual Reality Peripheral Network (VRPN) server. The CAVE uses a custom-built Unity environment to run VR experiences with Vertical Sync (VSync) set to 60 frames per second. The unity environment connects to the tracking systems via VRPN server using an ethernet connect and updates the tracked position on each rendered frame.

2.3.2 Virtual environment development and CAVE integration. Autodesk Revit was used to create a 3D model that represented a conventional cubic room that was then exported into the Unity game engine (2019.2.15) for CAVE integration. A matte plaster texture was applied to the three wall surfaces with a slight gloss texture of bumpy concrete applied to the floor. A matte wood texture was applied to the door, doorway and chair with a low gloss metal surface applied to the door handle. Once material color, texture settings and lighting had been applied to the model, the room was duplicated (Unity Prefabs) into three separately scaled rooms. Pre-baked lightmaps were applied for each scaled room to ensure consistent lighting and texture relative to the scale and 'realistic' as possible to view.

The control condition was designed using Standards Australia measurements for a residential internal door (820mm x 35mm x 2040mm) [reference of standards will be identified if the article is published], and room dimensions were modelled of the physical CAVE walls (3200mm x 3200mm x 2400mm). For neutrality, the resting state scene (no built environment) was rendered in black (R0, G0, B0, hue (degrees) = 0, saturation (%) = 0, brightness (%) = 0. As a result of the white finish of the projector screens, this black virtual background appears as a dark gray when displayed on the screens. All scale conditions were rendered with a white finish (R255, G255, B255, hue (degrees) = 0, saturation (%) = 0, and brightness (%) = 100, and smoothness = 50%). The scale variables included a 'small' condition where the room size was reduced to 75% and two conditions where the room was enlarged by 125% ‘large’ and 150% ‘extra-large’ compared to the 100% control.

2.3.3 Room configuration and setup. A wooden fixed chair with a seat pad for comfort and back support for posture consistency was positioned in the center of the CAVE, effectively within the center of each virtual room regardless of scale. The chair remained in the central position to ensure all participants were situated in the same location. Room lights were switched on for safety when a participant entered the CAVE, that displayed the resting state scene. After the participant was setup and briefed on the experiment procedure, the researcher turned off the room lights.

2.3.4 Indoor environmental quality (IEQ). CR100 Measurement and Control System with LoggerNet 4.6.2 software (Campbell Scientific, Inc) was used to acquire and record data. Prior to the experiment, we completed a test recording and calibrated the recording equipment to ensure the readings were accurate in accordance with EN ISO 7730 Fanger Comfort Model (Fanger, 1970).

IEQ data was recorded at 1-minute intervals which were date and time stamped. We averaged the 1-minute readings from the corresponding time stamped data within each participants session to create an overall average per person and then determined the average across all participants. Although the VR lab was acoustically soundproof and no talking occurred during the scene recordings, a handheld sound level meter was used to capture fluctuating mechanical equipment noises from the CAVE projector lamp ventilation and cooling system which could not be controlled. Sound level recordings were conducted at different intervals during experiments to establish an overall range across the 5-week period. Overall mean air and wet-bulb globe temperature was within the 21-25° C range for optimal performance (Seppänen & Fisk, 2006), the carbon dioxide concentration throughout the testing period was within the indoor air concentration range of 500-1500 ppm, and the mean relative humidity was under 50% (Seppänen & Fisk, 2004). Sound pressure levels were also within an accepted range for the experiment (Basner et al., 2014).

2.3.5 Self-report data. Self-report of emotion was collected using the self-assessment manikin (Figure 5), where three dimensions, pleasure, arousal, and dominance, are recorded by the participant using a visual 5-point scale (Bradley & Lang, 1994; Mehrabian, 1996). The participant used an iPad to complete the self-report using a Qualtrics survey at the end of each stimulus. No time limit was given for the self-evaluation and the researcher remained outside of the CAVE until the participant verbally signalled they had completed the evaluation.

2.4 Data Analysis

2.4.1 Physiological data. Physiological data were acquired using PowerLab 4/35 (ADI Instruments PL3504) with a respiratory belt transducer (ADI Instruments TN1132/ST), Ag/AgCl ECG electrodes (Ambu Bluesensor N) and SCR finger plate electrodes (ADI Instruments MLT118F). Data for all physiological measures were acquired at 1000 Hz, and for SCR circuit zero was applied before the first recording and a subject zero was undertaken between each condition recording. Online filtering parameters differed between measures: ECG -100 to 100 mV; SCR -40 to 40 μS; and respiration -10 to 10 V. Five channels were set to record and calculate ECG, SCR and respiration. Results were divided into time segments (10-60 seconds, 60-110 seconds) and one overall time block (10-110 seconds) to capture whether an effect occurred at onset but diminished because of habituation over the recording. Three data sets from participants were excluded in the SCR and respiration analysis due to equipment fault. In respiratory data, 10 seconds from the onset of recording was removed for the measure to be accurately detected. For consistency the last 10 seconds was also removed.

Heart rate variability (HRV) settings used a beat classification for RR intervals between 600 to 1400 ms and complexity of 1 to 1.5. Ectopic heartbeats were excluded from analysis. Detection was adjusted to a minimum peak height of 1.2 S.D. and typical QRS width between 80 ms over a 350 ms minimum period. A low-pass filter of 30 Hz was used. We analysed the RMSSD and SDRR time domain components of the QRS complex within the ECG recording in accordance with the Task Force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology (Camm et al., 1996). Respiration frequency was measured using the cyclic measurements function with scoring parameters of 1.3 standard deviation threshold for detecting minimum peak height. To accommodate the time lag in the equipment detecting the first breath after recording, the first 7 seconds and last final 7 seconds of the continuous file for each participant across conditions was removed. Due to technical issues in the recording, two files did not record correctly and were excluded from analysis.

We collected HRV through time-domain, frequency-domain, and non-linear measurements. Data was analysed using RStudio (Version 1.3.959). N = 2 HRV and breathing data sets were excluded from the analysis due to HRV arrythmia, however data for SCR were still incorporated. To correct for distribution, a log transformation (log10) was applied to both HRV and SCR data. To correct for normality, we removed outliers which fell below [Q1 – (1.5 X IQR)] and were above [Q3 + (1.5 X

IQR)]. A within subjects repeated measures ANOVA with the Greenhouse-Geisser correction for sphericity was used across the six physiological measures we analysed. To control for multiple comparisons, a false discovery rate (FDR) correction was applied to the results (Benjamini & Hochberg, 1995).

2.4.2 EEG. The EEG data were preprocessed using EEGLab (v2019.1) (Delorme & Makeig, 2004), an open source graphic user interface and toolbox plugin for MATLAB R2019b (v9.7.0.1471314, MathWorks, Inc). We applied a bandpass filter from 1 to 70 Hz (zero-phase Butterworth filter) on continuous EEG data. A 47-53 Hz notch-filter was applied to exclude electrical interference from the CAVE environment. We then removed eye channels and the Cz reference channel. Next, we rejected channels if the kurtosis value was >5 standard deviations outside the average and replaced information in those channels using a spherical spline interpolation. Data were subsequently re-referenced to the average of all electrodes. To aid the removal of recording noise we applied the SOUND algorithm using input parameters of 5 iterations to evaluate noise in each channel and 0.2 regularization level (lambda value) to control the amount of cleaning (Mutanen, Metsomaa, Liljander, & Ilmoniemi, 2018). Each participant's continuous EEG data were decomposed using independent component analysis (FastICA algorithm) (Hyvärinen & Oja, 2000), with artifactual components identified with assistance from the ICLabel plugin (Pion-Tonachini, Kreutz-Delgado, & Makeig, 2019). A component was removed if ICLabel classified the probability of that component containing brain data was less than 30% and the component was not in the 'other' category. The mean of the components removed for each subject was 6.16 ± 3.92.

Using the time-stamped event markers in the continuous recording, each file was then split into 120 second block files using the start marker for each condition. Data were segmented into three-second epochs for subsequent analyses. Finally, additional artefact rejection was performed to remove any remaining noisy epochs with data exceeding ± 150 μV using the EEGLab ‘pop_eegthresh’ function. After cleaning we calculated the average epochs remaining for each condition and participant (mean number of epochs = 39.5, ± 1.46). Lastly, we converted data from each participant/electrode to the frequency domain using the Fast Fourier Transform (FFT) with Hanning taper in the FieldTrip toolbox for EEG/MEG-analysis (1 Hz frequency steps between 1 to 70 Hz) (Oostenveld, Fries, Maris, & Schoffelen, 2011).

To calculate power in the different frequency bands, we created averages across each separate frequency band for each electrode: delta (1 to 3 Hz), theta (4 to 7 Hz) alpha (8 to 12 Hz), beta (13 to 29 Hz), low gamma (30 to 45 Hz) and high gamma (55 to 70 Hz). Power was then averaged over electrodes within three hypothesis-driven *a priori* regions of interest: frontal midline (AFz, Fz, FCz), frontal right-hemispheric (F10, F8, AF4, F6, FT8, F2, F4, FC6, FC4 and FC2), and frontal left-hemispheric sites (F9, F7, AF3, F5, FT7, F1, F3, FC5, FC3 and FC1). During *a posteriori* analysis of gamma lateralization, we selected sites from across the whole scalp to run an exploratory analysis (F3-F4, FT7-FT8, FC5-FC6, FC3-FC4, C3-C4, C5-C6, TP7-TP8, CP5-CP6, P7-P8, P9-P10). A lateralization index was generated to understand the power difference between the average over the frontal left and right regions of interest, where higher values correspond to stronger power in the right compared to the left regions of interest (Demaree, Everhart, Youngstrom, & Harrison, 2005).

$$(\boldsymbol{\alpha}) = (\boldsymbol{\alpha}\text{(right)} - \boldsymbol{\alpha}\text{(left)}) / (\boldsymbol{\alpha}\text{(left)} + \boldsymbol{\alpha}\text{(right)}).$$

For statistical tests, we removed values that caused the violation of normality assumptions (according to the Shapiro-Wilk test). We removed extreme values which fell below [Q1 – (1.5 X IQR)] and were above [Q3 + (1.5 X IQR)]. Overall statistical analysis was conducted in RStudio using a repeated measures ANOVA with G-G correction. To correct for multiple comparisons where significance was detected within-subjects, the false discovery rate (FDR) method was used (Benjamini & Hochberg, 1995). The FDR is an alternative approach to multiple testing which increases detection power over traditional methods for multiple testing (Genovese, 2015).

2.5 Code accessibility

Source data and analysis code to accompany this manuscript submission are all available to be viewed on Open Science Framework: https://doi.org/10.17605/OSF.IO/5MVN3.

3.0 Results

3.1 Overview

Six measures were pre-selected to analyse physiological response to robustly compare group differences in distribution, variability and skew (Rousselet, Pernet, & Wilcox, 2017). We calculated the power spectra of the five EEG frequency bands averaged across participants for each condition. Hypothesis driven *a priori* analyses for EEG data included increased right frontal alpha and theta band lateralization (Coan & Allen, 2004; Davidson, 2004) and increased frontal alpha and theta midline power (Aftanas & Golocheikine, 2001). Studies have indicated that lower alpha and theta power in the left- than right-hemisphere is associated with positive emotion, while lower power in the right- than left-hemisphere can be seen for negative emotion (Ahern & Schwartz, 1985; Demaree et al., 2005). Self-report rating changes were compared with ± direction of the physiological and EEG responses, to determine if the pattern of the two measurement types aligned. On inspection of the extracted raw data, an exploratory test was run *a posteriori* to analyse gamma frontal midline power and lateralization, alongside overall power spectral density across bandwidths for completeness. Participant socio-demographic and personality data were also reviewed *a posteriori* to understand if underlying characteristics in the study sample interacted with the themes emergent in the results. No significant effect was found, see Extended Data 2-2.

3.2 Increased power spectral density was found in the beta bandwidth to enlarged scale.

We found significant differences between the scale conditions for beta power across the average of all channels [F(4, 201) = 7.04, *p* = < .001, η^2_p = .110]. Power was significantly lower in resting state than: small [M_{diff} = -.041, SE_{diff} = .015, *t*(57.0) = -2.808, $p_{corrected}$ = .016, 95% CI (-.068, -.010)], control [M_{diff} = -.042, SE_{diff} = .013, *t*(57.0) = -3.101, $p_{corrected}$ = .015, 95% CI (-.069, -.015)], large [M_{diff} = -.036, SE_{diff} = .036, *t*(57.0) = -2.729, $p_{corrected}$ = .016, 95% CI (-.066, -.013)], and extra-large [M_{diff} = -067, SE_{diff} = .015, *t*(57.0) = -3.820, $p_{corrected}$ = <.001, 95% CI (-.095, -.040)]. There was also significant increase in power when comparing the small to the extra-large condition [M_{diff} = -027, SE_{diff} = .012, *t*(57.0) = -2.217, $p_{corrected}$ = .044, 95% CI (-.048, -.002)], the control to the extra-large [M_{diff} = .006, SE_{diff} = .013, *t*(57.0) = .445, $p_{corrected}$ = .018, 95% CI (-.046, -.008)], and the large to the extra-large [M_{diff} = -.032, SE_{diff} = .011, *t*(57.0) = -2.788, $p_{corrected}$ = .016, 95% CI (-.046, -.003)].

In the low-gamma bandwidth we found significant differences [F(4, 161) = 13.6, *p* = < .001, η^2_p = .229]. During post-hoc analysis we detected significantly lower power for resting state to: small [M_{diff} = -.184, SE_{diff} = .027, *t*(46.0) = -5.409, $p_{corrected}$ = < .001, 95% CI (-.200, -.100)], control [M_{diff} = -.128, SE_{diff} = .026, *t*(46.0) = -4.918, $p_{corrected}$ = < .001, 95% CI (-.177, -.076)], large [M_{diff} = -.129, SE_{diff} = .030, *t*(46.0) = -4.378, $p_{corrected}$ = < .001, 95% CI (-.188, -.076)], and extra-large [M_{diff} = -.173, SE_{diff} = .025, *t*(46.0) = -6.934, $p_{corrected}$ = < .001, 95% CI (-.222, -.131)]. We also detected a significant increase from the control to the extra-large in the low-gamma bandwidth, but this was lost after applying FDR correction for multiple comparisons. Lastly, an increase in high-gamma power was detected in scale conditions when compared to the resting state [F(4, 160) = 12.8, p = < .001, η^2_p = .217]. These effects were only seen between resting and the scale conditions: small ([M_{diff} = -.198, SE_{diff} = .040, t(46.0) = -4.949, $p_{corrected}$ = < .001, 95% CI (-.291, -.145)], control [M_{diff} = -.144, SE_{diff} = .037, t(46.0) = -3.905, $p_{corrected}$ = <.001, 95% CI (-.222, -.078)], large [M_{diff} = -.189, SE_{diff} = .040, t(46.0) = -4.708, $p_{corrected}$ = < .001, 95% CI (-.243, -.084)], and extra-large [M_{diff} = -.223, SE_{diff} = .035, t(46.0) = -6.382, $p_{corrected}$ = < .001, 95% CI (-.276, -.139)].

We also detected significant differences in the remaining bandwidths, however post-hoc analysis revealed these differences were contained between the resting state and built environment scale conditions. This included the delta bandwidth [F(3, 158) = 15.1, p = < .001, η^2_p = 0.229]. With differences between resting and the scale conditions: small ([M_{diff} = -.153, SE_{diff} = .031, t(51.0) = -5.001, $p_{corrected}$ = < .001, 95% CI (-.206, -.086)], control [M_{diff} = -.134, SE_{diff} = .029, t(51.0) = -4.598, $p_{corrected}$ = <.001, 95% CI (-.189, -.072)], large [M_{diff} = -.132, SE_{diff} = .029, t(51.0) = -4.578, $p_{corrected}$ = < .001, 95% CI (-.185, -.076)], and extra-large [M_{diff} = -.173, SE_{diff} = .031, t(51.0) = -5.628, $p_{corrected}$ = < .001, 95% CI (-.226, -.106)]. Similar effects were seen in the theta bandwidth [F(3, 164) = 13.0, p = <.001, η^2_p = .203]. Follow-up analysis indicated lower power was detected for resting state than small [M_{diff} = -.093, SE_{diff} = .021, t(51.0) = -4449, $p_{corrected}$ = <.001, 95% CI (-.131, -.049)], control [M_{diff} = -.083, SE_{diff} = .020, t(51.0) = -4.161, $p_{corrected}$ = <.001, 95% CI (-.125, -.047)], large [M_{diff} = -.095, SE_{diff} = .018, t(51.0) = -5.269, $p_{corrected}$ = <.001, 95% CI (-.137, -.063)], and extra-large [M_{diff} = -.110, SE_{diff} = .021, t(51.0) = -5.219, $p_{corrected}$ = <.001, 95% CI (-.155, -.074)]. Lastly, alpha waves, which are commonly found during awake rest, showed within-subject effects [F(2, 111) = 5.00, p = .007, η^2_p = .089], however follow-up analysis indicated that resting state alpha power was only significantly lower to the control condition [M_{diff} = .083, SE_{diff} = .026, $t(51.0)$ = 3.178, $p_{corrected}$ = <.001, 95% CI (.034, .136)]. Results are shown in Figure 2. Additional bandwidths are also presented in Extended Data Figure 2-3. Descriptives and significance values for all EEG power spectra are presented in Extended Data Figure 2-1 and 2-2.

3.4 Enlarged scale increased frontal midline power and lateralization in the gamma bandwidth.

An exploratory analysis to further investigate frontal midline and lateralization in the low and high gamma bandwidth was undertaken after analyzing the results of the overall power spectral density. Frontal midline power in the low-gamma bandwidth increased with the scale of the room [F(4, 207) =25.7, p = < .001, η^2_p = .255]. Post hoc comparisons showed significant differences between resting state and all conditions: small [M_{diff} = -.107, SE_{diff} = .019, t(53.0) = -5.737, $p_{corrected}$ = <.001, 95% CI (-.147, -.076)], control [M_{diff} = -.099, SE_{diff} = .018, t(53.0) = -5.552, $p_{corrected}$ = <.001, 95% CI (-.135, -.066)], large [M_{diff} = -.082, SE_{diff} = .018, t(53.0) = -4.488, $p_{corrected}$ = <.001, 95% CI (-.118, -.046)], and extra-large [M_{diff} = -.139, SE_{diff} = .017, t(53.0) = -8.100, $p_{corrected}$ = <.001, 95% CI (-.173, -.108)]. We also detected an increase in power from the control to the extra-large [M_{diff} = -.046, SE_{diff} = .016, t(64.0) = -2.882, $p_{corrected}$ = .020, 95% CI (-.070, -.012)], and the large to the extra-large [M_{diff} = -.031, SE_{diff} = .014, t(64.0) = -2.180, $p_{corrected}$ = .004, 95% CI (-.090, -.023)].

An effect of condition was also seen in the high-gamma bandwidth [F(4, 232) =16.6, p = < .001, η^2_p = .211]. Post-hoc analysis revealed differences between the resting state and all conditions: small [M_{diff} = -.164, SE_{diff} = .028, t(62.0) = -5.861, $p_{corrected}$ = <.001, 95% CI (-.211, -.100)], control [M_{diff} = -.137, SE_{diff} = .025, t(62.0) = -5.454, $p_{corrected}$ = <.001, 95% CI (-.188, -.089)], large [M_{diff} = -.132, SE_{diff} = .029, t(62.0) = -4.543, $p_{corrected}$ = <.001, 95% CI (-.185, -.069)], and extra-large [M_{diff} = -.192, SE_{diff} = .025, t(62.0) = -7.590, $p_{corrected}$ = <.001, 95% CI (-.239, -.141)]. We also found a difference between the control to extra-large [M_{diff} = -.055, SE

$_{diff}$ = .026, t(62.0) = -2.263, $p_{corrected}$ = .045, 95% CI (-.103, -.007)], and large to extra-large [M_{diff} = -.060, SE_{diff} = .026, t(62.0) = -2.320, $p_{corrected}$ = .045, 95% CI (-.113, -.010)].

An effect of condition on frontal midline power was found in the theta band [F(4, 181) = 9.23, p = < .001, η^2_p = .156]. Post hoc comparisons showed these differences were constrained to comparisons between the resting state to conditions, with a significant increase between resting state and all conditions: small [M_{diff} = -.094, SE_{diff} = .023, t(50.0) = -4.162, $p_{corrected}$ = <.001, 95% CI (-.138, -.052)], control [M_{diff} = -.087, SE_{diff} = .021, t(50.0) = -4.140, $p_{corrected}$ = <.001, 95% CI (-.128, -.045)], large [M_{diff} = -.093, SE_{diff} = .021, t(50.0) = -4.470, $p_{corrected}$ = <.001, 95% CI (-.133, -.051)], and extra-large [M_{diff} = -.103, SE_{diff} = .022, t(60.0) = -4.711, $p_{corrected}$ = <.001, 95% CI (-.146, -.067)]. We also detected an effect for alpha frontal midline power [F(3, 169) =8.58, p = < .001, η^2_p = .118]. However, these effects were limited to comparisons between resting state to the built environment scale conditions, which were lost during correction for multiple comparisons.

Significant differences were also detected in the frontal hemispheric theta lateralization [F(3, 145) = 10.2, p = < .001, η^2_p = .178]. Post-hoc analysis revealed the significant increases in theta lateralization was between resting state and the scale built environment conditions: small [M_{diff} = -.033, SE_{diff} = .008, t(47.0) = 4.092, $p_{corrected}$ = <.001, 95% CI (-.046, -.016)], control [M_{diff} = -.032, SE_{diff} = .008, t(47.0) = 4.014, $p_{corrected}$ = <.001, 95% CI (-.047, -.015)], large [M_{diff} = -.035, SE_{diff} = .008, t(47.0) = 4.339, $p_{corrected}$ = <.001, 95% CI (-.047, -.017)], and extra-large [M_{diff} = -.035, SE_{diff} = .008, t(47.0) = 4.327, $p_{corrected}$ = <.001, 95% CI (-.044, -.015)]. We also detected difference in frontal alpha lateralization [F(3, 124) = 3.71, p = .018, η^2_p =

.072]. Post-hoc analysis revealed there were differences between resting state and the conditions, but these did not survive correction. Results are shown in Figure 3. Descriptives and significance values for EEG frontal midline power and frontal hemispheric lateralization are presented in Extended Data Figure 2-1 and 2-2.

3.5 Autonomic response between resting state and the conditions were found, but not to variations in scale.

HRV within-subjects effects for time-domain showed an effect of condition in the root mean square successive difference (RMSSD) [$F(3, 198) = 3.89$, $p = .007$, $\eta^2_p = .064$]. RMSSD reflects changes to vagal tone and is less affected by changes in respiration (Shaffer & Ginsberg, 2017). Follow-up analysis indicated that resting state showed some differences with the scale conditions, but there was not a significant difference between the levels of scale. Specifically, RMSSD resting state values were significantly lower than control [$M_{diff} = .050$, $SE_{diff} = .015$, $t(57.0) = 3.395$, $p_{corrected} = .010$, 95% CI (.020, .079)], and the extra-large [$M_{diff} = .040$, $SE_{diff} = .014$, $t(57.0) = 2.819$, $p_{corrected} = .035$, 95% CI (.013, .069)], but we did not detect significant difference to the small or large conditions. We detected an effect in the standard deviation of the R-R interval (SDRR), [$F(4, 205) = 2.79$, $p = .032$, $\eta^2_p = .047$]. However, post-hoc analysis revealed these values did not survive correction for multiple comparisons.

Respiration measures analysed were the mean value and maximum minus minimum (Mx-Mn). Within-subjects comparisons for the mean [$F(3, 135) = 2.22$, $p = .096$, $\eta^2_p = .042$] and Mx-Mn [$F(3, 138) = 1.07$, $p = .368$, $\eta^2_p = .024$] did not reveal significant differences between conditions.

Skin conductance response (SCR) measures were the mean, and the maximum minus the minimum value (Mx-Mn) of the slope. The within-subjects analysis did not show significant differences between conditions in the mean [F(3, 115) = 1.68, $p = .170$, $\eta^2_p = .046$]. There was, however, a significant difference between conditions in Mx-Mn [F(3, 150) = 10.7, $p = < .001$, $\eta^2_p = .171$]. Post hoc comparisons for the Mx-Mn showed a significant increase from resting state to conditions with small [M_{diff} = -.234, SE_{diff} = .059, t(57.0) = -3.992, $p_{corrected}$ = .002, 95% CI (-.819, -.262)], control [M_{diff} = -.233, SE_{diff} = .061, t(57.0) = -3.814, $p_{corrected}$ = .004, 95% CI (-.803, -.248)], large [M_{diff} = -.266, SE_{diff} = .060, t(57.0) = -4.412, $p_{corrected}$ = $< .001$, 95% CI (-.884, -.323)] and extra-large [M_{diff} = -.249, SE_{diff} = .056, t(57.0) = -4.454, $p_{corrected}$ = $< .001$, 95% CI (-.926, -.345)]. Results are shown in Figure 4. Descriptives and significance values for physiological measures are presented in Extended Data Figure 4-1 and 4-2.

3.6 No association between self-reported emotion and changes in physiological response.

It is important to understand if participants can accurately identify changes to their emotional state. Currently, accepted practice during post occupancy evaluations of buildings is to complete surveys with building users to understand if their needs are being met. However, the degree to which subjective emotional judgments are associated with electrophysiological measures related to emotion is unclear. During the experiment, participants provided self-reports of their emotional state using the Self-Assessment Manikin. Self-report of pleasure showed an effect of condition [$F(4, 236) = 12.0$, $p = < .001$, $\eta^2 = .156$]. Post hoc comparisons showed significant positive increases between resting state and all conditions, small [$M_{diff} = .727$, $SE_{diff} = .123$, $t(65.0) = 5.904$, $p_{corrected} = <.001$, 95% CI (-.819, -.262)], control [$M_{diff} = .591$, $SE_{diff} = .126$, $t(65.0) = 4.695$, $p_{corrected} = <.001$, 95% CI (-.803, -.248)], large [$M_{diff} = .576$, $SE_{diff} = .122$, $t(65.0) = 4.709$, $p_{corrected} = <.001$, 95% CI (-.884, -.323)], and extra-large [$M_{diff} = .591$, $SE_{diff} = .126$, $t(65.0) = 4.695$, $p_{corrected} = <.001$, 95% CI (-.926, -.345)], but did not reveal significant differences between scale conditions. No significant effects were observed for self-reports of arousal [$F(4, 245) = 1.36$, $p = .251$, $\eta^2 = .020$] or dominance [$F(3, 225) = 1.78$, $p = .143$, $\eta^2 = .027$].

Using the baseline resting state scores as a comparator, we analysed if participants rated themselves higher or lower for each of the three measures and compared this to the direction of change in the most responsive physiological measure, SCR Mx-Mn. Using Pearson's r correlations, we found no relationship between the direction of SCR Mx-Mn change and self-report change across the

591 three dimensions of pleasure (r = .006, p = .96), arousal (r = .093, p = .46) and dominance (r = .14, p = .025) shown in Figure 5.

3.7 We did not detect a relationship between potential confounding variables such as order of exposure and IEQ range with the neurophysiological results.

As each participant experienced the resting state before a randomized set of conditions, we checked for stimulus habituation by comparing results of SCR Mx-Mn, and the averaged gamma EEG power spectra density with the order of exposure presented to each participant. We did not find a positive or negative linear relationship, which argues against the possibility that the difference between resting state and the scale conditions was due to the exposure order.

We measured indoor environmental quality (IEQ) variables within the CAVE throughout the study. Air temperature (°C) was stratified across 3 height levels of low (M = 22.2, ± SEM = .108), mid (M = 22.2, ± SEM = .106) and high (M = 22.3, ± SEM = .105). Wet-bulb globe temperature (°C), which measures apparent temperature, was stratified across 4 height levels of low (M = 22.1, ± SEM = .106), mid (M = 22.2, ± SEM = .102), high (M = 22.2, ± SEM = .104) and approximate head height for standing position (M = 23.1, ± SEM = .111). Air velocity (m/s) was also stratified across 4 levels of low (M = .076, ± SEM = .003), mid (M = .069, ± SEM = < .001), high (M = .070, ± SEM = .001) and head (M = .006, ± SEM = < .001). We also recorded overall relative humidity (%) (M = 45.4, ± SEM = .781) and carbon dioxide in parts per million (ppm) (M = 572, ± SEM = 2.92). Noise levels (dB) fluctuated due to mechanical projector lamp ventilation (M = 46.7, ± SEM = .383). Results are shown in Figure 2-1.

3.8 We did not detect a relationship between personality and autonomic responsiveness to conditions.

To understand if personality played a role in response to the built environment, we tested if differences in participants' personality accounted for differences in response to the built environment. Participants completed the abbreviated International Personality Inventory Pool (IPIP-NEO-120) prior to the experiment. To check for an association between autonomic reactivity in the built environment and personality we ran a correlation analysis using the most reactive physiological measure, SCR Mx-Mn. We did not observe any correlations as presented in Figure 2-2.

4.0 Discussion

With limited exploratory work conducted in the field (Bower, 2019), this study is the first to test how the scale of the built environment affects emotional and neurophysiological response with a rigorously controlled method, using virtual reality and indoor environmental quality monitoring. This study demonstrates that enlarged scale had a significant impact on brain oscillatory activity in the beta, low-gamma and high-gamma bandwidths, even after controlling for potentially confounding variables such as stimulus habituation (Tang, Smout, Arabzadeh, & Mattingley, 2018) and thermal comfort (refer to Extended Data 2-1). We also detected increases in measures of range for skin conductance (maximum minus minimum slope) and heart rate variability (root mean square of successive differences) to the built environment conditions, but not scale. Scale of the built environment was not seen to modulate autonomic response or anticipated EEG measures of frontal midline power or frontal lateralization within the theta and alpha bandwidths across participants. However, during *a posteriori* analysis we found increased frontal midline power in the low-gamma and high-gamma bandwidth, associated with increased scale between control to extra-large, and large to extra-large conditions. We also found increased left lateralization in the gamma bandwidth between the large and extra-large condition, suggesting changes in gamma midline power and lateralization may be a physiological marker of the impact of built environment scale. The study confirmed our hypothesis that participants' self-report of emotion for the dimensions of arousal and dominance do not correspond with autonomic or brain wave modulations. We did find a significant difference in self-report of pleasure between resting state and conditions, but not between scales, and this difference was not seen in self-report of arousal or dominance.

The results of this study indicate that changes in heart rate variability and SCR do occur during built environment exposures, which are modulated through the autonomic nervous system. This has been thought to correspond with limbic system activation, which is involved in our behavioural and emotional response. It is important to distinguish that these lowered levels of HRV and elevated SCR to the built environment scenes do not equate to a positive emotion or a better environment for our health. Likewise, we cannot rule out that these changes will result in long term negative effects, however research shows elevated arousal and stress over a long period of time can be detrimental to our health (Schneiderman, Ironson, & Siegel, 2005). Instead, this research provides the first step in demonstrating that the presentation of a virtual built environment, compared with resting state, modulates autonomic activity in measures of sympathetic and parasympathetic activity.

There are multiple theories for hemispheric lateralization in emotional processing studies. Increased asymmetry of the right hemisphere has been associated with emotional stimuli, regardless of valence (Müller et al., 2000; Müller, Keil, Gruber, & Elbert, 1999). From a neurocognitive perspective, it is unclear whether this relates to emotion processing, or other attentional or perceptual processes related to an enlarged built environment scale. We also detected EEG power spectra in the beta bandwidth increased from the small to the extra-large, control to the extra-large, and the large to the extra-large but did not differ between scale conditions for the remaining bandwidths. However, we did find significant differences between resting state and the scale conditions across most bandwidths. In contrast to our hypothesis, we did not detect increased alpha and theta frontal midline power or lateralization across scale conditions, which is associated with positive emotional response (Davidson, 1992; Ekman & Davidson, 1993). These findings suggest that although scale may not be involved in emotional processing, it may influence high frequency oscillatory processes, such as working memory and decision making (Spitzer & Haegens, 2017). However, we acknowledge that without source localization we are inferring the neural activity, and therefore our interpretations of the effects remain speculative. Future research exploring higher-frequency signals with EEG could consider utilizing an analysis approach incorporating source localization of the EEG to aid reducing the impact of any eye movement artifact in the signal (Carl, Açık, König, Engel, & Hipp, 2012; Hipp & Siegel, 2013). Another option for further research could be to use a data driven approach using large samples to perform quantitative EEG analysis.

The study also revealed that self-report of emotion was not an accurate indicator for increased autonomic nervous system response. Emotion processing studies investigating alignment between self-report and physiological indicators remain inconsistent. With some studies reporting consistency (Hagemann, Naumann, Becker, Maier, & Bartussek, 1998), while others remain inconsistent (Kassam & Mendes, 2013). Despite the lack of current consensus, this is an important finding for design professionals, as it indicates the need to shift practice in post occupancy evaluation of buildings. We suggest the findings highlight the need to go beyond self-report and observational data alone, as these do not capture effects that may not be consciously perceived or comprehended.

There is evidence widespread high-frequency activity is increased during a range of complex cognitive tasks (Fitzgibbon, Pope, Mackenzie, Clark, & Willoughby, 2004; Simos, Papanikolaou, Sakkalis, & Sifis, 2002). As we found preliminary evidence for the effect of enlarged scale in the higher frequency bandwidths, future studies are warranted to integrate this further. This could include a working memory activity during exposure to the built environment conditions, which could clarify if task-based performance is impacted (Jensen, Kaiser, & Lachaux, 2007). Previous studies have shown that during tasks where participants are required to perform a range of cognitive tasks to induce stress, indoor environmental factors such as temperature (Silva, de Souza, de Oliveira, & Andrade, 2019) and view to nature (Fich et al., 2014) modulate physiological response and impact performance. As it is suggested we have a threshold of tolerance to stressors, modulated by gene-environment interactions (Caspi & Moffitt, 2006), the built environment could act to increase or reduce the tolerance. Therefore, exposing participants to higher stress may heighten the effect of the built environment on neurophysiological response. It may also be that examining network-level responses through a technique, such as functional connectivity, is required to understand if scale has an effect on neural activity. Studies have indicated that techniques with greater temporal resolution may be more effective for detecting brain activity when measuring for emotional state change (Bekkedal, Rossi, & Panksepp, 2011).

As the study is exploratory, further work understanding the interplay between design elements is required. It is expected that this technique and singular approach can be further used with different design elements with larger, more complex scenes. The scene created was purposefully designed to be context neutral. This meant it was devoid of color, materiality/excessive texture, atypical geometry, and furnishings, which may indicate to the participant the context/setting. However, this is not realistic as we do not experience environments that have so little visual information. This study also relied on visual information processing to understand the effect of scale. Work is required to understand if similar physiological activity and neural encoding occurs when processing the built environment through other sensory modalities such as the auditory system through processing reverberation feedback to determine the scale of the space. Future research could steadily progress to complexity by exploring how these design elements of the environment interact with other enrichment components through studies involving motor activity, cognitive stimulation, and the presence of other people in the space.

The study also limited participants to those self-reporting they had no underlying mental health conditions. This may mean a broader more inclusive sample will enable us to understand if the built environment impacts those with pre-existing psychological, psychiatric, neurodevelopmental, and neurodegenerative conditions to a greater extent than the study sample.

Active debate continues over the ecological validity of virtual environments to simulate physical environments (Kalantari et al., 2021; Sanchez-Vives & Slater, 2005). Virtual reality enables a high level of environmental control over the design, testing and is cost-efficient when compared to the construction of physically built environments. While studies have explored the difference between virtually experienced and physically experienced spaces, in this research it was found that a CAVE can be a cost-effective method for the development of a controlled environment. Future work replicating the approach in physically created scaled spaces would be beneficial to understand if differences in responses to the two modalities exist.

The ability for built environment design to modulate neural processing may have implications on our cognitive, attentional, perceptual, and emotional functioning. With the potential to deliver significant public health, economic and social benefits to the entire community. This work generates new knowledge for industry and policy makers to enable enhanced understanding, prediction, and optimization of built environment design. It is important that attention is drawn to pursuing future studies that investigate if built environment design can provide a neuroprotective factor for individuals who are at increased risk of developing a psychological disorder due to other environmental and epigenetic stressors. This study provides a rigorous empirical framework for assessing the impact of the built environment on human emotion for future studies. The findings confirm that the buildings we inhabit play a role in determining our health.

Figure legends

<u>Figure 1.</u> Experimental design and setup. (A) Isometric view of conditions. Participants were presented with eyes open resting state, followed by four randomized scale conditions. Each scene lasted two-minutes, between which the resting state was displayed while the participant completed a self-report assessment of emotion. (B) Floor plan indicating the position of items in the experiment. Indoor environmental qualities (IEQ) variables were measured continuously, and all recording equipment was positioned outside of the participants field of view. (C) Diagram of equipment fitted to participant including stereoscopic tracking glasses, EEG system, respiratory belt, SCR finger cradles and ECG electrodes. Diagrams are representative, not drawn to exact scale.

<u>Figure 2.</u> Significant differences between the control and extra-large condition for EEG power spectral density was found in the beta bandwidth. To illustrate the differences, we have plotted EEG topographies and boxplots with quartile ranges and medians for the overall power spectra in the beta, low-gamma, and high-gamma bandwidths. Note the Cz site has been interpolated for this figure. (A) Beta 13 to 29 Hz; (B) Low-gamma 30 to 45 Hz with amplitude range; and (C) High gamma 55 to 70 Hz. **Figure 2-1.** Descriptives (mean / standard deviation) for EEG analysis. **Figure 2-2.** Statistical significance values for EEG analysis. Note: Power spectral density, frontal midline and theta and alpha lateralisation statistics are derived from parametric one-way repeated measures ANOVA's. *P* = P value, ^{FDR} = False discovery rate correction. **Figure 2-3.** EEG topographies and boxplots with quartile ranges and medians for the overall power spectra in the delta, theta, and alpha bandwidths. Note the Cz site has been interpolated for this figure. (A) Delta 1 to 3 Hz; (B) Theta 4 to 7 Hz with amplitude range; and (C) Alpha 8 to 12 Hz.

Figure 3. Significant differences in EEG low-gamma frontal midline power were found. (A) Power spectra plot showing power (dB) across frequencies. The low-gamma bandwidth (30 to 45 Hz) and high-gamma bandwidth (55-70 Hz) are highlighted with the gray shading box. The dip represents the 47-53 Hz notch filter applied to remove electrical interference from the CAVE environment. (B-C) Boxplots with quartile ranges and medians to show increased gamma midline power spectra. Each data point overlaid represents a participant's averaged response from the 2-minute exposure.

Figure 4. Physiological measures between the resting-state, small, control, large, and extra-large conditions. (A-F) Boxplots with quartile ranges and medians for physiological measures analysed using raw values. Each data point represents a participant's averaged response from the 2-minute exposure. Significance values (FDR-corrected) from the data after transform and removal of outliers have been superimposed to indicate where significant differences were found. All participants were exposed to the resting state first, before the randomized conditions. We did not detect a difference between the control and scale conditions, however significant differences were detected between the resting-state and built environment scale conditions were found in measures analyzing the change in range, such as maximum – minimum slope for skin conductance response and the root mean square successive difference for heart rate variability. **Figure 4-1.** Descriptives (mean / standard deviation) for physiological analysis. **Figure 4-2.** Statistical

significance values for physiological measures. Note: Statistics are derived from one-way repeated measures ANOVA's. *P* = P value, $^{FDR =}$ False discovery rate correction.

Figure 5. Correlations between self-assessment and physiological response. (A-C) Heatmap of the aggregated self-report responses across participants. The pictorial scale on the x-axis depicts the SAM dimensions of pleasure, arousal, and dominance. (D-F) Correlations were used to understand if a relationship between physiological response and self-report could be found. The data was obtained from averaging the response to built environment conditions and obtaining the absolute difference to the resting state condition for SCR Mx-Mn and the ± value from each domain in the self-assessment manikin.

Figure 6. Exposure order and comfort conditions. All indoor environmental quality data is organised by calendar day the reading was collected on (x-axis). Multiple points represent the number of participants from each day. (A-C) Measurements stratified by height data was required from to accommodate differences in temperature and air velocity.

Figure 7. Exploratory correlations between personality measures and physiological response. (A-E) Correlations between Openness, Conscientiousness, Extroversion, Agreeableness and Neuroticism (OCEAN) big five personality traits and the absolute difference in the averaged response across built environment conditions for galvanic skin response maximum minus minimum slope value (SCR Mx-Mn). No correlation was found.

5.0 References

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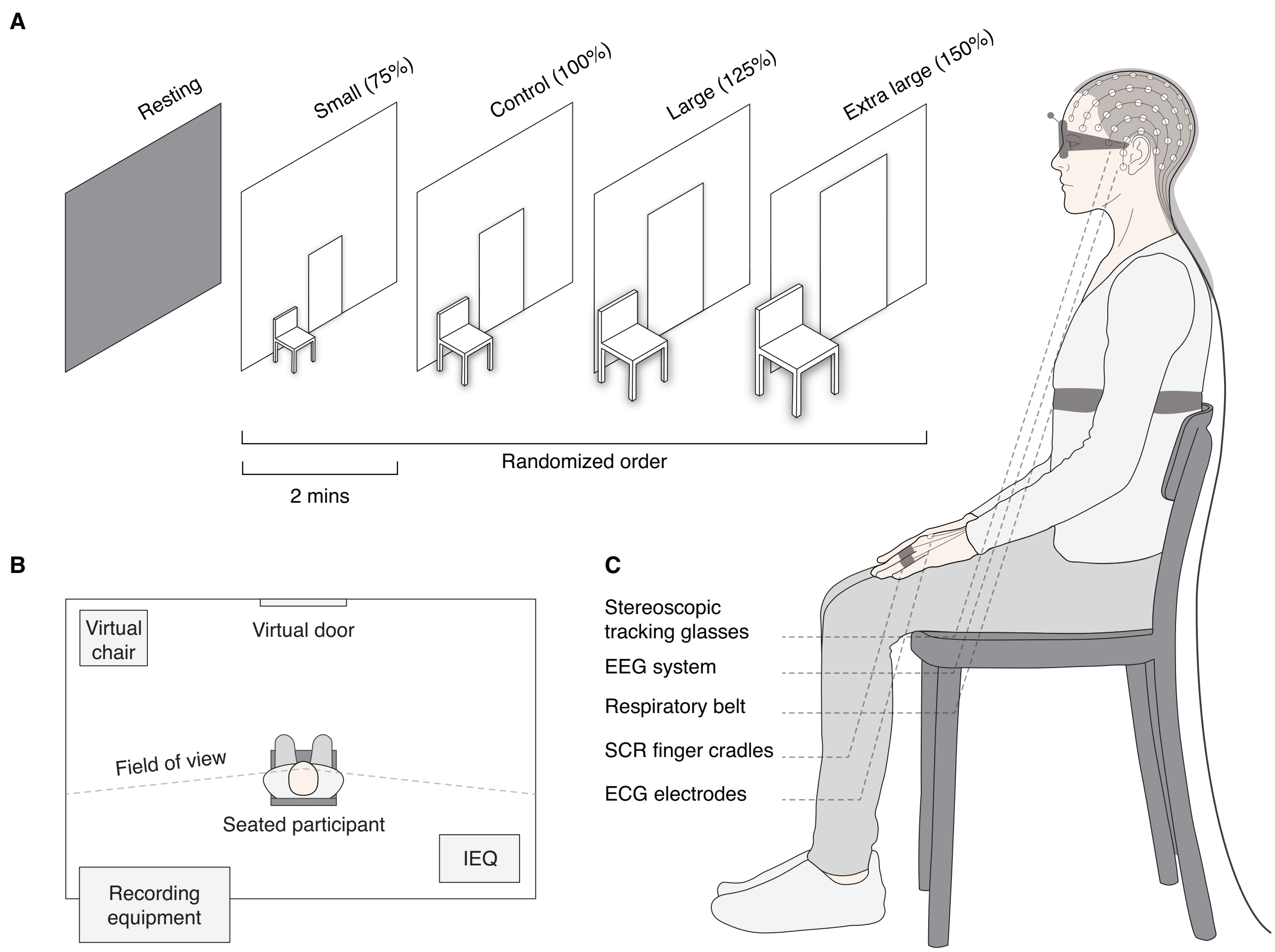
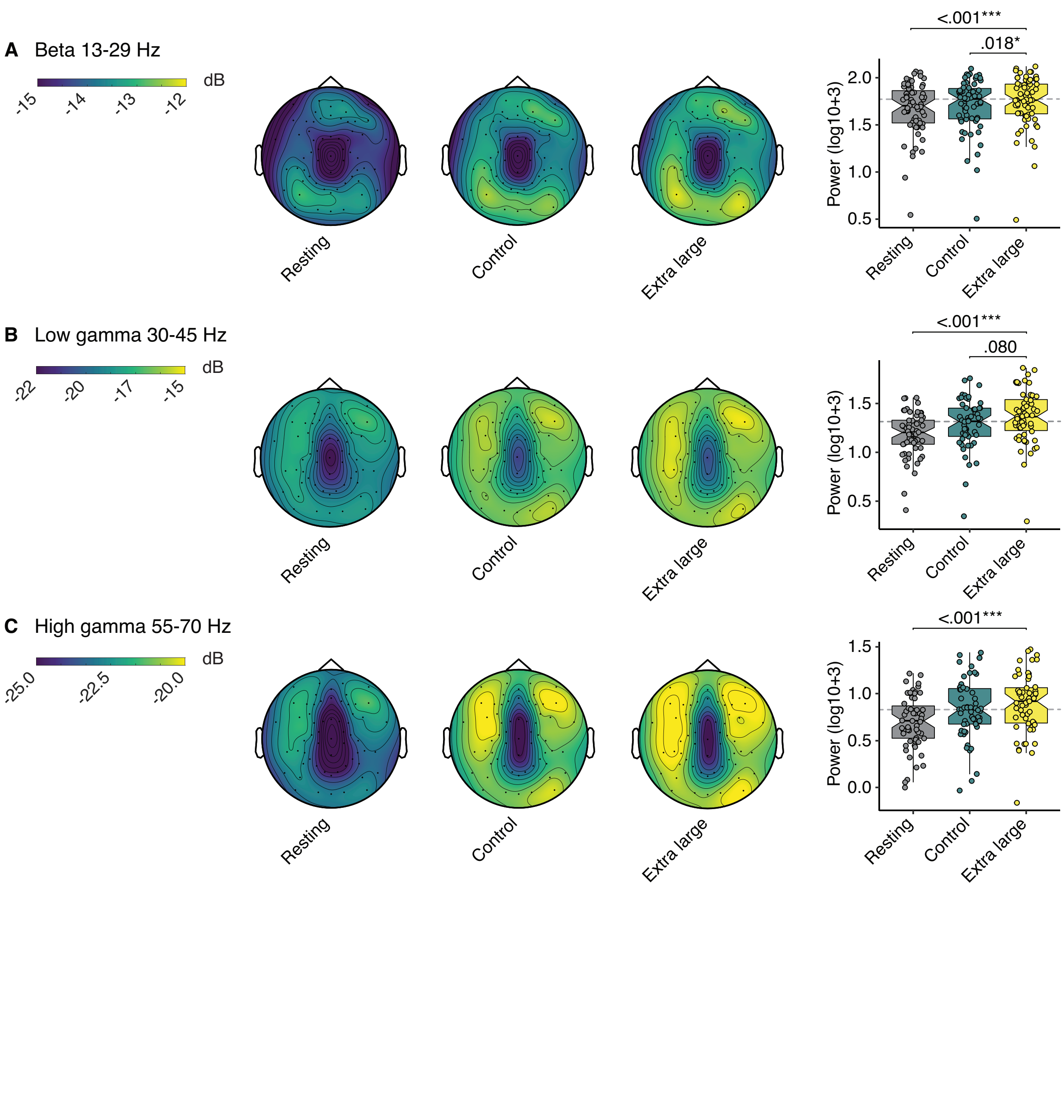
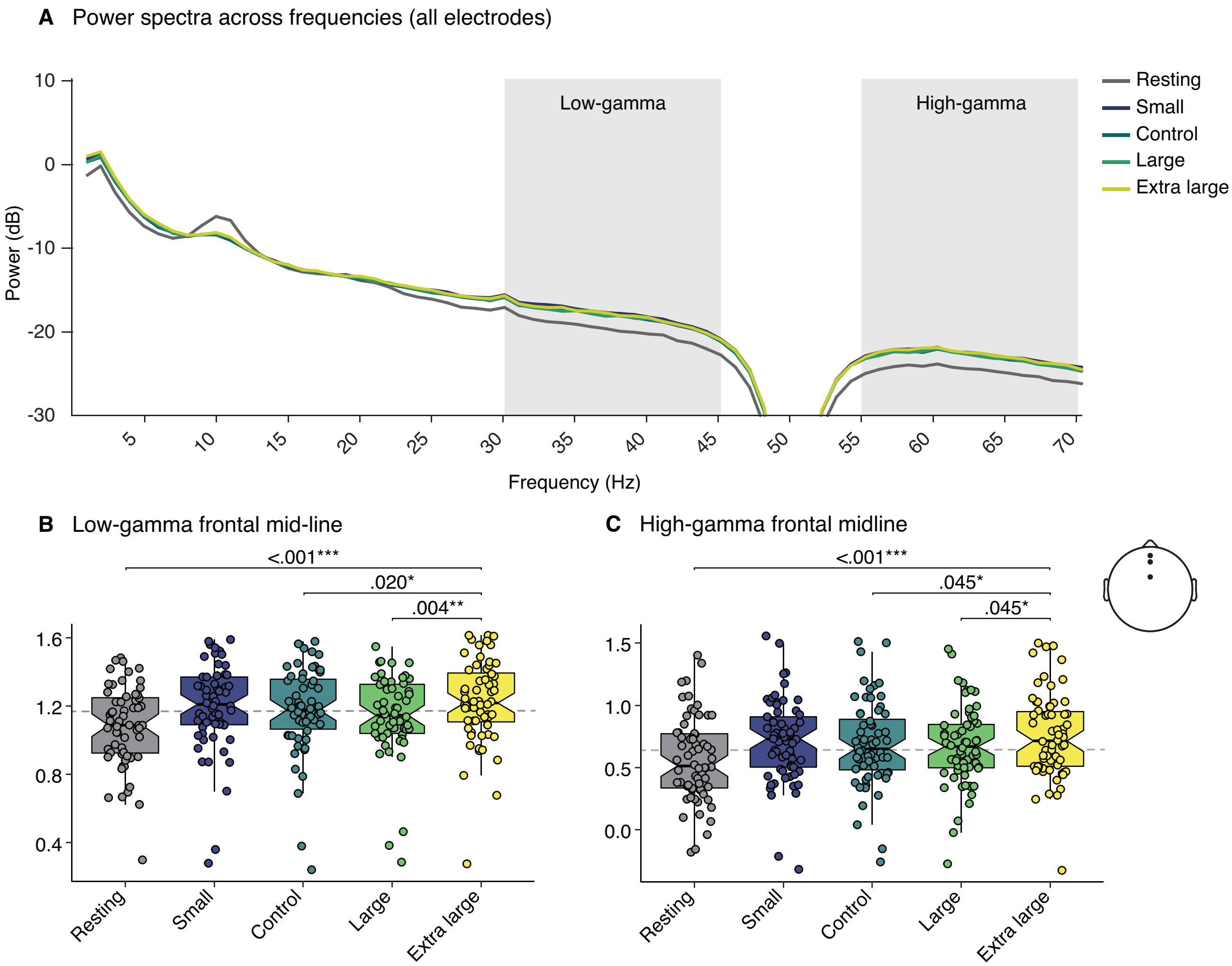
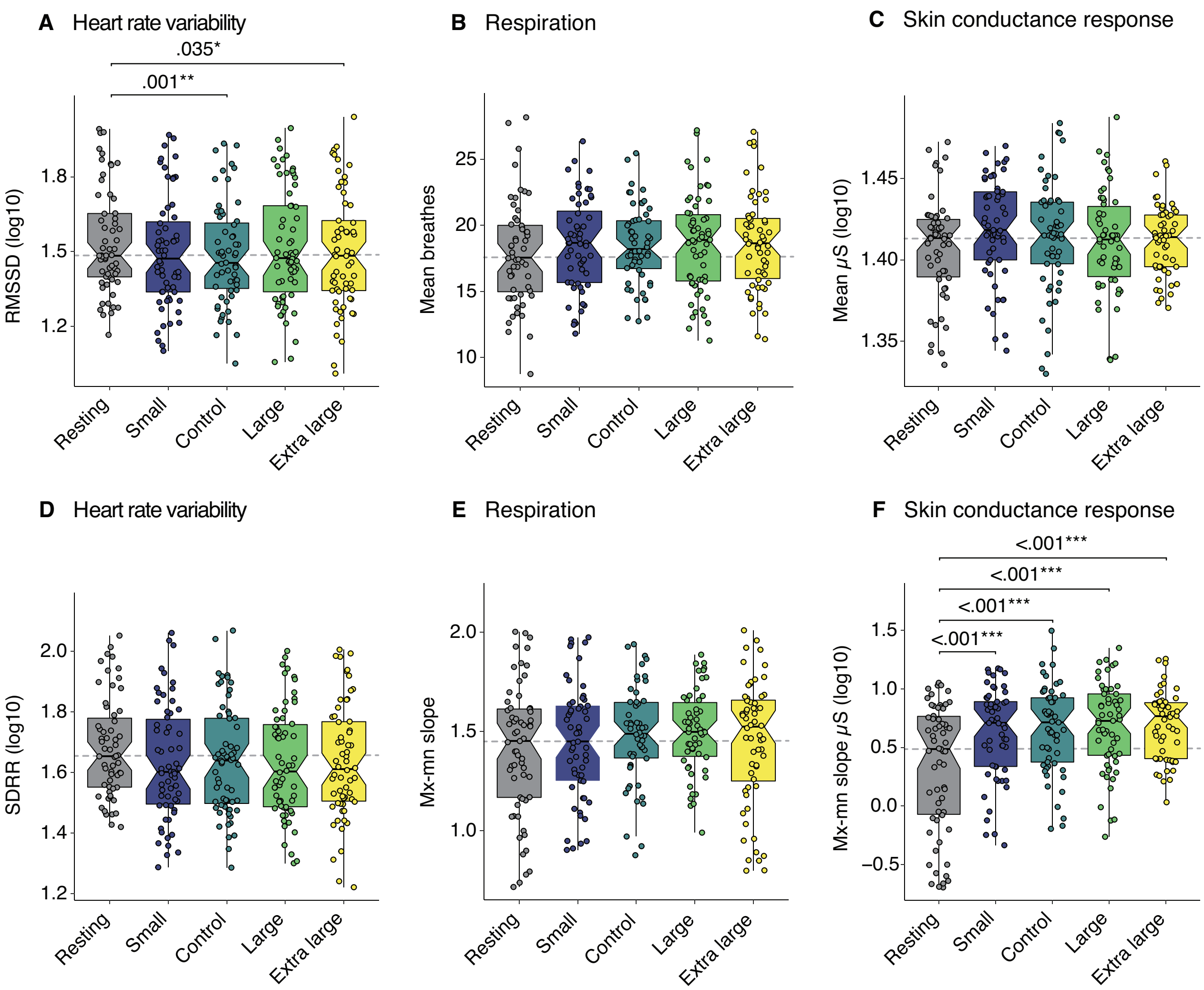
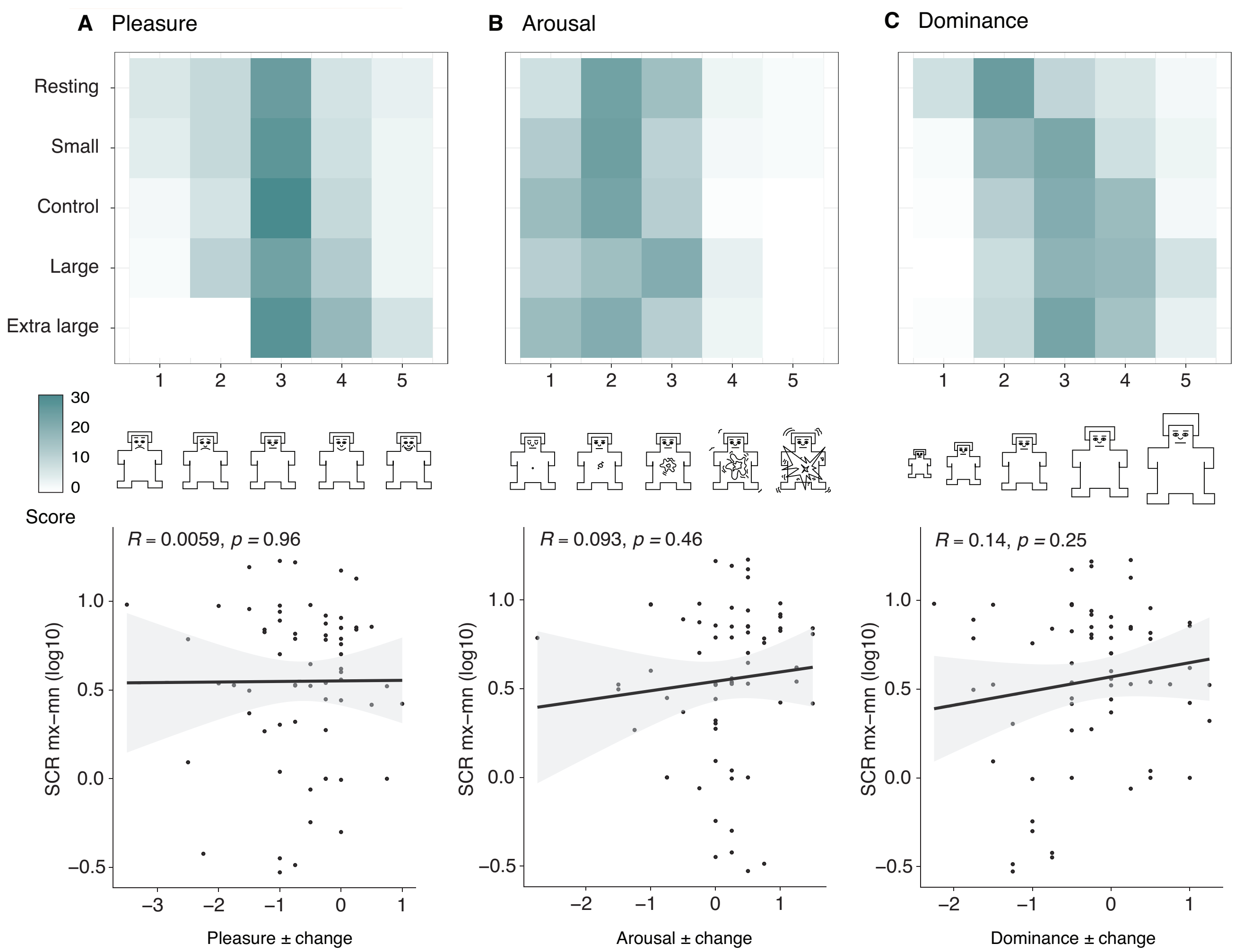

A
Resting
Small (75%)
Control (100%)
Large (125%)
Extra large (150%)
Randomized order
2 mins
B
Virtual chair
Virtual door
Field of view
Seated participant
IEQ
Recording equipment
C
Stereoscopic tracking glasses
EEG system
Respiratory belt
SCR finger cradles
ECG electrodes

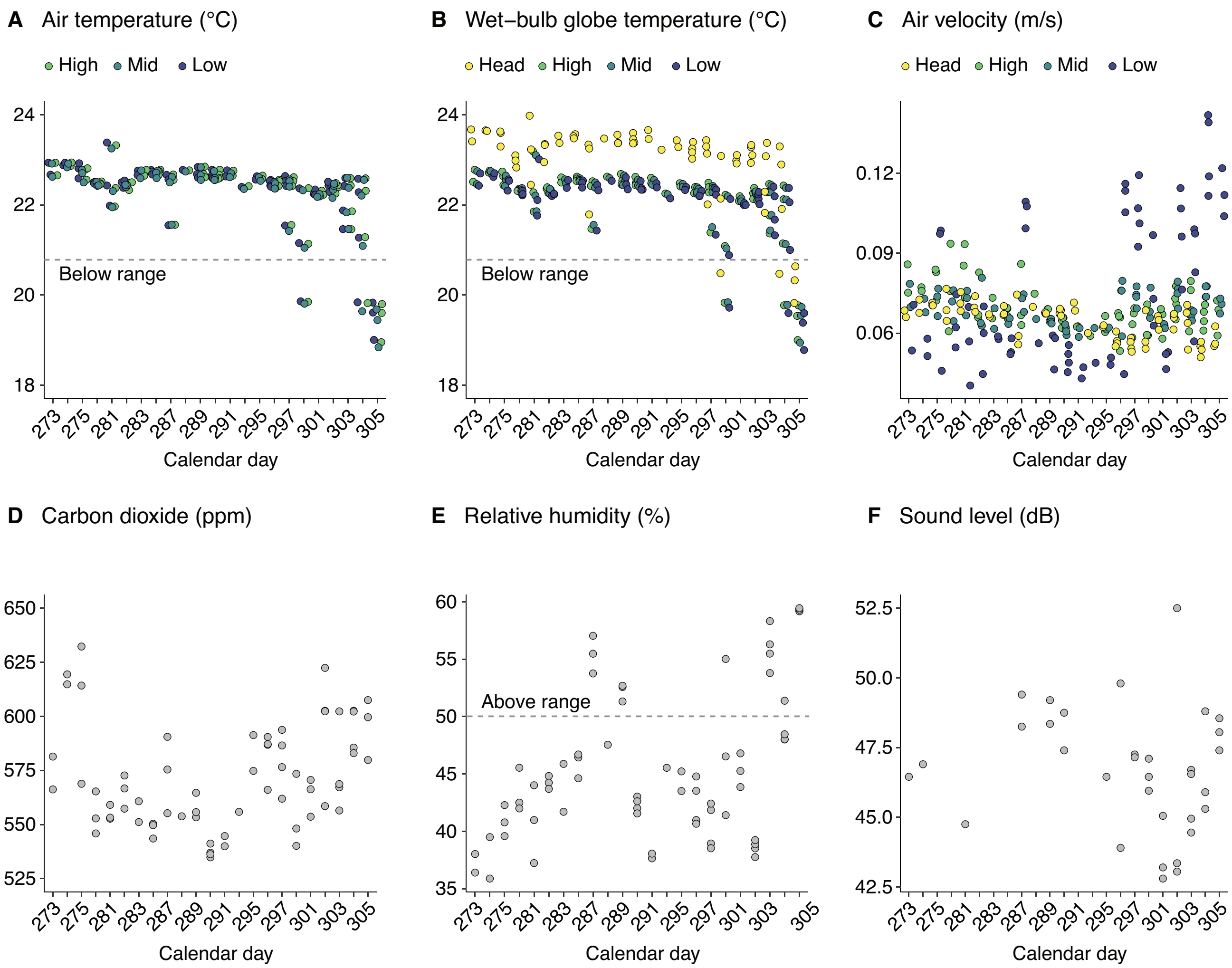

A Beta 13-29 Hz
dB
-15
-14
-13
-12
Resting
Control
Extra large
<.001***
.018*
Power (log10+3)
2.0
1.5
1.0
0.5
B Low gamma 30-45 Hz
-22
-20
-17
-15
.080
C High gamma 55-70 Hz
-25.0
-22.5
-20.0
0.0

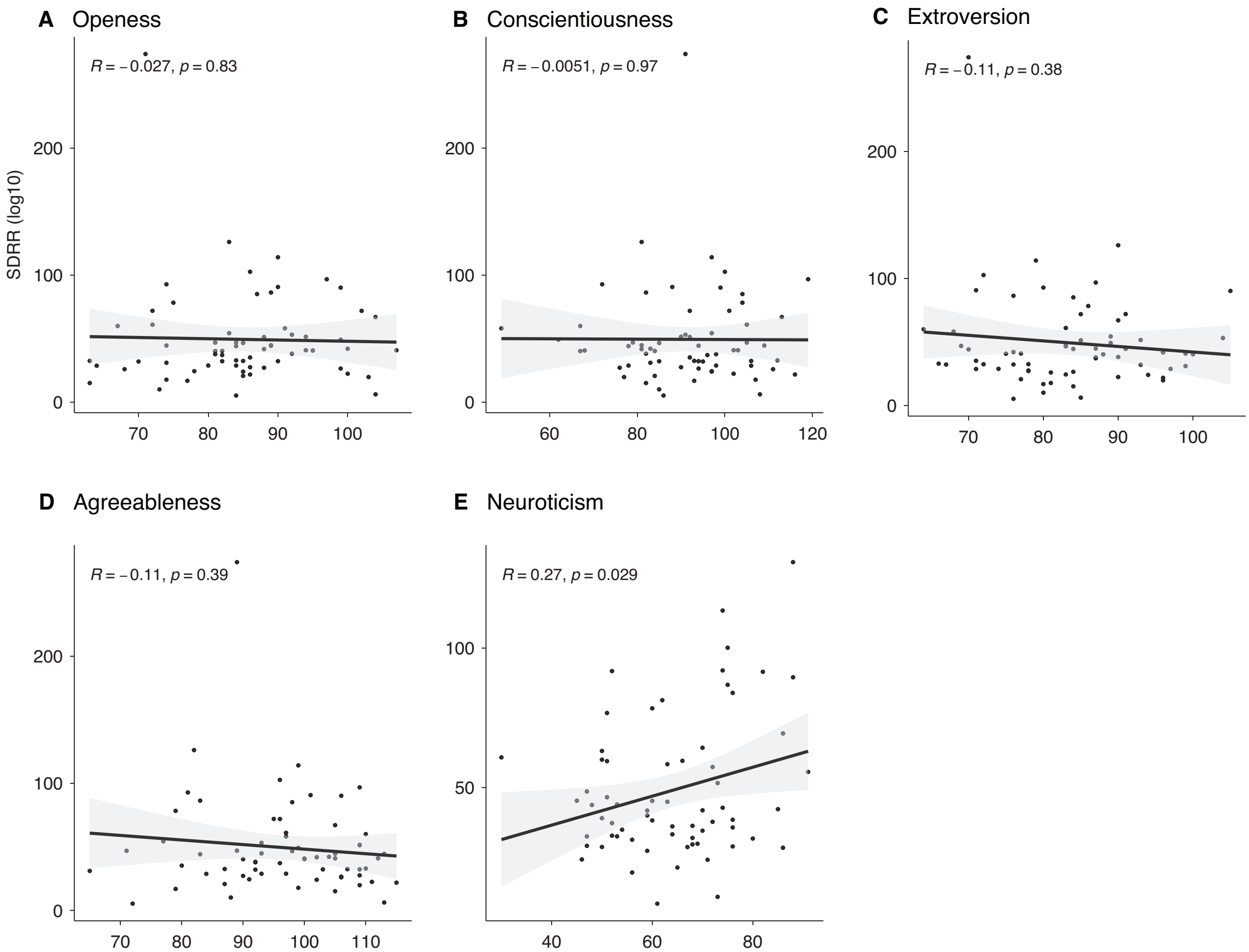

A Power spectra across frequencies (all electrodes)
Low-gamma
High-gamma
Resting
Small
Control
Large
Extra large
Power (dB)
Frequency (Hz)
B Low-gamma frontal mid-line
<.001***
.020*
.004**
Resting
Small
Control
Large
Extra large
C High-gamma frontal midline
<.001***
.045*
.045*



A Heart rate variability
.035*
.001**
RMSSD (log10)
1.2
1.5
1.8
B Respiration
Mean breathes
10
15
20
25
C Skin conductance response
Mean μS (log10)
1.35
1.40
1.45
D Heart rate variability
SDRR (log10)
1.2
1.4
1.6
1.8
2.0
E Respiration
Mx-mn slope
1.0
1.5
2.0
F Skin conductance response
<.001***
<.001***
<.001***
<.001***
Mx-mn slope μS (log10)
−0.5
0.0
0.5
1.0
1.5
Resting
Small
Control
Large
Extra large


A Pleasure
B Arousal
C Dominance
Resting
Small
Control
Large
Extra large
1
2
3
4
5
30
20
10
0
Score
R = 0.0059, p = 0.96
R = 0.093, p = 0.46
R = 0.14, p = 0.25
SCR mx−mn (log10)
1.0
0.5
0.0
−0.5
Pleasure ± change
Arousal ± change
Dominance ± change


A Air temperature (°C)
High Mid Low
24
22
20
18
Below range
273 275 281 283 287 289 291 295 297 301 303 305
Calendar day
B Wet−bulb globe temperature (°C)
Head High Mid Low
24
22
20
18
Below range
273 275 281 283 287 289 291 295 297 301 303 305
Calendar day
C Air velocity (m/s)
Head High Mid Low
0.12
0.09
0.06
273 275 281 283 287 289 291 295 297 301 303 305
Calendar day
D Carbon dioxide (ppm)
650
625
600
575
550
525
273 275 281 283 287 289 291 295 297 301 303 305
Calendar day
E Relative humidity (%)
60
55
50
45
40
35
Above range
273 275 281 283 287 289 291 295 297 301 303 305
Calendar day
F Sound level (dB)
52.5
50.0
47.5
45.0
42.5
273 275 281 283 287 289 291 295 297 301 303 305
Calendar day


A Openess
R = −0.027, p = 0.83
SDRR (log10)
0
100
200
70
80
90
100
B Conscientiousness
R = −0.0051, p = 0.97
0
100
200
60
80
100
120
C Extroversion
R = −0.11, p = 0.38
0
100
200
70
80
90
100
D Agreeableness
R = −0.11, p = 0.39
0
100
200
70
80
90
100
110
E Neuroticism
R = 0.27, p = 0.029
50
100
40
60
80