

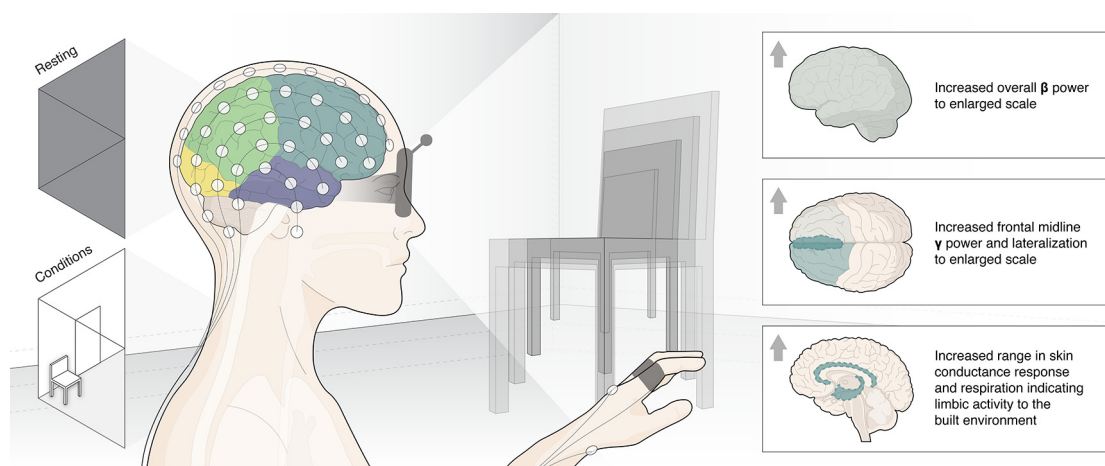
# Enlarged Interior Built Environment Scale Modulates High-Frequency EEG Oscillations

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## Visual 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, behavior, 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

## Significance Statement

Our empirical study provides a technique and approach for assessing the impact of built environment design on emotion. Using virtual reality (VR), we assessed autonomic nervous system, electroencephalography (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 (CAVE), while monitoring indoor environmental quality (IEQ). This research and technique enhance our understanding of how to predict, design, and optimize interior spaces for optimal mental health.

Environment (CAVE) and controlling for indoor environmental quality (IEQ), 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 (SCR) and heart rate variability (HRV) 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.

**Key words:** cave automatic virtual environment; electroencephalography; heart rate variability; respiration; scale; skin conductance

## 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 et al., 2018). Accordingly, understanding whether the buildings we inhabit affect 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 et al., 2017), impact cellular, molecular and behavioral outcomes (Nithianantharajah and Hannan, 2006; Janssen et al., 2018). Despite this, there have been few human studies investigating interior environments as a component of environmental enrichment (McDonald et al., 2018). Following work indicating the role of environmental enrichment on brain structure, function and behavior, 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 (Raskin, 1954; Alexander et al., 1977).

The concept of understanding whether room or enclosure scale affects behavior 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 behavior and interaction of space and people, is often studied (Evans et al., 1996). Similarly, in animal models the concept of “housing density” is explored (Whittaker et al., 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 (Vartanian et al., 2015; Coburn et al., 2020). 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 behavioral response (Levenson, 1988; Thayer and Lane, 2000; Hagemann et al., 2003). 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 et al., 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

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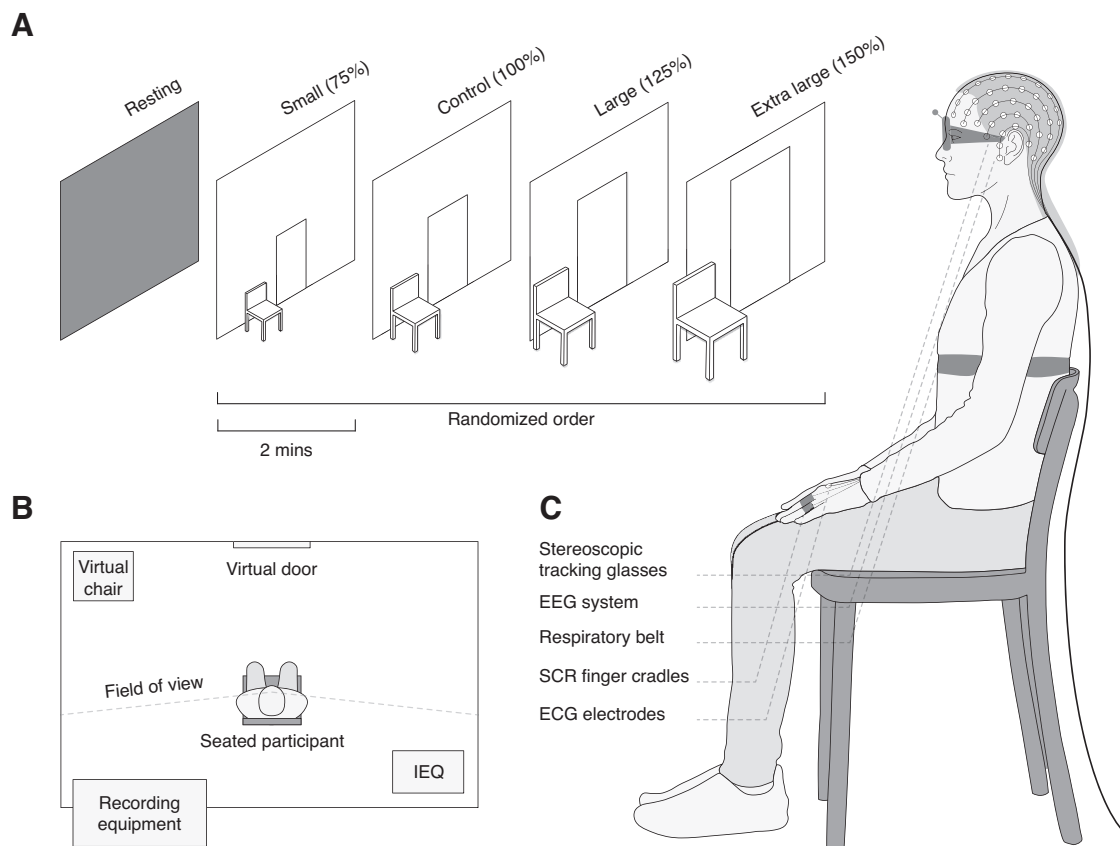
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**Figure 1.** Experimental design and setup. **A**, Isometric view of conditions. Participants were presented with eyes open resting state, followed by four randomized scale conditions. Each scene lasted 2 min, between which the resting state was displayed while the participant completed a self-report assessment of emotion. **B**, Floor plan indicating the position of items in the experiment. 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.

providing greater sensorimotor integration than virtual reality (VR) headsets (Sanchez-Vives and Slater, 2005; Bohil et al., 2011; Kalantari et al., 2021). 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 et al., 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 et al., 1999), attention (Müller et al., 2000), and memory (Tallon-Baudry et al., 1998). We expected changes to scale would result in increased frontal midline power and frontal hemispheric lateralization in the  $\theta$  and  $\alpha$  bandwidths, because of their association with emotion (Aftanas and Golocheikine, 2001; Coan and 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.

## Materials and Methods

To investigate our research questions, we examined whether 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- $\gamma$  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 AUD gift voucher as reimbursement for their time. An overview of the experimental design and setup is illustrated in Figure 1.

## Participants

The sample size for this study was determined by an a priori power analysis using G\*Power 3.1.9.3 (Faul et al., 2007).

Because of the limited robust studies conducted, a small to moderate effect size was selected ( $f = 0.15$ ) with one group and five measurements, a power of 0.95, a correlation among repeated measures of 0.6, and nonsphericity 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 =  $34.9 \pm 11.3$  years, four participants left-handed) aged between 18 and 55 years old; with no prior training or work experience in built environment design; and with no prior diagnosed psychiatric, neurologic, or neurodevelopmental conditions. A healthy adult sample was selected because of 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.

## Procedure

Participants were individually tested, and each session ran for ~90 min. On arrival, participants completed a secure web-based survey (Qualtrics), which took between 15 and 30 min. 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 and 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 before the experiment and prompted the opportunity to use the bathroom before the experiment to avoid bladder discomfort (Quintana and Heathers, 2014).

Before fitting electrophysiological equipment, skin surfaces on hand and wrist sites which would be in contact with ECG electrodes and the SCR cradles 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 min, 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-min scene exposure. The majority of impedances were kept under 50 k $\Omega$  with an average value of 25.2 k $\Omega$  (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 and 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 2 min 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 five-point visual self-assessment manikin. This process was repeated five times, with a total duration of ~15–20 min.

We measured indoor environmental quality (IEQ) variables within the CAVE throughout the study. These measures were analyzed 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.

## Equipment and stimuli

### CAVE

The CAVE consisted of three walls (3 m wide  $\times$  2.4 m high) and a floor (2.4 m wide  $\times$  3 m 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.

#### *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. Prebaked 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 (820 × 35 × 2040 mm) (Standards Australia 2017), and room dimensions were modelled of the physical CAVE walls (3200 × 3200 × 2400 mm). 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 with the 100% control.

#### *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 set up and briefed on the experiment procedure, the researcher turned off the room lights.

#### *IEQ*

CR100 Measurement and Control System with LoggerNet 4.6.2 software (Campbell Scientific, Inc) was used to acquire and record data. Before 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 were recorded at 1 min intervals which were date and time stamped. We averaged the 1 min 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 five-week period. Overall mean air and wet-bulb globe temperature was within the 21–25°C range for optimal performance (Seppänen and 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 and Fisk, 2004). Sound pressure levels were also within an accepted range for the experiment (Basner et al., 2014).

#### *Self-report data*

Self-report of emotion was collected using the self-assessment manikin where three dimensions, pleasure, arousal, and dominance, are recorded by the participant using a visual 5-point scale (Bradley and 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 signaled they had completed the evaluation.

#### *Data analysis*

##### *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  $\mu$ S; 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, 60–110 s) and one overall time block (10–110 s) to capture whether an effect occurred at onset but diminished because of habituation over the recording. Three datasets from participants were excluded in the SCR and

respiration analysis because of equipment fault. In respiratory data, 10 s from the onset of recording was removed for the measure to be accurately detected. For consistency the last 10 s 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 SD and typical QRS width between 80 ms over a 350 ms minimum period. A low-pass filter of 30 Hz was used. We analyzed the root mean square successive difference (RMSSD) and the SD of the R-R interval (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 SD threshold for detecting minimum peak height. To accommodate the time lag in the equipment detecting the first breath after recording, the first 7 s and last final 7 s of the continuous file for each participant across conditions was removed. Because of 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 nonlinear measurements. Data were analyzed using RStudio (version 1.3.959).  $N=2$  HRV and breathing datasets were excluded from the analysis because of HRV arrhythmia; however, data for SCR were still incorporated. To correct for distribution, a log transformation ( $\log_{10}$ ) was applied to both HRV and SCR data. To correct for normality, we removed outliers which fell below  $[Q1 - (1.5 \times IQR)]$  and were above  $[Q3 + (1.5 \times IQR)]$ . A within subjects repeated measures ANOVA with the Greenhouse–Geisser correction for sphericity was used across the six physiological measures we analyzed. To control for multiple comparisons, a false discovery rate (FDR) correction was applied to the results (Benjamini and Hochberg, 1995).

## EEG

The EEG data were preprocessed using EEGLab (v2019.1) (Delorme and 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- to 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  $>5$  SDs 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 five iterations to evaluate noise in each channel and 0.2 regularization level ( $\lambda$  value) to control the amount of cleaning (Mutanen et al., 2018). Each participant's continuous EEG data were decomposed using independent component analysis

(FastICA algorithm; Hyvärinen and Oja, 2000), with artifactual components identified with assistance from the ICLabel plugin (Pion-Tonachini et al., 2019). A component was removed if ICLabel classified the probability of that component containing brain data were  $<30\%$  and the component was not in the “other” category. The mean of the components removed for each subject was  $6.16 \pm 3.92$ .

Using the time-stamped event markers in the continuous recording, each file was then split into 120 s block files using the start marker for each condition. Data were segmented into 3-s epochs for subsequent analyses. Finally, additional artifact rejection was performed to remove any remaining noisy epochs with data exceeding  $\pm 150 \mu V$  using the EEGLab ‘pop\_eegthresh’ function. After cleaning we calculated the average epochs remaining for each condition and participant (mean number of epochs =  $39.5 \pm 1.46$ ). 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 and 70 Hz; Oostenveld et al., 2011).

To calculate power in the different frequency bands, we created averages across each separate frequency band for each electrode:  $\delta$  (1–3 Hz),  $\theta$  (4–7 Hz),  $\alpha$  (8–12 Hz),  $\beta$  (13–29 Hz), low- $\gamma$  (30–45 Hz), and high- $\gamma$  (55–70 Hz). Power was then averaged over electrodes within three hypothesis-driven a priori ROIs: 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 ROIs, where higher values correspond to stronger power in the right compared with the left ROIs (Demaree et al., 2005):

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

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  $[Q1 - (1.5 \times IQR)]$  and were above  $[Q3 + (1.5 \times IQR)]$ . 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 FDR method was used (Benjamini and Hochberg, 1995). The FDR is an alternative approach to multiple testing which increases detection power over traditional methods for multiple testing (Genovese, 2015).

## 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>.

## Results

### Overview

Six measures were preselected to analyze physiological response to robustly compare group differences in distribution, variability and skew (Rousselet et al., 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 and Allen, 2004; Davidson, 2004) and increased frontal  $\alpha$  and  $\theta$  midline power (Aftanas and Golosheikine, 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 and Schwartz, 1985; Demaree et al., 2005). Self-report rating changes were compared with  $\pm$  direction of the physiological and EEG responses, to determine whether the pattern of the two measurement types aligned. On inspection of the extracted raw data, an exploratory test was run *a posteriori* to analyze  $\gamma$  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 whether underlying characteristics in the study sample interacted with the themes emergent in the results. No significant effect was found, see Extended Data Figure 2-2.

### 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 ( $F_{(4,201)} = 7.04$ ,  $p \leq 0.001$ ,  $\eta_p^2 = 0.110$ ). Power was significantly lower in resting state than: small [ $M_{\text{diff}} = -0.041$ ,  $SE_{\text{diff}} = 0.015$ ,  $t_{(57.0)} = -2.808$ ,  $p_{\text{corrected}} = 0.016$ , 95% CI  $(-0.068, -0.010)$ ], control [ $M_{\text{diff}} = -0.042$ ,  $SE_{\text{diff}} = 0.013$ ,  $t_{(57.0)} = -3.101$ ,  $p_{\text{corrected}} = 0.015$ , 95% CI  $(-0.069, -0.015)$ ], large [ $M_{\text{diff}} = -0.036$ ,  $SE_{\text{diff}} = 0.036$ ,  $t_{(57.0)} = -2.729$ ,  $p_{\text{corrected}} = 0.016$ , 95% CI  $(-0.066, -0.013)$ ], and extra-large [ $M_{\text{diff}} = -0.067$ ,  $SE_{\text{diff}} = 0.015$ ,  $t_{(57.0)} = -3.820$ ,  $p_{\text{corrected}} \leq 0.001$ , 95% CI  $(-0.095, -0.040)$ ]. There was also significant increase in power when comparing the small to the extra-large condition [ $M_{\text{diff}} = -0.027$ ,  $SE_{\text{diff}} = 0.012$ ,  $t_{(57.0)} = -2.217$ ,  $p_{\text{corrected}} = 0.044$ , 95% CI  $(-0.048, -0.002)$ ], the control to the extra-large [ $M_{\text{diff}} = 0.006$ ,  $SE_{\text{diff}} = 0.013$ ,  $t_{(57.0)} = 0.445$ ,  $p_{\text{corrected}} = 0.018$ , 95% CI  $(-0.046, -0.008)$ ], and the large to the extra-large [ $M_{\text{diff}} = -0.032$ ,  $SE_{\text{diff}} = 0.011$ ,  $t_{(57.0)} = -2.788$ ,  $p_{\text{corrected}} = 0.016$ , 95% CI  $(-0.046, -0.003)$ ].

In the low- $\gamma$  bandwidth we found significant differences ( $F_{(4,161)} = 13.6$ ,  $p \leq 0.001$ ,  $\eta_p^2 = 0.229$ ). During *post hoc* analysis we detected significantly lower power for resting state to: small [ $M_{\text{diff}} = -0.184$ ,  $SE_{\text{diff}} = 0.027$ ,  $t_{(46.0)} = -5.409$ ,  $p_{\text{corrected}} \leq 0.001$ , 95% CI  $(-0.200, -0.100)$ ], control [ $M_{\text{diff}} = -0.128$ ,  $SE_{\text{diff}} = 0.026$ ,  $t_{(46.0)} =$

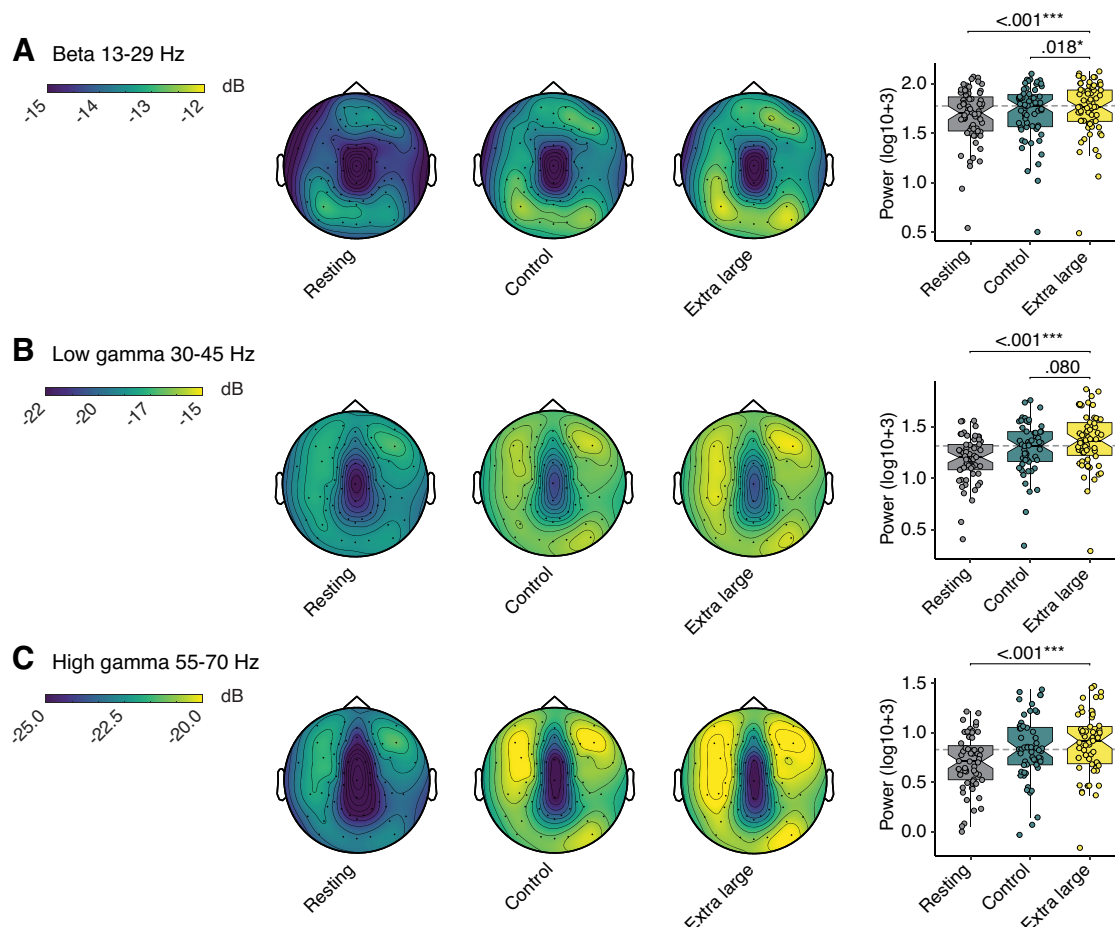
$-4.918$ ,  $p_{\text{corrected}} \leq 0.001$ , 95% CI  $(-0.177, -0.076)$ ], large [ $M_{\text{diff}} = -0.129$ ,  $SE_{\text{diff}} = 0.030$ ,  $t_{(46.0)} = -4.378$ ,  $p_{\text{corrected}} \leq 0.001$ , 95% CI  $(-0.188, -0.076)$ ], and extra-large [ $M_{\text{diff}} = -0.173$ ,  $SE_{\text{diff}} = 0.025$ ,  $t_{(46.0)} = -6.934$ ,  $p_{\text{corrected}} \leq 0.001$ , 95% CI  $(-0.222, -0.131)$ ]. 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 with the resting state ( $F_{(4,160)} = 12.8$ ,  $p \leq 0.001$ ,  $\eta_p^2 = 0.217$ ). These effects were only seen between resting and the scale conditions: small [ $M_{\text{diff}} = -0.198$ ,  $SE_{\text{diff}} = 0.040$ ,  $t_{(46.0)} = -4.949$ ,  $p_{\text{corrected}} \leq 0.001$ , 95% CI  $(-0.291, -0.145)$ ], control [ $M_{\text{diff}} = -0.144$ ,  $SE_{\text{diff}} = 0.037$ ,  $t_{(46.0)} = -3.905$ ,  $p_{\text{corrected}} \leq 0.001$ , 95% CI  $(-0.222, -0.078)$ ], large [ $M_{\text{diff}} = -0.189$ ,  $SE_{\text{diff}} = 0.040$ ,  $t_{(46.0)} = -4.708$ ,  $p_{\text{corrected}} \leq 0.001$ , 95% CI  $(-0.243, -0.084)$ ], and extra-large [ $M_{\text{diff}} = -0.223$ ,  $SE_{\text{diff}} = 0.035$ ,  $t_{(46.0)} = -6.382$ ,  $p_{\text{corrected}} \leq 0.001$ , 95% CI  $(-0.276, -0.139)$ ].

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 ( $F_{(3,158)} = 15.1$ ,  $p \leq 0.001$ ,  $\eta_p^2 = 0.229$ ). With differences between resting and the scale conditions: small [ $M_{\text{diff}} = -0.153$ ,  $SE_{\text{diff}} = 0.031$ ,  $t_{(51.0)} = -5.001$ ,  $p_{\text{corrected}} \leq 0.001$ , 95% CI  $(-0.206, -0.086)$ ], control [ $M_{\text{diff}} = -0.134$ ,  $SE_{\text{diff}} = 0.029$ ,  $t_{(51.0)} = -4.598$ ,  $p_{\text{corrected}} \leq 0.001$ , 95% CI  $(-0.189, -0.072)$ ], large [ $M_{\text{diff}} = -0.132$ ,  $SE_{\text{diff}} = 0.029$ ,  $t_{(51.0)} = -4.578$ ,  $p_{\text{corrected}} \leq 0.001$ , 95% CI  $(-0.185, -0.076)$ ], and extra-large [ $M_{\text{diff}} = -0.173$ ,  $SE_{\text{diff}} = 0.031$ ,  $t_{(51.0)} = -5.628$ ,  $p_{\text{corrected}} \leq 0.001$ , 95% CI  $(-0.226, -0.106)$ ]. Similar effects were seen in the  $\theta$  bandwidth ( $F_{(3,164)} = 13.0$ ,  $p \leq 0.001$ ,  $\eta_p^2 = 0.203$ ). Follow-up analysis indicated lower power was detected for resting state than small [ $M_{\text{diff}} = -0.093$ ,  $SE_{\text{diff}} = 0.021$ ,  $t_{(51.0)} = -4.449$ ,  $p_{\text{corrected}} \leq 0.001$ , 95% CI  $(-0.131, -0.049)$ ], control [ $M_{\text{diff}} = -0.083$ ,  $SE_{\text{diff}} = 0.020$ ,  $t_{(51.0)} = -4.161$ ,  $p_{\text{corrected}} \leq 0.001$ , 95% CI  $(-0.125, -0.047)$ ], large [ $M_{\text{diff}} = -0.095$ ,  $SE_{\text{diff}} = 0.018$ ,  $t_{(51.0)} = -5.269$ ,  $p_{\text{corrected}} \leq 0.001$ , 95% CI  $(-0.137, -0.063)$ ], and extra-large [ $M_{\text{diff}} = -0.110$ ,  $SE_{\text{diff}} = 0.021$ ,  $t_{(51.0)} = -5.219$ ,  $p_{\text{corrected}} \leq 0.001$ , 95% CI  $(-0.155, -0.074)$ ]. Lastly,  $\alpha$  waves, which are commonly found during awake rest, showed within-subject effects ( $F_{(2,111)} = 5.00$ ,  $p = 0.007$ ,  $\eta_p^2 = 0.089$ ); however, follow-up analysis indicated that resting state  $\alpha$  power was only significantly lower to the control condition [ $M_{\text{diff}} = 0.083$ ,  $SE_{\text{diff}} = 0.026$ ,  $t_{(51.0)} = 3.178$ ,  $p_{\text{corrected}} \leq 0.001$ , 95% CI  $(0.034, 0.136)$ ]. 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 Figures 2-1 and 2-2.

### 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- $\gamma$  and high- $\gamma$  bandwidth was undertaken after analyzing the results of the





**Figure 2.** 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.  $\beta$  13–29 Hz (A), low- $\gamma$  30–45 Hz with amplitude range (B), and high- $\gamma$  55–70 Hz (C).

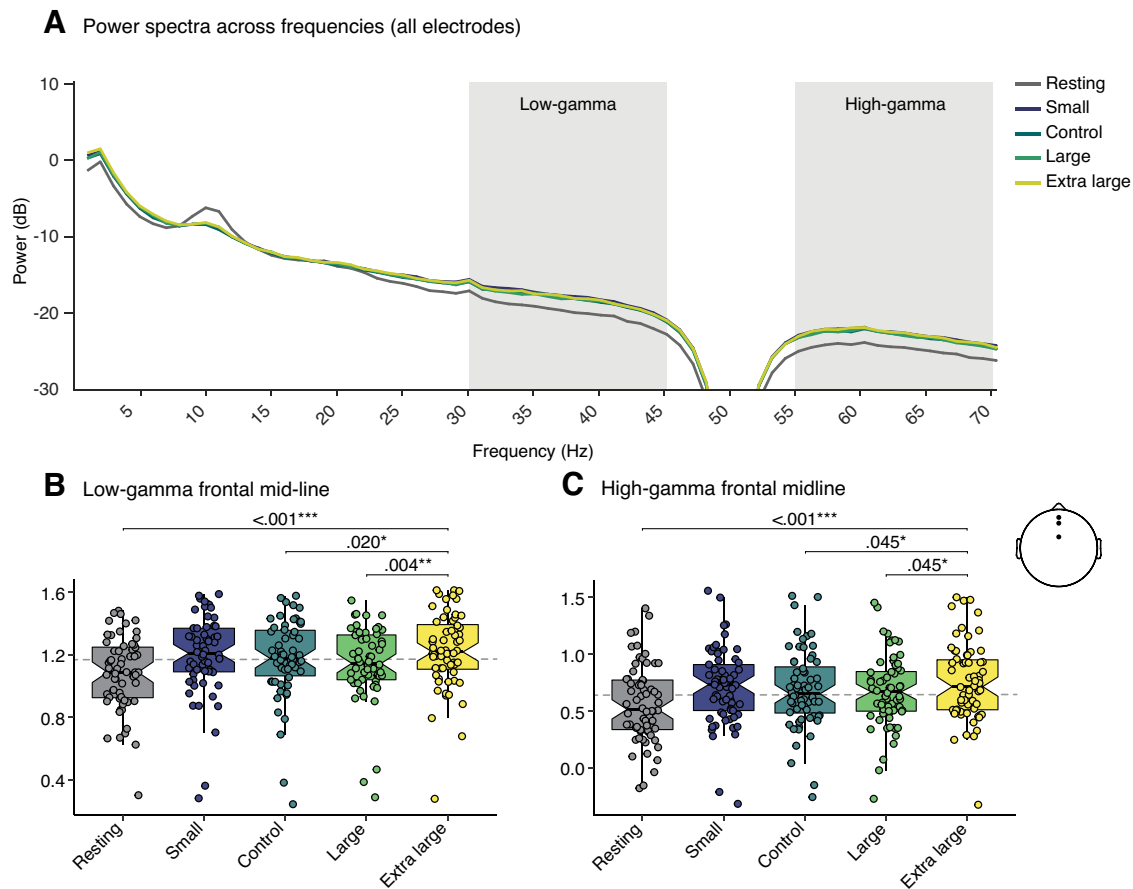
overall power spectral density. Frontal midline power in the low- $\gamma$  bandwidth increased with the scale of the room ( $F_{(4,207)} = 25.7$ ,  $p \leq 0.001$ ,  $\eta_p^2 = 0.255$ ). *Post hoc* comparisons showed significant differences between resting state and all conditions: small [ $M_{\text{diff}} = -0.107$ ,  $SE_{\text{diff}} = 0.019$ ,  $t_{(53.0)} = -5.737$ ,  $p_{\text{corrected}} \leq 0.001$ , 95% CI  $(-0.147, -0.076)$ ], control [ $M_{\text{diff}} = -0.099$ ,  $SE_{\text{diff}} = 0.018$ ,  $t_{(53.0)} = -5.552$ ,  $p_{\text{corrected}} \leq 0.001$ , 95% CI  $(-0.135, -0.066)$ ], large [ $M_{\text{diff}} = -0.082$ ,  $SE_{\text{diff}} = 0.018$ ,  $t_{(53.0)} = -4.488$ ,  $p_{\text{corrected}} \leq 0.001$ , 95% CI  $(-0.118, -0.046)$ ], and extra-large [ $M_{\text{diff}} = -0.139$ ,  $SE_{\text{diff}} = 0.017$ ,  $t_{(53.0)} = -8.100$ ,  $p_{\text{corrected}} \leq 0.001$ , 95% CI  $(-0.173, -0.108)$ ]. We also detected an increase in power from the control to the extra-large [ $M_{\text{diff}} = -0.046$ ,  $SE_{\text{diff}} = 0.016$ ,  $t_{(64.0)} = -2.882$ ,  $p_{\text{corrected}} = 0.020$ , 95% CI  $(-0.070, -0.012)$ ], and the large to the extra-large [ $M_{\text{diff}} = -0.031$ ,  $SE_{\text{diff}} = 0.014$ ,  $t_{(64.0)} = -2.180$ ,  $p_{\text{corrected}} = 0.004$ , 95% CI  $(-0.090, -0.023)$ ].

An effect of condition was also seen in the high- $\gamma$  bandwidth ( $F_{(4,232)} = 16.6$ ,  $p \leq 0.001$ ,  $\eta_p^2 = 0.211$ ). *Post hoc* analysis revealed differences between the resting state and all conditions: small [ $M_{\text{diff}} = -0.164$ ,  $SE_{\text{diff}} = 0.028$ ,  $t_{(62.0)} = -5.861$ ,  $p_{\text{corrected}} \leq 0.001$ , 95% CI  $(-0.211, -0.100)$ ], control [ $M_{\text{diff}} = -0.137$ ,  $SE_{\text{diff}} = 0.025$ ,  $t_{(62.0)} =$

$-5.454$ ,  $p_{\text{corrected}} \leq 0.001$ , 95% CI  $(-0.188, -0.089)$ ], large [ $M_{\text{diff}} = -0.132$ ,  $SE_{\text{diff}} = 0.029$ ,  $t_{(62.0)} = -4.543$ ,  $p_{\text{corrected}} \leq 0.001$ , 95% CI  $(-0.185, -0.069)$ ], and extra-large [ $M_{\text{diff}} = -0.192$ ,  $SE_{\text{diff}} = 0.025$ ,  $t_{(62.0)} = -7.590$ ,  $p_{\text{corrected}} \leq 0.001$ , 95% CI  $(-0.239, -0.141)$ ]. We also found a difference between the control to extra-large [ $M_{\text{diff}} = -0.055$ ,  $SE_{\text{diff}} = 0.026$ ,  $t_{(62.0)} = -2.263$ ,  $p_{\text{corrected}} = 0.045$ , 95% CI  $(-0.103, -0.007)$ ], and large to extra-large [ $M_{\text{diff}} = -0.060$ ,  $SE_{\text{diff}} = 0.026$ ,  $t_{(62.0)} = -2.320$ ,  $p_{\text{corrected}} = 0.045$ , 95% CI  $(-0.113, -0.010)$ ].

An effect of condition on frontal midline power was found in the  $\theta$  band ( $F_{(4,181)} = 9.23$ ,  $p \leq 0.001$ ,  $\eta_p^2 = 0.156$ ). *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 [ $M_{\text{diff}} = -0.094$ ,  $SE_{\text{diff}} = 0.023$ ,  $t_{(50.0)} = -4.162$ ,  $p_{\text{corrected}} \leq 0.001$ , 95% CI  $(-0.138, -0.052)$ ], control [ $M_{\text{diff}} = -0.087$ ,  $SE_{\text{diff}} = 0.021$ ,  $t_{(50.0)} = -4.140$ ,  $p_{\text{corrected}} \leq 0.001$ , 95% CI  $(-0.128, -0.045)$ ], large [ $M_{\text{diff}} = -0.093$ ,  $SE_{\text{diff}} = 0.021$ ,  $t_{(50.0)} = -4.470$ ,  $p_{\text{corrected}} \leq 0.001$ , 95% CI  $(-0.133, -0.051)$ ], and extra-large [ $M_{\text{diff}} = -0.103$ ,  $SE_{\text{diff}} = 0.022$ ,  $t_{(60.0)} = -4.711$ ,  $p_{\text{corrected}} \leq 0.001$ , 95% CI  $(-0.146, -0.067)$ ]. We also detected an effect for  $\alpha$  frontal midline power ( $F_{(3,169)} = 8.58$ ,





**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 (30–45 Hz) and high- $\gamma$  bandwidth (55–70 Hz) are highlighted with the gray shading box. The dip represents the 47- to 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-min exposure.

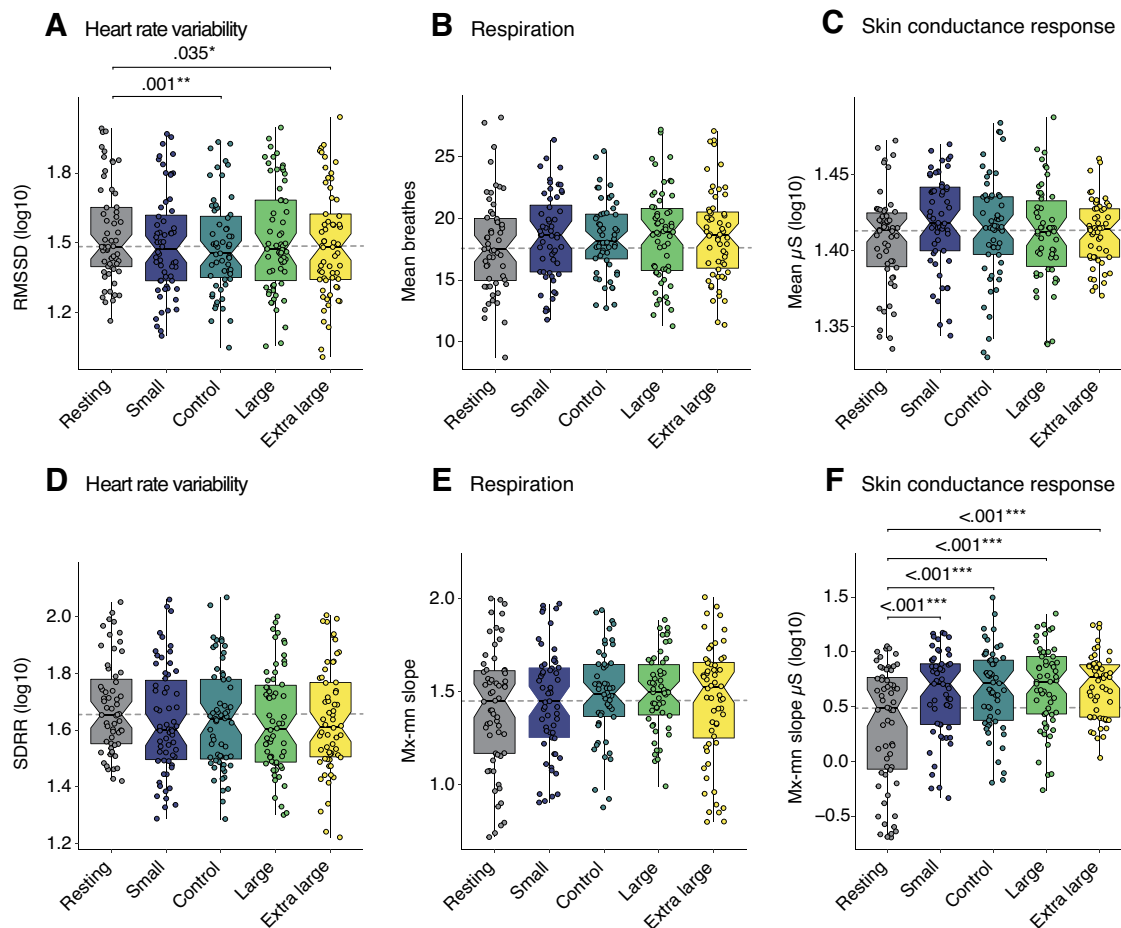
$p \leq 0.001$ ,  $\eta_p^2 = 0.118$ ). However, these effects were limited to comparisons between resting state to the built environment scale conditions, which were lost during correction for multiple comparisons.

Significant differences were also detected in the frontal hemispheric  $\theta$  lateralization ( $F_{(3,145)} = 10.2$ ,  $p \leq 0.001$ ,  $\eta_p^2 = 0.178$ ). *Post hoc* analysis revealed the significant increases in  $\theta$  lateralization was between resting state and the scale built environment conditions: small [ $M_{\text{diff}} = -0.033$ ,  $SE_{\text{diff}} = 0.008$ ,  $t_{(47.0)} = 4.092$ ,  $p_{\text{corrected}} \leq 0.001$ , 95% CI  $(-0.046, -0.016)$ ], control [ $M_{\text{diff}} = -0.032$ ,  $SE_{\text{diff}} = 0.008$ ,  $t_{(47.0)} = 4.014$ ,  $p_{\text{corrected}} \leq 0.001$ , 95% CI  $(-0.047, -0.015)$ ], large [ $M_{\text{diff}} = -0.035$ ,  $SE_{\text{diff}} = 0.008$ ,  $t_{(47.0)} = 4.339$ ,  $p_{\text{corrected}} \leq 0.001$ , 95% CI  $(-0.047, -0.017)$ ], and extra-large [ $M_{\text{diff}} = -0.035$ ,  $SE_{\text{diff}} = 0.008$ ,  $t_{(47.0)} = 4.327$ ,  $p_{\text{corrected}} \leq 0.001$ , 95% CI  $(-0.044, -0.015)$ ]. We also detected difference in frontal  $\alpha$  lateralization ( $F_{(3,124)} = 3.71$ ,  $p = 0.018$ ,  $\eta_p^2 = 0.072$ ). *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 Figures 2-1 and 2-2.

#### 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 RMSSD ( $F_{(3,198)} = 3.89$ ,  $p = 0.007$ ,  $\eta_p^2 = 0.064$ ). RMSSD reflects changes to vagal tone and is less affected by changes in respiration (Shaffer and 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 [ $M_{\text{diff}} = 0.050$ ,  $SE_{\text{diff}} = 0.015$ ,  $t_{(57.0)} = 3.395$ ,  $p_{\text{corrected}} = 0.010$ , 95% CI  $(0.020, 0.079)$ ], and the extra-large [ $M_{\text{diff}} = 0.040$ ,  $SE_{\text{diff}} = 0.014$ ,  $t_{(57.0)} = 2.819$ ,  $p_{\text{corrected}} = 0.035$ , 95% CI  $(0.013, 0.069)$ ], but we did not detect significant difference to the small or large conditions. We detected an effect in the SDRR ( $F_{(4,205)} = 2.79$ ,  $p = 0.032$ ,  $\eta_p^2 = 0.047$ ). However, *post hoc* analysis revealed these values did not survive correction for multiple comparisons.

Respiration measures analyzed were the mean value and maximum minus minimum (Mx-Mn). Within-subjects comparisons for the mean ( $F_{(3,135)} = 2.22$ ,  $p = 0.096$ ,  $\eta_p^2 =$



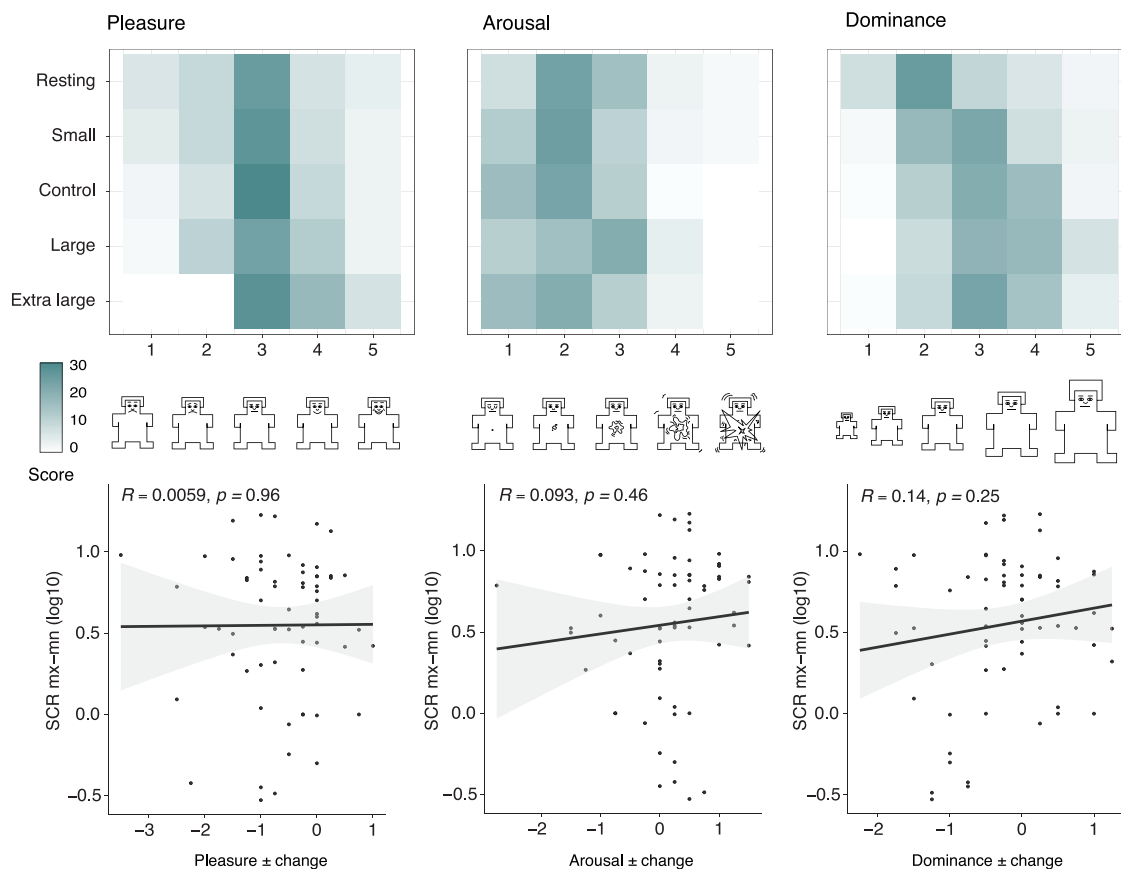
**Figure 4.** Physiological measures between the resting-state, small, control, large, and extra-large conditions. **A–F**, Boxplots with quartile ranges and medians for physiological measures analyzed using raw values. Each data point represents a participant's averaged response from the 2-min exposure. 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 SCR and the RMSSD for HRV.

0.042) and Mx-Mn ( $F_{(3,138)} = 1.07$ ,  $p = 0.368$ ,  $\eta_p^2 = 0.024$ ) did not reveal significant differences between conditions.

SCR measures were the mean and the Mx-Mn of the slope. The within-subjects analysis did not show significant differences between conditions in the mean ( $F_{(3,115)} = 1.68$ ,  $p = 0.170$ ,  $\eta_p^2 = 0.046$ ). There was, however, a significant difference between conditions in Mx-Mn ( $F_{(3,150)} = 10.7$ ,  $p \leq 0.001$ ,  $\eta_p^2 = 0.171$ ). *Post hoc* comparisons for the Mx-Mn showed a significant increase from resting state to conditions with small [ $M_{\text{diff}} = -0.234$ ,  $SE_{\text{diff}} = 0.059$ ,  $t_{(57.0)} = -3.992$ ,  $p_{\text{corrected}} = 0.002$ , 95% CI  $(-0.819, -0.262)$ ], control [ $M_{\text{diff}} = -0.233$ ,  $SE_{\text{diff}} = 0.061$ ,  $t_{(57.0)} = -3.814$ ,  $p_{\text{corrected}} = 0.004$ , 95% CI  $(-0.803, -0.248)$ ], large [ $M_{\text{diff}} = -0.266$ ,  $SE_{\text{diff}} = 0.060$ ,  $t_{(57.0)} = -4.412$ ,  $p_{\text{corrected}} \leq 0.001$ , 95% CI  $(-0.884, -0.323)$ ] and extra-large [ $M_{\text{diff}} = -0.249$ ,  $SE_{\text{diff}} = 0.056$ ,  $t_{(57.0)} = -4.454$ ,  $p_{\text{corrected}} \leq 0.001$ , 95% CI  $(-0.926, -0.345)$ ]. Results are shown in Figure 4. Descriptives and significance values for physiological measures are presented in Extended Data Figures 4-1 and 4-2.

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

It is important to understand whether participants can accurately identify changes to their emotional state. Currently, accepted practice during postoccupancy evaluations of buildings is to complete surveys with building users to understand whether 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 ( $F_{(4,236)} = 12.0$ ,  $p \leq 0.001$ ,  $\eta^2 = 0.156$ ). *Post hoc* comparisons showed significant positive increases between resting state and all conditions, small [ $M_{\text{diff}} = 0.727$ ,  $SE_{\text{diff}} = 0.123$ ,  $t_{(65.0)} = 5.904$ ,  $p_{\text{corrected}} \leq 0.001$ , 95% CI  $(-0.819, -0.262)$ ], control [ $M_{\text{diff}} = 0.591$ ,  $SE_{\text{diff}} = 0.126$ ,  $t_{(65.0)} = 4.695$ ,  $p_{\text{corrected}} \leq 0.001$ , 95% CI  $(-0.803, -0.248)$ ], large [ $M_{\text{diff}} = 0.576$ ,  $SE_{\text{diff}} = 0.122$ ,  $t_{(65.0)} = 4.709$ ,



**Figure 5.** Correlations between self-assessment and physiological response. (Top row) Heatmap of the aggregated self-report responses across participants for pleasure, arousal, and dominance. (Middle row) The pictorial scale on the x-axis depicts the SAM dimensions of pleasure, arousal, and dominance. (Bottom row) Correlations were used to understand if a relationship between physiological response and self-report could be found for pleasure, arousal, and dominance. 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  $\pm$  value from each domain in the self-assessment manikin.

$p_{\text{corrected}} \leq 0.001$ , 95% CI  $(-0.884, -0.323)$ ], and extra-large [ $M_{\text{diff}} = 0.591$ ,  $SE_{\text{diff}} = 0.126$ ,  $t_{(65,0)} = 4.695$ ,  $p_{\text{corrected}} \leq 0.001$ , 95% CI  $(-0.926, -0.345)$ ], but did not reveal significant differences between scale conditions. No significant effects were observed for self-reports of arousal ( $F_{(4,245)} = 1.36$ ,  $p = 0.251$ ,  $\eta^2 = 0.020$ ) or dominance ( $F_{(3,225)} = 1.78$ ,  $p = 0.143$ ,  $\eta^2 = 0.027$ ).

Using the baseline resting state scores as a comparator, we analyzed whether 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 three dimensions of pleasure ( $r = 0.006$ ,  $p = 0.96$ ), arousal ( $r = 0.093$ ,  $p = 0.46$ ), and dominance ( $r = 0.14$ ,  $p = 0.025$ ) shown in Figure 5.

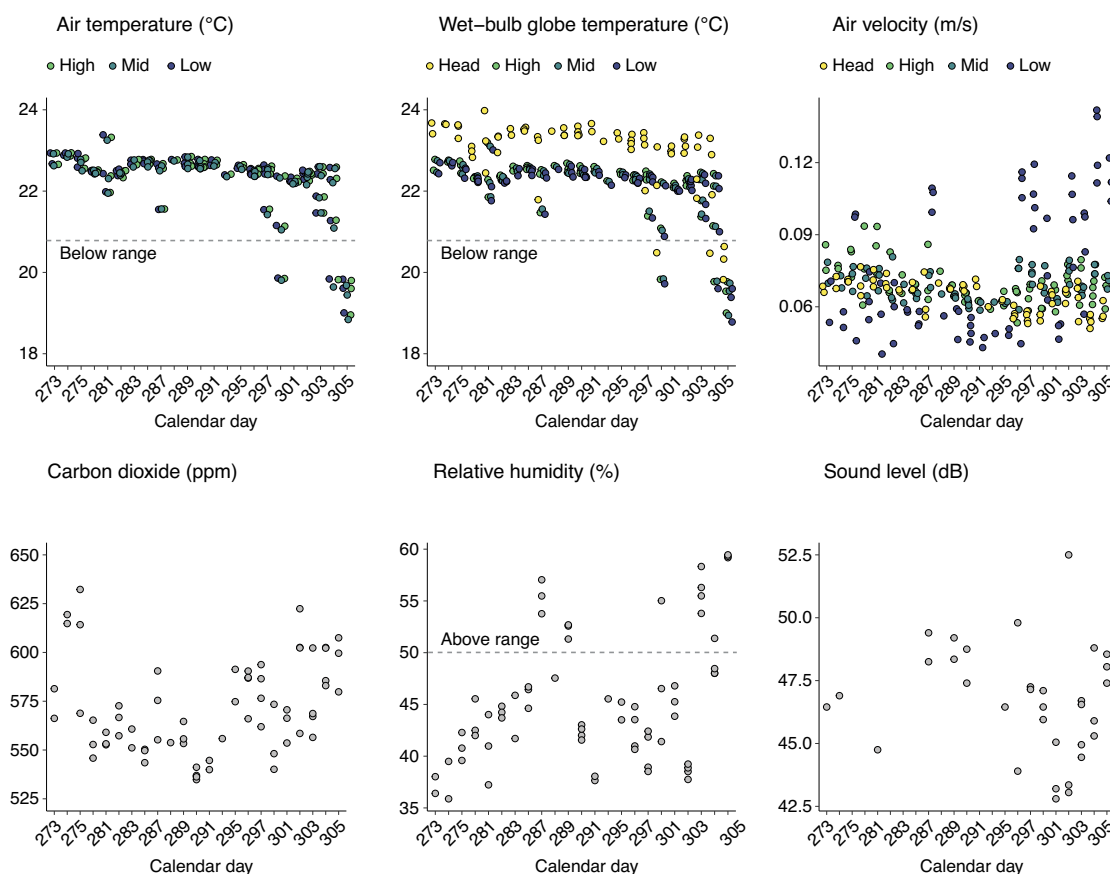
#### We did not detect a relationship between potential confounding variables such as order of exposure and IEQ range with the neurophysiological results

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 because of the exposure order.

We measured IEQ variables within the CAVE throughout the study. Air temperature ( $^{\circ}\text{C}$ ) was stratified across three height levels of low ( $M = 22.2 \pm \text{SEM} = 0.108$ ), mid ( $M = 22.2 \pm \text{SEM} = 0.106$ ), and high ( $M = 22.3 \pm \text{SEM} = 0.105$ ). Wet-bulb globe temperature ( $^{\circ}\text{C}$ ), which measures apparent temperature, was stratified across four height levels of low ( $M = 22.1 \pm \text{SEM} = 0.106$ ), mid ( $M = 22.2 \pm \text{SEM} = 0.102$ ), high ( $M = 22.2 \pm \text{SEM} = 0.104$ ), and approximate head height for standing position ( $M = 23.1 \pm \text{SEM} = 0.111$ ). Air velocity (m/s) was also stratified across four levels of low ( $M = 0.076 \pm \text{SEM} = 0.003$ ), mid ( $M = 0.069 \pm \text{SEM} \leq 0.001$ ), high ( $M = 0.070 \pm \text{SEM} = 0.001$ ), and head ( $M = 0.006 \pm \text{SEM} \leq 0.001$ ). We also recorded overall relative humidity (%;  $M = 45.4 \pm \text{SEM} = 0.781$ ) and carbon dioxide in parts per million (ppm;  $M = 572 \pm \text{SEM} = 2.92$ ). Noise levels (dB) fluctuated because





**Figure 6.** Exposure order and comfort conditions. All IEQ data are organized by calendar day the reading was collected on (x-axis). Multiple points represent the number of participants from each day. Measurements stratified by height data were required to accommodate differences in temperature and air velocity.

of mechanical projector lamp ventilation ( $M = 46.7 \pm \text{SEM} = 0.383$ ). Results are shown in Extended Data Figure 2-1.

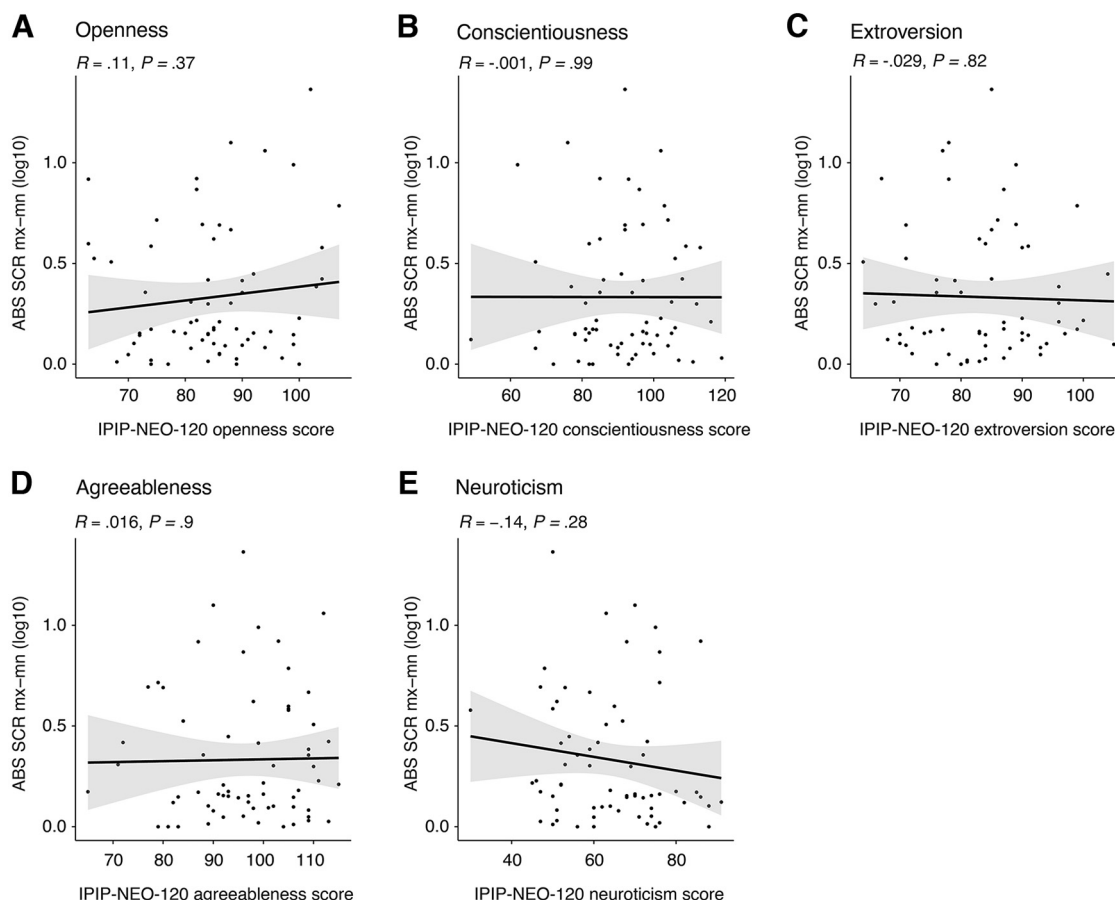
### We did not detect a relationship between personality and autonomic responsiveness to conditions

To understand whether personality played a role in response to the built environment, we tested whether differences in participants' personality accounted for differences in response to the built environment. Participants completed the abbreviated International Personality Inventory Pool (IPIP-NEO-120) before 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 7.

## 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 VR and IEQ 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 et al., 2018) and thermal comfort (see Fig. 6). We also detected increases in measures of range for skin conductance (Mx-Mn slope) and HRV (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



**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 skin conductance response Mx-Mn slope value (SCR Mx-Mn). No correlation was found.

this difference was not seen in self-report of arousal or dominance.

The results of this study indicate that changes in HRV 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 behavioral 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 et al., 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., 1999, 2000).

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 and 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 and 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 using an analysis approach incorporating source localization of the EEG to aid reducing the impact of any eye movement

artifact in the signal (Carl et al., 2012; Hipp and 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 et al., 1998), while others remain inconsistent (Kassam and 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 postoccupancy 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 (Simos et al., 2002; Fitzgibbon et al., 2004). 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 whether task-based performance is impacted (Jensen et al., 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 et al., 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 and 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 whether 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 et al., 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 whether 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 in 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 whether the built environment impacts those with preexisting 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 (Sanchez-Vives and Slater, 2005; Kalantari et al., 2021). VR enables a high level of environmental control over the design, testing and is cost-efficient when compared with 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 whether 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 whether built environment design can provide a neuroprotective factor for individuals who are at increased risk of developing a psychological disorder because of 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.

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