

Neural Predictors of Real-life Positive Anticipatory Experiences and Subjective Well-being

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Abstract

Positive anticipatory experiences form the basis of learning to maximize rewarding outcomes, which are key to daily happiness. However, how the brain's functional architecture underlying the process of adaptive learning is related to real-world positive anticipatory experiences and happiness remains unexplored. In the present study, we combined an experience sampling method and resting-state functional neuroimaging to identify the neural predictors of real-world positive anticipatory experiences and explore their relationships with subjective well-being (SWB). We quantified participants' accuracy in predicting positive events with the hyperbolic discounting function and the degree to which participants' affective states were influenced by positive future events using multilevel modeling. We found that individuals with higher accuracy in predicting upcoming positive events showed greater SWB, and this relationship was mediated by greater positive anticipatory feelings. Importantly, functional connectivity of the dorsal and ventral striatal-hippocampal networks significantly predicted the accuracy and positive anticipatory feelings, respectively. These dissociable but inter-related functional networks were further predictive of SWB. Our findings provide novel and ecologically valid evidence that the interplay between neural systems for value-based learning and memory plays an important role in orchestrating real-life positive anticipatory experiences and everyday SWB.

Keywords: positive anticipation, prediction accuracy, anticipatory feelings, striatum, hippocampus, experience sampling method, resting-state fMRI, subjective well-being

1. Introduction

The ability to accurately predict positive future events seems to be key to one's subjective well-being (SWB). Whether implicitly or explicitly, we constantly make predictions about future events, compare them with actual outcomes, and update our long-term memory accordingly, which in turn, is used to generate a new set of predictions (Hartley et al., 2021; Hutchinson and Barrett, 2019). During this process of adaptive learning, not only our expectations of the future *per se* but also whether such expectations are fulfilled can greatly influence our affective states. For instance, imagine a child who is expecting to get a gaming console for her birthday. This positive anticipation would elicit positive feelings, and the degree to which she experiences such feelings would increase with the likelihood of her receiving the expected gift. Finally getting a gaming console (i.e., fulfilled expectation) would make her happier than getting a book (i.e., unfulfilled expectation). Further, accumulated experiences of such fulfilled expectations, or accurate predictions followed by positive anticipatory feelings would contribute to her overall well-being.

Recent evidence suggests that realistic positive expectations are associated with greater well-being than unrealistic optimism or pessimism (de Meza and Dawson, 2021), and goal-directed and convincing positive anticipation (e.g., hope) is more predictive of SWB than general positive expectations (Pleeging et al., 2021). In contrast, disparities between one's positive expectations and actual outcomes can have significant negative impacts on affect and behavior (Park et al., 2021; Shepperd et al., 2015). Moreover, accurate predictions about upcoming positive events enable us to prepare cognitive, affective, and behavioral strategies toward reward (Grupe et al., 2013; Sharot, 2011; Sharot and Garrett, 2016), and help us to make optimal choices that yield better outcomes (de Meza and Dawson, 2021). Despite these far-reaching implications, how the accurate predictions of positive events influence everyday affective experiences and well-being in real-life contexts, and how the brain's functional architecture supports this relationship remain unexplored.

Previous research suggests that positive anticipatory processes are tightly associated with positive affective states. Anticipatory processes involve mental representations conveying episodic details of expected events with the relevant affective information (Benoit et al., 2014; Madore et al., 2016). During positive anticipation, mental simulations involving rewarding outcomes allow individuals to achieve positive affective states (Sanna, 2000). Moreover, positive anticipation itself holds significant utility involving positive anticipatory feelings (Caplin and Leahy, 2001; Loewenstein, 1987), and this experience can be boosted by the belief that positive outcomes are highly likely to occur (e.g., anticipating reward after viewing the cue predictive of the reward; Iigaya et al., 2020). In other words, individuals whose predictions of positive events have been accurate in the past are likely to have a greater perceived likelihood of their expectations being fulfilled. Therefore, we expected that higher accuracy in predicting positive events would be associated with increased positive anticipatory feelings. Also, given the link between positive feelings and SWB (Busseri, 2018; Diener, 2009; Schimmack, 2008), we hypothesized that individuals with higher accuracy in predicting positive events would show greater SWB than those with lower accuracy, and that this association would be mediated

by changes in positive affective states accompanied by the positive anticipation.

To identify the functional neural architecture associated with the accuracy of positive anticipation and its relevant affective states, we focus on functional connectivity (FC) between the neural systems for value-based learning and memory, which is believed to play a critical role in adaptive learning (Hartley et al., 2021; Knowlton and Castel, 2022) and anticipatory processes (Bulganin and Wittmann, 2015; Igaya et al., 2020). The ability to predict positive future events relies primarily on the memory processes that enable us to extract commonalities and regularities from past events (Gilbert and Wilson, 2007; Schacter et al., 2012, 2017; Sherman and Turk-Browne, 2020). The reward signals embodied in positive events are often prioritized in memory and this information forms the basis of mental models that can be used to guide the pursuit of valued outcomes (Hartley et al., 2021; Knowlton and Castel, 2022). This interplay between value-based learning and memory processes would help us access previously rewarded events and create the most relevant representations of positive future events, ultimately contributing to accurate representations of upcoming positive events concomitant with positive affective states.

Evidence from neuroscientific research has increasingly indicated that these processes are subserved by communication between the dopaminergic brain structures such as the striatum and the hippocampal and parahippocampal regions extending to the adjacent temporal cortex (Bulganin and Wittmann, 2015; Gruber et al., 2014; Igaya et al., 2020; Murty et al., 2015; Speer et al., 2014; Wittmann et al., 2005), which are known as neural substrates for reward processing and episodic memory, respectively. Therefore, we hypothesized that individual differences in the FC between these two neural systems would be associated with accuracy in predicting positive future events and the relevant affective states, which in turn would influence SWB.

More specifically, we expected that dissociable interactions of the hippocampal and parahippocampal regions with the dorsal and ventral parts of the striatum (dorsal and ventral striatal-hippocampal networks, hereafter) would be associated with the accuracy and changes in affective states: the FC of the dorsal striatal-hippocampal network would contribute to the accuracy in predicting upcoming positive events, whereas the FC of the ventral striatal-hippocampal network would be linked to the changes in affective states during positive anticipation. A broad range of research suggests that the dorsal striatum, including the caudate and putamen, is associated with cognitive processes and control of actions, whereas the ventral striatum, including the nucleus accumbens (NAcc), is related to affective states and motivation (Alexander et al., 1986; Cardinal et al., 2007; Delgado, 2007).

Of greater relevance to the present study, there is converging evidence suggesting that the anticipation of reward and the processing of information about reward outcomes can be attributed to the dorsal and ventral striatum, respectively (Balleine et al., 2007; O'Doherty et al., 2004; Salimpoor et al., 2011). Such reward-related information is known to be stored within the hippocampus and the adjacent temporal lobe (Hartley et al., 2021; Knowlton and Castel, 2022; Ritchey and Cooper, 2020). These regions take part not only in the recollection of past rewarding outcomes and the extraction of their common elements and regularities (Schacter et

al., 2012, 2017; Sherman and Turk-Browne, 2020), but also the process of episodic representations of emotional significance (Phelps, 2004; Richardson et al., 2004). Based on these findings, we reasoned that the hippocampal regions and adjacent temporal gyrus would be commonly engaged in the cognitive (i.e., prediction) and affective (i.e., positive anticipatory feelings) processes during the anticipatory experiences (Fig. 1B).

To test our hypotheses in real-life contexts, we combined an experience sampling method (ESM) with resting-state functional magnetic resonance imaging (rs-fMRI) (Fig. 1A-B). ESM tracks individuals' moment-to-moment experiences and fluctuations in affective states, from which we obtained real-life measures of accuracy in predicting positive events, changes in affective states, and momentary SWB (Fig. 1C, see Methods for the details). First, we tested whether the accuracy influences SWB via changes in affective states. With the rs-fMRI data, we performed a seed-based connectivity (SBC) analysis with the dorsal and ventral striatum as seed regions. We tested our hypothesis whether the FCs between these seed regions and regions involved in episodic memory would exhibit a double dissociation with the accuracy and changes in affective states, respectively. Finally, we examined the integrated relationships among individual differences in the functional neural architecture, the anticipatory experiences, and SWB.

2. Methods

2.1. Participants

Eighty-seven healthy college students were recruited through a university community website (mean age = 21.84, $SD = 2.03$, range of age = 19–31; 47 males and 40 females; Supplementary Table 1). Participants reported no current or past neurological or psychiatric diagnosis and reported no current severe depression or anxiety symptoms. The rs-fMRI data of 56 participants (mean age = 22.36, $SD = 2.33$, range of age = 19–31; 37 males and 19 females) were available because the remaining 31 participants were scanned with different scan protocols for a separate study. We included all the 87 participants in the behavioral analyses to establish the relationships between the accuracy in predicting positive events, change in affective states, and SWB. Among the 56 participants with the rs-fMRI data, one participant was excluded due to excessive head motion ($\geq 2.5\text{mm}$). The remaining 55 participants were included in the analyses involving FC. Behavioral results including only these participants are reported in the supplementary information. All participants read and signed written informed consent and were compensated with 50,000KRW (approx. 50USD). All experimental protocols, methods, and the collection of data were approved by the Institutional Review Board at Seoul National University.

2.2. fMRI data acquisition

All the participants were invited to a scan session where the high-resolution T1, rs-fMRI, and diffusion weighted images were obtained, followed by ESM surveys approximately two weeks later. Because the focus of our study is on FC associated with the ESM data, we used rs-fMRI

and T1 data. The diffusion images were collected for another study. All MRI data were acquired using a Siemens 3T Trio MRI scanner (Siemens Magnetom Trio) with a 32-channel head coil. The rs-fMRI data were collected using a gradient echo-planar imaging pulse sequence [repetition time (TR) = 2000 ms, echo time (TE) = 25 ms, field of view (FOV) = 192 x 192 mm, flip angle (FA) = 80°, voxel size = 3 x 3 x 3mm³, 38 interleaved axial slices with no gaps, and 200 volumes]. During the scanning, participants were asked to relax with their eyes open and maintain the fixation. High-resolution T1-weighted structural imaging data were acquired with a magnetization-prepared rapid gradient echo sequence (TR = 2300 ms, TE = 2.36 ms, FOV = 256 x 256 mm, FA = 9°, voxel size = 1 x 1 x 1 mm³, and 224 axial slices).

2.3. ESM

In order to measure expectations about future events, the actual occurrence of events, affective states, and SWB in real-life contexts, we adopted ESM using a mobile survey. The ESM has high ecological validity because it captures participants' moment-by-moment real-world experiences and behaviors in the natural flow of real life (Csikszentmihalyi, 2011; Hektner et al., 2007; Shiffman et al., 2008). Specifically, participants received a series of text messages containing a link to the survey five times a day for a week. A reminder was sent to the participants who did not respond to the survey for three times consecutively. On average, participants responded to 30.8 times ($SD = 5.710$) out of the 35 surveys that they received over a week, which yielded a response rate of 88.01% ($SD = 16.313$). All participants showed consistently high response rates, indicating their strong engagement in the study. The total number of time points included in the behavioral analyses was 2,680 with 87 participants.

In each survey, participants were asked to report (i) whether they anticipated a positive event to occur soon and if so, to select (ii) one from the following four domains that was relevant to the anticipated event: academic, work-related, social relationship domains, and others. Participants were also asked to report (iii) whether a positive event occurred between the previous survey and the current survey and if so, to select (iv) one from the four domains that was relevant to the experienced event. The moment-to-moment affective states were measured by asking participants (i) emotional valence: how good or bad they felt using an 11-point scale [0 (very bad) to 10 (very good)], (ii) interestedness: how interested they felt [0 (very bored) to 10 (very interested)], and (iii) activeness: how active they felt [0 (very inactive) to 10 (very active)]. To measure individuals' level of momentary SWB, two items reflecting cognitive and affective aspects of SWB (Diener et al., 2002) were included: (i) how satisfied they were with their lives [0 (very unsatisfied) to 10 (very satisfied)] and (ii) how happy they felt [0 (very unhappy) to 10 (very happy)]. Fig. 1A illustrates the design of ESM surveys.

2.4. Quantification of accuracy in predicting positive events, changes in affective states, and SWB using ESM data

To analyze the relationships between the accuracy, changes in affective states relevant to the positive anticipation, and momentary SWB, we operationally defined each variable as described below. First, the accuracy in predicting positive events was defined by calculating the ratio of weighted sum of correct predictions with the hyperbolic discounting function to the

total cases of positive future and past events. Specifically, we counted the number of cases that satisfied all the following three conditions: (i) at time t , a participant expected positive future event; (ii) a positive event occurred between time $t+1$ and time $t+n$; (iii) the domain of anticipated event at time t and the domain of experienced event between time $t+1$ and time $t+n$ corresponded with each other, in which n denotes the total time points in the ESM surveys. For example, when there was an expectation of positive future event at time t and the corresponding positive event happened at time $t+1$, this case was scored by 1, when the positive event occurred at time $t+2$, it was scored by $1/2$, and when the positive event occurred at time $t+n$, it was scored by $1/n$, reflecting temporal discounting of future reward value (Green and Myerson, 2004). In other words, we considered the participants' prediction as accurate only when the experienced positive event reported between time $t+1$ and $t+n$ was in the same domain as the anticipated positive event reported at time t . Then, the weighted sum of the number of accurate cases were divided by the total number of positive future and past events.

Second, we quantified the extent to which individuals' affective states were influenced by anticipation of upcoming positive events (i.e., changes in affective states). For this, we adopted linear mixed-effects models using lme4 package (Bates et al., 2015) in R (v. 4.0.4). In the models, anticipation of positive future events was coded as a dummy variable (1 = presence, 0 = absence) and ratings of participants' momentary affective states were entered as dependent variables. The multilevel models are defined as:

Level 1 model:

$$\text{Current affect}_{ij} = \beta_{0j} + (\text{anticipation of positive future event})\beta_{1j} + \varepsilon_{ij}$$

Level 2 model:

$$\beta_{0j} = \gamma_{00} + v_{0j}$$

$$\beta_{1j} = \gamma_{10} + v_{1j}$$

where the subscripts i and j denote measurements at level 1 (moment) and level 2 (participant), respectively and parameters v_0 and v_1 are random effects to be estimated. We used the value of β_{1j} as the extent to which individual j 's momentary affective state (i.e., emotional valence, interestedness, or activeness) was influenced by the presence of positive future events. β_{0j} denotes the random intercept (i.e., participant j 's affective state when positive future events are absent), which was included as the covariate in every analysis to control for the effect of individuals' baseline affective states. In our study, we used the term "change in affective states" to refer to the extent to which participants' affective states increased or decreased in the presence of positive future events compared to the reference point (i.e., absence of those events) without considering temporal dynamics.

Lastly, participants' experienced SWB was defined by averaging the moment-to-moment life satisfaction and happiness ratings across all time points within an individual. We also considered the life satisfaction and happiness ratings separately in the analyses.

2.5. Statistical analyses of behavioral data

To examine the associations among the accuracy, changes in affective states, and SWB, we first conducted multiple linear regression analyses using IBM SPSS (v.25). Specifically, we tested the predictive relationships between the accuracy and SWB, between the changes in affective states and SWB, and between the accuracy and changes in affective states. To ensure robustness and generalization of our regression models, we assessed the predictive performance of our regression models, with the leave-one-out cross-validation (LOOCV). In the LOOCV approach, the current dataset was divided into a training set and a testing set (i.e., a validation set), with one participant removed from the training set and $N-1$ participants used to build the predictive model. Then, we computed the mean squared error (MSE) to quantify the proximity of the predictions to the actual data. This process was iterated N times, such that each observation was used once as the validation data, and the resulting MSE values were subsequently averaged. This procedure was performed using the Python (v.3.11) packages ‘scikit-learn’ (v.1.2.2) and ‘statsmodels’ v.0.14.0 (Pedregosa et al., 2011; Seabold & Perktold, 2010). Then, by conducting mediation analyses using the PROCESS macro for SPSS (Hayes, 2013) with 5,000 bootstrap samples, we tested our hypotheses that the accuracy would increase SWB via positive changes in affective states. Our mediation models were further assessed with the LOOCV to enhance their stability and robustness, complementing the use of bootstrapping. This combination ensured a more reliable and accurate assessment of the predictive power of our models. In all the analyses, age and sex were included as covariates to control for their effects. Additionally, when examining the changes in affective states as variables for analysis, the intercepts of affective states were also included as covariates.

2.6. Preprocessing of fMRI data

All functional neuroimaging data were preprocessed and analyzed using the CONN toolbox (Whitfield-Gabrieli and Nieto-Castanon, 2012) v.20, implemented in SPM toolbox (v.12). We followed the CONN’s default preprocessing pipeline including functional realignment and unwarping, slice-timing correction, structural segmentation and normalization, functional normalization, outlier detection (ART-based scrubbing), and smoothing (FWMH kernel: 8 mm). For nuisance signal correction, the following parameters were included as nuisance regressors in the general linear model: six motion parameters (x , y , z , roll, pitch, and yaw), their mean-centered squares, their derivatives, and squared derivative (total 24 columns); scrubbing parameters as identified invalid scans; five principal components extracted from the white matter and CSF masks using the CompCor method (Behzadi et al., 2007). We did not use global signal regression to avoid a potential artifact regarding negative correlations (Murphy et al., 2009; Saad et al., 2012), which may make it hard to interpret the results. In addition, temporal band-pass filtering (0.01–0.1 Hz) was performed.

2.7. FC analysis

To examine the FCs of the dorsal and ventral striatum with other brain regions including the hippocampus and the adjacent temporal gyrus, we generated SBC maps. The six structures of striatum, consisting of bilateral dorsal striatum including the caudate and putamen and ventral striatum including the NAcc, were defined as seeds using the Harvard-Oxford atlas distributed

with FSL (<http://www.fmrib.ox.ac.uk/fsl/>) that provides adequate coverage of both cortical and subcortical brain regions. The connectivity strength was calculated using Pearson's bivariate correlation between the timeseries of seed regions and each individual voxel's timeseries from the individuals' SBC maps. The correlation coefficients were then normalized by Fisher's z transformation. To determine the regions showing a significant relationship of the SBC maps (i.e., seeded by each striatum) with the variables of our major interest (i.e., the accuracy of positive anticipation and changes in affective states), we performed multiple regression analysis at the voxel level, while controlling for age and sex. Additionally, when examining the changes in affective states as variables for analysis, the intercepts of affective states were also included as covariates.

We defined *a priori* anatomical search volume including the bilateral hippocampus, PHG and the adjacent middle temporal gyrus (MTG) created from the Harvard-Oxford atlas distributed with FSL, which are known to be involved in forming and reconstructing episodic memory and representing both past and future events (Iigaya et al., 2020; Ritchey and Cooper, 2020; Schacter et al., 2012, 2017; Sherman and Turk-Browne, 2020). We hypothesized that these regions would be commonly involved in the positive anticipatory processes, namely the accuracy in predicting positive events and changes in affective states during the positive anticipation. To correct for multiple comparison, we ran small volume correction family-wise error (SVC FWE) $P < 0.01$ within the ROI (i.e., the cluster including the bilateral hippocampus, PHG, and MTG) with initial voxel level threshold of $P < 0.005$.

The relationships between the average FC values associated with the accuracy and the average FC values associated with the changes in affective states were analyzed using the bivariate Pearson's correlation. In the correlation analyses, multiple comparisons were corrected using Bonferroni's method and the adjusted P -values were reported when applicable. Then, to evaluate the predictive relationships of the FCs associated with the accuracy and changes in affective states with SWB, we conducted the same regression and mediation analyses as well as LOOCV analyses, in the same vein as those performed with the behavioral data.

3. Results

3.1. Higher accuracy in predicting positive events is associated with greater positive changes in affective states.

To examine our hypothesis that higher accuracy in predicting positive future events would be associated with greater SWB via the relevant changes in affective states, we first examined whether the accuracy is predictive of the changes in affective states. We found that participants with higher accuracy showed greater changes in affective states (positive feelings: $B = 0.782$, $t = 3.558$, $P = 0.001$; interestedness: $B = 0.270$, $t = 2.094$, $P = 0.039$; activeness: $B = 0.287$, $t = 3.143$, $P = 0.002$) when anticipating positive events (Fig. 2A & Supplementary Table 2).

3.2. Both the accuracy and positive changes in affective states are associated with SWB.

Then, we tested whether the accuracy and changes in affective states predict SWB. Multiple

regression analyses showed that the accuracy and changes in positive feelings and interestedness significantly predicted life satisfaction, happiness, and the average of these two scores (i.e., SWB). Specifically, the accuracy predicted SWB ($B = 2.942$, $t = 3.395$, $P = 0.001$), life satisfaction ($B = 2.923$, $t = 3.284$, $P = 0.001$), and happiness ($B = 2.961$, $t = 3.419$, $P = 0.001$; Fig. 2B & Supplementary Table 2). Additionally, participants who experienced more positive feelings and interestedness when anticipating positive events reported greater SWB (positive feelings: $B = 0.610$, $t = 3.810$, $P < 0.001$; interestedness: $B = 1.258$, $t = 2.601$, $P = 0.011$), life satisfaction (positive feelings: $B = 0.673$, $t = 3.633$, $P < 0.001$; interestedness: $B = 1.124$, $t = 2.179$, $P = 0.032$), and happiness (positive feelings: $B = 0.547$; $t = 3.377$, $P = 0.001$; interestedness: $B = 1.391$, $t = 2.893$, $P = 0.005$; Fig. 2C & Supplementary Table 3A-C). However, the change in activeness was not related to any of the SWB measures (SWB: $B = 1.398$, $t = 1.903$, $P = 0.061$; life satisfaction: $B = 1.398$, $t = 1.832$, $P = 0.071$; happiness: $B = 1.398$, $t = 1.883$, $P = 0.063$).

3.3. Higher accuracy predicts greater SWB via change in positive feelings.

After examining the associations among our variables of interest, we tested our hypothesis that greater accuracy would influence SWB via the changes in affective states. Mediation analyses showed that the relationship between the accuracy and SWB was significantly mediated by the change in positive feelings (Fig. 2D; indirect effect: $B = 0.351$, standard errors (SE) = 0.167, 95% CI = [0.0704–0.7222]). The same mediation effects were found when life satisfaction (indirect effect: $B = 0.410$, $SE = 0.185$, 95% CI = [0.0934–0.8136]) or happiness (indirect effect: $B = 0.291$, $SE = 0.158$, 95% CI = [0.0232–0.6263]) scores were entered into the model as the outcome variable; Supplementary Fig. 1). However, the changes in interestedness or activeness did not mediate the association between the accuracy and SWB measures (Supplementary Fig. 2-3). To confirm that the fMRI data in this study reliably reflected our main behavioral results, we additionally performed all the same behavioral analyses with only 56 participants and found similar patterns to the aforementioned results (Supplementary Table 2†-3†; Supplementary Fig. 1†).

3.4. Dorsal striatal-hippocampal FC is associated with accuracy in predicting positive events.

After confirming the mediation model explaining the relationship between the accuracy, change in positive feelings, and SWB, we performed rs-fMRI analyses to identify FC associated with the accuracy and positive anticipatory experiences and their contribution to SWB. First, we examined whether the FCs between dorsal striatum and hippocampal regions are associated with the accuracy. After applying the ROI mask including the hippocampus, parahippocampal gyrus (PHG), and MTG, the resulting statistical maps identified significant clusters that showed positive associations of the accuracy with FC strength of (i) the left caudate with the left hippocampus/PHG [peak Montreal Neurological Institute (MNI) $x, y, z = -28, -22, -16$; SVC FWE $P = 0.003$], (ii) the right putamen with the left hippocampus (peak MNI $x, y, z = -28, -30, -12$; SVC FWE $P = 0.004$) and PHG (peak MNI $x, y, z = -18, 2, -34$; SVC FWE $P = 0.006$; Fig. 3A). When seeding the NAcc, however, the accuracy was not significantly associated with the FC strength between the bilateral NAcc and any hippocampal regions (For details and other FC result related to the accuracy, see Supplementary Table 4).

3.5. Ventral striatal-hippocampal FC is associated with change in positive feelings.

Then, we examined whether the FCs between the ventral striatum and hippocampal regions are associated with the changes in affective states. As hypothesized, the change in positive feelings was positively associated with the FC strength of the right NAcc with the left PHG / hippocampus (peak MNI $x, y, z = -18, -12, -26$; SVC FWE $P = 0.004$) and the right hippocampus (peak MNI $x, y, z = 26, -10, -22$; SVC FWE $P = 0.007$; Fig. 3B). The change in positive feelings was not significantly associated with the FC strength between the dorsal striatum seeds (i.e., caudate and putamen) and any hippocampal regions. However, we found significant positive correlation between the change in positive feelings and the FC strength of the left putamen with posterior MTG (pMTG) (peak MNI $x, y, z = -62, -30, -10$; SVC FWE $P = 0.008$; Supplementary Table 5A). Likewise, the change in interestedness was also associated with the FC strength of (i) the bilateral caudate with the bilateral pMTG and (ii) the left putamen with the bilateral pMTG (For details, see Supplementary Table 5B). Lastly, the change in activeness was not associated with any FC strength of the dorsal and ventral striatum with the ROI.

3.6. The dorsal and ventral striatal-hippocampal FCs are positively correlated.

After identifying the FCs related to the accuracy and changes in affective states, we examined associations between these FCs. Specifically, we focused on the relationships between the FCs associated with the accuracy and the FCs associated with the change in positive feelings, based on the behavioral result that only the change in positive feelings mediated the association between the accuracy and SWB (Fig. 2D). Bivariate correlation analyses revealed that participants with greater FCs in the accuracy-related dorsal striatal-hippocampal network were more likely to show greater FCs in the affect-related ventral striatal-hippocampal network. The right NAcc-hippocampal FCs associated with the change in positive feelings showed significant positive correlations with (i) the left caudate-hippocampal FC ($r(53) = 0.353$, Bonferroni-adjusted $P = 0.024$), (ii) the right putamen-hippocampal FC ($r(54) = 0.325$, Bonferroni-adjusted $P = 0.045$), and (iii) the right putamen-parahippocampal FC ($r(54) = 0.480$, Bonferroni-adjusted $P = 0.0006$; Fig. 3C). The other correlations between the FCs associated with the accuracy and change in positive feelings were not significant (Supplementary Table 6).

3.7. The dorsal and ventral striatal-hippocampal FCs are predictive of SWB.

So far, we identified the dissociable but interrelated FCs that were associated with the accuracy and the change in positive feelings. We then tested whether these FCs are predictive of SWB. Multiple regression analyses revealed that individuals with greater dorsal striatal-hippocampal FCs associated with the accuracy showed greater SWB (FC between the left caudate and hippocampus / PHG: $B = 4.832, t = 2.829, P = 0.007$; FC between the right putamen and left hippocampus: $B = 3.837, t = 2.090, P = 0.042$; FC between the right putamen and left PHG: $B = 4.652, t = 2.690, P = 0.010$; Fig. 4A). Similarly, the ventral striatal-hippocampal FCs associated with the change in positive feelings significantly predicted SWB (FC between the right NAcc and left hippocampus / PHG: $B = 2.683, t = 3.231, P = 0.002$; Fig 4B) (For details and the FCs associated with the accuracy and change in positive feelings predicting satisfaction

and happiness, see Supplementary Table 7A-B).

3.8. The dorsal striatal-hippocampal FC predicts SWB via the ventral striatal-hippocampal FC.

Given our mediation model addressing the relationships between the accuracy, change in positive feelings, and SWB (Fig. 2D), we analyzed how the FCs associated with the positive anticipatory experiences contribute to SWB. For this, we examined whether the dorsal striatal-hippocampal FCs associated with the accuracy can predict SWB via the ventral striatal-hippocampal FCs associated with the change in positive feelings. The mediation effects corresponding to the behavioral data were observed when entering the right putamen-left hippocampal FC associated with the accuracy as the predictor, the right NAcc-left hippocampal FC associated with the change in positive feelings as the mediator, and the SWB measures as the outcome variable (indirect effect of FC associated with the change in positive feelings on SWB: $B = 0.569$, $SE = 0.384$, 95% CI: [0.0104–1.4824]; Fig. 4C and on happiness: $B = 0.587$, $SE = 0.369$, 95% CI: [0.0218–1.4130]). However, this effect was not found when entering life satisfaction as the outcome variable (Supplementary Fig. 4A-B).

3.9. Cross-validation of the predictive relationships

To evaluate the predictive performance of our regression and mediation models, we compared MSEs obtained from the LOOCV with those derived from our initial regression and mediation analyses using the full data set. This comparison aimed to assess whether the MSEs obtained from the full data set are consistent with the distribution of MSEs derived from LOOCV. The results revealed a very close alignment between the MSEs from the full data set and from LOOCV, as presented in Supplementary Table 8 and Supplementary Fig. 5. Importantly, none of the MSEs from the full data set deviated from the distribution of individual MSEs or exceeded one standard deviation from the average MSEs from LOOCV. These findings underscore the reliability and generalizability of our proposed models, providing further support for their validity.

4. Discussion

In the present study, we investigated how the brain's functional architecture contributes to positive anticipatory experiences and happiness in real-life contexts by combining the ESM and rs-fMRI. With the model-based quantifications of real-life anticipatory experiences, we found that individuals with higher accuracy in predicting upcoming positive events showed greater SWB and this relationship was mediated by greater positive change in positive feelings accompanied by positive anticipation. The analyses on the functional neural networks revealed that distinct but interrelated networks, namely the dorsal and ventral striatal-hippocampal networks, were associated with the accuracy and changes in affective states, respectively. Furthermore, the FC strengths of these functional networks were predictive of the individual differences in SWB.

Our ESM data shows that the relationship between positive anticipatory experiences and happiness that has long been suggested in the literature (MacLeod and Conway, 2005; Quoidbach et al., 2009; Van Boven and Ashworth, 2007) is indeed instantiated in everyday life. The result that accurate prediction about upcoming positive events is associated with SWB provides real-life evidence supporting the importance of realistic positive anticipation (de Meza and Dawson, 2021; Pleeging et al., 2021). Unfulfilled positive expectations are known to be linked to negative emotions (e.g., disappointment, regret, and low self-esteem) and reduced well-being (Carroll et al., 2006; Robins and Beer, 2001; Sweeny and Shepperd, 2010). Indeed, in our data, the ratio of unfulfilled positive expectation was correlated with the negative change in emotional valence ($B = -0.398$, $t = -2.068$, $P = 0.042$; Supplementary Table 9).

More importantly, the present study suggests changes in positive feelings as a psychological mechanism that links the accurate prediction of positive events to happiness. As we expected, the relationship between the accuracy and SWB was mediated by changes in positive feelings. We reasoned that individuals with higher accuracy in predicting positive events may perceive greater likelihood of the positive anticipation to occur and more frequently experience their positive anticipations being realized. The perceived likelihood and the frequency of the actualized positive experiences would interact with each other to reinforce the positive anticipatory feelings. Considering that SWB is tightly associated with positive affect (Busseri, 2018; Diener, 2009; Schimmack, 2008), the increase in positive feelings resulted from the accurate positive anticipation may have contributed to daily SWB.

It is worth noting that there were significant positive correlations between the accuracy and changes in other affective states including activeness and interestedness. This result aligns with previous research indicating that positive anticipation prepares individuals with cognitive, affective, and behavioral strategies toward reward (Grupe et al., 2013; Sharot, 2011; Sharot and Garrett, 2016) so that they can utilize the upcoming events to maximize outcomes. A belief that upcoming positive events are highly likely to occur seems not only to elicit positive anticipatory feelings but also to prepare individuals to seek relevant information with increased interest and to actively pursue the related goals (Bagozzi and Pieters, 1998; Knutson and Greer, 2008). One of the reasons that only the positive change in emotional valence among the three affective states were found to mediate the relationship between the accuracy and SWB could be that the positive feelings are of the most closely linked to SWB. SWB, or subjective happiness (Lyubomirsky and Lepper, 1999), consists of aggregated experiences of positive affect and cognitive evaluation of satisfaction with life (Diener et al., 2002; Diener, 2009). Following this definition, we asked participants to report how happy and satisfied they were with their life at the moment of responding to the ESM surveys. Therefore, the effect of change in positive feelings might have been more readily captured in the mediation model with SWB as the dependent variable. There is a possibility that changes in other affective states could mediate the relationship between the accuracy and other aspects of well-being reflecting achievement or self-realization, such as psychological well-being (Ryff and Singer, 2008).

Another important finding of our study is that individual differences in the brain's FC patterns were associated with real-life positive anticipatory experiences. Previous studies using rs-fMRI

have provided valuable insights into the association between individual differences in the brain's functional connectivity patterns and overall well-being or happiness (Kong et al., 2015; Luo et al., 2014, 2016; Sato et al., 2019; Shi et al., 2018). However, they have mainly focused on FC associated with happiness, leaving the relevant psychological mechanisms underlying this association unexplored. In the present study, we identified the brain's FC patterns associated with the positive anticipatory experiences, which further predicted one's SWB.

Specifically, greater FCs in the dorsal and ventral striatal-hippocampal networks were associated with higher accuracy in predicting positive events and greater change in positive feelings when expecting positive events, respectively. These findings are well in line with the existing literature suggesting that the interplay between the neural systems for value-based learning and memory plays a critical role in adaptive learning and anticipatory processes (Hartley et al., 2021; Hutchinson and Barrett, 2019; Iigaya et al., 2020). Furthermore, we found the double dissociation between the dorsal and ventral striatal-hippocampal networks: the FC of the dorsal striatal-hippocampal network was reflective of the accuracy in predicting positive events but not of the change in positive feelings, and vice versa for the FC of the ventral striatal-hippocampal network. This distinction is consistent with previous findings that different processes of reward-related information have been attributed to the dorsal and ventral striatum (Balleine et al., 2007; Delgado, 2007; O'Doherty et al., 2004; Salimpoor et al., 2011).

The hippocampus and the adjacent temporal gyrus seem to be commonly involved in the entire processes of positive anticipation by interacting with both dorsal and ventral striatum. The well-known functions of hippocampal memory systems include recollecting past experiences, extracting commonalities and regularities across those experiences, and constructing representations of future events (Ritchey and Cooper, 2020; Schacter et al., 2012, 2017), all of which are crucial for generating accurate prediction (Sherman and Turk-Browne, 2020) and representations of episodic details comprising affective states (Phelps, 2004; Richardson et al., 2004). Interestingly, we found a significant positive correlation between the FCs of the dorsal and ventral striatal-hippocampal networks, suggesting the possibility that these two networks communicate with each other. This finding fits well with previous research demonstrating that cognitive (e.g., positive expectation in the context of our study) and affective (e.g., positive anticipatory feelings) processes are mediated by separate but interacting neural systems (Dolcos et al., 2011; LeDoux, 1989; Pessoa, 2008).

Further analyses integrating the neural and behavioral evidence revealed that individual differences in the functional neural networks associated with the anticipatory experiences contribute to SWB. First, we found that the FCs of both dorsal and ventral striatal-hippocampal networks significantly predicted momentary SWB, such that individuals with greater FCs in these networks were more likely to show greater SWB. Second, the mediation models analogous to the behavioral results showed that individuals with greater FC in the dorsal striatal-hippocampal network showed increased FC in the ventral striatal-hippocampal network, which in turn predicted higher SWB. These findings suggest that individual differences in the functional neural architecture involved in value-based learning and memory can contribute to real-life anticipatory experiences, which in turn influence SWB.

The present study has several limitations that need to be addressed. Firstly, general positivity or optimism may have resulted in most of our behavioral results. To rule out this possibility, we controlled for the effect of total frequency of positive expectations by including the number of total positive expectations as denominator. Also, we performed additional analyses on the effect of unexpected positive experiences and found no relationships with the changes in affective states (Supplementary Table 10). Rather, the ratio of unexpected positive experiences tended to be negatively correlated with the SWB measures (SWB: $B = -1.368$, $t = -1.878$, $P = 0.064$; life satisfaction: $B = -1.075$, $t = -1.430$, $P = 0.156$; happiness: $B = -1.661$, $t = -2.302$, $P = 0.024$). This suggests that neither general positive expectations nor the frequency of unexpected positive events were predictive of positive changes in affective states or SWB. At least in our study, overall positivity does not seem to be associated with change in positive anticipatory feelings and SWB. Secondly, caution should be taken when interpreting causal directions of our findings because the present study did not include experimental manipulation and most of our data analyses were correlational. Yet, we would like to note that we tried to include sufficient temporal gap (approximately two weeks) between the rs-fMRI and the EMS measures and performed the LOOCV to support the predictive power of our models. Lastly, the majority of our sample consisted of college students and the sample size is not large enough, which may limit the generalizability of our findings to other populations. Future research including broader populations and larger samples would offer a more comprehensive view of the relationship observed in our study.

In conclusion, the present study provides novel and ecologically valid evidence on the functional neural architecture associated with positive anticipatory experiences and SWB. By tracking individuals' moment-to-moment experiences in daily life, we found that accurate predictions of positive events have significant affective benefits leading to greater well-being. The interaction between neural systems involved in value-based learning and memory, namely the functional connectivity of striatal-hippocampal networks, seems to play an important role in individual differences in SWB by shaping different anticipatory experiences. Our findings extend scientific understanding of the relationships among the brain's functional architecture, positive anticipatory experiences, and SWB, bridging the gap between laboratory and real-life contexts.

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Data and Code Availability

The study materials, data, code for all analyses are available at <http://osf.io/t2ukb/>. The full dataset is not publicly available due to lack of informed consent and ethical approval but is available on request by qualified scientists.

Author contributions

S.S. and J-A.C conceived and designed the study. M. J collected data. W-G.S. elaborated the research questions and analyzed the data. W-G.S. and S.S. wrote the manuscript. I.C. and S.S. provided supervision on the study design and interpretation of the results.

Declaration of interests

The authors declare no competing interests.

Additional information

Supplementary Information is available for this paper.

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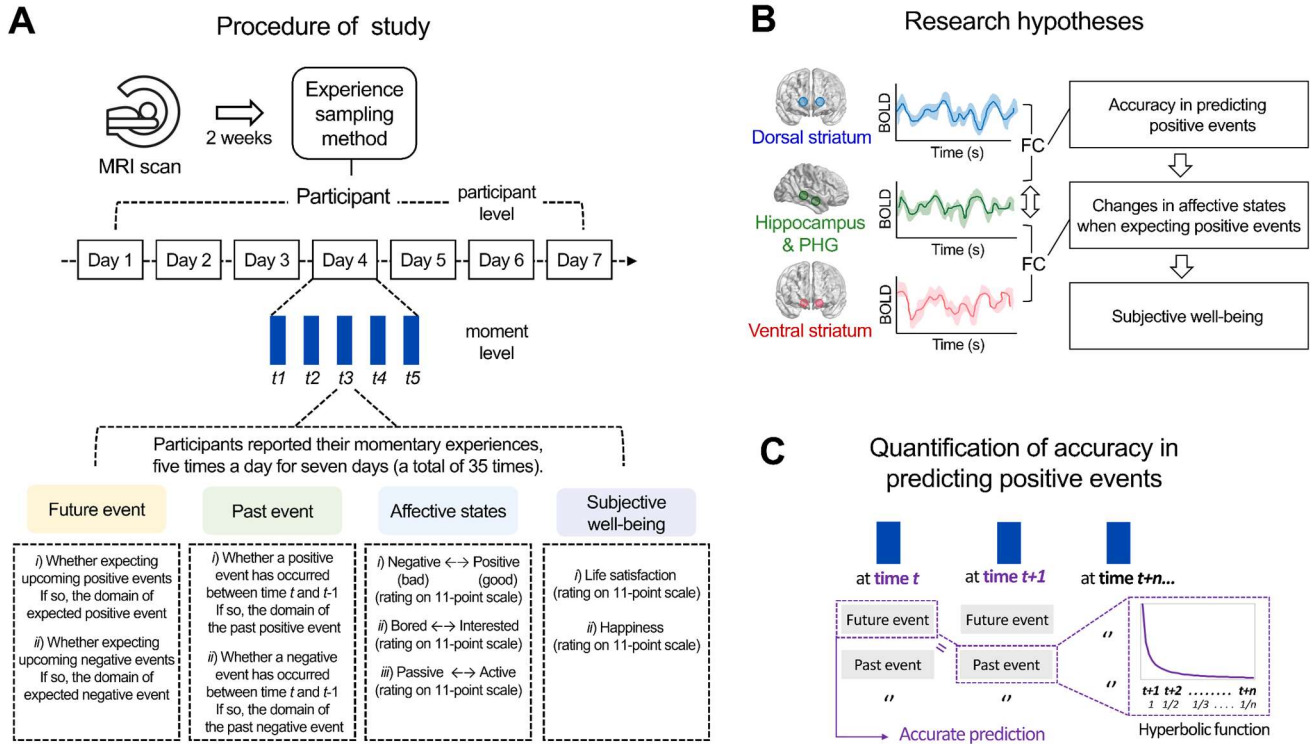


Fig. 1. Study design. (A) Participants ($n = 87$) were asked to report their momentary experiences, five times a day for a week two weeks after MRI scanning. The ESM surveys consisted of items measuring the existence of anticipation about positive or negative future events and their specific domains – either social, academic, work-related, or others, occurrence of positive or negative events and the specific domains of the events – either social, academic, work-related, or others, three domains of current affective states (i.e., emotional valence, interestedness, and activeness), and two domains of subjective well-being (i.e., life satisfaction and happiness). (B) We expected that the interplay between the regions involved in episodic memory (hippocampus, parahippocampal gyrus, and the adjacent temporal cortex) and value-based learning (striatum) would be associated with the positive anticipatory processes: the distinct but interrelated dorsal and ventral striatal-hippocampal networks were hypothesized to be related to the accuracy and changes in affective states, respectively. (C) The accuracy scores were calculated with the weighted sum of the number of positive events expected at time t that were actually occurred between time $t + 1$ and $t + n$ using the hyperbolic discounting function, divided by total number of positive future and past events.

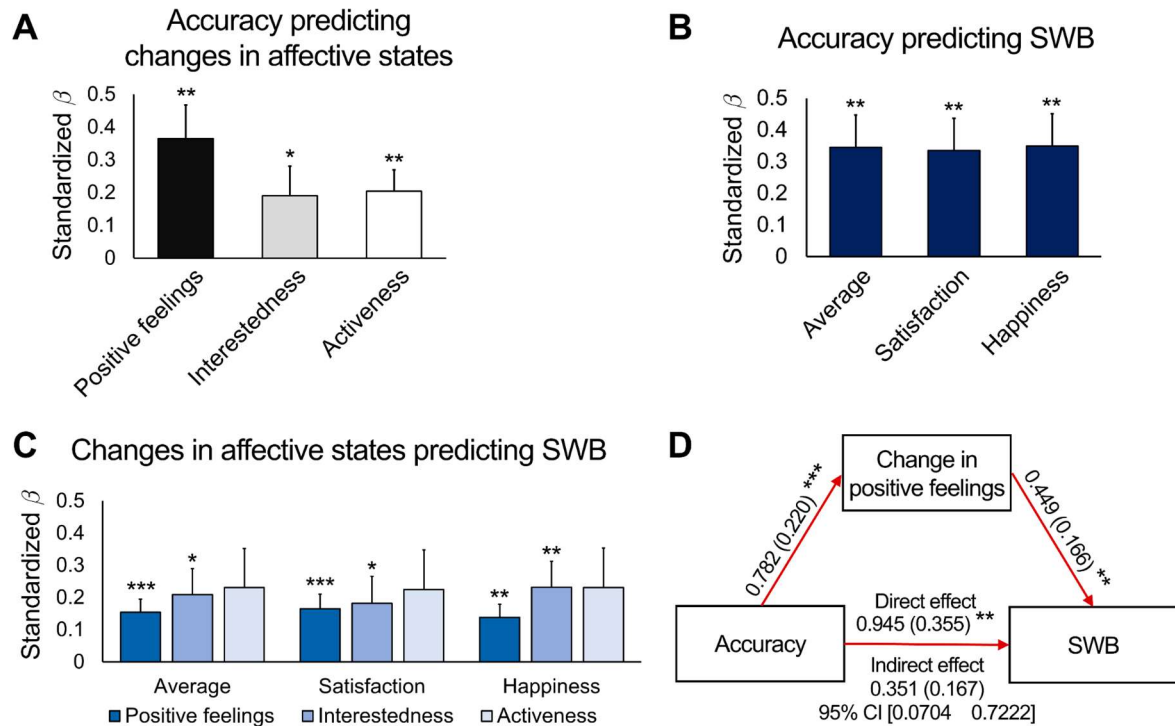


Fig. 2. Relationships among the accuracy, changes in affective states, and SWB. (A) Accuracy in predicting positive events was significantly correlated with the changes in affective states (positive feelings, interestedness, and activeness) accompanied by the positive anticipation. (B) The accuracy was predictive of SWB, life satisfaction, and happiness. (C) The changes in positive feelings and interestedness also predicted the SWB measures. (D) The change in positive feelings (i.e., positive changes in emotional valence) mediated the relationship between the accuracy and SWB (for the mediation results with life satisfaction and happiness, see Supplementary Fig. 1). Path coefficients are listed for each path with standard errors in parentheses * $P < 0.05$, ** $P < 0.01$, *** $P < 0.001$.

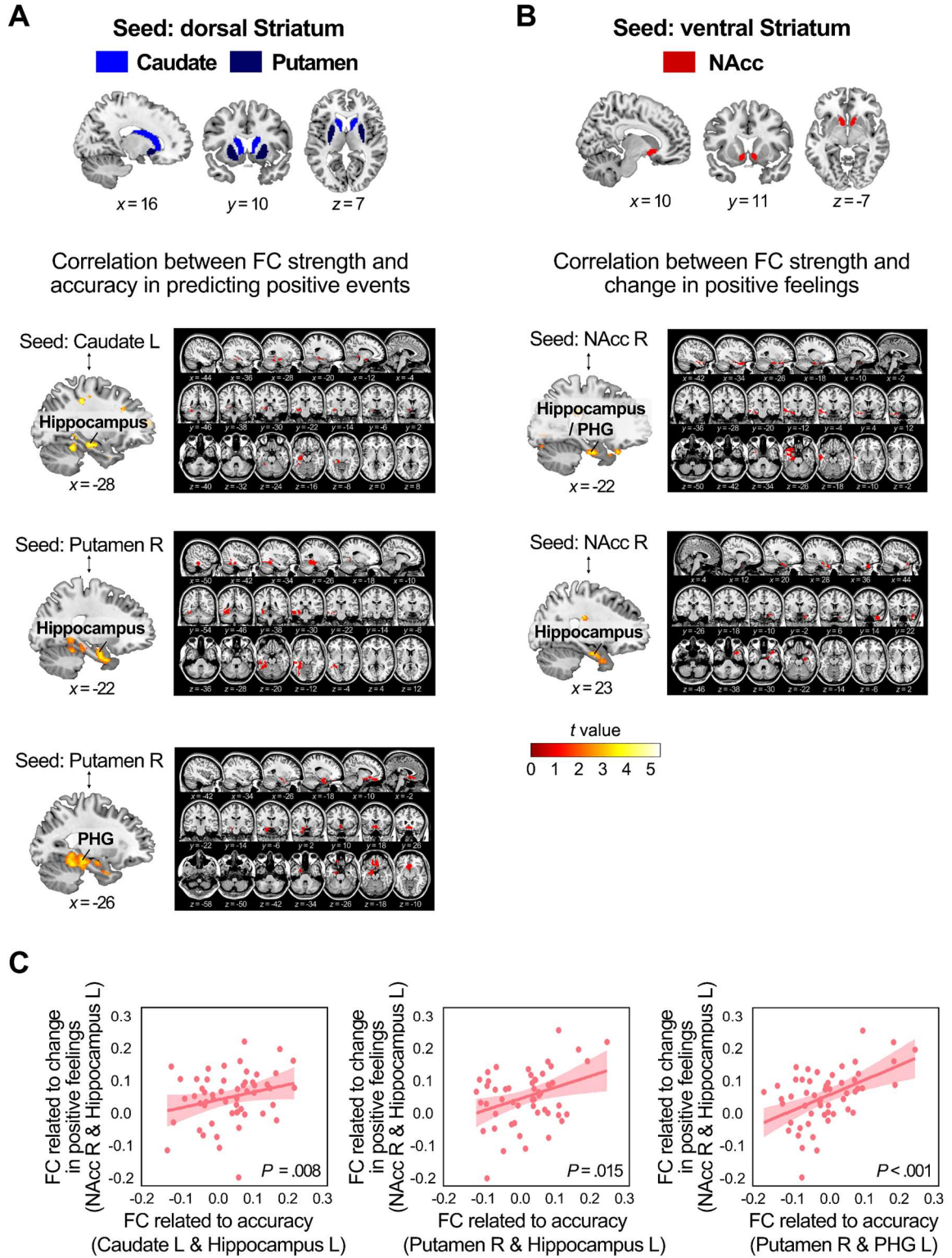


Fig. 3. Seed-based FC analysis results with the dorsal (caudate and putamen) and ventral striatum (NAcc) as seeds. (A) Accuracy in predicting positive events was positively correlated with the FC strength of *i*) the left caudate with the left hippocampus and *ii*) the right putamen with the left hippocampus and PHG. The accuracy was not associated with the FC strength between the NAcc and hippocampal regions. (B) The change in positive feelings was

associated with the FC between the right NAcc and bilateral hippocampal regions. None of the change in positive feelings was associated with FC of the caudate and putamen with the hippocampal regions. (C) The FCs associated with the accuracy and change in positive feelings were positively correlated with each other. For details of the brain regions and statistics, see Supplementary Table 4-6. NAcc, Nucleus Accumbens; PHG, parahippocampal gyrus; L, left; R, right. Whole-brain voxel-wise results with a threshold of uncorrected $P < 0.005$ and the cluster size of $k = 20$ are shown for illustration purpose. For the statistical tests, Small Volume Correction Family-Wise Error (SVC FWE) $P < 0.01$ with the *a priori* ROI (i.e., the cluster including the bilateral hippocampus, PHG, and MTG) was applied with initial voxel level threshold of $P < 0.005$.

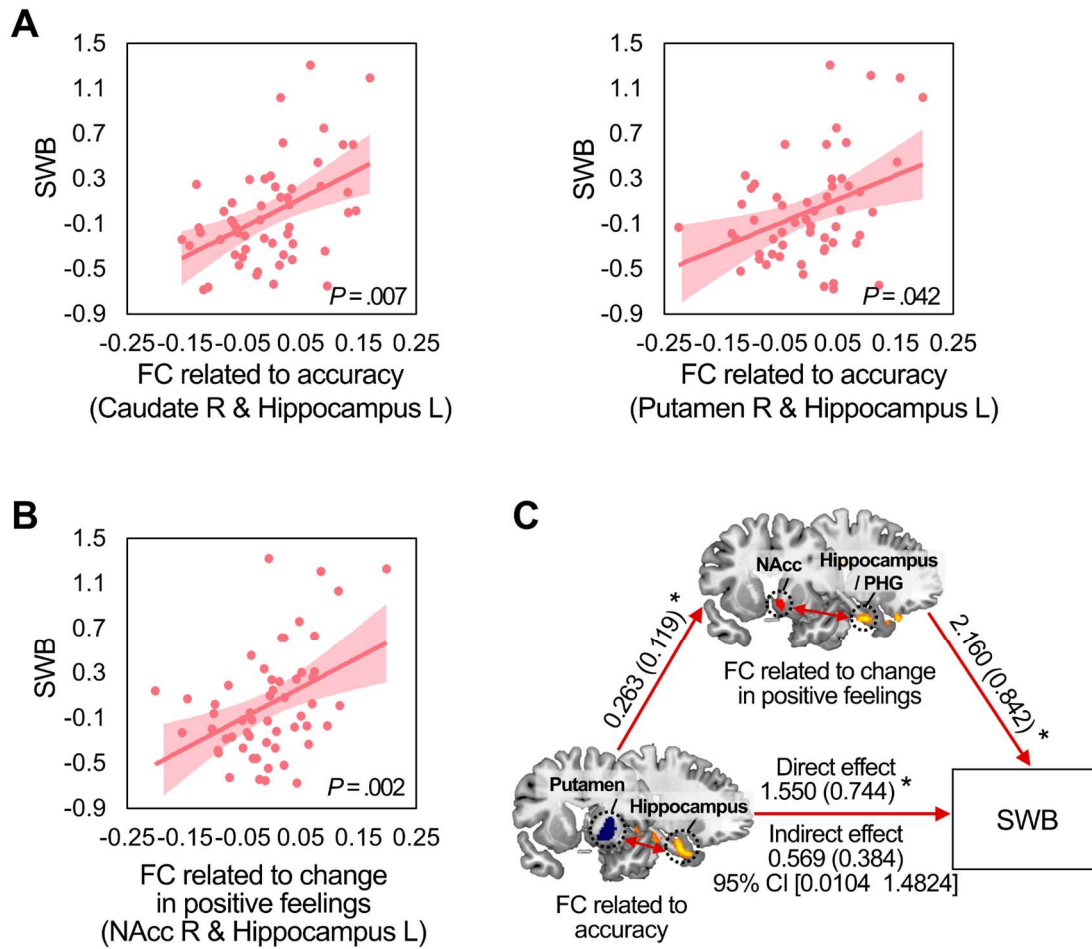


Fig. 4. Relationships between the striatal-hippocampal FCs associated with positive anticipatory processes and SWB. (A) The greater dorsal striatal-hippocampal FCs associated with the accuracy scores significantly predicted greater SWB. (B) The greater ventral striatal-parahippocampal FCs associated with the change in positive feelings predicted greater SWB. (C) Individuals with greater dorsal striatal-hippocampal FCs showed increased ventral striatal-hippocampal FCs, which in turn predicted SWB. Path coefficients are listed for each path with standard errors in parentheses * $P < 0.05$. L, left; R, right; SWB, subjective well-being.