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Neural representation of different 3D architectural images: An EEG study

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Abstract. Neuro-architecture seeks to define and better understand the relationships between our psychological state and the artificial structures in which we spend most of our time, and incorporate that insight into the design. However, little is known about the subjective judgment of real architectural models and the cognitive processes involved in aesthetic appreciation of architecture. In the present study, we used real and computer-designed images of bedrooms to address the underlying neural representations of different images of the same object. Thirteen participants were asked to judge the arousal and valence of their own emotional experiences after viewing each image. Furthermore, we used EEG recordings to study the regions of the brain involved in the processing of both types of images. Our results show that there are significant differences in the brain processing of both types of images, especially at early stages, and suggest that realistic images are more pleasurable, which could influence aesthetic judgment. These results emphasise the importance of generating familiar, realistic and recognisable images to improve people's acceptance.

Keywords: Neuro-architecture, EEG, aesthetic appreciation, 3D modeling

1. Introduction

Three-dimensional computer graphics (3D computer graphics, in contrast to 2D computer graphics) are illustrations that use a three-dimensional representation of geometric data, which are stored in a computer for rendering and presentation purposes [24]. In the last few decades, these 3D models have been used in a wide variety of fields. For example, the movie industry uses them for animated and real-life motion pictures [29] and the video game industry uses these 3D images as assets for computer and video games [36]. They are also useful in science and engineering, and have been used to build highly detailed models of chemical compounds [1] and for the design of new devices, vehicles and structures [6]. Furthermore, they can be used for the construction of 3D models of internal organs, derived from the images produced by clinical devices such as Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) scans, and in recent years the earth science community has started to construct 3D geological models as a standard practice [32]. All of these 3D models can be transformed into physical objects that are built from different materials with the help of 3D printers.

In this framework, architects have been using 3D modeling instead of hand-crafted designs and drawings since 1962 [12,42]. This procedure is normally employed to create 3D interior and 3D exterior mod-

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els [2,16]. Furthermore, different business firms are taking an interest in the creation of 3D product models, which demonstrates the significance of 3D architectural modeling.

By applying architectural 3D models, it is possible to envision final design results on a computer screen, which, in general, generates positive effects on potential customers [3,23]. Thus, we can visualise an entire building, or a given room, using 3D rendering, before the building is complete. This helps us modify details that must be changed before the actual construction begins, which is extremely cost-effective and saves a lot of time. However, little is known about the relationship between subjective judgment of real photographs and 3D architectural models and the neural mechanisms involved in the brain's processing of both types of images [44].

In the present study, we used real and computer-designed images to evaluate subjective arousal and valence after viewing representations of the same architectural space with different degrees of realism. Furthermore, we used electroencephalographic recordings (EEG) to study the neural activity patterns associated with both types of representation of the same object [15,19,43]. Our main goal was to investigate the main brain areas and possible time differences associated with the neural processing of each type of image [40]. Our results show that there are significant differences in the early stages of processing of both types of images and suggest that realistic images are more pleasurable, which could influence aesthetic judgment. These results provide some useful insights into the emotional response to a given image and how aesthetic judgments are made [31].

2. Methods

2.1. Participants

Thirteen participants (mean age: 24.2; range: 18.9–34.2; five men, eight women) participated in the study. Participants had no personal history of psychiatric illness or neurological, drug or alcohol abuse, and all had normal or 'corrected to normal' vision and good visual acuity. All subjects were right-handed with a laterality quotient of at least + 0.4 (mean 0.7, SD: 0.2) on the Edinburgh Inventory [34] to avoid bias due to possible variability between lefties and those who were right-handed. All subjects were informed about the aim and design of the study and gave their written consent for participation.

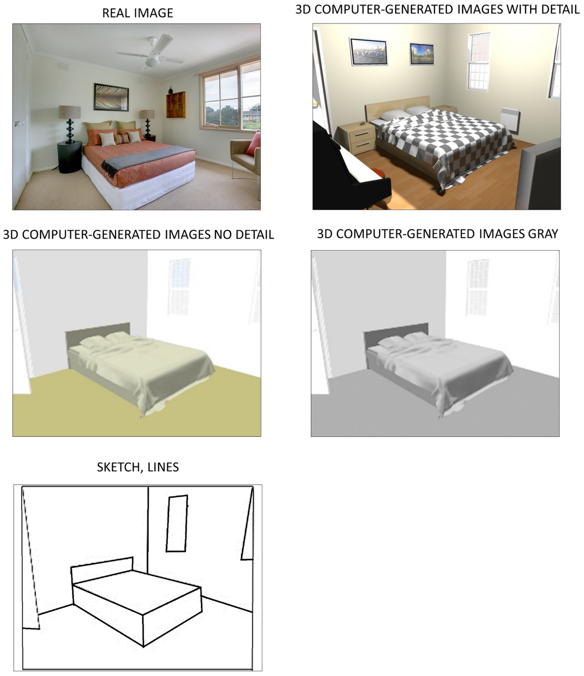

Fig. 1. Some representative images of bedrooms used in the study.

2.2. Stimuli

We used 50 different images that were divided into five different sets of images, with 10 images in each group. Groups were composed of real images (photographs), 3D computer-generated images with details (pictures, curtains, carpet, common objects, etc.), 3D computer-generated images with no details, 3D computer-generated images in gray (black and white images) and image sketches (only lines).

Figure 1 shows a representative sample. The computer-designed images were created with the help of 3D modeling software (Sweet Home 3D, which is freely available at http://www.sweethome3d.com). The photographs represented real rooms, with different decor and arrangements of furniture, windows, etc. The computer-designed rooms were similar and involved several room types with different arrangements of the door, windows and bed. All images were presented randomly, equated for luminance and contrast using a commercial stimulus presentation and experimental design system (STIM2, Compumedics, Charlotte, NC, USA).

2.3. Main experiment

Figure 2 summarises the experimental design. Each image was presented for 500 ms, followed by a black

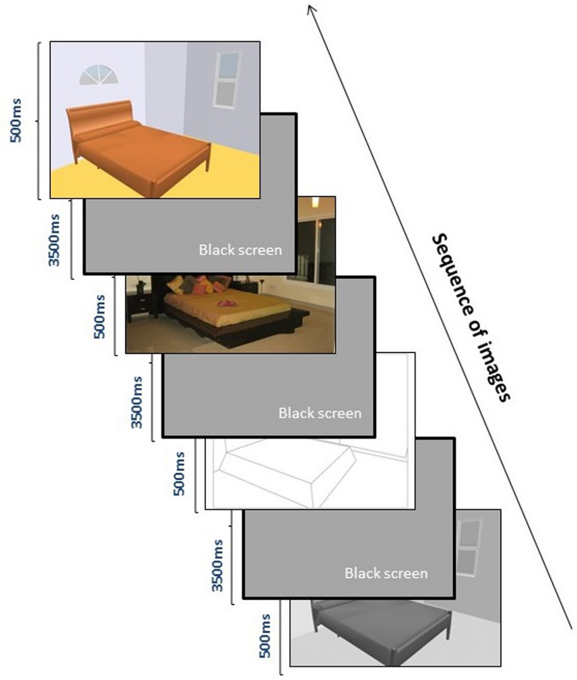

Fig. 2. Experimental design. The sequence of stimuli was presentation software (STIM2, Compumedics, Charlotte, NC, USA).

screen for 3500 ms. The images appeared in randomised order and only once. The participants were told that they would be asked to judge the arousal and valence of their own emotional experience after viewing each image (during the black screen period). Scales ranged from 1 (very unpleasant) to 9 (very pleasant).

2.4. EEG recordings

To assure good quality of EEG recordings, we asked subjects to remain as immobile as possible, avoiding blinking during image exposure while trying to keep their gaze towards the monitor centre.

EEG data was continuously recorded at a sampling rate of 1000 Hz from 64 brain locations using the extended international 10/20 Electrode Placement System [20], which is based on the relationship between the location of an electrode on the scalp and the underlying area of cerebral cortex (see Fig. 3). EEG was recorded via cap-mounted Ag-AgCl electrodes. A 64-channel NeuroScan SynAmps EEG amplifier (Compumedics, Charlotte, NC, USA) was used for EEG signal amplification and digitising. The electrodes were filtered using a 45 Hz low-pass filter and a 0.5 Hz high-pass filter. All recordings were performed in a dimly lit and silent room.

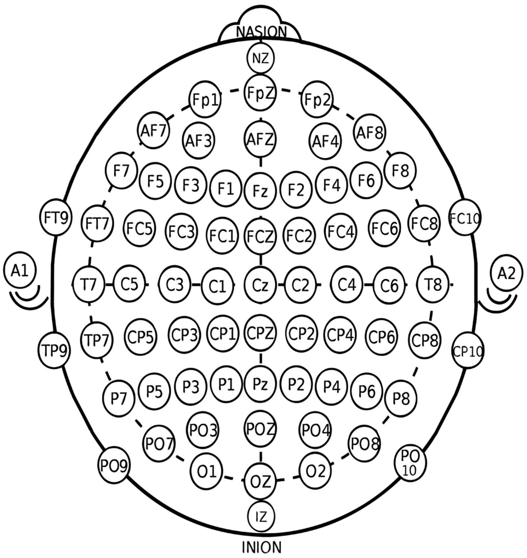

Fig. 3. Nomenclature for scalp electrode sites: the extended 10–20 electrode system.

2.5. Data analysis

To study event-related EEG dynamics, we extracted data in a time interval lasting 1200 ms (200 ms before stimulus onset to 1000 ms after stimulus). Signal processing was performed using Curry 7 software (Compumedics, Charlotte, NC, USA). As the EEG network is very sensitive to the reference choice, data were re-referenced to a Common.

Average Reference (CAR) [27]. Additionally, we used the frontal electrodes (FP1, FPZ, FP2, AF3 and AF4 (Fig. 3)) to eliminate artifacts and involuntary movements. The detected artifacts were corrected using standard Principal Component Analysis (PCA) techniques [17,28]. Furthermore, to constrain our analysis, we focused our study on topographic changes in EEG activity (see [4,22,26,33] for an overview). This procedure permits characterisation of brain electrical activity in terms of latency and scalp locations. Thus, the EEG scalp maps represent the voltage potential field on the whole head and are characterised by particular topography [30]. Therefore, we studied the changes in whole-scalp EEG activity over time, induced by every stimulus as a finite set of alternating spatially-stable activation patterns. To find the 3D distribution of the generating electrical activity, we used the standardised low-resolution brain electromagnetic tomography (sLORETA) on significant windows ($\alpha = 0.05$) [35].

To estimate the location and strengths of the current sources that generate the electrical activity, we used

Table 1

Subjective scores of different types of pictures (mean punctuation and standard deviation)

	Mean ± SD
Real images	7.02 ± 1.18
3D computer-generated images with details	6.33 ± 1.20
3D computer-generated images with no details	3.82 ± 1.36
3D computer-generated images in black and white	3.66 ± 1.65
Sketches	2.53 ± 1.69

dipole source-localisation (DSL) fitting. This technique resolves the EEG inverse problem by means of a nonlinear multidimensional minimisation procedure that estimates the dipole parameters that best explain the observed scalp potentials in a least-square sense. In this process, we assume that EEG is generated by one, but no more than, a few focal sources. The dipole source model can be further categorised as moving, fixing or rotating dipoles depending on the degree of freedom of parameters. In our study, we used a rotating dipole, which may be viewed as two independent dipoles whose orientation is allowed to vary with time [9]. Boundary Element Method (BEM) was used in the head reconstruction [45]. Topographical differences were tested using topographic analysis of variance (TANOVA), which allows quantifying differences in global dissimilarity of EEG activity between different conditions on a time-point by time-point basis. Significance level was $\alpha = 0.05$ and the number of repetitions was chosen to be $p = 1000$ [39].

3. Results

3.1. Subjective scores

We analysed the subjective scores of the participants in relation to the different types of images (real photographs, 3D computer-generated images with fine details, 3D computer-generated image without details, 3D computer-generated images in black and white and sketches). The average scores (Valence) for each group of pictures are shown in Table 1. An analysis of variance (ANOVA) showed that the different types of images used in our study had a significant effect on the subjective assessments ($p < 0.001$), except for real images and 3D computer-generated images with details, and for 3D computer-generated images without details or in black and white (see Table 1). In general, participants were more likely to judge as ‘more pleasant’ real images and 3D computer images with details.

3.2. EEG

Table 2 shows the main significant time windows for the comparison of the different groups of pictures using TANOVA ($\alpha = 0.05$). We found significant differences in stimulus-elicited activity between real images and 3D computer-generated images with details regarding the other types of images; that is, the 3D computer-designed images without details, the computer-generated images in black and white and the sketches.

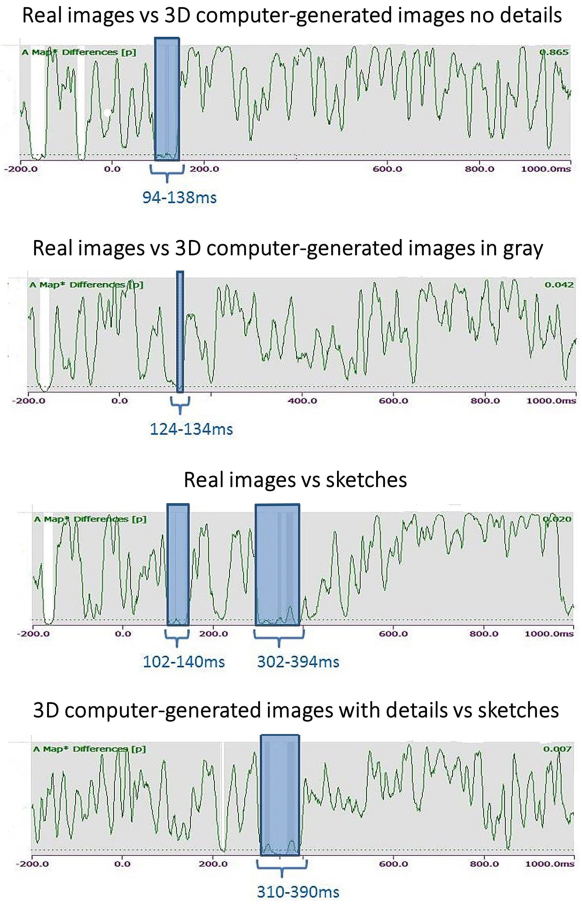

Fig. 4. Time points of significant differences in EEG activity for the different contrasts of images. TANOVA analysis, depicting 1 minus p-value across time. Significant p-values are plotted ($\alpha < 0.05$). The vertical rectangle contains significant differences.

When we analysed the differences between real images and 3D computer-designed images without details, we found that the differences started 94 ms after picture onset and lasted approximately 45 ms (Fig. 3). Furthermore, there were significant differences in stimulus-elicited activity between real photographs and 3D computer-designed images and 3D in black and white ($\alpha < 0.05$). These differences were delayed regarding previous comparisons, and started approximately 124 ms after picture presentation (Fig. 4).

Table 2

Comparison between EEG recordings using TANOVA technique while displaying different types of images ($\alpha = 0.05$)

	Real images	3D computer-generated images with details	3D computer-generated images with no details	3D computer-generated images black and white	Sketches
Real images	–	No difference	Window (94–138)	Window (124–134)	Window (102–140) and (302–394)
3D computer-generated images with details	No difference	–	No difference	No difference	Window (310–390)
3D computer-generated images with no details	Window (94–138)	No difference	–	No difference	No difference
3D computer-generated images black and white	Window (124–134)	No difference	No difference	–	No difference
Sketches	Window (102–140) and (302–394)	Window (310–390)	No difference	No difference	–

Table 3

Talairach coordinates in maximum current density obtained by sLORETA. Coordinates in mm

Window	x	y	z	x	y	z
		Real images			3D computer-generated images with no details	
94–138 ms	−4.1	−40.3	86.8	18.4	−37.2	53
		Preconeus and Brodman 31			Lingual Gyrus	
		Real images			3D Computer-generated images gray	
124–134 ms	3.1	−42.8	88.4	8.7	−36.5	64.4
		Preconeus and Brodman 31			Lingual Gyrus and Brodman 18	
		Real images			Sketches	
102–140 ms	3.1	−45.4	82.6	14.7	−44.7	54.3
		Preconeus and Brodman 31			Lingual Gyrus	
302–394 ms	26.1	29.2	13.2	−10.3	80.1	26.4
		Superior Temporal Gyrus			Media Frontal Gyrus	
		3D Computer-generated images with details			Sketches	
310–390 ms	22.2	13.1	24.7	−10.3	80.1	26.4
		Parahippocampal Gyrus			Media Frontal	

On the other hand, when we compared real images (photographs) with very simple drawings of bedrooms (sketches), we got two time windows with significant differences: 102–140 ms and 302–394 ms (Fig. 4).

3.3. *Dipoles*

Figure 4 shows the time points of significant differences in EEG activity for the different types of images using the TANOVA analysis. Since the rotating dipole solution enhances three-dimensional EEG source localisation, one rotating dipole source model was used in the time windows with significant differences indicated by the TANOVA analysis.

When we analysed real images versus 3D computer-generated images with no details and focused on the time window 94–138, we found significant differences in the dipoles for both different types of images. Figure 5A shows the location and coordinates of each dipole for this particular time window.

Figure 5B displays the dipoles for the comparison between real images and 3D computer-generated images in black and white for the time window 124–134 ms. Again, there are significant differences, and the same happens for the comparisons between real images and sketches, although in this case there were two time windows with significant differences. The first significant time window appeared approximately 102 ms after stimulus onset and lasted 39 ms (Fig. 5C). The second significant time window appeared later, at 310 ms, and had a duration of 81 ms (Fig. 5D). Curiously, when we looked at the differences between 3D computer-generated images with details and sketches, the time window was very similar to this second significant time window (310–390 ms, Fig. 5E).

3.4. *sLORETA*

Figure 6 shows the corresponding activation in terms of scalp maps for the comparison of the different types of images at the significant time windows described

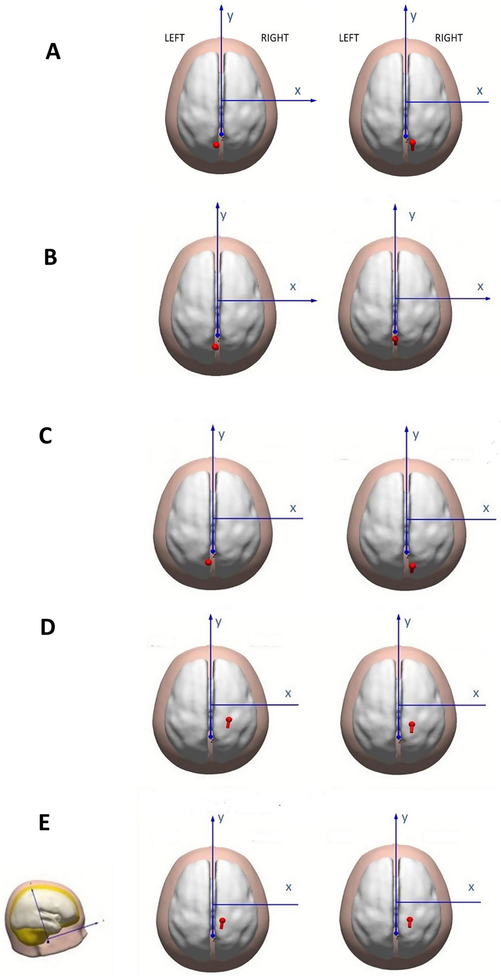

Fig. 5. (A–E): Head reconstruction and rotating dipoles in representative time windows. A: Comparison of real images vs 3D computer-generated images with no details (windows 94–138 ms); B: Real images vs 3D computer-generated images in gray (windows 124–134 ms); C and D: Real images vs sketches (windows 102–140 ms and 302–394 ms); E: 3D computer-generated images with details vs sketches (windows 310–390 ms).

previously. According to the results, activation was observed for different brain regions for the three representative time windows.

Table 3 displays the maximum current density results with sLORETA. Also indicated are Talairach coordinates and the cerebral areas where the maximum activation occurs, according to the reconstruction sLORETA.

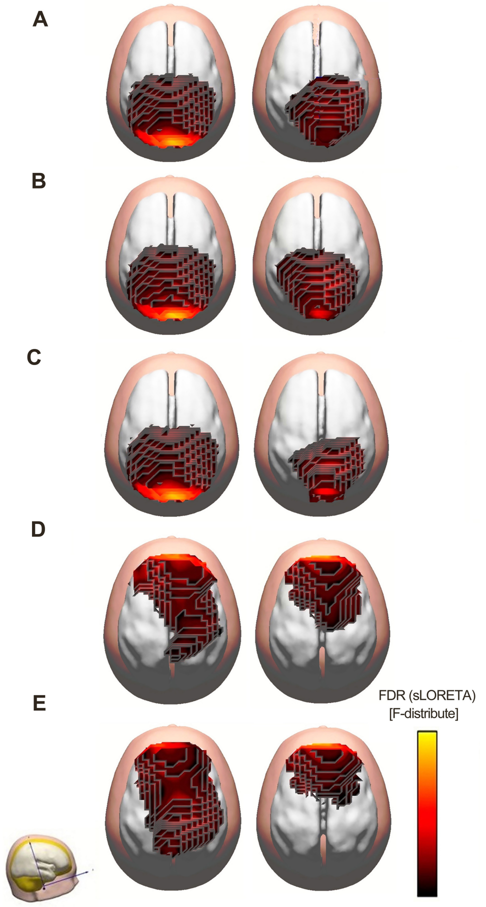

Fig. 6. (A–E): Head reconstruction and sLoreta reconstruction in representative time windows. A: Comparison of real images vs 3D computer-generated images with no details (windows 94–138 ms); B: Real images vs 3D computer-generated images in gray (windows 124–134 ms); C and D: Real images vs sketches (windows 102–140 ms and 302–394 ms); E: 3D computer-generated images with details vs sketches (windows 310–390 ms).

4. Discussion and conclusions

Neuroscientists and neuropsychologists have recently approached the traditional philosophical field of aesthetics, aiming to characterise the neural and evolutionary foundations of our species' ability to appreciate beauty and art [5,45]. This new approach, known as neuroaesthetics, has begun to provide some insights into the neurobiological bases of aesthetic appreciation [14,47], and could lead to novel observations useful for architectural design.

In this study, we used real images and computer-designed images of bedrooms with different grades of details to address the underlying neural representations of different images of the same object. We found significant differences in the subjective perception of images with details (furniture, clothing) and images without details (single bed, walls, windows and doors). The subjective scoring revealed that the participants preferred real images (photographs) or realistic computer-generated images over simpler images and sketches. Thus, realistic images are more pleasurable and could have a significant impact and influence on aesthetic judgment.

The analysis of EEG recordings shows that there are significant differences in the brain's processing of the different types of images. Thus, at early stages of processing, real images activate preferably the Brodman 31 brain area, which is related to episodic memory retrieval [21] and voluntary and involuntary recall [13], whereas computer-generated images without details, in black and white and sketches, activate other brain areas, which are close to the Brodman 18 brain area, and are mainly related to sustained attention to color and shape [25] and visuo-spatial information processing [8,46]. On the other hand, and at later stages, we found that real images and 3D computer-generated images with details activate brain areas located at the superior temporal gyrus and parahippocampal gyrus, which are related deductive reasoning [11], recognition memory, memory recall and retrieval [7], and the integration of visual elements into perceptual wholes [10]. In contrast, if the images are simpler (sketches), the activated area is the medial frontal rotation, which is mainly related with internal mental calculation [49] and memory encoding and recognition [18,37].

These differences in cognitive processing could be justified by the familiarity of the images. Thus, a number of psychological studies have shown that people usually prefer familiar stimuli; an effect currently explained under the umbrella of the processing fluency theory. In this context, Reber et al. [38] suggested that objects vary with regards to the fluency with which they are processed. Given that fluent processing is experienced as hedonically pleasurable, and that aesthetic experiences are strongly influenced by affective states, it follows that positive aesthetic experiences arise especially from confident processing, such as that afforded by prototypical examples of a category [48]. In this framework, the photographs and images with details are more familiar to most people and therefore they are perceived as being more pleasurable than the images without details. However, apart from familiarity, many other factors can influence results, such as image quality. Therefore, more studies are still needed.

Our results highlight the relevance of neuro-architecture and show that there are significant differences in the brain's processing of different types of architectural images, especially in the early stages of processing. These data could be helpful for a better understanding of the brain's processing of images and how aesthetic judgments are made. Furthermore, the results emphasise the necessity and importance of creating computer models as realistic as possible, and may help to provide new empirical foundations for architectural design. Nevertheless, there are still many open questions that require further investigation, especially about how multiple cortical regions might interact for the aesthetic experience.

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