applied sciences

MDPI

Article

Quantifying Emotional Responses to Traditional and Modern Architecture: The Case of US Federal Buildings

Alexandros A. Lavdas [1,2,3,*] and Ann Sussman [2]

1 Institute for Biomedicine, Eurac Research, Affiliated Institute of the University of Lübeck, Via Volta 21, 39100 Bolzano, Italy
2 The Human Architecture & Planning Institute, Inc., 43 Bradford St., Concord, MA 01742, USA; ann@thehapi.org
3 Department of Psychology, Webster University, Athens Campus, 9 Ipitou Street, 10557 Athens, Greece
* Correspondence: alexandros.lavdas@eurac.edu

Featured Application

Using computerized expression analysis to examine affective reactions to exposure to architecture.

Abstract

Current biometric tools, with facial expression analysis capabilities, enable us to more deeply examine affective correlates of exposure to architectural forms, especially when combined with eye-tracking and preference data. This study builds on earlier preference studies comparing seven pairs of traditional vs. modern civic buildings from the National Civic Art Society and an eye-tracking study with the same images from the Human Architecture and Planning Institute. It explores how metrics for engagement and positive emotional experience are correlated with exposure to traditional and modern forms. In agreement with other eye-tracking studies, as well as with the broader literature, the results indicate that traditional stimuli elicit positive affective responses, while modern stimuli result in negative responses across participants.

Keywords: biometrics; facial expression analysis; traditional architecture; modern architecture; federal buildings

1. Introduction

In recent decades, biometric measurement techniques have moved from specialized laboratory settings into everyday commercial and research applications. This transition has been largely driven by the widespread availability of affordable wearable sensors and by the rapid advances in digital platforms that enable data collection beyond controlled experimental environments. Together, these developments have reshaped the scope of empirical research on human perception and emotion, making it possible to involve larger, more heterogeneous participant groups while reducing logistical and financial barriers.

Within the disciplines of architecture, urban design, and environmental psychology, interest in biometric data has grown. At the same time, there is a persistent disconnect between expert-driven design paradigms, established in the first part of the twentieth century, and the lived experiences of users, with many contemporary architectural and urban forms continuing to be perceived by the public as unwelcoming, stressful, or emotionally alienating. Traditional design evaluation methods—expert reviews, theoretical reasoning,

Check for updates

Academic Editor: Roger Narayan

Received: 15 March 2026
Revised: 24 April 2026
Accepted: 28 April 2026
Published: 30 April 2026

and post-occupancy surveys—are certainly valuable, but they often capture only a partial picture of how environments are actually experienced in real time. This is a gap that the application of biometric measurements can help bridge.

Various parameters that contribute to a special type of connectedness between the viewer and the surroundings have been proposed, initially in a qualitative fashion through the pioneering work of Christopher Alexander [1,2]. It has since been shown [3,4] that exposure to certain types of fractal patterns [5] is associated with measurable positive physiological effects, regardless of whether these patterns are encountered in nature, architecture, or through the visual arts. While these findings do not establish causality in all contexts, they suggest that specific geometrical properties may play a role in shaping perceptual and affective responses. Interestingly, the Default Mode Network (DMN) of the brain (a functional network mostly related to "internal" thought processes, as opposed to externally provoked task execution) is active during the visual perception of fractals, indicating their privileged state in terms of their innate familiarity and, ultimately, perceptual fluency [6,7]. The DMN has been shown to represent esthetic appeal across visual domains, supporting the hypothesis correlating beauty with perceptual fluency [8].

A substantial body of research conducted over the past several decades has demonstrated numerous benefits associated with exposure to natural environments, including early evidence indicating enhanced postoperative recovery outcomes [9] and positive effects on mood [10], stress reduction [11], concentration and working memory [12–16], self-perceived health [17] and self-esteem [10,18] and a reduction in criminal behavior [19,20]. A brief exposure to nature has also been shown to reduce activity in the subgenual prefrontal cortex, associated with a self-focused behavioral withdrawal in healthy and depressed individuals, as well as self-reported rumination [21]. These findings collectively indicate that certain environmental characteristics—which are common in natural settings—are linked to measurable cognitive and affective benefits, although the specific contributing features remain an active area of research.

Artificial environments mimicking nature's geometrical qualities can also have positive effects [22,23]; these qualities are not restricted to fractality, as the work of pioneer Nikos Salingaros has shown [24–26]. Our processing ". . . system is acutely tuned to the visual complexity of the natural environment, specifically to respond positively to the highest levels of organized complexity. Fractals are an important component of this effect, but by no means represent the full gamut of connective qualities" [27]. There is also a hierarchy of scales, presence of local contrasts, and overall coherence, which collectively make up this "organized complexity". Rather than implying a direct equivalence between these properties and specific architectural styles, these insights suggest that environments incorporating such features may be more likely to elicit positive perceptual responses. The experience of beauty is frequently overlooked in contemporary architectural practice. However, it is not arbitrary; it can be understood as an emergent outcome of a complex, multiparametric evaluation of a given environment and should be considered a necessity, not a luxury [28].

Beyond the investigation of these features, there is a broad consensus in studies on human perception and emotion that the built environment profoundly shapes an individual's sensorimotor, emotional, and cognitive responses, and in recent years, much of this work has focused on the potential psychophysiological impact of the visual organization of our surroundings, whether natural or artificial [23,29–31]. Certain architectural properties, such as room proportions [32], wall curvature [33,34], and window arrangement and size [32,35,36], have been found to correlate with stress responses [37]. fMRI studies have been used to investigate responses to different scenes, such as natural vs. urban [38], or to various parameters of architecture and design, such as curved vs. rectilinear designs [39,40] or ceiling height [33], examining the relation between subject ratings and brain activations. These ratings can be judged by simple tests (such as approach–avoidance tests) or correlated to higher-level components, like coherence (ease of organizing and comprehending a scene), fascination (informational richness and generated interest), and hominess (personal ease and comfort) [41].

The present study builds on earlier work [42], which focused primarily on eye tracking as a tool for understanding visual attention in response to architectural stimuli. While eye tracking provides insight into what people look at and for how long (see also [43]), it offers limited information about the outcome of the emotional processing of the scenes. In that work, eye-tracking data was supplemented by an already available large-scale survey, enabling us to correlate declared preferences with eye-tracking results. Here, we add another layer, software-based facial expression analysis, in a fresh study with the same photos, to examine expression proxies of joy and engagement, with the hypothesis that these expression proxies would reveal a more positive reaction (positive change during stimulus exposure) in images of traditional rather than modern buildings, following the categorization used in the previous two studies with these images. By integrating biometric indicators associated with emotional arousal and valence, the study seeks to enrich existing evaluative frameworks with objective, quantifiable data. Such an approach does not claim to capture the full complexity of human emotion, but it can reveal patterns that might otherwise remain implicit or unrecognized. And, in our case, it benefits from existing preference data examined in a large Harris Poll by the National Civic Art Society (NCAS) [44].

We carried out the analysis of facial expressions using Affectiva, the AFFDEX engine of the behavioral research company iMotions software (version 10.1) [45], which is based on the Facial Action Coding System (FACS) developed by Ekman and Friesen [46] and the theory of basic universal emotions proposed by Ekman [47]. Action Units (AUs) are the fundamental building blocks of FACS, with each representing the contraction or relaxation of a specific facial muscle or muscle group. It should be noted that there are studies that have raised questions regarding the universality of the expression of emotions and, hence, the universal applicability of their analysis, noting that emotional expressions may not map consistently onto discrete categories, as observers often rely on contextual and cultural information to interpret facial movements rather than decoding fixed emotional signals [48]. Moreover, the accuracy of expression analysis depends on factors such as stimulus type, context, and observer characteristics (for non-automated systems) [49]. These considerations apply to all data in the present study, and it is not obvious how they could bias the results towards one or the other category; nonetheless, they could increase noise, and it should be noted that the interpretation of quantitative measurements of facial expression data as proxies for affective responses requires caution.

2. Materials and Methods

2.1. Software

The study used biometric software developed by iMotions (version 10.1) [45]. iMotions Online, released in 2020, combines webcam-based eye-tracking and facial expression analysis software. Data collected is stored on an online iMotions account and processed with iMotions software installed on a Windows-based computer.

2.2. Image Presentation and Data Acquisition

Participants were recruited through a publicly accessible call posted on GeneticsofDesign.com (the blog for the Human Architecture and Planning Institute) [50], supplemented by announcements disseminated via social media platforms, including Facebook, Twitter, LinkedIn, and ResearchGate, as well as through email distribution. No demographic targeting was implemented, and no demographic data were collected. Participants accessed the study through a web link using personal computers equipped with a webcam and were instructed to ensure adequate lighting conditions throughout the session to facilitate accurate data capture. Each study began with an initial calibration phase to configure the camera and software. Participants were first asked to indicate the type of device used (desktop, laptop, or tablet) and to grant access to their webcam. A visual guide indicating the desired head position was superimposed on the webcam feed, and participants were instructed to align their head accordingly and minimize movement during data recording. Subsequently, a sequence of black screens displaying white crosshairs at varying screen locations was presented individually. Participants were notified prior to each presentation and instructed to fixate on the crosshairs. No additional instructions, such as comparative or evaluative prompts, were provided. Then, 14 images were presented in a continuous video flow, for 4.5 s each with a fade-in/fade-out type of transition, without a black screen ever appearing. The images (14 in total) were photographs of traditional and modern civic architectures (Figure S1). The images, which were very closely matched in angle, brightness, and overall composition, were provided by the NCAS and originally used in pairs in a 2020-NCAS-sponsored Harris Poll [44] and our previous eye-tracking study of these images [42]. The only difference in the current study was the normalization of the sky, which was not relevant in the previous study, as eye-tracking data had been quantified only within the area of interest (the buildings themselves). In our current study, the images were projected individually, but with the same sequence as in the Harris Poll. All participants were presented with the visual stimuli in an identical sequence. The images were displayed at a resolution of 1920 $\times$ 1080 pixels. Each study concluded with post-calibration of the participants' webcam, employing crosshair fixation points analogous to those used in the initial calibration phase, in order to account for any potential head movement occurring during the intervening period. Fifty-nine people completed the study, and 112 people abandoned the study without completing it. Participant data were automatically uploaded to an online iMotions account. The images were labeled in pairs (Ia, Ib, IIa, IIb etc.), as a reference to their original pairing in previous studies (see above).

2.3. Analysis

When the collection of data was complete, the data were downloaded for processing on the iMotions desktop software, which coded and analyzed facial expressions. Facial expression metrics were derived using the Affectiva AFFDEX engine embedded in iMotions software, which is based on FACS. The software estimates the probability (0–100) of specific emotional expressions based on combinations of AUs detected in video frames.

Within the iMotions interface, a default probability threshold of 50 is provided and plotted to assist researchers in identifying when an emotional response is considered "detected" [45]. In the present study, this default threshold was retained and used solely for initial visualization and exploratory inspection of emotional responses within the iMotions environment.

The software, however, records continuous probability scores for emotions and for each analyzed frame and exports time-stamped raw values ranging from 0 to 100, allowing access to the full signal regardless of whether the detected probability exceeds the platform's predefined detection threshold. *Joy* is used as a proxy for positive affective valence, while *Engagement* is a weighted sum of multiple facial AUs, reflecting attentional and emotional activation rather than a discrete basic emotion. The software outputs frame-level probability values, which were aggregated over time intervals corresponding to stimulus presentation. All analyses were conducted on continuous probability values rather than thresholded detections. Frame-level image exclusion based on signal quality was applied as part of the default processing of the iMotions platform. If a face could not be properly detected or tracked due to poor quality, those specific frames or segments were rejected and did not produce valid emotion metrics [45]. The system also requires a minimum resolution and frame rate (720p at 30fps) for reliable processing, so inputs from participants not meeting these criteria are automatically rejected as a whole; there were no such cases in this study.

Subsequent quantitative analysis was conducted using the exported raw continuous data, enabling more detailed statistical processing outside the iMotions platform. By relying on the full continuous signal for calculations, the analysis preserved the variability of the recorded facial responses and avoided the information loss associated with binary thresholding.

For this, an interval of approximately 3.4 s during the image projection was examined for every image. This was to avoid the transitional (fade in/fade out) periods. Within this interval, to quantify affective response dynamics, a difference metric (Δ) was computed as Δ = Mean (last 50% of interval) − Mean (first 20% of interval). This metric was designed to capture within-stimulus change from a more transition-affected phase to a more stabilized phase of the response. Because stimuli were presented continuously with fade transitions, the early portion of each interval was expected to contain a larger proportion of onset-related and carryover effects from the preceding image, whereas the later portion was expected to better reflect the response to the current stimulus after initial settling. We emphasize that the exact temporal cut-points are heuristic rather than theoretically unique.

For each participant, Δ was computed separately for each of the 14 intervals, resulting in 14 values of Δ joy and 14 values of Δ engagement.

Then, two groups were formed, comprising the responses to exposure to traditional building images and the responses to exposure to modern building images, to test the hypothesis that the two types of images elicit different emotional responses. They were as follows:

Traditional stimuli: Ib, IIa, IIIb, IVa, Vb, VIa, VIIa.

Modern stimuli: Ia, IIb, IIIa, IVb, Va, VIb, VIIb.

For each participant, Δ values were first calculated for each stimulus interval. These Δ values were then averaged separately across Traditional and Modern stimuli to obtain participant-level category means. Paired t-tests, which, were appropriate given the size of the participant sample, were then conducted on these participant-level category means to evaluate whether the average Δ differed between Traditional and Modern stimuli.

To assess the potential influence of temporal position within the sequence, a sensitivity analysis was conducted excluding the initial and final portions of the recording. The first portion was excluded to account for potential novelty and calibration effects, while the final portion was excluded to account for possible cumulative effects such as fatigue or habituation over the course of the session rather than any intrinsic property of the final stimulus itself.

Mixed-effects analyses were conducted in R (version 4.5.3, via Rstudio, version 2026.01.2), using the lme4 and lmerTest packages. Models were estimated using restricted maximum likelihood (REML), and statistical significance was assessed using Satterthwaite approximation for degrees of freedom. Stimulus category (Traditional vs. Modern) was included as a fixed effect. To account for the repeated-measures structure of the data and potential variability across both participants and stimuli, crossed random intercepts were specified for participants and stimuli (images). More complex random-effects structures, including random slopes, were considered but not included because the limited number of stimuli per category (n = 7) does not support reliable estimation of such parameters. Model assumptions were assessed via inspection of residual distributions, which did not indicate substantial deviations from normality. However, the models exhibited singular fits, with some variance components estimated at or near zero, indicating limited ability to partition variability across levels.

3. Results

3.1. Thresholded Aggregation Results

A graph of thresholded aggregation metrics, as described above, was first produced for visual inspection (Figure 1). The plotted values represent the numbers of participants that had a signal above the pre-defined threshold during each 500 ms time bin. For both metrics, a fluctuation in their values is observed during the time course of the exposure to the images. In most cases, exposure to a traditional building increases the Joy metric, but this is not always true (no response to Vb). On the other hand, exposure to modern buildings usually reduces the Joy metric, again with one exception, IIIa showing two positive spikes within its exposure period. Ia and Ib show a different pattern, with Joy somewhat increasing and then dramatically decreasing during exposure to Ia (modern), increasing again dramatically during the transition period, and stabilizing at a somewhat lower level. For engagement, the response course profile is similar for the most part, although somewhat more granular. No further analysis was performed on the aggregation data, as we proceeded with the raw data.

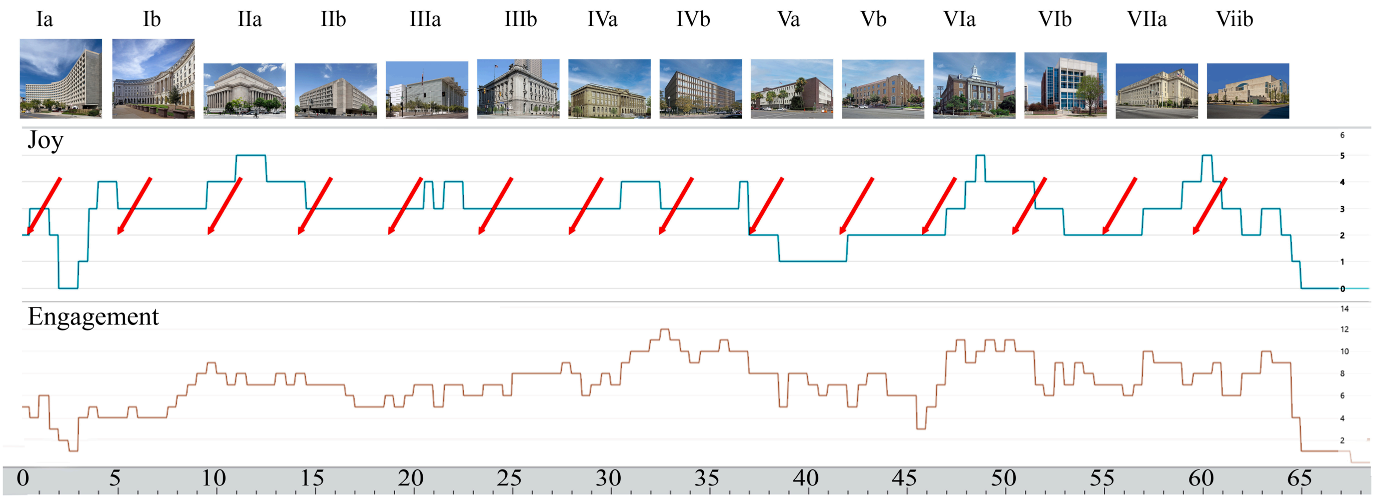

Figure 1. Thresholded aggregation metrics for Joy (**top**) and Engagement (**bottom**). Values represent the numbers of participants that had a signal above the pre-defined threshold during each 500 ms time bin. The red arrows indicate the time of appearance of the image in the top row. Time axis (in seconds) seen at the bottom.

3.2. Raw Expression Data Results

3.2.1. Individual Stimuli Analysis

Descriptive statistical analysis of individual stimuli reveals that mean changes in Joy and Engagement during each stimulus interval show fluctuation from one image to another, more so for Engagement than for Joy (Figure 2). The direction is overall the same, as shown in the thresholded aggregation metrics, with large standard deviations calculated.

3.2.2. Grouped Stimuli Analysis

The paired t-tests revealed significant differences between the two stimulus categories (Traditional and Modern, Figure 3, Table 1). For Joy, the mean Δ was higher during exposure to Traditional stimuli than Modern stimuli, indicating a more positive change in affective expression across the presentation interval for Traditional images. A similar pattern was observed for Engagement, with Traditional stimuli eliciting larger positive Δ values than Modern stimuli.

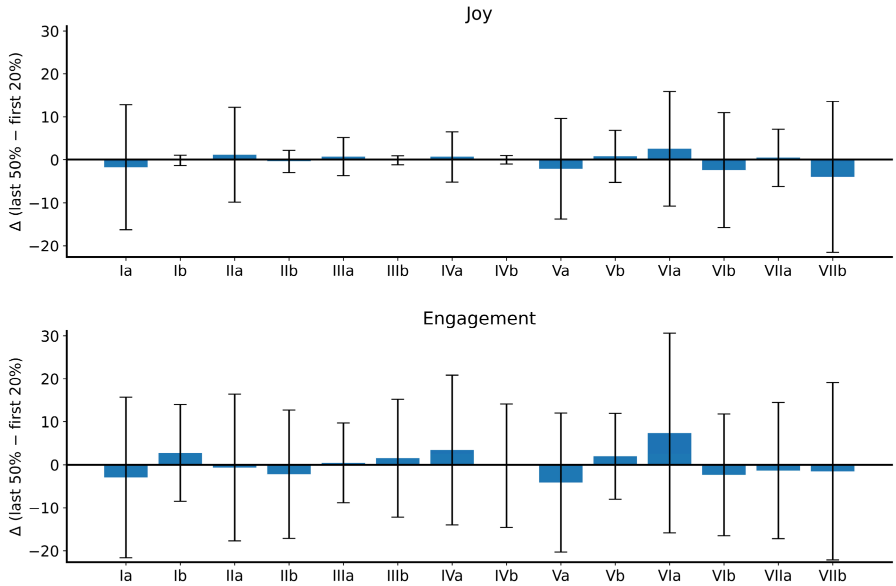

Figure 2. Δ and standard deviation (SD) calculated for Joy (**top**) and Engagement (**bottom**) for each of the 14 time intervals, representing 3.4 s from each stimulus.

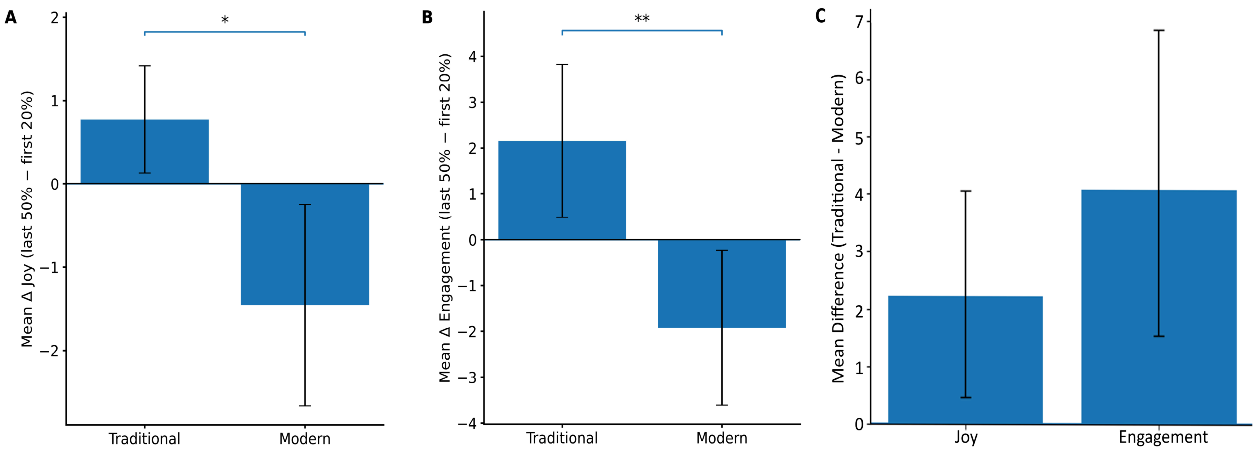

Figure 3. Mean Δ and confidence intervals calculated for Joy (**A**) and Engagement (**B**), and mean differences in the Traditional-Modern Δ (**C**). Significance determined via *t*-test, with * $p < 0.05$ and ** $p < 0.01$.

Table 1. Values represent participant-level category means and paired comparisons. Traditional stimuli show significantly higher Δ values than Modern stimuli for both measures.

Measure	Traditional (M ± SD)	95% CI (Traditional)	Modern (M ± SD)	95% CI (Modern)	Mean Difference (T − M)	t(df)	*p*-Value	Cohen's dz	SD Difference	95% CI (Difference)
Δ Joy	0.772 ± 2.521	[0.116, 1.428]	−1.457 ± 4.743	[−2.692, −0.222]	2.229	2.46 (58)	0.0168	0.32	6.958	[0.482, 4.056]
Δ Engagement	2.153 ± 6.538	[0.451, 3.855]	−1.921 ± 6.631	[−3.648, −0.194]	4.074	3.02 (58)	0.0037	0.39	10.330	[1.553, 6.864]

The paired comparison revealed a statistically significant difference between Traditional and Modern intervals, with ***p* = 0.017**. The mean paired difference (Traditional-Modern) was positive, indicating reduced Δ Joy during Modern intervals.

https://doi.org/10.3390/app16094406

A highly significant difference was also observed for Engagement, with $\boldsymbol{p = 0.0037}$. Again, the mean paired difference (Traditional–Modern) was positive, indicating reduced Δ Engagement during Modern intervals (Table 1).

To assess the potential influence of fixed stimulus order, an additional sensitivity analysis was conducted excluding the first and last images in the sequence. The resulting pattern remained directionally consistent with the primary analysis.

For Engagement, Traditional stimuli continued to show significantly higher Δ values than Modern stimuli. For Joy, the difference remained in the same direction but did not reach statistical significance in this analysis ($p = 0.059$). These findings suggest that the overall category pattern is not mainly driven by edge-position effects while also indicating that the Joy effect is less robust than the Engagement effect (Table S1).

These results indicate that the temporal trajectories of Joy and Engagement differed systematically between stimulus categories, with Traditional images eliciting positive changes in facial-expression dynamics during stimulus presentation and Modern buildings eliciting negative changes.

To assess the effect of stimulus category while accounting for both participant- and stimulus-level variability, linear mixed-effects models with crossed random intercepts were fitted. For Δ Joy, Traditional stimuli elicited significantly higher values than Modern stimuli ($p = 0.0096$). For Δ Engagement, a similar pattern was observed, with Traditional stimuli producing significantly higher values than Modern stimuli ($p = 0.0076$). Random-effects variance estimates indicated negligible participant-level variance ($\sigma^2 \approx 0$) and modest stimulus-level variance ($\sigma^2 = 0.28$ for Joy; $\sigma^2 = 1.61$ for Engagement), with substantially larger residual variance. Both models exhibited singular fits, suggesting limited power to estimate variance components despite significant fixed effects. These results indicate a consistent effect of stimulus category at the level of observed data, with Traditional stimuli associated with greater positive changes in both Joy and Engagement (Table S2).

4. Discussion

The present study investigated affective responses to the presentation of a series of images of traditional and modern federal buildings in the United States, by utilizing facial expression metrics as proxies for Joy and Engagement. Emotional responses play a central role in architectural experience, and it is well established that architectural forms and spatial qualities influence human perception, affect, and behavior [51]. In this study, Joy was used as an indicator of positive affective valence, which we hypothesized is correlated with exposure to traditional forms based on the existing literature discussed earlier, as well as the preference data from the Harris Poll of the same building images [44]. Engagement was used to capture the degree of attentional and emotional involvement elicited by the architectural images, and again, the hypothesis was based on the existing literature and on our previous work on the same images [42], which focused on eye-tracking, and had shown increased dwell time as well as decreased time to first fixation for traditional building images.

Rather than relying on static mean-level comparisons per interval, we quantified within-interval affective change by computing the difference between late-phase (last 50%) and early-phase (first 20%) response segments. This approach allowed us to capture modulation of responses within each stimulus presentation. Descriptive statistical analysis per image revealed substantial variability in the magnitude of Δ responses across participants, as reflected in the relatively large standard deviations observed for both Joy and Engagement. Such variability is expected in facial-expression-based affective measurements, where individual differences in emotional expressivity, baseline affect, and responsiveness to visual stimuli can be considerable [52].

However, when the stimuli were grouped in two categories, Traditional and Modern, it was found that the two categories elicited significantly different affective changes, with Traditional building images causing a positive affective change (Δ Joy and Δ Engagement), while Modern stimuli produced negative changes upon presentation. This may reflect differences in perceptual fluency or cognitive load associated with stimulus structure, as discussed in the introduction, and potentially also differences in semantic familiarity. Sensitivity analysis, performed by removing the first and last stimuli, confirmed our findings. The first stimulus occupies a unique position due to the absence of preceding context and may therefore be affected by novelty or initial calibration effects. The final stimulus is not perceptually distinct during viewing but may nevertheless be influenced by cumulative factors such as fatigue or habituation across the sequence. After these removals, the overall pattern remained directionally consistent with the primary analysis. For Engagement, the Traditional-versus-Modern difference remained statistically significant. For Joy, the effect remained in the same direction but did not reach statistical significance ($p = 0.059$). However, the trend is clear, and it is worth pointing out that a certain p value represents a probability, not a cut-off point, as it is often thought of [53]. These results suggest that the main category effect is not driven by edge-position stimuli, while also indicating that the Joy effect is less robust than the Engagement effect. Effect sizes based on within-subject comparisons further contextualize these findings. Cohen's dz indicated a small effect for Joy (dz $\approx$ 0.23 vs. 0.32 in the original analysis) and a small-to-moderate effect for Engagement (dz $\approx$ 0.37 vs. 0.39 in the original analysis), suggesting that the observed category differences, while consistent in direction, are modest in magnitude.

The mixed-effects analysis provided additional support for the conclusion that Traditional stimuli elicit more positive affective dynamics than Modern stimuli, as reflected in both Joy and Engagement measures. This effect remained statistically significant even when accounting for both participant- and stimulus-level variability using a crossed random-effects model. At the same time, the models exhibited singular fits and near-zero participant-level variance, indicating limited power to estimate variance components, particularly given the relatively small number of stimuli per category ($n = 7$). As a result, while the observed category effect is consistent within the present dataset, caution is warranted in generalizing beyond the specific set of stimuli used. This limitation reflects a common constraint in designs with relatively few items per condition, where separating item-specific effects from category-level effects remains statistically challenging. Future research should include a larger and more diverse set of stimuli to enable more reliable estimation of stimulus-level variability and to strengthen generalization of category-level (Traditional vs. Modern) conclusions. Consistent with previous work, results from this study indicate our preference for traditional facades incorporating elements of organized complexity, as discussed in the introduction and previously by us and other authors. Obviously, this is a discussion about biases, not about absolutes, as the findings that stimulus Vb (traditional) elicited no Joy response and that IIIa (modern) showed positive spikes indicate. We postulate that, for reasons that cannot be identified through the present analysis, IIIa is preferable to IIb, which is also modern, so that their sequential appearance drives this increase. The building in Vb, while categorized as "traditional", incorporates fewer elements of organized complexity (as described in the introduction) which may explain why it is not capable of driving the "Joy" metric, although it does positively affect the "Engagement" metric.

An important factor in this context is perceptual fluency—the ease with which sensory input is processed—and, among other lines of evidence, we have already mentioned the activation of the Default Mode Network (DMN) of the brain during the viewing of fractal patterns [6,7]. The DMN is typically suppressed when a person engages with the external environment. The DMN is not only active when fractals are viewed but also when one finds a visual artwork esthetically moving and represents esthetic appeal in a manner that generalizes across visual esthetic domains, such as artworks, landscapes, or architecture [8]. There is also data on the role of fractals in stress reduction, as mentioned earlier [3,4,23,54], and findings related to specific EEG responses to fractal patterns [55], all of which support the idea of a privileged status of fractals in terms of perceptual fluency.

Another factor is metabolic stress. Further supporting the notion of the existence of geometries which we are—or are not—"tuned" to is the finding that there are geometrical patterns whose processing requires increased effort from our visual system, as revealed by increased blood supply in certain areas; this is exactly what has been found for parallel stripes at a certain apparent distance and density [56]. Chronic metabolic stress, in turn, can lead to adverse effects through neuroinflammation, which has been correlated with a wide range of neurological disorders [57].

Given the critical role of rapid and appropriate responses to environmental cues in ensuring survival, impairments in early perceptual registration mechanisms may result in an elevated sense of threat and increased stress levels. More generally, environments that visually diverge from those which, based on our evolutionary history, are associated with safety may be more likely to elicit anxiety. When an environment is difficult to process or interpret, it may be perceived as unsafe; thus, there is additional stress on an higher, psychological level, in addition to the basic processing level discussed above. From a health perspective, sustained exposure to environments that facilitate perceptual fluency and reduce unnecessary stress may cumulatively contribute to improved psychological and physiological outcomes.

It can be argued that in today's architectural practice and education, these issues are not given the attention they deserve [58]. Interestingly, the debate surrounding architectural style has also entered political discussions, such as the 2020 U.S. Executive Order promoting "beautiful federal civic architecture," [59] which promoted the use of traditional and classical architectural forms in federal buildings. The polarizing political climate has made many see this as a partisan issue but, regardless of anything else, the present authors support the idea that it should be seen as a public health issue, given the data from various studies discussed in the introduction.

Regarding the present stimuli set, we now have evidence from three separate studies—the Harris Poll [44], our previous eye-tracking study [42], and the present work—converging in the same direction: subjective evaluation, gaze attraction and affective valence all favor traditional buildings. This is in addition to the plethora of other data pointing, either directly or indirectly, in this direction, as discussed earlier. Instead of ignoring such data, as is often the case, architects and authorities should join their efforts to help provide a better environment that will support the citizens' mental and physical health.

Limitations and Future Directions

Demographic data were deliberately not collected, which limits the generalizability of the results. Also, as in all studies using voluntary response sampling, there is a risk of bias; people scoring high in the personality trait *Openness to experience* are, somewhat counterintuitively, less likely to participate in surveys [60]. At the same time, participants could be motivated by a strong interest in the topic, which may not be representative of the general population. More specifically, for topics related to esthetics, it is conceivable that the people who are more likely to respond are those who would have a high score in the personality trait *Openness to esthetics*, or *trait Appreciation of Beauty* (tAoB), a specific subtrait within the trait *Openness to Experience,* making predictions regarding the scale and direction of self-selection bias difficult [61–63].

The Δ metric does not capture non-linear response curvature, but given the short time interval of exposure to each image, it was decided that it was more meaningful than an analysis with a higher temporal resolution, and the exact intervals of 20% and 50% are heuristic rather than uniquely determined. Facial expression analysis may be further complemented by physiological measures (e.g., EDA, HRV) for multimodal validation. Future work could extend this approach by modeling full temporal trajectories using functional data analysis and exploring predictive modeling of affective outcomes. The number of stimuli per category is rather small, but is in keeping with the aim of the present work, which was to act as a proof-of-principle study, using the same images that had been used in a large public survey [44] and also in previous eye-tracking work [42]. Future studies should include more stimuli, which will enable a more robust statistical analysis, as well as stimuli order randomization, which will help neutralize position effects. Dependence on proprietary software can, in principle, be thought of as a drawback, but it has to be noted that iMotions/AFFDEX has shown good correspondence with electromyography data [64] and has previously been used in clinical research [65].

The participant dropout rate in this study was quite high, which is in keeping with what has been observed before [42]; it can be postulated that this is related to the use of the webcam for data collection and potential concerns about privacy.

5. Conclusions

The present findings demonstrate that when comparing exposure to images of Traditional and Modern federal buildings, stimulus category significantly influences the temporal evolution of affective responses. By applying a kinetic within-interval metric and paired difference-based inference, we show that Traditional stimuli elicit positive affective modulation, while Modern stimuli result in negative affective modulation across participants. These results are in agreement with preference and eye-tracking results from the same dataset, as well as with the broader literature.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/app16094406/s1, Figure S1: The images that have been used as stimuli for this work. Table S1: Sensitivity analysis excluding the first and last stimuli in the sequence. Table S2: Linear mixed-effects models with crossed random intercepts used to assess the effect of stimulus category while accounting for both participant- and stimulus-level variability.

Author Contributions: Conceptualization, A.A.L. and A.S.; Methodology, A.A.L.; Software, A.A.L.; Formal Analysis, A.A.L.; Investigation, A.A.L.; Resources, A.A.L. and A.S.; Data Curation, A.A.L.; Writing—Original Draft Preparation, A.A.L.; Writing—Review and Editing, A.A.L. and A.S.; Visualization, A.A.L.; Supervision, A.A.L. and A.S.; Project Administration, A.A.L. and A.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: The topic is not ethically sensitive and the work was carried out in accordance with national and institutional legal and ethical requirements. The project followed institutional guidelines, and the internal ethics reference person in Eurac indicated that there is no need for ethics approval when surveys are not directly health related. Sensitive data or research involving human subjects undergo ethics approval through ethics research committees based in hospitals, and these committees do not assess projects like this study. Also, ethics concerns were assessed internally: participation was on a voluntary basis, and all participants were informed that the survey was anonymous and that all data would be only used for research and evaluated anonymously. To secure privacy, all data that was collected online was not accompanied by any identifiers/codes (IP addresses or others) and were analyzed anonymously, with no possibility of reidentifying the participants.

Informed Consent Statement: The study was carried out completely online, with anonymous users who responded to the call on social media and The Genetics of Design blog. So, video for analysis was recorded, but no other personal data. All users read a slide with this statement at the beginning: "By taking part in this study, you acknowledge that your data collected may be aggregated into final results to better understand the human experience of the built environment. No individual or personal data will be released.

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

Acknowledgments: The authors would like to thank Justin Shubow and the National Civic Art Society for providing the images that were used as stimuli for this work.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AUs	Action Units
DMN	Default Mode Network
FACS	Facial Action Coding System
NCAS	National Civic Arts Society

References

1. Alexander, C. *The Nature of Order: The Phenomenon of Life*; Center for Environmental Structure: Berkeley, CA, USA, 2002.
2. Alexander, C.; Ishikawa, S.; Silverstein, M. *A Pattern Language*; Oxford University Press: New York, NY, USA, 1977.
3. Taylor, R.P. Reduction of Physiological Stress Using Fractal Art and Architecture. *Leonardo* **2006**, *39*, 245–251. [CrossRef]
4. Taylor, R.P.; Spehar, B.; Van Donkelaar, P.; Hagerhall, C.M. Perceptual and Physiological Responses to Jackson Pollock's Fractals. *Front. Hum. Neurosci.* **2011**, *5*, 60. [CrossRef]
5. Mandelbrot, B.B. How long is the coast of Britain? Statistical self-similarity and fractional dimension. *Science* **1967**, *156*, 636–638. [CrossRef]
6. Fischmeister, F.P.; Martins, M.J.; Beisteiner, R.; Fitch, W.T. Self-similarity and recursion as default modes in human cognition. *Cortex* **2017**, *97*, 183–201. [CrossRef] [PubMed]
7. Martins, M.J.; Fischmeister, F.; Puig-Waldmüller, E.; Oh, J.; Geißler, A.; Robinson, S.; Fitch, W.; Beisteiner, R. Fractal image perception provides novel insights into hierarchical cognition. *NeuroImage* **2014**, *96*, 300–308. [CrossRef]
8. Vessel, E.A.; Isik, A.I.; Belfi, A.M.; Stahl, J.L.; Starr, G.G. The default-mode network represents aesthetic appeal that generalizes across visual domains. *Proc. Natl. Acad. Sci. USA* **2019**, *116*, 19155–19164. [CrossRef]
9. Ulrich, R.S. View through a window may influence recovery from surgery. *Science* **1984**, *224*, 417–419. [CrossRef]
10. Barton, J.; Pretty, J. What is the best dose of nature and green exercise for improving mental health? A multi-study analysis. *Environ. Sci. Technol.* **2010**, *44*, 3947–3955. [CrossRef] [PubMed]
11. Valtchanov, D.; Barton, K.R.; Ellard, C. Restorative Effects of Virtual Nature Settings. *Cyberpsychol. Behav. Soc. Netw.* **2010**, *13*, 503–512. [CrossRef] [PubMed]
12. Berman, M.G.; Jonides, J.; Kaplan, S. The Cognitive Benefits of Interacting With Nature. *Psychol. Sci.* **2008**, *19*, 1207–1212. [CrossRef]
13. Berman, M.G.; Kross, E.; Krpan, K.M.; Askren, M.K.; Burson, A.; Deldin, P.J.; Kaplan, S.; Sherdell, L.; Gotlib, I.H.; Jonides, J. Interacting with nature improves cognition and affect for individuals with depression. *J. Affect. Disord.* **2012**, *140*, 300–305. [CrossRef] [PubMed]
14. Berto, R. Exposure to restorative environments helps restore attentional capacity. *J. Environ. Psychol.* **2005**, *25*, 249–259. [CrossRef]
15. Bratman, G.N.; Daily, G.C.; Levy, B.J.; Gross, J.J. The benefits of nature experience: Improved affect and cognition. *Landsc. Urban Plan.* **2015**, *138*, 41–50. [CrossRef]
16. Kaplan, S. The Restorative Benefits of Nature—Toward an Integrative Framework. *J. Environ. Psychol.* **1995**, *15*, 169–182. [CrossRef]
17. Kardan, O.; Gozdyra, P.; Misic, B.; Moola, F.; Palmer, L.J.; Paus, T.; Berman, M.G. Neighborhood greenspace and health in a large urban center. *Sci. Rep.* **2015**, *5*, 11610. [CrossRef]
18. Pretty, J.; Peacock, J.; Hine, R.; Sellens, M.; South, N.; Griffin, M. Green exercise in the UK countryside: Effects on health and psychological well-being, and implications for policy and planning. *J. Environ. Plan. Manag.* **2007**, *50*, 211–231. [CrossRef]

19. Kuo, F.E.; Sullivan, W.C. Environment and crime in the inner city—Does vegetation reduce crime? *Environ. Behav.* **2001**, *33*, 343–367. [CrossRef]
20. Kuo, F.E.; Sullivan, W.C. Aggression and violence in the inner city—Effects of environment via mental fatigue. *Environ. Behav.* **2001**, *33*, 543–571. [CrossRef]
21. Bratman, G.N.; Hamilton, J.P.; Hahn, K.S.; Daily, G.C.; Gross, J.J. Nature experience reduces rumination and subgenual prefrontal cortex activation. *Proc. Natl. Acad. Sci. USA* **2015**, *112*, 8567–8572. [CrossRef] [PubMed]
22. Frumkin, H. Beyond toxicity: Human health and the natural environment. *Am. J. Prev. Med.* **2001**, *20*, 234–240. [CrossRef]
23. Joye, Y. Architectural lessons from environmental psychology: The case of biophilic architecture. *Rev. Gen. Psychol.* **2007**, *11*, 305–328. [CrossRef]
24. Salingaros, N.A. A Scientific Basis for Creating Architectural Forms. *J. Archit. Plan. Res.* **1998**, *15*, 283–293.
25. Salingaros, N.A.; Mehaffy, M.W. *A Theory of Architecture*; Umbau-Verlag: Solingen, Germany, 2006; 278p.
26. Salingaros, N.A. The laws of architecture from a physicist's perspective. *Phys. Essays* **1995**, *8*, 638–643. [CrossRef]
27. Salingaros, N. *Unified Architectural Theory: Form, Language, Complexity: A Companion to Christopher Alexander's "The Phenomenon of Life: The Nature of Order, Book 1"*; Oregon Sustasis Foundation: Portland, OR, USA, 2013.
28. Zeki, S. Beauty in Architecture: Not a Luxury—Only a Necessity. *Archit. Des.* **2019**, *89*, 14–19. [CrossRef]
29. Coburn, A.; Vartanian, O.; Chatterjee, A. Buildings, Beauty, and the Brain: A Neuroscience of Architectural Experience. *J. Cogn. Neurosci.* **2017**, *29*, 1521–1531. [CrossRef]
30. Dzhambov, A.M.; Markevych, I.; Hartig, T.; Tilov, B.; Arabadzhiev, Z.; Stoyanov, D.; Gatseva, P.; Dimitrova, D.D. Multiple pathways link urban green- and bluespace to mental health in young adults. *Environ. Res.* **2018**, *166*, 223–233. [CrossRef]
31. Hartig, T. Green space, psychological restoration, and health inequality. *Lancet* **2008**, *372*, 1614–1615. [CrossRef]
32. Cruz-Garza, J.G.; Darfler, M.; Rounds, J.D.; Gao, E.; Kalantari, S. EEG-based Investigation of the Impact of Classroom Design on Cognitive Performance of Students. *arXiv* **2021**, arXiv:2102.03629. [CrossRef]
33. Vartanian, O.; Navarrete, G.; Chatterjee, A.; Fich, L.B.; Gonzalez-Mora, J.L.; Leder, H.; Modroño, C.; Nadal, M.; Rostrup, N.; Skov, M. Architectural design and the brain: Effects of ceiling height and perceived enclosure on beauty judgments and approach-avoidance decisions. *J. Environ. Psychol.* **2015**, *41*, 10–18. [CrossRef]
34. Shemesh, A.; Leisman, G.; Bar, M.; Grobman, Y.J. A neurocognitive study of the emotional impact of geometrical criteria of architectural space. *Archit. Sci. Rev.* **2021**, *64*, 394–407. [CrossRef]
35. Fich, L.B.; Jönsson, P.; Kirkegaard, P.H.; Wallergård, M.; Garde, A.H.; Hansen, Å. Can architectural design alter the physiological reaction to psychosocial stress? A virtual TSST experiment. *Physiol. Behav.* **2014**, *135*, 91–97. [CrossRef]
36. Ergan, S.; Radwan, A.; Zou, Z.; Tseng, H.-A.; Han, X. Quantifying Human Experience in Architectural Spaces with Integrated Virtual Reality and Body Sensor Networks. *J. Comput. Civ. Eng.* **2019**, *33*, 04018062. [CrossRef]
37. 3M. 3M Visual Attention Software 2020. Available online: https://www.3m.com/3M/en_US/visual-attention-software-us/ (accessed on 16 May 2021).
38. Kim, T.-H.; Jeong, G.-W.; Baek, H.-S.; Kim, G.-W.; Sundaram, T.; Kang, H.-K.; Lee, S.-W.; Kim, H.-J.; Song, J.-K. Human brain activation in response to visual stimulation with rural and urban scenery pictures: A functional magnetic resonance imaging study. *Sci. Total Environ.* **2010**, *408*, 2600–2607. [CrossRef]
39. Vartanian, O.; Navarrete, G.; Chatterjee, A.; Fich, L.B.; Leder, H.; Modroño, C.; Nadal, M.; Rostrup, N.; Skov, M. Impact of contour on aesthetic judgments and approach-avoidance decisions in architecture. *Proc. Natl. Acad. Sci. USA* **2013**, *110*, 10446–10453. [CrossRef] [PubMed]
40. Bar, M.; Neta, M. Visual elements of subjective preference modulate amygdala activation. *Neuropsychologia* **2007**, *45*, 2191–2200. [CrossRef]
41. Chatterjee, A.; Coburn, A.; Weinberger, A. The neuroaesthetics of architectural spaces. *Cogn. Process.* **2021**, *22*, 115–120. [CrossRef]
42. Rosas, H.J.; Sussman, A.; Sekely, A.C.; Lavdas, A.A. Using Eye Tracking to Reveal Responses to the Built Environment and Its Constituents. *Appl. Sci.* **2023**, *13*, 12071. [CrossRef]
43. Sussman, A.; Hollander, J.B. *Cognitive Architecture: Designing for How We Respond to the Built Environment*, 2nd ed.; Routledge: New York, NY, USA, 2021.
44. NCAS. Americans' Preferred Architecture for Federal Buildings. 2020. Available online: https://www.civicart.org/americans-preferred-architecture-for-federal-buildings (accessed on 1 August 2023).
45. iMotions. 2023. Available online: https://imotions.com/ (accessed on 1 December 2023).
46. Ekman, P.; Friesen, W.V. *Facial Action Coding System: A Technique for the Measurement of Facial Movement*; Consulting Psychologists Press: Palo Alto, CA, USA, 1978.
47. Ekman, P. An argument for basic emotions. *Cogn. Emot.* **1992**, *6*, 169–200. [CrossRef]
48. Gendron, M.; Crivelli, C.; Barrett, L.F. Universality Reconsidered: Diversity in Making Meaning of Facial Expressions. *Curr. Dir. Psychol. Sci.* **2018**, *27*, 211–219. [CrossRef]

49. Salinas, F.; Ortiz, G.; Martínez, P. Recognition of emotions through facial expression analysis. *S. Fla. J. Dev.* **2021**, *2*, 2102–2118. [CrossRef]
50. theHapi. 2025. Available online: https://geneticsofdesign.com/ (accessed on 1 February 2026).
51. Pallasmaa, J. *The Eyes of the Skin: Architecture and the Senses*; Wiley: Hoboken, NJ, USA, 2012.
52. Hildebrandt, A.; Olderbak, S.; Wilhelm, O. Facial Emotion Expression, Individual Differences in. *Int. Encycl. Soc. Behav. Sci.* **2015**, 667–675. [CrossRef]
53. Grabowski, B. "P < 0.05" Might Not Mean What You Think: American Statistical Association Clarifies P Values. *J. Natl. Cancer Inst.* **2016**, *108*, djw194. [PubMed]
54. Joye, Y. Fractal Architecture Could Be Good for You. *Nexus Netw. J.* **2007**, *9*, 311–320. [CrossRef]
55. Hägerhäll, C.; Laike, T.; Taylor, R.P.; Küller, M.; Küller, R.; Martin, T.P. Investigations of Human EEG Response to Viewing Fractal Patterns. *Perception* **2008**, *37*, 1488–1494. [CrossRef]
56. Le, A.T.D.; Payne, J.; Clarke, C.; Kelly, M.A.; Prudenziati, F.; Armsby, E.; Penacchio, O.; Wilkins, A.J. Discomfort from urban scenes: Metabolic consequences. *Landsc. Urban Plan.* **2017**, *160*, 61–68. [CrossRef]
57. Valentine, C.; Steffert, T.; Mitcheltree, H.; Steemers, K. Architectural Neuroimmunology: A Pilot Study Examining the Impact of Biophilic Architectural Design on Neuroinflammation. *Buildings* **2024**, *14*, 1292. [CrossRef]
58. Salingaros, N.A.; Masden, K.G., II. Intelligence-Based Design: A Sustainable Foundation for Worldwide Architectural Education. *Archnet-IJAR Int. J. Archit. Res.* **2008**, *2*, 129–188.
59. Trump, D.J. *Executive Order on Promoting Beautiful Federal Civic Architecture*; The White House: Washington, DC, USA, 2020.
60. Valentino, N.A.; Zhirkov, K.; Hillygus, D.S.; Guay, B. The Consequences of Personality Biases in Online Panels for Measuring Public Opinion. *Public Opin. Q.* **2020**, *84*, 446–468. [CrossRef]
61. Costa, P. *Neo PI-R Professional Manual*; Psychological Assessment Resources: Odessa, FL, USA, 1992.
62. Costa, P.T.; McCrae, R.R. The five-factor model and the NEO inventories. *Oxf. Handb. Personal. Assess.* **2009**, *10*, 299–322.
63. Diessner, R.; Solom, R.D.; Frost, N.K.; Parsons, L.; Davidson, J. Engagement with beauty: Appreciating natural, artistic, and moral beauty. *J. Psychol.* **2008**, *142*, 303–332. [CrossRef]
64. Westermann, J.-F.; Schäfer, R.; Nordmann, M.; Richter, P.; Müller, T.; Franz, M. Measuring facial mimicry: Affdex vs. *EMG. PLoS ONE* **2024**, *19*, e0290569. [CrossRef] [PubMed]
65. Yiew, K.; Togher, L.; Power, E.; Brunner, M.; Rietdijk, R. Differentiating Use of Facial Expression between Individuals with and without Traumatic Brain Injury Using Affectiva Software: A Pilot Study. *Int. J. Environ. Res. Public Health* **2023**, *20*, 1169. [CrossRef] [PubMed]