Architecture with Feeling Research Study

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Stakeholder summary report

DEAKIN UNIVERSITY

Architecture with Feeling Research Study

Summary

Thank you for supporting our research study. We're delighted to share with you a brief overview of the findings. We have also provided a copy of the publications arising from the study following this summary.

Study aims

The aim of this research was to understand the effect of the built environment on emotion. When considering the 'built-environment' we were interested in understanding if the properties of interior spaces/rooms within buildings (such as houses, offices, schools and hospitals etc.) are impacting our emotional states. This involved looking at the activity happening in the brain and ways the body responds while we are in the built environment.

Methods

This study included 66 adult participants aged between 18 to 55 years of age. Participants were seated in the middle of a virtual reality room for approximately 20-minutes while we recorded brain activity, heart rate, breathing, sweat activity and self-report of emotion.

To measure brain activity, we used a technique called electroencephalography (EEG). This is where we record electrical activity in the brain through placing electrodes placed on the scalp.

We also recorded indoor environmental quality (air, light, sound) during the study and analysed other characteristics (demographics, personality) of participants.

Figure: Diagram of experimental setup, measures and brain regions of interest.

Main results

Enlarged room scale affects brain activity linked to attention and cognitive performance

Although we did not detect brain and body activity linked to emotional processing, we found evidence that enlarged scale of the built environment resulted in a type of brain activity usually linked to attention and cognitive performance. This could mean being in a larger room impacts your ability to perform tasks, such as remembering directions or responding to difficult questions, which we are currently investigating.

Publication: https://doi.org/10.1523/ENEURO.0104-22.2022

Blue coloured walls impact brain and body activity linked to emotional processing

We also found that blue coloured walls (when compared to white) impact brain and body activity linked to emotional processing. Here, we can compare the brain activity to other studies looking at types of emotional response to understand similarities. For example, the activity was similar to what we'd observe if you were presented with a smiling face. Note: Only a smaller subset of participants were involved in this part of the study.

Publication: https://doi.org/10.1111/psyp.14121

Changing the size and colour of a room also changes how different parts of the brain "talk" to one another

Lastly, we found that both enlarging and reducing scale enhanced resulted in changes in how different parts of the brain communicate to one another. This helps us to understand what types of processes are involved in the brain during exposure to different design characteristics of the built environment.
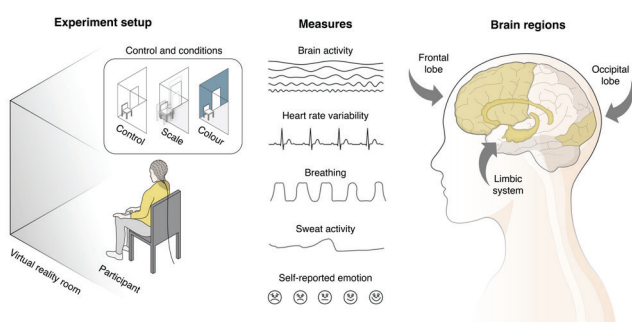
Publication: https://doi.org/10.1002/hbm.26061

Publication:

Enlarged interior built environment scale modulates high frequency EEG oscillations

Cognition and Behavior

Enlarged Interior Built Environment Scale Modulates High-Frequency EEG Oscillations

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Visual Abstract
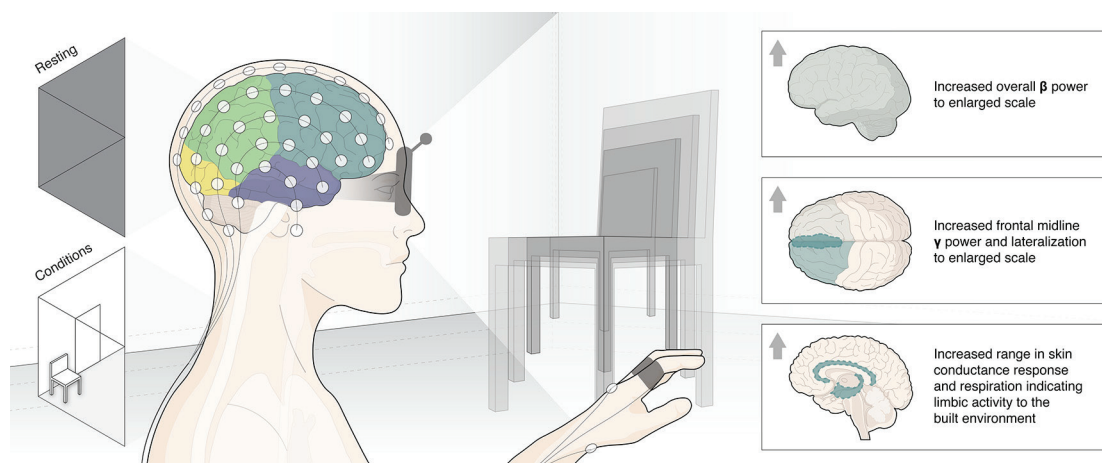
There is currently no robust method to evaluate how built environment design affects our emotion. Understanding emotion is significant, as it influences cognitive processes, behavior, and wellbeing, and is linked to the functioning of physiological systems. As mental health problems are becoming more 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

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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 β bandwidth. Frontal midline low-γ and high-γ 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 θ or α 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 (Nithiananthajah 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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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 γ 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 θ and α 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 α and θ bandwidths. In addition to our primary hypothesis-driven analyses, we conducted exploratory data driven analysis of low-γ and high-γ, 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 ± 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 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 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 × 2.4 m high) and a floor (2.4 m wide × 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 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, 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 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 $[Q1 - (1.5 \times IQR)]$ 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 (λ 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 ± 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 ± 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: δ (1–3 Hz), θ (4–7 Hz) α (8–12 Hz), β (13–29 Hz), low-γ (30–45 Hz), and high-γ (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 γ 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

eNeuro

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 α and θ band lateralization (Coan and Allen, 2004; Davidson, 2004) and increased frontal α and θ midline power (Aftanas and Golocheikine, 2001). Studies have indicated that lower α and θ 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 γ 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 β bandwidth to enlarged scale

We found significant differences between the scale conditions for β 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 [$M_{diff} = -0.041$, $SE_{diff} = 0.015$, $t_{(57.0)} = -2.808$, $p_{corrected} = 0.016$, 95% CI (−0.068, −0.010)], control [$M_{diff} = -0.042$, $SE_{diff} = 0.013$, $t_{(57.0)} = -3.101$, $p_{corrected} = 0.015$, 95% CI (−0.069, −0.015)], large [$M_{diff} = -0.036$, $SE_{diff} = 0.036$, $t_{(57.0)} = -2.729$, $p_{corrected} = 0.016$, 95% CI (−0.066, −0.013)], and extra-large [$M_{diff} = -067$, $SE_{diff} = 0.015$, $t_{(57.0)} = -3.820$, $p_{corrected} \leq 0.001$, 95% CI (−0.095, −0.040)]. There was also significant increase in power when comparing the small to the extra-large condition [$M_{diff} = -027$, $SE_{diff} = 0.012$, $t_{(57.0)} = -2.217$, $p_{corrected} = 0.044$, 95% CI (−0.048, −0.002)], the control to the extra-large [$M_{diff} = 0.006$, $SE_{diff} = 0.013$, $t_{(57.0)} = 0.445$, $p_{corrected} = 0.018$, 95% CI (−0.046, −0.008)], and the large to the extra-large [$M_{diff} = -0.032$, $SE_{diff} = 0.011$, $t_{(57.0)} = -2.788$, $p_{corrected} = 0.016$, 95% CI (−0.046, −0.003)].

In the low-γ 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 [$M_{diff} = -0.184$, $SE_{diff} = 0.027$, $t_{(46.0)} = -5.409$, $p_{corrected} \leq 0.001$, 95% CI (−0.200, −0.100)], control [$M_{diff} = -0.128$, $SE_{diff} = 0.026$, $t_{(46.0)} =$ −4.918, $p_{corrected} \leq 0.001$, 95% CI (−0.177, −0.076)], large [$M_{diff} = -0.129$, $SE_{diff} = 0.030$, $t_{(46.0)} = -4.378$, $p_{corrected} \leq 0.001$, 95% CI (−0.188, −0.076)], and extra-large [$M_{diff} = -0.173$, $SE_{diff} = 0.025$, $t_{(46.0)} = -6.934$, $p_{corrected} \leq 0.001$, 95% CI (−0.222, −0.131)]. We also detected a significant increase from the control to the extra-large in the low-γ bandwidth, but this was lost after applying FDR correction for multiple comparisons. Lastly, an increase in high-γ 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 ([$M_{diff} = -0.198$, $SE_{diff} = 0.040$, $t_{(46.0)} = -4.949$, $p_{corrected} \leq 0.001$, 95% CI (−0.291, −0.145)], control [$M_{diff} = -0.144$, $SE_{diff} = 0.037$, $t_{(46.0)} = -3.905$, $p_{corrected} \leq 0.001$, 95% CI (−0.222, −0.078)], large [$M_{diff} = -0.189$, $SE_{diff} = 0.040$, $t_{(46.0)} = -4.708$, $p_{corrected} \leq 0.001$, 95% CI (−0.243, −0.084)], and extra-large [$M_{diff} = -0.223$, $SE_{diff} = 0.035$, $t_{(46.0)} = -6.382$, $p_{corrected} \leq 0.001$, 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 δ bandwidth ($F_{(3,158)} = 15.1$, $p \leq 0.001$, $\eta_p^2 = 0.229$). With differences between resting and the scale conditions: small ([$M_{diff} = -0.153$, $SE_{diff} = 0.031$, $t_{(51.0)} = -5.001$, $p_{corrected} \leq 0.001$, 95% CI (−0.206, −0.086)], control [$M_{diff} = -0.134$, $SE_{diff} = 0.029$, $t_{(51.0)} = -4.598$, $p_{corrected} \leq 0.001$, 95% CI (−0.189, −0.072)], large [$M_{diff} = -0.132$, $SE_{diff} = 0.029$, $t_{(51.0)} = -4.578$, $p_{corrected} \leq 0.001$, 95% CI (−0.185, −0.076)], and extra-large [$M_{diff} = -0.173$, $SE_{diff} = 0.031$, $t_{(51.0)} = -5.628$, $p_{corrected} \leq 0.001$, 95% CI (−0.226, −0.106)]. Similar effects were seen in the θ 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 [$M_{diff} = -0.093$, $SE_{diff} = 0.021$, $t_{(51.0)} = -4449$, $p_{corrected} \leq 0.001$, 95% CI (−0.131, −0.049)], control [$M_{diff} = -0.083$, $SE_{diff} = 0.020$, $t_{(51.0)} = -4.161$, $p_{corrected} \leq 0.001$, 95% CI (−0.125, −0.047)], large [$M_{diff} = -0.095$, $SE_{diff} = 0.018$, $t_{(51.0)} = -5.269$, $p_{corrected} \leq 0.001$, 95% CI (−0.137, −0.063)], and extra-large [$M_{diff} = -0.110$, $SE_{diff} = 0.021$, $t_{(51.0)} = -5.219$, $p_{corrected} \leq 0.001$, 95% CI (−0.155, −0.074)]. Lastly, α 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 α power was only significantly lower to the control condition [$M_{diff} = 0.083$, $SE_{diff} = 0.026$, $t_{(51.0)} = 3.178$, $p_{corrected} \leq 0.001$, 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 γ bandwidth

An exploratory analysis to further investigate frontal midline and lateralization in the low-γ and high-γ bandwidth was undertaken after analyzing the results of the
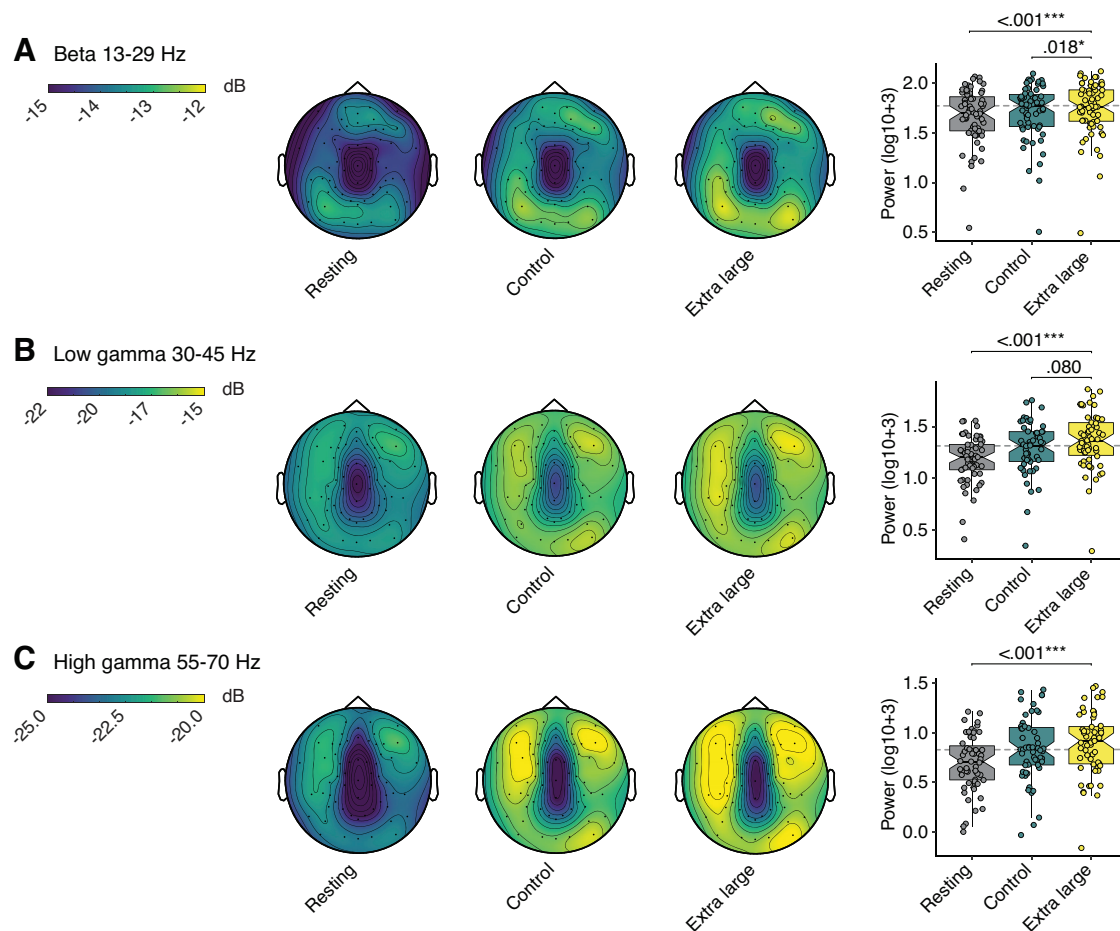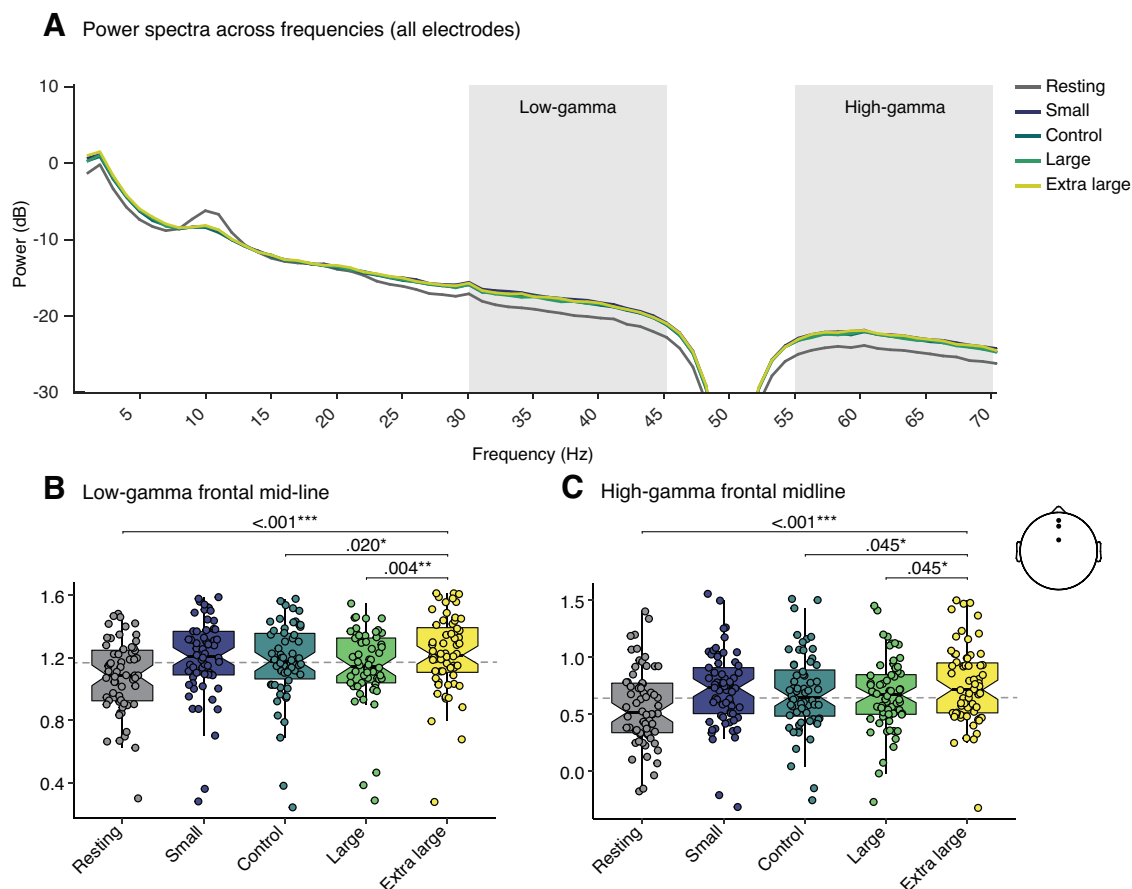
Figure 2. Significant differences between the control and extra-large condition for EEG power spectral density was found in the β bandwidth. To illustrate the differences, we have plotted EEG topographies and boxplots with quartile ranges and medians for the overall power spectra in the β, low-γ, and high-γ bandwidths. Note the Cz site has been interpolated for this figure. β 13–29 Hz (**A**), low-γ 30–45 Hz with amplitude range (**B**), and high-γ 55–70 Hz (**C**).

overall power spectral density. Frontal midline power in the low-γ 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 [$M_{diff} = -0.107$, $SE_{diff} = 0.019$, $t_{(53.0)} = -5.737$, $p_{corrected} \leq 0.001$, 95% CI (–0.147, –0.076)], control [$M_{diff} = -0.099$, $SE_{diff} = 0.018$, $t_{(53.0)} = -5.552$, $p_{corrected} \leq 0.001$, 95% CI (–0.135, –0.066)], large [$M_{diff} = -0.082$, $SE_{diff} = 0.018$, $t_{(53.0)} = -4.488$, $p_{corrected} \leq 0.001$, 95% CI (–0.118, –0.046)], and extra-large [$M_{diff} = -0.139$, $SE_{diff} = 0.017$, $t_{(53.0)} = -8.100$, $p_{corrected} \leq 0.001$, 95% CI (–0.173, –0.108)]. We also detected an increase in power from the control to the extra-large [$M_{diff} = -0.046$, $SE_{diff} = 0.016$, $t_{(64.0)} = -2.882$, $p_{corrected} = 0.020$, 95% CI (–0.070, –0.012)], and the large to the extra-large [$M_{diff} = -0.031$, $SE_{diff} = 0.014$, $t_{(64.0)} = -2.180$, $p_{corrected} = 0.004$, 95% CI (–0.090, –0.023)].

An effect of condition was also seen in the high-γ 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 [$M_{diff} = -0.164$, $SE_{diff} = 0.028$, $t_{(62.0)} = -5.861$, $p_{corrected} \leq 0.001$, 95% CI (–0.211, –0.100)], control [$M_{diff} = -0.137$, $SE_{diff} = 0.025$, $t_{(62.0)} =$

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

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

A Power spectra across frequencies (all electrodes)

B Low-gamma frontal mid-line

C High-gamma frontal midline

Figure 3. Significant differences in EEG low-γ frontal midline power were found. **A**, Power spectra plot showing power (dB) across frequencies. The low-γ bandwidth (30–45 Hz) and high-γ 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 γ midline power spectra. Each data point overlaid represents a participant's averaged response from the 2-min exposure.

$p \leq 0.001$, $\eta_{\mathrm{p}}^2 = 0.118$). 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 θ lateralization ($F_{(3,145)} = 10.2$, $p \leq 0.001$, $\eta_{\mathrm{p}}^2 = 0.178$). *Post hoc* analysis revealed the significant increases in θ lateralization was between resting state and the scale built environment conditions: small [$M_{\mathrm{diff}} = -0.033$, $SE_{\mathrm{diff}} = 0.008$, $t_{(47.0)} = 4.092$, $p_{\mathrm{corrected}} \leq 0.001$, 95% CI (–0.046, –0.016)], control [$M_{\mathrm{diff}} = -0.032$, $SE_{\mathrm{diff}} = 0.008$, $t_{(47.0)} = 4.014$, $p_{\mathrm{corrected}} \leq 0.001$, 95% CI (–0.047, –0.015)], large [$M_{\mathrm{diff}} = -0.035$, $SE_{\mathrm{diff}} = 0.008$, $t_{(47.0)} = 4.339$, $p_{\mathrm{corrected}} \leq 0.001$, 95% CI (–0.047, –0.017)], and extra-large [$M_{\mathrm{diff}} = -0.035$, $SE_{\mathrm{diff}} = 0.008$, $t_{(47.0)} = 4.327$, $p_{\mathrm{corrected}} \leq 0.001$, 95% CI (–0.044, –0.015)]. We also detected difference in frontal α lateralization ($F_{(3,124)} = 3.71$, $p = 0.018$, $\eta_{\mathrm{p}}^2 = 0.072$). *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 ($F_{(3,198)} = 3.89$, $p = 0.007$, $\eta_{\mathrm{p}}^2 = 0.064$). 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 [$M_{\mathrm{diff}} = 0.050$, $SE_{\mathrm{diff}} = 0.015$, $t_{(57.0)} = 3.395$, $p_{\mathrm{corrected}} = 0.010$, 95% CI (0.020, 0.079)], and the extra-large [$M_{\mathrm{diff}} = 0.040$, $SE_{\mathrm{diff}} = 0.014$, $t_{(57.0)} = 2.819$, $p_{\mathrm{corrected}} = 0.035$, 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 ($F_{(4,205)} = 2.79$, $p = 0.032$, $\eta_{\mathrm{p}}^2 = 0.047$). 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_{\mathrm{p}}^2 = $
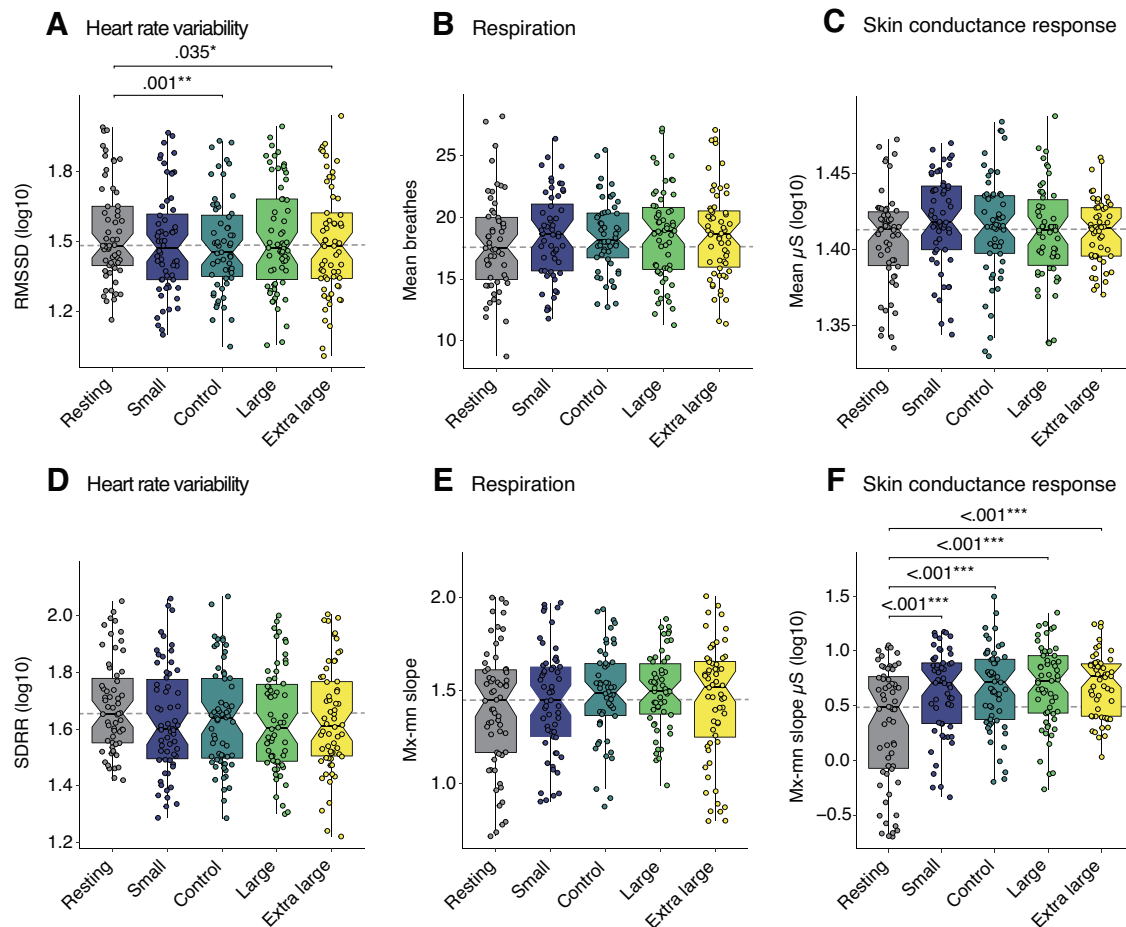
Figure 4. Physiological measures between the resting-state, small, control, large, and extra-large conditions. **A–F**, Boxplots with quartile ranges and medians for physiological measures analyzed using raw values. Each data point represents a participant's averaged response from the 2-min exposure. 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 [$M_{diff} = -0.234$, $SE_{diff} = 0.059$, $t_{(57.0)} = -3.992$, $p_{corrected} = 0.002$, 95% CI (−0.819, −0.262)], control [$M_{diff} = -0.233$, $SE_{diff} = 0.061$, $t_{(57.0)} = -3.814$, $p_{corrected} = 0.004$, 95% CI (−0.803, −0.248)], large [$M_{diff} = -0.266$, $SE_{diff} = 0.060$, $t_{(57.0)} = -4.412$, $p_{corrected} \leq 0.001$, 95% CI (−0.884, −0.323)] and extra-large [$M_{diff} = -0.249$, $SE_{diff} = 0.056$, $t_{(57.0)} = -4.454$, $p_{corrected} \leq 0.001$, 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 [$M_{diff} = 0.727$, $SE_{diff} = 0.123$, $t_{(65.0)} = 5.904$, $p_{corrected} \leq 0.001$, 95% CI (−0.819, −0.262)], control [$M_{diff} = 0.591$, $SE_{diff} = 0.126$, $t_{(65.0)} = 4.695$, $p_{corrected} \leq 0.001$, 95% CI (−0.803, −0.248)], large [$M_{diff} = 0.576$, $SE_{diff} = 0.122$, $t_{(65.0)} = 4.709$,
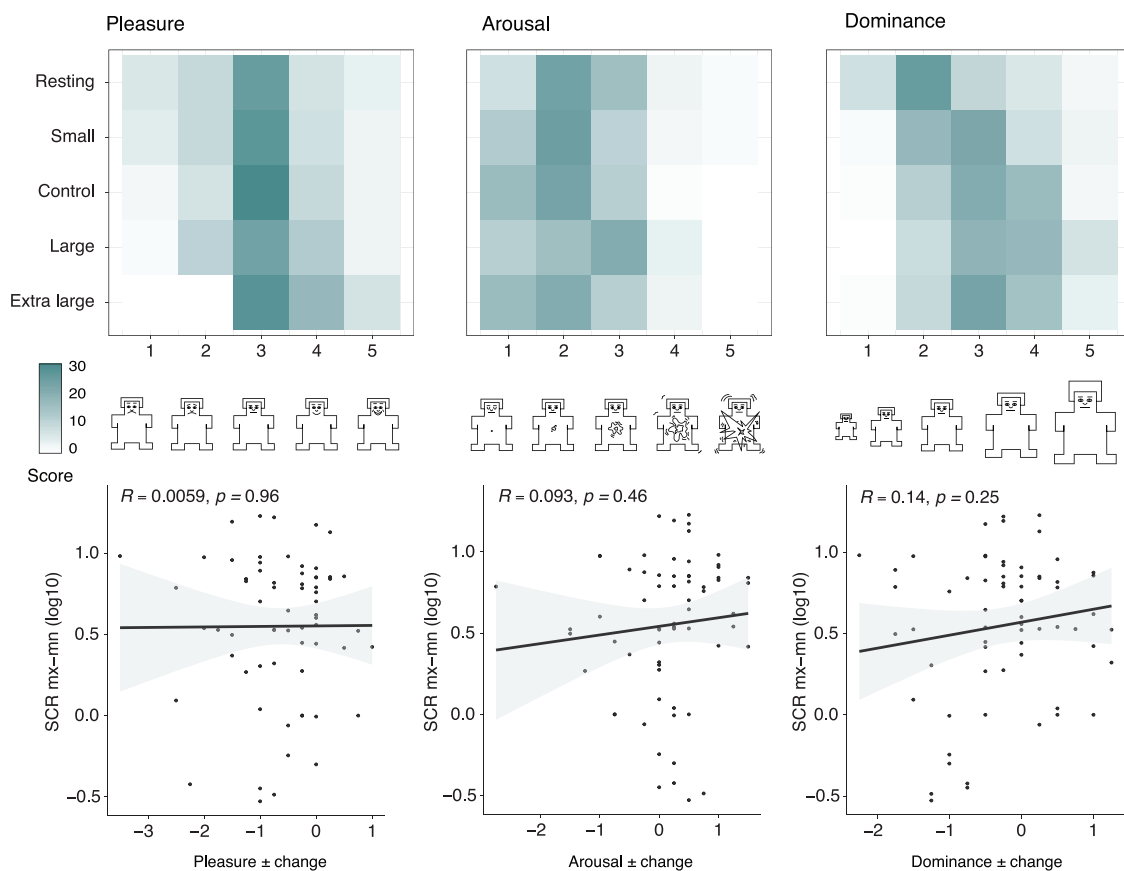
Figure 5. Correlations between self-assessment and physiological response. (Top row) Heatmap of the aggregated self-report responses across participants for pleasure, arousal, and dominance. (Middle row) The pictorial scale on the x-axis depicts the SAM dimensions of pleasure, arousal, and dominance. (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 ± value from each domain in the self-assessment manikin.

$p_{corrected} \leq 0.001$, 95% CI (–0.884, –0.323)], and extra-large [$M_{diff} = 0.591$, $SE_{diff} = 0.126$, $t_{(65.0)} = 4.695$, $p_{corrected} \leq 0.001$, 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 γ 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 (°C) was stratified across three height levels of low (M = 22.2 ± SEM = 0.108), mid (M = 22.2 ± SEM = 0.106), and high (M = 22.3 ± SEM = 0.105). Wet-bulb globe temperature (°C), which measures apparent temperature, was stratified across four height levels of low (M = 22.1 ± SEM = 0.106), mid (M = 22.2 ± SEM = 0.102), high (M = 22.2 ± SEM = 0.104), and approximate head height for standing position (M = 23.1 ± SEM = 0.111). Air velocity (m/s) was also stratified across four levels of low (M = 0.076 ± SEM = 0.003), mid (M = 0.069 ± SEM ≤ 0.001), high (M = 0.070 ± SEM = 0.001), and head (M = 0.006 ± SEM ≤ 0.001). We also recorded overall relative humidity (%; M = 45.4 ± SEM = 0.781) and carbon dioxide in parts per million (ppm; M = 572 ± SEM = 2.92). Noise levels (dB) fluctuated because
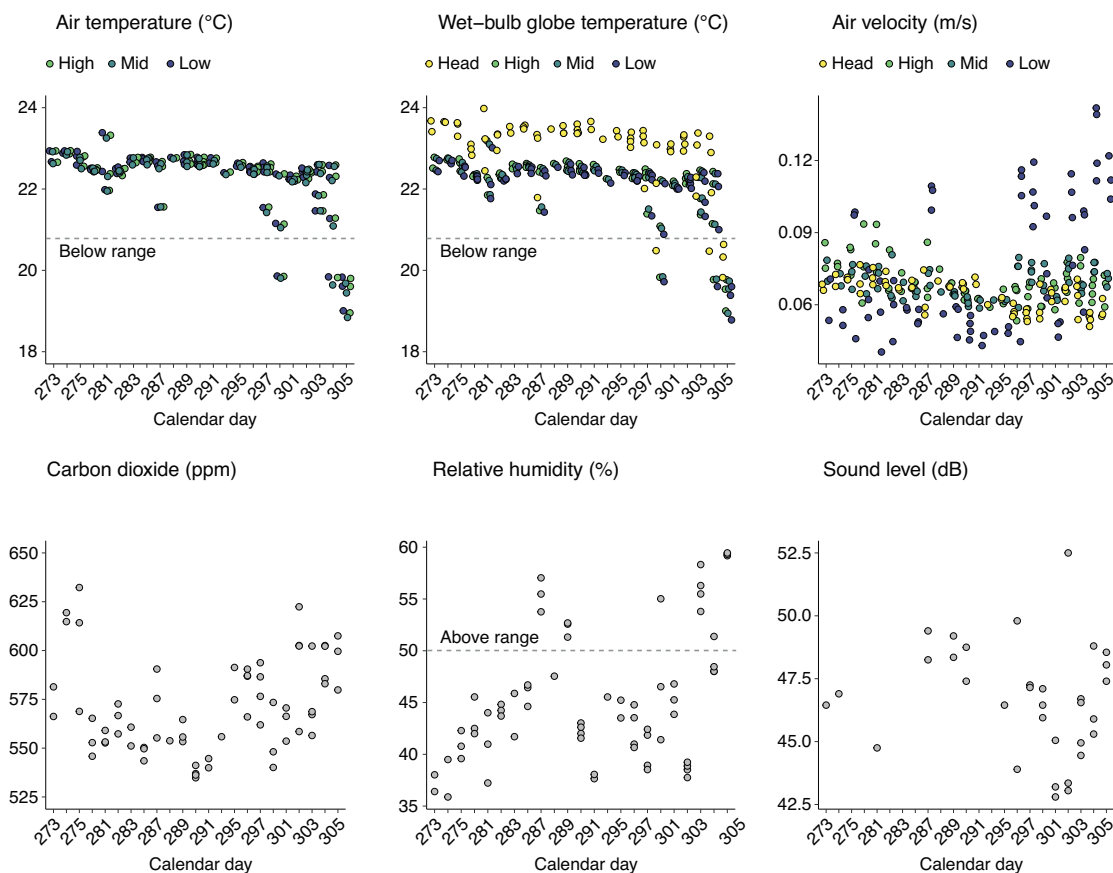
Figure 6. Exposure order and comfort conditions. All IEQ data are organized by calendar day the reading was collected on (*x*-axis). Multiple points represent the number of participants from each day. Measurements stratified by height data were required to accommodate differences in temperature and air velocity.

of mechanical projector lamp ventilation (M = 46.7 ± 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 β, low-γ and high-γ 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 θ and α bandwidths across participants. However, during a posteriori analysis we found increased frontal midline power in the low-γ and high-γ bandwidth, associated with increased scale between control to extra-large, and large to extra-large conditions. We also found increased left lateralization in the γ bandwidth between the large and extra-large condition, suggesting changes in γ 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
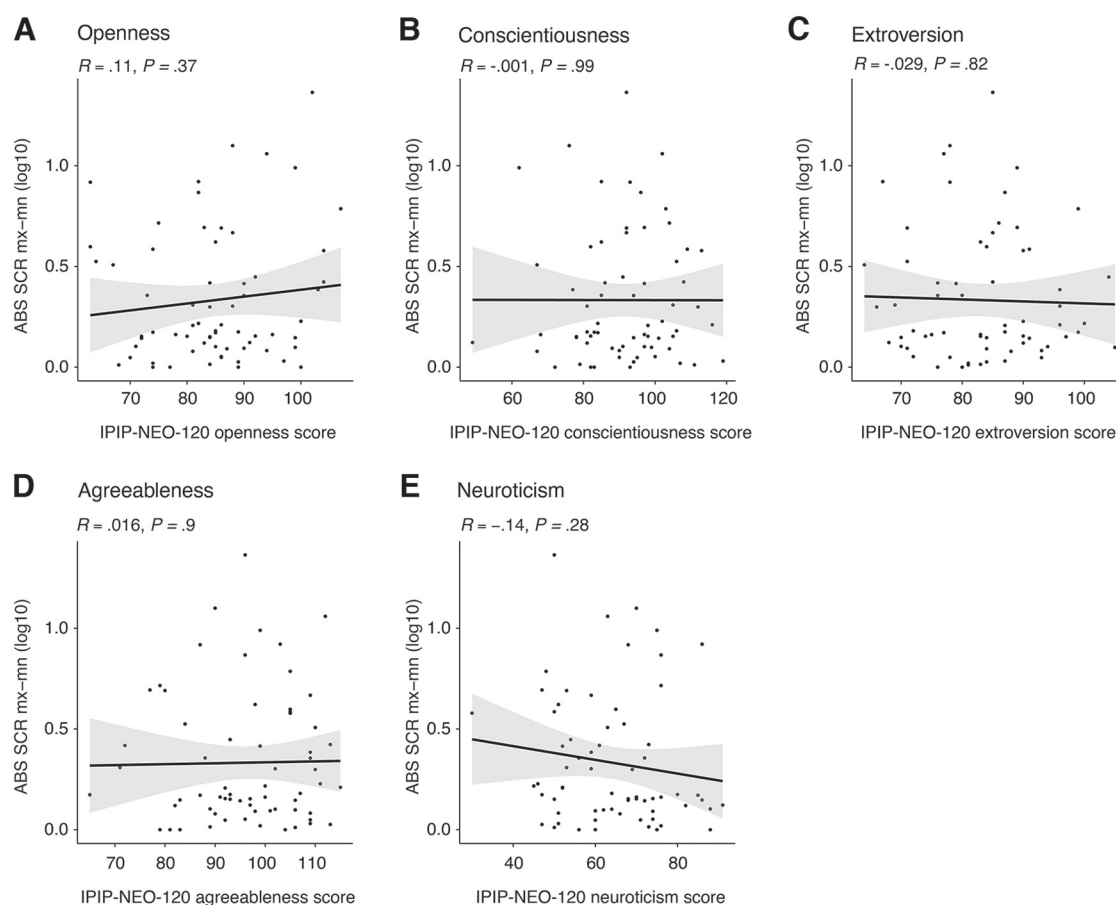
Figure 7. Exploratory correlations between personality measures and physiological response. **A–E**, Correlations between Openness, Conscientiousness, Extroversion, Agreeableness and Neuroticism (OCEAN) big five personality traits and the absolute difference in the averaged response across built environment 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 β bandwidth increased from the small to the extralarge, control to the extra-large, and the large to the extralarge 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 α and θ 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, neuro-developmental, 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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Publication:

Built environment colour modulates autonomic and EEG indices of emotional response

ORIGINAL ARTICLE

PSYCHOPHYSIOLOGY SPR WILEY

Built environment color modulates autonomic and EEG indices of emotional response

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Abstract

Understanding built environment exposure as a component of environmental enrichment has significant implications for mental health, but little is known about the effects design characteristics have on our emotions and associated neurophysiology. Using a Cave Automatic Virtual Environment while monitoring indoor environmental quality (IEQ), 18 participants were exposed to a resting state (black), and two room scenes, control (white) and condition (blue), to understand if the color of the virtual walls affected self-report, autonomic nervous system, and central nervous system correlates of emotion. Our findings showed that exposure to the chromatic color condition (blue) compared to the achromatic control (white) and resting-state (black, no built environment) significantly increased the range in respiration and skin conductance response. We also detected a significant increase in alpha frontal midline power and frontal hemispheric lateralization relative to blue condition, and increased power spectral density across all electrodes in the blue condition for theta, alpha, and beta bandwidths. The ability for built environment design to modulate emotional response has the potential to deliver significant public health, economic, and social benefits to the entire community. The findings show that blue coloring of the built environment increases autonomic range and is associated with modulations of brain activity linked to emotional processing.

KEYWORDS

cave automatic virtual environment, electroencephalography, environmental psychology, frequency analyses, heart rate variability, interior built environment design, respiration, skin conductance, virtual reality, visual perception

1 | INTRODUCTION

We have a limited understanding of the impact that built environment exposure has on our mental health (Anderson et al., 2018; Hoisington et al., 2019). Early life studies have shown the importance of environmental experience in shaping brain development (McLaughlin et al., 2014). In observational studies of individuals deprived of sensory

input in their physical and social environment (imprisonment, orphanages, etc.), participants demonstrate permanent alterations in brain structure and function (Mackes et al., 2020). Similarly, environmental enrichment studies in animal models demonstrate the substantial role that environment has on cellular, molecular and behavioral systems (Nithianantharajah & Hannan, 2006). An increasing number of studies are investigating the public health implications of built environment design. This includes functional properties (enabling movement and facilitating activities) (Benton et al., 2016; Kärmeniemi et al., 2018; Pinter-Wollman et al., 2018) and indoor environmental qualities (Tham et al., 2020). However, we are only beginning to disentangle and rigorously assess the impact of design characteristics such as color, texture, geometry, and scale (Bower et al., 2019). The novelty of social and physical environmental exposures inherent in daily life, alongside the ethical limitations of controlling environmental exposures over prolonged periods of human development, makes this difficult to investigate, with the relatively few studies conducted to date providing only weak evidence (Moore et al., 2018). Nevertheless, through isolating design characteristics of built environments and understanding confounding variables, we can begin to interrogate the impact our surroundings have on our neurophysiological response and, subsequently, mental health.

Color is an integral component of perception (Gegenfurtner, 2003) and has been recognized as an important design characteristic within built environments (Caivano, 2006). Spatially, it can distinguish areas for purpose, aid navigation (Jansen-Osmann & Wiedenbauer, 2004), guide behavior through social and contextual associations (Maier et al., 2009), and create illusionary distortions to our perception (Corney et al., 2009; Guibal & Dresp, 2004; von Castell, Hecht, & Oberfeld, 2018b). While in popular culture it has been suggested that color hue has direct effects on emotion, these associations have been linked to variations in lightness and chroma rather than hue (Schloss et al., 2020). A difficulty in synthesizing results from different studies is caused by the variety of color sources used. Studies conducted in relation to the impact of color on brain activity, as measured using electroencephalography (EEG) and/or physiological response in humans include those which use a light source: halogen, incandescent (Park et al., 2013), light-emitting diode (LED) (Chinazzo et al., 2020; Stamps, 2010); or ink-based source: ambient color (painted surfaces) (Ainsworth et al., 1993; von Castell, Stelzmann, et al., 2018), and stimulus color (dyed or printed material) (Gao & Xin, 2006; Yoto et al., 2007). Furthermore, studies have either explored the individual dimensions of color: Chroma (saturation) (Dresp-Langley & Reeves, 2014; Zieliński, 2016),

hue (pigmentation) (Mehta & Zhu, 2009), and value (brightness or darkness adjustment) (Knez, 2001; von Castell, Hecht, & Oberfeld, 2018a), or used an approach combining and reporting variations in dimensions. When the color is generated through a light source, color temperature is also measured to describe the characteristic of the visible light (Kraneburg et al., 2017; Lasauskaite & Cajochen, 2018). However, there remains difficulty understanding color perception due to variables such as surface materiality, geometry, light field structure, and the viewing position of the observer (Marlow et al., 2012), with research further indicating differences between ink-based and light-source color (Lee et al., 2020). Adding to the difficulty, when investigating the impact of color in the built environment, several recent virtual reality studies have used context-rich settings (bedroom, classroom, hospital waiting room) and have not controlled for indoor environmental qualities (IEQ) outside of the virtually presented environment (Cha et al., 2020; Lipson-Smith et al., 2020; Llinares et al., 2021). With the complexity of dimensions and influencing variables, it has been recognized that applied domains, such as architecture, frequently make assumptions on the effect of color on emotion, without adequately controlling and reporting conditions in the studies (Elliot, 2015; Wilms & Oberfeld, 2018).

Our association with color is also influenced by the intrinsic properties of light and the human visual system. Visual perception of color results from different power spectral distributions of light wavelengths and illumination levels of the environment, which modulate retinal photoreceptor response. As a result of these interacting variables, blue is harder for the human eye to focus on during high illumination levels (i.e., daylight and indoor lighting settings). Consequently, blue is less frequently used for signage and signaling where behavioral action and/or inhibition are critical for safety during daylight. The interaction of both biological and contextual learned responses are known as color-in-context theory (Elliot & Maier, 2012). Studies that explore our conditioning to color in signage have demonstrated blue is less likely to affect behavioral compliance (Braun & Silver, 1995). Similarly, when applied to the built environment, studies examining color-emotion associations within interior built environments have found that 'neutral' is the most-stated self-report to the color blue, compared to red, green, and gray, which invoke a range of emotional associations (Güneş & Olguntürk, 2020). As we cannot remove the social conditioning we experience to colors in our environment, we selected blue as a 'neutral' associated chroma to interrogate.

There is limited research in this field, and results remain highly variable, with no accepted standards of practice and/or conclusive meta-analysis currently available to understand the impact of built environment

color on emotional and neurophysiological response. However, techniques to measure autonomic activity such as heart rate variability (HRV), respiration, and skin conductance response (SCR), can enable us to objectively understand the emotional experience. Physiological findings from the impact of blue color on emotion are inconsistent, with mixed findings on whether HRV is increased with blue color (Küller et al., 2009), decreased (AL-Ayash et al., 2016), or unaffected (Jacobs & Hustmyer, 1974). Similarly, it is unclear what effect blue has on SCR, with contradictory findings on whether an effect exists; and where an effect is found, disparity in whether it results in a positive or negative response (Mikellides, 1990; Rajae-Joordens, 2011). Reduced HRV has been suggested as an indicator of less favorable health, with an increased risk of chronic heart disease (Dekker et al., 2000). Similarly, greater variability in respiration and skin conductance response range are associated with higher levels of arousal and anxiety (Chattopadhyay et al., 1975; Masaoka & Homma, 1997), and increased physiological arousal is associated with anxiety, which can have detrimental effects on cognitive performance (Maloney et al., 2014). Consequently, if we could optimize autonomic responses through color in the built environment, we may be able to support these conditions. Another non-invasive technique that can be used to understand the impact of color is EEG. EEG is a non-invasive technique that measures neural oscillations, enabling us to investigate modulations in brain activity. Emerging research indicates that EEG can be used to classify and detect color stimuli (Göksel Duru & Alobaidi, 2021), and that color can influence attentional capture (Wu et al., 2020), however, the link between color and emotion is yet to be established. Studies investigating emotion using EEG have found frontal midline power (Aftanas & Golocheikine, 2001) and frontal hemispheric lateralization can be used as neurophysiological correlates. Specifically, 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 (Coan & Allen, 2004; Davidson, 2004).

In this study, we investigated whether the blue ambient wall color of an interior room would result in modulation of autonomic, EEG, and self-report indicators of emotion. We selected blue due to previous studies indicating it invokes the most neutral self-report of emotion association. A Cave Automatic Virtual Environment (CAVE) was used to create an environmentally controlled and cost-effective simulation, enabling greater sensorimotor integration than virtual reality headsets (Kalantari et al., 2021; Sanchez-Vives & Slater, 2005). Chromatic adaptation was avoided through the achromatic black resting state prior

to exposure (Jameson et al., 1979). We selected the color blue and matched the properties to a popular paint sample from a large local paint manufacturer to achieve greater ecological validity of a color sample we are exposed to in built settings. The virtual built environment included visual cues in the form of a closed door and a chair within the scene to help participants determine the height, width, and surface depth (Brouwer et al., 2005) (Figure 1). We also collected participant socio-demographic and personality data to understand if characteristics in the study sample interacted with the results. We expected the visually salient nature of the color condition would result in increased autonomic response (Zieliński, 2016), and higher frontal and occipital activation in the theta and alpha bandwidths, as these are associated with emotion (Aftanas & Golocheikine, 2001; Coan & Allen, 2004; Davidson, 1992). Due to the neutral color-emotion association, we expected self-report of pleasure and dominance would remain consistent while arousal would be increased.

2 | RESEARCH DESIGN AND METHOD

The study was approved by the Deakin University Human Research Ethics Committee and carried out in accordance with relevant guidelines and regulations. All participants provided informed and written consent. Participants were offered a $20.00 AUD gift voucher as reimbursement for their time.

2.1 | Participants

Eighteen right-handed adult participants aged between 18 and 55 years old (8 women, mean age = 34.5 ± 9.87 years) were recruited for this study via university and community advertisements. This was a subset of the participants from a study investigating scale. Due to the experimental nature of the study and to reduce confounding variables we selected a healthy adult sample. To be included, participants had to meet the following criteria: (1) Normal or corrected-to-normal vision, (2) able to speak and read English, (3) no prior psychiatric, neurological, or neurodevelopmental conditions, and (4) no prior experience or training in built environment design.

2.2 | Procedure

The study took place over a one-week period at Deakin University Waurn Ponds Campus, Geelong, Victoria,
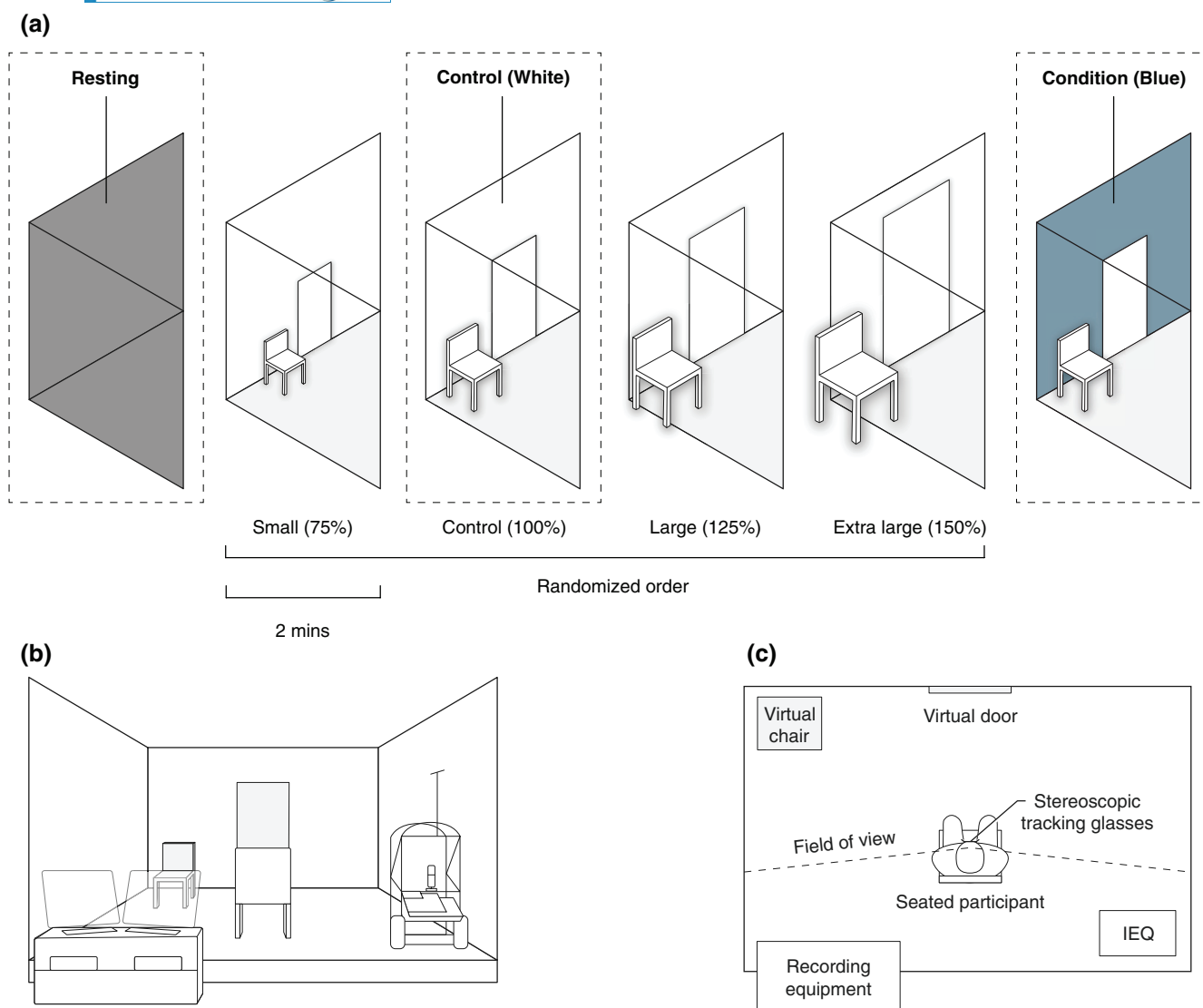
FIGURE 1 Experimental design and setup. (a) Isometric cut away of conditions (including the three scale conditions not included in this study), (b) one-point perspective of the mixed reality environment showing virtual features in gray (chair, door) and the physical environment and equipment in white. (c) Floor plan indicating the position of items in the experiment. Participants were presented with eyes open resting state, followed by four randomized scale conditions (not analyzed in this paper). In this study, we analyzed the blue condition which was presented after the scale conditions in conjunction with the black resting state and white control condition. Each scene lasted two-minutes, between which the resting state was displayed while the participant completed a self-report assessment of emotion. Indoor environmental quality (IEQ) variables were measured continuously, and all recording equipment was positioned outside of the participants' field of view. Diagrams are representative, not drawn to exact scale.

Australia. Each session ran for approximately 90-min, and participants were tested individually. On arrival, participants completed demographics and personality questionnaires. Participants were next fitted with the equipment prior to being brought into the experiment room. Skin surfaces were cleaned before fitting physiological equipment and a 64-channel cap (Philips Hydrocel Geodesic Sensor Net 64-channel HCGSN) was used for acquiring EEG data. The cap was soaked in an electrolyte solution and towels were placed over the participants' lap and shoulders for comfort and to protect the cords before the cap was fitted. EEG data were recorded using Net Station 5 Geodesic EEG software, version 5.4.2 (Electrical Geodesics Inc), and acquired at a sampling rate of 1000 Hz, with Cz as the online reference. A continuous recording was created for each participant and was manually time-stamped by the researcher at the start and end of each 2-min scene exposure using markers. Most impedances were kept under 50 kΩ (considered an acceptable level of impedance for this system) with an average value of 25.2 kΩ ($SD = 7.75$).

Participants were seated in the CAVE for a total duration of approximately 15–20 min to complete the experiment. No natural light was present in the experimental room, overhead lights were turned off during the experiment and participants were tested within daylight hours. Previous studies have suggested that time and duration of blue light exposure can modulate cardiovascular physiological effects (Chellappa et al., 2017). This has thought to be linked to the endogenous circadian timing system, which can trigger changes in blood pressure, vascular tone, heart rate (HR), and variation in beat-to-beat intervals such as SDRR and RMSSD (Boudreau et al., 2012). We conducted an a-posteriori analysis on time of day to confirm this did not influence responsivity to color (see Supporting Information).

We elected to run a static resting-state study where participants sat immersed in the space, rather than setting a task and/or involving physical movement, as this has been thought to affect cognition and memory (Pettijohn & Radvansky, 2016). The seated position mitigated for participant height variability and helped minimize artifact in the electrophysiological measures. The rationale for the static resting-state technique is that isolating design elements will enable further understanding of which features within the built environment make a difference before they can be combined to understand the effect of multiple design characteristics. Each session began with a resting state recording with eyes open to establish baseline. Participants were then exposed to six scenes displayed for two-minutes each in randomized order, using a generated plan for 100 subjects in one block (seed 28107). Three of these scenes are not included in this paper as they were related to modulating room-scale. A period of two-minutes per condition was selected to ensure sufficient EEG data to epoch for stability in connectivity analysis (van Diessen et al., 2015), while avoiding habituation from the experimental conditions and nature of the scenes that could confound the results (O'Gorman, 1977). The two-minute recording period is not uncommon for this type of study (Rogala et al., 2020; Vellante et al., 2020). 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 (Bradley & Lang, 1994; Mehrabian, 1996). During the scene the researcher was outside of the CAVE, monitoring data quality in the recordings.

2.3 | Equipment and stimuli

2.3.1 | Cave automatic virtual environment

The CAVE consisted of three walls (3 m wide × 2.4 m high) and a floor (2.4 m wide × 3 m long), each with

Barco Galaxy NW-12 stereoscopic projectors connected to a series of image generators (computers) with Nvidia Quadro P6000 graphics cards. Quadro Sync II cards at 120 Hz (60 Hz per eye) were used to frame lock the projectors to ensure rendered images were displayed at the same time. An optical-based tracking system consisting of eight cameras tracked user movements within the CAVE to LED markers located on the stereoscopic glasses. 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 connection and updates the tracked position on each rendered frame.

2.3.2 | Virtual environment development and CAVE integration

We created a 3D model that represented a conventional cubic room in Autodesk Revit that was then exported into the Unity game engine (2019.2.15) for CAVE integration. We next applied textures, using a matte plaster texture to the three wall surfaces, a slight gloss texture of bumpy concrete to the floor, a matte wood texture to the door, doorway, and chair, and 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 separate rooms to represent the conditions. 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 built environment conditions were designed using Standards Australia measurements for a residential internal door for reference scale (820 mm × 35 mm × 2040 mm) (Standards Australia, 2017), and room dimensions were modeled of the physical CAVE walls (3200 mm × 3200 mm × 2400 mm). The resting-state scene (no built environment) was rendered in black (R0, G0, B0, hue (degrees) = 0, saturation (%) = 0, brightness (%) = 0. However, due to white finish of the projector screens, while we created a virtual scene with a black background, this appears as a dark gray when displayed on the screens. In the control (white) condition, the wall surfaces were rendered with a white finish (R255, G255, B255, hue (degrees) = 0, saturation (%) = 0, and brightness (%) = 100, and smoothness = 50%). For a realistic color scene, the condition (blue) wall surfaces were rendered with Dulux 'Post Boy A359' (R122, G155, B173, hue (degrees) = 198, saturation (%) = 35.3, brightness (%) = 67.8,

and smoothness = 50%). Data on the indoor environmental quality (IEQ) were collected throughout the study to ensure any fluctuations to these properties linked to data which may influence emotion and neurophysiological response were minimized.

2.3.3 | Indoor environmental quality

We acquired data using CR100 Measurement and Control System with LoggerNet 4.6.2 software (Campbell Scientific, Inc). A test recording was completed prior to the experiment to calibrate the equipment, ensuring the readings were accurate in accordance with EN ISO 7730 Fanger Comfort Model (Fanger, 1970).

We recorded IEQ data 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 5-week data-collection 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).

2.4 | **Data analysis**

2.4.1 | Physiological data

We acquired physiological data 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, 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.

For HRV, we analyzed 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). Ectopic heartbeats were excluded from the analysis. We adjusted detection to a minimum peak height of 1.2 *SD* and typical QRS width between 80 ms over a 350 ms minimum period. Beat classification for RR intervals was set between 600 and 1400 ms with a complexity of 1 to 1.5. We also applied a low-pass filter of 30 Hz. We used the cyclic measurements function for respiration frequency with scoring parameters of 1.3 standard deviation threshold for detecting minimum peak height. Due to time lag in-breath detection at the beginning of the recording, the first and final 7 s of the continuous file for each participant across conditions were removed.

Finally, we extracted physiological data using LabChart Pro 8.1.16 (AD Instruments) and analyzed the results using RStudio (Version 1.3.959). To correct for distribution, a log transformation (log10) was applied to the physiological data. A within subjects repeated measures ANOVA with the Greenhouse–Geisser (G-G) correction for sphericity was used across the measures we analyzed. To control for multiple comparisons, the False Discovery Rate (FDR) method was applied to the results (Benjamini & Hochberg, 1995).

2.4.2 | EEG data

Pre-processing was conducted using the EEGLab plugin (v2019.1) (Delorme & Makeig, 2004) for MATLAB R2019b (v9.7.0.1471314, MathWorks, Inc). Continuous EEG data were bandpass filtered from 1 to 70 Hz (zero-phase Butterworth filter) in EEGLab. To exclude electrical interference from the CAVE environment we applied a 47 to 53 Hz notch-filter. We removed eye channels and the Cz reference channel. We then rejected channels if the kurtosis value was >5 standard deviations outside the average and replaced information in those channels using a spherical spline interpolation. We then re-referenced data to the common average reference of all channels. Next, we applied the SOUND algorithm to aid in the removal of recording noise 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). Independent component analysis (FastICA algorithm) was then performed (Hyvärinen & Oja, 2000), with artifactual components identified with assistance from the ICLabel plugin (Pion-Tonachini et al., 2019). A component was removed if the probability of that component containing brain data was less than 30% and the component was not in the 'other' category.

To separate the data into conditions, we used event markers to split each continuous file from the participant into 120 second block files using the start marker for each condition. We then segmented the data into three-second epochs, resulting in 40 epochs per participant. We then performed additional artifact rejection to remove any data exceeding $\pm150\,\mu V$ using the EEGLab 'pop_eegthresh' function. To check on data quality, we calculated the average epochs remaining after cleaning for each condition and participant (mean epoch = 39.7, $\pm.535$). Finally, data from each participant/electrode were converted 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). We then 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 a priori regions of interest: frontal midline (AFz, Fz, FCz), frontal right-hemispheric sites (F10, F8, AF4, F6, FT8, F2, F4, FC6, FC4, and FC2), and frontal left-hemispheric sites (F9, F7, AF3, F5, FT7, F1, F3, FC5, FC, and FC1). To understand the hemispheric difference, we generated a lateralization index (Thut et al., 2006) to understand the difference between the average over the frontal left and right regions of interest:

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

Using this index, higher values correspond to stronger power in the right than the left hemisphere.

Lastly, we applied a log transform (log10) to correct for distribution. We removed outliers that caused the violation of normality assumptions (according to the Shapiro–Wilk test) prior to statistical analysis. A within subjects repeated measures ANOVA with G-G correction was used across the EEG data. To correct for multiple comparisons where significance was detected within subjects, the false discovery rate (FDR) method was applied to post-hoc comparisons (Benjamini & Hochberg, 1995).

3 | RESULTS

3.1 | Overview

To study the effects of room color on physiological responses, we examined the mean and range indices of heart rate/variability, skin conductance response, and respiration. We investigated the power spectra, frontal lateralization, and midline power in the alpha and theta bandwidths. For completeness, the power-spectra of the remaining bandwidths are presented in Tables 1 and 2. We also investigated self-report responses compared to

TABLE 1 Descriptives (mean/standard deviation) for physiological analysis

Condition	Resting	Control (white)	Condition (blue)
HRV RMSSD (log10) mean/SD	1.58/.235	1.53/.209	1.52/.207
HRV SDRR (log10) mean/SD	1.69/.158	1.66/.151	1.66/.145
Resp mean (log10) mean/SD	1.26/.093	1.25/.087	1.24/.142
Resp mx-mn (log10) mean/SD	.130/.078	.042/.146	1.30/.361
SCR mean/SD	−.104/7.00	−.303/2.18	.225/3.09
SCR mx-mn (log10 + 1) mean/SD	.220/.085	.198/.089	.638/.256

TABLE 2 Statistical significance values for physiological measures

Condition	Resting		Control (white)
Comparison	Control (white)	Condition (blue)	Condition (blue)
HRV RMSSD (log10) P/P^{FDR}	.026*/.044*	.029*/.044*	.489/.489
HRV SDRR (log10) P/P^{FDR}	.236/.708	.485/.728	.777/.777
Resp mean (log10) P/P^{FDR}	.516/.955	.955/.955	.757/.955
Resp mx-mn (log10) P/P^{FDR}	.008**/.008**	<.001***/<.001***	<.001***/<.001***
SCR mean P/P^{FDR}	.903/.903	.851/.903	.537/.903
SCR mx-mn (log10 + 1) P/P^{FDR}	.599/.599	<.001***/<.001	<.001/<.001***

Note: Statistics are derived from one-way repeated measures ANOVA's. $P = p$ value, ^{FDR} = false discovery rate correction.

*$p \le .05$, **$p \le .01$, ***$p \le .001$.

physiological and EEG responses to determine if there was a relationship.

3.2 | Blue colored room increases autonomic variability in skin conductance response and respiration

SCR range (i.e., maximum minus minimum slope) significantly differed across the resting state, white control and blue condition [$F(1, 18) = 71$, $p = <.001$, $\eta^2_p = .845$]. Post-hoc comparisons showed that the blue (condition) room range was greater than the resting state [$M_{diff} = -.491$, $SE_{diff} = .056$, $t(13.0) = -8.839$, $p_{corrected} = <.001$, 95% CI ($-.612, -.371$)], and also significantly greater than the white (control) room [$M_{diff} = -.505$, $SE_{diff} = .056$, $t(13.0) = -8.994$, $p_{corrected} = <.001$, 95% CI ($-.581, -.360$)]. There was no difference between the resting state and white control [$M_{diff} = .015$, $SE_{diff} = .028$, $t(13.0) = -.085$, $p_{corrected} = .599$, 95% CI ($-.045, .074$)]. We did not detect an effect of condition on mean SCR [$F(1, 23) = .068$, $p = .869$, $\eta^2_p = .004$].

A similar pattern was observed in respiration where we did not detect an effect of condition for the mean respiration rate [$F(1, 18) = .071$, $p = .833$, $\eta^2_p = .005$], but there was an effect of condition for the Mx-Mn slope [$F(1, 20) = 199$, $p = <.001$, $\eta^2_p = .921$]. Follow-up analyses indicated that respiration range increased for the blue condition when compared to the white control [$M_{diff} = -1.258$, $SE_{diff} = .085$, $t(17.0) = -14.77$, $p_{corrected} = <.001$, 95% CI ($-1.438, -1.078$)], and when compared to the resting state [$M_{diff} = -1.170$, $SE_{diff} = .082$, $t(17.0) = -14.28$, $p_{corrected} = <.001$, 95% CI ($-1.343, -.997$)]. Respiration range decreased for the white control when compared to the resting state [$M_{diff} = .088$, $SE_{diff} = .030$, $t(17.0) = 2.98$, $p_{corrected} = .008$, 95% CI ($.026, 1.50$)].

An effect of condition was seen in the root mean square successive difference (RMSSD), our primary measure of heart rate variability [$F(2, 27) = 4.45$, $p = .026$, $\eta^2_p = .218$]. Post-hoc analysis showed RMSSD decreased in the blue condition compared to the resting state [$M_{diff} = .058$, $SE_{diff} = .024$, $t(16.0) = 2.390$, $p_{corrected} = .044$, 95% CI ($.007, .109$)], and also decreased for the white control compared to the resting state [$M_{diff} = .045$, $SE_{diff} = .018$, $t(16.0) = 2.456$, $p_{corrected} = .044$, 95% CI ($.006, .084$)]. We found no difference between the white control and blue condition [$M_{diff} = .013$, $SE_{diff} = .018$, $t(16.0) = .707$, $p_{corrected} = .489$, 95% CI ($-.025, .051$)].

No effect of condition was found for heart rate variability measured by the standard deviation of the R-R interval (SDRR) [$F(2, 26) = .678$, $p = .448$, $\eta^2_p = .041$]. Results are shown in Figure 2, with descriptives and p-values for each comparison presented in Tables 1 and 2.

3.3 | Correlates of emotional response were detected in the alpha bandwidth for frontal midline power and frontal hemispheric lateralization

To investigate emotion-related EEG results, we compared the frontal midline power and frontal lateralization in theta and alpha bandwidths. An effect of condition was seen in the frontal midline power in the alpha bandwidth [$F(1, 22) = 4.09$, $p = .047$, $\eta^2_p = .194$]. Post hoc analysis showed that alpha midline power was increased in the blue condition in comparison to the control [$M_{diff} = -.093$, $SE_{diff} = .0024$, $t(17.0) = -3.874$, $p_{corrected} = .003$, 95% CI ($-.143, -.042$)]. There was no significant difference between the resting state and blue condition [$M_{diff} = .041$, $SE_{diff} = .054$, $t(17.0) = .760$, $p_{corrected} = .458$, 95% CI ($-.074, .156$)], or resting state to the white control [$M_{diff} = .134$, $SE_{diff} = .058$, $t(17.0) = 2.307$, $p_{corrected} = .051$, 95% CI ($.011, .257$)]. We did not detect an effect for theta midline power [$F(2, 30) = 2.27$, $p = .125$, $\eta^2_p = .118$].

An effect was detected in frontal lateralization within the alpha bandwidth [$F(2, 24) = 9.34$, $p = .002$, $\eta^2_p = .384$]. Post-hoc analysis revealed there was significantly greater lateralization, with higher left side amplitude over the right, in the blue condition relative to the white control [$M_{diff} = -.034$, $SE_{diff} = .015$, $t(16.0) = -2.25$, $p_{corrected} = .003$, 95% CI ($-.067, -.006$)]. We also found greater lateralization in the white control, compared to the resting state [$M_{diff} = .051$, $SE_{diff} = .021$, $t(16.0) = -2.45$, $p_{corrected} = .059$, 95% CI ($.007, .096$)], however this did not survive correction. We did not detect an effect for lateralization in the theta bandwidth [$F(2, 27) = 3.19$, $p = .058$, $\eta^2_p = .186$]. Figure 3 illustrates the power spectra across frequencies and the alpha frontal midline and lateralization results. Descriptives and p-values for each comparison are presented in Tables 1 and 2.

3.4 | Significant differences in power spectral density in the theta, alpha, and beta bandwidths between white and blue room conditions were detected

We found a significant effect across the averaged power spectra for theta, alpha and beta bandwidths. An effect was detected in theta amplitude [$F(2, 31) = 12.6$, $p = < .001$, $\eta^2_p = .425$]. Follow-up analysis indicated that theta amplitude was increased for the white control when compared to the resting state [$M_{diff} = -.068$,
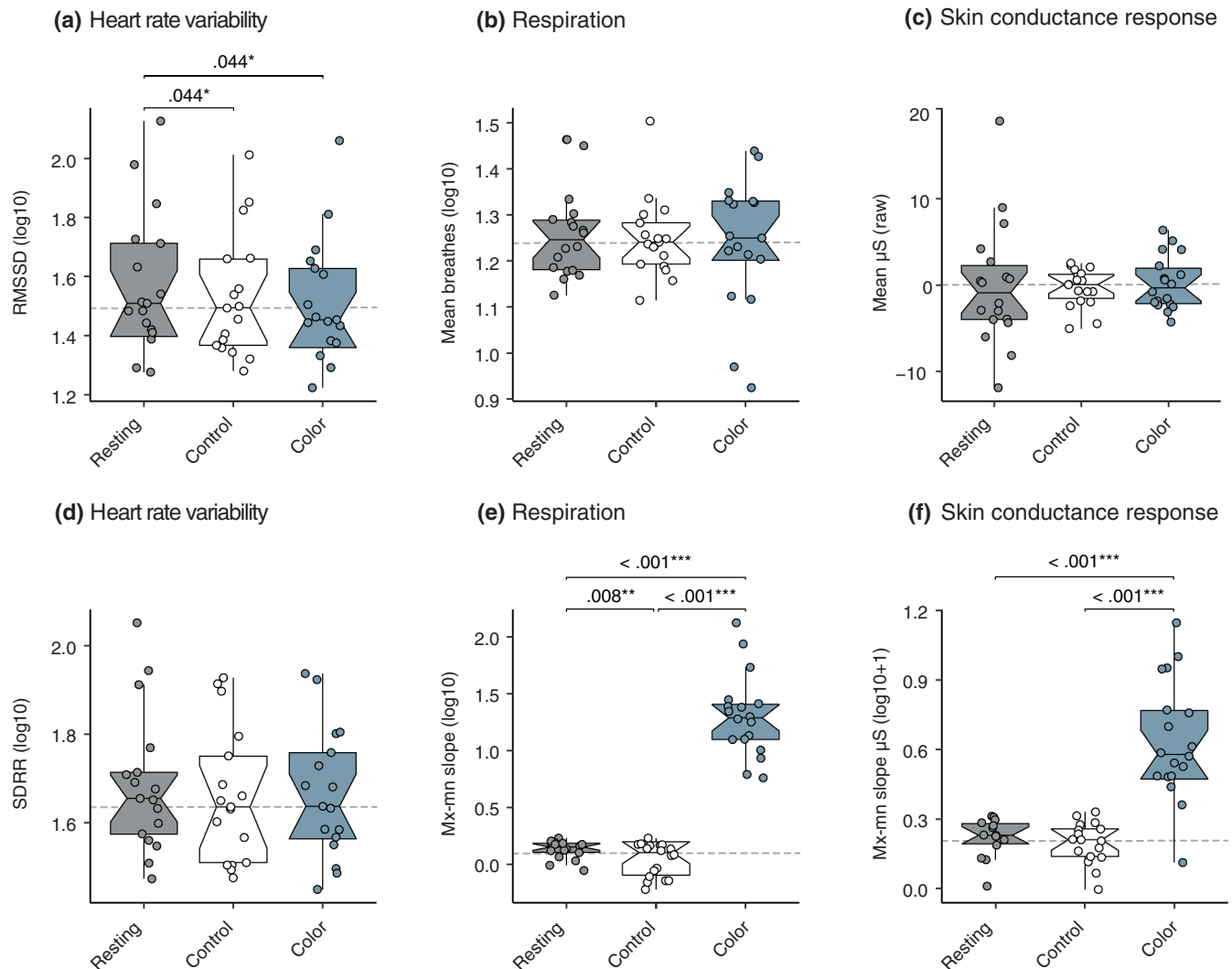
FIGURE 2 Physiological measures between the resting-state, control, and color condition. (a–f) boxplots with quartile ranges and medians for physiological measures analyzed using transformed values with outliers removed. Each data point represents a participant's averaged response from the 2-min exposure. 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 control (white) and condition (blue). Mean values did not show an effect, however, measures analyzing the change in range, such as maximum—minimum slope for skin conductance response and respiration, showed differences.

$SE_{diff} = .027$, $t(17.0) = -2.49$, $p_{corrected} = .024$, 95% CI $(-.126, -.010)$], increased for the blue condition when compared to the resting state [$M_{diff} = -.126$, $SE_{diff} = .026$, $t(17.0) = -4.78$, $p_{corrected} = <.001$, 95% CI $(-.181, -.070)$], and increased for the blue condition when compared to the white control [$M_{diff} = -.058$, $SE_{diff} = .021$, $t(17.0) = -2.73$, $p_{corrected} = < .001$, 95% CI $(-.102, -.013)$]. Alpha changes were also detected [$F(1, 23) = 3.52$, $p = .062$, $\eta^2_p = .172$]. Alpha amplitude decreased for the blue condition when compared to the white control [$M_{diff} = -.091$, $SE_{diff} = .028$, $t(17.0) = -3.200$, $p_{corrected} = .015$, 95% CI $(-.150, -.031)$]. There was also an effect on beta activity [$F(2, 25) = 10.5$, $p = <.001$, $\eta^2_p = .412$]. Post-hoc comparisons showed

that there was a significant decrease in amplitude during the blue condition when compared to the resting state [$M_{diff} = -.132$, $SE_{diff} = .032$, $t(15.0) = -4.16$, $p_{corrected} = <.001$, 95% CI $(-.200, -.064)$], a decrease during the white control when compared to the resting state [$M_{diff} = -.074$, $SE_{diff} = .032$, $t(15.0) = -2.29$, $p_{corrected} = .037$, 95% CI $(-.142, -.005)$], and a decrease during the blue condition in comparison to the white control [$M_{diff} = -.058$, $SE_{diff} = .022$, $t(15.0) = -2.72$, $p_{corrected} = .024$, 95% CI $(-.104, -.013)$]. Although we detected differences within the remaining bandwidths, follow-up analysis revealed these were not between the white control and blue condition. This included delta [$F(1, 30) = .004$, $p = .370$, $\eta^2_p = .292$], low gamma [$F(2,$
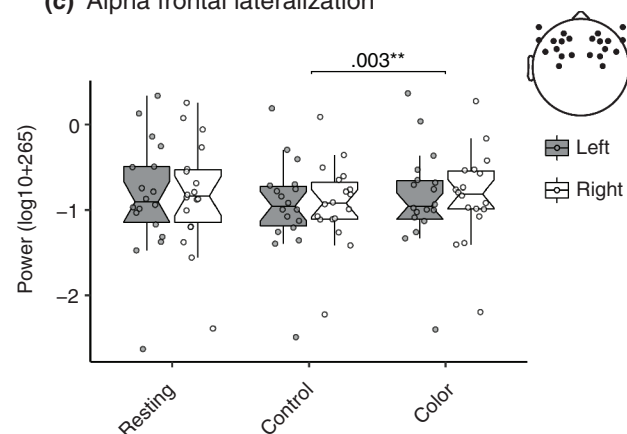
(a) Power spectra across frequencies
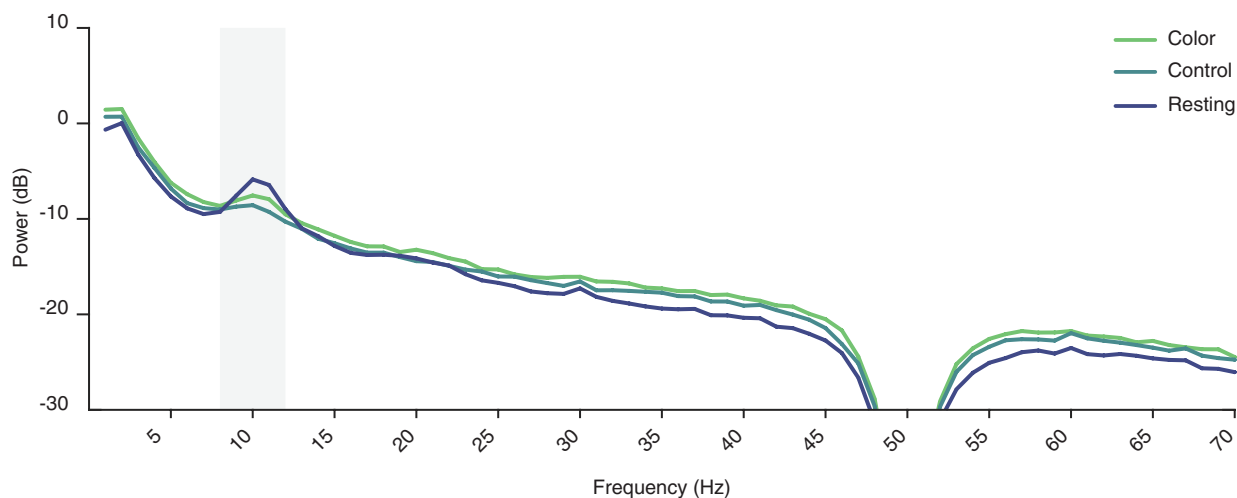
(b) Alpha frontal mid-line
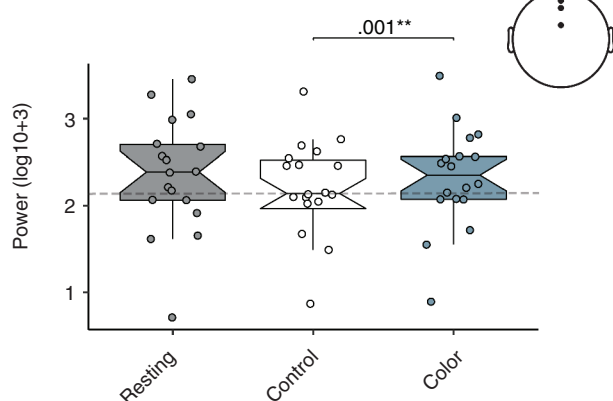
(c) Alpha frontal lateralization

FIGURE 3 Significant differences in EEG alpha frontal midline power and frontal hemispheric lateralization were found. (a) Power spectra plot showing power (dB) across frequencies. The alpha bandwidth (8 to 12 Hz) is 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) Boxplot with quartile ranges and medians to show increased alpha midline power spectra and frontal lateralization. (c) Hemisphere (gray for left, white for right) with significance overlaid from calculating the lateralization index showing increased left hemispheric lateralization in the alpha bandwidth.

28) = 6.46, p = .007, η^2_p = .275], and high gamma [F(2, 30) = 4.61, p = .022, η^2_p = .213] amplitudes.

Results are shown in Figure 4, with descriptives and p-values for each comparison presented in Tables 3 and 4.

3.5 | Self-report to the color condition

Currently the relationship between subjective emotional judgments and electrophysiological measures related to emotion is unclear. During the experiment participants self-reported their emotional state using the Self-Assessment Manikin. Self-report of pleasure showed an effect of condition [F(2, 28) = 3.95, p = .037, η^2 = .189]. Post-hoc comparisons revealed the only difference for

self-report of pleasure was an increase from resting state to control [M_{diff} = .722, SE_{diff} = .240, t(17.0) = 3.010, $p_{\text{corrected}}$ = .024, 95% CI (.216, 1.23)]. We did not see any effect in self-reported arousal [F(2, 34) = .791, p = .462, η^2 = .044] or dominance [F(2, 29) = 1.23, p = .300, η^2 = .068].

3.6 | Summary

Overall, our findings show the blue condition in contrast to the white control increased autonomic response in skin conductance and respiration range. Although a decrease in mean values was found for heart rate variability, these were not significant. We also found the blue condition
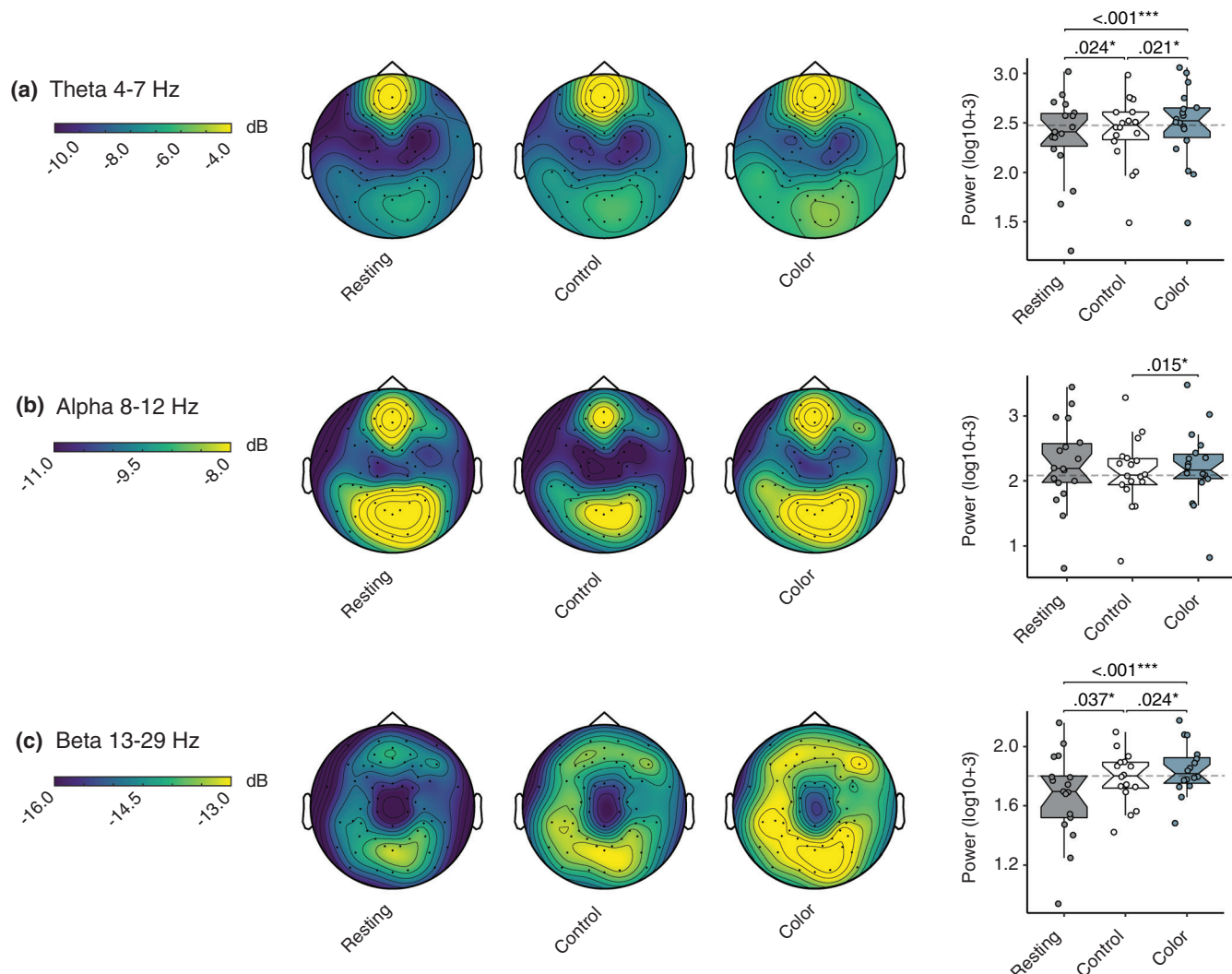
FIGURE 4 Significant differences in EEG power spectral density in theta, alpha, and beta bandwidths were detected. To illustrate the differences, we have plotted EEG topographies and boxplots with quartile ranges and medians for the overall power spectral density in the theta, alpha, and beta bandwidths. (a) Theta 4 to 7 Hz with amplitude range of −10 to −4 decibels. (b) Alpha 8 to 12 Hz with an amplitude range −11 to −8 decibels. (c) Beta 13 to 29 Hz with an amplitude range −16 to −13 decibels.

when compared to the control increased the EEG power spectral density in theta, alpha, and beta bandwidths, and increased left frontal hemispheric lateralization and frontal midline power in the alpha bandwidth. Lastly, we did not detect a relationship between self-report of emotion between the blue condition to the control.

4 | DISCUSSION

We investigated if there are detectable differences in emotion-related autonomic and central nervous system processing when changing the design characteristic of color within a virtual built environment, and if participant changes in self-reported emotion correspond with measures of autonomic and central nervous system modulations. We presented an interior built

environment with minimal features to reduce contextual influence while controlling for comfort variables. Our findings showed that an autonomic measure of variability in heart rate (RMSSD) decreased when exposed to the blue condition, while measures of range in respiration and skin conductance response significantly increased. Power spectral density increased in the blue condition compared to the white across theta, alpha, and beta. As expected, we also found EEG frontal hemispheric lateralization and frontal midline power in the alpha bandwidth increased in the blue chromatic condition in contrast to the white achromatic control. Contrary to expectations, we did not detect evidence that color significantly affected SDRR, or skin conductance response and respiration mean values. The study also showed that participants' self-report of emotion did not correspond with measures of autonomic response.

TABLE 3 Descriptives (mean/standard deviation) for EEG analysis

Condition	Resting	Control (white)	Condition (blue)
Power spectral density (log10)			
Delta 1 to 3 Hz (log10 + 3) mean/*SD*	3.03/.456	3.11/.384	3.16/.455
Theta 4 to 7 Hz (log10 + 3) mean/*SD*	2.36/.431	2.42/.346	2.48/.383
Alpha 8 to 12 Hz (log10 + 3) mean/*SD*	2.26/.661	2.13/.528	2.22/.565
Beta 13 to 29 Hz (log10 + 3) mean/*SD*	1.67/.297	1.79/.177	1.84/.172
Low Gamma 30 to 45 (log10 + 3) mean/*SD*	1.22/.300	1.35/.369	1.39/.342
High Gamma 55 to 70 (log10 + 3) mean/*SD*	.769/.356	.922/.418	.962/.384
Frontal hemispheric lateralization			
Theta 4 to 7 Hz (log10 + 200) mean/*SD*	2.20/.164	2.27/.092	2.24/.183
Alpha 8 to 12 Hz (log10 + 265) mean/*SD*	2.33/.184	2.25/.192	2.29/.195
Frontal midline power spectral density			
Theta 4 to 7 Hz (log10 + 3) mean/*SD*	2.75/.437	2.78/.481	2.36/.660
Alpha 8 to 12 Hz (log10 + 3) mean/*SD*	2.36/.660	2.22/.538	2.32/.581

TABLE 4 Statistical significance values for EEG analysis

Condition	Resting		Control (white)
Comparison	Control (white)	Condition (blue)	Condition (blue)
Power spectral density (log10)			
Delta 1 to 3 Hz (log10 + 3) P/P^{FDR}	.060/.073	.003**/.009**	.073/.073
Theta 4 to 7 Hz (log10 + 3) P/P^{FDR}	.024*/.024*	<.001***/<.001***	.014*/.021*
Alpha 8 to 12 Hz (log10 + 3) P/P^{FDR}	.040*/.060	.474/.474	.005**/.015*
Beta 13 to 29 Hz (log10 + 3) P/P^{FDR}	.037*/.037*	<.001***/.001**	.016*/.024*
Low Gamma 30 to 45 (log10 + 3) P/P^{FDR}	.021*/.032*	.009**/.027*	.272/.272
High Gamma 55 to 70 (log10 + 3) P/P^{FDR}	.019*/.038*	.025*/.038*	.524/.524
Frontal hemispheric lateralization			
Theta 4 to 7 Hz (log10 + 200) P/P^{FDR}	.070/.105	.042*/.105	.576/.576
Alpha 8 to 12 Hz (log10 + 265) P/P^{FDR}	.034*/.051	.458/.458	.001**/.003**
Frontal midline power spectral density			
Theta 4 to 7 Hz (log10 + 3) P/P^{FDR}	.262/.283	.072/.216	.283/.283
Alpha 8 to 12 Hz (log10 + 3) P/P^{FDR}	.034*/.051	.458/.458	.001**/.001**

Note: Statistics are derived from parametric one-way repeated measures ANOVA's. P = p value, ^{FDR} = false discovery rate correction.

*$p \leq .05$, **$p \leq .01$, ***$p \leq .001$.

This may reflect that we are unable to accurately identify and/or express our emotions to the built environment, or that the responses occur without conscious processing. Overall, this study demonstrates that color in the built environment modulates various indicators of neurophysiological activity in healthy adults.

The results of this study raise questions on how color exposure in the built environment may have a role in modulating our emotions. In emotional processing studies, higher frontal left hemispheric lateralization has been associated with positive emotions (Davidson, 1992; Ekman & Davidson, 1993). Given that stronger left lateralization was found in the blue condition, this might indicate the blue condition had a positive effect on participants. However, before claims can be made further work is needed to contrast the results with the effect of other hues, exposure time, type of activity being undertaken in the environment, and time of day. In contrast to the EEG results, increased range of skin conductance response and respiration have been shown to indicate elevated arousal

and stress, which can have a negative impact on the body over long periods of time (Schneiderman et al., 2005). As we did not detect differences to the mean of autonomic measures, the significantly larger SCR and respiration range for the blue condition may simply reflect the perception of the changed environment rather than a distinct emotional response.

As mentioned, participants in this study were a subset of those who took part in our built environment scale study. Although the sample size for the color condition was smaller than that for the scale conditions, the color condition resulted in a clearer effect (Bower et al., 2021). While it is unclear why the effect is more pronounced, the division in dorsal and ventral visual streams involved in visual processing could account for the differences (Milner & Goodale, 2006). If this were the case, we might expect the ventral (perception) pathway to be primarily activated during color exposure (Kravitz et al., 2013), whereas the dorsal (action) pathway would be required during the processing of scale due to the need to determine distances and spaces in comparison to the body (Oliver & Thompson-Schill, 2003). As it is suggested that the dorsal stream is associated with less visual awareness (Milner, 2012), and EEG is less likely to detect underlying brain activity, this could account for the difficulty in establishing autonomic differences to changing scales.

There have been different ways to approach study designs and reporting parameters when investigating the impact of color on emotional and neurophysiological responses. This may underpin the lack of consensus on the impact of built environment color at present. In this study, we selected a popular wall paint color for greater ecological validity, which we presented in the CAVE through projecting a LED image. Most studies previously conducted in virtual reality do not account for and explain how contextual features such as room function (clinical waiting area, school classroom, household bedroom, etc.) may influence responses, making it difficult to disentangle the role of built environment design from memories, associations, and preconceptions of the function and role of the built environment. This must be recognized as a critical study design parameter, as learnt autonomic response to a salient emotional association of the environmental context (i.e., fear of clinical waiting area) will confound responses measures (Baeuchl et al., 2015). We also raise concern where studies using virtual reality do not report the physical environment conditions (setting, people, and comfort variables) outside of the virtual space the study was conducted in, which also endangers ecological control.

Vast resources are consumed when creating our built environments. While these environments meet certain building codes and standards, there is no certainty in the impact they are having on our brain and body functioning.

When altering or retrofitting a building, color is an economic and practical design characteristic to alter. For instance, changing the color of space through lighting or ink (paint, fabric, etc.) requires no changes to the structure and materiality of the building, whereas creating, for instance, a larger space with higher ceilings and curved panels may require floorplate demolition, specialized time-intensive carpentry and will encounter constraints in the loadbearing structure. These variables also come with significant economic and embodied energy costs, adding to the structure's long-term environmental sustainability. Changing built environment color also increases accessibility for a broader portion of the population to modify their environment, particularly those in the rental market and shared residences where there are limits to what can be altered. However, further studies are required to build complexity into experimental design to understand the interaction of design elements and social interactions before factoring in variables such as prior experiences (positive/negative conditioning from life experiences etc.).

This study has several limitations. Firstly, as the experiment also contained scale conditions, the blue color condition was presented at the end so we could not randomize the order of presentation. As a result, further work is required to rule out that the results are not due to a violation of expectation. However, as data were averaged across a two-minute period it is less likely to have confounded the design compared to an event-related potential study design. Next, as we selected a naturalistic design, we cannot disentangle the effects of hue, saturation, and brightness because the blue stimulus differed from the white stimulus in colorimetric dimensions. We also note that the room was not symmetrical in the furnishings present, with the built environment scene including a chair on the left-hand side of the room. Although this could influence the regions of brain activity, our results indicated a leftward increase in EEG power spectra, which would not explain a visuospatial attention bias. Finally, this study used a sample of participants who identified as having 'normal or corrected to normal vision' and self-reported they had no pre-existing psychological, psychiatric, neurodevelopmental, and neurodegenerative conditions. Future studies should delve into larger inclusive samples, conduct an assessment to assess the participants' color vision perception and ensure the colorimetric properties of the virtual environment are reported alongside the true colors from a spectrometer. This will enable us to break apart and understand the impact color has on a more representative sample of the population.

Although environmental enrichment studies explore whether environmental novelty is beneficial for cognitive function and mental health (Rojas-Carvajal et al., 2022), it is still not well understood what the

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thresholds are between positive environmental stimulation effect and a negative stress response to the changes. Therefore, understanding what balance is needed for optimal mental health remains an unsolved yet important research question. While designers have long made claims about the emotional impact of the built environment on people, there has been a lack of empirical evidence investigating what impact design characteristics of the built environment have on emotional states and neurophysiological responses. While this study only investigated the impact of one hue, it provided the opportunity for us to gauge differences in the effect of color compared to scale on emotional and neurophysiological responses. This study provides evidence that the color of the built environment modulates biological systems associated with emotion and aids our understanding of the differences in processing different built environment design characteristics.

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Functional brain connectivity during exposure to the scale and color of interior built environments

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Functional brain connectivity during exposure to the scale and color of interior built environments

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Abstract

Understanding brain activity linked to built environment exposure is important, as it may affect underlying cognitive, perceptual, and emotional processes, which have a critical influence in our daily life. As our time spent inside buildings is rising, and mental health problems have become more prevalent, it is important we investigate how design characteristics of the built environment impact brain function. In this study, we utilized electroencephalography to understand whether the design elements of scale and color of interior built environments modulate functional brain connectivity (i.e., brain network communication). Using a Cave Automatic Virtual Environment, while controlling indoor environmental quality responsible for physiological comfort, healthy adult participants aged 18–55 years (66 for scale, subset of 18 for color), were exposed to context-neutral indoor room scenes presented for two-minutes each. Our results show that both enlarging and reducing scale enhanced theta connectivity across the left temporoparietal region and right frontal region. We also found when reducing the built environment scale, there was a network exhibiting greater high-gamma connectivity, over the right frontoparietal region. For color, the condition (blue) contrasted to our achromatic control (white) increased theta connectivity in the frontal hemispheres. These findings identify a link between theta and gamma oscillations during exposure to the scale and color of the built environment, showing that design characteristics of the built environment could affect our cognitive processes and mental health. This suggests that, through the design of buildings, we may be able to mediate performance and health outcomes, which could lead to major health and economic benefits for society.

KEYWORDS

brain connectivity, cortical oscillations, electroencephalography (EEG), environmental psychology, immersive virtual reality, spatial cognition, visual perception

1 | INTRODUCTION

It is estimated we spend approximately 90% of our time inside buildings (Klepeis et al., 2001). During the COVID-19 pandemic this time increased, and our exposure to a variety of built environments such as workplaces, schools, community, and commercial venues diminished as strict restrictions, regulations, and lockdown protocols were imposed to limit socially driven virus transmission occurrences. As a

result, much of the population experienced reduced environmental enrichment in the form of in-person social interactions and varied physical surrounds. Environmental enrichment refers to the environmental conditions facilitating enhanced sensory, cognitive, and motor stimulation (Nithianantharajah & Hannan, 2006). Studies have begun to reveal that this lack of enrichment has had adverse effects on mental health (Amerio et al., 2021; Stieger et al., 2021), with confined quarantine environments found to be most mentally detrimental (Brooks et al., 2020) and akin to the negative psychological effects resultant from sensory deprivation in the physical and social environment (Mackes et al., 2020). However, despite the greater time spent indoors, there is little research investigating the impact of interior built environments on brain activity (Bower et al., 2019; Moore et al., 2018). As mental health issues in society continue to rise, and indoor environments play a key role in our lifestyles, it is critical we understand whether the design of built environments impact our brain function, and if so, recognize the implications this might have on our cognitive, attentional, perceptual, and emotional functioning.

Understanding the impact of built environment exposure on brain activity is inherently complex due to the vast quantity and variety of spaces we visit or occupy, and our pre-existing associations and memories linked to built environments, which can confound the results. Often, we also hold goal orientated behaviors when immersed in the built environment, resulting in spatial priming, where we use a memory from prior perceptual experience to optimize our focus and behavior and increase task efficiency (Sanocki & Epstein, 1997). While studies have broadly investigated differences in neural processing between naturalistic and urban environments (Norwood et al., 2019; Roe et al., 2013), external environments are subject to many confounding variables such as atmospheric conditions (weather and climate), how they are presented (still images, virtual reality [VR], or field-based exposure), how they are constructed (complexity and materiality) and how they are composed (viewpoint and perspective). Inside buildings, the overarching context of the building (residential, commercial, educational, and healthcare); comfort properties (thermal comfort, indoor air quality, lighting, and acoustics); contents (furniture, fixtures, equipment, and other physical artifacts); and occupants (social distances, interactions, and relationships) also increase the variation in what we are exposed to. Emerging research is investigating whether we can measure the impact of built environment design characteristics on brain activity. Some studies have taken a macro approach by determining broad descriptors of complex built environments, such as "fascination," "coherence," and "homeliness" (Coburn et al., 2020), while others have employed an incremental method by breaking down the built environment into fundamental physical design elements, such as "geometry," "texture," "scale," and "color," to understand them at the microlevel before building complexity into the experimental design (Bower et al., 2022a, 2022b).

Electroencephalography (EEG) is a noninvasive and temporally precise method for analyzing neural activity during different tasks and conditions, such as in response to visual stimuli. While previous studies using EEG to investigate the impact of the built environment on brain activity have analyzed spectral power (Llinares et al., 2021; Vecchiato et al., 2015), and event-related potentials (Djebbara

et al., 2019), no work to date has examined functional connectivity. Originating from neuroimaging, functional connectivity describes the temporal correlation between two distinct neurophysiological events, to understand whether there is a statistical relationship between the activity recorded at different spatial regions within the brain (Friston, 1994). Functional connectivity can therefore provide an indication of the pattern and strength of communications between different brain regions (i.e., brain circuits or networks), both local (short-range) and global (long-range). Functional connectivity studies have predominantly used data from neuroimaging techniques, such as functional magnetic resonance imaging (fMRI); however, a growing body of work has begun using EEG. The use of EEG enables greater ecological validity for participant experience as they are not restricted to the supine position in a confined space when undergoing a scan. Current work investigating functional connectivity in fMRI data have contrasted vastly different stimuli, with a focus on understanding the difference between natural versus human-made built environment scenes (Kühn et al., 2021). Critically, this work found that functional connectivity was able to detect changes in neural activity that was undetected in participant self-report. However, there are constraints on ecological validity in the testing environment (clinical/confined MRI setting) and stimuli (photographic scene).

In this study, we investigated whether functional connectivity could be used to elucidate the impact of the built environment on our brain activity, in the context of scale and color. We selected these two variables as they can be perceived without the need of additional visual properties or sensory processes. This limits the complexity expected in neural processing, as the addition of other properties (i.e., luminance and/or texture to perceive form) or additional sensory inputs (i.e., touch and/or movement to perceive texture) are found to involve different processing mechanisms (Whitaker et al., 2008). Understanding the implications of scale applied to the built environment is not new, with studies that have investigated room size on behavioral measures (Evans et al., 1996; Wolfe, 1975), self-report (Sander et al., 2019), and more recently, brain processing of distances when exposed to scale categories varying in magnitude from room to continent (Peer et al., 2019). However, prior studies often do not distinguish between the physical and social environment, making it difficult to understand whether there is a direct effect of the physical environment. We are also at an early stage of understanding the impact of color (Elliot, 2015), with studies often presenting methodological problems (Wilms & Oberfeld, 2018). Nevertheless, there is a growing body of emerging work investigating the relationship between built environment color and self-reported mood (Lipson-Smith et al., 2021), attention, and memory (Llinares et al., 2021).

Here, we test a rigorously controlled method to measure EEG functional connectivity during exposure to scale and color of interior built environment scenes. The use VR and indoor environmental quality monitoring, makes this a novel and robust approach to understanding the connection between the built environment and neuroscience. This study follows earlier work where we investigated changes in self-report, power spectral analysis, and physiological indictors to scale and color of the built environment (Bower et al., 2022a, 2022b). A Cave Automatic Virtual Environment (CAVE) was used to expose

participants to indoor built environment scenes, a cost-effective and controlled technique which enables greater sensorimotor integration than VR headsets (Kalantari et al., 2021; Sanchez-Vives & Slater, 2005). The virtual built environment scene we modulated in scale and color was a room which included a closed door and a chair, providing participants visual cues to determine height, width, and surface depth (Brouwer et al., 2005). These items were selected to be most neutral of the environmental context, with their dimensions modeled from the local regulatory standards for a controlled approach. Participants were presented with an eyes-open resting-state, followed by four randomized scale scenes, where the room, door, and chair changed in scale (75%, 100%, 125%, and 150%). Finally, a color scene (blue) was presented at the end. All scenes lasted two-minutes, between which the resting-state was displayed while a self-report task was completed (not reported in this manuscript). Due to the exploratory nature of this study, we took a data-driven approach without specific predictions. We ran comparisons of connectivity for each of the canonical EEG frequency bands averaged across participants for each condition, using t tests to compare between conditions (Figure 1).

2 | MATERIALS AND METHODS

2.1 | Participants

66 healthy adult volunteers (31 females, age = 34.9 ± 11.3 years) participated in the scale component of this study, while 18 participants participated in both the scale and color component (8 females, age = 34.5 ± 9.87 years). All participants provided written, informed consent approved by the Deakin University Human Research Ethics Committee. No participants reported prior diagnosed psychiatric, neurological, or neurodevelopmental conditions, or previous training or work experience in built environment design. 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 visual acuity.
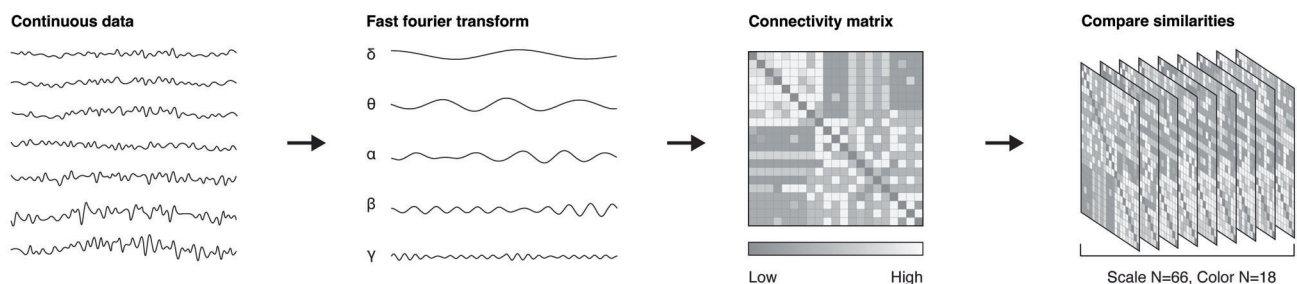
2.2 | Experimental design

An eyes open resting-state was incorporated at the start and between each of the scenes for two-minutes. Participants were seated comfortably in the center of the CAVE and instructed to keep their eyes-open and pay attention to the scene they would be presented with. They were then exposed to four randomized (100 subjects, 1 block, seed 28107) achromatic built environment scenes, and one chromatic color condition at the end. Each scene was presented for two-minutes, before the CAVE returned to the resting-state display. This study used an eyes-open resting-state design due to the visual nature of the stimuli. Participants were exposed to varying built environment scenes using a standard sitting posture which is not uncommon for the type of study or real-world behavior within the built environment. This helped minimize differences in head height and reduced movement artifact in recordings; however, it is worth noting subject
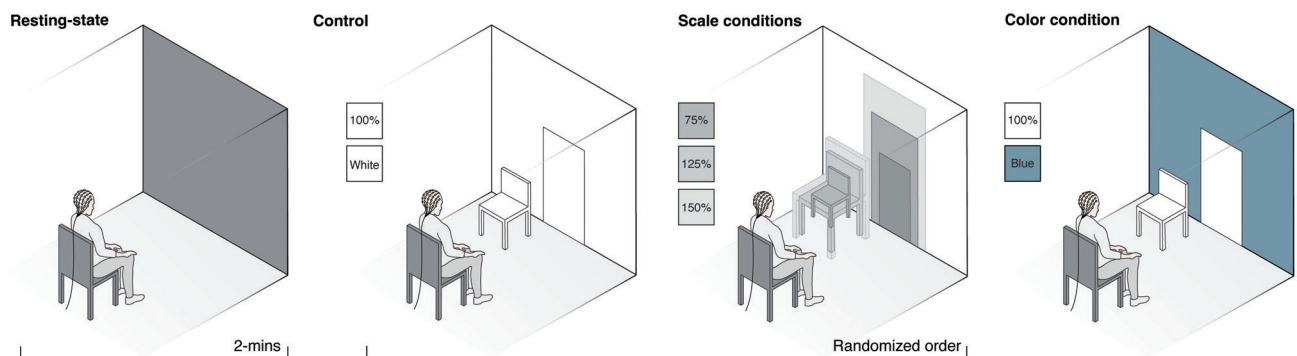
FIGURE 1 Experimental conditions and data processing pipeline schematic. (a) Isometric schematic of the experimental conditions. (b) Summary of the analysis pipeline transforming electroencephalography (EEG) data for functional brain connectivity analysis. Diagrams are representative, not drawn to exact scale/numbers.

positioning can alter the neurophysiological activity (Puce & Hämäläinen, 2017). We elected not to involve task-based measures as these would distract from the scene exposure, and that it is not uncommon to spend time within buildings without necessarily performing a task or planning an action. However, we recognize this is an under examined area of research, warranting future exploration. A period of two-minutes per condition was selected to ensure sufficient EEG data to epoch for stability in connectivity analysis (van Diessen et al., 2015), while avoiding habituation from the experimental conditions and nature of the scenes that could confound the results (O'Gorman, 1977).

The virtual built environment scene we modulated in scale was a room which included a closed door and a chair, providing participants visual cues to determine height, width, and surface depth (Brouwer et al., 2005). These items were selected to be most neutral of the environmental context, with their dimensions modelled from the local regulatory standards for a controlled approach. The scale scenes included a control scale scene (100%), modeled to the dimensions of Standards Australia for a residential internal door (Standards Australia, 2017), and three-scale conditions where the scene was reduced in scale: small (75%), or increased: large (125%), and extra-large (150%). We selected the color blue as previous studies examining color-emotion association within interior built environments have found it is most neutral to participants (Güneş & Olguntürk, 2020), and due to the intrinsic properties of light and human visual system, blue is less frequently used for signage to affect behavioral action and/or inhibition responses (Braun & Silver, 1995). To achieve greater ecological validity of a color we might encounter in built settings, we matched the properties to a popular paint from a large local manufacturer. The experimental conditions are illustrated in Figure 1 and listed in Table 1.

2.3 | Apparatus

The CAVE consisted of three projector walls (3 m wide × 2.4 m high) and a floor (2.4 m wide × 3 m long), each with Barco Galaxy NW-12 stereoscopic projectors. Projectors connected to a series of image generators consisting of Nvidia Quadro P6000 graphic cards, synced using Quadro Sync II cards at 120 Hz (60 Hz per eye) to render images at the same time. An optical-based tracking system connected back to a Virtual Reality Peripheral Network (VRPN) Server (eight cameras, 240 Hz with submillimeter accuracy) tracked used movement through active LED markers located on the stereoscopic glasses. These were calibrated to ensure there was no conflict between eye height and postural cue (Leyrer et al., 2015). The VR environment was built using Unity with Vertical Sync (VSync) set to 60 frames per second.

To account for physiological comfort variables which could impact on the results, we measured and reported indoor environmental quality variables. Data were acquired through the CR100 Measurement and Control System with LoggerNet 4.6.2 software (Campbell Scientific, Inc.) at one-minute intervals which were date and time stamped. We then averaged the one-minute recordings of each session to create an average per participant session, and then average across all participant sessions. Variables recorded included interval sound pressure levels, overall mean air and wet-bulb globe temperature, carbon dioxide concentration, and relative humidity. These were all within acceptable range for optimal performance as previously reported in Bower et al. (2022a) and Bower et al. (2022b).

2.4 | EEG acquisition and analyses

EEG data were acquired using a 64-channel EEG system (Philips Hydrocel Geodesic Sensor Net 64-channel HCGSN) and recorded using Net Station 5 Geodesic EEG software, version 5.4.2 (Electrical Geodesics Inc.) using a sampling rate of 1000 Hz, with Cz as the online reference. We created a continuous recording with manual time stamps at the start and end of each two-minute scene exposure using markers for each participant. We preprocessed the EEG data 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.). Data were band-pass filtered (1–70 Hz; zero-phase Butterworth filter) with a notch filter (47–53 Hz) to remove electrical interference from the CAVE environment. 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

TABLE 1 All scale scenes were rendered with a white finish (R255, G255, B255, hue [°] = 0, saturation [%] = 0, and brightness [%] = 100, and smoothness [%] = 50). The resting-state scene was rendered black (R0, G0, B0, hue [°] = 0, saturation [%] = 0, brightness [%] = 0). Finally, the color condition presented last had wall surfaces were rendered in blue (R122, G155, B173, hue [°] = 198, saturation [%] = 35.3, brightness [%] = 67.8, and smoothness [%] = 50)

	Scale (%)	Color (RGB)	Hue (°)	Saturation (%)	Brightness (%)	Smoothness (%)
Resting-state	N/A	R0, G0, B0	0	0	0	N/A
Control	100	R255, G255, B255	0	0	100	50
Small	75	R255, G255, B255	0	0	100	50
Large	125	R255, G255, B255	0	0	100	50
Extra large	150	R255, G255, B255	0	0	100	50
Color	100	R122, G155, B173	198	35.3	67.8	50

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 et al., 2019). We then extracted into conditions and segmented into three-second epochs, resulting in 40 epochs per participant. Full details regarding EEG artifact correction and additional preprocessing are provided in the Extended Data Appendix (Supporting Information).

2.5 | Functional connectivity

The EEG signal was subjected to a frequency transform using a single Hanning taper (1–70 Hz, frequency resolution of 1 Hz) to return the complex Fourier spectra for each subject/electrode across each EEG frequency band in 1 Hz steps: delta (1–3 Hz), theta (4–7 Hz), alpha (8–12 Hz), beta (13–30 Hz), low-gamma (30–45 Hz), and high-gamma (55–80 Hz). We compared phase-based connectivity between all electrodes for each frequency band using the weighted phase lag index (wPLI) in FieldTrip toolbox for EEG/MEG-analysis (Hardmeier et al., 2014; Oostenveld et al., 2011). wPLI was selected to minimize any effects related to volume conduction (Cohen, 2015; Plonsey & Heppner, 1967; Stinstra & Peters, 1998) (Figure 1).

2.6 | Statistical analysis

The analysis was performed using the Network-Based Statistic (NBS) Toolbox v1.2 (Zalesky et al., 2010; Zalesky et al., 2012) and MATLAB R2019b (v9.7.0.1471314, MathWorks, Inc.). The NBS approach is a method based on the graph model, which controls the family-wise error rate when comparing pairwise relations between neural elements (Zalesky et al., 2010). The primary threshold (test-statistic) was 3.2 for the control to scale (equivalent to $p = .002$), and 3.4 for color (equivalent to $p = .003$) conditions. The secondary significant threshold was set to $p = .025$ (two-tailed) for family-wise corrected cluster analysis (5000 permutations). BrainNet Viewer v1.7 (Xia et al., 2013) (http://www.nitrc.org/projects/bnv/) was used for visualizing the results. We also extracted the average connectivity strength across the significant subnetworks identified through NBS for each participant and condition. We then averaged these values to visually compare the difference in connectivity strength which we exported to RStudio (Version 1.3.959) for analysis and visualization.

3 | RESULTS

3.1 | Changes to built environment scale increased functional connectivity in the theta and high-gamma bandwidths

Scale was found to modulate connectivity in the theta and high-gamma bandwidths. Theta connectivity was increased when comparing the control to the small condition (20 edges, 15 nodes, $p = .010$).

When comparing the control to the small condition, NBS identified a significant network of increased theta connectivity (20 edges, 15 nodes, $p = .006$). The identified network encompassed left temporal and parietal regions, as well as bilateral frontal regions. We also found a significant network of increased theta activity when comparing the control to the large condition (35 edges, 26 nodes, $p = .005$). This was asymmetrically spread across the brain, in the left hemisphere and across the midline from the left temporal to right frontal region. We also observed between-condition effects in the theta range with increased connections when comparing the small to the large condition (24 edges, 16 nodes, $p = .005$). The network identified by NBS for small to large predominantly comprises frontal activity in the right hemisphere, connecting to the left temporal region (Figure 2). In the high-gamma range, the NBS identified increased connectivity when comparing the control to small condition (20 edges, 12 nodes, $p = .015$). This activity was concentrated in the right frontoparietal region (Figure 3). However, we did not detect any significant connectivity within the remaining conditions.

3.2 | Exposure to built environment control scale scene modulated functional connectivity in the alpha and low-gamma activity
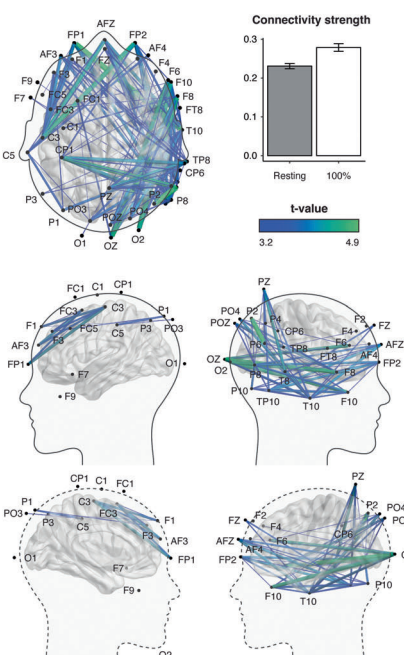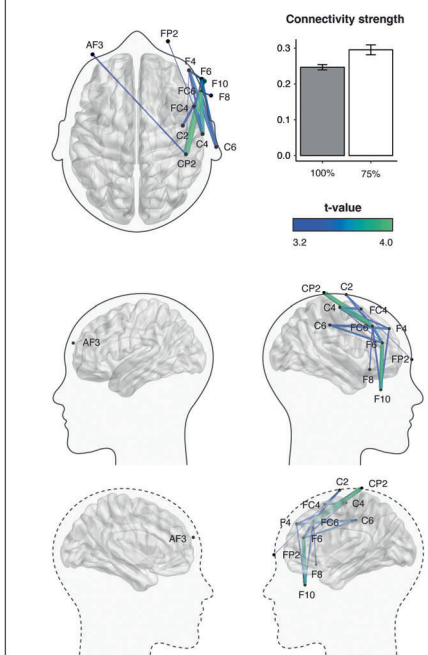
We also detected a significant subnetwork of connectivity in the alpha and low-gamma bandwidths. However, this was confined to the eyes-open resting-state and control in both bands. Increased alpha connectivity from the resting to control (116 edges, 42 nodes, $p = <.001$) was widespread, comprising electrodes over frontal, central and posterior regions. Although widespread, there was significant clustered activity in the right temporo-occipital region. In the low-gamma range, the NBS identified increased connectivity networks when comparing the resting-state to the control condition (25 edges, 16 nodes, $p = .011$). This was largely confined to the right occipital region. We did not detect any significant connectivity changes within the delta, beta, or low-gamma frequencies (Figure 3).

3.3 | Color (blue) increased functional connectivity in the theta bandwidth

We also found color modulated functional connectivity in the theta bandwidth. When comparing the control white scene with the blue condition, the NBS identified a significant network of increased theta connectivity (15 edges, 15 nodes, $p = .023$). This network consisted of interhemispheric activity across the frontoparietal region. We did not detect differences between the resting-state and white control condition, suggesting the presentation of the achromatic built environment scene itself did not affect functional connectivity. The NBS also revealed a significant network of increased activity in the low-gamma range when comparing the resting-state to the color condition (11 edges, 10 nodes, $p = .022$). This was clustered in the right occipital region. No significant changes were detected in the remaining delta, alpha, or high-gamma bandwidths (Figure 4).
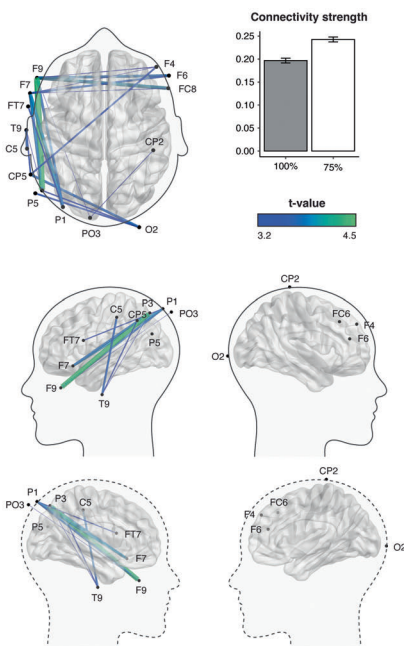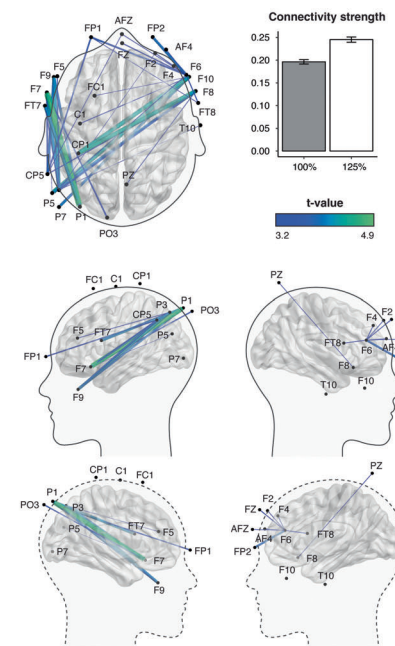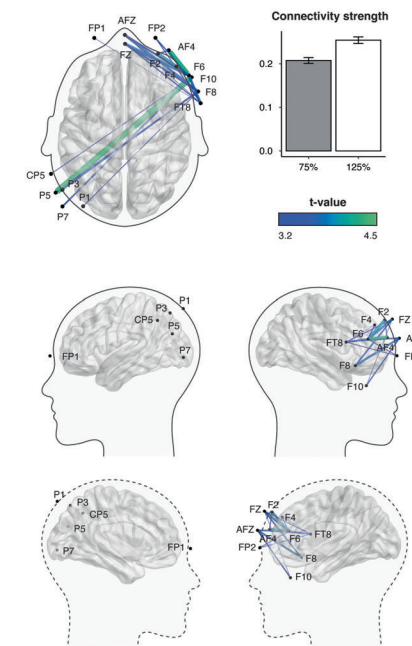
FIGURE 2 Effects of built environment scale on whole brain functional connectivity in the theta bandwidth. Images illustrate the functional subnetworks identified using the network-based statistic (NBS). Group differences obtained using a t-statistic of 3.2, which are depicted by the color gradient scale. Thickness of edges corresponds to functional connectivity strength (Pearson correlation). Clockwise top to bottom: Axial view, bar graphs depicting the average connectivity strength across all edges of the significant subnetworks (error bars denote SEM), lateral and medial views.
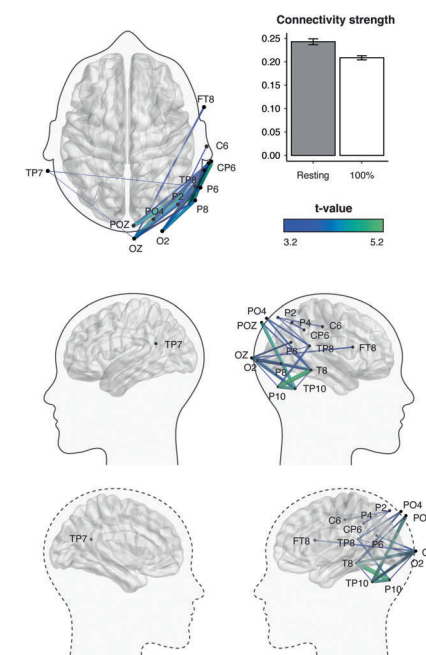
FIGURE 3 Effects of built environment scale on whole brain functional connectivity in the alpha and gamma bandwidths. Images illustrate the functional subnetworks identified using the network-based statistic (NBS). Group differences obtained using a t-statistic of 3.2, which are depicted by the color gradient scale. Thickness of edges corresponds to functional connectivity strength (Pearson correlation). Clockwise top to bottom: Axial view, bar graphs depicting the average connectivity strength across all edges of the significant subnetworks (error bars denote SEM), lateral and medial views.

(a) Control to color (theta)

Edges = 15, Nodes = 15, $P = .023$
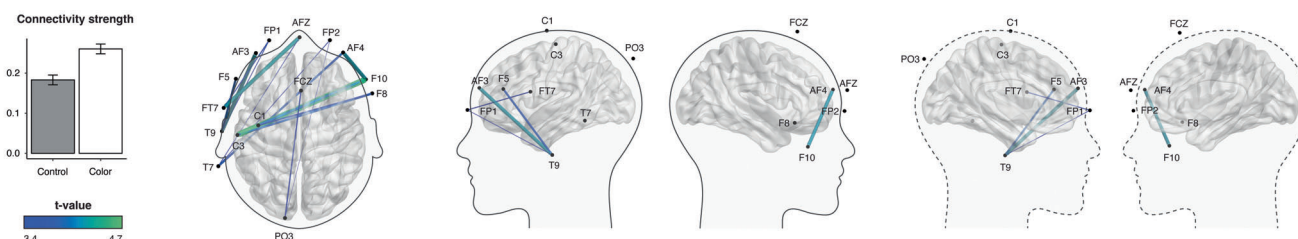
(b) Resting to color (low-gamma)

Edges = 11, Nodes = 10, $P = .023$
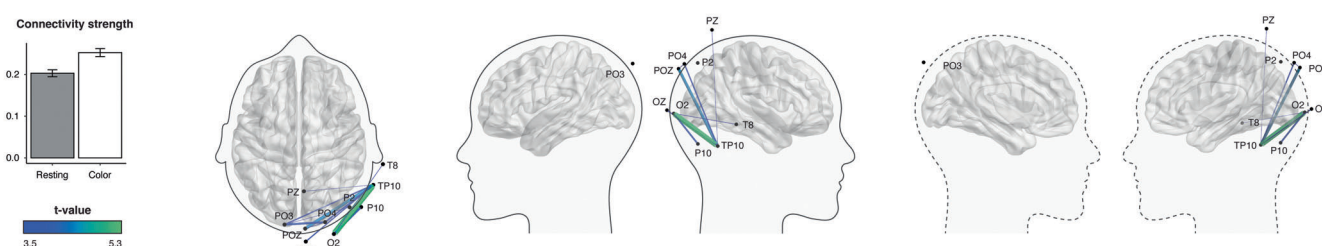
FIGURE 4 Effects of color on whole brain functional connectivity in the theta and gamma bandwidths. Group differences obtained using a t-statistic of 3.4, which are depicted by the color gradient scale. Thickness of edges corresponding to functional connectivity strength (Pearson correlation). Left to right: Bar graphs depicting the average connectivity strength across all edges of the significant subnetworks (error bars denote SEM), axial view, lateral, and medial view.

4 | DISCUSSION

This study interrogated whether the design characteristics of scale or color of interior built environments affect functional connectivity within the brain. Using a controlled approach through a CAVE, monitoring IEQ variables responsible for physiological comfort, and ensuring the scene was contextually neutral, we were able to detect differences in functional connectivity to smaller and larger built environment scale, and color in theta oscillations. We found that decreasing (control to small) and increasing (control to large, small to large) the scale of the built environment resulted in theta connectivity enhancement. We also detected increased high-gamma connectivity comparing the control to small condition. Differences in alpha and low-gamma connectivity were also found, but these were between the control and eyes-open restingstate rather than scale conditions. When analyzing color, theta functional connectivity was also found to increase between the control (white) and color (blue) condition. Significant low-gamma connectivity also increased from the resting-state to the color condition. These findings are indicative of an association between exposure to different elements of the built environment and patterns of functional connectivity within the brain. Although further investigation is required to replicate this finding and understand the precise neural mechanisms involved, the application of these findings may have implications for several underlying processes such as cognitive, attentional, perceptual, and emotional functioning.

This initial study was interested in examining the neural correlates of changes to the scale and color of interior built environments, and future work will attempt extend these initial findings by exploring brain behavior relationships between the neural response and emotional, cognitive, and social behaviors. A key strength of this study is the use of the CAVE with EEG and IEQ monitoring to ensure ecological validity. Only a handful of studies worldwide have combined EEG measurement with an immersive CAVE environment (Bower et al., 2022a; Bower et al., 2022b; Edelstein et al., 2008; Pavone et al., 2016; Pezzetta et al., 2018; Vecchiato et al., 2015; Zappa et al., 2019), and our study is the first we are aware of which further controlled for IEQ variables and context within the space. Although debate exists around embodiment and the need for studies where participants move through spaces, we believe it is important to also understand the impact of being still within a space, as we spend a significant amount of time in prolonged stationary positions. That is, sitting in a school classroom or an office, or lying in a hospital bed. As a result of COVID-19 protocols to reduce transmission, practices which had encouraged movement in the built environment such as shared desk and workspaces (encouraging workers to move locations) and using circulation spaces (stairwells and corridors) for dual functionality (additional workspace, etc.), has been discouraged. This has increased the exposure we have to a static environment, therefore, having an evidence base to elucidate differences or similarities between our responses when immersed in built environments

in both stationary and mobile situations, is critical to our understanding.

Although this is a relatively nascent field of research, the findings of this study can be explored through the oscillatory bandwidths and brain connectivity patterns to interpret the underlying cognitive meaning of findings and the type of processes involved. However, with limited work conducted in this field, we caution that interpreting these findings remains speculative. As this study employed an eyes-open resting-state design, functional brain connectivity patterns consistent with activation of the default mode network, dorsal attention network, and visual processing networks would be expected. Attentional studies have suggested functional connectivity between the prefrontal and parietal cortex, are involved in visuospatial attention, with leftward hemispheric activity involved when attention is focused (Heinen et al., 2017). This pattern aligns with our results for reducing (control to small) and enlarging scale (control to large) in the theta bandwidth, suggesting the change in scale may have activated the visuospatial attentional network. Where the change in scale was greater in distance (small to large), we detected frontal right hemispheric connectivity. Activity lateralized to the right side of the brain including the temporoparietal junction and the ventral frontal cortex have also been found to interrupt cognitive activity when a stimulus of behavioral importance is detected (Corbetta & Shulman, 2002). This may explain the functional connectivity we found in the theta bandwidth when scale increased, as it may have triggered a need to adjust behavior of interaction with the substantially different scale.

Mismatch negativity, an electrophysiological response reflecting automatic detection of a violation of expectation in the sensory environment (Pazo-Alvarez et al., 2003), can also offer a perspective for interpreting the results. Studies have also suggested frontal midline theta is involved in conflict responses, making it a potential candidate for communicating top-down control across networks (Cavanagh & Frank, 2014; Nigbur et al., 2012). Here, our results could indicate the sensory stimulus input does not align with memories and prediction of an interior room, resulting in a conflict response.

Finally, it is important to understand the potential neurocognitive significance of the bandwidths we detected. Theta oscillations have broadly been linked to sensory information processing and transfer of information across brain regions (Colgin, 2013), as well as memory encoding and retrieval (Klimesch, 1996; Staudigl & Hanslmayr, 2013). Similarly, as gamma is proposed to be involved in perceptual feature binding, the results may reflect brain processes involved in memory formation, as part of a process to assist in future recollection (Burgess & Ali, 2002). However, given gamma activity is associated with undertaking complex cognitive tasks (Fitzgibbon et al., 2004), it is worth exploring in future studies whether the involvement of high-frequency activity has an impact on task performance-based measures.

Several limitations should be considered when interpreting the results of this study. In particular, the exposure time to the built environment conditions. We selected a two-minute task free exposure to each of the scenes to limit habituation and fatigue. This may not reflect long-term effects of built environment scale exposure as we spend a substantial amount of time inside buildings. Our experimental length also affected what we were able to test. Here, we opted not to extend the study length by also randomizing variations in the chair and door location. Future research could explore whether changing these locations under the same conditions elicits a different response. We also note the color variable of this study was limited to white and blue, future work could include other color levels. Next, there may be differences in resting-state EEG functional connectivity versus performing task-based activities, warranting further investigation. There are also spatial limitations in using EEG to determine functional connectivity. However, using fMRI, which provides excellent spatial resolution, significantly limits the ecological validity of the study, as participants are required to be horizontal and in a highly constrained spatial environment with a head cage. One possible compromise is to pursue magnetoencephalography (MEG) which could improve spatial resolution while also enabling the participant to have greater immersion through a virtual projection. The development of optically pumped magnetometer-based MEG also has the potential to progress the field further (Seymour et al., 2021). Finally, this study used a CAVE as an environmentally controlled and cost-effective simulation, enabling greater sensorimotor integration than VR headsets. Although early studies validate there is no significant difference in neurophysiological measures between real-world and virtual-environment stimuli (Kalantari et al., 2021), it is still important to ensure findings are replicable. Further research is required to go beyond examining the general effect of the environment to understand exactly how the exposure might interact with task-based processes that reflect the real-world dynamics of workplace activities, caregiving at home, and so forth. Similarly, it is important we unravel the relationships and effect of additional variables of the built environment (context, comfort, contents, occupants) through carefully disentangling and testing these in subsequent studies.

The results of this study provide exciting insights into how the brain is affected by our built environment surrounds, helping us to generate a research foundation where we can produce guidelines that enable a proactive building design approach for optimizing cognitive processes and supporting mental health. Recognizing the value and integrating neuroscience methods will be a pivotal step forward for the future of research and practice in the built environment discipline. We believe this research, as a component of the growing field of environmental psychology, needs to be a core component of built environment theory, education, and practice. Similarly, it is important for the field of neuroscience to recognize, report, and account for factors in the physical environment, as these may unwittingly alter experimental results. The next step to this research is determining what these connectivity changes reflect, and whether they might reflect conflict response (thus, potentially relating to health), or a cognitive response to the environment (with ramifications for education, healthcare, residential, commercial, and workplace settings). Crucially, debate is required to unravel the ethical implications and responsibilities of policy makers, planners, and building designers to ensure built environments are supportive and have a positive effect on mental health of the public. We believe it is important that we further interrogate the

impact of building design on a broader subset of the population to further untangle whether built environment design is one of the underpinning elements of environmental enrichment which can serve as a neuroprotective factor for both healthy and clinical subsets of the population. This research will help us predict and evaluate the effect of the built environments we inhabit on brain and body functioning, so we can work towards designing buildings for optimal cognitive function and mental health.

CONFLICT OF INTEREST

The authors declare no conflict of interests.

DATA AVAILABILITY STATEMENT

The code and data that support the findings of this study are available in Open Science Framework (https://osf.io/9bsxe/?view_only=4f62dd37a189494a803e0d4d59f58a2b).

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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