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The psychological-characteristic and neural correlates of individual differences in affective responses to visual narratives

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Abstract

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Human individuals often go through different affective states even under the same circumstances. Such differences may in turn make us, as individuals, interpret or react to identical events differently. Therefore, it is important to identify the sources that contribute to the inter-individual variability in affective processing for a comprehensive explanation of human behavior. Here, I explored such sources in the psychological-characteristic and neural domains, respectively. Importantly, in this exploration, I focused on the affective (valence and arousal) responses to visual-narrative stimuli (VNs), considering that such stimuli are likely to evoke affective responses in a manner close to that occurring in daily life and effective in driving subtle and nuanced differences across individuals. Then I sought the correlates of the across-individual variability in affective responses both in the domain of psychological characteristics and in that of brain activity. In the former, I acquired high-dimensional datasets in both affective-response and psychological-characteristic domains from the same pool of individuals and performed canonical correlation analysis in conjunction with principal component analysis. I found a single robust mode of population covariation, which relates the 'psychosocial' measures in the psychological-characteristic domain to the 'accuracy' and 'sensitivity' measures of arousal responses to VNs. This suggests the 'social assets' as one of the psychological-characteristic sources of the across-individual variability in arousal responses to VNs. In the latter, I acquired functional magnetic resonance imaging (fMRI) signals while subjects were viewing the VNs and sought the brain regions whose fMRI responses to VNs are correlated not only with the across-individual averages of behavioral affective responses to VNs but also with the factor governing the inter-subject similarity structure of the affective responses to VNs. I found that the structure of between-individual similarity in affective responses is governed by one of the so called *Anna-Karenina* structures where the individuals in the majority's affective responses were quite close to the normative responses (thus quite similar to one another) whereas the individuals in the minority's responses far away from the normative responses in an idiosyncratic manner (thus quite different form one another). Then I found that the structure of between-individual similarity in fMRI responses to VNs in the anterior insular in right hemisphere closely resembles the *Anna-Karenina* structure of between-individual similarity found in behavioral valence responses to VNs. This suggests the anterior insular in right hemisphere as one of the brain regions that are correlated with the across-individual variability in valence responses to VNs. The findings in my thesis, put together, suggest that, in the domain of psychological characteristics, the psychosocial assets were a prominent source for the across-individual variability in *polarized arousal responses* to VNs whereas, in the domain of brain activity, the cortical responses to VNs in the right-hemisphere insular uniquely—out of the valence-associated regions—share with the valence responses to VNs the (*Anna-Karenina*) structure of inter-individual similarity.

Keywords: affective processing, visual narratives, individual differences, psychological characteristics, fMRI, inter-subject representational similarity analysis

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Chapter 1. General Introduction

1.1 Substantive individual differences and the importance of identifying their correlates in the psychological characteristics and neural domains

According to Darwin (Darwin & Prodger, 1998), animals and humans alike have evolved to express their internal emotional state not only to protect themselves from immediate threats but also to communicate important messages to their colleagues nonverbally. The latter function of emotion expression—as a nonverbal communication medium—has been considered important for human social cognition and elaborated by the empirical findings that at least six (Ekman, 1992; Ekman & Friesen, 1971; Ekman, Sorenson, & Friesen, 1969) or up to nine (Elfenbein & Ambady, 2002; Tracy & Matsumoto, 2008; Tracy & Robins, 2008) categorical emotions are tightly associated with distinct nonverbal expressions, and those expressions are robustly displayed and recognized across cultures. Some emotions, especially those six to nine emotions mentioned above, appear to be universal at high degrees. On the other hand, there has been evidence also showing that perception of emotion varies across cultures at significant degrees (Gendron, Roberson, van der Vyver, & Barrett, 2014; Jack, Garrod, Yu, Caldara, & Schyns, 2012). Furthermore, even within the same culture, individuals substantively differ in their affective reactivity, exhibiting different responses (e.g., from being mildly surprised, to shivering, and even to crying) to the same object or event (e.g., a scene in a horror movie).

The appraisal processes (Klaus R Scherer, Schorr, & Johnstone, 2001; C. A. Smith & Lazarus, 1993), multi-component compositions (Kuppens, Van Mechelen, Nezlek, Dossche, & Timmermans, 2007; Stouten, De Cremer, & Van Dijk, 2005), or unfolding dynamics (Lewis, 2005; C. A. Smith & Lazarus, 1993) of affective state have been suggested to be among many factors contributing to such individual differences (Kuppens, Stouten, & Mesquita, 2009). Specifically, the appraisal process is based on an individual's idiosyncratic life-long history of experiences, making affective experience highly subjective. The multi-component nature of affect implies that the same affect (e.g., negative affect) may differ in actual composition across individuals, which leads to finely nuanced variations in affective experience

(Ellsworth & Scherer, 2003). The literature on emotion dynamics indicates that individuals substantively differ in duration (Verduyn, Delvaux, Van Coillie, Tuerlinckx, & Van Mechelen, 2009) and in the variability of intensity over time (Kuppens, Van Mechelen, Smits, De Boeck, & Ceulemans, 2007; Larsen, 1987).

Not surprisingly, considering these factors contributing to individual differences in affective processing, individual differences in affective responses are far greater than those in any other mental functions (Davidson, 1992, 1998), on which the field of personality research is grounded. In this sense, i.e., to understand what makes people individuals, it is crucial to identify the systematic structures of individual differences in affective responses and elucidate how such structures relate to (i) what aspects of psychological characteristics such as long-lasting personality traits, psychosocial states, and psychiatric symptoms and to (ii) what patterns of neural activity and what parts of the brain. Advancing such identification and elucidation would not just advance our understanding of the idiosyncratic nature of human affective processing but also provide practical solutions to the problems in diverse social or clinical situations. For instance, effective pedagogical strategies can be tailored to individuals based on individual differences in affective state to enhance the communication between tutors and students (Harley et al., 2016). Identification of the affective response styles that are associated with certain mental disorders on social networks can be used as an indirect yet highly natural probe for detecting high-susceptible individuals from a normal population (Zhou, Hu, & Wang, 2019). Also, identification of the brain activities that reflect the structure of individual differences in affective responses can offer useful information about the brain mechanisms responsible for the subjective aspects of affective processing, which in turn would help diagnose and treat the abnormal affective processing in a clinical setting.

1.2. Preview of the studies presented in the thesis

In this thesis, I attempted to identify the psychological-characteristic features and the brain activities that are related to the inter-individual variability in affective processing. Importantly, in doing so, I focused on the affective (valence and arousal) responses to visual-narrative stimuli (VNs), considering that such stimuli are likely to evoke affective responses in a manner close to that occurring in daily life and effective in driving subtle and nuanced differences across individuals. I created a library of VNs such that they can induce various affective states and developed affective-response measures that characterize the individual affective response style. And then, with those affective-response measures in hand, I searched for the global structure connecting the individual differences in affective response to visual narratives and the psychological characteristic using a multivariate analysis method (Chapter 2). Furthermore, I sought the brain areas whose fMRI responses to VNs are correlated not only with the across-individual averages of affective responses to VNs but also with the factor governing the inter-subject similarity structure of the affective responses to VNs (Chapter 3). Lastly, I summarized and discussed the results of Chapter 2 and 3, and suggested future directions based on the findings (Chapter 4).

Chapter 2. Multivariate association between affective responses to visual narratives and psychological characteristics

2.1. Introduction

A large volume of work has been carried out to associate affective responses with psychological characteristics across individuals. These studies can be sorted in terms of what aspects of affective responses were probed, namely 'accuracy', 'bias', 'variability', and 'differentiability'. Previous studies that probed the accuracy of affective responses (Demenescu, Kortekaas, den Boer, & Aleman, 2010a; Keltner & Kring, 1998; Kohler, Walker, Martin, Healey, & Moberg, 2009; Kring & Campellone, 2012; Lyusin & Ovsyannikova, 2016; Matsumoto et al., 2000; Mayer, Salovey, Caruso, & Sitarenios, 2003), which refers to how less deviated an individual's affective responses are from the population norm, reported its association with personality traits or mental problems. For instance, individuals with extraversion and neuroticism traits tended to be high and low, respectively, in the accuracy of affective responses (Matsumoto et al., 2000). Clinical problems, such as depression, anxiety, and schizophrenia, typically showed negative associations with the accuracy of affective responses (Demenescu et al., 2010a; Keltner & Kring, 1998; Kohler et al., 2009; Kring & Campellone, 2012). Previous studies on the bias of emotion or affective responses (Aluja et al., 2015; Tok, Koyuncu, Dural, & Catikkas, 2010; Waugh, Thompson, & Gotlib, 2011), which refers to how biased an individual's responses are toward a certain emotion category (e.g., 'happy') or affective state (e.g., 'positive side on the valence axis'), reported its associations with psychosocial factors or personality traits. For instance, individuals with good coping skills tended to be positively biased in valence (Waugh et al., 2011), or those with openness traits were positively biased both in valence and arousal (Tok et al., 2010). The variability of affective responses refers to how inconsistent an individual's affective responses to the same event or highly similar events are (Kuppens, Oravecz, & Tuerlinckx, 2010; Kuppens, Van Mechelen, Nezlek, et al., 2007) and has been reported to show a positive relationship with neuroticism and a negative relationship with agreeableness (Kuppens, Van Mechelen, Nezlek, et al., 2007). Lastly, the differentiability of affective states (also dubbed "emotion granularity") refers to how finely an individual can discriminate affective states—how sensitive an individual is in detecting subtle nuances or differences between affective situations (Emery, Simons, Clarke, & Gaher, 2014; Erbas, Ceulemans, Lee Pe, Koval, & Kuppens, 2014; Smidt & Suvak, 2015). Individuals with high differentiability of affective states are reported to exhibit high scores of self-esteem (Erbas et al., 2019).

We note that the previous studies mentioned above were mostly designed to test theories or hypotheses about the relationship between certain aspects of affective responses and psychological characteristics relying on pairwise comparison analysis methods. Even when multiple affective-response measures and different psychological characteristics were collected within single studies, only bivariate relationships were mostly inspected (Lopes, Salovey, & Straus, 2003; Klaus R. Scherer & Scherer, 2011). This 'hypothesis-driven and regional' approach taken by these previous studies may efficiently address their respective 'regional' questions by testing the predictions of interest. Despite this merit, the 'hypothesis-driven and regional' approach may not be ideal for revealing the systematic and global structure that governs the across-individual covariation between the domain of affective responses and that of psychological characteristics, especially when considering the aforementioned factors contributing to large individual differences in affective responses. Specifically, the hypothesis-driven and regional approach may be insensitive to the presence or absence of a potential structure that can be defined only in a multidimensional space of affective responses or psychological characteristics. In other words, a significant pairwise correlation does not warrant its participation in the true global structure that governs the relationship between the two domains (Fish, 1988; Thompson, 1994). Likewise, an insignificant pairwise correlation does not necessarily mean that it does not contribute to the true global structure (Stürmer, Busanello, Velho, Heck, & Haygert-Velho, 2018).

The goal of the current work is to identify the systematic and global structure that governs the across-individual covariation between the domain of affective responses to visual narratives and that of psychological characteristics. To achieve this goal effectively, we took the 'data-driven and global' approach – as an alternative to the hypothesis-driven and regional approach – and considered several other important aspects, as follows. First, we used visual narrative stimuli, 15-second long film excerpts of various genres, to probe affective responses. Visual narratives can be considered ideal for promoting the across-individual variability because they contain the aforementioned ingredients contributing to individual differences of affective responses: various affective states are expected to be unfolded (Lewis, 2005; Sander, Grandjean, & Scherer, 2005) as people undergo the appraisal process (Klaus R Scherer et al., 2001; C. A. Smith & Lazarus, 1993) by integrating multiple cues under complex and natural contexts (Kuppens, Van Mechelen, Nezlek, et al., 2007; Stouten et al., 2005). Second, we collected as many and diverse measures as possible in both domains. As for the domain of psychological characteristics, we collected a total of 68 measures using 19 different batteries of psychometric questionnaires, which cover the subdomains including 'personality', 'psychosocial factors', and 'clinical problems'. As for the domain of affect, we acquired two-dimensional ('arousal' and 'valence') affective-state responses to visual narratives and derived the four measures that have been reported by the previous work to be associated with certain psychological characteristics (we named the measures as 'accuracy', 'bias', 'consistency', and 'sensitivity'). Lastly, we carried out multivariate analyses to discover a global structure of the across-individual covariation between the affective-response and psychological-characteristics domains. In doing so, to address the known limitations of multivariate analysis methods associated with the dimensionality and interpretability issues, we conducted the canonical correlation analysis (CCA) (Hotelling, 1936) in conjunction with the principal component analysis (PCA) (Pearson, 1901), which allowed us to effectively search a compact and interpretable feature space for significant across-individual covariations between specific styles of affective responses and particular profiles of psychological characteristics.

To anticipate results, the multivariate analyses on the data collected from 86 individuals revealed a single robust mode of covariation that links the domains of affective responses and psychological characteristics. Specifically, the 'accuracy' and 'sensitivity' measures of arousal responses in the affect domain and many 'psychosocial-factor' measures in the psychological-characteristics domain contributed to the mode of population covariation. Based on further analyses on those measures with significant contributions, we reached an interpretation that the mode reflects the tendency of individuals characterized with positive social perspectives to show polarized arousal responses to visual narratives.

2.2. Methods

Participants

We recruited 86 Korean undergraduate students of similar ages (41 females, $M_{age} = 21.4$, age range: 18–24 years; Table 1). We justified the sample size by proceeding with simulations for power and specificity (see **Appendix A** for detail). All participants were interviewed by trained clinicians to be prescreened for neurological and/or psychiatric disorders. Six participants who had high (moderate to severe) Beck Depression Inventory (BDI) or Beck Anxiety Inventory (BAI) scores were excluded from further analysis. Participants all had a normal or corrected-to-normal vision. In addition, participants were also cataloged for their sex, age, IQ, and family income to statistically de-confound the individual differences that might potentially confound the relationship between psychological characteristics and affective responses to VNs. This study was approved by the Seoul National University Research Ethics Committee, and informed written consent was obtained from all participants prior to actual participation.

Table 1. Demographic summary of participants

Demographic variables		Frequency (n)	Percentage (%)
Sex	Male	45	52.3
	female	41	47.7
Age	18-20	28	32.6
	20-24	58	67.4
Monthly household income	less than $ 1,000	2	2.3
	$ 1,000-$ 1,999	2	2.3
	$ 2,000-$ 2,999	10	11.6
	$ 3,000-$ 3,999	11	12.8
	$ 4,000-$ 4,999	13	15.1
	$ 5,000-$ 5,999	12	14.0
	$ 6,000-$ 6,999	9	10.5
	$ 7,000-$ 7,999	3	3.5
	$ 8,000-$ 8,999	8	9.3
	$ 9,000-$ 9,999	3	3.5
	$ 10,000 or more	10	11.6
	Not stated	3	3.5
IQ	91-100	2	2.3
	101-110	13	15.1
	111-120	36	41.9
	121-130	30	34.9
	131-140	5	5.8
Total		86	100.0

Psychological-characteristic measures

To acquire a comprehensive and unbiased set of psychological characteristics, we used a total of 19 psychometric questionnaires that were associated with diverse taxonomies that capture individual differences. These taxonomies included: (i) the personality taxonomies that capture individual differences in relatively enduring behavioral tendencies based on the ‘Big Five’ model (Goldberg, 1990; McCrae & Costa, 1987), the ‘Reinforcement Sensitivity’ theory (J. A. Gray, 1981; Jeffrey A. Gray, 1982), and Cloninger’s ‘Psychobiological model of temperament and character’ (Cloninger, Svrakic, & Przybeck, 1993); (ii) the psychosocial-factor taxonomies that capture individual differences in capacity for recovery after significant adversity (Luthar, Cicchetti, & Becker, 2000), in-person social support (Cohen & Wills, 1985; D. Russell, Peplau, & Cutrona, 1980), perceived social rank (Adler, Epel, Castellazzo, & Ickovics, 2000), capacity for empathy (M. H. Davis, 1980), perceived quality of life (Group, 1993), recent life experience (Sarason, Johnson, & Siegel, 1978), and attitude towards themselves (M. Rosenberg, 1965); (iii) the clinical-problem taxonomies that capture individual differences in propensity for major mental problems such as personality disorders (First, Benjamin, Gibbon, Spitzer, & Williams, 1997), anxiety disorders (Aaron T Beck, Epstein, Brown, & Steer, 1988; Spielberger & Gorsuch, 1983), substance abuse (Babor et al., 1992; Heatherton, Kozlowski, Frecker, & Fagerstrom, 1991), suicidal thinking (Aaron T. Beck, Kovacs, & Weissman, 1979), , and affective disorders (Akiskal, Akiskal, Haykal, Manning, & Connor, 2005). A full list of the psychological-characteristic measures and psychometric questionnaires is available in the **Appendix B** (Tables 1-3). All the questionnaires were provided in Korean, being translated if needed.

Since it took roughly 5 hours to complete the entire questionnaires, participants brought the questionnaires their home and turned in their answers a week later. Considering the cognitive burden on participants (Tourangeau, 1984), we instructed them to fill in the questionnaires over multiple days by taking breaks of sufficient length. To prevent the incompletion of the questionnaires (Bowling, 2005), we checked whether there exist any missed or inappropriate responses to items upon reception of the questionnaires and, if so, asked participants to respond to such items on site.

Visual narrative stimuli

One of my colleagues (Y.K.), a film expert who majored in film art and worked in film-editing companies, built the library of visual narratives (VNs) by referring to the Internet Movie Database (IMDb) and Schaefer and his colleagues' work (Schaefer, Nils, Sanchez, & Philippot, 2010) relying on the following guidelines. First, the referred video sources were diverse and balanced in the genre, including action adventure, biography, comedy, documentary, drama, family, fantasy, mystery, horror, romance, sci-fi, sport, thriller, and western genres. Second, the scenes were selected such that they collectively covered a wide range of affective states, both in the valence and arousal dimensions. Third, every excerpt consisted of events that constituted a coherent piece of storytelling, such that it *could be* readily described with a few sentences. The last guideline was considered to ensure that an affective state was induced as a 'visual story' unfolds for each clip.

Most of the VNs were excerpted from motion pictures (130 clips from 124 different motion pictures). Some affective states (e.g., states of low arousal and neutral valence) rarely occur in the motion-picture database that we referred to. To cover such affective states, music videos (7 clips from 4 music videos) or TV commercials (7 clips from 4 TV commercials) were also referred to. There is no specific reason to believe that these non-motion-picture clips differ from the motion-picture clips in the effectiveness of inducing affective states because both types of clips induce affective states with visual stories in the same manner. Notwithstanding, we confirmed that the affect measures acquired using only the 130 motion-picture clips were highly correlated with those using the entire clips (**Appendix C**, panel B). More details of the VNs are provided in the **Appendix D**.

All VNs were edited to be 15-second long, which is close to the length of commercial ads on TV or the Internet. They were made soundless to focus on nonverbal affect perception and standardized in size (1400-pixel width, 744-pixel height), temporal frequency (24 frames per second), and color format (8-bit RGB). Stimulus presentation and collection of participants' responses were controlled using Psychophysics Toolbox extensions (Brainard & Vision, 1997; Kleiner et al., 2007; Pelli, 1997) in conjunction with MATLAB 2014b on an iMac computer with OS X (Apple Inc.).

Affect rating task

On each trial, participants were asked to indicate their affective states after viewing freely (and without fixation) a 15-second VN displayed on the computer screen. Affect ratings were collected for the dimensions of valence and arousal using the 9-point self-assessment manikin scale (SAM) (Bradley & Lang, 1994). Participants were given as much time as they required to rate stimuli before submitting their final ratings to the computer system. The rating session consisted of 6 blocks of 24 trials, and the order of 144 VNs was randomized across participants. Four practice trials were completed prior to the main task to ensure that participants understood the instructions. The data from these practice trials were excluded from the analysis.

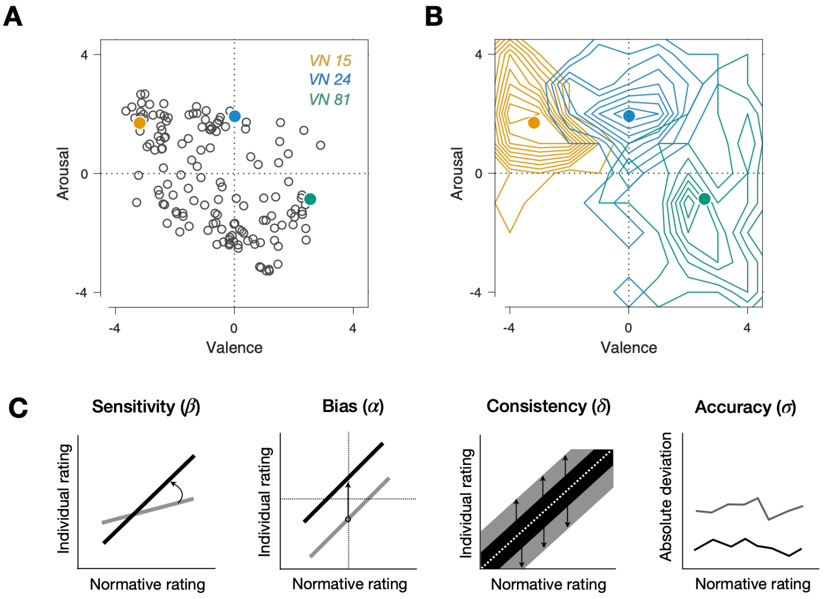


Figure 1. The procedure of acquiring affective responses and defining affect measures. **(A-B)** Affect-rating responses to visual narratives (VNs). **(A)** Normative (i.e., averaged across participants) rating responses to the 144 VN stimuli plotted in the affective-state space of valence and arousal. The colored dots are the normative responses to the three example VN stimuli (VN 15, VN 24, and VN 81). **(B)** Contour histograms of individual affect ratings of the three example VN stimuli. The colored dots are the same as the corresponding ones in A. **(C)** Definition of the affect measures. Left three panels: the 'bias', 'sensitivity', and 'consistency' measures were defined by regressing individual participants' affect rating responses onto the normative responses. Schematic examples of regression lines or confidence intervals are shown for individuals with high (black) and low (gray) scores of the 'bias' (left), 'sensitivity' (middle), and 'consistency' (right) measures. Right panel: the 'accuracy' measures were defined as the mean of absolute deviations from the normative responses. Example vectors of the absolute deviations are shown for individuals with high (black) and low (gray) scores of the 'accuracy' measure.

The across-participant averages of the affective states assigned to the VNs (**Figure 1A**) were widely distributed over both dimensions of the affective space, exhibiting a typical 'V-shape' pattern –valence scores tend to bifurcate toward the negative and positive poles as arousal scores increase –, which has been repeatedly reported in previous work (Carvalho, Leite, Galdo-Álvarez, & Gonçalves, 2012; Deng, Yang, & Zhou, 2017). We also expected that our VNs would induce substantial individual variability in affective responses. Indeed, the rating scores for the same VNs varied considerably between individuals (**Figure 1B**), which resulted in standard deviations ranging from 0.63 to 1.88 in the valence dimension and from

1.10 to 2.02 in the arousal dimension.

Affect-response measures

Having confirmed that the VNs covered the affective space in a representative manner while inducing sufficient individual differences (**Figure 1A,B**), we quantified those individual differences with a set of 'affect-response measures', which measures how much the affect rating patterns of individuals deviate from the 'normative' pattern in several aspects. Here, the 'normative' pattern refers to the distribution of affect ratings averaged across all participants for the entire library of VNs (**Figure 1A**). This population average can be considered as the 'typical' affect responses that are shared across participants and thus represent empirical approximations of the 'normative' affective states induced by the VNs.

Specifically, for a given individual i, the normative response was calculated as the average across the entire population except for the individual i. We then linearly regressed the participant i's response to a visual narrative l, $r^{i,l}$, onto the normative ratings, r^{l}_{norm}, over the 144 VNs using the following regression model:

$$r^{i,l} = \alpha^{i} + \beta^{i} r^{l}_{norm} + \varepsilon^{i,l}$$

, where $\varepsilon^{i,l}$ is the error, which was minimized to estimate the intercept, α^{i}, and slope, β^{i}. To get the best-unbiased estimators of regression coefficients, the regression model was fit using the method of weighted least squares rather than ordinary least squares, because VNs differed substantially in across-participant variability (standard deviations ranged from 1.10 to 2.02 for arousal ratings and from 0.63 to 1.88 for valence ratings). As a result, squared residual errors were weighted by the reciprocals of variances (James, Witten, Hastie, & Tibshirani, 2013). After fitting the regression model, we computed the proportion of the variance of $r^{i,l}$ explained by the linear regression onto r^{l}_{norm}, δ^{i}. This triplet of regression parameters, $\{\alpha^{i}, \beta^{i}, \delta^{i}\}$, provides a complementary set of distinct aspects that reflect how an individual's affective responses deviate from the normative responses, as follows: α^{i} reflects the extent to which a given individual i's affective responses are biased, providing a 'bias' measure; β^{i} reflects how sensitively a given individual i's affective responses change as the normative responses change, providing a 'sensitivity' measure; δ^i reflects how noisy or unpredictable a given individual i's affective responses are, providing a 'consistency' measure (**Figure 7C).** Besides these measures based on regression analysis, we calculated the accuracy measures that have widely been used by the previous studies on individual differences in affective responses (Lyusin & Ovsyannikova, 2016; Matsumoto et al., 2000; Nowicki & Duke, 1994). The 'accuracy' measure, σ^i, was defined as the mean of absolute deviations from the normative responses across all 144 VNs. The sign was reversed (-1×mean of absolute deviation) so that higher values mean higher degrees of accuracy. Considering the possibility that individual differences may exist independently between the two dimensions, the regressions and the accuracy calculation were performed separately for the arousal and valence dimensions. In sum, the way a given individual assigns affective states to the VNs was described by a vector of eight measures, $\theta^i = \{\alpha_a^i, \beta_a^i, \delta_a^i, \sigma_a^i, \alpha_v^i, \beta_v^i, \delta_v^i, \sigma_v^i\}$, where the subscripts, a and v denote the two subdomains of affect, 'arousal' and 'valence', respectively.

Canonical correlation analysis (CCA)

To meet the prerequisites of CCA and to avoid redundancy, we preprocessed the raw psychological-characteristics data, an 80 × 68 (subject × individual-characteristics measures) matrix C_{R1}, and the raw affect measures data, an 80 × 8 (subject × affect measures) matrix A_{R1}, before carrying out the CCA in the following procedure. First, the raw measures were screened for extreme distributions of values by applying two criteria, 'extreme homogeneity' and 'extreme outliers'. A distribution with 'extreme homogeneity' was defined as one in which more than 90% of participants had an identical single value, whereas a distribution with 'extreme outliers' was defined as one in which the average squared deviation of values from their median was smaller by 100-fold than the maximum squared deviation, as follows:

$$\max_i d^i > 100 \times mean(d);$$

$$d^i = \left[\theta^i - median(\theta)\right]^2$$

, where θ^i refers to a participant i's psychological-characteristics or affect measure. Only one psychological-characteristics measure was excluded in this step, which resulted in C_{R2} (80×67 matrix) for the psychological-characteristics data and A_{R2}(=A_{R1}) for the affect-measure data. Next, to avoid the unwanted effects of hidden outlier values and to satisfy the assumption of normal distribution, which is required of the CCA (Stephen M. Smith et al., 2015; Wang et al., 2020), we rescaled the values of C_{R2} and A_{R2} into rank values and then 'Gaussianized' those rank-scaled values by mapping them onto the normalized value space (Van der Waerden, 1952), producing C_R and A_R (**Figure 2A, B**).

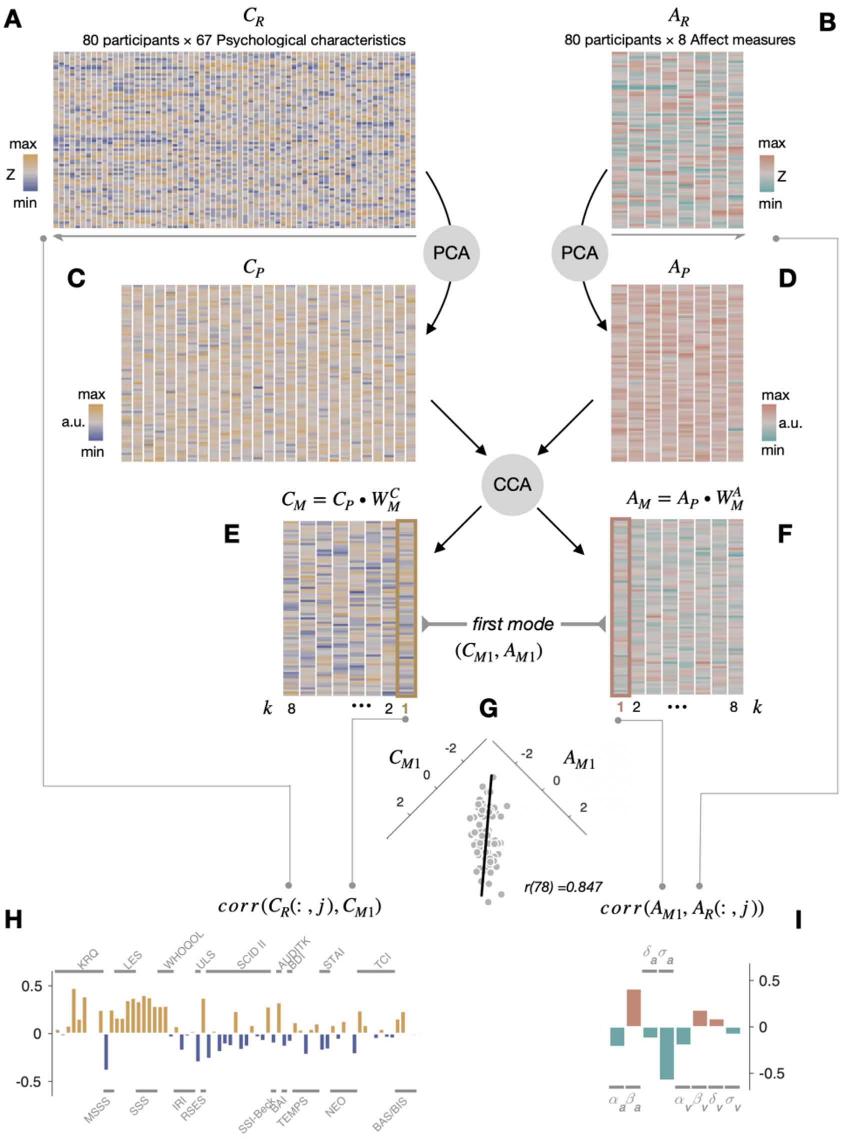


Figure 2. The procedure of the multivariate analyses. (A) A matrix of psychological-characteristics measures (C_R). Columns, 67 screened measures. Rows, 80 screened

participants. The rows are identical among the matrices shown in A-F. The color hues and saturations of pixels correspond to the signs and strengths, respectively, of the normalized psychological-characteristics scores. **(B)** A matrix of affect-response measures (A_R). Columns, 8 measures. The color hues and saturations correspond to the signs and strengths, respectively, of the normalized affect-response measures. **(C)** A PCA-score matrix for the psychological-characteristics measures (C_P). Columns, 27 subject-wise eigenvectors with largest eigenvalues. In the actual analysis, the number of eigenvectors was varied from 8 to 30. **(D)** A PCA-score matrix for the affect-response measures (A_P). Columns, eight subject-wise eigenvectors. **(C, D)** The color hues and saturations of pixels correspond to the signs and strengths, respectively, of the normalized PCA scores. **(E)** A CCA-score matrix of the psychological-characteristics measures (C_{Mk}). Columns, eight canonical variates. **(F)** A CCA-score matrix of the affect-response measures (A_{Mk}). Columns, eight canonical variates. **(E, F)** The color hues and saturations of pixels correspond to the signs and degrees, respectively, of the normalized CCA scores. **(G)** There was a strong and significant correlation between the canonical variates paired in the first (k = 1) CCA mode. The CCA scores of the first canonical psychological-characteristics variate (C_{M1}) are plotted against those of the first canonical affective variate (A_{M1}) over individual participants (gray dots). A line is the linear regression of A_{M1} onto C_{M1}. **(H)** Correlations of C_{M1} with the individual columns of C_R in A. The order of bars is identical to that of the columns in A. **(I)** Correlations of A_{M1} with the individual columns of A_R in B. The order of bars is identical to that of the columns in B.

Next, the PCA was conducted on C_R and A_R, which resulted in C_P and A_P (**Figure 2A,B**), to avoid the overfitting due to the high dimensionality of the psychological-characteristics measures and to orthogonalize the individual measures in C_R and A_R. In building C_P, the number of PCs was varied from 8 to 30 because it may affect the results of CCA. This particular range of PC numbers was determined by applying two criteria: (i) more than 60% of the total variance of C_R should be explained; (ii) the canonical correlation should be significant. As for A_P, the number of PCs was fixed to 8. The subjects-to-subjects covariance matrix was fed into eigenvalue decomposition to determine subject-wise eigenvectors with the largest eigenvalues for each measure type (Stephen M. Smith et al., 2015). As a result, 100 % of the total variance of E_R was explained by E_P while 61.35% (for 8 eigenvectors) to 92.18% (for 30 eigenvectors) of the total variance of C_R was explained by C_P. Although the dimension of A_R was low, we applied PCA to A_R because we wanted to use the procedure identical to that used for C_R (but the results remain almost unchanged whether PCA was applied to A_R or not). To prevent potential confounds with socio-demographic factors, C_P and A_P were de-confounded for age, sex, IQ, and income scores prior to CCA. Specifically, those socio-demographic variables underwent a rank-based inverse normal transformation and were regressed out from both C_P and A_P.

We conducted the CCA on C_P and A_P using the '*canoncorr*' function in the Statistics and Machine Learning Toolbox of MATLAB. The CCA initially identified an orthogonal set of 'pairs of canonical variates' ($\{(C_{M1}, A_{M1}), (C_{M2}, A_{M2}), \dots, (C_{Mk}, A_{Ck}), \dots, (C_{Mn}, A_{Mn})\}$) that maximizes the pairwise correlations between linear combinations of C_P and A_P. The first CCA mode, (C_{M1}, A_{M1}), was defined as follows:

$$(C_{M1}, A_{M1}) = (C_P \cdot W_{M1}^C, A_P \cdot W_{M1}^A),$$

$$\text{where } \left(W_{M1}^C, W_{M1}^A\right) = \max_{W_{M1}^C, W_{M1}^A} \operatorname{corr}(C_P \cdot W_{M1}^C, A_P \cdot W_{M1}^A)$$

Similarly, the remaining CCA modes, $\{(C_{M2}, A_{M2}), \dots, (C_{M\mathrm{k}}, A_{Mk}), \dots, (C_{M\mathrm{n}}, A_{Mn})\}$ were sequentially defined by finding a pair of vectors, W_{Mk}^C and W_{Mk}^A, which maximizes the correlation between paired variates, C_{Mk} and A_{Mk}, with a constraint that these newly added variates, C_{Mk} and A_{Mk}, must be orthogonal (uncorrelated) to all the preceding modes (**Figure 2E, F**). To assess the statistical significances of the CCA modes, we permuted C_P over participants 10,000 times and computed the correlation for each pair of the corresponding columns of C_M and A_M.

As the final step, we computed the correlations of the paired canonical variates that constitute the significant first CCA mode, C_{M1} and A_{M1}, with their raw measures, C_R and A_R, respectively, to identify the specific psychological characteristics and the affect-response measures that covary across participants via the first CCA mode.

2.3. Results

Distribution and reliability of the affect-response measures

The across-participant distributions of the affect-response measures are summarized in **Table 2**. For the measures of consistency (δ) and accuracy (σ), the distribution means were greater in valence than in arousal (δ: $t(158) = 3.62, p < 0.001$; σ: $t(158) = 4.75, p < 0.001$). By contrast, for all the measures except for sensitivity (β), the standard deviations of the distributions were greater in arousal than in valence (α: $F(79, 79) = 6.54$, $p < 0.001$; β: $F(79, 79) = 1.41, p = 0.127$; δ: $F(79, 79) = 2.26, p < 0.001$; σ: $F(79, 79) = 3.10, p < 0.001$).

Table 2. Summary statistics of affect-response measures.

Measures	Arousal		Valence	
	μ	SD	μ	SD
Bias (α)	0.00	0.70	0.00	0.27
Sensitivity (β)	0.99	0.30	1.00	0.25
Consistency (δ)	0.68	0.14	0.75	0.09
Accuracy (σ)	-1.18	0.39	-0.94	0.22

We evaluated the reliability of the affect-response measures in two aspects. First, when the trials were split into two subsets, such that two different sets of VN stimuli were used in those two subsets, the measures were highly consistent between those subsets (see **Appendix C.** for detailed procedures and results). Second, the affect-response measures remain consistent even when the normative affect responses (i.e., across-participant average responses) were defined from much a smaller number of subjects (see **Appendix E.** for detailed procedures and results).

Distribution of the psychological-characteristics measures

We classified the psychological characteristics measures into three groups, namely the 'psychosocial factors', 'clinical problems', and 'personality' measures, depending on the original purposes of the questionnaires (**Figure 3A**). For the purpose of screening out the measures with unhealthy across-participant distributions, we inspected whether a given distribution contains a few individuals with extremely outlying scores (**Figure 3B**) and whether it is too narrow for individuals to be distinguished from one another (**Figure 3C**). As a result, the FTND (Fagerström Test for Nicotine Dependence) measure was screened out because its distribution was extremely narrow (i.e., too homogenous because 95% of the participants were non-smokers; **Figure 3E**) compared to the remaining variables (the distributions of two example measures are shown in **Figure 3D, F**).

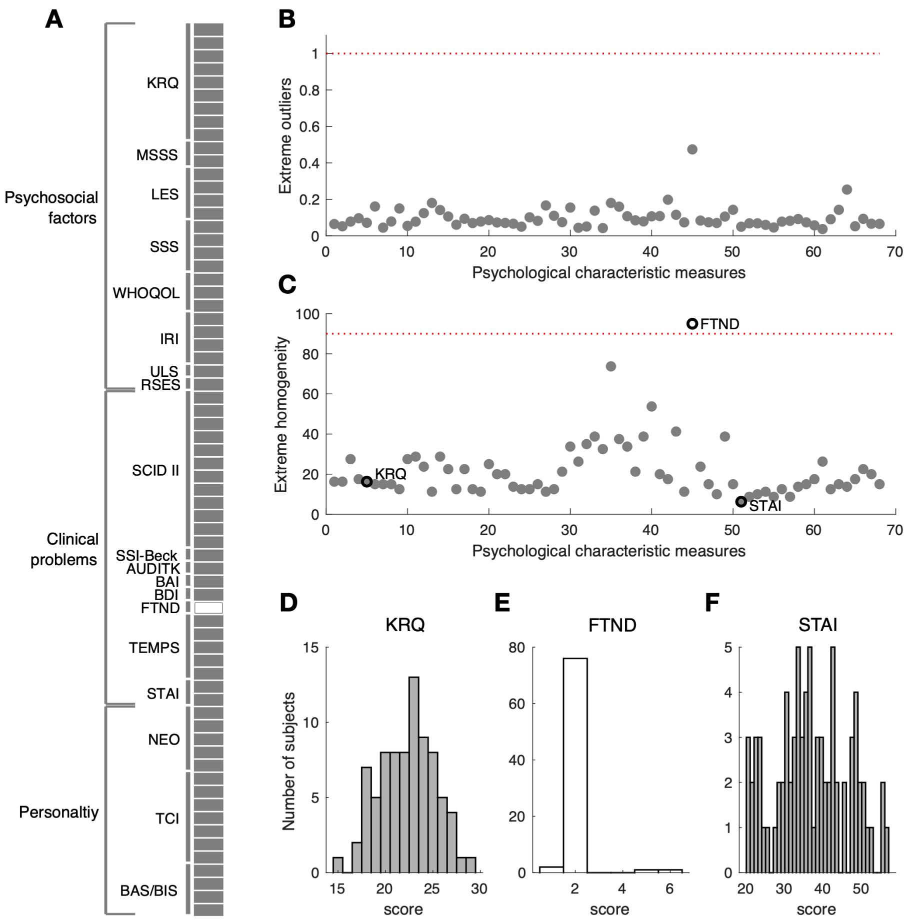


Figure 3. Distribution analysis of the psychological-characteristics measures. (A) The group identities and measure numbers of the 19 psychological-characteristics questionnaires. The questionnaires from which individual measures (horizontal bars) and the groups to which the questionnaires belong are indicated by the word labels with vertical bars and brackets, respectively. The measure that was not used for further analysis is indicated by the horizontal empty bar. **(B,C)** Results of the distribution analysis. **(B)** None of the measurements had extremely outlying scores, as indicated by the dots that all fell below the criterion (the red dotted line). **(C)** A single measure (FTND) had an extremely homogenous distribution, in which the majority (95%) of participants had the same score, as indicated by the dot located above the criterion (a red dotted line). **(D-F)** The distributions of three example measures. By comparing the distribution shapes and their corresponding scores in C, the exceptionally strong homogeneity of the FTND distribution can readily be appreciated. KRQ, Korean resilience quotient; MSSS, MacArthur scale of subjective social status; LES, life experiences survey; SSS, Social Support Scale; WHOQOL, world health organization quality of Life; IRI, interpersonal reactivity index; ULS, UCLA Loneliness Scale; RSES, Rosenberg self-esteem scale; SCID-II, structured clinical interview schedule for DSM-IV Axis-II disorder; SSI-Beck, Beck scale for suicidal ideation; AUDIT-K, Alcohol Use disorder identification test; BAI, Beck anxiety inventory; BDI, Beck depression inventory; FTND, Fagerström Test for Nicotine Dependence; TEMPS, temperament evaluation of Memphis, Pisa, Paris and San Diego; STAI, state-trait Anxiety Inventory; NEO, revised NEO personality inventory; TCI, temperament and character inventory; BAS/BAS, behavioral approach/inhibition system.

The robustness of the first CCA mode

Regardless of the varying number of PC components that used to define the psychological-characteristics input to CCA (C_P; see **Methods** for the rationale for choosing the 23 different PC numbers), only the first CCA mode remains significant (permutation-test results are shown in **Table 3**; see Methods for the detailed procedure of permutation tests). In what follows, given this robustness of the first mode, we assessed the contributions of the raw measures (i.e., the individual columns of C_M and A_M) to the population covariation between the psychological-characteristics and affect-response domains based on the correlations between the canonical variables of the first CCA mode (C_{M1} and A_{M1}) and the raw measures (C_R and A_R), as graphically illustrated in **Figure 2H, I**.

Table3. Correlation coefficient and permutation test result of the first CCA mode

Number of principal components		$corr(C_{M1}, A_{M1})$	p
Affect measures	Psychological characteristics		
8	8	0.69	0.002
	9	0.70	0.002
	10	0.70	0.004
	11	0.72	0.003
	12	0.73	0.003
	13	0.74	0.007
	14	0.75	0.006
	15	0.76	0.005
	16	0.78	0.003
	17	0.79	0.003
	18	0.80	0.003
	19	0.80	0.007
	20	0.80	0.009
	21	0.80	0.011
	22	0.80	0.019
	23	0.80	0.033

	24	0.83	0.006
	25	0.83	0.013
	26	0.84	0.009
	27	0.85	0.014
	28	0.85	0.017
	29	0.85	0.024
	30	0.85	0.035

The psychological-characteristics measures contributing to the first CCA mode

To identify the psychological-characteristics measures contributing significantly to the CCA mode, we tested the significance of the correlation of the first-mode psychological-characteristics variate (C_{M1} in **Figure 2**) with the individual, raw psychological-characteristics measures (individual columns of C_R in **Figure 2**). We repeated this significance test 23 times, one for each of the 23 first-mode variates defined using the 23 different numbers of PCs (**Table 3**). Finally, we judged a given measure to be the one that makes a robust contribution to the CCA only when it showed more than 22 significant ($p < 0.05$ with the Benjamini-Hochberg method) correlations with the 23 first-mode variates. As a result, we identified a total of 10 measures. Their across-variate averages of correlations are summarized in **Figure 4A**. (For the psychological-characteristic measures that failed to meet this rather strict criterion (22 significant results out of 23 tests) but showed at least one significant correlation with the psychological-characteristics variate (C_{M1}), see **Appendix F** panel A, C.

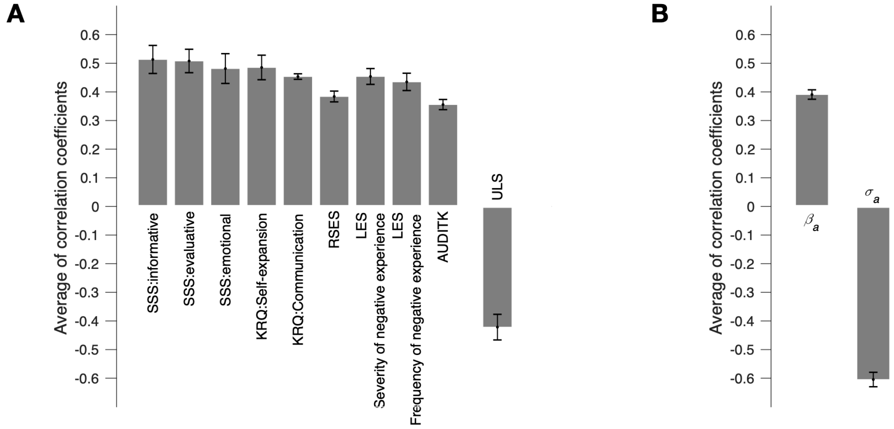


Figure 4. The contributions of the psychological-characteristics and affect-response measures to the CCA mode. (A) The across-variate averages of the correlations between the raw measures of psychological characteristics and the first-mode psychological-characteristics variate (C_{M1}). **(B)** The across-variate averages of the correlations between the raw measures of affective responses and the first-mode affect-response variate (E_{M1}). **(A, B)** Only the raw measures that showed significant correlations with more than 22 out of the 23 different CCA variates are shown. Error bars, 95% confidence intervals**.** SSS, social support scale; KRQ, Korean resilience quotient; RSES, Rosenberg self-esteem scale; LES, life experience survey; Audit-K, Alcohol Use Disorder Identification Test; ULS, UCLA Loneliness Scale.

Most of the measures that make robust contributions to the CCA belong to the 'psychosocial factors' class, especially those that are known to reflect the degree to which a given individual receives various kinds of social support from the life environment. The individuals' psychological-characteristics variate (C_{M1}) tended to increase as they reported that they receive a wider range of social support (three measures of 'social support scale (SSS)'), are more connected to others ('self-expansion' measure of 'Korean resilience quotient (KRQ)'), are more able to establish and maintain social relationships ('communication' measure of KRQ), have higher degrees of overall self-esteem ('Rosenberg self-esteem scale (RSS)'), experienced more severe and frequent negative life events (two measures of 'life experience survey (LES)') or feel lesser degrees of subjective loneliness and social isolation ('UCLA loneliness scale (ULS)').

Among the measures that do not belong to the 'psychosocial' class, only one measure, 'Audit-K' in the 'clinical-problem' class, robustly contributed to the

CCA. The psychological-characteristics variate (C_{M1}) tended to increase as the scores of 'Audit-K', which indicates the degree of excessive alcohol drinking, increased.

The affect-response measures contributing to the first CCA mode

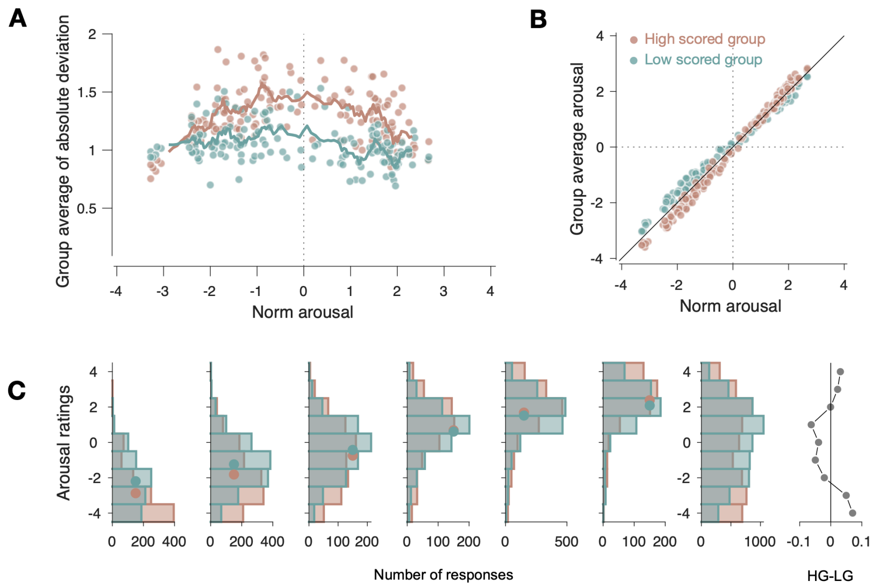
Using the same procedure and criterion used for the psychological-characteristic measures, we identified the affect-response measures that make robust contributions to the CCA mode. As a result, two measures in the arousal dimension were identified, the 'accuracy (σ_a)' and 'sensitivity (β_a)' measures (**Figure 4B**). (For the affect-response measures that showed at least one significant correlation with the affect-response variate (A_{M1}), see **Appendix F, panel B and D**.)

The affect-response variate of the CCA mode (A_{M1}) tended to increase as the accuracy measure decreased and the sensitivity measure increased. Since the accuracy measure reflects an extent to which a given individual's responses deviate from the normative responses (the rightmost panel in **Figure 2I**), the negative correlation between σ_a and A_{M1} means that the individuals with higher values of the affect-response variate tended to show the arousal responses that are more deviant from the population-average responses to the visual narrative stimuli. On the other hand, the sensitivity measure reflects an extent to which changes between a given individual's responses to different VNs are greater than those expected from the normative responses to VNs (the second left panel in **Figure 2I**). Therefore, the positive correlation between β_a and A_{M1} means that the individuals with higher values of the affect-response variate tended to show the arousal responses that are more exaggerated than the population-average responses.

Polarized arousal responses in the individuals with high CCA variates

Having identified the two arousal measures contributing to the CCA mode, we carried out further analysis to find a critical feature that jointly describes the relationships of the accuracy and sensitivity measures with the CCA mode in a unified manner.

As the first step of the analysis, we classified the individuals into two groups based on their canonical-variate scores (A_{M1}) and plotted the group-averaged values of absolute deviation of arousal responses from the normative responses (**Figure 5A**) and arousal responses (**Figure 5B**) against the normative responses across the 144 VNs. The canonical-variate scores (A_{M1}) used here was the one defined with the CCA based on 27 PCs, which produced the most representative results. The absolute deviations were greater for the almost entire range of the normative responses in the high-variate-score group (**Figure 5A**) while the reported arousal scores varied more steeply as a function of the normative response in the high-variate-score group (**Figure 5B**). As a plausible scenario that is coherent with both of these two patterns, we considered the possibility that the individuals with high variate scores tend to show more 'polarized arousal responses' than those with low variate scores. Specifically, the extent to which responses are 'polarized' refers to the extent to which responses are attractively biased toward both of the two extreme poles. Thus, if a given individual's responses are more polarized than the normative responses, her or his responses will be not just more deviant from the normative responses but also more exaggerated than the normative responses.



Normative rating interval	*nr* < -2	-2< *nr* <-1	-1< *nr* <0	0< *nr* <1	1< *nr* <2	2 < *nr*	all
F-Test	F(918,918)=0.96 *p*=0.55	F(1399,1399)=1.34 p<0.01	F(799, 799)=0.55 p<0.01	F(599, 599)=1.62 p<0.01	F(1478,1479)=1.62 p<0.01	F(599, 599)=1.23 p=0.01	F(5757, 5758)=1.49 p<0.01
Kurtosis	*HG*: 3.53 *LG*: 2.37	*HG*: 2.69 *LG*: 3.01	*HG*: 2.24 *LG*: 2.72	*HG*: 3.10 *LG*: 3.74	*HG*: 4.30 *LG*: 5.13	*HG*: 5.56 *LG*: 5.73	*HG*: 1.76 *LG*: 2.16
Skewness	*HG*: 1.14 *LG*: 0.34	*HG*: 0.56 *LG*: 0.23	*HG*: 0.06 *LG*: -0.19	*HG*:-0.66 *LG*: -0.58	*HG*:-1.10 *LG*: -1.00	*HG*:-1.44 *LG*: -1.19	*HG*: 0.01 *LG*: -0.12

Figure 5. Polarized arousal responses in the individuals with high CCA variates. (A) The averaged absolute deviations of arousal responses from the normative responses plotted against the normative responses for the high (maroon dots) and low (teal dots) A_{M1}-score groups. The lines are the moving averages (window size, 10) of the averaged absolute deviations. **(B)** The averaged arousal responses plotted against the normative responses for the high and low A_{M1}-score groups. **(C)** The comparison of the distributions of arousal responses between the high and low A_{M1}-score groups. Top, the histograms of arousal responses that are binned according to the normative response (six panels from left), the merged histograms of the entire arousal responses (the second-rightmost panel), and the relative differences in proportion between the merged histograms (the rightmost panel, where 'HG' and 'LG' stand for the high and low A_{M1}-score groups, respectively). The histograms for the high and low A_{M1}-score groups are shown in maroon and teal, respectively. Bottom, the table summarizes the statistics of the histograms shown above. The columns' locations are matched to the histograms that they describe. *nr* stands for the normative responses.

To confirm the 'polarized-arousal-response' scenario, we compared the distributions of arousal rating scores between the low-variate-score and high-variate-score groups (**Figure 5C**). As anticipated by the 'polarized-arousal-response' scenario, the response distributions were indeed different between the two groups (see F-test results at the bottom of **Figure 5C**) and more polarized in the high-variate-score group than in the low-variate-score group (see kurtosis and skewness results at the bottom of **Figure 5C**). For the merged distributions (the second-rightmost panel of **Figure 5C**), the kurtosis was significantly lower—i.e., flatter—in the high-variate-score group (1.76) than in the low-variate-score group (2.16). This difference in kurtosis resulted mainly from the fact that the arousal responses were more polarized in the high-variate-score group than in the low-variate-score group. The tendency of making polarized arousal responses in the high-variate-score group was also evident in the local distributions that were binned according to the normative responses (the 6 panels from left in **Figure 5C**). As the range of the normative responses becomes lower or higher (i.e., approaches toward extreme values), the response distributions become more skewed in the high-variate-score group than in the low-variate-score group (as indicated by the skewness values in **Figure 5C**). On the other hand, as the range of the normative responses approaches toward intermediate values, the response distributions become flatter in the high-variate-score group than in the low-variate-score group (as indicated by the kurtosis values in **Figure 5C**).

We also inspected the distributions of the valence responses with the same procedure used for the arousal responses but did not find substantial differences between the high-variate-score group and the low-variate-score group **(S4 Fig**).

We note that there is a, rather trivial, alternative account for the observed differences in distributions between the high and low A_{M1}-score groups: such differences may also arise from the differences in the overall tendency of given individuals to *report* extreme values whatever being measured. To address this issue, we (i) estimated such tendency for the individual participants from their reports in the psychological-characteristics questionnaires, (ii) de-confounded the data for such tendency, and (iii) repeated the CCA analysis (for details, see methods in **Appendix G)**. The results of this de-confounded CCA were quite similar to those of the original CCA: the arousal accuracy ($\hat{p}$ =100%, $E(r) = -0.55$) and arousal sensitivity ($\hat{p}$ =74%, $E(r) = 0.28$) still showed the robust relationship with psychosocial factors similar to our main findings (see **Appendix G. Figure 1** for details). These results suggest that the polarized arousal responses are unlikely to be explained away by the overall tendency of reporting extreme values.

Comparisons of the pairwise correlations and the results of the

multivariate analysis

To directly compare our work with previous work, which mostly took the hypothesis-driven regional approach based on pairwise correlations, and also to further understand the structure of population co-variation between the psychological-characteristics and affect-response domains, we calculated pairwise Pearson correlations for all the possible pairs between the measures of the two domains (left panel of **Figure 6**) and compared those correlations with the CCA variates (right panel of **Figure 6**). By comparing the Pearson correlations and the CCA-variate correlations, all the possible relationships between the measures of the two domains can be classified into four different types, as follows: first, the relationships that were insignificant in both types of correlation; second, those that were significant in Pearson correlation but insignificant in CCA correlation; third, those that were insignificant in Pearson correlation but significant in CCA correlation; lastly, those that were significant in both types of correlation. We note that all the ‘significant’ Pearson correlations turned out insignificant after being corrected for multiple comparisons (Benjamini-Hochberg correction).

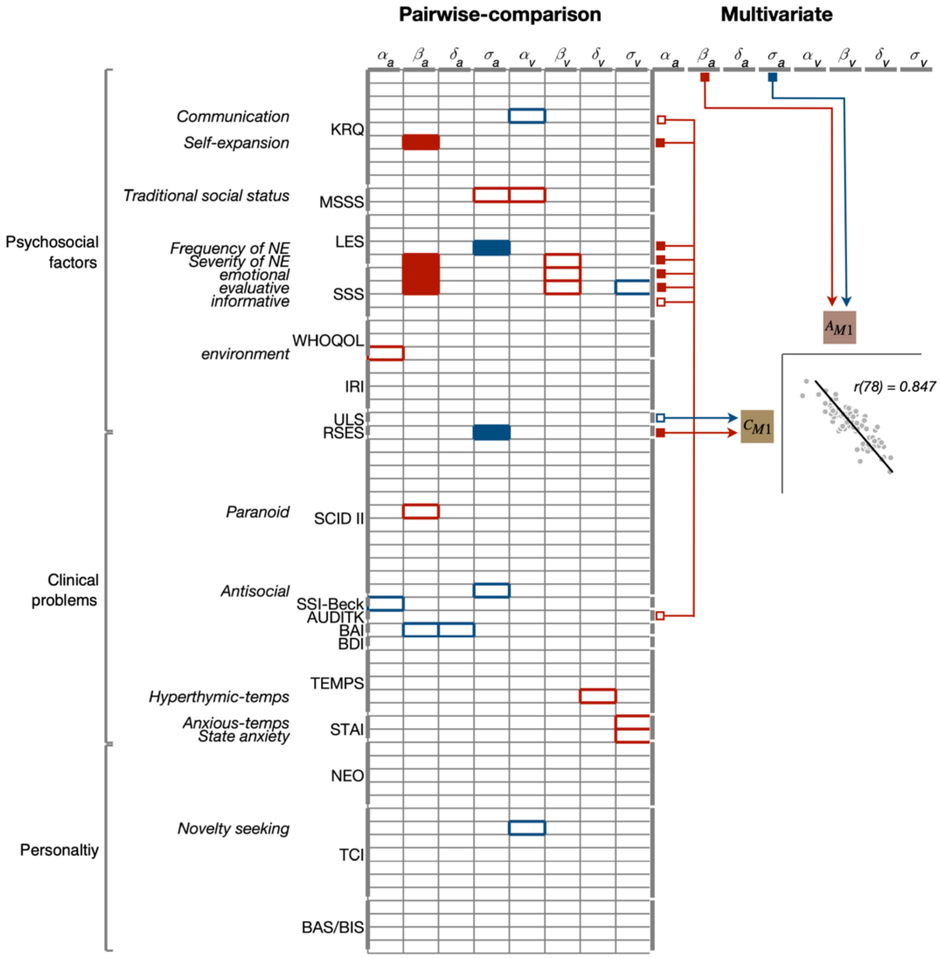


Figure 6. Comparisons of the pairwise correlations and the results of the multivariate analysis. Left, the rows and columns of the matrix represent the psychological-characteristics and affect-response measures, respectively. The empty rectangles mark the pairs of measures that were significant in Pearson correlation but did not make significant contributions to the CCA mode. The solid rectangles mark the pairs of measures that not only were significant in Pearson correlation ($p < 0.05$, uncorrected for multiple comparisons) but also made significant contributions to the CCA mode. Colors of the rectangles indicate the signs of Pearson correlation (red, positive; blue, negative). Right, the schematic structure of the CCA mode illustrated based on the correlations of the measures with the CCA variates. The inset plots the psychological-characteristics variate against the affect-response variate over individual participants, which is identical to the panel of Fig 2G. The empty squares mark the measures that made significant contributions to the CCA mode but failed to show significant Pearson correlations. The solid squares mark the measures that not only made significant contributions to the CCA mode but also showed significant Pearson correlations. Colors of the squares indicate the signs of correlations with the CCA variates (red, positive; blue, negative). KRQ, Korean resilience quotient; MSSS, MacArthur scale of subjective social status; LES, life experiences survey; SSS, Social Support Scale; WHOQOL, world health organization quality of Life; IRI, interpersonal reactivity index; ULS, UCLA Loneliness Scale; RSES, Rosenberg self-esteem scale; SCID-II, structured clinical interview schedule for DSM-IV Axis-II disorder; SSI-Beck, Beck scale for suicidal ideation; AUDIT-K, Alcohol Use disorder identification test; BAI, Beck

anxiety inventory; BDI, Beck depression inventory; TEMPS, temperament evaluation of Memphis, Pisa, Paris and San Diego; STAI, state-trait Anxiety Inventory; NEO, revised NEO personality inventory; TCI, temperament and character inventory; BAS/BAS, behavioral approach/inhibition system.

Many (17) relationships fell into the class in which their Pearson correlation was significant but their CCA correlation was insignificant (those marked by empty rectangles in the left panel of Fig 6). On the other hand, four psychological-characteristics measures (KRQ-communication, SSS-informative, ULS, and Audit-K, which are marked by the empty squares in the right panel of Fig 6), despite their significant correlations with the CCA variate, did not show significant Pearson correlations either with the arousal sensitivity measure (β_a) or with the arousal accuracy measure (σ_a). On the contrary, six psychological-characteristics measures (KRQ-self-expansion, LES-frequency of negative experience, LES-severity of negative experience, SSS-emotional, SSS-evaluative, and RSES) not just contributed, jointly with the arousal sensitivity (β_a) and accuracy (σ_a) measures, to the CCA mode (as marked by the solid squares in the right panel of Fig 6) but also showed significant Pearson correlations with those two affect-response measures (as marked by the solid rectangles in the left panel of Fig 6). This result, if we put together the signs of Pearson and CCA correlations, helps us interpret a refined structure of the CCA mode. That is, the CCA mode mainly consists of the positive covariation of the arousal sensitivity measure in the affect-response domain with the KRQ-self-expansion, LES-severity of negative experience, SSS-emotional, and SSS-evaluative in the psychological-characteristics domain (as indicated by the solid red rectangles in the left panel of **Figure 6**) and the negative covariation of the arousal accuracy measure in the affect-response domain with the LES-frequency of negative experience, and RSES measures in the psychological-characteristics domain (as indicated by the solid blue rectangles in the left panel of **Figure 6**).

2.4. Discussion

Being motivated to identify a systematic structure that governs the population covariation between the affect-response and psychological-characteristics domains, we took a data-driven and global approach by carrying out a series of multivariate analyses on a high-dimensional data set consisting of the eight affect-response measures and 68 psychological-characteristics measures that were acquired from a cohort of 86 human participants. Having had identified a single, robust, canonical mode of covariation using the CCA in conjunction with PCA, we projected that canonical mode back onto the raw measures in both domains and carried out further analyses to explore 'interpretable' inter-domain relationships underlying the canonical mode. We found one such relationship: individuals who can be characterized by being 'rich in psychosocial assets' tend to show 'polarized arousal responses' to affect-inducing VNs.

Polarized arousal responses

Emotion differentiation, which is also known as emotion granularity (Smidt & Suvak, 2015), refers to people's ability to distinguish between similar affects. In the studies which probed categorical emotion responses in the two-dimensional affective space (Barrett, 2004; Nook, Sasse, Lambert, McLaughlin, & Somerville, 2017), individuals with high emotion differentiability showed affective responses that were widely distributed mainly along the 'arousal' dimension, which can be interpreted to correspond to the polarized responses in the arousal dimension contributing to the canonical mode in the current work (**Figure 5C**). On the other hand, another previous work reported that individual differences in emotion differentiation were positively correlated with those who show high degrees of resilience and self-esteem (Erbas et al., 2014; Smidt & Suvak, 2015), which matches the psychosocial measures contributing to the canonical mode in the current work. Put together, these reports on emotion differentiation appear highly consistent with the canonical mode of population covariation and our interpretation of it.

Association between psychosocial assets and polarized arousal responses

We conjecture that the observed tight linkage between richness in psychosocial assets and polarized arousal responses might have to do with a phenomenon called "the social sharing of emotions (Rimé, Mesquita, Boca, & Philippot, 1991)" and an influential view developed upon this phenomenon (Rimé, 2009). According to this view, affective experiences are not short-lived and intrapersonal but actively shared with other individuals, functioning as social signals of communicating one's internal states, which eventually promotes social interactions. For instance, by crying, a baby can send a parent a signal of hunger, and that signal, in turn, triggers further interactions between the baby and the parent. Supporting this view, intensive affect experiences are known to be more likely to be expressed to others (James J. Gross, John, & Richards, 2000; Herring, Burleson, Roberts, & Devine, 2011; E. L. Rosenberg & Ekman, 1994) and even discussed with others to some degree (Rimé, Philippot, Boca, & Mesquita, 1992). For example, people tend to talk more with strangers after watching together the movies that are emotionally intense than after watching those that are not (Luminet, Bouts, Delie, Manstead, & Rimé, 2000). According to this view, the individuals who showed more polarized arousal responses to the visual narratives, compared to those who showed less polarized responses, in the current work are more likely to express their affect to others in their daily life and thus more likely to be engaged in social interactions. And such increased social interactions would be translated into the high scores on the psychosocial factors that indicate the richness in psychosocial assets, such as those that reflect 'receiving more social supports', 'feeling connected with others', 'having good communication with others', and 'subjective feeling of heightened self-esteem'.

Another possibility is that individuals with abundant psychosocial factors are likely to engage in more frequent and diverse social transactions, which are known to be a crucial driving force for affect development over early life (Atzil & Gendron, 2017; Ruffman, Taumoepeau, & Perkins, 2012; Taumoepeau & Ruffman, 2008). Specifically, frequent social transactions allow interacting individuals to co-experience external events, such as contextual goals, action outcomes, and affective expressions, and internal events, such as thoughts and feelings, in diverse social situations. These synchronously shared events would confer infants or children with opportunities of learning the complex statistical structure that relate diverse contextual or expressive cues and internal affective states (Brooks & Meltzoff, 2015; Brown & Dunn, 1991). In Bayesian perspectives (Baker, Saxe, & Tenenbaum, 2009;

Ong, Zaki, & Goodman, 2015) it is this learned statistical structure of external (observable) cues and internal (latent) states—often dubbed 'generative model'—that fundamentally constrains the way individuals attribute affective states to other people or events. According to this line of thoughts, the participants with richness in psychosocial factors in our study were likely to learn the statistical structures with wider scopes and more diverse repertoires, and thus to read out wider ranges of affective states from identical visual narratives. To conclude on a speculative note, the expanded affect attribution might reflect the expanded "prior" distribution of affective states owing to sampling of diverse affective experience over life time, as demonstrated for sensory experience by a recent animal study (Berkes, Orbán, Lengyel, & Fiser, 2011).

We stress that the proposed account above should be considered as one plausible hypothesis for the observed association between the affect-response and psychological-characteristics domains. Thus, the validity of this hypothesis must be verified in empirical studies.

Association between negative life experiences and polarized arousal responses

The CCA mode identified in the current work indicates that the tendency of showing polarized arousal responses was also associated with that of having negative experiences more frequently and severely. As a hypothetical account for this association, we considered a possibility that stressful life events are likely to make individuals react to affect-inducing stimuli more sensitively. In line with this possibility, it has been reported that reading stressful stories tends to make people better categorize affects (Daudelin-Peltier, Forget, Blais, Deschênes, & Fiset, 2017; Hänggi, 2004), which could be interpreted as increasing the level of attention to affective events under uncertain and threatening situations (Daudelin-Peltier et al., 2017).

A negligible contribution of clinical problems to the population covariation

Previous studies reported that some affect measures are correlated across individuals with the psychological-characteristics measures on mental disorders ('clinical problems' according our labeling scheme), especially the anxiety-related measures (Aluja et al., 2015; Demenescu, Kortekaas, den Boer, & Aleman, 2010b). However, the contribution of the clinical-problem measures to the population covariation between the affect and characteristics domains was almost negligible, if any, in the current work. Although we acquired many ($N = 24$) clinical-problem measures from a comprehensive set of diverse and representative questionnaires, we found that none of them, except for one ('alcohol-use' measured with Audit-K), significantly contributed to the population covariation. The outcomes of the pairwise comparison analysis (Figure 6, left) suggest one plausible reason for the difference between the previous and current works. Initially, we found many significant pairwise correlations including the clinical-problem measures from the questionnaires such as SCID-II, SSI Beck, BAI, TEMPS, and STAI. However, they all fail to be significant once corrected for multiple comparison. This suggests that the correlations involving clinical-problem measures were reported to be significant in the previous work because they were tested individually in isolation despite not being sufficiently strong to survive the correction for multiple comparisons. To be sure, we do not insist that those pairwise comparisons are inappropriate. They served the main purpose of the previous work, which was to verify specific hypothesis-driven predictions. Our findings suggest that the contribution of clinical-problem measures to the population covariation between the affect-response and psychological-characteristics domains is not as strong as the psychosocial measures.

As mentioned above, the measure of 'alcohol-use', unlike all the other clinical-problem measures, was significantly correlated with the canonical mode of population covariation. We considered two possible scenarios for this correlation. First, alcohol overuse might have impaired cognitive ability in general, including affect processing. This scenario seems consistent with previous clinical studies (Castellano et al., 2015) reporting the correlation between alcohol use disorders and inaccuracy in facial affect perception, because one feature of polarized affect responses is the increased deviations from normative (average) response—i.e., inaccuracy in affective response. As an alternative scenario, it is possible that individuals who are socially active (Cox & Klinger, 1988) or under stressful situations (Cooper, Russell, Skinner, Frone, & Mudar, 1992) are prone to alcohol consumption. In line with the latter scenario, the pairwise correlation analysis on our data showed that the alcohol measure was positively correlated both with the frequency of negative experiences ($r = 0.3, p < 0.01$) and with the severity of negative experiences ($r = 0.26, p = 0.02$).

No significant relationship of personality measures with affect measures

Previous studies reported that a few psychological-characteristics measures of personality traits are significantly correlated with affective responses. For example, it has been reported that valence responses to static images are biased positively and negatively in individuals with extraversion and neuroticism traits, respectively (Revelle & Scherer, 2009; Tok et al., 2010). These previous reports suggest at least some significant pairwise correlations of those trait measures with some of valence measures in our data. However, we could not find such correlations at all, needless to mention no involvement of those traits in the between-domain population covariation. In that regard, none of the remaining measures of personality show significant correlations with any of the affect response measures or the population covariation either (only one TCI measure (harm avoidance) showed a significant correlation with the bias measure of valence but failed to survive the correction of multiple comparisons). We conjecture that the difference in affect-inducing stimuli between the previous work (simple static images) and the current work (complex unfolding-over-time narratives) might have resulted in different results. Alternatively, the visual narrative stimuli used in the current work might not have created a sufficient degree of variability in valence responses, as hinted by the standard deviations in the valence measures being somewhat smaller than those in the arousal measures (**Table 2**).

Other contributions of the current work to affect research

Apart from identifying the robust mode of population covariation between the affect-response and psychological-characteristics domains, the current work makes several useful contributions to the scientific investigation of individual differences in affect responses. First, we found that there are substantive individual differences in 'arousal' responses to the same stimuli and that those differences can be predicted by profiling individuals for the psychological-characteristics measures, particularly the psychosocial measures. This warns against the possibility that even the same experimental manipulation of affect using laboratory stimuli may end up with inducing substantially different degrees of 'subjective (or effective) arousal' responses across individuals. This, in turn, calls for the attention to the necessity of controlling for such individual differences in affect induction effects by taking into account the tight linkage found in our study between the polarized arousal-response style and the rich profile of psychosocial assets. Second, for the purpose of promoting fine-grained individual differences in affective responses, we developed a large number (N=144) of film excerpts that induce a wide range of affective states by visually unfolding stories over time. This library of visual narratives can be used to tap into individual differences in contextual effects on affect (Barrett, Mesquita, & Gendron, 2011; Wieser & Brosch, 2012) or subtle and nuanced affect processing, such as emotion granularity (Barrett, 2004). No significant interindividual association between affect responses and clinical problems was found in our non-patient cohort of subjects. However, such association might be found in clinical populations. In this regard, our library of visual narratives can be considered as a natural—thus ecologically valid and unobtrusive—means of detecting the affective symptoms specific to certain psychiatric disorders, such as schizophrenia, which tend to be accompanied by affect impairment (Bell, Bryson, & Lysaker, 1997; Kring & Campellone, 2012). Lastly, CCA, as one of the popular multivariate analyses, efficiently explores the association between two multivariate collections of variables by finding linear combinations of each collection that maximize a linear correlation coefficient between the two collections. The current work demonstrated the power of CCA in discovering latent structures of covariation hidden in high-dimensional data sets such as psychological-characteristics measures and diverse aspects of affect responses. Furthermore, as demonstrated previously (Stephen M. Smith et al., 2015), the current work showed that CCA becomes even more powerful when it is used in conjunction with another multivariate analysis that compresses high dimensional data into a low dimensional space such as PCA, which allowed us to back-project the CCA mode onto raw—thus interpretable—measures.

Chapter 3. Identification of the brain regions that share the structure of inter-individual similarity with behavioral affective responses to visual narratives

3.1. Introduction

In the first part of my thesis, I explored the correlates of individual variability in affective responses to VNs in the domain of psychological characteristics. In the second part, I set out to conduct an fMRI experiment to identify the correlates in the domain of brain activity. I expect that identifying those correlates will provide informative clues regarding the sources of the individual differences in affective responses to VNs when interpreted in the light of the knowledge on the brain basis of emotion that has been accumulated and established with previous brain imaging studies. The rationale behind this expectation is as follows. As widely assumed in the emotion literature (James J Gross, 2015; Mauss, Levenson, McCarter, Wilhelm, & Gross, 2005; K. N. Ochsner, 2014; Rangel, Camerer, & Montague, 2008; Sabatinelli et al., 2011) emotion processing requires a complex set of representations or operations of diverse kinds, which are reportedly implemented by a corresponding set of the neural activities in many brain areas or networks. In principle, any representation or operation in such a set can be a candidate source of individual differences in affect responses to VNs. Next, suppose a specific brain area (or network) wherein the individual differences in neural responses to VNs are correlated with those in behavioral affect responses to VNs. Then, we can reasonably infer that the representations or operations supported by that specific brain area (or network) are likely to contribute to the emergence of the individual differences in affect responses to VNs.

Importantly, the core of the above rationale consists in the current knowledge about the brain basis of emotion. As such knowledge bases, I referred to two separate lines of work that have been guided by different—competing yet thus complementary for my purpose—perspectives on how the brain underlies emotion (Lindquist, Wager, Kober, Bliss-Moreau, & Barrett, 2012). According to the first perspective (typically referred to as 'locationist account), emotion consists of a countable number of basic, discrete category emotions that cannot be decomposed

Table 4. Summary of the locationist approach and constructionist approach mapping

Brain region	Locationist approach	Constructionist approach
Amygdala	Fear [1]	Core affect – Realizing core affect [2] – Detecting motivationally salience stimuli (novelty, uncertainty) [3]
Anterior insular	Disgust [4]	Core affect – Affective feeling & body sensation [5] – Attention allocation [6]
Orbitofrontal cortex	Anger [7]	Core affect – Integrating exteroceptive and interoceptive sensation to guide behavior [8]
Anterior cingulate cortex	Sadness [9]	Core affect – Realizing core affect [10] – Regulation of affect [11]
Periaqueducal gray	Rage, fear, joy, distress, love, lust [12]	Core affect – Behavioral adaptation [13]
Dorsomedial prefrontal cortex, medial temporal lobe, posterior cingulate cortex	-	Conceptualization – Realizing emotion experience [14]
Anterior temporal lobe, Ventrolateral prefrontal cortex	-	Conceptualization – Reference space for discrete emotion[15]
Dorsolateral prefrontal cortex	-	Executive attention – Emotion regulation [16]
Visual cortex	-	– Experience of emotion [17]

References. [1](M. Davis, 1992; LeDoux, 2007; Öhman, 2009); [2] (Adolphs, 2008; Pessoa, 2010) ; [3](Blackford, Buckholtz, Avery, & Zald, 2010; Moriguchi et al., 2011; Weierich, Wright, Negreira, Dickerson, & Barrett, 2010); [4](Jabbi, Bastiaansen, & Keysers, 2008; Wicker et al., 2003); [5](Arthur D Craig, 2002; A. D. Craig, 2003; Arthur D Craig, 2009); [6](Eckert et al., 2009; Uddin, 2015); [7](Murphy, Nimmo-Smith, & Lawrence, 2003; Vytal & Hamann, 2010); [8](Kringelbach & Rolls, 2004; Rolls, Hornak, Wade, & McGrath, 1994); [9](Murphy et al., 2003; Vytal & Hamann, 2010); [10](Devinsky, Morrell, & Vogt, 1995); [11](Etkin, Büchel, & Gross, 2015); [12](Panksepp, 2004); [13](Gregg & Siegel, 2001; Mobbs et al., 2007); [14](Barrett, 2006, 2009b; Buckner, Andrews-Hanna, & Schacter, 2008); [15](Rosen et al., 2004; Zahn et al., 2009); [16](Etkin et al., 2015; Kevin N Ochsner et al., 2004); [17](Lindquist et al., 2012) further, such as ‘fear’, ‘anger’, ‘disgust’, ‘sadness’, and ‘happiness’ (Ekman & Cordaro, 2011; Izard, 2011; Panksepp & Watt, 2011), and distinct brain areas or networks are devoted respectively to those discrete category emotions (Calder, 2003; Ekman, 1999; Izard, 2011; Panksepp, 2004). Thus, under the locationist-account perspective, the brain basis of emotion can be summarized by a direct mapping between the discrete category emotions and the specific brain areas or networks. For example, ‘fear’, ‘disgust’, ‘anger’, and ‘sadness’ have been related to the amygdala, the insular cortex, the orbitofrontal cortex, and the anterior cingulate cortex, respectively (see **Table 4** for the comprehensive summary of the locationist-approach mapping and the associated references).

By contrast, the second perspective to the brain basis of emotion (typically referred to as ‘constructionist account) views emotions as psychological events that emerge out of ‘basic psychological operations’ that are not necessarily confined to emotion processing per se (Barrett, 2009a; Duncan & Barrett, 2007; Pessoa, 2008). This view, by nature, falls under a general umbrella of cognitive-neuroscience approaches sharing the assumption that those psychological operations are common to diverse domains including those other than emotion processing (Cole & Schneider, 2007; Dosenbach et al., 2006; Stephen M Smith et al., 2009; Van Snellenberg & Wager, 2009; Wager, Jonides, Smith, & Nichols, 2005; Wager & Smith, 2003). According to the constructionist view, the basic domain-general operations that are recruited in emotion processing include ‘core affect’—the operation of experiencing raw affective sensations as body symptoms or feelings, ‘conceptualization’—the operation of making core-affective sensations meaningful in a context using prior experience, ‘executive attention’—the operation of prioritizing certain core-affective sensations or conceptualized representations for conscious awareness, and those operations are implemented respectively in different “assemblies of neurons distributed within certain brain networks (Lindquist et al., 2012).” For example, ‘core affect’ is related to the network of areas including the amygdala, insula, orbitofrontal cortex, and anterior cingulate cortex; ‘conceptualization’ includes the ventromedial prefrontal cortex, dorsomedial prefrontal cortex, medial temporal lobe, and posterior cingulate cortex; ‘executive attention’ includes the dorsolateral prefrontal cortex and ventrolateral prefrontal cortex (see **Table 4** for the comprehensive summary of the constructionist-approach mapping and the associated references).

I note that it remains a subject of debate which of the locationist and constructionist accounts is a better paradigm for relating brain activity to emotion behavior (Bach & Dayan, 2017). However, to the purpose of the current work, the brain-emotion maps built by the two accounts together offer two complementary ways of inferring the sources of individual differences in affect responses from the neural correlates of those individual differences: the map built on the locationist account will indicate which emotion categories are likely to contribute to the individual differences whereas that on the constructionist account will indicate in which basic operations individuals differ.

With these two different maps in hand, as two complementary guides, I conducted the fMRI experiment in search of the neural correlates of individual differences in affect responses to VNs. I acquired fMRI measurements while participants were viewing VNs (VN scans) or the scrambled images whose motion energy matched the VN scans (SM scans), which were introduced to control for fMRI signals associated with simple motion energy. Then I applied the inter-subject representational similarity analysis (RSA) to the fMRI measurements to identify the neural correlates of individual differences in affect responses to VNs. Previous studies reported that substantial fractions of the brain activity are synchronized between individuals when they watch natural movie stimuli (Hasson et al., 2009; Hasson et al., 2008; Hasson, Nir, Levy, Fuhrmann, & Malach, 2004; Nummenmaa et al., 2012), using the inter-subject correlation (ISC) analysis. The extent to which the brain responses are synchronized depended on several factors including the affective intensity and the attention level of movies (Lahnakoski et al., 2014; Nummenmaa et al., 2012). Recently, researchers explored the brain activities signifying the individual differences using the ISC analysis in conjunction with the RSA (Kriegeskorte, Mur, & Bandettini, 2008). This conjunctive approach turned out quite useful, identifying the brain responses whose correlated dynamics between individuals reflect the individual differences in cognitive behavior or personality (Chen, Jolly, Cheong, & Chang, 2020; Finn et al., 2020). For the purpose of identifying the brain activities that are associated with the individual differences in affect responses to VNs, I applied this conjunctive approach, which will be referred to as the ‘inter-subject RSA’, the fMRI measurements acquired from the human individuals who were watching the VN stimuli described in Chapter 2.

Before applying the inter-subject RSA analysis, I first conducted the parametric modulation analysis to define the brain regions that were reliably modulated by the average valence and arousal responses. Fourteen and ten regions of interest (ROIs) were defined for arousal and valence dimensions, respectively for further inter-subject RSA analysis. Then, I explored the geometric structure of affective responses to find the sources of inter-subject similarities of affective responses to VNs by adopting t-distributed stochastic neighbor embedding (t-SNE). Based on Finn and her colleagues' study (Finn et al., 2020), I made an inter-subject similarity matrix of valence responses and arousal responses, respectively, following a structure called “AnnaK minimum”, which effectively reflected the geometric structure of affect responses. Lastly, I carried out inter-subject RSA between the inter-subject similarity matrices of affect responses and those of fMRI responses to VNs to find out whether the geometric structures, which determined the inter-subject similarity of affect responses, also reflect the inter-subject similarity of fMRI responses.

3.2. Methods

Participants

Seventy healthy adults (32 females, M_{age} = 21.5 years, age range: 18–24 years), who also participated in the previous behavioral study (3.1–3.4), participated in the neuroimaging study. Two participants with severe head motion (exceeding 0.9 mm) were excluded from analysis. This study was approved by the Seoul National University Institutional Review Board, and informed written consent was obtained from each participant before participating in the study.

Visual narrative viewing scan (VN scan)

Participants were instructed to passively view the visual narrative stimuli while lying in the scanner, akin to watching a movie. A fraction of the visual narrative stimuli developed in the previous behavioral experiment (3.1–3.4; 72 out of 144 VN stimuli). Each participant underwent three runs of functional magnetic resonance imaging (fMRI) scanning. Each run consisted of twenty-six 15-second-long visual narratives, which were presented consecutively, taking 6 minutes and 30 seconds. We applied a resolve (fade in and out) technique during the transition between stimuli to minimize abrupt transient signals in the sequential presentation.

Scrambled motion scan (SM scan)

The SM scan runs were administered to control for the brain activity driven by the low-level sensory features of the original VN stimuli and the eye movements made by participants viewing the VN stimuli. Each VN scan run was followed by a corresponding SM scan run that consisted of scrambled images whose motion energy was matched to that in the preceding VN scan run. To control for eye movements, participants performed an eye-tracking task by directing their gaze at the fixation target (white circle), which replayed the trajectory of eye movements made by themselves in the preceding VN scan run.

MRI acquisition

FMRI data were acquired with a 3T Siemens Magnetom Trio scanner (Siemens, Erlangen, Germany) using a 32-channel head coil. Three-dimensional magnetization-prepared rapid acquisition with gradient-echo T1-weighted anatomical images were acquired using the following parameters: repetition time (TR), 1.9 s; echo time (TE), 2.36 ms; flip angle (FA), 9°; voxel size, $1 \times 1 \times 1$ mm^3; and matrix size, 256×256. Functional scans were acquired using an echo-planar imaging sequence with the following parameters: TR, 1.5 s; TE, 30 ms; FA, 90°; voxel size, $3 \times 3 \times 3$ mm^3; matrix size, 96×80; field of view: 250 mm; and 46 slices. All subjects underwent seven functional scans while observing stimuli that were presented using the MATLAB software 2015b (The MathWorks Inc.).

Parametric modulation analysis

FMRI data were preprocessed using the SPM12 software (https://www.fil.ion.ucl.ac.uk/spm/software/spm12/). Raw functional images were realigned, unwarped, slice-timing corrected, and co-registered to each subject's T1-weighted image. The images were then normalized to the Montreal Neurological Institute (MNI) template, resliced to $2 \times 2 \times 2$ mm voxel space, and spatially smoothed (8 mm full-width at half-maximum).

To identify brain regions showing correlations with the across-individual averages of affective responses to VNs, the parametric modulation analysis was conducted with SPM12. We used average arousal responses and valence responses as regressors for the first-level analysis and included affect regressors to regress out head motion-related effects. The t-maps from the VN scan are presented with python nilearn.plotting module (https://nilearn.github.io/plotting/index.html).

Inter-subject representational similarity analysis (RSA)

To identify the brain regions signifying the individual differences in affective responses to VN stimuli, we carried out the inter-subject representational similarity analysis. The inter-subject RSA, an extended version of the inter-subject correlation analysis (Hasson et al., 2008; Hasson et al., 2004), allows for identifying regions wherein the inter-subject pattern of representational similarity (Finn et al., 2020; Kriegeskorte et al., 2008) for the VN stimuli in brain activity closely matches that in affective responses. The rationale behind applying the inter-subject RSA to our data is that, if a given brain region is involved in representing the 'subjective' affective responses to the VN stimuli, the patterns of brain activity over the stimuli will be similar between the individuals who showed the similar patterns of affective responses over the stimuli.

The inter-subject RSA was carried out in the following steps. First, we define 5 mm radius spherical regions-of-interest (ROIs) centered on the peak voxel of the area (**Table 5** for arousal and **Table 6** for valence) that showed a significant relationship with arousal and valence, respectively, from the parametric modulation analysis result. Thus, fourteen ROIs for arousal and ten ROIs for valence were created. Second, we built a pair of inter-subject correlation matrix in fMRI activity for each of the arousal ROIs (CM_{VN}^{fa} and CM_{SM}^{fa}) and the valence ROIs (CM_{VN}^{fv} and CM_{SM}^{fv}). The pair-wise correlation between subjects were computed based on the time series of fMRI activity during the VN scan runs for CM_{VN}^{fa} and CM_{VN}^{fv} and those during the SM scan runs for CM_{SM}^{fa} and CM_{SM}^{fv}. As a result, fourteen correlation matrices for CM_{VN}^{fa} and CM_{SM}^{fa} and ten correlation matrices for CM_{VN}^{fa} and CM_{SM}^{fa} were created in the domain of brain activity. Third, in the domain of affective responses, we built a inter-subject correlation matrix, CM_{VN} indicating how similar a pair of participants' affective responses to visual narratives. It consisted of the inter-subject correlation coefficients either in the arousal rating scores (CM_{VN}^{a}) or in the valence rating scores (CM_{VN}^{v}) over the VN stimuli, which had been acquired in the chapter 2 experiment.

Lastly, the correspondence between the brain-activity and affective-response domains was evaluated by computing the Spearman correlation coefficients for the lower triangle parts of the inter-subject similarity matrix between the two domains. The analysis results were expressed as whole-brain similarity maps. Maps were thresholded using the Mantel permutation test, and this was repeated 1,000 times to generate a null distribution of the Spearman correlation used to compute p-values. We corrected for the multiple comparison across the ROIs using FDR (Benjamini & Hochberg, 1995).

3.3 Results

Parametric modulation analysis for the normative (across-individual average) affective responses to VNs

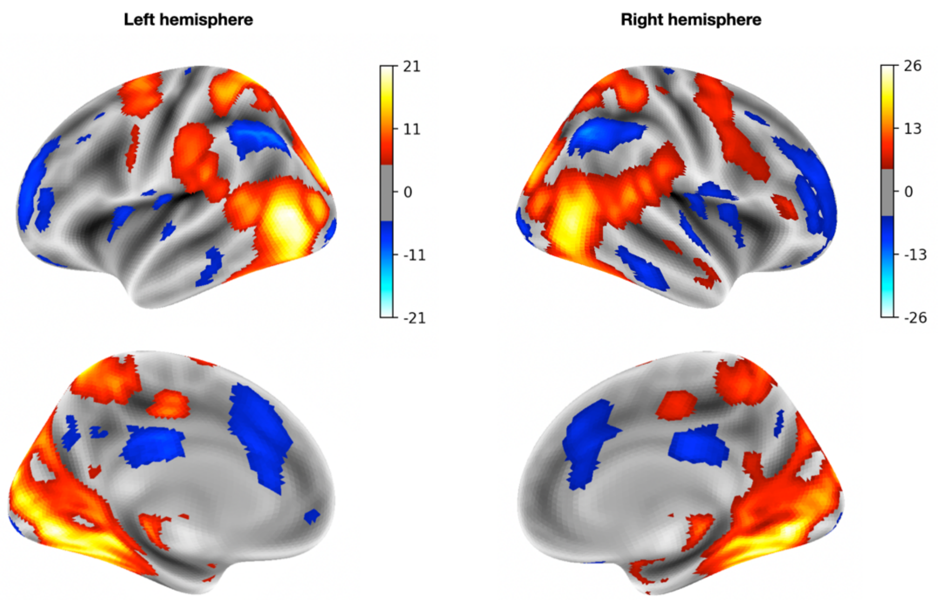


Figure 7. Parametric modulation analysis for the normative arousal responses to VNs. Activation map of sensitivity to arousal (*FDR* < 0.05). Color bar indicates the t-value.

Table 5. Centers of the brain regions that were significantly correlated with the normative arousal responses to VNs

Region name	Extent	t-value	MNI coordinates X	Y	Z
Positive sign					
Lingual gyrus	45716	28.16	10	-72	-6
Temporal occipital fusiform gyrus	45716	25.70	28	-56	-12
Lateral occipital cortex	45716	23.88	44	-64	2
Dorsolateral prefrontal cortex	2288	12.13	40	0	56
Precentral Gyrus	244	10.42	14	-20	44
Ventrolateral prefrontal cortex	295	9.61	54	34	6
Middle temporal gyrus	483	7.83	60	4	-22
L amygdala	127	6.96	-20	-6	-22
Negative sign					
R Lateral occipital cortex (Superior division)	2133	-16.67	44	-64	52
L Lateral occipital cortex (Superior division)	1783	-13.51	-48	-62	50
Occipital pole	898	-13.19	-24	-98	-12
Occipital pole	898	13.99	26	-96	-10
Inferior temporal gyrus	864	-10.24	60	-30	-22
Posterior cingulate cortex	635	-9.38	4	-28	28

Note. R: right hemisphere, L: left hemisphere, MNI: Montreal Neurological Institute.

I conducted the parametric modulation analysis to identify the brain regions whose activity is significantly modulated by the normative (across-individual average) arousal and valence responses to VNs. I found that the normative arousal responses to VNs positively modulated the fMRI activities in the lingual gyrus, fusiform gyrus, lateral occipital cortex, dorsolateral prefrontal cortex, precentral gyrus, ventrolateral prefrontal cortex, middle temporal gyrus and left amygdala. On the other hand, the occipital cortex in superior division, occipital pole, inferior temporal gyrus, and posterior cingulate cortex were negatively correlated with the arousal responses (**Figure 7; Table 5**).

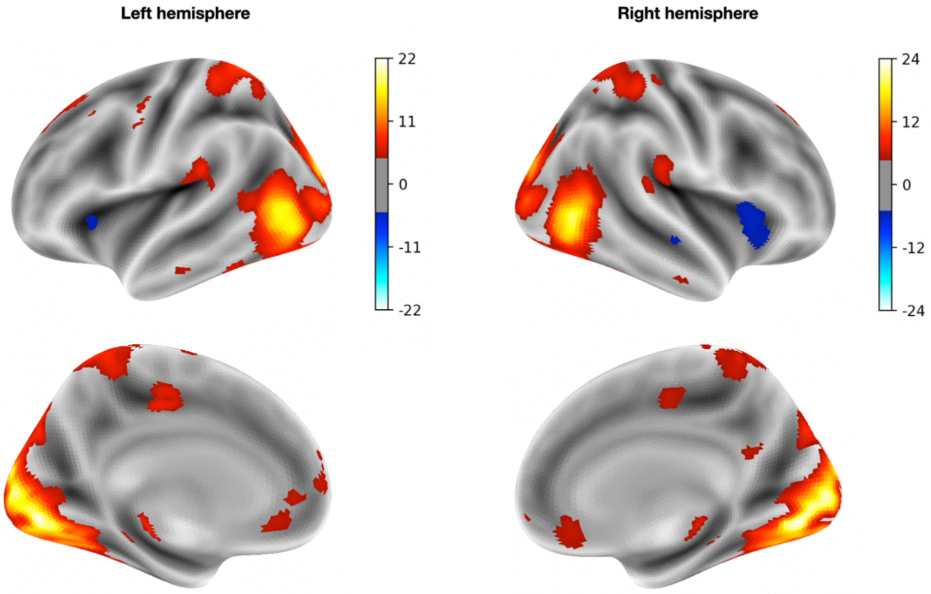


Figure 8. Parametric modulation analysis for the normative valence responses to VNs. Activation map of sensitivity to valence (*FDR* < 0.05). Color bars indicate t-values.

Table 6. Centers of the areas of activation that were significantly correlated with the normative valence responses to VNs

Region name	Extent	t-value	MNI coordinates		
			X	Y	Z
Positive sign					
R occipital pole	21007	22.34	10	-92	8
L occipital pole	21007	22.02	-4	-94	6
R lateral occipital cortex	21007	22.46	46	-66	0
L lateral occipital cortex	21007	19.46	-46	-70	0
L hippocampus	179	10.89	-20	-30	-6
R hippocampus	165	10.80	22	-28	-6
Superior frontal gyrus	500	8.39	-24	30	54
Dorsomedial prefrontal cortex	926	7.00	-4	54	4
Ventromedial prefrontal cortex	926	6.61	6	32	-14
Negative sign					
Insular cortex	299	-5.93	36	20	4

Note. R: right hemisphere, L: left hemisphere, MNI: Montreal Neurological Institute.

I found that the normative valence responses to VNs positively modulated the fMRI responses in the occipital pole, lateral occipital cortex, hippocampus, superior frontal gyrus, dorsomedial prefrontal cortex, and ventromedial prefrontal cortex. On the other hand, the fMRI responses in the insular cortex were negatively correlated with the normative valence responses (**Figure 8, Table 6**). A list of all the areas that showed significant responses to the normative arousal and valence responses to VNs are summarized in **Tables 5** and **6**.

Inter-subject representational similarity analysis (RSA)

Next, I applied inter-subject representational similarity analysis (IS-RSA) to the ROIs that were significantly modulated by the normative arousal or valence responses to VNs (the areas listed in **Table 5** and **6**) to identify the brain regions in which the inter-subject representational similarity reflects the inter-subject representational geometry of the behavioral affective responses to VNs. Specifically, IS-RSA was carried out in the following steps. As the first step, I defined the inter-subject representational geometry of the behavioral affective responses to VNs by plotting the individuals' affective responses to VNs in a multivariate space and then identified what kind of similarity metric governs that representational geometry. Secondly, for each ROI, I quantified the inter-subject similarity in brain activity by assessing how similar the vector of fMRI responses to VNs are between paired individuals and then

evaluated how well the inter-subject similarity in brain activity is determined by the behavioral similarity metric that governs the inter-subject representational geometry in affective responses to VNs. Lastly, for the ROI(s) that turned out significant in the second step, I carried out further analyses and visualizations to better characterize the shared geometry of individual differences between the brain and affective responses on VNs.

The inter-subject representational geometry of behavioral affective responses to VNs. To define the representational geometry of inter-subject similarity in affective responses to VNs, I applied t-distributed stochastic neighbor embedding (t-SNE; (Van der Maaten & Hinton, 2008) to the data matrices consisting of individuals' vectors of affective responses to VNs, respectively for arousal and valence responses. t-SNE is ideal for the current purpose because it allows for mapping a set of high-dimensional (72 dimensions in my case because each response vector consists of the responses to 72 VNs) data points to a two-dimensional space wherein close neighbors (i.e., individual subjects in my case) remain close and distant neighbors remain distant (Kobak & Berens, 2019) and it is also capable of addressing the data with non-linearity prevalent in cognitive and neural datasets (Belkina et al., 2019).

The representational geometry captured by t-SNE appeared to match the so-called *Anna-Karenina* structure, in which the individuals in the majority flock together around the center of the space while those in the minority are scarcely scattered around the edge of the space (**Figure 9A,B**). The arousal and valence data shared this *Anna-Karenina* structure. Next, from this highly centralized structure, I conjectured that the center of the t-SNE space is likely to represent the normative (across-individual average) response vector and, accordingly, that the behavioral metric that governs the representational geometry is likely to be how close a given individual's responses are to the normative responses. I corroborated this conjecture by indexing the individuals' affective responses with 'normativity' (as indicated by the colors of dots in **Figure 9A,B**) based on their rank correlations with the normative responses in the representational-geometry space. The normativity well governed the representational geometry of inter-subject similarity: the individuals with high normativity (reddish dots in **Figure 9A,B**) were positioned closely to the center as the majority while those with low normativity (blueish dots in Fi**gure 9A,B**) were scattered along the edge of the space. Next, to further specify the way the normativity governs the inter-subject similarity in affective responses, I examined which of the several subtypes of *Anna-Karenina* structure best accounts for the inter-subject similarity in affective responses to VNs. The inter-subject similarity was best captured by the 'minimum-score' subtype of *Anna-Karenina* structure (Finn et al., 2020), where the inter-subject similarity for a given pairs of subjects can well be predicted by the normativity of the subject with a smaller value of normativity (**Figure 9C-F)**. In what follows, for each of the ROIs (14 ROIs for arousal, 10 ROIs for valence), I evaluated whether the inter-subject similarity in the pattern of fMRI responses to VNs reflects the representational geometry of inter-subject similarity in the pattern of affective responses to VNs.

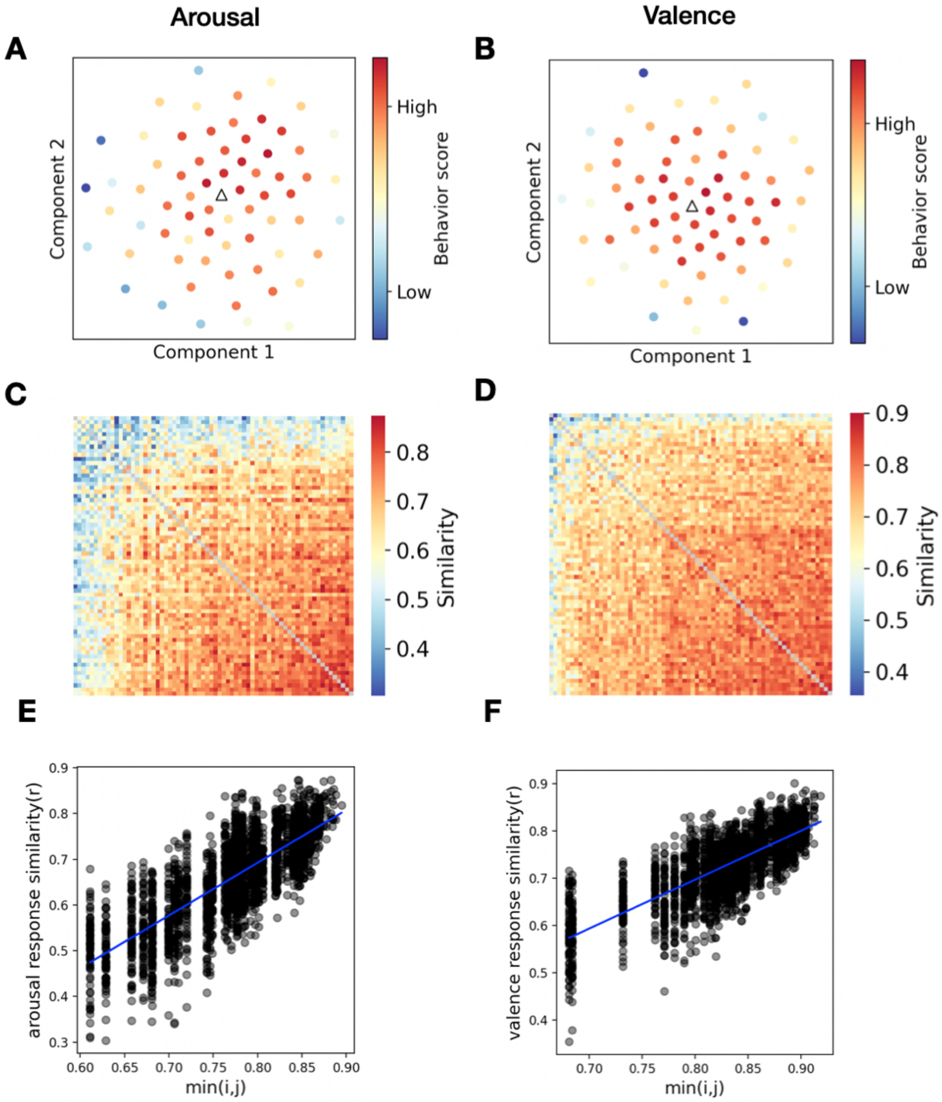


Figure 9. The inter-subject representational geometry of behavioral affective responses to VNs. (A,B) Individual differences in affective responses were mapped in the 2-dimensional space through t-SNE (t-Distributed Stochastic Neighbor Embedding). Color indicates a score of the normativity. **(C,D)** A pairwise affective response similarity matrix. Participants are ordered along rows and columns by their normativity scores (low to high). Each cell presents the correlation between a pair of participants' affective responses to visual narratives. **(E,F)** Strong association between inter-subject similarity of affective responses and the 'minimum-score' subtype of *Anna-Karenina* structure. Left side for the arousal responses and right side for the valence responses.

The fMRI responses in the right-hemisphere anterior insular cortex (rAIC) closely reflect the representational geometry of inter-subject similarity in

affective responses. Given the minimum-type *Anna-Karenina* structure in the behavioral domain—for both arousal and valence responses, I evaluated each ROI by how well the pairwise similarity in fMRI responses to VNs, which was quantified by spearman correlation coefficient, is regressed onto the normativity score of the subject with a smaller value of normativity for a given pair. Any of the 14 'arousal' ROIs did not show a significant regression. Out of the 10 'valence' ROIs, the significant regression (r = 0.121, p = 0.0069, $corrected\ p$ = 0.059) was found only in the anterior insular cortex in the right hemisphere (rAIC; **Figure 10A,B**). Notably, when the individuals were sorted in the order of the normativity in their valence responses to VNs, the inter-subject correlation matrix of fMRI responses to VNs also displayed the structure that closely resembles the representational geometry of inter-subject similarity in valence responses to VNs (**Figure 10C**). To be sure, we confirmed that these results cannot be ascribed to the trivial association between valence responses and low-level visual features by showing that no significant regression was found in the SM scans.

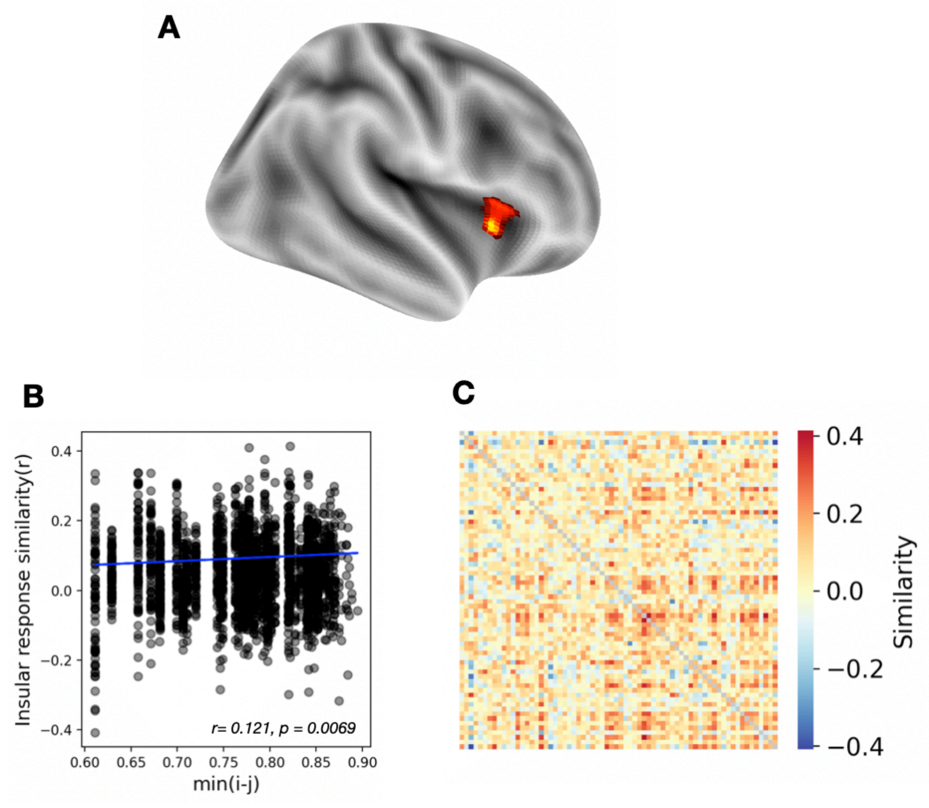


Figure 10. The inter-subject RSA result. (A) Right anterior insular cortex showing a significant association with inter-subject valence response similarity. **(B)** A significant association between inter-subject similarity of fMRI responses to VNs and the 'minimum-score' subtype of *Anna-Karenina* structure obtained from the valence responses. **(C)** The inter-subject correlation matrix of fMRI responses to VNs.

3.4 Discussion

As mentioned in Introduction (3.1), I will interpret the results in the light of the two brain-emotion maps built on the locationist and constructionist accounts, as follows. The parametric modulation analysis identified a total of 24 ROIs as the correlates of the normative (averaged across subjects) affect responses to VNs. I will compare those 24 ROIs against the brain areas defined by the two maps. This comparison may inform us of which category emotions—according to the locationist account—or which basic psychological operations—according to the constructionist account—that played important roles in affect responses to the VNs used in the current work. Next, more importantly, I identified the AIC as the correlate of the individual differences via inter-subject RSA. Based on the category emotions and basic operations associated with the AIC on the locationist and constructionist maps, respectively, I will attempt to infer the sources of the individual differences in affect responses to VNs. Lastly, I will conclude by discussing the contributions and limitations of the current work to the understanding of the nature and sources of individual differences in affect processing in general.

Relating the brain regions tuned to the normative affect responses to category emotions or basic operations

A total of 14 and 10 ROIs were identified as the brain regions tuned to the normative arousal and valence responses, respectively, to VNs. Among them, only two ROIs (8.3%), the amygdala (arousal correlate) and the AIC (valence correlate), are found on the locationist map (the second column of **Table 4**). As the amygdala is dedicated to 'fear' on the locationist map, the positive correlation of the amygdala with the normative affect responses can be interpreted to reflect the fact that the 'fear' emotion category tends to have high values of arousal (J. A. Russell, 2003). The negative correlation of the AIC with the normative valence is consistent with the dedication of AIC to 'disgust' on the locationist map. In sum, the projection of the ROIs onto the locationist map suggests that the VNs used in the current study were likely to be effective in inducing negative category emotions of 'fear' and 'disgust.'

By contrast, as many ROIs as 18 out of 24 (75%) could be sorted into all of the 6 major clusters on the constructionist map (the third column of **Table 4**). The amygdala implements the operation of realizing 'core affect' sensations, especially those that are novel or motivationally salient; the AIC implements the operation of realizing 'core affect' sensations, especially those associated with body and feeling; the posterior cingulate cortex and the dorsomedial prefrontal cortex implements the operation of 'conceptualizing (making meaningful)' the core affect sensations using prior knowledge; the medial temporal lobes (hippocampal regions) implements the operation of 'conceptualizing (making meaningful)' the core affect sensations using memory; the ventrolateral prefrontal cortex implements the operation of 'conceptualizing (making meaningful)' the core affect sensations using discrete linguistic labels; the dorsolateral prefrontal cortex implements the operations of 'executive control' such as attention and emotion regulation; the occipital lobe implements the operation of supporting exteroceptive perception, which, together with interoceptive perception, contribute to the unified conscious experience of the self in the context. In sum, the projection of the ROIs onto the constructionist map indicates that the VNs used in the current study were very effective in recruiting all the basic, representative operations comprising human emotion processing.

Relating the AIC to the sources of individual differences in affect responses to VNs

Having learned that the brain regions identified as being modulated by the normative affect responses are better captured with the constructionist account, I focus on the basic operations to which the constructionist account assigned the AIC to infer the plausible sources of the individual differences in affect responses to VNs. According to the constructionist account, the AIC plays two important roles in the operation of realizing 'core affect' sensations. On the one hand, it is involved in bodily sensation and feelings in awareness (Arthur D Craig, 2002, 2009). On the other hand, the AIC is also involved in 'reorienting (switching)' attention to salient events occurring abruptly in the environment (Eckert et al., 2009) as a hub of the ventral frontoparietal network (Corbetta, Patel, & Shulman, 2008; Corbetta & Shulman, 2002). In this regard, the locationist's association of the AIC with 'disgust' can be reinterpreted to reflect the bodily feelings caused by novel (unexpected) stimuli. Given these two roles of the AIC in the 'core affect' operation, the finding that the AIC responses to VNs closely reflects the individual differences in valence responses to VNs suggests the possibility that individuals substantively differ in reorienting their attention to the unfolding events—especially those associated with bodily sensations or feelings with some hedonic (probably negative kinds) values—that occur unexpectedly over time (about 15 seconds) during VNs. For example, some individuals, compared to others, are more sensitive to new bodily sensations that were triggered by certain objects or events in the movie scene so they readily prioritize their inner attention to those sensations. Such differences in 'reorientation' sensitivity are likely to contribute eventually to the differences in affect responses to VNs. Given that the VNs used in the current study were quite effective in recruiting all of the major six brain networks composing the brain basis of emotion built on the constructionist's account, the AIC's sole contribution to individual differences points out the core affective system of reorienting to incoming bodily sensations as one of the main sources of individual differences in affect responses.

Linking the individual differences in affective processing to those in brain activity in terms of representational geometry

'Representational geometry' refers to the geometric structure of a set of entities, which can be objects or individuals depending on the context, represented as a point in a space spanned by the dimensions of data (Edelman, 1998; Gardenfors, 2004; Shepard, 1958, 1987; Tversky, 1977). Here the dimensions of data can be considered as the length of a vector of properties or responses used to characterize the behavior of entities. For example, desks can be characterized by multiple properties, including 'width', 'length', 'height', 'color', 'weight', and so on. Representational geometry captures the relationship among entities in such a high-dimensional space and provides useful information, especially about the structure of inter-entity similarity within a given set.

In search of the neural correlates of the individual differences in certain behaviors, including affective (emotion) responses, most previous studies pursued the rather simple correspondence in the inter-subject similarity between brain activity and behavior of interest (Chen et al., 2020; Nguyen, Vanderwal, & Hasson, 2019; Nummenmaa et al., 2012). Of course, the presence of such correspondences indicates the presence of information that is associated with the individual differences in a certain region of interest, but nothing further. In this regard, the current study goes beyond the previous studies by relating the individual differences in affective processing to those in brain activity in terms of representational geometry. Specifically, the current work was able to discover a set of novel findings by capitalizing on representational geometry. First, the current work, for the first time to my knowledge, not only showed that the representational geometry of the individual differences in affective processing—insofar as those to VNs—can be characterized by minimum-type *Anna-Karenina* structure but also identified the normativity scores of individuals (how similar the affective response patterns of a given individual is to the normative—across-individual average—responses) as the main factor governing the representational geometry. Second, the current work, rather than seeking the 'blind'—without exactly knowing the content of correspondence—correspondence in the similarity between brain activity and affective behavior, specifically examined whether, for a given brain region, its across-subject variability in cortical responses to affective stimuli resembles the representational geometry of inter-subject similarity in affective responses to the same affective stimuli. Third, as a result, the current study, rather than reporting a collection of many brain regions in an undistinguished manner, singled out a brain region, the rAIC, whose activity displays the structure of inter-subject similarity that is isomorphic with that of the inter-subject similarity in affective responses.

AIC, a cortical site for affective awareness?

Previous work has been relating the insular cortex to an amazing variety of functions, from interoception to emotion, motivation, reward processing, risk-taking behavior, and empathy, to name a few (see (Gogolla, 2017) for review). Given this seemingly multi-functional involvement of the insular cortex, there have been several proposals about what would be the key function of the insular cortex that unites all those previously reported functional involvements. I conjecture that one such proposal may help provide a parsimonious account of the finding in the current work.

According to this proposal (Arthur D Craig, 2009), the AIC is an ideal brain region for representing all moment-by-moment (now) subjective feelings when considering its functional involvement in interoceptive re-representation of virtually all kinds of body feelings in conjunction with the prominent theories of emotion processing such as the James-Lange theory. In addition, this proposal stresses the involvement of the AIC in awareness based on the realization that what is common to all the tasks associated with the AIC is to do with awareness (Arthur D Craig, 2009).

This view of the AIC as the neural locus for representing all moment-by-moment subjective feelings appears to provide a parsimonious account for why the responses to VNs in the AIC closely resemble the representational geometry of the inter-subject similarity in valence responses to VNs. This is so because, if any given brain region supposedly represents all moment-by-moment subjective feelings, the brain activity in that area of a given individual would dynamically fluctuate in synchrony with what that individual is feeling while viewing a series of movie clips. In this light, the findings in the current study corroborate the view of the AIC as the neural locus for representing all moment-by-moment subjective feelings by separating out the AIC as the locus of resemblance to the representational geometry of inter-subject similarity in valence responses from all other brain regions whose activity is correlated only with the normative valence responses but fails to discern the individual differences in valence responses.

Chapter 4. Conclusion and perspectives

4.1 Summary and conclusion

In the first study, I applied a data-driven approach to identify a systematic structure that governs the population covariation between the affect-response to VNs and psychological-characteristic domains. My approach differs from that of previous studies in several important aspects, which include the use of natural affect-inducing stimuli, a comprehensive set of psychological-characteristic measures, and the use of multivariate analysis methods. Specifically, I carried out a series of multivariate analyses on a high-dimensional dataset consisting of eight affect-response measures and 68 psychological-characteristic measures acquired from a cohort of 86 participants. I identified a single, robust, canonical mode of covariation using CCA in conjunction with PCA, and we projected this canonical mode back onto the raw measures in both domains to further explore 'interpretable' inter-domain relationships underlying the canonical mode. This resulted in the identification of one such relationship: individuals who were characterized as being 'rich in psychosocial assets' tended to show 'polarized arousal responses' to affect-inducing VNs.

In the second study, I acquired functional magnetic resonance images from the participants viewing the VNs used in the first experiment. Then I conducted the parametric modulation analysis to identify the brain regions whose fMRI responses were modulated by the across-individual averages of affective ratings and the inter-subject representational similarity analysis to determine the brain regions associated with the individual differences in affective responses to VNs. I found that the inter-subject similarity in valence responses was tightly linked with that in brain activities of the right anterior insular.

4.2 Future directions

We considered the generalizability of our findings to other populations and, in particular, to different cultures. We intentionally recruited participants to form a culturally homogenous population to minimize individual differences in affective responses to VNs that may be attributed to cultural differences. However, it would be valuable to determine whether our findings can be replicated in different age groups or non-Asian cultures. If replicated, the canonical mode of population covariation identified in the current work may be considered a highly generic feature of the relationship between psychological characteristics and affective responses to VNs. However, even if our findings are not replicated, differences between cultures will offer valuable insight into cultural differences in affect processing. Furthermore, the methods used in the current work may be translated into research on affect in clinical populations, such as schizophrenia or affective and anxiety disorder patients. For example, given the link between affect perception and social functioning in schizophrenia patients (Hooker & Park, 2002) and between negative valence bias and maladaptive social functioning in affective and anxiety disorder patients (Hofmann, Sawyer, Fang, & Asnaani, 2012; Rutter et al., 2019), the CCA analysis may help reveal a robust and refined covariation structure that relates to specific aspects of affective responses based on disorder subtypes, symptoms, spectra, or stages. In addition, considering the link between schizophrenia and difficulties in integrating affect perception with context (Kring & Elis, 2013), the VN stimuli used in the current work may be particularly suited to determining the exact nature of affective deficits in people with schizophrenia. Finally, in addition to examining how affective experiences are represented in the brain, the current work may be extended by using brain imaging measures, such as anatomical structure or functional connectivity, as a third domain of the multi-domain CCA. The generalized Addictive Kernel Canonical Correlation Analysis method (Bae et al., 2020) that allows us to find multi-group and nonlinear relationships is one technique that may be used for such explorations. These extensions will help elucidate the neural basis underlying the canonical mode of population covariation between the affect-response and psychological-characteristic domains.

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Appendices

Appendix A. Power analysis and sample size justification

Methods

To determine the number of participants that warrants sufficient degrees of is the type I error rate), and of power (1-β, where β is the type II error rate) as well, we proceeded as follows. First, following the convention, we initially set α to .05 for specificity. This initial α was corrected roughly to be .005 by Bonferroni correction to avoid the inflation of the type I error due to multiple comparisons intrinsic to our CCA analysis, which tests a total of 8 hypotheses. Second, following the convention, the power (sensitivity) was set to .8. Third, since the effect size for correlation comparison is defined as Q–the absolute difference between Fisher-z-transformed r values–and Q of .3 is conventionally considered as a medium effect size (Cohen, 1988), the target effect size was set to .3 in the unit of Q. Fourth, to derive the 'null-hypothesis' distribution of the correlations between the canonical variates paired in the first CCA mode ($r(C_{M1}, A_{M1})$), we generated 10,000 bootstrap samples of data set from the 68 and 8 standardized normal distributions of the individual characteristic measures and the affect measures, respectively, and carried out the PCA and CCA analyses using the same procedure described above. Then we transformed the 10,000 bootstrap samples $r(C_{M1}, A_{M1})$ to Fisher z values, which provided us with the 'null-hypothesis' distribution of $z_{r(C_{M1},A_{M1})}$. Fifth, we created the 'alternative hypothesis' distribution of $z_{r(C_{M1},A_{M1})}$ by adding the target effect size (Q = .3) to the 'null-hypothesis' distribution of $z_{r(C_{M1},A_{M1})}$. Finally, we repeated the fourth and fifth steps as we vary the number of participants and determined the minimum number of participants that satisfies the pre-determined values of specificity (1- α =.995) and power (1-β = .8). This analysis suggested 70 as the minimum number of participants (S1 Appendix. Fig1). Based on this result, we judged that eighty participants were sufficient for the multivariate analyses used in the current work.

Results

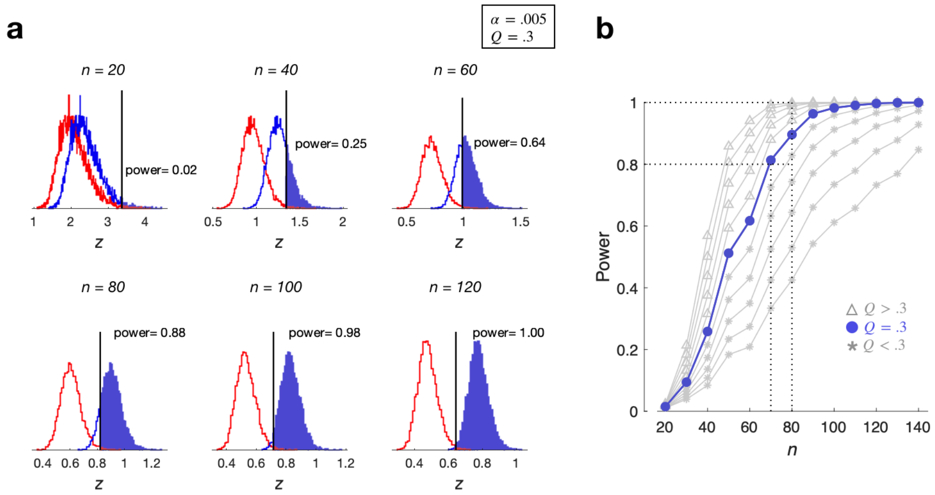

Fig1. Results of simulation for sample size determination.
(a) Example pairs of 'null-hypothesis (red)' and 'alternative-hypothesis (blue)' probability distributions of Fisher-z-transformed canonical correlation coefficient, with a pre-determined effect size (Q = .3). In each panel, the black vertical line demarcates the critical z value. The type I error (α = .005) corresponds to the area under the red curve for the z values that are greater than the critical value; The power (1- the type II error (β)) corresponds to the area under the blue curve for the z values that are greater than the critical value. As the number of participants (n) increases, the 'null hypothesis' and 'alternative hypothesis' probability distributions become increasingly apart from each other, which results in the increase in power. (b) Changes in power as a function of sample size under a fixed value of α (.005) and different effect sizes. Individual curves were acquired using different effect sizes, ranging from .2 to .4. With the pre-determined target effect size (Q = .3; blue curve), the power reached its pre-determined target level (.8) when the sample size was 70, as indicated by the left dotted vertical line. When the sample size was 80, which was the actual number of participants used for the data analysis, the expected effect size is greater than 3.8 and the expected power value is close to 1.

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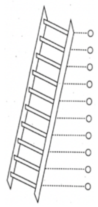
Appendix B. Specifications of psychological-characteristic measures

Table 1. Psychosocial factors category

Questionnaires	Descriptions	Measures
KRQ (Korean Resilience Quotient-53)	This measures the ability to cope with difficulties in life and to grow mentally by adapting to the environment. This is a modified version of the Resilience Quotient Test (RQT), which was developed by Reivich and Shatte (Reivich & Shatte, 2003), translated into Korean(J. Kim, 2011). It consists of 9 sub-categories. A total of 53 items are rated on a 5-point scale from 1, "not at all true for me", to 5, "very true for me".	1. *Appreciation*: degree of appreciation for everyday life 2. *Life satisfaction*: degree of satisfaction by focusing on what one can do well 3. *Self-positivity:* degree to which one believes things will get better 4. *Self-expansion:* degree to which one feels connected to others 5. *Empathy*: ability to read others' thoughts and feelings 6. *Communication*: ability to establish and maintain relationships 7. *Causal analysis*: ability to see problems positively and find solutions accurately 8. *Impulse control*: ability to motivate and control oneself 9. *Emotion regulation*: ability to remain calm under pressure
SSS (Social Support Scale)	This was developed by Park(J.-W. Park, 1985) to measure the degree of social support experienced by an individual. It consists of 4 sub-categories. Items are rated on a 5-point scale from 0 (not at all) to 4 (very much).	1. *Emotional support:* experiencing respect, attention, affection, and trust 2. *Evaluative support*: receiving comments from others about one's own behavior 3. *Informative support:* gaining information to solve personal problems 4. *Material support:* direct support when needed, such as money
RSES (Rosenberg Self-Esteem Scale)	This tool assesses individual global self-esteem, including both positive and negative feelings towards oneself. It consists of 10 items. The original version is sc	It has no sub-categories. *Example of an item:* "On the whole, I am satisfied with myself."

Questionnaires	Descriptions	Measures
	ored on a 5-point scale, but the Korean version is scored on a 4-point scale from strongly dis agree (1) to strongly ag ree (4).	
MSSS (MacArthur Scal e of Subjective S ocial Status)	This is a ten-point sc ale using a ladder m odel that measures s ubjective social statu s. The subject is ask ed to consider the la dder as a social struc ture and mark his/he r social position. This consists of two su b-categories.	1. *Traditional social status*: my position in social structure 2. *Community social status:* my position in my surroundings  Mark your position on a ladder.
LES (Life Experience s Survey)	This is a self-report qu estionnaire that measur es positive and negativ e experiences of the las t year and their influen ce. It was developed by Sarason et al.(Sarason, Johnson, & Siegel, 19 78), and was translated to and standardized fo r Korean(Lee, 1993). P articipants are asked to indicate whether they experienced 57 events, and, if so, to additiona lly rate those experienc es on a 7-point scale fr om -3 (very bad) to 3 (very good). It takes ab out 10 minutes to comp lete.	1. *Positive frequency:* frequency of experiencing positive events 2. *Positive severity*: sum of scores on positive events 3. *Negative frequency:* frequency of experiencing negative events 4. *Negative severity*: sum of scores on negative events
WHOQOL (World Health O rganization Qual ity of Life – BR EF)	This is the Korean v ersion of the WHOQ OL-brief (Min, Lee, Kim, Suh, & Kim, 2 000), which consists	1. *Physical health*: quality of life in physical health 2. *Social relationships*: quality of life in social relationship

Questionnaires	Descriptions	Measures
	of 26 items, each rated on a 5-point scale (1, not at all; 2, a little; 3, a moderate amount; 4, very much; 5, an extreme amount). It has 3 sub-categories.	3. *Environmental*: quality of life in environmental factors
IRI (Interpersonal Reactivity Index)	This questionnaire measures empathy ability. It was developed by Davis(Davis, 1980) and translated into Korean(S. Park, 1994). It has 4 sub-scales and consists of 28 items, each scored on a 5-point scale (from "does not describe me well" to "describes me very well").	1. *Perspective taking*: tendency to put oneself in others' positions 2. *Fantasy*: tendency to take the feelings and actions of virtual characters, such as characters in movies, as one's own 3. *Empathic concern*: tendency to have feelings or interests toward others, such as warmth, sympathy, and compassion 4. *Personal distress*: tendency to feel uncomfortable and feel pain when seeing the unhappiness and suffering of others
ULS (UCLA Loneliness Scale)	This is a self-report questionnaire that measures subjective loneliness and social isolation, and was developed by Russell and colleagues(Russell, Peplau, & Cutrona, 1980). It consists of 20 items, each rated on a 4-point scale.	This has no sub-categories. *Example of an item:* "I feel left out." 1. Never, 2. Rarely, 3. Sometimes, 4. Often

Table 2. Clinical problems category

Questionnaires	Descriptions	Measures
STAI (State-Trait Anxiety Inventory)	This was developed by Spielberger and colleagues(Spielberger & Gorsuch, 1983), and measures anxiety in normal adults. It is a self-report questionnaire consisting of 20 items that assess state anxiety and 20 items that measure trait anxiety. Items are rated on a 4-point scale from "almost never" to "almost always".	1. *State anxiety*: Undesirable short-lived feelings in specific situations 2. *Trait anxiety:* Undesirable long-lasing feelings in general situations
SCID-II (Structured Clinical Interview Schedule for DSM-IV Axis-II Disorder)	This is used to diagnose psychological personality disorders(First, Benjamin, Gibbon, Spitzer, & Williams, 1997). It has been used to diagnose the Axis-II diseases in the DSM-lV system. Participants answer "yes" or "no" to a total of 119 items, each of which describes a certain experience or behavior under a certain situation. It has 12 sub-categories.	1. *Avoidant*: A personality characterized by avoiding people since they are afraid of being rejected by others 2. *Dependent*: A personality characterized by being extremely dependent on others 3. *Obsessive-compulsive*: A personality characterized by being tied up with orderliness, rules, and the details of things 4. *Passive-aggressive*: A personality characterized by showing hostility or aggression in a passive way without direct expression 5. *Depressive*: A personality characterized by depressed mood, a lack of motivation, interest, and mental activity, irritability, loss of appetite, insomnia, constant sadness, and anxiety 6. *Paranoid*: A personality characterized by consistently having doubts of being betrayed by others or of

Questionnaires	Descriptions	Measures
		being harmed by surroundings 7. *Schizotypal*: A personality characterized by social isolation, magical thinking, impaired consciousness, relationship delusions, and hallucinations 8. *Schizoid*: A personality characterized by no interest in social relationships (to be alone) 9. *Histrionic*: A personality characterized by extremely dramatic and exaggerated behavior and excitability to attract attention 10. *Narcissistic*: A personality characterized by exhibiting an extremely high self-importance or an excessive need for admiration 11. *Borderline*: A personality characterized by unstable fluctuations in emotion, behavior, and interpersonal relationships 12. *Antisocial*: A personality characterized by ignoring other people's rights and feelings
SSI-Beck (Beck Scale for Suicidal Ideation)	This was originally developed by Beck, Kovacs, and Weissman(Beck, Kovacs, & Weissman, 1979), and measures suicidal ideation during a clinician's interview. Shin and colleagues(K. B. Park & Shin, 1991) modified this to a self-report assessment (Cronbach's alpha = 0.8), which was adopted in the present	It has no sub-categories. *Example of an item:* "Do you have a desire to live?" a. Strongly b. Weakly c. None

Questionnaires	Descriptions	Measures
	study. It consists of 19 items.	
Audit-K (Korean version of the Alcohol Use Disorder Identification Test)	This was developed by the World Health Organization (WHO) for early screening of diseases due to excessive alcohol drinking. We used the modified version of the Audit-K from Kim and colleagues(C.-G. Kim et al., 2014). It consists of 10 items.	It has no sub-categories. *Example of an item:* "How often do you drink an alcoholic beverage?" 0) never. 1) Monthly or less 2) 2–4 times a month 3) 2–3 times a week 4) 4 or more times a week
BAI (Korean - Beck Anxiety Inventory)	This is a self-report questionnaire that measures anxiety symptoms. It consists of 21 items, and each item is rated on a 4-point scale from "not at all" to "severely".	It has no sub-categories. *Example of an item:* "Feeling hot."
BDI (Korean - Beck Depression Inventory)	This is a self-report questionnaire that measures depression symptoms. It consists of 21 items, which include cognitive, emotional, motivational, and physical symptoms, and items are rated on a 4-point scale of 0 to 3.	It has no sub-categories. *Example of an item:* Sad. 0) I do not feel sad. 1) I feel sad. 2) I am sad all the time and I can't snap out of it. 3) I am so sad and unhappy that I can't stand it.
FTND (Fagerström Test for Nicotine Dependence)	This is a shortened form of Fagerström Tolerance Questionnaire, which assesses the degree of physical dependence on nicotine. It was translated and standardized in Korea(S. M. Park et al.,	It has no sub-categories. *Example of an item:* "Do you smoke more frequently in the morning?" 1) Yes; 2) No

Questionnaires	Descriptions	Measures
	2004). It consists of 6 items.	
TEMPS-A (Temperament Evaluation of Memphis, Pisa, Paris and San Diego auto-questionnaire version)	This tool measures 5 types of temperament. Participants are instructed to check whether each of the 110 items of temperament matches their own (yes/no).	1. *Depressive*: e.g., "I am a sad, unhappy person." 2. *Cyclothymic:* e.g., "My mood often changes for no reason." 3. *Hyperthymic:* e.g., "I often get many great ideas." *4. Irritable:* e.g., "When angry, I snap at people." *5. Anxious:* e.g., "I am often fearful of someone in my family coming down with a serious disease."

Table 3. Personality category

Questionnaires	Descriptions	Measures
TCI (Temperament a nd Character Inv entory)	This is a self-report qu estionnaire that measu res personality traits. I t consists of 7 sub-sca les and 240 items.	1. *Novelty seeking:* Tendency to be stimulated by potential reward cues and new or mysterious stimuli 2. *Harm avoidance*: Tendency to be excessively worried about dangerous or repelled against disgusting stimuli 3. *Reward dependence*: Tendency to respond strongly to social compensation signals 4. *Persistence:* The tendency to sustain rewarded behaviors, even without any more rewards 5. *Self-directedness:* Ability to create situations to achieve his/her own goal and values 6. *Cooperativeness*: Ability to perceive oneself as a part of society 7. *Self-transcendence*: Ability to accept and identify the universe and nature, and feel unity with them

Questionnaires	Descriptions	Measures
NEO (Revised NEO-Personality Inventory)	This is an assessment of adult personality based on the Five-Factor model. We adopted a shortened form of the NEO-personality inventory that consists of 60 items, each rated on a 5-point scale from "very false for me" to "very true for me".	1. *Neuroticism*: Tendency to have impulsive and unstable emotions and difficulties in coping with stress 2. *Extraversion*: Tendency to interact with others and attract other people's attention 3. *Openness to experience*: Tendency to exhibit a strong imagination, creativity, abundant emotion, having lots of ideas, and being artistic 4. *Agreeableness*: Tendency to help others by establishing intimate relationships and trusting others with warm feelings 5. *Conscientiousness*: Tendency to be confident, systematic, and deliberate in work processes, and to have a strong sense of responsibility
BAS/BIS (Behavioral Approach/Inhibition System)	Several theories have suggested that the Behavioral Approach System (BAS) and the Behavioral Inhibition System (BIS) are crucial for personality; the former is to make a move toward something desired, whereas the latter is to regulate aversive motivation. A Korean version, modified by Kim and Kim(K. Kim & Kim, 2001), was used in our study to measure the sensitivity of each system. It consists of 20 items, each rated on a 4-point scale from "almost never" to "almost always".	1. *BAS Drive*: e.g., "I go out of my way to get things I want." 2. *BAS Fun Seeking*: e.g., "I'm always willing to try something new if I think it will be fun." 3. BAS Reward Responsiveness: e.g., "When I'm doing well at something, I love to keep at it." 4. BIS: e.g., "I feel worried when I think I have done poorly at something important."

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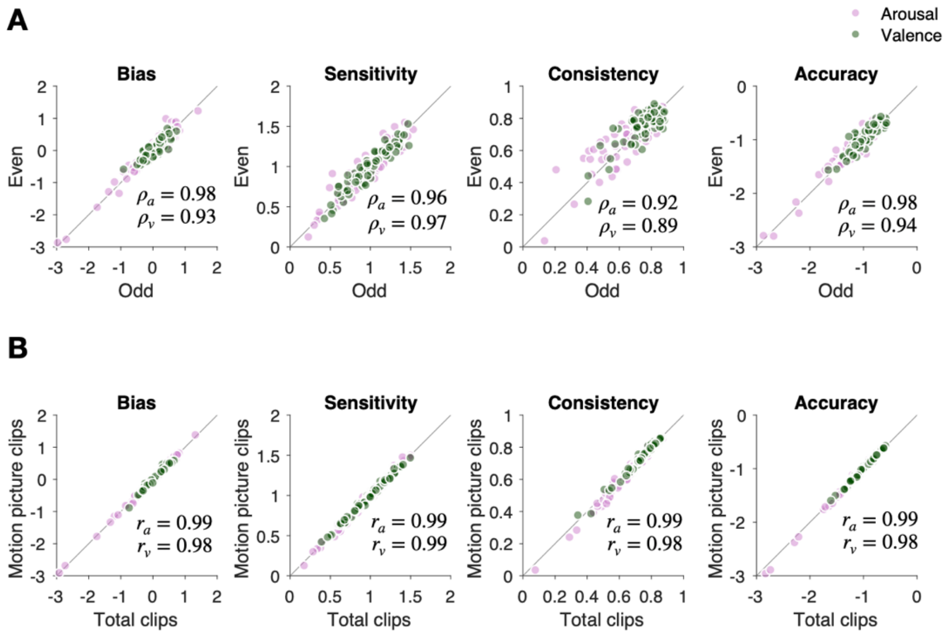
Appendix C. Reliability of affect measures over visual narrative stimuli.



(A) Split-half reliability. To evaluate how consistently visual narrative stimuli contribute to the reliable estimation of affect measures, we carried out split-half reliability tests for all of the 8 affect measures, $\{\alpha_a^i, \beta_a^i\ \delta_a^i, \sigma_a^i, \alpha_v^i, \beta_v^i, \delta_v^i, \sigma_v^i\}$. For each type, two sets of affect measures were separately estimated by calculating affect rating responses to two separate halves of visual narrative stimuli on their respective normative (i.e., across-participant averaged) responses. Here, to match the representativeness between the halved sets, the visual narrative stimuli were first sorted by affect ratings of relevance (i.e., 'arousal' (pink), 'valence' (green)) and then split into odd- and even-ranked sets. The split-half reliability was evaluated using the Spearman-Brown formula: $\rho = \frac{2r}{1+r}$, where r is the correlation coefficient between the even and odd sets. For all of the 8 types (α_a^i, α_v^i for the first panel; β_a^i, β_v^i for the second panel; δ_a^i, δ_v^i for the third panel; σ_a^i, σ_v^i for the fourth panel), the affect measures were consistent between the odd and even sets. **(B)** Reliability between the affect measures acquired with the entire VN stimuli (144 video clips) and those acquired only with the VN stimuli excerpted from affective pictures (130 video clips). The 14 non-motion-picture clips were excerpted from music videos or commercials. The reliability was evaluated by computing the Pearson correlation coefficients between the two sets. The format and arrangement were identical to those used in A.

Appendix D. List of visual narratives.

VN #	Film title	Year	Source type	Description
1	Spider-Man	2002	Movie	boys and girls laugh in the school bus
2	Marley & Me	2008	Movie	a man and his dog have a good time
3	Paris, Texas	1984	Movie	isolated man in the badlands
4	Stalker	1979	Movie	girl sitting silently in the kitchen
5	The Champ	1979	Movie	crying boy in front of lying man with gloves
6	The Piper	2015	Movie	omens in the mountain village
7	Fearless	2006	Movie	two men fight in front of a large crowd
8	Spider-Man	2002	Movie	Spiderman flies between buildings
9	Life of Pi	2012	Movie	a boy with a tiger watches an illusion of a whale
10	Fearless	2006	Movie	a man trains in martial arts alone in the meadow
11	Stand by Me	1986	Movie	a boy leaves another forever
12	Oldboy (remake)	2013	Movie	a woman driving away to leave is lonely
13	World War 2	1945 (2015)	Movie	dead bodies on the battlefield
14	Oldboy	2003	Movie	one man holds the other's tie to prevent suicide
15	Fight Club	1999	Movie	one man commits suicide in front of the other
16	Local Festival	2015	Commercial	many people dance in the club with djing
17	Kung Fu Hustle	2004	Movie	gangsters are dancing in a hall
18	A Harvey Nichols Christmas 2013	2013	Commercial	a family exchanges Christmas gifts
19	Oldboy	2003	Movie	camera chases footsteps to an empty, snowy space
20	Lorde - Royals	2014	Music Video	a man wakes up in the morning
21	Spider-Man	2002	Movie	a boy leaves his girlfriend in the cemetery
22	Gravity	2013	Movie	an astronaut loses her line and moves far away
23	The Conjouring	2013	Movie	a mother checks the bedroom because of sinister supernatural forces
24	Banlieue 13	2004	Movie	a man runs away from his enemies
25	Billy Elliot	2000	Movie	a boy bounces up and down with delight in his house

VN #	Film title	Year	Source type	Description
26	Out of Africa	1985	Movie	a little aircraft flies over the mountain
27	Andy Warhol's Empire	1964	Movie	a night-time image of the empire state building
28	Apocalypse Now	1979	Movie	a soldier with war trauma wants to commit suicide
29	Million Dollar Baby	2004	Movie	an old man leaves an almost-dead girl in the hospital
30	Carry	1976	Movie	a girl is covered in pigs blood due to another girl's malicious trick
31	Whiplash	2014	Movie	a young man plays the drums enthusiastically to impress his teacher
32	The Dark Knight	2008	Movie	batman chases the joker and bad guys are in the tunnel
33	E.T. - The Extra Terrestrial	1982	Movie	a boy and the E.T. (alien) are flying across the moon
34	Death in Venice	1971	Movie	gentle waves on the ocean
35	The Tree of Life	2011	Movie	eclipse and corona
36	Dallas Buyers Club	2013	Movie	angry sick man with his medical staff
37	Life is Beautiful	1997	Movie	very young boy wandering through ruins after the war
38	A Tale of Two Sisters	2003	Movie	a girl opens a tied bloody sack nervously
39	Magnolia	1999	Movie	speeding ambulance in the rainy road
40	Kill Bill: Vol. 1	2003	Movie	a woman fights against villains in a hall
41	Nobody knows	2004	Movie	boys and girls play happily in the playground
42	British Airways	2014	Commercial	an airplane flies across the blue sky
43	Ulysses' Gaze	1995	Movie	a boat carries a statue along the river
44	Europa Europa	1990	Movie	a soldier feels sad during the war
45	My Girl	1991	Movie	a girl is crying in front of a dead boy at a funeral
46	Epitaph	2007	Movie	a bleeding ghost near a girl on the hospital bed
47	Jaws	1975	Movie	a woman is eaten by a shark while swimming
48	Mad Max: Fury Road	2015	Movie	a woman drives her truck to escape from enemies
49	Alvin and the Chipmunks - The Road Chip	2015	Movie	chipmunks and people dance to the music
50	El Gran Azul	1988	Movie	a boy is swimming with a dolphin in the

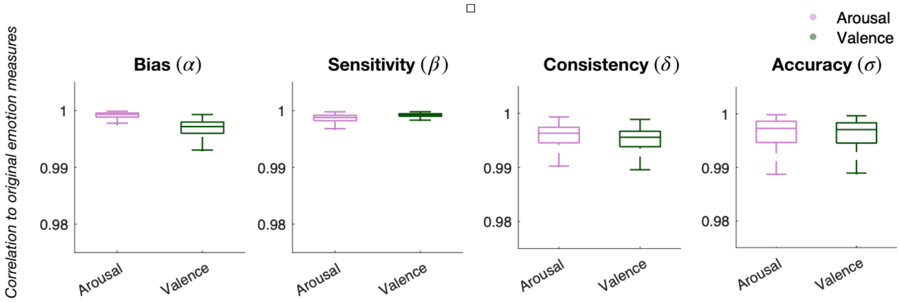
VN #	Film title	Year	Source type	Description
	(The Big Blue)			night sea
51	Nostalgia	1983	Movie	a man walks across the ruins carrying a candle
52	Full Metal Jacket	1987	Movie	a fat soldier shoots himself in front of his colleague
53	Romeo and Juliet	1996	Movie	a girl shoots herself in front of her lover's dead body
54	Misery	1990	Movie	a woman breaks a man's leg using a hammer
55	12 Angry Men	1957	Movie	two men in a serious confrontation
56	Star Wars - Return of the Jedi	1983	Movie	spaceships fight in space
57	The Wedding Singer	1998	Movie	a man singing for a woman in front of crowds on an airplane
58	Love Letter	1995	Movie	a boy and a girl build memories
59	2001: A Space Odyssey	1968	Movie	fantastic lights lead to another universe
60	The Basketball Diaries	1995	Movie	a boy fails to meet his mother in front of her house
61	Knockin' on Heaven's Door	1997	Movie	a man sends his friend to heaven on the beach
62	The Shining	1980	Movie	a man breaks the door with an axe where a woman is hiding
63	The Cure	1997	Movie	a detective chases a bad man
64	Ashes of Time	1994	Movie	two warriors fight on the beach
65	Buena Vista Social Club	1999	Movie	old musicians play their instruments happily
66	Sigur Ros - Olsen Olsen	1999	Music Video	many people wait peacefully for an outdoor live concert
67	The Cure for Insomnia	1987	Movie	a flower sways in the wind
68	Inside Llewyn Davis	2013	Movie	a musician singing in front of a fat man, but the man is bored
69	The Kid	1921	Movie	A rich man takes a child away from a poor man
70	Se7en	1995	Movie	a young detective shoots the villain's head in front of an old detective
71	Psycho	1960	Movie	an anonymous killer tries to kill a bathing woman
72	Dragon Inn	1992	Movie	a lot of Asian warriors fight in the desert
73	Campaign - Daddy for Citroen	2013	Commercial	a dad and his children have a enjoyable time
74	Aerolineas - Despegue	2013	Commercial	airplane's flight

VN #	Film title	Year	Source type	Description
75	The Life of Oharu	1952	Movie	many people walk around the town
76	Leaving Las Vegas	1995	Movie	a man is driving and drinking alcohol
77	Titanic	1997	Movie	a young man dives into the sea to save his lover
78	Vertigo	1958	Movie	a man has a nightmare about falling due to vertigo
79	Mission: Impossible	1996	Movie	a secret agent leaks special information as a espionage act
80	Terminator 2: Judgement Day	1991	Movie	motorbike chase between T-1000 and the terminator
81	Christmas in August	1998	Movie	a man and a woman have a good time
82	Raw for the Oceans - G Star	2014	Commercial	natural marine creatures
83	Wavelength	1967	Movie	a normal empty room
84	Solaris	1972	Movie	an old man walks sadly in the bush
85	Marley & Me	2008	Movie	an old dog, a member of the family, is dying
86	Omen	1976	Movie	a priest is killed by a falling spike as a curse
87	X-Men: First Class	2011	Movie	a boy meets a transforming girl
88	The Matrix	1999	Movie	two men fight on a rooftop
89	Pulp Fiction	1994	Movie	a man and a woman dance: rivalry
90	The Baraka	1992	Movie	an Asian landscape - mountains, fall, temple
91	The Tree of Life	2011	Movie	gas explodes in space
92	Maboroshi	1995	Movie	a woman sees and participates in the funeral at the beach
93	Atonement	2007	Movie	a soldier is seeing girls' dead bodies.
94	Let Me In	2010	Movie	a bully's dead head sinking next to a boy in a swimming pool
95	Skyfall	2012	Movie	a secret agent fails to shoot a villain
96	Kingsman: The Secret Service	2014	Movie	a secret agent fights against villains in a church
97	The Godfather	1972	Movie	many guests celebrate with a newly married couple at a wedding party
98	Relaxing video	2015	Ungrouped	two sheep are grazing leisurely in a meadow
99	The Tree of Life	2011	Movie	the corona shines

VN #	Film title	Year	Source type	Description
100	Sigur Ros - Rembihnutur	2012	Music Video	a weeping young woman in a house
101	Philadelphia	1993	Movie	a man says goodbye to a patient
102	The Texas Chainsaw Massacre	1974	Movie	a woman runs away from a killer and a passing truck hits him
103	Armageddon	1998	Movie	several astronauts dismantle a time bomb
104	The Fast and the Furious	2001	Movie	a man chases another man riding a motorbike
105	La Boum	1980	Movie	a boy and a girl share music with headphones
106	2014 Cannes Lions Winners	2014	Commercial	a woman jumps bed to bed high over the sky
107	Walker	2012	Movie	an ascetic monk walks very slowly down the street
108	Cast Away	2000	Movie	a distressed man makes friends through volley ball
109	Eternal Sunshine of the Spotless Mind	2004	Movie	a woman leaves her lover, but the man does not catch her
110	The Descent	2005	Movie	the women who explores caves is eaten by monsters
111	The Texas Chainsaw Massacre	2003	Movie	a woman hides behind the wall to avoid being caught by a killer
112	The Lord of the Rings: The Return of the King	2003	Movie	two armies fight against each other
113	Chungking Express	1994	Movie	a young woman dances to music in a store
114	Relaxing video	2015	Ungrouped	small and calm waves in the sea
115	Café Lumière	2003	Movie	passengers sit in the subway
116	Snowpiercer	2013	Movie	a girl and a boy put their first foot on the snow field
117	Inside Out	2015	Movie	the yellow fairy (Joy) feels sad because the purple fairy (Bing Bong) dies slowly
118	Cube	1997	Movie	a man is brutally murdered in the labyrinth
119	Scream	1996	Movie	a girl fights against a masked killer
120	Avatar	2009	Movie	an alien man flies with a dragon-like creature in the sky
121	Singin' in the Rain	1952	Movie	a man sings and dances happily in the rainy street
122	Relaxing video	2015	Ungrouped	a peaceful forest landscape

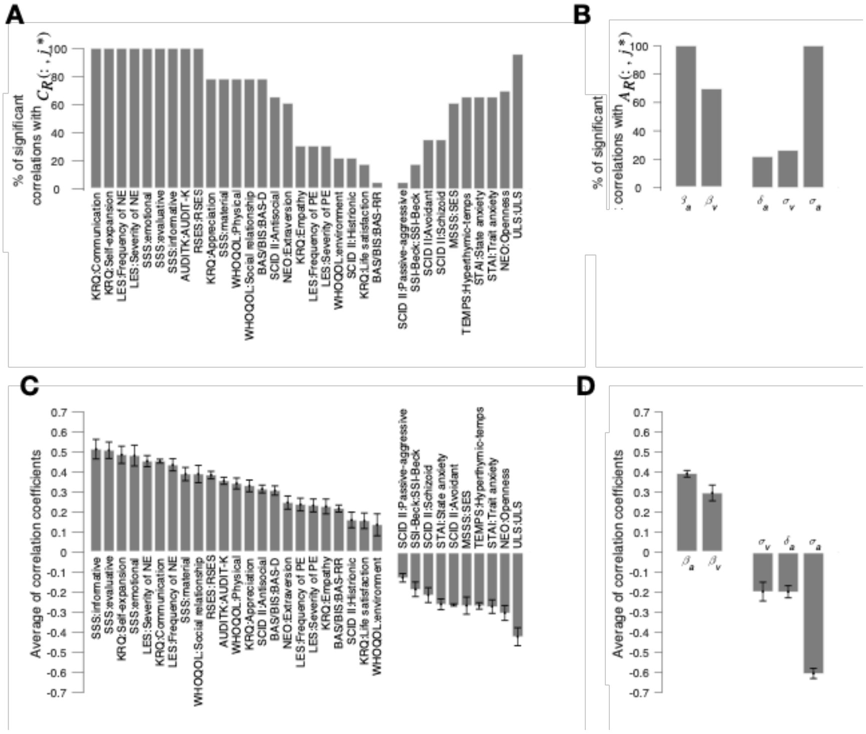
VN #	Film title	Year	Source type	Description
123	Café Lumière	2003	Movie	a man records ambient sound (environmental sound) on the train platform
124	The Shawshank Redemption	1994	Movie	an old man (Brooks) hangs himself in the house
125	Harry Porter and the Half Blood Prince	2009	Movie	boys and girls mourning their principal
126	Crimson Peak	2015	Movie	a bloody ghost threatens people in the castle
127	The Good, The Bad, and the Ugly	1966	Movie	two gunmen duel in the wilderness
128	The Avengers	2012	Movie	Iron Man and Thor fight in the dark forest
129	Mamma Mia!	2008	Movie	women in a town dance joyfully
130	Relaxing video	2015	Ungrouped	a peaceful sunset on the shore
131	The Tree of Life	2011	Movie	a floating jellyfish in the sea
132	Lost in Translation	2003	Movie	a lonely woman sees an oriental wedding in the temple
133	Interstellar	2014	Movie	a man says goodbye to an old woman in the hospital
134	Orphan	2009	Movie	a girl tries to kill another little girl in a car
135	The Hurt Locker	2008	Movie	a solider finds a bomb in the car and tries to dispose of it
136	Transformers: Revenge of the Fallen	2009	Movie	robots (Optimus Prime and villains) fight in the desert
137	Love Story	1970	Movie	two lovers play happily on the snowfield
138	The Tree of Life	2011	Movie	a woman enjoys sunlight on the beach
139	The Tree of Life	2011	Movie	marine creatures floating in the sea
140	The Mist	2007	Movie	a man is sobbing beside a car and soldiers pass by him
141	Dead Poets Society	1989	Movie	a boy shoots himself in his father's library and the father cries
142	The Cabin in the Woods	2012	Movie	terrible monsters murder solders in front of elevators
143	The Peacemaker	1997	Movie	a woman and a man try to dispose of a time bomb in a church
144	The Longest Yard	2005	Movie	two football teams have a game in the stadium

Appendix E. Invariance of affect measures to different ways of defining normative affect responses.



To investigate to what extent affect measures are affected by the different ways of defining the normative (across-participant averaged) responses, we repeated the calculation while varying the sub-population of participants that contributed to the normative responses. The size of the subgroup was fixed to 40. For each of the 8 affect measure types, the calculation was repeatedly conducted on 2,000 different pairs of normative response sets. As a result, there were 8 sets of calculations. For each of these sets, we computed the across-participant correlations of the affect-measure scores from these samples with the original affect-measure scores and plotted the medians and ranges of correlations (α_a^i, α_v^i for the first panel; β_a^i, β_v^i for the second panel; δ_a^i, δ_v^i for the third panel; σ_a^i, σ_v^i for the fourth panel).

Appendix F. The detailed contributions of the psychological characteristics and affect-response measures to the CCA mode



(A, B) The proportion of CCAs in which given psychological-characteristics measures or affect-response measures showed a significant correlation with their corresponding CCA variates (C_{M1} or A_{M1}). There was a total of 23 different CCAs, which differed in the number of principal components that were used as input matrices. Only the measures that showed equal to or more than one significant correlation with the CCA variates are shown. **(C,D)** The across-variate averages of the correlations of the psychological characteristics or affect-response measures with their corresponding CCA variates (C_{M1} or A_{M1}). Error bars, 95% confidence interval. KRQ, Korean resilience quotient; LES, life experiences survey; SSS, Social Support Scale; AUDIT-K, Alcohol Use disorder identification test; RSES, Rosenberg self-esteem scale; WHOQOL, world health organization quality of Life; BAS/BAS, behavioral approach/inhibition system; SCID- II, structured clinical interview schedule for DSM-IV Axis-II disorder; NEO, revised NEO personality inventory; SSI-Beck, Beck scale for suicidal ideation; MSSS, MacArthur scale of subjective social status; TEMPS, temperament evaluation of Memphis, Pisa, Paris, and San Diego; STAI, state-trait Anxiety Inventory; ULS, UCLA Loneliness Scale.

Appendix G. De-confounding the CCA for the overall tendency of making extreme reports

Methods

We de-confounded the CCA for the across-participant variability in the overall (non-specific) tendency of choosing extreme reports (Naemi, Beal, & Payne, 2009) (e.g., going for 1 or 5, instead of 2 or 4, on the 5-point scale even when subjective feelings are rather moderate), as follows. First, we estimated this 'extreme response style' based on the patterns of reports shown in the NEO questionnaire. The NEO was chosen because it consists of the largest number of items (60 items) with 5-point scales and the individual items probe different aspects of personality traits so that the extremity of reports per se is unlikely to be associated with particular personality traits. Second, the extreme response style was quantified by calculating the percentage of endpoint responses (i.e., 1 or 5) over all the 60 items. Lastly, as was previously done for the socio-demographic variables, the extreme response style underwent a rank-based inverse normal transformation and then were regressed out from both C_P and A_P prior to the CCA.

Results

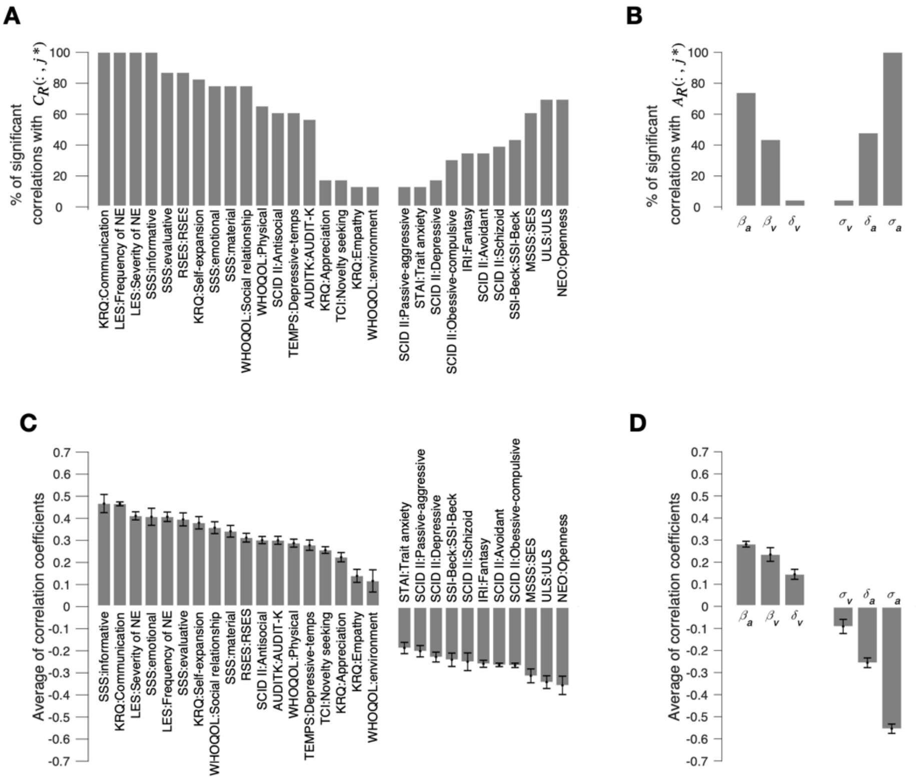


Figure 1. The results of the CCA analysis in which 'extreme response style' was regressed out. The format is identical to that used in S4 Fig. KRQ, Korean resilience quotient; LES, life experiences survey; SSS, Social Support Scale; RSES, Rosenberg self-esteem scale; WHOQOL, world health organization quality of Life; SCID- II, structured clinical interview schedule for DSM-IV Axis-II disorder; TEMPS, temperament evaluation of Memphis, Pisa, Paris, and San Diego; AUDIT-K, Alcohol Use disorder identification test; TCI, temperament and character inventory; STAI, state-trait Anxiety Inventory; SSI-Beck, Beck scale for suicidal ideation; IRI, interpersonal reactivity index; MSSS, MacArthur scale of subjective social status; ULS, UCLA Loneliness Scale; NEO, revised NEO personality inventory.

Reference

Naemi, B. D., Beal, D. J., & Payne, S. C. (2009). Personality Predictors of Extreme Response Style. *Journal of Personality, 77*(1), 261-286.

초 록

사람들은 종종 같은 상황에 대해서도 다른 감정 상태를 경험합니다. 이러한 차이가 개인마다 동일한 사건을 다르게 이해하고 행동하게끔 합니다. 그러므로 인간 행동을 포괄적으로 이해하기 위해서는 감정 반응의 개인간 변동성에 기여하는 원인이 무엇인지 규명하는 것이 중요합니다. 이에 본 논문에서는 개인의 심리적 특성과 뇌활동에서 그 근원을 찾아보았습니다. 특히 본 연구에서는 우리 일상에서 쉽게 접할 수 있고 미묘한 개인차 감정 반응을 유도할 수 있는 시각 내러티브 자극에 대한 정서 반응(정서가 및 각성도)에 집중하였습니다. 그리고 감정 반응에 대한 개인의 변동성과 심리적 특징 및 뇌 활성화와의 관련성을 탐구하였습니다. 첫번째 연구에서는 동일한 집단 (86명의 학부생)의 참가자들로부터 감정 반응(8개 측정치)과 심리적 특성(68개 측정치) 영역 모두에서 고차원 데이터를 얻어 주성분 분석 및 정준상관분석을 수행하였습니다. 감정 반응의 개인차를 나타내는 측정치는 시각 내러티브 자극에 대한 평균 반응 대해 각 개인의 반응을 회귀 분석 하여 정의하였습니다. 그리고, 심리 특성 데이터는 성격, 심리사회적 요인, 그리고 임상적 문제 분류를 기반으로 한 19개의 서로 다른 심리 측정 설문지를 통해 얻었습니다. 이렇게 얻어진 두 영역의 데이터를 정준 상관 분석하여 감정의 각성 측면의 '정확도'와 '민감도'가 심리사회적 요인과 강력하게 연관되어 있음을 발견하였습니다. 이러한 발견은 심리적 특징 중 사회적 자산 요인이 시각 내러티브에 대한 각성도 반응의 개인차와의 밀접한 연관성을 가지고 있음을 나타냅니다. 두번째 연구에서는 앞선 연구에서 사용한 시각 내러티브 자극을 이용하여 실험 자극을 만들고 이를 보는 동안 참가자들의 뇌활동을 기능적자기공명영상으로 측정하였습니다. 측정된 뇌영상 이미지에서 평균 감정 반응에 따라 변화하는 뇌영역을 찾기 위해 매개 변수 조절 분석을 하였고, 이 중 감정 반응의 개인차와 연관된 영역을 찾기 위해 참가자 간 표현 유사성 분석을 진행했습니다. 분석 결과, 개인간 감정 반응의 유사성은 *안나-카레니나* 구조 중 하나를 나타냈는데, 즉, 대다수 감정 반응이 평균에 가까운 사

람들은 유사성이 크게 나타나고, 소수의 개인들은 평균 감정 반응과 거리가 먼 반응을 하고 유사성도 떨어짐을 확인할 수 있었습니다. 그리고 시각 내러티브에 대한 기능적 자기공명영상 반응 패턴 중 우측 섬엽에서 시각 내러티브에 대한 정서가 반응에서 보이는 *안나-카레니나 구조*와 밀접한 관련성을 나타내는 것을 발견했습니다. 이것은 섬엽이 시각 내러티브에 대한 정서가 반응의 개인차 변동성과 관련된 영역임을 나타냅니다. 본 학위 논문 연구의 발견을 요약하면, 심리적 특성에서는 심리적 사회 자산이 시각 내러티브에 대한 양극화된 각성 반응의 개인간 변동성에 영향을 주는 주요 요인이었고, 뇌신경 활동에서는 정서가와 관련을 보이는 우측 섬엽이 시각 내러티브에 대한 참가자간 정서가 반응의 유사성과의 관련성을 보이는 주요 요인임을 발견하였습니다.

주요어: 감정 처리 과정, 시각 내러티브, 개인차, 심리적 특징, 기능적 자기공명영상, 참가자간 표현 유사성 분석
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