

Awe is characterized as an ambivalent affect in the human behavior and cortex

Jinwoo Lee^{1,2}, Danny Dongyeop Han³, Seung-Yeop Oh⁴, Jiook Cha^{1,2,3,5}

Affiliations

¹ Department of Brain and Cognitive Sciences, Seoul National University, South Korea

² Department of Psychology, Seoul National University, South Korea

³ Interdisciplinary Program of Artificial Intelligence, Seoul National University, South Korea

⁴ REnii studio, South Korea

⁵ Institute of Psychological Science, Seoul National University, South Korea

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Author Note:

We have no conflicts of interest to disclose. Correspondence concerning this article should be addressed to Jinwoo Lee, MS, and Jiook Cha, PhD, Building 16, Gwanak-ro 1, Gwanak-gu, Seoul, South Korea. Email: Jinwoo Lee (adem1997@snu.ac.kr) and Jiook Cha (connectome@snu.ac.kr)

Supplementary Note 1 – VR stimulus design and validation

We collaborated with a professional filmmaker to design four audio-integrated 360° immersive videos using Unreal Engine (version 5.03). Each video lasted 120 seconds. Three of the videos were designed to evoke awe: *Space* (SP), *City* (CI), and *Mountain* (MO), while the other one, *Park* (PA), served as a control stimulus, designed not to include any awe-related factors. To investigate whether ambivalence is consistently observed in various awe experiences, we varied the clip themes, the VR cues of awe-related two dimensions – perceived vastness and the need for accommodation, and the perceptual features across the awe-inducing videos.

Firstly, considering that awe is most intensively triggered by massive landscapes (Chirico et al., 2018; Keltner & Haidt, 2003; Shiota et al., 2007; Yaden et al., 2019), we differentiated the theme of the scenery across awe clips: SP featured supernatural landscapes (i.e., black holes and planets in space), CI showcased urban landscapes (i.e., cityscape viewed from the top of skyscrapers), and MO depicted natural one (i.e., mountain scenery).

Secondly, following the qualitative framework to design immersive VR clips that effectively elicit awe (Chirico et al., 2018), we aimed to represent the two key dimensions of awe, perceived vastness and a need for accommodation, through different cues in each video. Each video was designed so that perceivers would first experience vastness during the initial 60 seconds and then feel a need for accommodation in the latter 60 seconds. For example, in SP, participants watched a giant black hole approaching, consuming everything and ultimately drawing them in, followed by the sudden appearance of Earth from space. Different sub-components were applied to realize each dimension across clips. Perceived vastness can be induced through perceptual (e.g., ‘width’ and ‘height’) and conceptual cues (e.g., ‘complexity’)(Chirico et al., 2017; Chirico et al., 2018). MO was designed to evoke vastness through perceptual width, CI through height, and SP through conceptual complexity. For the need for accommodation, we introduced surprise cues in each video around the 60-second mark as a trigger of accommodation (Chirico et al., 2017; Chirico et al., 2018), tailored to the context of each video to ensure that the cause of surprise did not overlap across videos. The design of three awe-inducing clips is summarized in **Supplementary Fig 1a**.

Lastly, to prevent awe from being driven by specific perceptual factors, we intentionally composed the three awe videos with different audiovisual information. We synchronized visual content with ambient sounds using open-source audio samples from Freesound (<https://freesound.org>) and GarageBand (version 10.4.6). To verify our design, we calculated three perceptual features known to predict perceivers’ emotional responses – color hue (Dael et

al., 2016; Suk & Irtel, 2010), brightness (Kurt et al., 2017), and loudness (Thao et al., 2019) – every second for each stimulus and visualized their time-course dynamics. We qualitatively confirmed that each video exhibited very different temporal dynamics for all features (see **Supplementary Fig 1b**).

Supplementary Note 2 – Frontal Alpha Asymmetry (FAA) and Principal Component Analysis (PCA)

As a control analysis of our CEBRA-based decoding analysis, we also conducted the same task with FAA value (i.e., handcrafted valence index of EEG signals) and PCA embeddings (i.e., conventional unsupervised and linear dimensionality reduction approach). First, to extract PCA embeddings, we input the STFT-processed EEG features and computed latent embeddings with dimensions ranging from one to nine. We identified the 6-dimensional embedding as the optimal latent space due to its modest predictive performance with the fewest dimensions (see **Supplementary Fig 2**). As a result, we used the six principal component of each participant-clip datum for the pairwise decoding analysis. Second, FAA value was defined as the difference in alpha band power between the F4 and F3 channels for each timepoint in the STFT-featured EEG sequence. These two channels were selected based on previous studies (Brzezicka et al., 2017; Quaedflieg et al., 2016; Van Der Vinne et al., 2017).

Supplementary Note 3 – Hidden Markov Model (HMM) analysis

We employed HMM to estimate which features distinguish the representation of affective states corresponding to each valence label in EEG signals. Specifically, we identified the hidden state transition timepoints of a given neural feature x using HMM. If a transition timepoint fell within ± 3 seconds of a valence transition timepoint observed in the participant-reported feeling dynamics via keypress, we defined it as a ‘match.’ The ‘match rate’ was then calculated as the ratio of matches to the total number of transitions, and its statistical significance was evaluated through 1,000 permutation tests.

Following the framework of previous literature (Vaccaro et al., 2024), we assessed the statistical significance of the feature x ’s match rate while accounting for its large variability across participants and clips. Our approach involves the following steps:

First, the match rate $M_{(i,j,x)}$ for feature x in participant i and clip j is calculated using HMM, where the number of hidden state transitions is set to match the number of valence transitions observed in the actual feeling dynamics. Second, to calculate the null match rate $Q_{(i,j,x)}$, the timepoints of feature x are randomly shuffled, and the match rate with the feeling

dynamics is calculated using the same procedure with HMM. This process is repeated to obtain a set of null match rates $Q_{(i,j,x)}^{(1)}, Q_{(i,j,x)}^{(2)}, \dots, Q_{(i,j,x)}^{(N)}$. Third, the mean difference $D_{(i,j,x)}$ is calculated as the difference between $M_{(i,j,x)}$ and the average null match rate $\bar{Q}_{(i,j,x)}$. Fourth, to calculate a single mean difference value for feature x , the average of $D_{(i,j,x)}$ across all participants and clips is computed, denoted as $\bar{D}_x$. To compute the null distribution of $\bar{D}_x$, for each $Q_{(i,j,x)}^{(n)}$, the difference from $\bar{Q}_{(i,j,x)}$ is computed, and the average of these differences across all participants and clips is calculated, yielding $\bar{D}_x^{*(n)}$ for each permutation. This process generates the null distribution $\bar{D}_x^{*(1)}, \bar{D}_x^{*(2)}, \dots, \bar{D}_x^{*(N)}$. Finally, the P value for $\bar{D}_x$ is calculated as the proportion of values in the null distribution that are greater than $\bar{D}_x$. We used 1,000 times of permutation test for this procedure (i.e., $N = 1,000$).

Using mean difference in the match rate as a statistical test, instead of directly using the match rate, effectively adjusts for individual-level variability by normalizing the scale according to the number of state transitions. This allows for more reliable group-level inference by mitigating large differences in scale that would otherwise arise due to the number of state transitions in the match rate.

For the selection of feature x , we adopted both a channel-centric and a frequency band-centric approach. In the channel-level analysis, we aggregated the five band-specific features corresponding to each of the 19 channels and used them as inputs to the HMM, resulting in a total of 19 fitted HMM models. In the frequency-level analysis, we aggregated the 19 channel-specific features for each of the five frequency bands and used them as inputs, leading to a total of five fitted HMM models.

Supplementary Table 1. Statistical differences in key demographics and awe ratings between the participants included and excluded in the electrophysiological analysis

	Included (<i>N</i> = 27)	Excluded (<i>N</i> = 16)	<i>P</i> _{FDR}
Demographics			
male; <i>N</i> (%)	13 (48.1)	7 (43.8)	.960
age years; <i>M</i> (<i>SD</i>)	20.2 (1.8)	20.3 (1.7)	.960
AWE-S ratings			
for SP; <i>M</i> (<i>SD</i>)	4.7 (0.6)	4.4 (0.7)	.559
for CI; <i>M</i> (<i>SD</i>)	4.6 (0.5)	3.8 (1.0)	.070
for MO; <i>M</i> (<i>SD</i>)	4.3 (0.8)	4.1 (1.0)	.960

Note. Statistical difference of the categorical variable (i.e., male) between groups was assessed by Brunner-Munzel test. For the other variables, we applied two-sided t-test. All *P* values were FDR corrected.

Supplementary Table 2. Associations between emotion-related sensory features of VR stimuli and participants' real-time valence ratings

	positive vs. neutral			ambivalent vs. neutral			negative vs. neutral		
	β	SE	P	β	SE	P	β	SE	P
Time	.151	.063	.017*	.051	.065	.432	.074	.079	.351
Brightness	3.762	.122	$< 2 \times 10^{-16}***$	1.361	.115	$< 2 \times 10^{-16}***$	-1.194	.136	$< 2 \times 10^{-16}***$
Hue	1.591	.119	$< 2 \times 10^{-16}***$	.268	.091	.003**	-.546	.111	$9 \times 10^{-7}***$
Loudness	1.621	.093	$< 2 \times 10^{-16}***$	.558	.093	$2 \times 10^{-9}***$	1.629	.107	$< 2 \times 10^{-16}***$

Note. We tested multinomial mixed logistic regression model predicting valence label for every time point using sensory features and two random intercepts of participants and clips as follows: $\text{valence}_t = t + \text{brightness}_t + \text{hue}_t + \text{loudness}_t + (1|\text{sub}) + (1|\text{clip})$. All continuous variables were standardized and normalized, and all iterations were completed until the model converged. * $P < .05$; ** $P < .01$; *** $P < .001$.

Supplementary Table 3. Statistical differences in post-trial valence and arousal ratings between conditions

	SP vs. PA				CI vs. PA				MO vs. PA			
	<i>t</i>	<i>df</i>	<i>d</i>	P_{FDR}	<i>t</i>	<i>df</i>	<i>d</i>	P_{FDR}	<i>t</i>	<i>df</i>	<i>d</i>	P_{FDR}
Valence												
ambivalent(int)	2.957	42	.451	.005**	2.946	42	.449	.005**	5.118	42	.780	$2 \times 10^{-5***}$
ambivalent(dur)	3.684	42	.562	.001***	3.372	42	.514	.002**	5.179	42	.790	$2 \times 10^{-5***}$
positive(int)	1.427	42	.218	.352	-.443	42	-.068	.660	1.206	42	.184	.352
positive(dur)	-3.312	42	-.505	.003**	-3.618	42	-.552	.002**	-3.178	42	.485	.003**
negative(int)	-.295	42	-.045	.769	2.562	42	.391	.021*	3.024	42	.461	.013*
negative(dur)	.421	42	.064	.676	4.297	42	.655	$1 \times 10^{-4***}$	5.243	42	.800	$1 \times 10^{-5***}$
Arousal	5.810	42	.886	$7 \times 10^{-7***}$	7.404	42	1.129	$6 \times 10^{-9***}$	9.301	42	1.418	$3 \times 10^{-11***}$

Note. 'int' and 'dur' denote intensity and duration of the affective feelings, respectively. * $P_{\text{FDR}} < .05$;

** $P_{\text{FDR}} < .01$; *** $P_{\text{FDR}} < .001$.

Supplementary Table 4. Statistical differences in decoding performances of latent neural-feeling space embeddings across conditions and analytic approaches

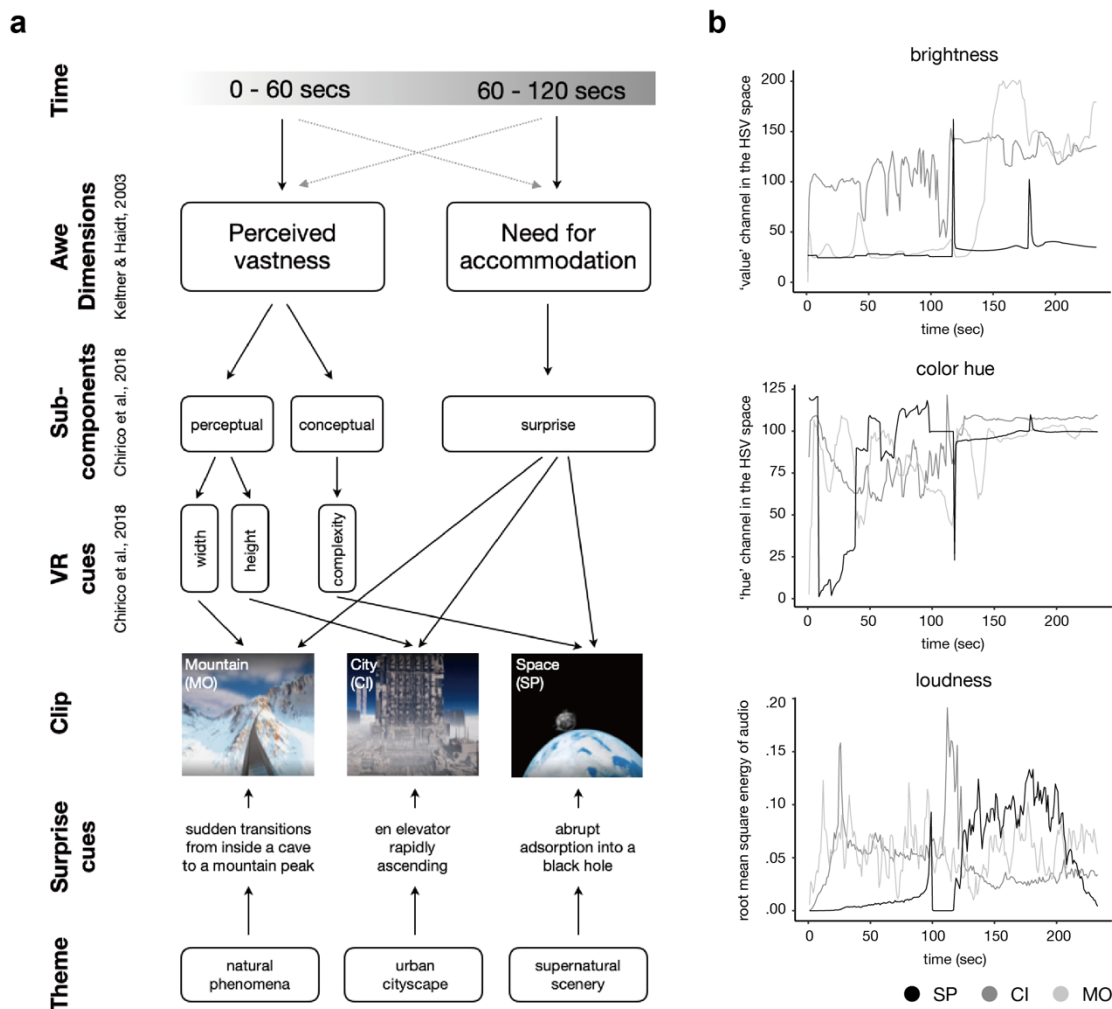
	across participants				across clips			
	<i>t</i>	<i>df</i>	<i>d</i>	<i>P</i> _{FDR}	<i>t</i>	<i>df</i>	<i>d</i>	<i>P</i> _{FDR}
within CEBRA embeddings								
<i>aligned vs. random</i>	7.829	718	.674	5×10 ^{-14***}	2.882	286	.392	.007**
<i>aligned vs. not-aligned</i>	4.532	718	.390	1×10 ^{-5***}	2.868	286	.390	.007**
<i>not aligned vs. random</i>	3.297	718	.284	.001**	.014	286	.002	.989
between embeddings								
<i>aligned</i>								
CEBRA vs. PCA	11.366	178	1.694	1×10 ^{-22***}	3.910	70	.921	3×10 ^{-4***}
CEBRA vs. FAA	13.047	178	1.945	3×10 ^{-27***}	4.948	70	1.166	1×10 ^{-5***}
<i>not-aligned</i>								
CEBRA vs. PCA	3.240	178	.483	.002**	-.358	70	-.084	.721
CEBRA vs. FAA	4.985	178	.743	4×10 ^{-6***}	1.238	70	.292	.330
<i>random</i>								
CEBRA vs. PCA	-0.241	178	-.036	.810	.250	70	.059	.803
CEBRA vs. FAA	2.087	178	.311	.058	1.995	70	.470	.128

Note. **P*_{FDR} < .05; ***P*_{FDR} < .01; ****P*_{FDR} < .001.

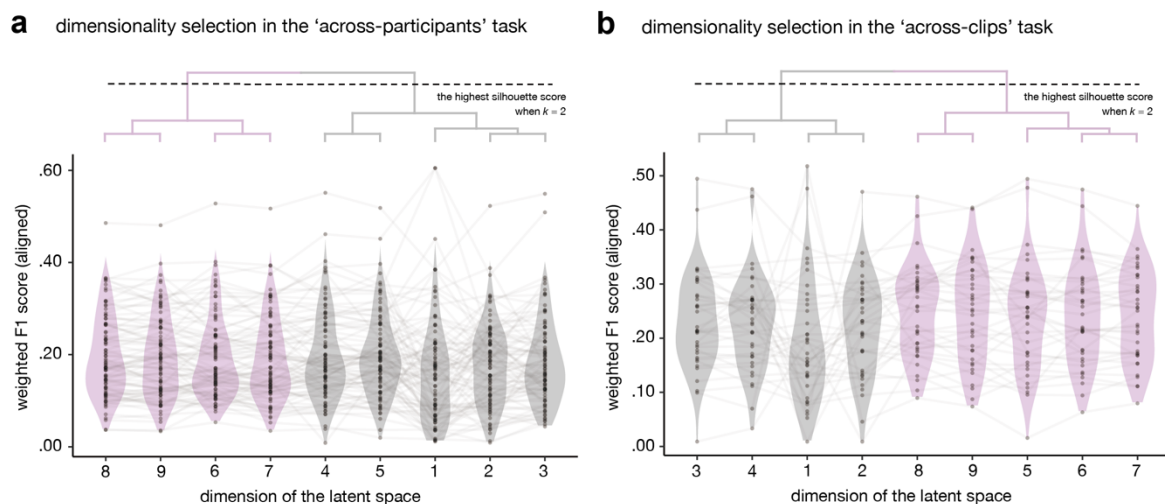
Supplementary Table 5. Match rate and statistical significance between each EEG channel's hidden state transitions and self-reported feeling transitions

channel	match rate	mean difference	<i>P</i>
P7	.367	.005	.417
P4	.424	.028	.220
Cz	.412	.048	.110
Pz	.336	.084	.006**
P3	.388	.012	.362
P8	.449	.013	.335
O1	.397	.032	.187
O2	.264	-.045	.912
FC6	.419	.027	.201
F8	.365	.027	.206
C4	.356	-.005	.557
F4	.322	.029	.183
AF4	.348	.068	.014*
Fz	.355	.095	.002**
C3	.329	.026	.187
F3	.305	.014	.325
AF3	.233	-.022	.778
FC5	.329	.060	.024*
F7	.336	.021	.249

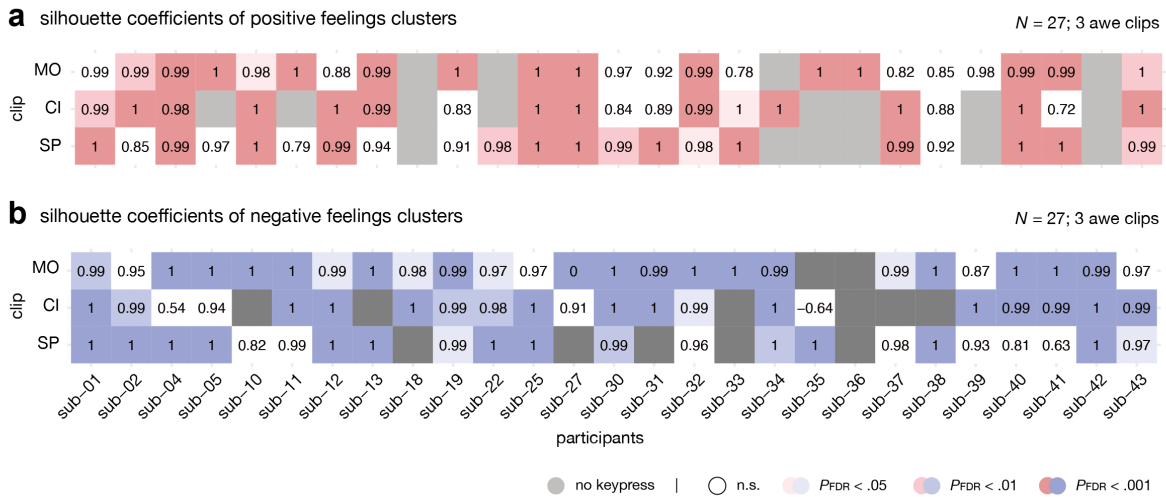
Note. * $P < .05$; ** $P < .01$; *** $P < .001$.



Supplementary Fig 1. Design of VR clips to induce diverse awe experience using distinct awe-related cues and sensory profiles. **a**, we designed the three awe-inducing VR clips to evoke distinct awe experiences while incorporating key dimensions of awe, each implemented through different sub-components in the VR environment. The common structure (i.e., 'awe dimensions') was based on the core dimensions of awe, which was formulated by the qualitative literature (Keltner & Haidt, 2003). To ensure that each awe dimension was distinctly represented in the VR environment, we applied the qualitative framework which suggests distinct sub-components of perceived vastness and relevant VR cues (Chirico et al., 2018). **b**, the heterogeneous temporal patterns of visual and acoustic features in three awe-inducing clips.



Supplementary Fig 2. Dimensionality selection for PCA-driven latent neural-feeling space. **a**, the test performances in the 'across participants' task. Hierarchical clustering analysis identified clusters with high performance in decoding other participants' valence sequence (purple violin plots). Each sample point indicates the possible pair of train-test participants in the given clip. **b**, the test performances in the 'across clips' task. Each sample point indicates the possible pair of train-test clips in the given participant.



Supplementary Fig 3. Silhouette coefficients of positive and negative valence clusters in personalized latent neural-feeling spaces. **a**, silhouette coefficients of positive feelings clusters within each participant's latent neural-feeling spaces. Color intensity indicates the statistical significance of the silhouette coefficients. Gray cells means that the participant did not report positive (or negative) feelings during watching the clip. Some participants have a gray cell (i.e., not respond positive or negative feelings in the keypress) because 27 participants included in this analysis were chosen in terms of whether they responded ambivalent feelings for more than 5% of the total duration across all awe-inducing clips, rather than positive or negative feelings. **b**, silhouette coefficients of negative feelings clusters within each participant's latent neural-feeling spaces.

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