doi:10.1093/scan/nsu001 SCAN (2014) 9, 1942–1951

Future planning: default network activity couples with frontoparietal control network and reward-processing regions during process and outcome simulations

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We spend much of our daily lives imagining how we can reach future goals and what will happen when we attain them. Despite the prevalence of such goal-directed simulations, neuroimaging studies on planning have mainly focused on executive processes in the frontal lobe. This experiment examined the neural basis of process simulations, during which participants imagined themselves going through steps toward attaining a goal, and outcome simulations, during which participants imagined events they associated with achieving a goal. In the scanner, participants engaged in these simulation tasks and an odd/even control task. We hypothesized that process simulations would recruit default and frontoparietal control network regions, and that outcome simulations, which allow us to anticipate the affective consequences of achieving goals, would recruit default and reward-processing regions. Our analysis of brain activity that covaried with process and outcome simulations confirmed these hypotheses. A functional connectivity analysis with posterior cingulate, dorsolateral prefrontal cortex and anterior inferior parietal lobule seeds showed that their activity was correlated during process simulations and associated with a distributed network of default and frontoparietal control network regions. During outcome simulations, medial prefrontal cortex and amygdala seeds covaried together and formed a functional network with default and reward-processing regions.

Keywords: planning; episodic simulation; fMRI; default network; frontoparietal network; reward processing

INTRODUCTION

Episodic future simulation, our ability to construct and imagine a hypothetical personal event or series of events in the future (Taylor and Schneider, 1989; Schacter *et al.*, 2008), has been at the center of much recent behavioral and functional magnetic resonance imaging (fMRI) research (e.g. Buckner and Carroll, 2007; Gilbert and Wilson, 2007; Schacter *et al.*, 2007; Szpunar, 2010; for a recent review, see Schacter *et al.*, 2012). In everyday life, people frequently engage in episodic future simulation (Klinger and Cox, 1987; D'Argembeau *et al.*, 2011) and tend to plan and anticipate personal goals when they do so (Baird *et al.*, 2011; D'Argembeau and Mathy, 2011). Two types of such goal-directed simulations will be the focus of this study: (i) imagining attaining a desired goal and (ii) constructing a detailed plan of how to reach a certain goal (Taylor and Pham, 1996; Oettingen and Gollwitzer, 2010). A large body of research has examined different aspects of planning, including diverse planning tasks (Hayes-Roth and Hayes-Roth, 1979; Shallice, 1982; Garden *et al.*, 2001), theoretical models of planning (e.g. Miller *et al.*, 1960; Ajzen, 1991) and planning deficits due to neurological damage (e.g. Penfield and Evans, 1935; Morris and Ward, 2005). In contrast, episodic future simulations, specifically in the context of personal goals and plans, have received comparatively little attention (for discussion, see Schacter, 2012).

A few behavioral studies on personal goal achievement have investigated the effects of episodic future simulations (e.g. Taylor *et al.*, 1998; Papies *et al.*, 2009; Chan and Cameron, 2011; Spreng and Levine, 2013). In a series of experiments measuring undergraduates' performance on midterm exams and a class project, Taylor and Pham (Pham and Taylor, 1999; Taylor and Pham, 1996, 1999) found that 'process simulations', during which students imagined the steps they should take in order to obtain a good grade or complete a project (imagining where and when they would study, what measures they would have to take in order to progress in their studying) proved more beneficial than 'outcome simulations', during which students envisioned themselves having achieved the goal of a good grade (being handed their exam with an A grade, feeling happy). Compared with students in the outcome simulation condition, participants in the process simulation condition started studying earlier, spent more hours studying, performed better on exams, were less anxious and suffered from the planning fallacy to a smaller extent. In a related line of research on 'implementation intentions', where participants form an association between a cue and the desired behavior ('If I encounter X, then I will perform Y'; Gollwitzer, 1999; Gollwitzer and Sheeran, 2006), implementation intentions that were accompanied by mental simulations of the future behavior rendered the goal behavior more likely to be carried out (Gollwitzer and Brandstätter, 1997; Papies *et al.*, 2009). For example, participants who had formed implementation intentions to write a report on how they spent Christmas Eve by specifying and visualizing when and where they would start to write the report were more likely to complete the assignment earlier and within the specified time window than participants who had only formed goal intentions (Gollwitzer and Brandstätter, 1997).

Unlike episodic simulations of the steps to be taken toward a goal, simulations of desired future outcomes allow us to pre-experience the events' affective impact and reward value (Boyer, 2008). This characteristic of outcome simulations has been shown to attenuate temporal discounting, the tendency to devalue delayed relative to immediate rewards (Peters and Büchel, 2010a; Benoit *et al.*, 2011). In the paradigms used by Benoit *et al.* (2011) and Peters and Büchel (2010a), participants were presented with immediate and delayed rewards and engaged in episodic simulations of future events that they could experience if they received the reward. This episodic simulation condition was compared with either wait time (Peters and Büchel, 2010a) or a semantic estimation of what the reward could purchase (Benoit *et al.*, 2011). If participants imagined events they associated

Received 25 August 2014; Revised 1 December 2013; Accepted 30 December 2014
Advance Access publication 3 February 2014
The authors are grateful to Felipe De Brigard for his help with PLS analyses. This research was funded by National Institute of Mental Health grant R01MH60941, awarded to D.L.S.
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with receiving a reward, they tended to overcome any temporal discounting bias, that is, they expressed more willingness to wait for a delayed but larger reward. Imagining personal future events has also been linked to the eventual enactment of these events (Spreng and Levine, 2006, 2013; Weiler *et al.*, 2010). Even though participants were not specifically instructed to imagine future personal goals, Spreng and Levine (2013) found that 59–64% of the imagined personal future events, which were supposed to be probable and specific in time and place, had actually occurred a year after participants simulated those events.

So far, no fMRI study has examined and compared the neural underpinnings of episodic simulations of the steps leading up to a personal goal and the events associated with achieving the desired goal. However, neuroimaging studies of episodic future simulations have consistently shown activations in the default network, a set of interconnected brain regions consisting of medial prefrontal cortex (mPFC), posterior cingulate cortex (pCC), medial and lateral temporal regions, and posterior inferior parietal lobule (pIPL; e.g. Gusnard and Raichle, 2001; Buckner *et al.*, 2008; D'Argembeau *et al.*, 2010; Yeo *et al.*, 2011). In two recent fMRI studies on episodic simulations that were directed toward a specific goal, default network regions were shown to form functional networks with task-relevant regions outside of the default network (Spreng *et al.*, 2010; Gerlach *et al.*, 2011). In one such study, Gerlach *et al.* (2011) required participants to simulate the process of solving a problem using a certain object (e.g. getting a friend's ring off your finger using soap) and revealed that default network regions and executive dorsolateral prefrontal cortex (dlPFC) were functionally coupled during the simulation. Spreng *et al.* (2010) provided participants with the steps necessary to complete different life goals and asked them to sequence these goals into a coherent imaginative plan that could lead to the achievement of the goals. During this planning task, activity in the default network was coupled with the entire frontoparietal control network, consisting of rostrolateral prefrontal cortex (rlPFC), middle frontal gyrus (MFG), anterior insula/frontal operculum, dorsal anterior cingulate cortex (daCC), precuneus (PCu) and anterior inferior parietal lobule (aIPL; Vincent *et al.*, 2008; see also Spreng and Schacter, 2012, and Spreng *et al.*, 2013 for replication and extension).

Neuropsychological and neuroimaging studies of classic planning paradigms, such as the Tower of Hanoi or the Multiple Errands Task, have also consistently implicated prefrontal cortex regions though none of these tasks involved episodic simulation of personal goals (e.g. Luria, 1966; Eslinger and Damasio, 1985; Goldstein *et al.*, 1993; Morris and Ward, 2005). DlPFC activity has been repeatedly associated with improved performance on executive planning tasks such as the Tower of London (e.g. Baker *et al.*, 1996; Dagher *et al.*, 1999; Rowe *et al.*, 2001), as well as more realistic multitasking procedures (e.g. Burgess *et al.*, 2000), suggesting that it plays a role in coordinating and maintaining behavior sequences and goals (Norman and Shallice, 1980; Botvinick, 2008; Badre and D'Esposito, 2009).

Findings from patients with ventromedial prefrontal cortex (vmPFC) lesions have indicated that these patients are insensitive to future consequences and are often unable to decide on which steps to take toward a goal (Eslinger and Damasio, 1985; Bechara *et al.*, 1994). VmPFC, which is also a default network region that has been tied to self-referential processing (e.g. Gusnard *et al.*, 2001; Amodio and Frith, 2006; Jenkins and Mitchell, 2007; D'Argembeau *et al.*, 2010), should thus play a role in the ability to simulate future outcomes. A more rostral region of mPFC has also been implicated in the ability to pre-experience outcomes, particularly if they are associated with positive valence or rewards (Sharot *et al.*, 2007; D'Argembeau *et al.*, 2008; Benoit *et al.*, 2011). In addition to mPFC, the experience of emotional valence and reward has been linked to a system of interconnected brain regions involved in affective and reward processing, including nucleus accumbens (NAcc), amygdala, insula, anterior cingulate cortex (aCC) and thalamus (e.g. Peters and Büchel, 2010b; Liu *et al.*, 2011).

In the present fMRI study of realistic episodic simulations about personal goals, we examined patterns of brain activation for process simulations, during which participants imagined themselves going through a number of idiosyncratic steps toward achieving a goal, and outcome simulations, during which participants imagined a number of personal events they associated with achieving a goal. Based on studies of similar goal-directed simulations and executive planning (Baker *et al.*, 1996; Spreng *et al.*, 2010; Gerlach *et al.*, 2011), we hypothesized that participants' process simulations would recruit regions of the default and frontoparietal control networks. We expected activity in core nodes of these networks, such as pCC in the default network (Fransson and Marrelec, 2008; Hagman *et al.*, 2008; Buckner *et al.*, 2009), and aIPL and dlPFC in the frontoparietal control network (Vincent *et al.*, 2008; Spreng *et al.*, 2013) to be coupled as a functional network during process simulations.

As outcome simulations allow participants to pre-experience the affective impact and reward value of achieving a goal, we hypothesized that they would be associated with regions that have been linked to emotion processing, such as the amygdala (e.g. Bechara *et al.*, 1999, 2003), and reward processing, such as the NAcc and aCC (e.g. Peters and Büchel, 2010a,b; Liu *et al.*, 2011). Given the prospective, self-referential nature of outcome simulations, we also expected default network regions, in particular mPFC based on its aforementioned role in the simulation of consequences and reward value (Eslinger and Damasio, 1985; D'Argembeau *et al.*, 2008; Benoit *et al.*, 2011), to be coupled with reward-processing regions.

MATERIALS AND METHODS

Participants

Twenty-eight healthy, right-handed young adults (mean age = 21.2 years, s.d. = 2.8; range = 18–28 years; 20 women) with normal or corrected-to-normal vision and no history of psychiatric or neurological conditions provided written consent and participated in the experiment in accordance with the guidelines of the Committee on the Use of Human Subjects in Research at Harvard University. All participants were native English speakers and were recruited from Harvard University and Boston University. Data from an additional three participants were discarded due to excessive movement in the scanner (one participant) and non-compliance with the task reflected in post-scan interviews (two participants).

Materials

The stimulus set consisted of 102 goals based on a large sample of personal goals we collected from an independent group of 21 young adults that were matched to our scanned group in terms of age [$t(47) = 1.56$, $P = 0.125$], gender [$\chi^2(1) = 2.10$, $P = 0.15$] and education [$t(47) = 1.06$, $P = 0.293$; see Supplementary Table S1 for the list of goals]. This independent group was asked to generate at least 150 realistic personal goals that were attainable within the next 5 years and comprised neither habitual activities nor significant milestones such as graduating from college or getting married. We constrained the goals that participants were asked to provide in such a way as to limit variability within the stimulus set. For each goal, participants indicated four sequential steps they would take to reach the goal and four events or activities they associated with having accomplished the goal. For instance, for the goal of going on vacation, many participants imagined going online to compare prices for different destinations, booking a trip, packing a suitcase and getting on a plane. Swimming in a pool, having a meal of local specialties, going snorkeling and

sleeping in were activities many participants associated with having achieved the goal of going on vacation. Participants also provided a rating of each goal's desirability on a scale of 1–100 (100 being most desirable).

We determined 102 goals to be similarly desirable ($t < 1$) and reliable across the sample such that at least six out of 21 participants needed to have generated a goal for it to be included in the dataset. Common goals ranged from self-improvement (e.g. eating healthier food, improving your wardrobe) to new skill acquisition (e.g. learning to drive stick shift, learning how to paint), to activities with friends and family (e.g. going on family vacation, being in a friend's wedding). All goals were adapted to be 3–6 words long and to apply to both process and outcome simulations. Six goals were used for practice trials and 96 for fMRI scanning.

Design and procedure

Prior to scanning, participants became familiar with all in-scanner tasks by completing six practice trials. The practice trials included three trials for the process simulation, for which they imagined two, three and four steps necessary to achieve a goal, and three trials for the outcome simulation condition, for which they imagined 2, 3 and 4 plausible events associated with achieving the goal. We asked participants to produce a specific number of steps or events for each simulation in order to make the two conditions as equivalent as possible. This procedure also allowed us to test whether the number of imagined steps or events affected neural activity for each type of simulation. Following the practice trials, participants were asked to recount the content of their simulations to ensure task compliance. In order to elicit realistic, idiosyncratic process and outcome simulations, we did not to prescribe the specific steps or events participants imagined.

In the scanner, participants were presented with eight experimental runs of 12 goal simulation trials. Goals were randomized and counterbalanced across conditions, number of steps/events and participants, so that each run contained six outcome and six process simulations without repetitions across conditions. All experimental trials were intermixed with varying periods of an odd/even task ranging from 5 to 10 s in duration (Stark and Squire, 2001): participants saw a number from 1 to 9 in the center of the screen and indicated through a button press whether it was odd or even; they had 2.5 s to do so for each number. Fixation, which typically elicits default network activity (Stark and Squire, 2001), was not used as a direct comparison task for process and outcome simulations, as we expected default network regions to also be engaged in process and outcome simulations.

For process simulation trials, participants were instructed to imagine themselves going through a set number of steps (2, 3 or 4) that would help them achieve a given goal. In outcome simulation trials, participants simulated a set number of events that they associated with having achieved a given goal. Both the instructions and the goal itself remained on screen for the duration of all trials. Trial duration was self-paced with a maximum duration of 30 s. Next, participants had 2.5 s to provide a success rating indicating whether they were able to generate a simulation and adhere to the task instructions. Runs were approximately 8 min long, and visual stimuli were presented in black, blue (process goals) or green (outcome goals) on a white background using a Lenovo Thinkpad laptop that runs EPrime.

Following the scan, participants received a randomized list of all the goals and were asked to provide a brief written description of each step/event imagined, which served as a manipulation and task compliance check. Participants also provided behavioral ratings for each trial: on a scale of 1–7, they rated how detailed and difficult to generate each simulation had been (1 = least detailed/difficult, 7 = most detailed/difficult) and also indicated with a 'yes' or 'no' whether a given goal was one they wanted to pursue in real life. Participants also provided ratings on a 1–7 scale for how important and desirable the goal was, how confident they were that they would complete the goal, how motivated they were to achieve it and how difficult they thought it would be to achieve the goal. It took participants 1.5–2 h to complete this post-scan interview. The written descriptions of each imagined step or event allowed us to verify participants' adherence to the experimental manipulation. Any written description that was incomplete or did not comply with task instructions in the post-scan interview or that was rated unsuccessful in the scanner was excluded from behavioral and fMRI analyses.

fMRI data collection

We acquired high-resolution three-dimensional T1-weighted anatomical images [repetition time (TR), 2530 ms; echo time (TE), 3.44 ms; flip angle (FA), 7°; 1.0 mm^3 isotropic voxels] as well as all functional images using a 3 T Tim Trio scanner (Siemens) with a 12-channel phased-array head coil. We collected the data for each participant's eight experimental runs using a gradient-echo echo-planar pulse sequence sensitive to blood oxygenation level-dependent (BOLD) contrast (TR, 2500 ms; TE, 30 ms; FA, 90°; $2 \times 2 \times 2$ mm^3 voxels; 39 axial slices parallel to the plane of the anterior commissure–posterior commissure; 0.5 mm gap between slices). Participants' head motion was minimized with a pillow and two padded clamps. They wore earplugs to decrease scanner noise and held a button box in their right hand. All visual stimuli were projected onto a screen at the head of the magnet bore, which participants viewed through a reflection in a mirror on top of the head coil.

fMRI data

Preprocessing

We used SPM2 (Wellcome Department of Cognitive Neurology, London, UK, www.fil.ion.ucl.ac.uk/spm) to preprocess all fMRI data. After excluding the first four volumes of each run to avoid T1-equilibration effects, we corrected the data for slice-dependent time shifts and for head motion within and across runs using a rigid body correction. Images were normalized to the standard space of the Montreal Neurological Institute (MNI) atlas and smoothed with a 6 mm full-width-at-half-maximum Gaussian kernel resulting in a voxel size of 2 mm^3.

Partial least squares

In order to analyze task-related brain activation, we performed a multivariate partial least squares analysis (PLS; McIntosh *et al.*, 1996; McIntosh *et al.*, 2004; Krishnan *et al.*, 2011). PLS identifies whole-brain activity patterns related to experimental tasks and is sensitive to distributed voxel response. It calculates a set of orthogonal components (latent variables, LVs) that best explain the covariance of distributed voxels across the whole brain with the experimental tasks. In contrast to univariate analyses, PLS thus does not examine the activity of any single voxel independently but instead identifies patterns of activity that covary with task conditions. In addition, it extracts these whole-brain activity patterns in one step, which renders correcting for multiple statistical comparisons unnecessary. Permutation tests determine the statistical significance of the LV as a whole, and bootstrap resampling with replacement determines the reliability of the effects.

The whole-brain data were analyzed as blocks of variable duration set to participants' self-paced simulation intervals. In the first PLS analysis, we reported on simulation and outcome conditions, collapsing across the different numbers of imagined steps or events. PLS calculated a set of LVs based on the covariance matrix of the mean BOLD signal for each block and the experimental tasks: process

simulations, outcome simulations and odd/even judgments. This calculation, which involved singular value decomposition of the matrix, resulted in a singular value for each orthogonal LV. The first LV always has the largest singular value, i.e. it explains the largest proportion of the covariance between the BOLD signal and the experimental conditions. The statistical significance of each LV was calculated using a permutation test with 500 permutations. The correlation matrix was thereby randomly reordered 500 times, and each time the singular values for a new set of LVs were calculated. By comparing each resulting singular value of an LV to the original singular value, PLS establishes the probability of the permuted singular values that exceed the original value.

Each brain voxel was assigned a weight, or 'salience', that reflects the covariance of its activity with the task on each LV. The sum of the product of each voxel's by each voxel's BOLD signal resulted in a so-called brain score for each participant, task and LV. Brain scores indicate to what extent each participant expresses the LV's brain pattern. We calculated 100 bootstrap samples with replacement to determine whether the saliences for the brain voxels across participants for each LV were reliable based on the voxels' standard error (Efron and Tibshirani, 1985; Davidson and MacKinnon, 2000). We considered voxels with a bootstrap ratio (BSR; salience/standard error) > 2.58, $P < 0.01$, to be reliable. Local maxima, which we reported as MNI coordinates, were defined as voxels with the highest BSR within 2 cm^3 around them, consisted of clusters of more than 20 reliably activated voxels, and were more than 10 voxels apart from the next voxel peak. We calculated 95% confidence intervals for each BSR and determined two conditions to be reliably different from each other if their confidence intervals did not overlap.

In a second block PLS analysis, we divided the process and outcome simulation trials into trials with 2, 3 and 4 steps/events. This also allowed us to test whether the number of imagined steps or events affected neural activity for each type of simulation.

Task-related functional connectivity

We hypothesized that during process simulation, default and frontoparietal control network regions would be functionally coupled. During outcome simulations, we expected default and reward-processing regions to form a functional network. In order to test these hypotheses, we conducted a task-related functional connectivity analysis using 'seed' PLS (McIntosh, 1999; Krishnan *et al.*, 2011). Seed PLS examines the relationship between the activity of a set of seed regions and the activity in the rest of the brain. Across participants, the mean BOLD signal values of each group of seeds were correlated with the activity in all other brain voxels and combined into a matrix. Singular value decomposition of this matrix resulted in a set of orthogonal LVs. Each LV had a pattern of covariance for each seed region with the rest of the brain (singular profile; Figures 5 and 7) and a pattern of brain regions that covaried reliably with the seed activity (singular image; Figures 6 and 8). The significance and reliability of the pattern of connectivity of the distributed functional network were determined using permutation tests and bootstrap resampling as described earlier.

For process simulations, we extracted mean BOLD signal values from pCC (−10 −34 30), left aIPL (−46 −48 42), right aIPL (46 −50 46), left dlPFC (−34 32 45) and right dlPFC (40 44 26) along with their 26 neighborhood voxels, which provide a more reliable estimate of the activity in the region given anatomical variability than that of a single voxel. These seeds were derived from the peak activations with the highest BSRs in the block PLS analysis comparing process with outcome simulations (see Table 3) and also make up critical components of the frontoparietal control and default network in line with our a priori hypothesis. We also extracted mean BOLD signal values from mPFC (−10 58 28), left amygdala (−20 −6 −14) and right amygdala (16 −2 −20) for the outcome simulation condition. All three peaks stemmed from the PLS analysis comparing outcome and process simulations (see Table 4). For this seed PLS analysis, we required a BSR of 3.29 for peaks, which approximates a $P < 0.001$.

RESULTS

Behavioral findings

Participants rated 95% (s.d. = 4%) of simulation trials in the scanner as successful and correctly identified 90% (s.d. = 5%) of all odd/even trials, confirming their ability to successfully perform all experimental tasks. According to the exclusion criteria described earlier, we were able to use 90% (s.d. = 7%) of goal trials for behavioral and fMRI analyses. Simulation periods increased significantly in duration according to the number of steps and events participants were instructed to imagine [$F(2, 54) = 109.44$, $P < 0.001$, $\eta_p^2 = 0.80$], providing evidence of participants' task compliance, and did not differ significantly between conditions [$F(1, 27) = 3.54$, $P = 0.07$, $\eta_p^2 = 0.12$]. On average, it took participants 18 s (s.d. = 4) to simulate two steps/events, 21 s (s.d. = 5) to simulate three steps/events and 24 s (s.d. = 4) to imagine four steps/events associated with a given goal.

Post-scan ratings

Participants were able to generate detailed goal simulations ($M = 4.58$ out of 7 for all scalar ratings, s.d. = 0.64) and remembered their outcome simulations to be slightly more detailed than their process simulations (see Table 1 for descriptive statistics per condition and paired *t*-tests). Participants found it relatively easy to think of steps or events for each goal in the scanner ($M = 2.87$, s.d. = 0.82) or to achieve the given goals in real life ($M = 3.55$, s.d. = 0.81). On average, participants shared 59% (s.d. = 14%) of the presented goals and categorized a slightly higher percentage of the goals for which they had undergone outcome simulations as personal goals. Based on the relatively low novelty ratings ($M = 3.09$, s.d. = 0.88), participants had apparently given many of the given goals prior consideration. They were quite confident that they would be able to achieve the presented goals ($M = 4.23$, s.d. = 0.70) and were motivated to do so ($M = 3.75$, s.d. = 0.64). Goals in the outcome simulation condition were evaluated to be somewhat more important ($M = 3.74$, s.d. = 0.69) and desirable ($M = 4.38$, s.d. = 0.74) than goals in the process simulation condition (importance: $M = 3.50$, s.d. = 0.72; desirability: $M = 4.03$, s.d. = 1.00); across conditions participants found the presented goals to be quite desirable ($M = 4.27$, s.d. = 0.71) and important ($M = 3.65$, s.d. = 0.73).

Table 1 Post-scan interview characteristics

	Process	Outcome	Paired *t*-tests	
	M (s.d.)	*M* (s.d.)	*t*	*P*-value
Detail	4.45 (0.67)	4.7 (0.73)	2.44	0.02
Generation	2.82 (0.85)	2.94 (0.91)	1.04	0.31
Goal	0.56 (0.17)	0.62 (0.16)	3.07	0.005
Importance	3.50 (0.72)	3.74 (0.69)	3.94	0.001
Desirability	4.03 (1.00)	4.38 (0.74)	2.39	0.02
Novelty	3.09 (0.91)	3.10 (0.91)	0.12	0.91
Confidence	4.26 (0.82)	4.23 (0.65)	−0.26	0.80
Motivation	3.81 (0.95)	3.82 (0.63)	0.07	0.95
Achievement	3.79 (1.37)	3.53 (0.82)	−1.44	0.16

Behavioral ratings on a scale of 1–7 of each goal simulation (1 = least, 7 = most). 'Generation' refers to how difficult it was to generate steps or events; 'achievement' refers to how difficult it would be to achieve the goal in real life. 'Goal' was coded as a binary variable (1 = personal goal, 0 = not a personal goal). All paired *t*-tests had 27 degrees of freedom and were two-tailed.

These results show that participants' process and outcome simulations were relatively equivalent and confirm that the provided goals were relatable as well as relevant.

fMRI results

Partial least squares

The primary block PLS analysis resulted in two significant LVs. The first LV dissociated the two simulation tasks from the odd/even control task ($P < 0.001$; Figure 1). Both goal simulation tasks were associated with increased activity in default network regions relative to the odd/even task (see Table 2 and Figure 2). This robust default network activity encompassed all of the main default network nodes, including posterior parietal and retrosplenial cortex (rSC), vmPFC, posterior parietal lobule, inferior frontal gyrus, as well as anterior and medial temporal lobes (Gusnard and Raichle, 2001; Buckner *et al.*, 2008; Supplementary Table S2 for odd/even > goal simulation peaks).

As the first LV accounted for most of the covariance in the data (95.63%), we conducted a second PLS analysis with only the two experimental conditions in order to specifically target differences between process and outcome simulations (see also, St.-Laurent *et al.*, 2011). This analysis resulted in a significant pattern of activity that accounted for 100% of the covariance in the data ($P = 0.02$; Figure 1) and identified brain regions where BOLD signal differed between process and outcome simulations. Regions that showed increased activity during process simulations compared with outcome simulations pertained to both the frontoparietal control and the default network (see Table 3 and Figure 3): bilateral aIPL, anterior insula, dlPFC, PCu and MFG make up the frontoparietal control network (Vincent *et al.*, 2008; Spreng *et al.*, 2010; Niendam *et al.*, 2012), whereas pCC, rSC, superior frontal gyrus and the inferior frontal gyrus are part of the default network (Buckner *et al.*, 2008; Spreng *et al.*, 2013). In contrast, outcome simulations were associated with increased BOLD signal in bilateral mPFC, inferior frontal gyrus and amygdala (see Table 4 and Figure 4).

The secondary PLS analysis of process and outcome simulations with different numbers of steps and events tested whether the number of imagined steps/events modulated neural activity. Its results closely resembled those of the previous analysis: The first LV dissociated both simulation conditions from the odd/even condition, accounting for 75% of the variance ($P < 0.001$), whereas a significant second LV dissociated process from outcome simulations and explained 9% of the variance ($P = 0.03$) but did not differentiate between conditions with different numbers of steps or events. Even a separate PLS analysis comparing only process simulations with 2, 3 or 4 imagined steps did not reach significance (LV accounting for 60% of the covariance in the data, $P = 0.07$). An analogous analysis of outcome simulations with different numbers of events rendered no significant LV (accounting for 55% of the variance; $P = 0.25$).

Task-related functional connectivity

The seed PLS analysis for process simulations resulted in a significant pattern of task-related functional connectivity with one significant LV that accounted for 53% of the covariance ($P < 0.001$). Activity in

Table 2 Peak regions of activation for goal simulation > odd/even judgments

Lat	Region	BA	MNI coordinates			BSR
			x	*y*	*z*	
Goal simulation > odd/even judgments						
R	PHG	35/28	24	−34	−18	11.62
L	IFG	47/11	−40	28	−14	10.99
L	msPFC	6	−14	12	58	10.87
L	AG	39	−44	−72	32	10.04
L	IFG	45	−50	26	14	9.85
R	CT		42	−62	−42	9.76
R	PostCG	3	26	−30	62	7.48
L	Caud		−12	10	14	6.08
L	UC		−8	−88	−38	5.40
R	MTG	39	48	−60	24	5.07
R	MFG	6	30	12	48	4.96
R	IFG	11	36	38	−16	4.40
R	PCu	7	14	−58	60	3.99
R	mPFC	9	10	56	32	3.85

Lat, laterality; B, bilateral; L, left; R, right; BA, Brodmann's area; AG, angular gyrus; Caud, caudate; CT, cerebellar tonsil; IFG, inferior frontal gyrus; msPFC, medial superior prefrontal cortex; MTG, middle temporal gyrus; PHG, parahippocampal gyrus; PostCG, postcentral gyrus; UC, uvula of the cerebellum. Locations of the maxima are reported in the stereotaxic coordinates of MNI space.

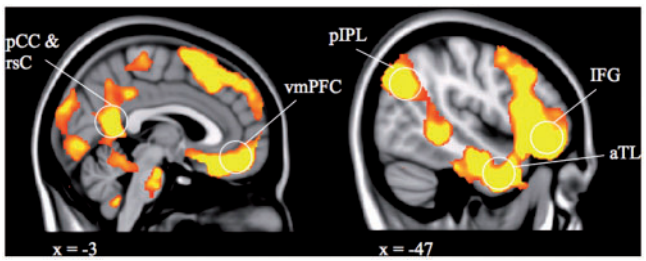

Fig. 2 Goal simulations > odd/even judgments. Activations in regions of the default network, including pCC, rsC, vmPFC, pIPL, inferior frontal gyrus and anterior temporal lobe (aTL).

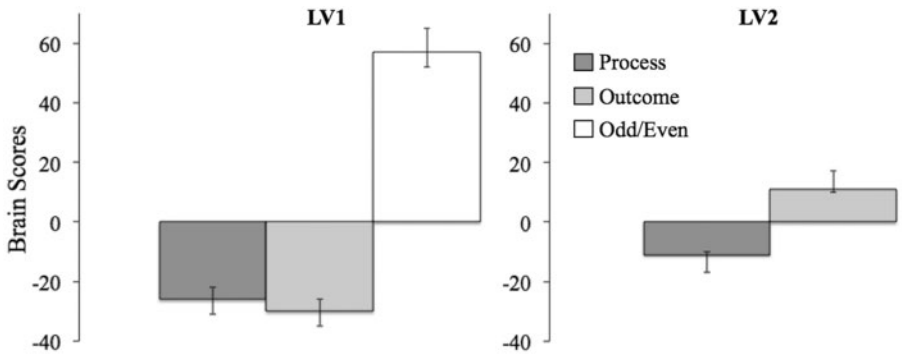

Fig. 1 Block PLS analysis mean brain scores per condition. Data are shown for the PLS analysis that included the control condition (LV1) and the analysis that focused on the experimental conditions (LV2). Error bars represent the 95% bootstrapped confidence intervals.

Table 3 Peak regions of activation for process simulation > outcome simulation

Lat	Region	BA	MNI coordinates			BSR
			x	*y*	*z*	
Process simulation > outcome simulation						
R	dlPFC	9	40	44	26	6.79
L	aIPL	40/7	−46	−48	42	5.89
R	aIPL	40/7	46	−50	46	5.71
B	pCC	23/31	−10	−34	30	5.69
L	islC		−16	−78	−44	5.61
R	MFG	32/8	6	30	34	5.23
R	PHG		34	−34	8	4.80
R	MFG	6	12	−8	54	4.69
B	PCu	7	0	−72	58	4.64
L	DC		−20	−92	−24	4.62
R	LG	18	4	−96	−2	4.36
L	islC		−34	−62	−40	4.34
R	PreCG	6	36	−6	38	4.28
L	dlPFC	9	−34	32	45	4.20
R	aINS	13	36	16	−4	4.05
L	MFG	6	−32	2	60	4.02
L	MTG	37	−48	−42	−10	4.02
L	FP	10	−26	52	−8	4.00
R	IFG	45	46	20	8	3.96
L	aINS	13	−32	−22	6	3.96
L	islC		−40	−78	−42	3.93
L	mCC	24	−6	0	26	3.92
L	PreCG	6	−52	−4	14	3.90
R	STG	38	46	−2	−18	3.90
L	ITG	37	−60	−62	−14	3.86
L	aINS	13	−36	12	6	3.85
L	FP	10	−26	48	20	3.84
R	FP	10	30	66	4	3.84
R	Thal		20	−10	18	3.77
R	Thal		22	−22	12	3.71
R	PostCG	3	50	−14	26	3.70
R	OP	18	30	−84	−20	3.66
L	STG	22	−48	−4	−6	3.63
R	GP		20	−2	2	3.62
R	STG	22	62	4	2	3.61
L	MFG	6	−30	−4	40	3.59
L	PC		−26	−68	−26	3.58
R	islC		24	−78	−48	3.39
L	SFG	6	−22	24	56	3.33
R	TC		54	−60	−30	3.27
L	PostCG	3	−36	−28	64	3.22
L	CC		−30	−38	−36	3.22
L	Thal		−10	−22	12	3.20
L	PCu	19	−28	−78	46	3.16
R	aIPL	40	52	−28	36	3.16
R	FG	37	56	−60	−14	2.86

aINS, anterior insula; CC, culmen of the cerebellum; DC, declive of the cerebellum; FG, fusiform gyrus; FP, frontal pole; GP, globus pallidus; islC, inferior semilunar lobule of the cerebellum; ITG, inferior temporal gyrus; LG, lingual gyrus; mCC, midcingulate cortex; OP, occipital pole; PC, pyramis of the cerebellum; PreCG, precentral gyrus; SFG, superior frontal gyrus; STG, superior temporal gyrus; TC, tuber of the cerebellum; Thal, thalamus. Other abbreviations can be found in the footnote of Table 2.

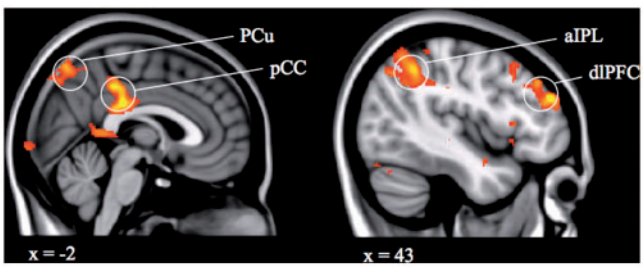

Fig. 3 Process simulation > outcome simulation. Activations in regions of the default network, including pCC, and regions of the frontoparietal network, such as PCu, aIPL and dlPFC.

Table 4 Peak regions of activation for outcome simulation > process simulation

Lat	Region	BA	MNI coordinates			BSR
			x	*y*	*z*	
Outcome simulation > process simulation						
R	mPFC	9	8	58	20	4.81
L	IFG	47	−28	30	−10	4.21
B	aCC	24	−2	22	10	3.99
L	AMG		−20	−6	−14	3.96
L	IFG	46	−48	38	0	3.78
L	mPFC	9	−10	58	28	3.72
L	IFG	45	−56	22	18	3.52
R	IFG	46	50	36	8	3.47
R	AMG		16	−2	−20	3.18

AMG, amygdala. Other abbreviations can be found in the footnotes of Tables 2 and 3.

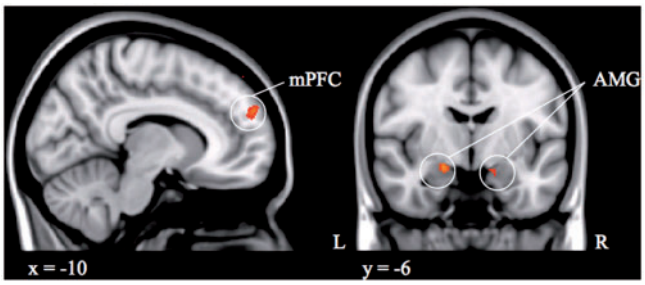

Fig. 4 Outcome simulation > process simulation. Activations in regions of the default network (mPFC) and of the limbic system (bilateral amygdala).

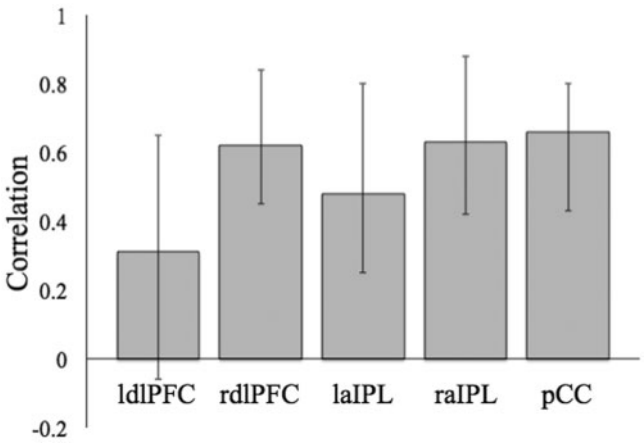

Fig. 5 Correlations of activity in bilateral dlPFC, aIPL and PCC with their respective brain scores show how activity in the five seeds covaries with activity in the entire network. Error bars represent 95% bootstrapped confidence intervals, which indicate no significant differences in the pattern of connectivity between the five seed regions.

bilateral dlPFC, aIPL and pCC seeds was significantly correlated with the whole-brain pattern, and the five seed regions reliably covaried together (see Figure 5). The regions that were functionally connected with the seeds during process simulations were part of the default network, such as mPFC, IFG and medial temporal lobe, as well as the frontoparietal control network, such as MFG, rlPFC and PCu (see Table 5 and Figure 6).

Table 5 Peak regions functionally connected with pCC, bilateral aIPLs and bilateral dlPFC seeds during process simulations

Lat	Region	BA	MNI coordinates			BSR
			x	*y*	*z*	
L	dlPFC	9	−32	58	24	7.32
R	dlPFC	9	44	42	28	7.13
L	IPL	13	−44	−46	28	6.47
L	PC		−14	−86	−28	6.35
L	pCC	31	−14	−44	34	6.34
L	aCC	32	−6	20	34	6.34
R	aIPL	40	46	−54	54	6.07
R	mCC	24	2	−18	42	5.93
R	CT		22	−64	−42	5.84
L	Med		−4	−48	−50	5.80
R	MFG	6	18	16	56	5.73
L	PreCG	6	−26	−6	68	5.71
R	CT		12	−58	−32	5.59
R	pCC	29	6	−42	10	5.56
R	PHG	34	24	2	−16	5.48
L	MFG	8	−36	28	40	5.42
R	Caud		12	8	18	5.40
L	TP	38	−50	14	−12	5.36
R	IFG	13	44	30	2	5.30
L	isIC		−32	−74	−46	5.28
L	PHG	23	−18	2	−18	5.20
R	MOG	18	36	−76	10	5.15
L	PHG	19	−24	−50	−10	5.10
R	isIC		12	−76	−40	5.07
R	STG	41	46	−30	2	5.04
L	PreCG	6	−46	−6	24	5.04
L	PreCG	4	−42	−12	42	5.03
R	Thal		4	−16	6	4.93
R	PHG	27	36	−26	−12	4.88
R	FG	37	42	−60	−20	4.80
L	PARC	6	−2	−30	70	4.72
L	PCu	7	−8	−64	40	4.67
R	PCu	19	32	−70	34	4.65
L	MOG	19	−30	−82	18	4.61
B	CUN	18	0	−78	24	4.51
R	MTG	20	58	−38	−12	4.49
R	FP	8	34	36	48	4.41
L	CT		−38	−56	−48	4.38
R	Mid		10	−16	−14	4.31
L	IFG	9	−38	12	24	4.29
R	IFG	9	40	14	22	4.23
R	IFG	45	60	30	4	4.10
L	MTG	21	−60	−30	−16	4.08
L	MOG	19	−52	−74	−2	4.05
R	PCu	7	16	−70	36	4.04
R	STG	42	70	−30	14	3.99
R	PreCG	6	40	0	26	3.99
L	msFG	6	−4	−4	72	3.98
R	CT		42	−52	−36	3.94
R	PCu	7	6	−64	40	3.76
L	INS	13	−34	−24	4	3.72
L	LN		−14	−2	4	3.59

CUN, cuneus; INS, insula; LN, lentiform nucleus; Med, medulla; Mid, midbrain; MOG, middle occipital gyrus; msFG, medial superior frontal gyrus; PARC, paracentral lobule; TP, temporal pole. Other abbreviations can be found in the footnotes of Tables 2–4.

For outcome simulations, one significant LV accounted for 51% of the variance ($P = 0.01$) in the seed PLS analysis. The two amygdala seeds and the mPFC seed reliably covaried together and were significantly correlated with the composite whole-brain score (see Figure 7). The resulting functional network included vmPFC, rsC and medial temporal lobe regions that are commonly associated with the default network (see Table 6 and Figure 8). Regions that have been implicated in reward processing were also functionally recruited during outcome simulations, including NAcc, aCC, caudate, thalamus, MFG and vmPFC (Liu *et al.*, 2011).

DISCUSSION

This study examined the neural correlates of our ability to imagine a series of steps leading up to a goal and to simulate what it would be like to achieve a goal. Participants engaged in process simulations, during which they imagined a number of steps they would take toward achieving a given goal. This task required them to project themselves into the future, generate a number of plausible steps, put them into a coherent sequence and simulate themselves going through these steps, all the while keeping in mind the end goal. Process simulations recruited default network as well as frontoparietal control network regions, which converged with evidence from fMRI studies of related planning and problem-solving simulations (Spreng *et al.*, 2010; Gerlach *et al.*, 2011). Components of the frontoparietal network, such as dlPFC, have been linked to cognitive control (e.g. Botvinick, 2008; Badre and D'Esposito, 2009; Packer and Cunningham, 2009) and executive planning processes in both healthy samples (e.g. Baker *et al.*, 1996; Burgess *et al.*, 2000; Rowe *et al.*, 2001) and lesion patients (e.g. Goldstein *et al.*, 1993; Luria, 1966; Morris and Ward, 2005). DlPFC activity was not correlated with information load, suggesting that the involvement of executive processes cannot be accounted for by increasing task demands. Many recent findings have provided evidence that the default network supports self-projection and prospection (Buckner and Carroll, 2007; Spreng and Grady, 2010; Andrews-Hanna, 2012), and that pCC acts as one of its critical connector hubs (Fransson and Marrelec, 2008; Hagman *et al.*, 2008; Buckner *et al.*, 2009). Our seed PLS analysis confirmed that defining nodes of the default and frontoparietal control networks (pCC, aIPL and dlPFC) behaved as a functional network during process simulations and were connected with a distributed network of regions that consisted of other default and frontoparietal control network regions, including MFG, IFG, rlPFC, PCu and PHG. These findings provide more evidence that the default and frontoparietal control networks are coactive during goal-directed simulations that require cognitive control (Spreng, 2012). The results fit with the hypothesized role of the frontoparietal control network, which is thought to regulate activity in the default network and the dorsal attention network, whose activation has been linked to exogenous stimuli (Corbetta and Shulman, 2002; Spreng *et al.*, 2010; Smallwood *et al.*, 2011; Gao and Lin, 2012). In the present task, the frontoparietal control network may have shielded the default network from distracting exogenous stimuli and supported the simulation of complex internal plans though this hypothesis goes beyond the evidence presented in this study and should be tested in future research.

During outcome simulations, participants imagined what it would be like to achieve a given goal. They were prompted to generate and imagine themselves in a number of events they associated with reaching a goal, which allowed them to pre-experience the affective impact that these events could have on them. Compared with process simulations, we found outcome simulations to be associated with increased activity in mPFC, a main node of the default network (e.g. Buckner *et al.*, 2008; Andrews-Hanna *et al.*, 2010), and the amygdala, a region that has consistently been linked to emotion processing (e.g. Bechara *et al.*, 1999, 2003). Across many studies, mPFC has shown increased activation in response to self-referential processing (e.g. Macrae *et al.*, 2004; Jenkins and Mitchell, 2007; Mitchell *et al.*, 2011), including thinking about personal compared with non-personal future goals (D'Argembeau *et al.*, 2010). Participants in this study were significantly more likely to consider a given goal for which they had generated outcome simulations a personal future goal and also rated it higher

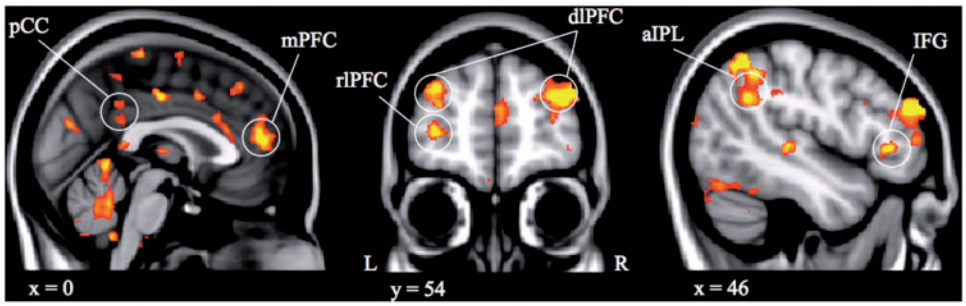

Fig. 6 Regions of the distributed functional network in the seed PLS analyses of process simulations.

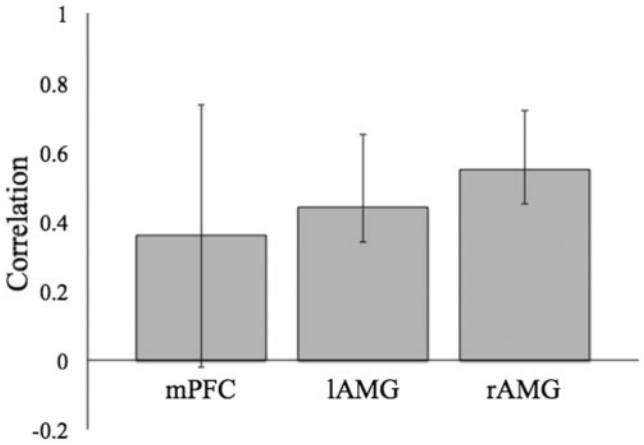

Fig. 7 Correlation of activity in mPFC and bilateral amygdala seeds with their respective brain scores show how activity in the three seeds covaries with activity in the entire network. Error bars represent 95% bootstrapped confidence intervals, which indicate no significant differences in the pattern of connectivity between the three seed regions.

in importance and desirability. These ratings may be explained by the reward-emphasizing nature of outcome simulations, which might have led participants to identify more with the goals whose achievement they imagined.

A functional connectivity analysis confirmed that mPFC activity was significantly correlated with bilateral amygdala activity during outcome simulations, and that the three seed regions were also connected to a distributed network of regions consisting of other default network regions (e.g. vmPFC, rsC, HC) and regions involved in the anticipation and evaluation of rewards and outcomes, including aCC, NAcc, MFG, caudate and medial thalamus (e.g. Schulz, 2000; Peters and Büchel, 2010a,b; Liu *et al.*, 2011). Activation in the mPFC seed region has been linked to imagining positive events and goals that promoted positive actions (Sharot *et al.*, 2007; D'Argembeau *et al.* 2008; Packer and Cunningham, 2009) and to evaluating possible rewards and outcomes (Montague *et al.*, 2006; Rushworth and Behrens, 2008; Benoit *et al.*, 2011; Liu *et al.*, 2011). Other components of the reported functional network, such as aCC, amygdala and the hippocampus, have been shown to be coactive when participants envisioned possible rewards, with the effect of alleviating reward delay discounting (Peters and Büchel, 2010a). Finally, vmPFC is presumed to play a role in the ability to anticipate future consequences and to decide on goals to pursue (Eslinger and Damasio, 1985; Bechara *et al.*, 1994), which aligns with its recruitment during outcome simulations. The present findings reveal how default network and reward-processing regions can act together to generate simulations of desired future outcomes, thereby facilitating decision-making about future goals.

Table 6 Peak regions functionally connected with mPFC and bilateral amygdala seeds during outcome simulations

Lat	Region	BA	MNI coordinates			BSR
			x	*y*	*z*	
R	AMG		16	−2	−16	9.60
R	LG	19	26	−72	4	9.18
L	PHG	28	−18	−18	−20	8.49
R	CC		24	−32	−34	8.35
L	LG	19	−28	−70	4	8.23
L	SPL	7	−24	−66	56	7.58
L	DC		−20	−70	−20	7.36
L	Med		−2	−30	−44	7.28
R	Caud		18	−10	22	7.21
R	FG	37	46	−60	−20	6.82
L	Caud		−14	10	22	6.81
L	rsC	29	−2	−36	0	6.38
L	Pons		−10	−24	−24	6.36
L	LN		−16	0	−4	6.19
R	OP	18	2	−98	18	6.16
R	Pons		4	−42	−30	5.99
R	FG	19	22	−54	−10	5.96
L	aCC	32	−2	22	32	5.94
L	aCC	32	−2	36	20	5.75
R	PCu	7	2	−72	56	5.62
L	msFC	6	−2	28	66	5.55
L	FP	10	−32	46	12	5.37
L	TC		−34	−80	−26	5.29
R	Thal		26	−26	10	5.17
L	Put		−30	4	14	5.14
R	NAcc		12	10	−10	5.06
R	MFG	6	2	8	52	4.99
L	LG	18	−2	−64	2	4.80
L	HC		−40	−34	−6	4.77
L	Thal		−26	−32	8	4.73
R	SPL	7	22	−58	68	4.66
L	PCu	7	−8	−56	74	4.66
L	STG	22	−46	−20	−8	4.61
R	SOG	19	42	−74	38	4.60
L	CT		−18	−42	−50	4.52
L	MFG	9	−28	34	30	4.42
B	vmPFC	10	0	56	0	4.40
R	PreCG	4	28	−24	72	4.36
R	aCC	32	8	14	38	4.35
B	mPFC	8	0	36	40	4.25
L	FP	10	−12	64	20	4.21

HC, hippocampus; Put, putamen; SOG, superior occipital gyrus; SPL, superior parietal lobule. Other abbreviations can be found in the footnotes of Tables 2–5.

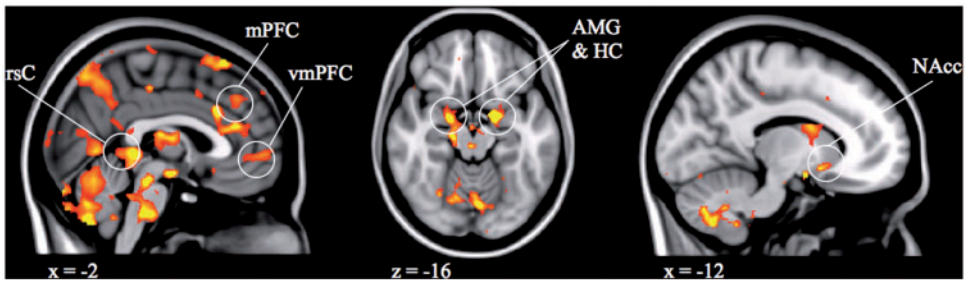

Fig. 8 Regions of the distributed functional network in the seed PLS analysis of outcome simulations.

Our results provide further evidence of the default network's involvement in goal-directed episodic simulations and its ability to flexibly pair with both frontoparietal control and reward-processing regions to support such simulations. These findings were based on process and outcome simulations of goals to which participants could relate but which they were not necessarily trying to meet in their own lives at the time of study. If all of the goals had been self-generated and immediately relevant to participants, we would have expected mPFC, which has been linked to self-referential processing (e.g. Macrae *et al.*, 2004) and imagining personal as opposed to non-personal future goals (D'Argembeau *et al.*, 2010), to be even more strongly activated in both experimental conditions. It is also useful to consider our findings in the context of the adaptive value of process and outcome simulations. Behavioral studies of process and outcome simulations have suggested that both types of simulation can help us achieve goals but may do so in different ways (e.g. Taylor and Pham, 1999; Benoit *et al.* 2011). Although process simulations may aide the implementation of plans to reach a goal by laying out the exact steps necessary to achieve it, outcome simulations may help us choose beneficial long-term goals if, for example, the ability to make far-sighted decisions in the context of temporal discounting (Peters and Büchel, 2010a; Benoit *et al.*, 2011) extends to the choice of personal goals. However, the exact mechanisms behind these potential benefits have to be explored further. By providing initial insights into the brain networks that subserve process and outcome simulations, this study has helped to lay the groundwork for further behavioral and neuroimaging investigations.

SUPPLEMENTARY DATA

Supplementary data are available at *SCAN* online.

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