If you're happy and you know it:
Neural correlates of self-evaluated psychological health and well-being

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Number of words: 4966

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Positionality statement

In acknowledgement that our identities influence our approach to science (Roberts et al., 2020) we wish to provide the reader with information about our backgrounds. At the time this manuscript was drafted, one author self-identified as an Iranian-American man of color, one author self-identified as a White, cisgendered, heterosexual woman, and one author self-identified as a White, cisgendered, heterosexual woman who is a first-generation scholar and second-generation American. These identities, in combination with our experiences living in and receiving training in psychological science in the United States of America, have shaped our conceptualizations of psychological health and well-being, belonging, and social capital in late adolescents' transition to college.

Abstract

Psychological health and well-being has important implications for individual and societal thriving. Research underscores the subjective nature of well-being, but how do individuals intuit this subjective sense of well-being in the moment? This preregistered study addresses this question by examining the neural correlates of self-evaluated psychological health and their dynamic relationship with trial-level evaluations. Participants ($N = 105$) completed a self-evaluation task and made judgments about three facets of psychological health and positive functioning—well-being, ill-being, and social connectedness. Consistent with preregistered hypotheses, self-evaluation elicited activity in the default mode network, and there was strong spatial overlap among constructs. Trial-level analyses assessed whether and how activity in *a priori* regions of interest—pgACC, vmPFC, and VS—were related to subjective evaluations. These regions explained additional variance in whether participants endorsed or rejected items but were differentially related to evaluations. Stronger activity in pgACC was associated with a higher probability of endorsement across constructs, whereas stronger activity in vmPFC was associated with a higher probability of endorsing ill-being items, but a lower probability of endorsing well-being and social items. These results add nuance to neurocognitive accounts of self-evaluation and extend our understanding of the neurobiological basis of subjective psychological health and well-being.

Keywords: positive neuroscience, self-reflection wellness, social connectedness, vmPFC, pgACC

Much of our day-to-day lives is oriented toward being well. Importantly, research suggests that a more complete picture of psychological health includes not only the absence of disease and illness (World Health Organization, 1948), but also positive psychological functioning. Across many facets of life, the prospect of feeling good and functioning well is associated with broadly desirable outcomes—from higher wages (Diener, 2000; Staw, Sutton, & Pelled, 1994) and community engagement (Helliwell, 2006; Helliwell & Putnam, 2004), to lower divorce rates (Waite, 1995) and better health outcomes (Brand et al., 2010; Haar & Roche, 2010; Chida & Steptoe, 2008; Lyubomirsky, King, & Diener, 2005; Zilioli, Slatcher, Ong, & Gruenewald, 2015; Boyle, Buchman, Barnes, & Bennett, 2010; Boyle et al., 2012). Despite continued debate about what constitutes the “good life” or well-being, there is relative agreement that a person’s psychological health depends on their own *subjective* evaluation (Diener, Lucas, et al., 2018). But how do individuals intuit this subjective sense of well-being in the moment? Leveraging functional magnetic resonance imaging (fMRI) to address this question in a sample of late adolescents, this preregistered study examines the neural underpinnings of evaluating one’s own well-being and how these neural responses are dynamically related to perceptions of well-being in the moment.

Multifaceted nature of well-being

Research suggests that ill-being and well-being are related, but distinct phenomena (e.g., Headey, Kelley, & Wearing, 1993; Keyes & Ryff, 2003; Suldo & Shaffer, 2008). For example, longitudinal evidence suggests that while older adults experience lower levels of mental illness (e.g., depression, anxiety) than younger adults, these groups do not differ in level of well-being (Westerhof & Keyes, 2010). Among those with mental illness, variability in psychological functioning may be related to differences in well-being (Keyes, 2005). Additional evidence for

the dissociability of well-being and ill-being comes from physiological research indicating that the association between well-being and a given neuroendocrine or cardiovascular biomarker are generally not accompanied by significant, inverse associations between that same biomarker and ill-being (or vice versa; Ryff et al., 2006). Across the lifespan, another unique predictor of psychological health is a sense of social connectedness (Keyes, 1998; Larson, 1993, 1996). Indeed, perceived social support mitigates the effects of negative life events on well-being (Diener, Diener, et al., 2018). In adults, marital satisfaction has been shown to buffer against day-to-day fluctuations in happiness more than time spent with others (Waldinger & Schulz, 2010). Social connectedness is similarly critical for well-being during adolescence. Self-reported social support is associated with greater life satisfaction (Suldo & Huebner, 2004), and longitudinally, adolescents' satisfaction of relatedness needs are associated with later improvements in quality of life (Gillison et al., 2008). Taken together, these findings suggest that a complete model of psychological health is one that includes well-being, ill-being, and social connectedness as unique facets.

Neuroscience of psychological health and self-evaluation

Given the strong connection between well-being and physical health, researchers have become increasingly interested in the neural correlates of well-being. This line of inquiry has focused primarily on how individual differences in self-reported well-being are related to measures of structural anatomy or resting state functional connectivity (Kong et al., 2019; Kong, Hu, et al., 2015; Kong, Wang, et al., 2015; Lewis et al., 2014; Luo et al., 2016, 2017; Maeda et al., 2021; Sato et al., 2015; Shi et al., 2018), or brain activity while processing affective stimuli (Heller et al., 2013; Morelli et al., 2018; Puccetti et al., 2021; van Reekum et al., 2007; Waldinger et al., 2011). However, to understand how individuals intuit their own, subjective

sense of well-being in the moment requires examination of dynamic relationships between well-being evaluations and brain activity *within-person*. Trial-level analyses in which brain signals within regions of interest (ROIs) are extracted and used to predict task-related behavior is becoming increasingly common for studying such dynamic brain-behavior relationships within-person (Barendse et al., 2020; Cosme et al., 2019; Shenhav & Karmarkar, 2019; Wilson et al., 2021).

Despite a robust body of literature on the neural correlates of self-evaluation in response to trait words, we are unaware of any studies assessing neural responses during self-evaluation of subjective psychological health. This is surprising given that the self-reflective process of evaluating one's own well-being may be directly implicated in psychological health. During self-evaluation, adults and adolescents reliably engage cortical midline structures (CMS), including perigenual anterior cingulate cortex (pgACC) and anterior rostral/ventral medial prefrontal cortex (mPFC); medial posterior parietal cortex (mPPC); and ventral striatum (VS) as well (Denny et al., 2012; Northoff & Hayes, 2011; Pfeifer & Berkman, 2018). Much of the work in this field has used relatively neutral traits, although some have used stimuli with explicitly positively or negatively valenced traits (Barendse et al., 2020; Chavez et al., 2016; Elder et al., 2022; Frewen et al., 2013; Lemogne et al., 2009) or positive and negative feedback (van Schie, Chiu, Rombouts, Heiser, & Elzinga, 2018). Further, most studies used personality traits that were sampled broadly without considering self-concept domain. Those that have assessed specific domains found differences in the degree of CMS involvement when comparing across domains (e.g., Jankowski et al., 2014; Moran et al., 2006; van der Cruisen et al., 2017, 2018), but the domains investigated vary across studies, making it difficult to identify consistencies in these results.

Nevertheless, there are general patterns described in the literature of what can be considered representational gradients—particularly within mPFC—that may help guide predictions about how an individual’s sense of subjective psychological health is constructed in the brain. Trait evaluations that are oriented more towards self and close others are typically represented more ventrally than those referencing distant others (Mitchell et al., 2005). The mPFC is also implicated in future-oriented and abstract thought, including prospection (Spreng & Grady, 2010). Subjective value is likewise represented in vmPFC (Clithero & Rangel, 2014), which may also reflect personal relevance (Doré et al., 2019; Kim & Johnson, 2015). Given that psychological health consists of multiple facets that vary in degree of sociality, abstractness, future orientation, and positive or negative affect, it is plausible that there is meaningful variation across constructs in the neural representation of an individual’s sense of subjective well-being.

The present study

Building on these findings, the goal of the current preregistered study was to investigate the neural basis for how individuals construct and access their own subjective sense of well-being in the moment. While in the MRI scanner, participants completed a self-evaluation task and made judgments about three facets of psychological health and positive functioning: well-being (positive affect, life satisfaction, competence, meaning), ill-being (anxiety, depression, anger), and social connectedness (relatedness, belonging, social support). We conducted preregistered 1) whole-brain conjunction and contrast analyses to identify the similar and distinct neural correlates of evaluating these facets of psychological health, and 2) multilevel logistic regression analyses to test whether activity in *a priori* regions of interest implicated in general self-evaluation and affective processing—pgACC, vmPFC, and VS—are dynamically associated with trial-level subjective evaluations of well-being.

Based on previous findings on the neural basis of self-referential processing, we expected to see robust activity in cortical and subcortical midline structures, including pgACC, vmPFC, and VS, during self-evaluation relative to a control condition. However, we also explored how these different constructs associated with psychological health (well-being, ill-being, and social connectedness) may be represented in both similar and distinct ways. In trial-level analyses, we expected that neural predictors would explain additional variance beyond behavior. We hypothesized that vmPFC would be related to endorsements across all constructs (well-being, ill-being, social connectedness) due to its role in valuation and decision making. Similarly, because pgACC is implicated in self-referential processing across a variety of domains, we expected that pgACC would also be related to endorsements regardless of construct. Although we did not have strong hypotheses regarding distinctive effects of VS across constructs, one possibility is that VS would track valence such that greater activity in VS is related to endorsements of well-being and social connectedness and rejections of ill-being.

Methods

Open practices statement

The analysis code and behavioral and trial-level ROI data are available in the project repository at https://github.com/dsnlab/happy_scripts. Unthresholded statistical maps for this effect and all others reported in this manuscript can be found on NeuroVault (Gorgolewski et al., 2015; <https://neurovault.org/collections/NWIKSNNW>). These analyses were preregistered <https://osf.io/x2zra>, but we deviated from this plan in several places. First, we originally planned to model item valence as a predictor, but this made interpretation of model parameter estimates challenging because only the social construct included both positive and negative items, whereas well-being included only positive items and ill-being included only negative items. To facilitate

interpretation, we reverse-coded the four negative items in the social construct so that rejections of negative items were coded as positive endorsements of social connectedness. Second, we accounted for differences in processing time between constructs by including log-transformed reaction time in the trial-level analyses. Models without reaction time are included in Supplementary Material. Third, we originally planned to conduct trial-level representational similarity analyses, but the task was not appropriately optimized for this and resulted in unstable estimates. For completeness, we report the results in Supplementary Material. Finally, we preregistered individual difference analyses but given the within-person focus of this manuscript, these are out of scope and not included here.

Participants

Participants were 113 incoming freshmen (0 non-binary, 41 men, 72 women) at the University of Oregon enrolled in a longitudinal study on health and well-being during the transition to college. Detailed information about recruitment and inclusion criteria are provided in Supplementary Material. We excluded participants if they did not comply with task instructions ($n = 4$) or have useable responses ($n = 1$), or if they had missing data due to a technical failure ($n = 1$) or exhibited excessive head motion ($n = 1$). Two participants were excluded from whole-brain analyses because they did not complete both task runs. One participant was excluded from trial-level analyses conducted in native space because we were unable to collect a T1-weighted anatomical image to create individualized regions of interest. Because the trial-level analysis could include the data from participants with a single task run, two participants excluded from the whole-brain analyses were included in this analysis in order to reduce bias. This yielded a total of 104 participants for whole-brain analyses and 105 participants for the trial-level analysis. This study was approved by the University of Oregon

Institutional Review Board; all participants gave written informed consent and were compensated for their participation. Demographic information is reported in Supplementary Material.

Self-evaluation task

While being scanned, participants completed a self-evaluation task (adapted from Moore, 2015; available online at <https://github.com/dsnlab/svc-wellbeing>), in which they alternated between making self-evaluations (“self” condition) and judging the malleability (“change” condition) of words or short phrases related to three constructs associated with psychological health and positive functioning: well-being, ill-being, and social connectedness. The stimuli were selected from a large pool of items from psychological health questionnaires using factor analysis (see Supplementary Material). Example items in each of the constructs include *happy*, *satisfied with life*, and *joyful* (well-being); *anxious*, *depressed*, and *feel worthless* (ill-being); *loved*, *feel supported*, and *cared for* (social). The full list of items for each construct can be found in the Supplementary Material. In the self condition, participants reported whether each of the stimuli described themselves; in the control (change) condition, participants reported whether each item was something that could change for people in general. The experimental task (Figure 1) was a 2×3 repeated measures factorial ANOVA design, with the following factors and levels: Instruction (self or change) and Construct (well-being, ill-being, or social).

Figure 1. Self-evaluation task design consisting of 6 alternating self and control (change) blocks per run. Each block began with a 5s instruction, followed by 6 words or phrases, each presented

for 4.7s. Each trial was followed by a jittered black screen for approximately 0.3s and a black screen was presented for 5s between blocks.

This task was administered across two runs and each run contained 36 trials. Stimuli were presented and responses were recorded in MATLAB 2017b (The MathWorks, Inc., Natick, Massachusetts, United States), using the Psychtoolbox 3 (Brainard, 1997; Kleiner et al., 2007). The task was a mixed design in which items from each construct were nested within alternating self and change blocks. Each word or phrase was presented once per run in either the self or change condition. To facilitate generalizability beyond the specific stimuli used in the task (Westfall et al., 2017), each participant saw 12 items from each construct randomly selected from a larger set of 18 items per construct. Participants responded “yes” or “no” to each item using a button box. Response keys (index or middle finger) were counterbalanced across participants. Within each run, the trial order was optimized to maximize contrast estimation using a genetic algorithm (Wager & Nichols, 2003).

Neuroimaging data acquisition and preprocessing

Neuroimaging data were acquired on a 3T Siemens Skyra scanner at the University of Oregon Lewis Center for Neuroimaging. Scan sequence information is listed in Supplementary Material. Neuroimaging data were preprocessed using fMRIPrep 1.1.4 (Esteban et al., 2019). Preprocessing details appear in Supplementary Material, but briefly, anatomical images were segmented and normalized to MNI space using FreeSurfer (Fischl, 2012); functional images were susceptibility distortion corrected, realigned, and coregistered to the normalized anatomical images. For whole-brain analyses in MNI space, preprocessed functional data were smoothed using a 6mm full-width at half maximum (FWHM) smoothing kernel; for ROI analyses in native space, images were smoothed with a 2mm FWHM smoothing kernel.

Whole-brain main effects

In first-level statistical analyses, event-related condition effects were estimated using a fixed-effects general linear model and convolving the canonical hemodynamic response function with stimulus events using SPM12 (Wellcome Department of Cognitive Neurology; <http://www.fil.ion.ucl.ac.uk/spm>). Separate regressors were entered for conditions of interest (self well-being, self ill-being, self social, change well-being, change ill-being, change social) and the duration was modeled as stimulus onset to response. Trials in which no response was made were modeled as a separate condition of no interest and each missed event was modeled as the full duration of stimulus presentation (4.7s). An additional regressor was included for the instruction period at the beginning of each block. Realignment parameters were transformed into five motion regressors, including absolute displacement from the origin in Euclidean distance and the displacement derivative for translation and rotation separately, and a single “trash” regressor for images with motion artifacts (i.e., striping) identified using automated motion assessment via the confounds file generated by fMRIPrep (Cosme et al., 2018) and visual inspection. These regressors were included as covariates of no interest. One participant was excluded from the group-level analysis for having >15% unusable volumes, which was more than 5 *SD* from the mean ($M = 1.47\%$, $SD = 2.70\%$). All data were high-pass filtered at 100 seconds and temporal autocorrelation was modeled using the FAST method (Corbin et al., 2018). Linear contrasts for each condition of interest versus rest were estimated across runs for each participant and used as inputs in second-level analyses.

The second-level main effect of self versus change was modeled as a 2×3 within subject repeated measures ANOVA using a flexible factorial model in SPM12. To correct for multiple comparisons, cluster-extent thresholding was implemented using AFNI version 18.2.04 (Cox, 1996). In accordance with recent guidelines (Cox et al., 2017), the spatial autocorrelation

function was first estimated for each subject and task run separately using AFNI's 3dFWHMx, and then averaged across subjects. To determine probability estimates of false-positive clusters given a random field of noise, Monte-Carlo simulations were conducted with AFNI's 3dClustSim using the average autocorrelation across subjects. A voxel-wise threshold of $p < .0001$ and cluster extent of $k > 42$ was estimated (voxel dimensions = 2 mm³) to achieve a whole-brain familywise error rate of $\alpha = 0.01$.

Conjunction and contrast analyses

To assess the degree of spatial overlap between the three constructs of psychological health, we compared activation maps for well-being self > well-being change, ill-being self > ill-being change, and social self > social change, separately. Because it is not possible to retrieve these contrasts from the flexible factorial model used in the self > change analysis, we generated these contrast maps using one-sample t-tests in SPM12. We then thresholded each contrast map using the same approach described above and qualitatively compared spatial representations by overlaying these images on one another. For completeness, we also conducted exploratory contrast analyses to determine the unique self > change effects of each construct with respect to the other two (e.g., [well-being self > ill-being & social self] > [well-being change > ill-being & social change]). These contrasts were extracted from the flexible factorial model.

ROI definition

We defined three *a priori* bilateral ROIs for pgACC, vmPFC, and VS (see Figure 3) using the HCP MMP 1.0 cortical parcellation atlas (Glasser et al., 2016). Further details describing the definition process are provided in Supplementary Material.

Figure 2. A priori regions of interest (ROIs) used in the similarity, trial-level, and individual difference analyses. ROIs were created using the HCP MMP 1.0 cortical parcellation atlas (Glasser et al., 2016) and FreeSurfer subcortical segmentation atlas (Fischl et al., 2002). pgACC = perigenual anterior cingulate cortex, vmPFC = ventromedial prefrontal cortex, VS = ventral striatum; these ROIs are depicted in the blue, purple, and green, respectively.

Trial-level analysis

To investigate the extent to which activity in brain regions associated with self-evaluation and affective processing (i.e., pgACC, vmPFC, VS) are related to item-level endorsements, we used multilevel logistic regression with neural data from each trial. First-level statistical analyses were conducted in native (i.e., non-normalized) space. Each trial was entered in the model as a separate regressor (rather than grouped by condition). Trial duration was specified as described in the univariate contrast analysis section, and the same motion parameter modeling procedure was adopted. The resulting statistical maps for each trial were concatenated to create a beta-series (Rissman et al., 2004). To calculate the mean BOLD signal across the voxels in each ROI, we use the 3dmaskave function in AFNI 18.2.04 (Cox, 1996). For each participant, we extracted the mean parameter estimate of BOLD signal within each ROI for each trial in the beta-series. Parameter estimates were standardized within participant and ROI to account for differences in

variability between individuals and ROIs. Outliers that were 3 *SD* from the median ($N = 324$ or 0.74% of trials) were excluded and only trials within the self condition were modeled.

We conducted multilevel logistic regression in R using the `glmer` function in the `lme4` package (Bates et al., 2015). In a series of nested models, trial-level item endorsements (yes or no) were regressed on the fixed effects of construct (well-being, ill-being, or social), ROI (pgACC, vmPFC, and VS), the interactions between construct and ROI, grand-mean centered log-transformed reaction time and the interactions between construct and reaction time. Intercepts were allowed to vary across participants. We estimated the following nested models and compared model fit using chi-square difference tests. All ROIs were included in the same model in order to assess their unique relationships with endorsements. We report parameter estimates and statistics from the best fitting model. We converted log-odds parameter estimates to marginal probabilities using the `ggeffects` package (Lüdtke, 2018) and estimated multilevel model effect sizes by calculating R^2 according to the guidelines in Lorah (2018) using the `performance` package (Lüdtke et al., 2021). To estimate descriptive correlations between ROIs and account for the nested structure of trials within participants, we calculated repeated measures correlations using the `rmcorr` package (Bakdash & Marusich, 2017).

Results

Whole-brain main effects

To investigate brain regions that were associated with self-evaluation of psychological health and well-being, we contrasted BOLD signal between the self and change conditions (see Figure 3). Consistent with prior studies on self-referential processing and self-evaluation, for self > change, we observed robust BOLD signal increases in regions within the default mode network. This included cortical midline structures, such as bilateral pgACC, sgACC, vmPFC,

medial orbitofrontal cortex (mOFC), and posterior parietal cortex (PCC); lateral cortical regions, including inferior parietal lobule (IPL) and middle temporal gyrus (MTG); and subcortical regions, such as bilateral VS and hippocampus. For change > self, we observed increased BOLD signal in regions within the frontoparietal control network, such as bilateral ventrolateral and dorsolateral prefrontal cortex, and PPC; and the salience network, including bilateral dorsal anterior cingulate cortex and anterior insula. All clusters and peak coordinates are listed in Table 1. Contrast tables were generated using BSPMVIEW (Spunt, 2016).

Figure 3. Univariate main effects for instruction. Results are thresholded at $p < .0001$ and $k = 42$. Cluster extent (k) is measured in 2 mm^3 voxels.

Table 1

Regions, MNI coordinates, cluster extent, and peak t values for the main effects of instruction

Contrast	Region	MNI Coordinates (x, y, z)			Extent (k)	Peak t
Self > Change	L Mid Orbital Gyrus	-4	60	-6	8186	15.87
	R Rectal Gyrus	8	40	-10	8186	12.94
	L Olfactory cortex	-4	16	-6	8186	11.23
	L Precuneus	-6	-64	20	11730	12.12
	L Calcarine Gyrus	-2	-86	-6	11730	10.11
	R Lingual Gyrus	16	-100	-2	11730	6.91
	L Lingual Gyrus	-16	-90	-10	11730	3.98
	L Rolandic Operculum	-44	-4	16	2656	6.84
	L Precentral Gyrus	-40	-18	58	2656	6.76
	L Postcentral Gyrus	-60	-20	26	2656	6.32

	L Hippocampus	-24	-22	-14	520	6.33
	L Inferior Temporal Gyrus	-44	-24	-20	520	5.13
	L Parahippocampal Gyrus	-24	-6	-28	520	4.01
	R IFG (pars Orbitalis)	26	16	-20	76	6.29
	R Superior Temporal Gyrus	66	-34	26	754	6.27
	L MCC	-6	-6	50	527	6.22
	R Hippocampus	26	-18	-14	303	6.17
	R Parahippocampal Gyrus	38	-44	0	303	4.70
	L Middle Temporal Gyrus	-64	-10	-12	272	6.15
	R Middle Temporal Gyrus	60	-6	-14	127	5.75
	R Precentral Gyrus	56	4	38	71	5.65
	L IFG (pars Orbitalis)	-40	30	-16	124	5.59
	L Superior Frontal Gyrus	-18	38	36	128	5.08
	R Insula Lobe	44	0	16	62	4.96
	R Posterior-Medial Frontal	6	-4	60	49	4.79
	L Middle Occipital Gyrus	-42	-78	32	64	4.75
	R Superior Temporal Gyrus	48	-28	-2	89	4.44
<i>Change > Self</i>	R Middle Temporal Gyrus	72	-28	-14	848	3.95
	L Inferior Parietal Lobule	-52	-52	54	2215	14.89
	L Superior Parietal Lobule	-26	-72	62	2215	4.48
	L Angular Gyrus	-60	-64	30	2215	4.35
	L Middle Orbital Gyrus	-46	54	-4	4652	13.78
	L Middle Frontal Gyrus	-46	28	40	4652	10.56
	L Middle Frontal Gyrus	-30	18	62	4652	9.93
	R Inferior Parietal Lobule	48	-52	54	1821	13.01
	R Middle Orbital Gyrus	44	56	-2	5918	12.59
	R Middle Frontal Gyrus	46	24	46	5918	12.14
	R Medial Frontal Gyrus	22	50	-16	5918	6.82
	L Superior Medial Gyrus	0	34	44	1483	10.58
	L Posterior Medial Frontal	-4	16	52	1483	8.22
	L Inferior Temporal Gyrus	-62	-42	-20	1040	9.62
	R IFG (pars Orbitalis)	32	28	-2	297	9.06
	L Precuneus	-6	-72	48	685	8.14
	L IFG (pars Orbitalis)	-32	26	-4	153	7.96
	R Cerebellum (Crus 2)	10	-82	-26	87	7.00
	R Inferior Temporal Gyrus	68	-30	-20	848	6.72
	R Middle Temporal Gyrus	66	-44	-2	848	4.56
	L Cerebellum (Crus 2)	-12	-82	-26	110	6.50
	L Superior Frontal Gyrus	-18	50	-20	179	6.31
	R Cerebellum (Crus 1)	30	-64	-32	204	6.19
	R Cerebellum (Crus 2)	42	-76	-46	366	6.15
	R Superior Orbital Gyrus	12	14	-18	90	5.98
	L Cerebellum (Crus 2)	-40	-76	-48	240	5.83
	L PCC	-6	-30	26	68	4.92

Note. Cluster family-wise error correction for $\alpha = 0.01$ and $p < .0001$ is $k = 42$. Cluster extent (k) is measured in $2 \times 2 \times 2$ mm voxels.

Conjunction and contrast analyses

We assessed spatial similarity among psychological health constructs for the self > change contrast by conducting a statistical conjunction analysis, interpreted qualitatively via visualization in Figure 4A. On the whole, we observed strong spatial overlap among constructs within core regions involved in self-evaluation, such as pgACC, sgACC, vmPFC, mOFC, PCC, and VS. Ill-being items were associated with expansion of spatial extent into more dorsal aspects of mPFC, as well as the presence of additional clusters of activation in regions such as left inferior frontal gyrus, bilateral mid cingulate cortex, and right middle temporal gyrus, fusiform gyrus, and temporal parietal junction. However, exploratory contrasts revealed that only the clusters in left inferior frontal gyrus and right middle temporal gyrus were actually unique to ill-being (Figure 4B). For social items, activation extended into more anterior and ventral regions in mPFC and more dorsal regions in PCC and precuneus, and was associated with additional clusters of activation in left middle temporal gyrus and anterior temporal cortex. The clusters in anterior mPFC, left middle temporal gyrus, and precuneus were unique to social items. Clusters of activation associated with well-being items showed expanded spatial extent in left posterior insula and postcentral gyrus, and right hippocampus, but these were not unique to well-being.

Figure 4. Conjunction and contrast analyses. A) Conjunction analysis for self > change within each construct separately. B) Contrasts for the interaction between self > change and each construct > the average of the other two. No clusters survived thresholding for well-being > ill-being & social. Contrasts were thresholded at $p < .0001$, $k = 42$ (voxels are 2 x 2 x 2mm).

Trial-level analysis

We used multilevel logistic regression to investigate the degree to which psychological health construct (well-being, ill-being, social) and mean BOLD signal in *a priori* ROIs—pgACC, vmPFC, and VS—was associated with whether participants answered yes or no to each item in the self-evaluation task. ROI descriptive statistics are reported in Table 2. We tested a

series of nested models to determine whether adding neural predictors explained additional variance beyond a base model, which included construct (well-being, ill-being, social), log-transformed reaction time, and their interaction. As expected, the best fitting model was the ROI interaction model, which included the ROIs and their interactions with construct (Table 3). This model fit the observed data well ($R^2 = .53$).

Table 2

Means, Standard Deviation, and Repeated Measures Correlations Among ROIs

ROI	<i>M</i>	<i>SD</i>	1	2	3
1. pgACC	0.04	1.03	–		
2. vmPFC	0.15	1.02	0.84 [0.83, 0.85]	–	
3. VS	0.21	1.03	0.41 [0.39, 0.45]	0.45 [0.43, 0.48]	–

Note. N = 3,694 trials in the self condition. All correlations are statistically significant, $p < .001$. 95% confidence intervals are bracketed. Correlations adjust for trials nested within participant using multilevel modeling ($df = 3,588$).

Table 3

Model Comparison of Trial-Level Models

	AIC	BIC	χ^2	<i>df</i>	<i>p</i>
Base model	3113.82	3157.32	–	–	–
ROI model	3100.49	3162.63	19.34	3	< .001
ROI interaction model	3082.28	3181.71	30.21	6	< .001

As expected, there was a high probability of endorsing positively valenced well-being (marginal $P = .90$, 95% CI [.88, .92]) and social connectedness items (marginal $P = .91$, 95% CI [.88, .93]), and a low probability of endorsing negatively valenced ill-being items (marginal $P = .27$, 95% CI [.24, .30]). Greater than average pgACC activity (i.e., a 1 *SD* increase) was associated with a higher probability of endorsing well-being (marginal $P = .93$, 95% CI [.90, .96]), social items (marginal $P = .94$, 95% CI [.91, .96]), and ill-being items (marginal $P = .28$, 95% CI [.22, .34]), though this relationship was weaker for ill-being items. In contrast, greater than average vmPFC activity was associated with a higher probability of endorsing ill-being items (marginal $P = .33$, 95% CI [.27, .39]), but with a lower probability of endorsing well-being (marginal $P = .87$, 95% CI [.82, .91]) and social items (marginal $P = .85$, 95% CI [.80, .89]).

Greater than average VS activity was associated with directional increases in the probability of endorsing well-being (marginal $P = .91$, 95% CI [.88, .93]) and social items (marginal $P = .91$, 95% CI [.88, .93]), and decreases for ill-being items (marginal $P = .26$, 95% CI [.22, .30]), but these relationships were not statistically significant. Log-odds and statistics for all parameters in the model are included in Table 4.

Figure 5. Predicted probabilities from the ROI interaction model as a function of construct. Individual points are the predicted probabilities for each trial observation. pgACC = perigenual anterior cingulate cortex, vmPFC = ventromedial prefrontal cortex, VS = ventral striatum.

Table 4

Parameter Estimates and Statistics for the Model Including Log-Transformed Reaction Time

Parameter	b	z	p
Intercept (well-being)	1.89 [1.68, 2.11]	16.93	< .001
RT	-3.16 [-3.74, -2.57]	10.52	< .001
Construct (ill-being)	-2.95 [-3.20, -2.70]	23.58	< .001
Construct (social)	0.09 [-0.20, 0.37]	0.59	.552
pgACC	0.45 [0.08, 0.82]	2.37	.018

vmPFC	-0.39 [-0.76, -0.02]	2.09	.037
VS	0.11 [-0.11, 0.33]	0.98	.328
RT x Construct (ill-being)	3.16 [2.46, 3.86]	8.89	< .001
RT x Construct (social)	-0.03 [-0.82, 0.75]	0.08	.935
Construct (ill-being) x pgACC	-0.39 [-0.83, 0.05]	1.73	.083
Construct (social) x pgACC	0.07 [-0.44, 0.57]	0.26	.792
Construct (ill-being) x vmPFC	0.76 [0.32, 1.20]	3.35	< .001
Construct (social) x vmPFC	-0.23 [-0.75, 0.29]	0.88	.381
Construct (ill-being) x VS	-0.18 [-0.45, 0.09]	1.32	.187
Construct (social) x VS	-0.04 [-0.34, 0.27]	0.24	.811

Note. Parameter estimates (*b*) are log-odds. RTs were grand-mean centered and units are in seconds. Neural ROI parameter estimates were standardized within participant and ROI to preserve individual differences and are therefore not *Z*-scores.

Discussion

Psychological health and well-being has important implications for individual and societal thriving. Research underscores the subjective nature of well-being, but how do individuals intuit this subjective sense of well-being in the moment? This preregistered study addressed this question by examining the neural correlates of self-evaluated psychological health and their dynamic relationship with trial-level evaluations of well-being. We focused on three constructs related to psychological health—well-being, ill-being, and social connectedness. We observed robust activity in cortical and subcortical midline structures during self-evaluation relative to the control condition. The spatial profiles of the constructs were largely overlapping, though evaluating ill-being was associated with relatively greater activity in the salience and frontoparietal networks. Trial-level analyses assessed whether and how activity in brain regions associated with affect and self-referential processing were related to subjective evaluations. Trial-specific neural activity in pgACC, vmPFC, and VS explained additional variance in whether participants endorsed or rejected items, and activity in pgACC and vmPFC was differentially related to endorsements on a trial-by-trial basis. Specifically, stronger activity in pgACC was associated with a higher probability of endorsement across constructs, whereas stronger activity in vmPFC was associated with a higher probability of endorsing ill-being items,

but a lower probability of endorsing well-being and social items. Together, these results suggest that subjective sense of well-being is intuited using the same neural architecture underlying other forms of self-referential processing, but highlight the differential roles of pgACC and vmPFC.

Given the robust body of research on the neural correlates of self-referential processing, we had strong predictions that compared to the control condition, self-evaluation of psychological health would elicit increased neural activity in cortical and subcortical midline structures. In line with this prediction, participants showed relatively greater BOLD signal in bilateral pgACC, sgACC, vmPFC, mOFC, PCC, and VS. In this well-powered sample, we also observed increased activity in bilateral hippocampus, and lateral cortical areas, including MTG and IPL. These results are consistent with prior self-evaluation studies in adolescents using a mix of positively and negatively valenced words or phrases as stimuli (Elder et al., 2022; Jankowski et al., 2014; Pfeifer et al., 2013; van der Crujsen et al., 2018). Although these patterns were relatively consistent across psychological health constructs, the spatial conjunction analysis showed that ill-being items were associated with more dorsal extension of activation in the mPFC, whereas social items elicited more ventral extension of responses in mPFC. In addition, exploratory construct contrasts revealed relatively greater activation in the salience and frontoparietal networks for ill-being items, potentially reflecting differences in valence (Frewen et al., 2013; van Schie et al., 2018), or indicating greater conflict or cognitive control demands (Botvinick et al., 2004).

Extending these whole-brain analyses, we examined how specific *a priori* brain regions associated with self-evaluation and affective processing (pgACC, vmPFC, VS) were dynamically related to subjective evaluations of well-being. Despite not having strong predictions about the role of VS in self-evaluation, we reasoned that due to its role in affective processing, VS might

track with item valence and found directional (but not statistically significant) evidence for this. We expected that both pgACC and vmPFC would track evaluations on a trial-by-trial basis. Greater than average pgACC activity was associated with an increased probability of responding yes across all psychological health constructs. In contrast, while vmPFC also tracked responses, greater than average vmPFC was associated with a higher probability of endorsing ill-being items, but a lower probability of endorsing well-being and social items (i.e., a higher probability of rejecting them). These results are consistent with previous findings that activity in vmPFC predicts choices on a trial-by-trial basis (Barendse et al., 2020; Cosme et al., 2019; Engelmann, Meyer, Fehr, & Ruff, 2015; Shenhav & Karmarkar, 2019; Wilson et al., 2021), and that stronger activity in pgACC and vmPFC is associated with a higher probability of endorsing negatively valenced traits as self-descriptive (Barendse et al., 2020). However, the pattern of results in vmPFC—that is, a higher probability of endorsing negative ill-being items and rejecting positive well-being and social items—suggests it’s uniquely involved in evaluations that go “against the grain.” This dovetails with recent work describing a network-based model of self-concept structure showing that greater vmPFC activity is negatively associated with a measure (outdegree centrality) implicated in favorable and coherent self-evaluations (Elder et al., 2022).

Overall, these results are consistent with the hypothesis that pgACC and vmPFC are not only engaged during self-reflection, but also play a direct role in evaluation (Barendse et al., 2020; Shenhav & Karmarkar, 2019) and the construction of individuals’ subjective sense of psychological health and well-being. Their roles are complementary but distinctive. Prior work on the neural correlates of self-referential processing that were not powered for such granular assessment on a trial-by-trial basis (e.g., due to small samples or collapsing across trials in univariate analyses) have tended to view these frontal midline components as relatively

interchangeable, but this study reveals the nuance in how this network collectively supports intuitive access to a subjective sense of well-being at a given moment.

Limitations and future directions

Despite notable strengths, such as extending self-evaluation beyond traits to examine personal psychological health and assessing trial-level relationships between the brain and behavior, these results should be considered in light of several limitations. First, the sample consisted solely of incoming college freshmen. Although these results are consistent with findings from a sample of 10-13 year old adolescents (Barendse et al., 2020), future studies should examine these relationships with a broader age range and more diverse, non-college samples. Second, the task design prohibited us from examining the unique relationships between psychological health constructs and valence as preregistered.

Finally and critically, this study was conceptualized within a relatively White, Western, and individualistic framework of psychological health that assumes universality (Christopher & Hickinbottom, 2008), but neglects systemic factors that have historically excluded specific groups, such as enslaved Africans and their descendants, and continue to limit and shape opportunities for well-being. In fact, some scholars have argued that psychological health as a construct is fundamentally anti-Black (Patterson, 1982). We recognize the role that psychological science has played in pathologizing, oppressing, and incarcerating Black and other racially minoritized people (see American Psychological Association, n.d.; Auguste et al., 2022). Therefore, we urge researchers to critically interrogate predominant models of psychological health and well-being, and incorporate a broader range of perspectives that acknowledge these historical and cultural contexts (e.g., Christopher & Howe, 2014; Dudgeon, 2020; Johnson & Carter, 2020; Mosley et al., 2020).

Conclusions

A complete picture of whether someone is “doing well” includes more than merely the absence of mental illness, but also positive functioning and social connectedness. The present study extended current methods for studying the neurobiological basis of psychological health and well-being by examining the neural correlates of self-evaluated psychological health and their dynamic relationship with trial-level evaluations of well-being. Overall, our results indicated strong consistency across constructs in the network of brain regions engaged by self-reflection and suggest that pgACC and vmPFC play direct yet distinct roles in subjective evaluation.

Acknowledgements

This work was supported by R21 DA043015 (PI: Pfeifer) and F31 CA232357 (PI: Cosme). We thank Garrett Ross for thoughtful, critical feedback on the manuscript, and for essential assistance with recruitment, data collection, and project management. We also thank John Flournoy for assistance with the factor analysis, Dagmar Zeithamova for methodological consultation, Elliot Berkman for insightful feedback while preparing the manuscript, and the Lewis Center for Neuroimaging for facilitating our ability to scan over 100 incoming freshmen in 10 weeks.

Author contribution statement

DC, AM, and JHP designed the study. DC and AM collected the data. DC analyzed the data. DC and AM wrote the manuscript, and JHP provided critical feedback on it.

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Supplementary material

If you're happy and you know it:
Neural correlates of self-evaluated psychological health and well-being

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Participant recruitment and inclusion criteria

Participants indicated interest in participating in this paid research study while registering for summer orientation, and were subsequently contacted and screened for eligibility. Participants were eligible if they were incoming freshmen between 17-19 years old, right-handed, had not previously attended college at a different institution, and were planning to live on campus during their first year of college. Potential participants were not enrolled if they endorsed one or more of the following items: diagnosis of a psychiatric, learning, or neurologic disorder; presence of disordered eating or diagnosis of a condition that significantly impacted their diet; use of psychotropic medications; significant visual impairment or color blindness; concussion or other brain trauma; MRI contraindications (e.g. metal implants, biomedical devices, pregnancy).

Sample demographics

After exclusions, the final sample included: 0 non-binary participants, 37 men, and 68 women. All participants were 17-19 years old ($M = 18.02$, $SD = 0.24$). Twenty-five percent of participants ($N = 26$) identified as first-generation college students. Subjective socioeconomic status is reported in Table S2. The racial and ethnic composition of the sample is reported in Table S1. Participants self-reported their race and ethnicity using the following categories based on the National Institutes of Health policy: American Indian or Alaska Native, Asian, Black or African American, Hispanic or Latino/Latina/Latinx, Native Hawaiian or Other Pacific Islander, and White. With respect to race and ethnicity, our sample was largely representative of the 2018 University of Oregon freshman class as a whole, which reported the following racial and ethnic identities: 7% Asian American, 3% Black or African American, 15% Hispanic or Latino/Latina/Latinx, 9% Multi-ethnic, 0.5% Native American, 0.7% Native Hawaiian or Other Pacific Islander, and 64% White.

Table S1.

Racial and ethnic composition of the sample

Race	Hispanic or Latina/Latino/Latinx			
	Yes		No	
	<i>N</i>	%	<i>N</i>	%
Asian	—	—	10	9.6
Black or African American	—	—	3	2.9
More than one race	6	5.8	9	8.7
Native Hawaiian or Other Pacific Islander	—	—	1	1.0
Prefer not to state	4	3.8	—	—

White	10	9.6	62	59.6
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Table S2.

Sample subjective socioeconomic status

Response	<i>N</i>	%
Not enough money to get by	1	1.0
Just enough money to get by	31	29.8
We only have to worry about money for fun or extras	56	53.8
We never have to worry about money	17	16.3

Self-evaluation task stimuli

Well-being is conceptualized in a variety of ways in the literature, but there is consensus that well-being is comprised of positive states that contribute to overall psychological health independently of negative states, or ill-being. In other words, well-being and ill-being are related but distinct constructs and not merely opposite ends of a single continuum. Furthermore, social connectedness also exerts independent effects on psychological health. With these findings in mind, we adopted a data-driven approach to generate the stimuli used in the self-evaluation task (described below) and conducted a factor analyses using data from an independent sample of college students ($N = 110$, 63 females, as defined by sex assigned at birth). Participants rated 170 items taken from various mental health and well-being questionnaires, including: PERMA-Profiler (Butler & Kern, 2016), Psychological Well-being (Ryff & Keyes, 1995), Positive Youth Development (Geldhof et al., 2014), EPOCH Model of Adolescent Wellbeing (Kern et al., 2016), Perceived Stress Scale (Cohen et al., 1983), and Center for Epidemiological Studies–Depression, 10 item (Andresen et al., 1994). For each item, participants rated how true each item was for them on a 4-point Likert-type scale (1 = Not at all true, 4 = Extremely true). We then conducted a series of factor analyses using the psych package (Revelle, 2018) in R 3.5.1 (R Core Team, 2018; <https://www.r-project.org/>) to select items for the self-evaluation task. The goal of these analyses was to create three unique components related to psychological health: well-being, ill-being, and social connectedness. First, to explore the structure of the data, we ran a principal component analysis without rotation and extracted 6 components based on visual inspection of a scree plot of the eigenvalues. This analysis revealed components relating to well-being, ill-being, and social connectedness, but for all but the well-being factor, the factor loadings were mediocre (highest loadings < 0.58). Consequently, we chose to allow items to correlate and ran a principal component analysis with three components using a promax rotation to recover components relating to ill-being, and social connectedness. We then used the factor loadings to select 20-40 items for each component and included reverse coded items in the social connectedness component. We vetted the items for uniqueness, clarity, and readability, and selected 18 distinct items for each component to be used in the self-evaluation task. Item loadings and analytic code from this analysis and all other analyses reported here can be found on the Open Science Framework project for this manuscript (<https://osf.io/x2zra>).

Stimuli used in the self-evaluation task

Well-being. Happy, satisfied with life, live a purposeful life, joyful, achieve goals, optimistic, live a meaningful life, hopeful, love life, interested in life, have direction, capable, positive, like myself, cheerful, proud, full of energy, engaged in tasks

Ill-being. Anxious, overwhelmed, nervous, unable to cope, feel rejected, depressed, stressed, sad, afraid of being hurt, feel worthless, worn out, tired, fearful, feel unimportant, unhappy, lonely, feel invisible, feel useless

Social connectedness. Am cared for, comfortable with friends, have good friends, loved, trusted, have support systems, have warm relationships, have trusting relationships, feel supported, helped by friends, help others, well-liked, belong in social group, feel encouraged, alienated, isolated, neglected, angry

Neuroimaging data acquisition and preprocessing

We acquired a high-resolution anatomical T1-weighted MP-RAGE scan (TR/TE = 2500.00/3.43ms, 256×256 matrix, 1mm thick, 176 sagittal slices, FOV = 208×208 mm), functional images with a T2*- weighted echo-planar sequence (72 axial slices, TR/TE = 2000.00/25.00ms, 90-degree flip angle, 104×104 matrix, 2mm thick, FOV = 208×208 mm), and opposite phase encoded echo-planar images to correct for magnetic field inhomogeneities (72 axial slices, TR/TE = 6390.00/47.80ms, 90-degree flip angle, 104×104 matrix, 2mm thick, FOV = 208×208 mm).

Neuroimaging data were preprocessed using fMRIPrep 1.1.4 (Esteban et al., 2019, RRID:SCR_016216), which is based on Nipype 1.1.1 (Gorgolewski et al., 2011; Gorgolewski et al., 2019), RRID:SCR_002502). The T1-weighted (T1w) image was corrected for intensity non-uniformity (INU) using N4BiasFieldCorrection (Tustison et al., 2010, ANTs 2.2.0), and used as T1w-reference throughout the workflow. The T1w-reference was then skull-stripped using antsBrainExtraction.sh (ANTs 2.2.0), using OASIS as target template. Brain surfaces were reconstructed using recon-all (FreeSurfer 6.0.1, RRID:SCR_001847, Dale, Fischl, & Sereno, 1999), and the brain mask estimated previously was refined with a custom variation of the method to reconcile ANTs-derived and FreeSurfer-derived segmentations of the cortical gray-matter of Mindboggle (Klein et al., 2009, RRID:SCR_002438). Spatial normalization to the ICBM 152 Nonlinear Asymmetrical template version 2009c (Fonov et al., 2009), RRID:SCR_008796) was performed through nonlinear registration with antsRegistration (ANTs 2.2.0, RRID:SCR_004757, Avants, Epstein, Grossman, & Gee, 2008), using brain-extracted versions of both T1w volume and template. Brain tissue segmentation of cerebrospinal fluid (CSF), white-matter (WM) and gray-matter (GM) was performed on the brain-extracted T1w using fast (FSL 5.0.9, RRID:SCR_002823, Zhang, Brady, & Smith, 2001).

For each of the two functional runs per subject (across all tasks and sessions), the following preprocessing was performed. First, a reference volume and its skull-stripped version were generated using a custom methodology of fMRIPrep. A deformation field to correct for susceptibility distortions was estimated based on two echo-planar imaging (EPI) references with opposing phase-encoding directions, using 3dQwarp (AFNI). Based on the estimated susceptibility distortion, an unwarped BOLD reference was calculated for a more accurate co-registration with the anatomical reference. Head-motion parameters with respect to the BOLD reference (transformation matrices and six corresponding rotation and translation parameters) are estimated before any spatiotemporal filtering using mcflirt (FSL 5.0.9, Jenkinson, Bannister, Brady, & Smith, 2002). The BOLD time-series were resampled onto their original, native space by applying a single, composite transform to correct for head-motion and susceptibility distortions. These resampled BOLD time-series will be referred to as preprocessed BOLD in original space, or just preprocessed BOLD. The BOLD reference was then co-registered to the T1w reference using bbregister (FreeSurfer) which implements boundary-based registration

(Greve & Fischl, 2009). Co-registration was configured with nine degrees of freedom to account for distortions remaining in the BOLD reference. The BOLD time-series were resampled to surfaces in fsnative space. The BOLD time-series were resampled to MNI152NLin2009cAsym standard space, generating a preprocessed BOLD run in MNI152NLin2009cAsym space.

Several confounding time-series were calculated based on the preprocessed BOLD: framewise displacement (FD), DVARS and three region-wise global signals. FD and DVARS are calculated for each functional run, both using their implementations in Nipype (following the definitions by Power et al., 2014). The three global signals are extracted within the CSF, the WM, and the whole-brain masks. Additionally, a set of physiological regressors were extracted to allow for component-based noise correction (CompCor; Behzadi, Restom, Liau, & Liu, 2007). Principal components are estimated after high-pass filtering the preprocessed BOLD time-series (using a discrete cosine filter with 128s cut-off) for the two CompCor variants: temporal (tCompCor) and anatomical (aCompCor). Six tCompCor components are then calculated from the top 5% variable voxels within a mask covering the subcortical regions. This subcortical mask is obtained by heavily eroding the brain mask, which ensures it does not include cortical GM regions. For aCompCor, six components are calculated within the intersection of the aforementioned mask and the union of CSF and WM masks calculated in T1w space, after their projection to the native space of each functional run (using the inverse BOLD-to-T1w transformation). The head-motion estimates calculated in the correction step were also placed within the corresponding confounds file. All resamplings can be performed with a single interpolation step by composing all the pertinent transformations (i.e., head-motion transform matrices, susceptibility distortion correction when available, and co-registrations to anatomical and template spaces). Gridded (volumetric) resamplings were performed using `antsApplyTransforms` (ANTs), configured with Lanczos interpolation to minimize the smoothing effects of other kernels (Lanczos, 1964). Non-gridded (surface) resamplings were performed using `mri_vol2surf` (FreeSurfer). Many internal operations of fMRIPrep use Nilearn 0.4.2 (Abraham et al., 2014, RRID:SCR_001362), mostly within the functional processing workflow. For more details of the pipeline, see the section corresponding to workflows in fMRIPrep's documentation.

ROI definition

We defined three a priori bilateral ROIs for pgACC, vmPFC, and VS (see Figure 3) using the HCP MMP 1.0 cortical parcellation atlas (Glasser et al., 2016) and the FreeSurfer segmentation atlas (Fischl et al., 2002). These ROIs were mapped to participants' T1-weighted anatomical scans using FreeSurfer 6 (Fischl, 2012). Cortical ROIs were specified by identifying parcels that overlapped with the medial prefrontal cluster from the group-level `self > change` contrast and were divided into vmPFC (including L_p32_ROI, L_10r_ROI, and L_10v_ROI parcels) and pgACC ROIs (including L_a24_ROI, L_25_ROI, and L_s32_ROI parcels) based on anatomical location. The VS ROI was defined by combining the nucleus accumbens and putamen segmentations. All ROIs were concatenated and binarized using the `fslmaths` function in FSL 5.0.10 (Jenkinson, Beckmann, Behrens, Woolrich, & Smith, 2012). This process yielded individually defined pgACC, vmPFC, and VS ROIs for each participant in native space.

Trial-level analyses without reaction time

We included reaction time in the model reported in the main manuscript to control for its confounding effects. However, the original preregistered model did not include reaction time.

For transparency, we report the results without reaction time in Table S3. These results are directionally consistent with the results including reaction time; all terms except the interaction between vmPFC and construct (ill-being) tended to be weaker and were not statistically significant.

Table S3

Parameter estimates and statistics for the preregistered model not including reaction time

Parameter	<i>b</i>	<i>z</i>	<i>p</i>
Intercept (well-being)	2.01 [1.81, 2.21]	19.89	< .001
Construct (ill-being)	-3.06 [-3.29, -2.83]	26.15	< .001
Construct (social)	-0.09 [-0.34, 0.15]	0.74	.460
pgACC	0.25 [-0.06, 0.55]	1.60	.110
vmPFC	-0.23 [-0.53, 0.08]	1.47	.142
VS	0.13 [-0.05, 0.30]	1.40	.161
Construct (ill-being) x pgACC	-0.19 [-0.58, 0.19]	0.99	.321
Construct (social) x pgACC	0.02 [-0.40, 0.43]	0.08	.934
Construct (ill-being) x vmPFC	0.59 [0.20, 0.98]	2.98	.003
Construct (social) x vmPFC	-0.08 [-0.50, 0.35]	0.37	.715
Construct (ill-being) x VS	-0.19 [-0.43, 0.04]	1.61	.106
Construct (social) x VS	-0.08 [-0.32, 0.17]	0.62	.533

Note. Parameter estimates (*b*) are log-odds. Neural ROI parameter estimates were standardized within participant and ROI to preserve individual differences and are therefore not *Z*-scores.

Trial-level similarity analysis

Here we report results from the preregistered similarity analysis conducted on a trial-by-trial basis. Please note that we report these results for the sake of completeness and fidelity to the preregistration; these estimates are likely to be unstable because the task design was not optimized for similarity analysis (Zeithamova et al., 2017). For each participant, we extracted the patterns of activity for each *a priori* ROI (pgACC, vmPFC, VS) on a trial-by-trial basis. To do this, we created a “beta-series” by running another first-level GLM that modeled each trial as a separate regressor (Rissman et al., 2004). We included the same motion regressors as described in the main manuscript. From the 72 beta maps created, we selected the 36 maps for the trials in the self condition (18 in each run) and extracted the parameter estimates for each voxel in each ROI. Because trials within runs are highly correlated, we calculated trial correlations across runs (i.e., trials in run 1 were only correlated with trials in run 2). In each run there are 18 items in the self condition, so for each participant, we generated 324 correlations for each ROI. Correlations were then converted to *Z* values using a Fisher *Z*-transformation and averaged across participants for each construct pair and ROI. As shown in Figure S1, none of these variables were correlated on a trial-by-trial basis with this task design.

Figure S1. Mean Fisher Z-transformed correlations between task runs as a function of psychological health construct, calculated within the self condition only on a trial-by-trial basis.