IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Date of publication xxxx 00, 0000, date of current version xxxx 00, 0000.

Digital Object Identifier 10.1109/ACCESS.2024.Doi Number

Quantifying objective and perceived image quality through EEG and eye-tracking

Changhyun Lim,[1,†] Hyun-Jun Jeon,[1,†] Woojae Jung,[1] Youngshin Kwak,[1] Myong Young Lee,[2] Jung Hyun Ham,[2] Hyun Bin Joo,[2] Oh-Sang Kwon,[1] and Dongil Chung[1]

[1]Department of Biomedical Engineering, Ulsan National Institute of Science and Technology, Ulsan, Republic of Korea
[2]TV Picture Quality Development Gr., TV R&D Center of LG Electronics, Republic of Korea

†These authors contributed equally to this work

Corresponding author: Oh-Sang Kwon, Dongil Chung (e-mail: oskwon@unist.ac.kr, dchung@unist.ac.kr).

This work was supported in part by UNIST internal funding (1.240015.01), KBRI basic research program through Korea Brain Research Institute funded by Ministry of Science and ICT (24-BR-03-08), the National Research Foundation of Korea (NRF-2020S1A3A2A02097375), and LG Electronics.

ABSTRACT Image quality evaluation of electronic displays is inherently subjective. To date, user studies in focus groups and viewers' self-reports have been the primary sources of feedback used as judgment criteria for the display quality. However, little has been known whether the measured responses to visual stimuli, other than self-reports, reflect the objective and subjective levels of image quality on displays. Here, we used electroencephalogram (EEG) and eye-tracking to investigate whether individuals' neural and physiological responses to visual stimuli track three objectively discerned levels of image quality, as well as their self-ratings on vividness. Our findings reveal that event-related potentials (ERPs) at 200-300 msec after stimulus onset in the frontocentral brain region, as well as saccade and blink frequencies, significantly tracked (cluster-based permutation $p < 0.05$) the objective perspective of image quality. In contrast, ERPs at 600 msec in the frontolateral region and saccade peak velocity tracked (cluster-based permutation $p < 0.05$) the subjective evaluation of image quality. Individuals' pupil diameter successfully tracked (cluster-based permutation $p < 0.05$) both objective and subjective perspectives of image quality. These patterns highlight both the shared characteristics and measurable distinctions between objective image quality and subjective vividness ratings. This study demonstrates the effectiveness of EEG and eye-tracking as quantitative tools for assessing objective image quality disparities and the subjective affective nuances of users' visual display experiences, potentially reducing reliance on self-reports.

INDEX TERMS EEG, Eye-tracking, Image quality, Neurophysiological marker

I. INTRODUCTION

Most of the modern media contents are delivered through electronic displays. To enhance user experience and optimize human interaction with displays, various studies have explored the impacts of different display conditions (e.g., different levels of luminance, contribution of blue lights, depth of display, and display curvature) on increasing image quality [1-3]. Developments over the most recent decade have been focusing on accomplishing high-end 'natural image quality' rather than simply enhancing optical characteristics (e.g., resolution, brightness), by which the display can deliver more realistic contents and even induce more empathetic responses to viewers [4]. Given the subjective nature of such psychological responses, the importance of assessing subjective image quality other than objective measures (e.g., contrast, sharpness, brightness) has been stressed [5]. In stark contrast to objective measures, there are currently no alternative methods available to examine individuals' subjective image quality assessments aside from directly collecting self-reports. Several attempts have been made to develop statistical models using objective image quality measures to predict users' subjective image quality assessment results [6, 7]. These studies suggested that the structural variation of images or a combination of objective features (e.g., contrast, sharpness, brightness) can explain individuals' image quality assessments. However, these models only accounted for group-level associations and fail to explain differences in assessments across individuals. Here, we propose that individuals' neural and physiological

responses to different levels of image quality can be used to measure their subjective assessments.

In the field of Cognitive Neuroscience, numerous studies showed that individuals' neurophysiological signals reflect their emotional states, perception of presented information [8-12]. For example, eye-tracking has been used to extract individuals' gaze, saccade, and eye-blinking information, reflecting the level and the shifting of one's attention [1]. Eye-tracking is often conducted in conjunction with measuring pupil dilation, which is associated with arousal level, affective states, and various types of value-related information being processed [9, 13-15]. Based on these previous reports, we expected that eye-tracking data could serve as a pivotal tool in elucidating subjective image quality assessment, where the requirement extends beyond understanding the consequences of visual processing to encompass the subjective interpretation of the processed information.

Electroencephalogram (EEG) is another highly accessible and frequently used tool in the field of vision studies [10, 11, 16]. It has been shown that the early stage of visual processes, including the recognition of the presentation of visual stimuli, state of attention, and the detection of visual features that violate expectations, is represented as event-related potentials (ERPs) within a few hundred milliseconds after the stimulus onset [12, 17-19]. In addition, previous studies showed that evoked EEG responses to emotion-eliciting pictorial stimuli not only capture the outcomes of low-level cognitive processes but also that of affective processes, which is known to be rather complex and subjective [20-22]. In particular, low-level characteristics of the presented stimuli (e.g., contrast or luminance) were represented in the early period of such evoked EEG responses [23], while arousal levels associated with the stimuli were captured in the later period [20, 21, 24]. There were several attempts to use EEG in studying individuals' responses to viewing displays [25, 26]. However, the emphasis in these studies has been on identifying viewers' fatigue rather than on detecting individuals' assessments of the display's image quality (c.f., evaluation of display blurriness [27]).

While subjective evaluations using Likert rating scales provide direct input from participants, they are susceptible to response biases and may fail to capture individuals' subconscious or covert responses. In contrast, eye-tracking and EEG have been shown to effectively capture covert information processing in the brain, making them valuable tools for assessing subjective phenomena like image quality in a more objective and quantifiable manner. In this study, we aim to assess whether physiological and neurological measures can reliably track subjective evaluations of image quality, offering an objective complement to traditional self-reports.

In the current study, we collected EEG and eye-tracking data while participants were viewing image stimuli prepared at different levels of image quality. We selected these methods over alternative neuroscientific tools (e.g., positron emission tomography (PEG), functional magnetic resonance imaging) for two main reasons. First, we assumed that users' responses to visual stimuli occur instantaneously, similar to forming a first impression of a product. Both EEG and eye-tracking offer fine temporal resolution (on the order of milliseconds, compared to seconds in functional MRI or minutes in PET), making them well-suited for capturing such rapid cognitive responses. Second, a potential application of our finding lies in industry where user experience is assessed across a broad range of potential buyers and users. Given this context, we selected EEG and eye-tracking because they are highly accessible, potentially portable, and relatively cost-effective compared to other neuroscientific tools. As an objective criterion for image quality, we benchmarked an image quality enhancement algorithm called 'White-boosting', a novel algorithm available on a commercially available TV set designed to enhance image quality by adjusting luminance. Individuals were instructed to view the presented stimuli and self-report perceived image quality as well as their perception of image-associated emotion for each stimulus. Both EEG and eye-tracking data were analyzed to examine the neurophysiological representation of objective and/or subjective image quality.

II. MATERIAL AND METHODS

A. DISPLAY SETTINGS: 'WHITE-BOOSTING' MODE

In the current study, a commercial display, 55-inch 4K OLED TV, C1 Series (LG Electronics Inc., South Korea) was used. To simulate different levels of image quality, we benchmarked the 'White-boosting' algorithm available on the TV set. Under the white-boosting settings, pixels with low saturation undergo a substantial increase in luminance. In a previous study, it was shown that increasing the White-boosting setting enhances individuals' evaluations of the vividness of the image content [28]—a positive attribute of a visual stimuli. To manipulate the image quality to vary along this direction, the highest image quality was configured to replicate the colorimetric characteristics of the display with the White-boosting mode set to high, while the lowest image quality was configured to mimic the display with the function turned off. In the experiment, three levels of White-boosting modes (off, low, and high) and two chromaticity gamut settings (Digital Cinema Initiatives-Protocol 3 (DCI-P3) [29] and standard RGB (sRGB) [30]) were simulated while the TV was set to have maximum White-boosting level. The degree of luminance increment of each pixel was determined by

saturation. Lower saturation had higher increment ratio. Fig. 1 shows the measured chromaticity of the primaries and tone curves where the White-boosting level was turned off and set to high, respectively. Note that White-boosting algorithm did not alter the chromaticity and the luminance of the primary colors but doubled the luminance of white.

a

	White boost: Off			White boost: High		
	x	y	Y	x	y	Y
Red	0.682	0.318	96.2	0.682	0.318	95.5
Green	0.251	0.681	298.9	0.251	0.681	300.8
Blue	0.144	0.049	37.3	0.144	0.049	38.2
White	0.282	0.287	449.4	0.280	0.287	907.7

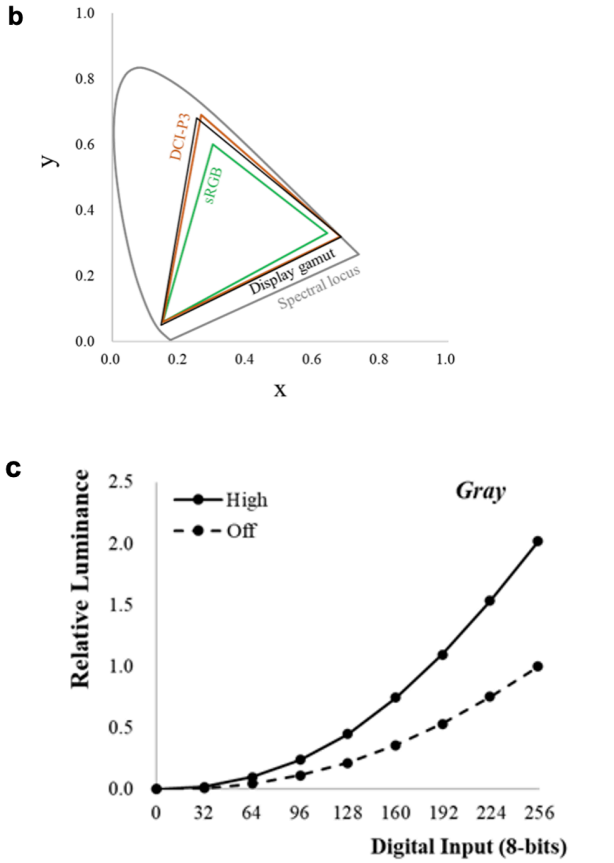

FIGURE 1. CIE xy chromaticity and tone curves of display after simulation. (a) CIE xyY values of White and Red, Green, Blue primary colors were measured for White-boosting off and high settings. (b)The chromaticity gamut area of the experimental display is comparably wide to that of DCI-P3. (c) Luminance of the gray scales was measured and normalized compared to the peak luminance of the White-boosting off setting. It is notable that the luminance of white for the High setting is twice as high as that for the Off setting.

B. PARTICIPANTS

Nineteen college students were recruited from Ulsan National Institute of Science Technology (UNIST). None of the participants reported a history of neurological or psychiatric disorder, traumatic brain injury, or vision-related health issues. Data from two participants were excluded due to partial data loss during the saving process. After the exclusion, final sample included 17 participants (male/female = 15/2, age = 22.0 ± 2.4). All participants reported normal or corrected-to-normal vision under soft contact lenses. The current study was approved by the Institutional Review Board (IRB) of Ulsan National Institute of Science and Technology (UNISTIRB-22-63-A). All participants provided written informed consent prior to their participation and were paid for their participation. All experimental procedures were performed in accordance with relevant guidelines and regulations approved by the IRB. No statistical methods were used to predetermine the sample size. However, the sample size of 17 was chosen based on previous studies in similar experimental contexts, which used comparable sample sizes and demonstrated sufficient sensitivity to detect significant features from EEG and eye-tracking measures [11, 16, 27].

C. EXPERIMENTAL PROCEDURE

The stimuli for the current study were images selected from the International Affective Picture System (IAPS) database [31], which can be mapped onto the arousal-valence model dimensions. To control for the effects of image-elicited emotion on image quality assessment, we selected images based on their average valence ratings reported in the original database (scaled 1-7, 1=negative, 7=positive); 14 negative, 14 neutral, and 14 positive images were selected within the range of 2-3.5 (mean = 2.75, SD = 0.49), 3.5-6.5 (mean = 5.14, SD = 0.23), and 6.5-8 (mean = 6.94, SD = 0.36), respectively. Arousal levels are relatively higher for the negative or positive images compared to neutral images, and thus we intentionally matched the arousal levels only between positive and negative images (two-sample t-test, $t26 = 1.43$, $p = 0.17$). Each IAPS image was used as input to generate images with different objective image quality. Specifically, original images were adjusted to three levels of White-boosting (off, low, high) and two levels of color-gamut (DCI-P3, sRGB). In total, individuals went through 504 trials ([42 IAPS image] × [3 White-boosting] × [2 color-gamut] × [2 repetition]) of image rating.

With the White-boosting adjustment, pixels with low saturation undergo a substantial increase in luminance. Consistent with the findings of the previous study [28], it was expected that this enhancement will further amplify the vividness of the image content. To examine EEG and eye-tracking data specific to each image, participants were shown one image at a time, depicted in a single TV set. Although the evaluation setting differs from our behavioral pilot study, we expected that vividness rating would capture individuals' relative assessments of image quality. Before the image rating started, participants were reminded of the rating criterion, i.e., vividness. In addition to the vividness rating block, we introduced two additional blocks where individuals were instructed to rate the arousal or valence of the same set of images, presented in a pseudorandom order. By including

these blocks, we provided conditions in which implicit neural and physiological representations of objective image qualities could be examined, along with that during explicit evaluation. The order of the three rating blocks was counterbalanced across participants.

Throughout the rating task, participants completed three blocks of ratings, wherein they were instructed to assess a series of images prepared as described above (Fig. 2a). Participants were informed of the evaluation criterion to apply (vividness, arousal, or valence) at the beginning of each block. Following an initial brief fixation screen, the prepared set of images was presented in a pseudorandom sequence, and participants were instructed to provide their ratings on a 6-point Likert-scale at their own pace. A 6-point Likert scale was chosen to minimize participants' hand movements during the task and reduce potential motion artifacts in concurrent neurophysiological signal measurements. A crosshair was overlaid at the center of each image immediately after the participant's response, and the screen transitioned to the next stimulus after a brief interval. To investigate neural and physiological responses associated with image quality assessment, we recorded EEG and eye-tracking data throughout the entire rating task (Fig. 3a).

We controlled for background lighting by conducting all experimental procedures in a dark room, eliminating potential interference from external light sources. While participants were not explicitly screened for prior experience with similar tasks, the task design did not involve paired comparisons, minimizing potential learning effects during the experiment.

D. EEG ACQUISITION AND ANALYSES

EEG were recorded using a actiCHamp EEG system (Brain Products GmbH, Germany), a 32-channel (Ag/AgCl electrode) actiCap recording system (Brain Products GmbH, Germany), and a sampling rate of 500 Hz (Fig. 3b). We used the Cz channel as the reference and the FPz channel as the ground. Impedance of all channels were maintained below 10 kΩ. EEG data analyses were conducted using EEGLAB version 2022.1 (Swartz Center for Computational Neuroscience, University of California at San Diego, CA) and MATLAB R2021a (Mathworks Ltd., Natick, MA). Raw EEG data were filtered using a 0.1-100 Hz band-pass filter and a 55-65 Hz notch filter. We used the Common Average Reference (CAR) and additionally, Independent Component Analysis (ICA) to correct for eye movement. The preprocessed EEG data were sliced into epochs, with each epoch encompassing EEG responses from -500 to 1000 msec around the stimulus onset (Fig. 3c). Baseline correction was applied using a 200-msec pre-cue window. Epochs were visually inspected, and those with peak amplitudes exceeding 100 mV were excluded.

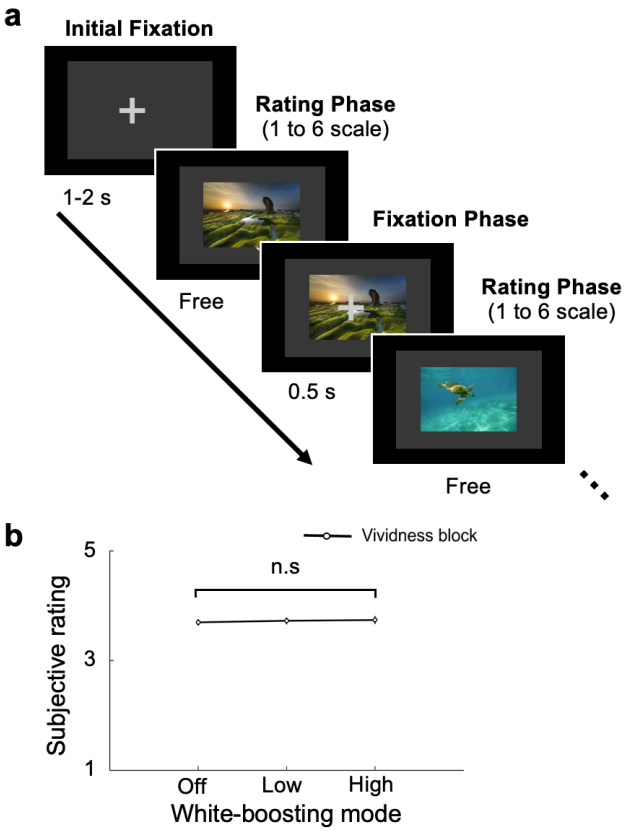

FIGURE 2. Experimental procedures and behavioral results. (a) Participants were asked to evaluate vividness, valence, or arousal of a series of images. The task followed a block design, wherein each block required participants to evaluate either vividness, valence, or arousal (block order was counterbalanced). At the beginning of each block, participants were informed of the specific evaluation criterion to apply. A selected set of images were simulated to six different conditions (three White-boosting modes [High, Low, Off] × two color gamut [DCI-P3, sRGB]) and all the prepared images were presented in a pseudo-random order. While watching a series of images, participants were instructed to report their subjective ratings at their own pace using a 6-point Likert scale. For illustrative purpose, license free images were used in depicting the task scheme. (b) Self-reports on the subjective vividness rating were comparable across all three White-boosting modes. Error bars indicate s.e.m; n.s., not significant.

E. EYE-TRACKING AND ANALYSES

Binocular eye movement data were recorded using an infrared eye tracker, EyeLink 1000 Plus (SR Research Ltd., Kanata, Canada), at a sampling rate of 1000 Hz. The eye tracker was mounted on a desk for each participant, and their head and chin were stabilized using a headrest during recording. Prior to data collection, each participant underwent a standard five-point calibration and validation procedure to ensure accurate gaze tracking. Calibration accuracy was verified, and recalibration was performed if the average error exceeded 0.5 degrees. In the current study, blinks and saccades were identified for each eye using EyeLink's standard criteria, followed by linear interpolation of these intervals. Specifically, for blinks, interpolation was applied between 150 msec pre- and post-blink. The mean interpolated data from both eyes were then band-pass filtered between 0.02-4 Hz using third-order Butterworth filters to isolate relevant signal frequencies. The

preprocessed data were normalized within each block by z-scoring, standardizing pupil diameter changes relative to each block's mean and standard deviation. From the eye-tracking data, extracted measures of eye movement and pupillometric patterns included: saccade and blink frequency, mean duration of saccades and blinks, peak velocity of saccades, mean pupil diameter within each trial, and the temporal dynamics of pupil diameter (Fig. 3d,e). When analyzing pupil diameter responses, epochs were defined to encompass responses from -200 to 1500 msec around the stimulus onset, with baseline correction achieved by subtracting the mean pupil size measured at the stimulus onset.

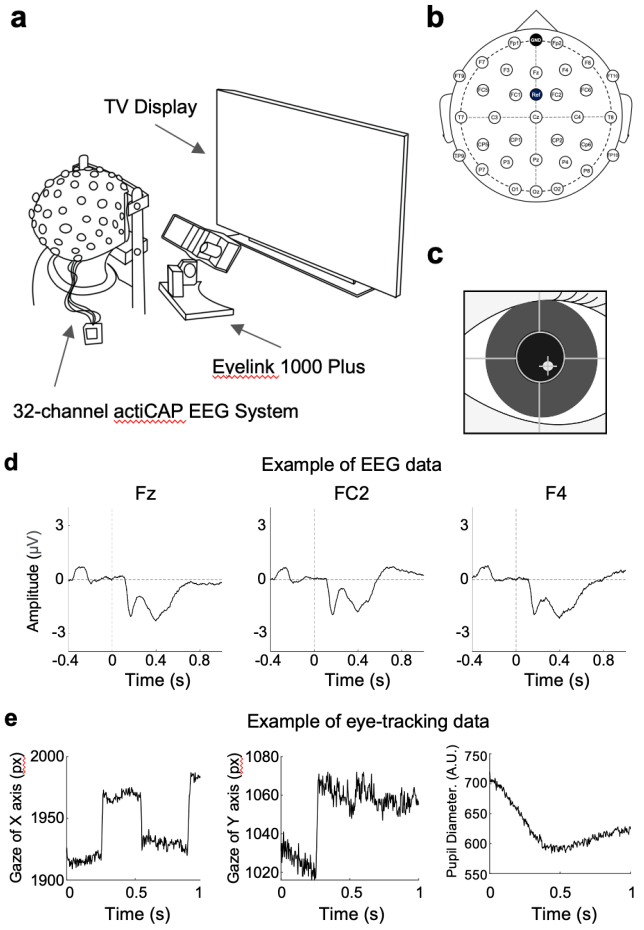

FIGURE 3. Experimental setup for neural and physiological measurements. (a) Participants were seated in front of an eye-tracker, wearing an EEG electrode cap, while they viewed the TV display. To maximize the data quality, participants' foreheads and chins securely positioned on a headrest. (b) EEG recordings were obtained from 32 Ag/AgCl electrodes mounted on a cap, extending the international 10/20 system. (d) The example of EEG data illustrate time series data from three exemplary channels (Fz, FC2, and F4) is depicted. (c) The infrared eye-tracker was used to measure the pupil center and corneal reflection for eye gaze calculation, in addition to capturing pupil diameter. (e) The example data illustrate the changes in eye gaze and pupil diameter over time.

F. STATISTICAL ANALYSES

To test the impacts of objective White-boosting modes on individuals' subjective ratings, we used repeated measures Analysis of Variance (rmANOVA). When examining the neural and physiological representation of the White-boosting modes, we used a repeated measures Analysis of Covariance (rmANCOVA) for EEG and eye-tracking measures where the mean valence and arousal ratings associated with stimuli, derived from the original IAPS database, were entered as covariates-of-no-interest. All data from the three rating blocks (vividness, arousal, and valence) were pooled, and to address potential differential effects across blocks, block identity was included as additional main factor.

Note that the test was conducted for all time-points within the epoch (and for all channels in the case of EEG analyses), which allowed us to explore the temporal representation as well as the average patterns. To correct for multiple comparisons, we used cluster-based permutation testing [32]. Cluster-based permutation testing was chosen because it is particularly well-suited for data with spatiotemporal dependencies, such as EEG and eye-tracking. Traditional correction methods, such as the Bonferroni correction, treat each data point as independent, which can be overly conservative and increase the likelihood of false negatives (Type II error). In contrast, the cluster-based permutation method identifies clusters of adjacent significant effects rather than isolated data points, thereby preserving sensitivity. Moreover, unlike parametric correction tests, cluster-based permutation does not assume a specific data distribution, making it robust for analyzing non-normally distributed neurophysiological data. The threshold for cluster formation was set at an F-test significance level of $p = 0.005$. Cluster mass was computed across time and space points, and adjacent significant time-space points were merged as the same cluster. Significance was determined by comparing the cluster mass to the maximum cluster size obtained through 95% chance permutations (1000 random permutations); each permutation involved resampling a pseudo-group of the same size as the original group, with replacement. Only clusters exceeding this maximum size were considered significant, using a one-tailed alpha level of 0.05 [23, 33].

To investigate the representation of subjective vividness ratings, we performed multiple linear regression analyses where the single-trial EEGs or pupil diameter from the vividness rating block was dependent variable, and subjective ratings (vividness, arousal, and valence) were set as independent variables. As in the investigation of the objective White-boosting modes, the regression analyses were conducted for all time-points within the epoch and for all channels in the case of EEG analyses. The threshold for cluster formation was set at a t-test significance level of $p = 0.005$, and cluster significance was determined using a two-tailed alpha level of 0.05.

III. RESULTS

A. SELF-REPORTS ON VIVIDNESS LACK SENSITIVITY IN CAPTURE THE SEQUENTIAL ADJUSTMENTS OF WHITE-BOOSTING

To assess whether objective White-boosting modes were reflected in subjective ratings, we compared individuals' ratings from the vividness rating block across different levels of White-boosting. In contrast to our pilot study, in which two displays were set to different levels of White-boosting and presented side-by-side, subjective vividness ratings in the current study showed only subtle differences (Off = 3.69, Low = 3.72, High = 3.74), and the scores were statistically comparable across different modes ($F(2,32) = 1.63$, $p = 0.21$; Fig. 2b). We additionally examined whether adjustments in White-boosting influenced individuals' evaluations of emotions associated with the images. However, there was no clear evidence indicating significant effects of White-boosting adjustments on emotion evaluation (Valence: $F(2,32) = 0.71$, $p = 0.50$; Arousal: $F(2,32) = 0.59$, $p = 0.56$; Fig. S1). One may argue that individuals' subjective ratings in the current study might be simply too noisy. This is unlikely given that the valence and arousal ratings collected from the participants were highly correlated with the normative ratings from the original database ([34]; Valence: $r = 0.91$, $p < 0.0001$, Arousal: $r = 0.79$, $p < 0.0001$). These results suggest that, as suspected, behavioral self-reports might lack sensitivity to capture individuals' differential assessments of image qualities induced by White-boosting adjustments.

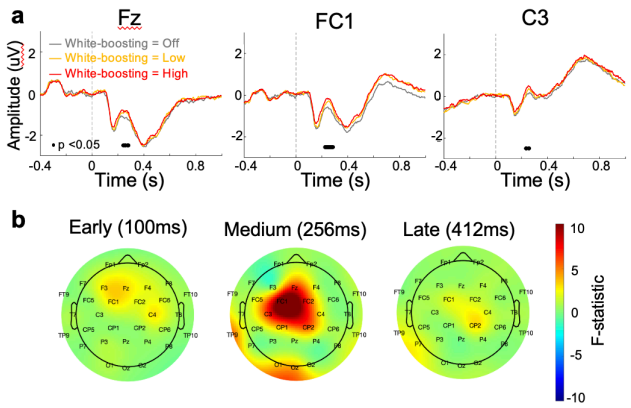

FIGURE 4. Objective White-boosting modes manifest in distinct EEG responses. (a) Participants exhibited distinctive EEG patterns in response to three different White-boosting modes. Data from the Fz, FC1, and C3 channels are depicted as exemplar electrodes demonstrating significant effects of White-boosting modes. Specifically, ERP peak amplitudes between 200-300ms after the stimuli onset on these channels were significantly higher for stimuli with high White-boosting (red) compared to that with White-boosting mode turned off (gray); black underlines indicate statistically significant time periods (cluster-based permutation, $p < 0.05$). (b) Topographical representation of F-statistics across 31 EEG channels is illustrated for three time points after the stimuli onset. Statistically significant impacts of White-boosting modes were specifically observed in the frontocentral region around 250ms after the stimuli onset.

B. EEG AND EYE-TRACKING FEATURES REFLECT WHITE-BOOSTING ADJUSTMENTS

To investigate the neural instantiation of White-boosting effects, we compared ERPs across three levels of White-boosting modes. Three frontocentral channels (Fz, FC1, C3) showed significant ERP differences approximately 200-300 msec after stimulus onset (Fig. 4a). Specifically, ERP peak amplitudes were highest for the mode with the highest White-boosting, and vice versa. Note that such effects of White-boosting adjustments were specific to the aforementioned time window and the frontocentral region (Fig. 4b, Fig. S2). Consistent with previous studies using emotional stimuli [20, 21, 24], a positive potential approximately 400-800 msec after stimulus onset reflected the influence of image-associated arousal and valence (Fig. S3).

Next, the impacts of White-boosting adjustments on eye-movement and pupillometric measures were examined. In terms of eye-movement, we found significant effects in the frequencies of saccade and eye blinking (Fig. 5, S4). The saccade frequency exhibited a significant negative association with the level of White-boosting modes ($F(2,32) = 4.93$, $p = 0.014$; Fig. 5a). Specifically, saccades occurred less frequently under the high level of White-boosting compared to the White-boosting Off setting (post-hoc Tukey test, $p = 0.011$). Similarly, blink frequency showed a decreasing association with the increasing level of White-boosting ($F(2,32) = 5.53$, $p = 0.0087$; Fig. 5b), with the Tukey test confirming significantly fewer blinks at the White-boosting High level compared to the White-boosting Off level ($p = 0.033$). Note that the effects of image-associated arousal and valence ratings were account for as the effects of covariates-of-no-interest (Fig. S5). Together, these results suggest that White-boosting adjustments have a notable modulation effect in visual exploration.

Pupillometric measures showed largely the same responses to White-boosting adjustments. Specifically, the mean pupil diameter decreased as a function of the level of adjustments ($F(2,32) = 35.46$, $p < 0.001$; Fig. 5c), with the Tukey test indicating the smallest pupil diameter for the highest level of White-boosting ($p < 0.001$ for all post-hoc paired comparisons). The temporal dynamics of pupil diameter revealed a distinct pattern marked by a sudden drop around 340 msec after the stimulus onset followed by a gradual rise (Fig. 5d). This negative deflection of pupil diameter was significantly more exaggerated under the higher level of White-boosting adjustments ($F(2,32) = 3.39$, $p = 0.046$). The post-hoc Tukey test confirmed that each level was significantly distinguishable from the others ($p < 0.001$). See Figure S5 for the effects of image-associated arousal and valence on pupillometric measures, which were regressed out as covariates from these results. Note that the White-boosting algorithm involves an increase in luminance for a part of image pixels. Our findings mirror previous research that

showed a strong association between pupil diameter and the luminance of stimuli [35].

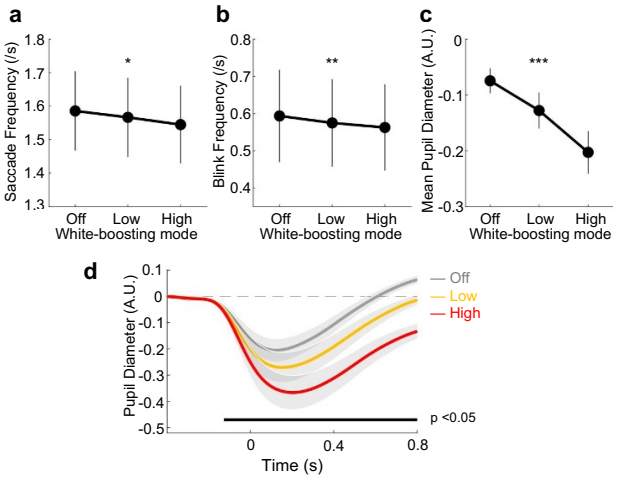

FIGURE 5. Objective White-boosting modes manifest in distinct eye movement and pupillometric patterns. Participants' (a) saccade frequency, (b) blink frequency, and (c) mean pupil diameter were significantly different for different levels of White-boosting modes. Error bars indicate s.e.m.; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. (d) The temporal dynamics of pupil diameter revealed distinct patterns corresponding to the levels of White-boosting mode, consistent with the observations in (c). Shaded areas represent s.e.m. and black underlines indicate statistically significant time periods (cluster-based permutation, $p < 0.05$).

C. EEG AND EYE-TRACKING FEATURES REFLECT SUBJECTIVE VIVIDNESS ASSESSMENTS

To investigate neural and physiological representation of subjective vividness ratings, we analyzed EEG and eye-tracking data from the vividness rating block. First, to illustrate differential EEG and pupil responses, image rating trials were classified into three equal-sized subgroups (dull, mid, and vivid) based on individuals' subjective vividness ratings. Each image was presented 12 times ([3 White-boosting] * [2 color-gamut] * [2 repetition]) throughout the entire task, and the average rating across all 12 rating attempts was used to determine the subgroup assignment, which allowed us to examine the representation of subjective evaluation independent of objective levels of White-boosting adjustments.

The ERPs from the F4 channel showed differential patterns among the three subgroups approximately 600 msec after the stimulus onset (Fig. 6a). Specifically, the ERP amplitude was highest on vivid trials (i.e., trials with top 33.3% vividness ratings) and lowest on dull trials (bottom 33.3%). Subsequent multiple linear regression analyses confirmed that the level of positive deflection reflected individuals' subjective vividness ratings (β1) even after controlling for potential confounding factors associated with each stimulus (arousal and valence ratings) (Fig. 6b, S6). Beta coefficients for arousal and valence ratings were not significantly different from zero. These results remained consistent in the additional residual regression analysis (Fig. S7), demonstrating the robustness of the findings.

Analysis of eye-tracking metrics revealed a perceptible trend correlating with the vividness ratings assigned by participants. First, stimuli perceived as more vivid elicited a slight decrease in saccade peak velocity (Fig. 7a). The multiple regression analysis substantiated this observation, as the beta coefficient for vividness ratings revealed a negative correlation with statistical significance (β1, t(16) = -2.78, p = 0.013; Fig. 7b). In contrast, the beta coefficients for arousal and valence ratings did not reach statistical significance (Arousal (β2): t(16) = -0.018, p = 0.99; Valence (β3): t(16) = 1.48, p = 0.16). This pattern suggests that higher subjective vividness evaluations are associated with a measurable reduction in saccade peak velocity.

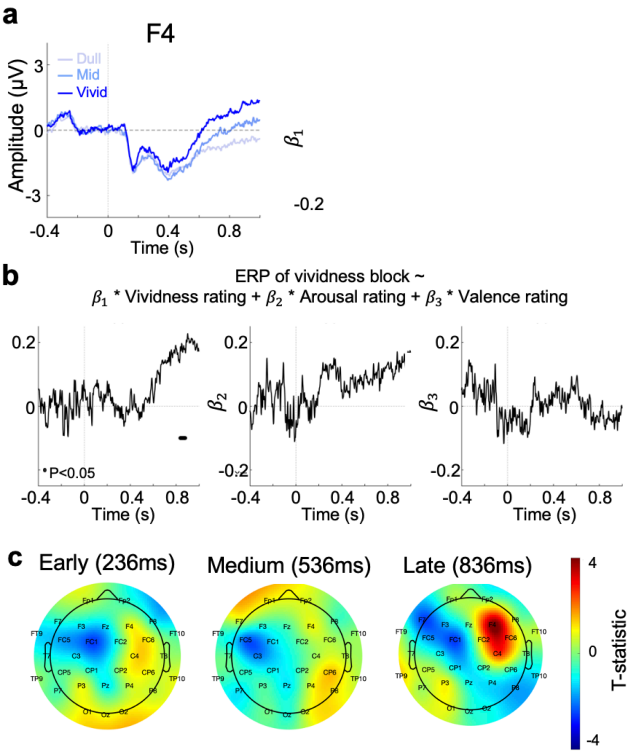

FIGURE 6. Vividness ratings manifest in distinct EEG responses. (a) All stimuli were categorized into three groups (dull, mid, and vivid) based on individuals' subjective vividness ratings. ERP amplitudes in the F4 channel exhibited distinct patterns among the three image groups, particularly at a later period. (b) Multiple linear regression analysis revealed that the representation of individuals' subjective vividness ratings as a late positive potential remained significant even after controlling for subjective arousal and valence ratings about the stimuli. β_1, β_2, and β_3 indicate regression coefficients for Vividness, Arousal, and Valence ratings, respectively. Shaded areas represent s.e.m. and black underlines indicate statistically significant time periods (cluster-based permutation, $p < 0.05$). (c) Topographical representation of t-statistics across 31 EEG channels is illustrated for three time points after the stimuli onset. Statistically significant impacts of subjective vividness rating were observed primarily in the frontal region on the right hemisphere around 830ms after the stimuli onset.

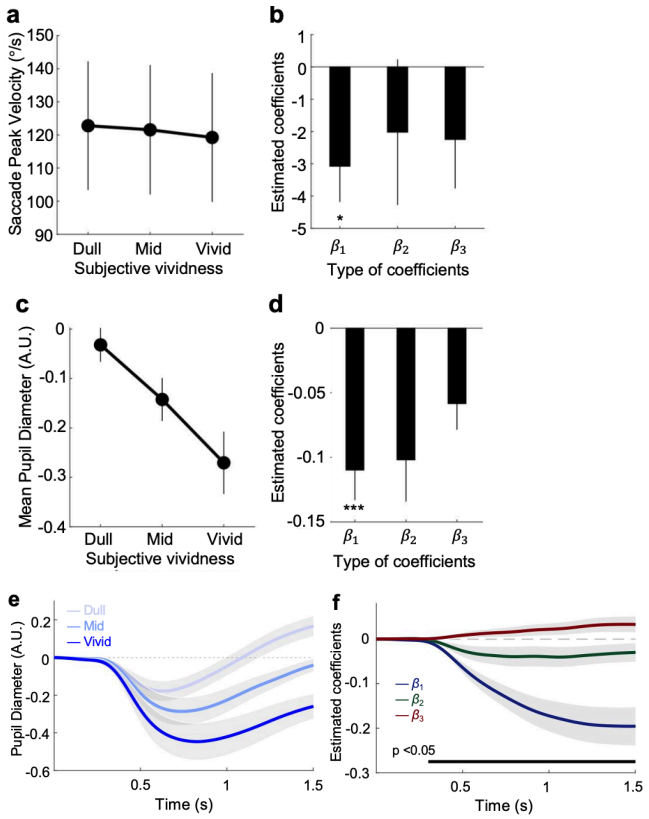

FIGURE 7. Vividness ratings manifest in distinct eye movement and pupillometric patterns. All stimuli were categorized into three groups (dull, mid, and vivid) based on individuals' subjective vividness ratings. (a) Saccade peak velocity and (c) mean pupil diameter patterns are illustrated for each level of subjective vividness ratings. (b, d) Multiple linear regression analysis revealed that the representation of individuals' subjective vividness ratings as a slower saccade velocity or a smaller pupil diameter remained significant even after controlling for task-irrelevant ratings about the stimuli. β_1, β_2, and β_3 indicate regression coefficients for Vividness, Arousal, and Valence ratings, respectively. Error bars represent s.e.m.; * $p < 0.05$, *** $p < 0.001$. (e) The temporal dynamics of pupil diameter are illustrated for each level of subjective vividness ratings. (f) Regression coefficients for the three subjective ratings over time are depicted. Shaded areas represent s.e.m. and black underlines indicate statistically significant time periods (cluster-based permutation, $p < 0.05$).

Pupil diameter findings showed largely the same trend. We observed a decrease in mean pupil diameter associated with higher vividness ratings (Fig. 7c). Once again, the regression analysis revealed a significant beta coefficient for vividness (β1, t(16) = -4.72, p < 0.001; Fig. 7d), while coefficients for arousal and valence remained non-significant (Arousal (β2): t(16) = -1.66, p = 0.12; Valence (β3): t(16) = 1.60, p = 0.13). This trend suggests that the subjective experience of vividness could be quantitatively assessed through changes in pupil diameter, indicating a physiological correlation with how vividness is visually processed. Note that the observed negative associations between pupil diameter and vividness ratings align with previously reported pupil responses to bright illusion [36], which is often associated with bright stimuli and may result in a reduction in pupil size.

The temporal dynamics of pupil diameter depicted separately for the equal-sized vividness subgroups (dull, mid, and vivid) mirrored the patterns observed for the objective White-boosting modes, showing significant shifts in response to the stimuli's vividness (Fig. 7e). Based on the regression analysis, the beta coefficient for vividness ratings (β1) exhibited a significant drop, becoming statistically notable shortly after the onset of the stimulus (306 msec post-onset; t(16) = -2.12, p = 0.05; Fig. 7f). In contrast, the coefficients for arousal (β2) and valence (β3) did not reach statistical significance. These results underscore the nuanced and dynamic physiological response to visual vividness, highlighting the intricate relationship between subjective experience and ocular metrics. Note that these results remained consistent in the additional residual regression analysis (Fig. S8).

IV. DISCUSSION

In the current study, we investigated whether EEG and eye-tracking data represent display quality objectively manipulated by the White-boosting algorithm, an image quality enhancement algorithm available on a commercially available TV set. In addition, we explored potential association between these measures and subjective reports of display quality. Our findings reveal that features extracted from EEG and eye-tracking data capture differences in objective image quality. Shared and dissociable sets of features significantly reflected individuals' subjective vividness ratings. These results showcase the potential of using neural and physiological measures to bridge the gap between objective display metrics and subjective visual comfort, opening doors for personalized TV settings based on neurophysiological responses.

Typical display viewing situations involve only one display, and therefore individuals rarely have the opportunity to compare the image quality of multiple displays. Diverging from such a naturalistic setting, many laboratory experiments in psychophysics use a form of two-alternative forced-choice (2AFC) procedures, wherein participants are asked to compare the image quality of different displays placed side-by-side [37]. On the contrary, the current study employed a single-display task in which participants rated consecutively presented images. The data acquired from evaluating the quality of a single image at a time were expected to be much noisier than our pilot 2AFC data regarding the vividness of images, given that individuals' performance in absolute judgment tasks is known to be poorer than in relative judgment tasks [38]. As anticipated, our self-report data on vividness did not show significant differences tracking objective changes in image quality (i.e., White-boosting). Nevertheless, this choice of task paradigm allowed us to examine the neural and physiological representations of the assessed absolute characteristics of images, as well as to investigate individuals' subjective

responses to a more naturalistic viewing situation. Given the potential of separable brain circuits involved in absolute versus relative value representation [39], our task design offer a better benchmark for future applications in measuring individuals' subjective image quality assessment using neural and physiological evidence.

A previous study reported that the amplitude and latency of P300, an ERP peak observed around 300 msec after the event onset, are associated with the blurriness of images [27]. The study presented a reference image before each target image to evaluate, thus linking the reported EEG feature to the detection of differences between two consecutively presented images. As described above, the current study was designed to induce the representation of the quality of images per se, rather than to induce error detection. Despite the difference in task design, our data confirmed that, consistent with the previous study, P300 responses from the frontocentral channels represented the objective image quality manipulated in the current study. Given that the self-reports on vividness did not significantly correlate with the objective quality, one might suspect that participants did not follow the instruction and made random responses throughout the task, raising questions about the interpretation of the associated ERP responses. Yet, this is unlikely because individuals' self-reports regarding other characteristics of presented images (arousal and valence ratings), along with the associated ERP responses, closely matched and validated the results from previous studies [20, 21, 24, 34]. These results suggest that the sensitivity of neural representation to the image quality of displays may be higher than that of self-reports.

In previous research, it was suggested that the late positive potential (LPP) is associated with emotionally arousing stimuli [20, 21, 24]. Expanding this view, we identified that regardless of individuals' subjective ratings on emotional responses (both arousal and valence), the LPP represents individuals' subjective vividness ratings. This ERP feature observed at a later period was clearly distinguishable from the earlier P300, suggesting that the objective and subjective impacts of image quality are both represented separately at a neural level. These findings align with previous studies. The earlier ERP feature likely reflects low-level perceptual processing, such as detecting image blurriness or contrast differences [24, 27, 40], while the later feature is associated with higher-level cognitive processes, including subjective evaluation of image content and emotional arousal [20, 21, 24]. In contrast to self-ratings, which often fail to sensitively capture individuals' implicit beliefs and unconscious brain processes [41-43], these ERP features underscore the complementary role of neural measures in bridging the gap between objective assessments and subjective evaluations of image quality.

There was a stark difference in the physiological responses to the examined image quality. Unlike the unique EEG features, our eye-tracking data showed that a common pupillometric feature reflects both the objective image quality and individuals' subjective ratings on vividness. The pupillometric responses to the White-boosting modes are consistent with previous studies, which have shown that pupil diameter decreases as the brightness of observed content increases [35, 44, 45]. Based on our regression results, we can rule out an alternative explanation that the associated pupil responses simply reflect the image-induced arousal level [8], and instead suggest that the observed pupillary responses demonstrate the low-level perceptual impacts of the White-boosting, as observed in examples of visual illusions [36, 45]. We also found evidence suggesting potential impacts of the image quality enhancement on higher-level cognition. Although not exactly the same, closely related eye movement measures—saccade and blink frequency, and saccade peak velocity—reflected the image quality or individuals' ratings to a comparable extent. This suggests that the enhancement of image quality increases induced attention level and cognitive loads during the viewing of the images [8, 46, 47]. Together, our data demonstrate the feasibility of using eye-tracking to capture both the objective optical characteristics and viewers' subjective evaluation of a display.

The current study has the following limitations. First, the current study had a relatively small sample size of 17 participants. It is possible that with a larger sample size, subtle trends in self-reports on vividness might show statistical differences among different levels of White-boosting modes. Still, our data in the arousal and valence blocks successfully replicated the behavioral and neural results of previous studies, demonstrating the validity of all our approach and the corresponding results. Second, the neural and physiological features identified as predictors of individuals' subjective responses were specific to self-reports on vividness—a measure aligned with the intended quality enhancement algorithm. It is uncertain whether the same set of features would be discovered if another axis of self-report, appropriately capturing image quality, were used. Third, we did not examine the impacts of prolonged screen time on both the user's experience (i.e., vividness) and its neurophysiological representation. Future studies may address this gap and evaluate the robustness of the features discovered in the current study.

Nevertheless, our data suggest that, unlike self-reports, which can be subjective and inconsistent, neurophysiological data may provide more stable and personalized features for optimizing image quality. Several practical challenges exist in implementing such a personalized optimization approach. First, the system may require additional hardware, such as EEG or eye-tracking devices, increasing both complexity and

cost, thereby limiting accessibility for general consumers. Recent advancements in lightweight and cost-effective wearable technologies offer promising avenues for reducing hardware costs. Additionally, optimizing the system to rely on a minimal dataset—focusing on key neurophysiological markers—could further mitigate costs by streamlining data acquisition and processing. Second, scalability is another critical concern, particularly in adapting the system for diverse user populations. Future studies should directly investigate the degree to which the predictive model generalizes across individuals, reducing the need for extensive individual calibration. By addressing these challenges, the proposed framework could offer a scalable and cost-efficient solutions for enhancing user experience in real-world applications.

V. CONCLUSION

The viewing experience of displays does not merely improve with enhanced optical characteristics (e.g., higher resolution), but also requires tailored settings for each individual to optimize subjective evaluation and approach realism (e.g., lively, natural, and vivid) [48-50]. To quantify the extent to which individuals respond to image quality adjustments, we used EEG and eye-tracking recordings, two methods previously validated to be useful in explaining a broad range of individual differences and mental illness [13, 51]. By exploring neurophysiological features reflecting display quality, our data show the feasibility of using EEG and eye-tracking to evaluate not only objective image quality but also the impact of manipulated image quality on individuals' subjective perception. Our findings provide a neurophysiological explanation about the impact of visual stimuli on human responses, offering insights into bridging the gap between objective display metrics and individuals' visual comfort.

ACKNOWLEDGMENT

This work was supported in part by UNIST internal funding (1.240015.01), KBRI basic research program through Korea Brain Research Institute funded by Ministry of Science and ICT (24-BR-03-08), the National Research Foundation of Korea (NRF-2020S1A3A2A02097375), and LG Electronics.

REFERENCES

[1] S. Benedetto, A. Carbone, V. Drai-Zerbib, M. Pedrotti, and T. Baccino, "Effects of luminance and illuminance on visual fatigue and arousal during digital reading," Computers in human behavior, vol. 41, pp. 112-119, 2014.

[2] N. Na, K. A. Jeong, and H.-J. Suk, "Do curved displays make for a more pleasant experience?," in Human Vision and Electronic Imaging XX, 2015, vol. 9394: SPIE, pp. 421-426.

[3] Y. Liu, X. Guo, Y. Fan, X. Meng, and J. Wang, "Subjective assessment on visual fatigue versus stereoscopic disparities," Journal of the Society for Information Display, vol. 29, no. 6, pp. 497-504, 2021.

[4] E.-J. Lee and S.-B. Lee, "Emotional image quality evaluation technology for display devices," Journal of the Korean Institute of Illuminating and Electrical Installation Engineers, vol. 23, no. 3, pp. 10-17, 2009.

[5] H. Zhang, D. Li, Y. Yu, and N. Guo, "Subjective and Objective Quality Assessments of Display Products," Entropy, vol. 23, no. 7, p. 814, 2021.

[6] K. Gu, J. Qiao, X. Min, G. Yue, W. Lin, and D. Thalmann, "Evaluating quality of screen content images via structural variation analysis," IEEE transactions on visualization and computer graphics, vol. 24, no. 10, pp. 2689-2701, 2017.

[7] K. Gu, D. Tao, J.-F. Qiao, and W. Lin, "Learning a no-reference quality assessment model of enhanced images with big data," IEEE transactions on neural networks and learning systems, vol. 29, no. 4, pp. 1301-1313, 2017.

[8] V. Skaramagkas et al., "Review of eye tracking metrics involved in emotional and cognitive processes," vol. 16, pp. 260-277, 2021.

[9] Y. Lu, W.-L. Zheng, B. Li, and B.-L. Lu, "Combining Eye Movements and EEG to Enhance Emotion Recognition," in IJCAI, 2015, vol. 15: Buenos Aires, pp. 1170-1176.

[10] J. E. Kamienkowski, M. J. Ison, R. Q. Quiroga, and M. Sigman, "Fixation-related potentials in visual search: A combined EEG and eye tracking study," Journal of vision, vol. 12, no. 7, pp. 4-4, 2012.

[11] S. Scholler et al., "Toward a direct measure of video quality perception using EEG," IEEE transactions on Image Processing, vol. 21, no. 5, pp. 2619-2629, 2012.

[12] J. R. Folstein and C. Van Petten, "Influence of cognitive control and mismatch on the N2 component of the ERP: a review," Psychophysiology, vol. 45, no. 1, pp. 152-170, 2008.

[13] Y. Sin, H. Seon, Y. K. Shin, O.-S. Kwon, and D. Chung, "Subjective optimality in finite sequential decision-making," PLoS Computational Biology, vol. 17, no. 12, p. e1009633, 2021.

[14] K. Lim, X. Li, and Y. Tu, "Effects of curved computer displays on visual performance, visual fatigue, and emotional image quality," Journal of the Society for Information Display, vol. 27, no. 9, pp. 543-554, 2019.

[15] T. Partala and V. Surakka, "Pupil size variation as an indication of affective processing," International journal of human-computer studies, vol. 59, no. 1-2, pp. 185-198, 2003.

[16] L. Lindemann and M. Magnor, "Assessing the quality of compressed images using EEG," in 2011 18th IEEE international conference on image processing, 2011: IEEE, pp. 3109-3112.

[17] J. Polich, "Updating P300: an integrative theory of P3a and P3b," Clinical neurophysiology, vol. 118, no. 10, pp. 2128-2148, 2007.

[18] S. A. Hillyard and M. Kutas, "Electrophysiology of cognitive processing," Annual review of psychology, vol. 34, no. 1, pp. 33-61, 1983.

[19] C. Dickter and I. Gyurovski, "The effects of expectancy violations on early attention to race in an impression-formation paradigm," Social neuroscience, vol. 7, no. 3, pp. 240-251, 2012.

[20] B. N. Cuthbert, H. T. Schupp, M. M. Bradley, N. Birbaumer, and P. J. Lang, "Brain potentials in affective picture processing: covariation with autonomic arousal and affective report," Biological psychology, vol. 52, no. 2, pp. 95-111, 2000.

[21] A. Keil, M. M. Bradley, O. Hauk, B. Rockstroh, T. Elbert, and P. J. Lang, "Large-scale neural correlates of affective picture processing," Psychophysiology, vol. 39, no. 5, pp. 641-649, 2002.

[22] Y. Cimtay and E. Ekmekcioglu, "Investigating the use of pretrained convolutional neural network on cross-subject and cross-dataset EEG emotion recognition," Sensors, vol. 20, no. 7, p. 2034, 2020.

[23] K. Eroğlu, O. Osman, T. Kayıkçıoğlu, and P. Kurt, "Determining the effect of emotional images brightness on EEG signals by classification algorithms," Multidimensional Systems and Signal Processing, vol. 33, no. 3, pp. 835-861, 2022.

[24] M. Codispoti, V. Ferrari, and M. M. Bradley, "Repetition and event-related potentials: distinguishing early and late processes in affective picture perception," Journal of cognitive neuroscience, vol. 19, no. 4, pp. 577-586, 2007.

[25] K. Yue et al., "Investigate the Neuro Mechanisms of Stereoscopic Visual Fatigue," IEEE Journal of Biomedical and Health Informatics, vol. 26, no. 7, pp. 2963-2973, 2022.

[26] Z. Long, L. Liu, X. Yuan, Y. Zheng, Y. Niu, and L. Yao, "Assessment of 3D visual discomfort based on dynamic functional connectivity

analysis with HMM in EEG," Brain Sciences, vol. 12, no. 7, p. 937, 2022.
[27] L. Jia, Y. Tu, L. Wang, X. Zhong, and Y. Wang, "Study of image quality using event-related potentials and eye tracking measurement," Journal of the Society for Information Display, vol. 26, no. 6, pp. 339-351, 2018.
[28] W. Jung, Y. Kwak, K. J. Kang, and M. Y. Lee, "79-3: Image Quality Change by White-Boost Function of WRGB OLED Display," in SID Symposium Digest of Technical Papers, 2023, vol. 54, no. 1: Wiley Online Library, pp. 1117-1120.
[29] SMPTE-EG-0432-1:2010, "Digital source processing - color processing for D-Cinema," The Society of motion picture and television engineers, 2010. [Online]. Available: https://www.document-center.com/standards/show/SMPTE-EG-0432-1.
[30] IEC, "Multimedia systems and equipment - Colour measurement and management - Part 2-1: Colour management - Default RGB colour space - sRGB (IEC 61966-2-1:1999)," International Electrotechnical Commission, p. 51, 1999. [Online]. Available: https://webstore.iec.ch/publication/6169#additionalinfo.
[31] P. J. Lang, M. M. Bradley, and B. N. Cuthbert, International affective picture system (IAPS): Affective ratings of pictures and instruction manual. NIMH, Center for the Study of Emotion & Attention Gainesville, FL, 2005.
[32] E. Maris and R. Oostenveld, "Nonparametric statistical testing of EEG-and MEG-data," Journal of neuroscience methods, vol. 164, no. 1, pp. 177-190, 2007.
[33] A. G. E. Collins and M. J. Frank, "Neural signature of hierarchically structured expectations predicts clustering and transfer of rule sets in reinforcement learning," Cognition, vol. 152, pp. 160-169, 2016.
[34] P. Lang and M. M. Bradley, "The International Affective Picture System (IAPS) in the study of emotion and attention," Handbook of emotion elicitation and assessment, vol. 29, pp. 70-73, 2007.
[35] A. B. Watson and J. I. Yellott, "A unified formula for light-adapted pupil size," Journal of vision, vol. 12, no. 10, pp. 12-12, 2012.
[36] B. Laeng and T. Endestad, "Bright illusions reduce the eye's pupil," Proceedings of the National Academy of Sciences, vol. 109, no. 6, pp. 2162-2167, 2012.
[37] B. W. Keelan and H. Urabe, "ISO 20462: a psychophysical image quality measurement standard," in Image Quality and System Performance, 2003, vol. 5294: SPIE, pp. 181-189.
[38] N. Stewart, G. D. Brown, and N. Chater, "Absolute identification by relative judgment," Psychological review, vol. 112, no. 4, p. 881, 2005.
[39] F. Grabenhorst and E. T. Rolls, "Different representations of relative and absolute subjective value in the human brain," Neuroimage, vol. 48, no. 1, pp. 258-268, 2009.
[40] G. F. Potts, Y. Hirayasu, B. F. O'Donnell, M. E. Shenton, and R. W. McCarley, "High-density recording and topographic analysis of the auditory oddball event-related potential in patients with schizophrenia," Biological Psychiatry, vol. 44, no. 10, pp. 982-989, 1998.
[41] S. Na et al., "Computational mechanisms underlying illusion of control in delusional individuals," Schizophrenia research, vol. 245, pp. 50-58, 2022.
[42] D. Chung, K. Yun, and J. Jeong, "Decoding covert motivations of free riding and cooperation from multi-feature pattern analysis of EEG signals," Social cognitive and affective neuroscience, vol. 10, no. 9, pp. 1210-1218, 2015.
[43] S. Na et al., "Humans use forward thinking to exploit social controllability," elife, vol. 10, p. e64983, 2021.
[44] C. Ellis, "The pupillary light reflex in normal subjects," The British journal of ophthalmology, vol. 65, no. 11, p. 754, 1981.
[45] Y. Kinzuka, F. Sato, T. Minami, and S. Nakauchi, "Effect of glare illusion-induced perceptual brightness on temporal perception," Psychophysiology, vol. 58, no. 9, p. e13851, 2021.
[46] A. Maffei and A. Angrilli, "Spontaneous blink rate as an index of attention and emotion during film clips viewing," Physiology & Behavior, vol. 204, pp. 256-263, 2019.
[47] Y. Tanaka, "Arousal level and blink activity," Shinrigaku kenkyu: The Japanese Journal of Psychology, vol. 70, no. 1, pp. 1-8, 1999.
[48] L. Christophers, C. T. Lee, and B. Rooney, "Exploring Subjective Realism: Do evaluative realism and felt realism respond differently to different cues?," International Journal of Human-Computer Studies, vol. 175, p. 103027, 2023.
[49] G. Gonçalves, H. Coelho, P. Monteiro, M. Melo, and M. Bessa, "Systematic review of comparative studies of the impact of realism in immersive virtual experiences," ACM Computing Surveys, vol. 55, no. 6, pp. 1-36, 2022.
[50] J. A. Redi, Y. Zhu, H. De Ridder, and I. Heynderickx, "How passive image viewers became active multimedia users: New trends and recent advances in subjective assessment of quality of experience," Visual signal quality assessment: Quality of experience (QoE), pp. 31-72, 2015.
[51] H. Lee et al., "Persistent impacts of smoking on resting-state EEG in male chronic smokers and past-smokers with 20 years of abstinence," Scientific Reports, vol. 13, no. 1, p. 3907, 2023.

Changhyun Lim received his M.S. degree in biomedical engineering from the Ulsan National Institute of Science and Technology, Ulsan, Korea, in 2024. His research interests include neural and physiological analysis to quantify image quality and computational modeling of sequential decision-making.

Hyun-Jun Jeon received his B.S. degree in Human Factors Engineering in 2018 from the Ulsan National Institute of Science and Technology (UNIST), South Korea. He is currently pursuing an integrated M.S.-Ph.D. program at UNIST. His research interests include human motion perception and computational modeling of perceptual processes.

Woojae Jung received his B.S degree in Human Factors Engineering and M.S degree in Biomedical Engineering from Ulsan National Institute of Science and Technology, Ulsan, South Korea in 2022 and 2024, respectively. His research interests include display color appearance and image quality assessment.

Youngshin Kwak received B.S. (physics) and M.S. (physics) degrees in 1995 and 1997 from Ewha Women's University, Seoul, South Korea. After completing her PhD studies at the Colour & Imaging Institute, University of Derby, UK, in July 2003, she worked for Samsung Electronics, South Korea. Since February 2009, she is working as a professor at Biomedical Engineering department, Ulsan National Institute of Science and Technology (UNIST), South Korea. She served as CIE Division1 (Vision and Colour) director from 2015 to 2023. Her main research interests include the color appearance modeling, visual appearance, and the image quality.

Myong Young Lee is a Research Fellow of the Department of TV Picture Quality Development of LG Electronics Ltd., South Korea. His research interests lie in the area of picture quality enhancement and color engineering for OLED and LCD display. In recent years, he has focused on evaluating and measuring method for picture quality of display and collaborated actively in the development of international standards at the IEC and elsewhere.

Jung Hyun Ham serves as a Research Professional in the TV image quality development department at LG Electronics Ltd., South Korea, where she leverages her expertise in display metrology and perceptual image quality. She is actively involved in the development of international standards, particularly with IEC and ICDM. In recent years, her primary research focus has been on developing methodologies to quantify and enhance image quality in TV applications.

Hyun Bin Joo is a Specialist of the Department of TV Picture Quality Development of LG Electronics Ltd., South Korea. His research interests picture quality evaluation and measuring method for OLED and LCD display. In recent years, he has focused on evaluating and measuring method for picture quality of display and collaborated actively in the development of international standards at the IEC TC100 and TC110.

Oh-Sang Kwon received the doctoral degree in psychological sciences from Purdue University in 2009. He is an associate professor with the department of biomedical engineering, UNIST (Ulsan National Institute of Science and Technology) in Ulsan, South Korea. His research interests include human visual perception, perceptual/cognitive biases, perception-action interaction, and perceptual learning.

Dongil Chung is an Associate Professor and a PI of the Decision Neuroscience and Cognitive Engineering Lab at Ulsan National Institute of Science and Technology, South Korea. His research interests focus on the neural and psychological foundation of valuation and decision-making. As a decision neuroscientist trained in bioengineering, my work takes a multidisciplinary approach that integrates behavioral economics, neuroimaging, psychology, decision neuroscience, and machine learning.