Dimensions of Experience: Exploring the Heterogeneity of the Wandering Mind

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Abstract

The tendency for the mind to wander to concerns other than the task in hand is a fundamental feature of human cognition, yet the consequence of variations in its experiential content for psychological functioning are not well understood. Here, we adopted a multivariate pattern analysis approach, simultaneously decomposing experience sampling data with neural functional connectivity data, revealing dimensions that simultaneously describe individual variation in self-reported experience and default mode network connectivity. We identified dimensions corresponding to traits of positive, habitual thoughts and spontaneous task-unrelated thoughts. These dimensions were uniquely related to aspects of cognition, such as executive control and the ability to generate information in a creative fashion, and independently distinguished well-being measures. These data provide the most convincing evidence to date for an ontological view of the mind-wandering state as encompassing a broad range of different experiences and that this heterogeneity underlies its complex relationship to psychological functioning.

Keywords: mind-wandering, default mode network, content regulation, ontology of spontaneous thought.

Introduction

Although our minds frequently wander from events in the here-and-now, or any task being performed, the functional consequences of this state remain poorly understood (Mittner, Hawkins, Boekel, & Forstmann, 2016; Seli, Risko, Smilek, & Schacter, 2016; Smallwood & Andrews-Hanna, 2013). Some studies link mind-wandering to unhappiness (Killingsworth & Gilbert, 2010), others suggest it facilitates recovery from negative emotional states (Poerio, Totterdell, Emerson, & Miles, 2016; Ruby, Smallwood, Engen, & Singer, 2013). Mind-wandering is associated with poorer performance on executively demanding tasks (McVay & Kane, 2009; Mrazek et al., 2012), yet studies of problem solving suggest it may promote creativity (Baird et al., 2012; Smeekens & Kane, 2016). This wide range of associated functional outcomes is puzzling - if mind-wandering is a homogeneous construct, then it is unclear why it should be associated with such a complex array of often opposing outcomes. To reconcile this contradictory evidence, mind-wandering has been suggested to be heterogeneous, encompassing multiple states, with differential contents and underlying cognitive architectures (Smallwood & Andrews-Hanna, 2013). According to this ontological perspective, different functional associations arise from different 'types' of experience, explaining the range of functional outcomes observed in the literature.

In the current study, we recruited 165 participants and obtained data on (a) the organization of the brain at rest using functional magnetic resonance imaging (fMRI) (b) the content and form of experience recorded across different days, (c) cognitive functions assessed by a comprehensive battery of tasks (including memory, creativity, and executive control) and (d) psychological well-being via questionnaires. Our procedure is presented in Figure 1. These data allowed us to use novel multivariate analysis methods to test the hypothesis that there are different types of mind-wandering, with unique neural and experiential patterns, accounting for unique variance in the psychological profile of our sample.

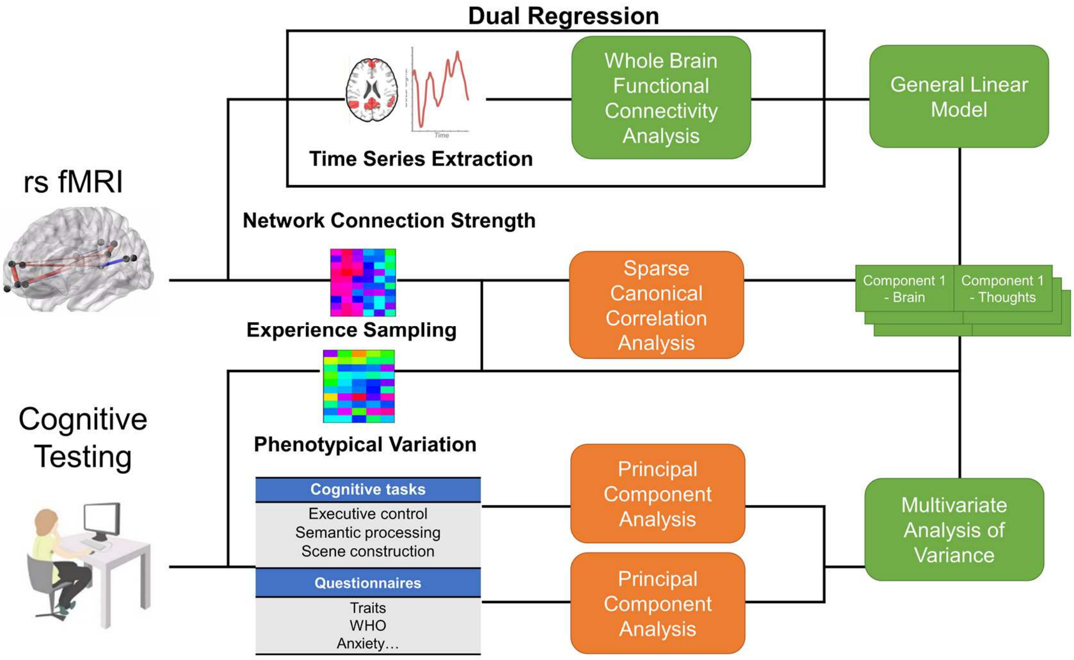

Figure 1. Schematic of the procedure and analysis strategy employed in the current study.

We used functional connection strength to characterize the neural organization of each individual. We selected regions for our analysis based on evidence that task-unrelated thoughts are linked to concurrent increases in activity in medial prefrontal cortex (mPFC) and posterior cingulate cortex (pCC) and lateral parietal cortex (for meta-analyses, see Fox, Spreng, Ellamil, Andrews-Hanna, & Christoff, 2015; Stawarczyk & D'Argembeau, 2015) - regions that make up the core of the default mode network (DMN; Buckner, Andrews-Hanna, & Schacter, 2008). During mind-wandering, it is believed that these regions interact with other areas of cortex, in particular, temporal lobe regions associated with memory representation that are also allied to the DMN. For example, the hippocampus activates early during mind-wandering (Ellamil et al., 2016) while connectivity between lateral and medial aspects of the temporal lobe and the DMN core predicts individual variation in features of mind-wandering, such as its episodic content (Karapanagiotidis, Bernhardt, Jefferies, & Smallwood, 2017; Smallwood et al., 2016). Contemporary accounts of mind-wandering argue the DMN may be important for automatic aspects of cognition (Christoff, Irving, Fox, Spreng, & Andrews-Hanna, 2016). Other studies have highlighted links with lateral prefrontal cortex important for executive control when mind-wandering is more deliberate (e.g. Golchert et al., 2017).

We applied multivariate pattern analysis to the neuro-cognitive and experiential data to identify different types of mind-wandering. If the DMN is important for automatic aspects of cognition (Christoff et al., 2016), states linked to high levels of connectivity within this system may have experiential features reflecting more automatic types of cognition. Our a priori decision to focus on the DMN core to derive patterns of experience limits our ability to observe interactions with regions outside of this system, so we used whole brain functional connectivity to characterize these links for each type of experience. Based on prior studies (e.g. Ellamil et al., 2016; Golchert et al., 2017; Smallwood et al., 2016), we expected this analysis to identify connections with regions in the temporal lobe or the executive system. This pattern would confirm the hypothesized accounts of the DMN as important in integrating neural information (Margulies et al., 2016; Smallwood et al., 2016). Having characterized different types of mind-wandering in both brain and experience, we used these to test the hypothesis that different categories of experience are related to different functional outcomes. We performed an individual differences analysis to understand whether our characterized types of mind-wandering have unique functional associations, including better creativity, worse executive control or levels of well-being. We expected different patterns of experience to capture different psychological profiles explaining the heterogeneous pattern of functional outcomes that have been linked to the mind-wandering state in previous studies (Smallwood & Andrews-Hanna, 2013).

Methods

Participants

One hundred and sixty-five healthy participants were recruited from the University of York (female = 99; age range 18 – 31, *M* = 20.43, *SD* = 2.63). Our sample size was selected as being approximately double those used in our prior studies (e.g. Smallwood et al., 2016). Assuming a typical correlation of between .20 and .30 (Hemphill, 2003), a sample size of at least 125 is recommended in order to have 95% confidence that a correlation of typical size is present and greater than 0. Participants were right handed, native English speakers, with normal/corrected vision and no history of psychiatric or neurological illness. Participants underwent MRI scanning, completed an online questionnaire and then attended three two-hour behavioral testing sessions to complete a battery of cognitive tasks. The behavioral sessions took place within a week of the scan. Eight participants were excluded from the multivariate pattern analysis because they failed to complete all of the behavioral testing sessions. In total 157 participants were included in the multivariate pattern analysis and the comparison with cognitive performance. One hundred and forty-two participants completed both the behavioral testing sessions and questionnaires and were included in the analysis associated with well-being. Participants were rewarded with either a payment of £80 or a commensurate amount of course credit. All participants provided written consent prior to the fMRI session and the first behavioral testing session. Ethical approval was obtained from the Ethics committee of the University of York Department of Psychology and the University of York Neuroimaging Centre.

MRI acquisition

Structural and functional data were acquired using a 3T GE HDx Excite MRI scanner utilizing an eight-channel phased array head coil (GE) tuned to 127.4 MHz, at the York Neuroimaging Centre, University of York. Structural MRI acquisition in all participants was based on a T1-weighted 3D fast spoiled gradient echo sequence (TR = 7.8 s, TE = minimum full, flip angle= 20°, matrix size = 256 x 256, 176 slices, voxel size = 1.13 x 1.13 x 1 mm). Resting-state activity was recorded from the whole brain using single-shot 2D gradient-echo-planar imaging (TR = 3 s, TE = minimum full, flip angle = 90°, matrix size = 64 x 64, 60 slices, voxel size = 3 x 3 x 3 mm3, 180 volumes). Participants viewed a fixation cross with eyes open for the durations of the nine minute functional MRI resting state scan. A FLAIR scan with the same orientation as the functional scans was collected to improve co-registration between subject-specific structural and functional scans.

Questionnaires

We administered a battery of questionnaires to comprehensively assess a diverse range of trait-level individual differences that have been previously related to mind-wandering. These questionnaires captured the trait-like features of participants' psychological state, particularly aspects of well-being. The complete details of the questionnaires are presented in the supplementary materials.

Behavioral testing sessions

The trait profiles captured by questionnaires were complemented by measures of task performance on a range of cognitive tasks. Behavioral tasks were selected to measure a broad range of cognitive attributes including semantic and episodic memory, executive control and measures of fluency and creativity. These measures were assessed in three sessions. Each session began with a task to index the content and form of mind-wandering (0-back / 1-back task) followed by the other cognitive measures. The order of sessions and the order of tasks was counterbalanced across individuals. Details of the 0-back / 1-back task are presented below. The complete details of other cognitive tasks are described in the supplementary materials.

0-back / 1-back task. We assessed the contents of experience during mind-wandering in the context of a simple task that manipulated working memory load using a block design (see Konishi, McLaren, Engen, & Smallwood, 2015; Medea et al., 2016 for prior published examples of this task). This task was performed at the beginning of each laboratory session to minimize the contribution of participant fatigue to this experiential measures. Measuring experience over three days provided us with a more comprehensive description of participants' trait-level mind-wandering than would have been possible in a single experimental session.

In both conditions non-target trials involved the presentation of pairs of shapes appearing on the screen divided by a vertical line. The pairs could be: a circle and a square, a circle and a triangle, or a square and a triangle for a total of six possible pairs (two different left/right configurations for each). The pairs never had shapes of the same kind (e.g. a square and a square). In both tasks, following an unpredictable sequence of non-target trials, a target trial was presented in which participants had to make a manual response. The target was a small stimulus presented in either blue or red across conditions, with the color counterbalanced across participants. In the 0-back condition, the target was flanked by one of two shapes and participants had to indicate by pressing the appropriate button which shape matched the target shape. In the 1-back condition, the target was flanked by two question marks and participants had to respond depending on which side the target shape was on the prior trial. Responses were made using the left and right arrow keys. Fixation crosses presentation ranged from 1.3–1.7 seconds in steps of 0.05 seconds, non-targets were varied from 0.8–1.2 seconds in steps of 0.05 seconds. Targets always ranged from 2.1–2.5 seconds in steps of 0.05 seconds and a response from participants did not end the target presentation.

There were eight blocks in one session, and each block consisted of two to four mini blocks. Each block contained either the 0-back or 1-back condition. The change of condition was signaled by the presentation of the word ‘SWITCH’ that remained on screen for five seconds. The order of conditions was counterbalanced across participants and the whole task lasted around 25 minutes. In each mini block, there was one target trial and the number of non-target trials preceding the targets varied between one and six. The participants’ performance is measured by their efficiency, calculated as: $\text{Efficiency} = -\frac{\text{average response time}}{\text{accuracy}}$. For ease of interpretation, efficiency scores were reversed, so that higher scores indicated better performance.

In order to sample different features of participants’ ongoing experiences, we used multidimensional experience sampling (MDES; Medea et al., 2016; Ruby et al., 2013; Smallwood et al., 2016). This technique uses self-report to assess the contents of experience on a number of dimensions. The thought probes first asked participants to rate their level of task focus (‘My thoughts were focused on the task I was performing’) on a sliding scale from 0 (completely off-task) to 1 (completely on task). Participants then answered 12 randomly presented questions regarding the content and form of their experience at the moment just before they were probed. These questions (described in Table 1) were based on prior studies adopting this approach to measure self-generated thought (Medea et al., 2016; Ruby et al., 2013; Smallwood et al., 2016). At the moment of target presentation there was a 20% chance of a thought probe being presented instead of a target with a maximum of one probe per condition block of 0-back and 1-back. In each session, an average of 14.07 (*SD* = 3.30, range 6 – 25) MDES probes occurred; in the 0-back condition an average of 7.02 (*SD* = 2.36, range 2 – 14) MDES probes occurred and in the 1-back condition an average of 7.04 (*SD* = 2.24, range 1 – 15) occurred. In total we sampled 7006 examples of experience in this study. In the current analysis, we calculated the mean scores of each question across the three sessions for each participant. The MDES scores were first transformed into z-scores for mean-centering and unit-variance scaling. The scores described the average momentary experience in each dimension. We use this score in the multivariate analysis later.

Table 1.

Multiple Dimension Experience Sampling questions in 0-back / 1-back task.

Dimensions	Questions	0	1
Focus	My thoughts were focused on the task I was performing.	Not at all	Completely
Future	My thoughts involved future events.	Not at all	Completely
Past	My thoughts involved past events.	Not at all	Completely
Self	My thoughts involved myself.	Not at all	Completely
Other	My thoughts involved other people.	Not at all	Completely
Emotion	The content of my thoughts was:	Negative	Positive
Images	My thoughts were in the form of images.	Not at all	Completely
Words	My thoughts were in the form of words.	Not at all	Completely
Vivid	My thoughts were vivid as if I was there.	Not at all	Completely

Vague	My thoughts were detailed and specific.	Not at all	Completely
Habit	This thought has recurrent themes similar to those I have had before.	Not at all	Completely
Evolving	My thoughts tended to evolve in a series of steps.	Not at all	Completely
Spontaneous	My thoughts were:	Spontaneous	Deliberate

Neuroimaging data pre-processing and analysis

Resting-state fMRI. Functional and structural data were pre-processed and analyzed using FMRIB's Software Library (FSL version 4.1, www.fmrib.ox.ac.uk/fsl). Individual FLAIR and T1 weighted structural brain images were extracted using Brain Extraction Tool (BET). Structural images were linearly registered to the MNI-152 template using FMRIB's Linear Image Registration Tool (FLIRT). The resting state functional data were pre-processed and analyzed using the FMRI Expert Analysis Tool (FEAT). The individual subject analysis involved: motion correction using MCFLIRT; slice-timing correction using Fourier space time-series phase-shifting; high-pass temporal filtering (Gaussian-weighted least-squares straight line fitting, with sigma = 200s); Gaussian low-pass temporal filtering, with sigma = 2.8s; six motion parameters (as estimated by MCFLIRT) regressed out; cerebrospinal fluid and white matter signal regressed out (top five PCA components, CompCor method). No spatial smoothing and no global signal regression were applied.

Network strength analysis. To describe the functional architecture of the DMN, we transformed the resting state BOLD time series into connection strength values of the selected regions for each participant. The regions of interest (ROIs) were obtained from connectivity-based functional parcellation studies of the DMN by Bzdok and colleagues (Bzdok et al., 2013, 2016; Bzdok, Eickenberg, Grisel, & Thirion, 2015; Eickhoff, Laird, Fox, Bzdok, & Hensel, 2016; Eickhoff, Thirion, Varoquaux, & Bzdok, 2015). There were 16 selected target network nodes, including sub-regions located in the bilateral temporal parietal junction (TPJ), ventromedial prefrontal cortex (vmPFC), dorsomedial prefrontal cortex (dmPFC) and posteromedial cortex (PMC; see Figure 3a). The ROI masks and the related functional connectivity network produced with Neurosynth core tools (https://github.com/neurosynth/neurosynth) can be found on NeuroVault: http://neurovault.org/collections/2275/. First, we extracted and then averaged the time series of all voxels within the 6mm sphere masks of the given regions. Second, we created 16 × 16 symmetrical correlation matrices representing the network of the regions that was computed for all the individual subjects. The off-diagonal of each correlation matrix contained 120 unique region-region connection strengths. This approach provided a measure of connection strength of the region-region coupling of the DMN for each participant.

Multivariate pattern analysis. We performed a sparse canonical correlation analysis (SCCA) on the connection strength data and MDES scores, to yield different dimensions that simultaneously described neural organization and experience. Canonical correlation analysis (CCA) is an advanced multivariate technique that identifies distinct components between two variables spaces (Hardoon, Szedmak, & Shawe-Taylor, 2004). In our case, brain region connection strength values and experiential reports gained through MDES. This modelling approach allows linear combinations of the two variable vectors with correlations among variables to be determined and, unlike principal component analysis and independent component analysis, produces dimensions in which the biological data is simultaneously constrained by psychological measures (and vice versa). To enhance the interpretability of the decomposition solutions we used a variant of CCA penalized by L_1-regularization, SCCA (see Hastie, Tibshirani, & Wainwright, 2015). This was achieved by setting a maximum number of brain or behavior variables to exactly zero, results in a regularized version of the singular value decomposition. A reliable and robust implementation of the SCCA method was retrieved as R package from CRAN (PMA, penalized multivariate analysis). In the current analysis, the L_1 penalty on resting state functional connectivity was set to 0.3 and to 0.5 for the MDES results. Other parameters were set as default. In this way, our analysis performed low-rank (i.e. described an overall network pattern by parsimonious set of connectivity causes), conjoint (i.e. respected variance in brain and behavior at once), and sparse (i.e. automatically found unimportant variables) decomposition of experience and neural data.

Stability analyses. We performed two analyses to assess the stability of the solutions produced by SCCA. First, for each participant, we excluded the MDES data of one random day, and then re-calculated the average scores for these question. We repeated the decomposition on this new set of MDES data and the network connection strength. This corroborative quantitative assessment provides insight into the robustness of the obtained findings by a permutation analysis that left one day out at a time. In particular, this procedure addresses whether either the first day (when participants may be learning how to respond to the experience sampling method) or the last day (when participants may have lower levels of motivation) might unduly bias the decomposition solutions. If the average momentary MDES responses are stable across three sessions, then they should yield similar latent components. Second, we acquired bootstrap samples as a permutation analysis to estimate the variance and generalizability of the sample to the population. The bootstrap resamples, each reflecting an alternative data sample that we could have obtained from the same distribution, was created by random sampling with replacement. The identical SCCA computation was then reiterated individually on each of the 1000 perturbed versions of the actual data sample. This approach enables quantitative assessment of the quality of the original SCCA estimates by inferring confidence intervals (see Figure S1 in Supplementary Materials for the distributions). We selected latent components that were consistent across the decomposition of the original sample, a leave-one-day out sample, and a bootstrap sample, as those are the stable components that were less biased by the session effect and closer to our best estimation of population. We formalized the similarity of these two types of resampling by conducting a formal conjunction of the solutions generated through these different methods of resampling. To quantify the similarity between the components we performed a conjunction that highlights the *common* elements of each solution. The feature conjunctions were calculated as follow: $Feature\ Conjunction = \begin{cases} 0,\ when\ \sqrt[2]{Canonical\ Weight_{\mathrm{LODO}}\ \times\ Canonical\ Weight_{BOOTS}} < 0.1 \\ 1,\ when\ \sqrt[2]{Canonical\ Weight_{\mathrm{LODO}}\ \times\ Canonical\ Weight_{BOOTS}} > 0.1 \end{cases}$ .In addition, because bootstrapping produces a population estimation of our sample, we used the latent component weights produced by this method to compute component scores. This set of scores would be used in all subsequent analyses. The source code for this analysis is available at https://github.com/htwangtw/DimensionsOfExperience.

Whole brain analysis. A limitation in our analysis is that we focused on the DMN to describe patterns of thought. To overcome this limitations, we generalized the types of experience provided by the SCCA by assessing their associations with areas outside of the DMN using a process conceptually similar to dual regression (Beckmann, Mackay, Filippini, & Smith, 2009). To perform these analyses the resting state functional data were pre-processed and analyzed using the FMRI Expert Analysis Tool (FEAT). For the individual subject pre-processing involved, please see Resting-state fMRI for details.

Following these pre-processing steps we used a mask produced by the average of the DMN ROIs to determine the time series that described this neural system. This time series was used in a whole brain functionality analysis for each participant. This allowed us to produce a subject-specific spatial map based on the selected ROIs and these maps were used as dependent measures in our group level analysis. To test whether the functional connectivity of the DMN ROIs associated with the canonical components we conducted a group level analysis using FMRIB's Local Analysis of Mixed Effects stage 1 (FLAME 1). We included the two canonical components on thought reports only, group mean and Jenkinson's mean frame-wise displacement (FD) (Jenkinson, Bannister, Brady, & Smith, 2002), to control for spurious correlations that may emerge from movement, as explanatory variables in the full model. The Jenkinson's mean FD was calculated by the motion power statistic function in Configurable Pipeline for the Analysis of Connectomes (C-PAC; https://fcp-indi.github.io/). A 50% probabilistic grey matter mask was applied to the result maps and the results were thresholded at the whole-brain level using cluster-based Gaussian random field theory, with a cluster-forming threshold of $Z = 2.6$, and a Family-Wise Error corrected cluster significance level of $p< 0.05$. Unthresholded maps were uploaded onto Neurovault and can be found here: http://neurovault.org/images/43189/.

Principal components analysis. To summarize the questionnaire and task data we performed an initial data reduction step using principal components analysis (PCA) in SPSS (IBM, version 24). This analysis was performed separately for the questionnaires and task measures. One hundred and forty-five participants' data were included in the questionnaire items analysis and 157 in the behavioral tasks analysis. The behavioral task measures were converted into z-scores to avoid data distortions derived from the difference in score means. Missing data was imputed by mean scores in both analyses. Kaiser-Meyer-Olkin measure of sampling adequacy (KMO) and Bartlett's test of sphericity were conducted to measure the sampling adequacy of the model. Components were selected based on the elbow in the scree plot (see Figure S2 in Supplementary Materials) and varimax rotation was used to maximize the distinctiveness of each solution.

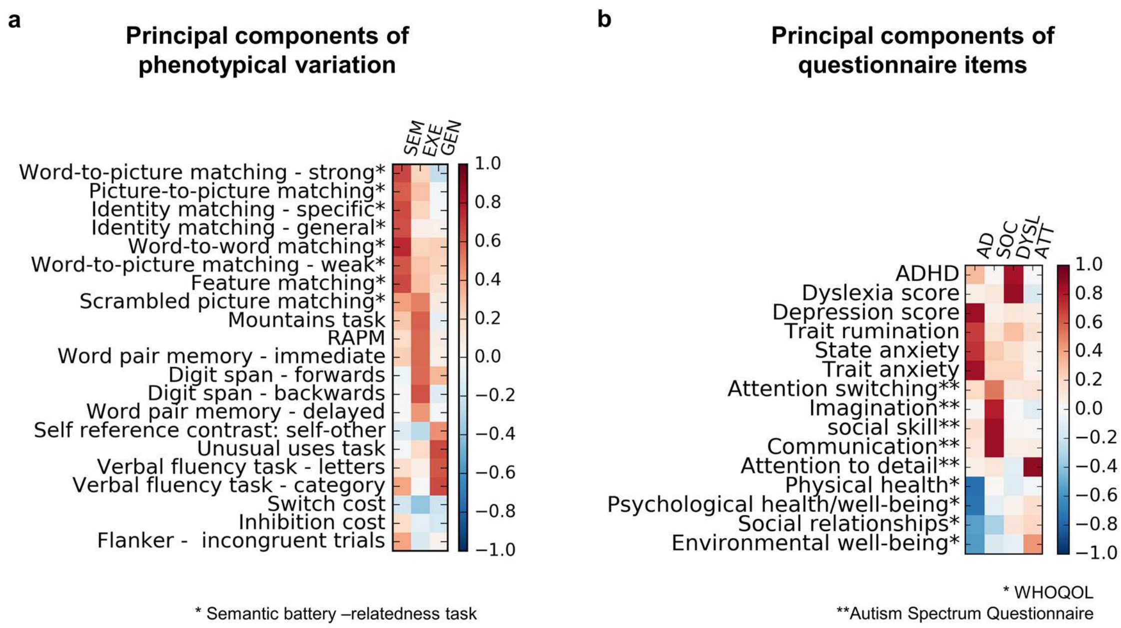

Figure 2.

The results of a decomposition of the battery of (a) laboratory tasks collected in this experiment and (b) questionnaires. The heat map describes the loadings of each measure. For the scree plots describing the Eigen values for each dimension, please refer to Figure S2 in Supplementary Materials. In (a), the components are (i) semantic memory (SEM); (ii) executive control (EXE); (iii) the generation of information (GEN). In (b) the components are (i) affective disturbance (AD); (ii) social interaction (SOC); (iii) dyslexia (DYSL); (iv) attention to detail (ATT).

In the PCA of the phenotypical variation measured by laboratory tasks, Bartlett's test of sphericity was significant ($\chi^2(210) = 775.01$, $p < .001$), indicating that it is appropriate to apply PCA to these data. The Kaiser-Meyer-Olkin measure of sampling adequacy indicated that there were good relationships among the variables in the current sample was acceptable (KMO = 0.79). The PCA of task performance revealed three principal components with a clear elbow after the third component observed in the scree plot. The three orthogonal components accounted for 41% of the total variance with produced component loading patterns shown in Figure 2a. The three components, which accounted for 24%, 8% and 7% of the variance respectively, can be interpreted as the three aspects of cognitive functioning: (i) semantic memory (SEM); (ii) executive control (EXE); (iii) the generation of information (GEN, including letter or category fluency and the generation of creative solutions).

In the PCA of the questionnaire data, Bartlett's test of sphericity was significant ($\chi^2(105) = 919.78$, $p<0.001$), indicating that PCA is an appropriate model for the data and the Kaiser-Meyer-Olkin measure of sampling adequacy indicated that there were strong relationships among the variables (KMO = 0.82). The application of PCA to the questionnaire data revealed four components with a clear elbow after the fourth component observed in the scree plot. The four orthogonal components accounted for 65% of the total variance with produced component loading patterns shown in Figure 2b. The four components accounted for 35%, 14%, 9% and 7% of the variance respectively. The first component was anchored at one end by high levels of depression and rumination and at the other by high levels of well-being, termed as 'Affective Disturbance'. The second component was associated with high scores on four of the five autism subscales, excluding the attention to detail subscale. The third component loaded on both components of ADHD and dyslexia. The fourth component loaded on trait anxiety and high levels of attention to detail as measured by the Autism Spectrum Quotient. We analyzed these data using a MANOVA in which the dependent variables were the PCA loadings produced by the decomposition of the questionnaires and the independent variables were the canonical component loadings.

Results

Determining consistent categories of experience

We applied SCCA to the network connection strength values among regions of interest in the DMN and the average scores on the experiential reports gained in the laboratory. We accepted 13 canonical components generated by SCCA (see Figure S3 in Supplementary Materials for the complete set). Of these initial components, two were consistent when we randomly removed the MDES reports of one day per participant and when bootstrapping was used to provide a more comprehensive description of the sample (see Methods). The consistency of these patterns across the three different analyses indicates that in *qualitative* terms they are not unduly biased by a particular session of our study and are likely to provide adequate estimation to the population (Figure 3b). These stable components are presented in Figure 3c in which we show both the Bootstrapping (BOOTS) and as well as the analysis that randomly excluded one session (restricted temporal sampling, RTS), and the common elements of each solutions.

Canonical component 1 reflects a pattern of stronger coupling within the mPFC, as well as between the left inferior parietal cortex (TPJ-2). This pattern of integration within key nodes of the DMN was associated with descriptions of experience as positive, evolving and habitual. We will refer to this as *positive-habitual* experiences. Canonical component 2 was associated with relatively weak patterns of coupling between the pCC bilaterally (TPJ-2 and -4) and regions of the mPFC (vmPFC-1, 5 & 6). This component was associated with thoughts that were task unrelated and non-deliberate. We will refer to this component as *spontaneous off-task* experiences.

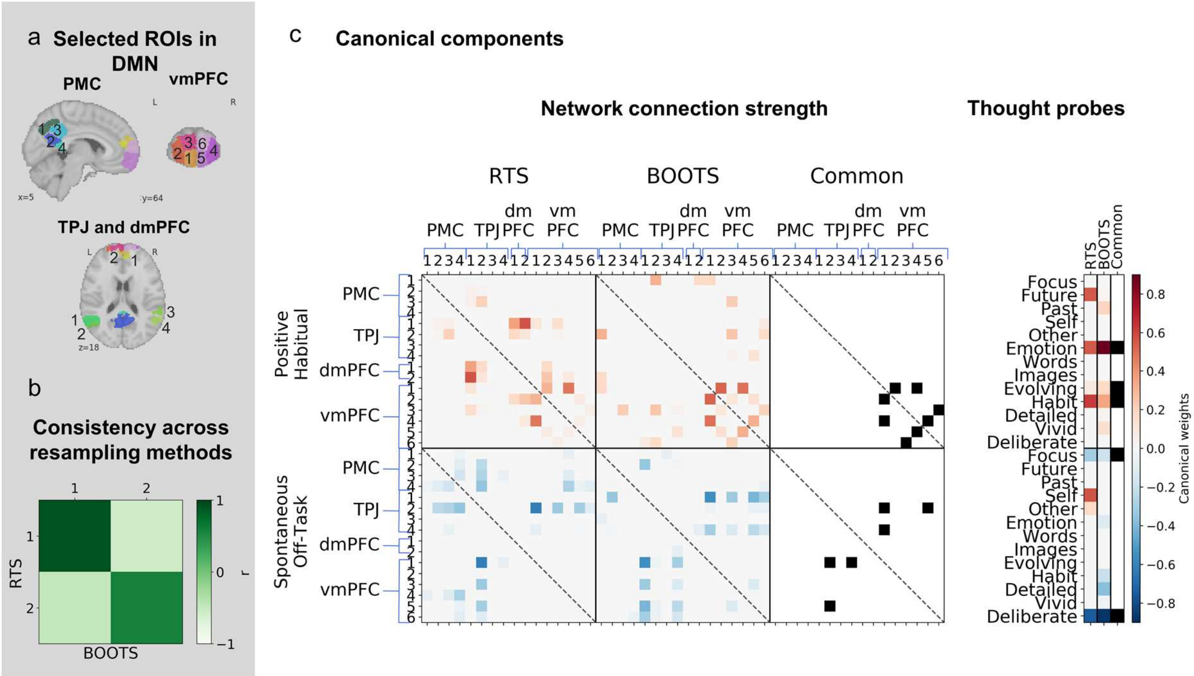

Figure 3. Results of the multivariate pattern analysis.

The upper sub panel (a) describes the regions of interest from which the network connection strength was calculated while the lower panel (b) describes the correlation between the different decomposition solutions. The right panel (c) is the results of SCCA conducted on the network connection strength values of key nodes of the DMN at rest and self-reports of experience during a laboratory task. The different rows of the matrix reflect the different neurocognitive categories produced by this analysis. The different columns describe different applications designed to assess the consistency of the solutions restricted temporal sampling (RTS) describes the canonical components produced when the data from one day of each participant was randomly removed from the decomposition. Bootstrapping (BOOTS) describes the solution produced using bootstrapping (see Methods for details). We highlighted the conjunction features between RTS and BOOTS in the right column 'Common'.

Validating the categories of experience

Having identified two reliable dimensions of neurocognitive experience, we tested whether these patterns accounted for additional variance in the measures that we collected in our experiment. Our first analysis involved a whole brain analysis aimed at determining if the different patterns of experience were associated with differential communication from the DMN to other areas of the brain. In this analysis, we first employed dual regression to calculate the subject-specific spatial maps describing the correlation of DMN and the whole brain, and then used these spatial maps as dependent measures in a group level multiple regression in which the participants' variation in positive habitual and spontaneous off-task experiences were both explanatory variables of interest (See Methods). This analysis revealed a pattern of regions whose connectivity was differentially related to the dimensions of positive habitual and spontaneous off-task experiences. These regions were the left temporo-parietal cortex, left hippocampus/entorhinal cortex, left lateral middle temporal gyrus and the left pre-supplementary region. Extraction of the connectivity in this network and plotting these against the different types of experience revealed that these regions showed a pattern of connectivity that was linked to the expression of positive-habitual experiences but was unrelated to levels of spontaneous off-task experiences. These data are consistent with previous studies that show medial-temporal connectivity with the DMN is linked to aspects of spontaneous experience such as episodic thought (Karapanagiotidis et al., 2017) and online studies that show that activity in this region is important during mind-wandering states (e.g. Ellamil et al., 2016). It also confirm theoretical accounts of states of mind-wandering as relying on regions that fall outside of the core of the DMN, such as the pre-supplementary motor area (pre-SMA; Christoff et al., 2016).

Next, we explored whether the different canonical components had specific implications for performance on the tasks in which we assessed the experience (i.e. the 0-back and the 1-back conditions of the laboratory task). Since the SCCA depends on resting state data which was recorded independently of the task, we were unable to estimate the canonical components separately for each task. Consequently, in these analyses we explored whether overall differences in canonical component loadings across participants were associated with performance efficiency on the 0-back / 1-back tasks. We used a repeated measures analysis of variance in which the dependent variable was the efficiency with which participants performed the 0-back and 1-back task respectively. This analysis revealed a significant interaction between task efficiency and variation in our spontaneous-off task component ($F(1, 154) = 6.43$, $p = .012$, $\eta^2_p = .04$). Decomposition of this interaction showed that participants scoring higher on spontaneous off-task experience performed better on the 0-back condition ($t(151) = 2.38$, $p = .019$, $\eta^2_p = .04$, 95% CI [0.01, 0.11]) and worse on the 1-back condition ($t(151) = -2.55$, $p = .012$, $\eta^2_p = .04$, 95% CI [-0.15, -0.02]). The differential relationship between the levels of spontaneous-off task experience and performance on the0-back / 1-back task is summarized in the form of a scatter plot in Figure 4. These data confirm accounts that suggest that attentional lapses linked to mind-wandering are context dependent, tending to impact negatively during demanding tasks (Smallwood & Andrews-Hanna, 2013); they are also consistent with prior studies suggesting that context regulation may be more problematic for spontaneous than deliberate mind-wandering (see also Seli et al., 2016).

Finally, we used Multivariate Analysis of Variance (MANOVA) to determine how the patterns of experience revealed by SCCA are related to the decompositions of the battery of cognitive performance and questionnaire measures. In this analysis, principal components analysis scores describing either phenotypical variation or questionnaire measures on each of the components of cognitive function were the independent variables and the individual loadings for each of the two canonical components describing experience from the SCCA were the dependent variables. For the analysis of phenotypical variation, this produced two significant results with the executive control component ($F(2, 152) = 5.84$, $p = .006$, $\eta^2_p = .065$) and the generation of information component ($F(2, 152) = 3.41$, $p = .007$, $\eta^2_p = .065$). Higher loadings on the positive-habitual component ($F(1, 153) = 9.84$, $p = .002$, $\eta^2_p = .060$) were associated with worse performance on tasks requiring executive control ($t(153) = -3.14$, $p = .002$, $\eta^2_p = .060$, 95% CI [-0.32, -0.07]) and higher loadings on the spontaneous-off task experience component ($F(1, 153) = 10.15$, $p = .002$, $\eta^2_p = .062$) were associated with better performance on tasks involving the generation of information (such as creativity) ($t(153) = 3.19$, $p = .002$, $\eta^2_p = .062$, 95% CI [0.08, 0.33]). This indicates that two of the experiential components identified by the SCCA were uniquely associated with poor performance on executively demanding tasks and better performance on measures of creativity: both aspects of psychological functioning that have previously been linked to mind-wandering (e.g. Baird et al., 2012; McVay & Kane, 2009). The relationships for both neurocognitive dimensions are summarized in the form of a scatter plot in Figure 4.

In terms of the relationship to the questionnaire decomposition, we found a significant association with the first principal component ($F(2, 151) = 3.76$, $p = .026$, $\eta^2_p = .05$) which captured affective disturbance. This revealed two significant relationships: (i) a strong association with the positive-habitual component ($F(1, 152) = 6.13$, $p = .014$, $\eta^2_p = .04$), suggesting a negative association between positive-habitual thought and levels of affective disturbance ($t(152) = -2.48$, $p =.014$, $\eta^2_p = .04$, 95% CI [-0.29, 0.03]), and (ii) an association with the spontaneous-off task experience component ($F(1, 152) = 4.55$, $p = .035$, $\eta^2_p = .03$) suggesting that higher loadings on the spontaneous-off task component were associated with higher levels of affective disturbance ($t(152) = 2.13$, $p = .035$, $\eta^2_p = .03$, 95% CI [0.11, 0.28]). This analysis demonstrates that the different canonical component components have dissociable associations with respect to well-being, capturing aspects of the bi-directional relationship between the mind-wandering state and affective disturbance highlighted by prior research (e.g. Killingsworth & Gilbert, 2010; Ruby et al., 2013). Importantly, our analysis demonstrates that the different canonical components have dissociable associations with respect to well-being, demonstrating that our method captures both elements of the apparently contradictory analysis linking the mind-wandering state to well-being that has been highlighted by prior research.

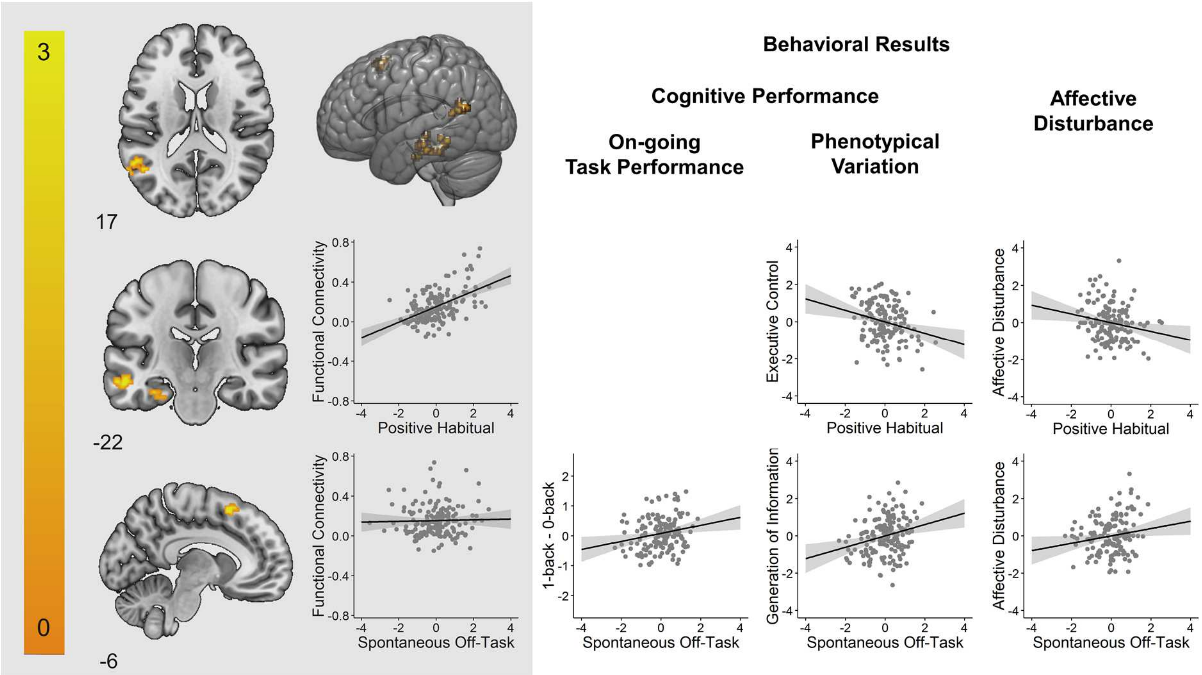

Figure 4.

The relationship between the different neural-cognitive components and the laboratory and questionnaire measures. The left panel (a) shows the result of whole brain analysis characterizing the correlation between connectivity between the DMN mask and different neural regions and the different experience components. The right panel (b) describes the relationship between the different canonical components with measures of well-being and task performance.

The effect of motion. One concern with resting state functional connectivity arises from the possibility that the connectivity matrices are unduly affected by individual differences in motion (Power et al., 2014). Consistent with the possibility that motion may influence our results we observed a correlation at the group level between the positive–habitual component ($r(155) = .363$, $p <. 001$) but not for the spontaneous off-task experience component ($r(155) = -.097$, $p = .229$). Hence we assessed the contribution of this association to our results linking positive-habitual thought to our measured phenotypes. We performed a series of step-wise analyses to identify the contribution that motion makes to the phenotypical associations with positive-habitual thought. In these analyses the canonical component was the dependent variable, we entered the principal components describing cognition or well-being in the first step and the mean FD as calculated by Jenkinson and colleagues in the second step. Including motion significantly improved the predictive value of the model for well-being and cognition (Well-being: Model 1: $R^2 = .06$, $F(4, 152) = 2.21$, $p = .07$, $\eta^2_p = 0.06$, Model 2: $R^2 = .19$, $F(5, 151) = 6.95$, $p <.001$, $\eta^2_p = 0.19$, Model Change: $R^2_{Change}= .13$, $F_{Change}(1, 151) = 24.51$, $p < .001$; Cognition: Model 1: $R^2 = .07$, $F(3, 153) = 3.92$, $p = .010$, , $\eta^2_p = .07$, Model 2: $R^2 = .18$, $F(4, 152) = 8.22$, $p < .001$, $\eta^2_p = 0.18$, Model Change: $R^2_{Change}= .11$, $F_{Change}(1, 152) = 19.65$, $p <. 001$). In the case of well-being, the explained variance of the affective disturbance component was not improved with the inclusion of motion (Model 1: Affective Disturbance $\beta = -.20$, $t(152) = -2.48$, $p = .014$, $\eta^2_p = .04$, 95% CI [-0.29, -0.03]; Model 2: Affective Disturbance $\beta = -.20$, $t(151) = -2.59$, $p =.011$, $\eta^2_p = .05$, 95% CI [-0.28, -0.03], Model 2: Mean FD $\beta = .36$, $t(151) = 4.94$, $p<.001$, $\eta^2_p = .14$, 95% CI [3.29, 7.67]). Thus the relationship between affective disturbance and positive-habitual thought remained largely unchanged by the inclusion of motion as nuisance variable. In the case of cognition, executive control accounted for less variance in the positive-habitual component when Mean FD was included (Model 1: Executive Control $\beta = -.24$, $t(153) = -3.14$, $p = .002$, $\eta^2_p = .06$, 95% CI [-0.32, -0.07], Model 2: Executive Control β = -.16, $t(152) = -2.17$, $p = .032$, $\eta^2_p = .03$, 95% CI [-0.25, -0.01]; Model 2: β = -.34, Mean FD $t(152) = 4.43$, $p < .001$, $\eta^2_p = .11$, 95% CI [4.82, 12.56]).

Unlike the well-being analysis, motion explained a substantial amount of variance that was shared in the relationship between executive control and positive-habitual thought. To explore whether the positive-habitual component reflected an artefact of motion, we selected participants for whom movement greater than 0.2mm occurred on less than 5% of the resting state data (N = 134) and re ran the SCCA with the identical pipeline. This produced similar solutions for both positive-habitual and spontaneous off-task thought (see Supplementary Figure S4). Importantly, positive-habitual thought was not significant correlated with motion ($r(132) = .10$, $p = .236$) but was correlated with poor executive control ($r(155) = -.26$, $p = .001$; see Table S1 in supplementary materials for the full set of correlations). This final analysis shows that in a more restricted sample in which motion does not correlate with either latent component, we still observe a relationship between positive-habitual thought and poor executive control.

Discussion

Using multivariate pattern analysis, our study demonstrated that the content of the mind-wandering state is heterogeneous and confirmed hypotheses that different types of experience have differing functional associations (Smallwood & Andrews-Hanna, 2013). Using a novel analysis strategy we simultaneously decomposed self-reports of experience with descriptions of neural organization, revealing dimensions of experience with unique phenotypical associations: positive-habitual experiences and spontaneous off-task thoughts.

Poor executive control, a well-documented association of mind-wandering (McVay & Kane, 2009) predicted variation in positive habitual thoughts. This pattern of thinking was linked to coupling in the mPFC, a region important for assigning value to neural signals (Roy, Shohamy, & Wager, 2012). It is possible that deficits in executive control during mind-wandering emerge because of problems in assigning value to an external task, a view supported by evidence that financial motivation limits the impact of mind-wandering on performance (Mrazek et al., 2012). We found that spontaneous off-task experiences simultaneously underlie the association between mind-wandering and tasks of creativity (Baird et al., 2012) as well as problems in performing tasks requiring continuous monitoring of external information. Finally, while positive-habitual experiences are linked to improved well-being, spontaneous off-task experiences are associated with increased affective disturbance, capturing the apparent contradiction that mind-wandering can be associated with both negative (e.g. Killingsworth & Gilbert, 2010) and positive (e.g. Poerio et al., 2016) emotional states. Together these data provide the most convincing evidence to date that experience during mind-wandering unfolds along a set of underlying dimensions and that these explain many of the phenotypical associations that have hitherto been associated with the mind-wandering state (Smallwood & Andrews-Hanna, 2013).

Our study also demonstrates the complex contribution of the DMN makes to cognition. Strong DMN connectivity at rest was associated with an increased tendency for positive-habitual thoughts about the future, corroborating previous research linking the DMN to mental time travel (Karapanagiotidis et al., 2017; Schacter, Addis, & Buckner, 2007). Participants also rated these experiences as habitual, a pattern that supports accounts of the role of the DMN in cognition as emphasizing automatic influences during mind-wandering (Christoff et al., 2016). Spontaneous off-task thoughts, in contrast, showed weaker integration between core DMN regions and were linked to poor performance on the 1-back task, a context when task performance depends on the DMN functioning as a coherent network (Konishi et al., 2015). More generally, we found that states of high connectivity within the DMN (positive habitual thoughts) were associated with more functional coupling to regions outside of the core network - a key prediction of the view that activity within the DMN reflects the integration of information from across the cortex (Margulies et al., 2016). It is important to note that our analysis shows that the behavior of the DMN at rest contains information about individual variation in the type of experiences that emerge during mind-wandering. These data *should not* be taken as evidence that this system is exclusive in its role in mind-wandering. Indeed, our whole brain regression provides quantitative evidence that the interactions of DMN with other regions, including those in the medial temporal lobe and the executive system (e.g. pre-SMA), are also important. In this way our study supports recent theoretical perspectives (e.g. Christoff et al., 2016; Margulies et al., 2016), as well as prior empirical results (e.g. Ellamil et al., 2016; Golchert et al., 2017; Smallwood et al., 2016) highlighting that regions other than the DMN core are important for mind-wandering.

There are a number of limitations in the current analysis. First, our study focused on describing mind-wandering as a trait. Prior work has shown similarities between state and trait measures of mind-wandering in terms of (a) neural processing (e.g. trait: Smallwood et al., 2016; state: Christoff, Gordon, Smallwood, Smith, & Schooler, 2009; Stawarczyk, Majerus, Maquet, & D'Argembeau, 2011) and (b) psychological processes such as working capacity (e.g. *trait*: McVay & Kane, 2009; *state*: Mrazek et al., 2012) and happiness (e.g. trait: Ruby, Smallwood, Engen, et al., 2013; state: Killingsworth & Gilbert, 2010). Nonetheless there are certain aspects of mind-wandering that can only be understood by treating it as a state, such as its temporal features (Christoff et al., 2016). Second, our study measured mind-wandering in the laboratory. Although there is a correspondence between mind-wandering in laboratory and naturalistic settings, (e.g. McVay, Kane, & Kwapil, 2009), its form and content may depend on the contexts in which the experience emerges. Consequently, our findings should be supplemented by studies examining the occurrence of different types of experience in ecologically valid settings. Finally, our study did not find evidence for links with tasks that rely on semantic memory or for links to psychological traits other than well-being. This may have been due to our selection of neural regions, or from our selection of questions. Prior studies have linked regions in the temporal lobe to the contents of thought (e.g. Smallwood et al., 2016), a pattern of data that are consistent with a role of the semantic system in spontaneous thought (Binder, Desai, Graves, & Conant, 2009). Other work has highlighted awareness of mind-wandering as important in traits such as ADHD (Franklin et al., 2014). We anticipate that extending the selected regions of cortex and the aspects of experience measured may extend our understanding of the mind-wandering state to encompass forms of semantic processing and additional psychological traits.

In closing, our study provides the strongest evidence to date that the mind-wandering state is heterogeneous in its content, neural basis and functional associations. We describe two neurocognitive dimensions capturing associations with attentional lapses, creativity and well-being, confirming much of the research on mind-wandering conducted over the last decade. However, we also provide an explanation for why scientific accounts of mind-wandering have been dominated by controversy, such as its relationship to happiness (Killingsworth & Gilbert, 2010), creativity (Smeekens & Kane, 2016), executive control (McVay & Kane, 2009) and the DMN (Gilbert, Dumontheil, Simons, Frith, & Burgess, 2007). Our data suggest these debates emerge from an erroneous assumption that mind-wandering is a unitary psychological construct, when it is in fact, made up of distinct states with unique neural correlates and functional associations. This ontological uncertainty has led to artificial controversies that hinder the development of a mature science of internal experience.

Although our findings do not capture the full range of experiential dimensions on which the mind can wander, they convincingly demonstrate that it is untenable to characterize mind-wandering as a uniform experience. As a discipline, we must embrace methodologies and analytical techniques that capture the complex nature of internal experiences, allowing us to accurately determine the contribution that they make to our lives.

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Author Contributions

JS, EJ, HW, CM designed the study. HW, CM and GP collected data. The analysis pipeline was constructed by DB and HW. Data analysis was performed by HW, CM and GP under the supervision of DB, JS and EJ. HW and JS drafted the manuscript. GP, DB provided critical revisions. All authors approved the final version of the manuscript prior to submission.

References

Baird, B., Smallwood, J., Mrazek, M. D., Kam, J. W. Y., Franklin, M. S., & Schooler, J. W. (2012). Inspired by distraction: Mind wandering facilitates creative incubation. *Psychological Science*, *23*(10), 1117–1122. http://doi.org/10.1177/0956797612446024

Beckmann, C. F., Mackay, C. E., Filippini, N., & Smith, S. M. (2009). Group comparison of resting-state FMRI data using multi-subject ICA and dual regression. OHBM.

Binder, J. R., Desai, R. H., Graves, W. W., & Conant, L. L. (2009). Where is the semantic system? A critical review and meta-analysis of 120 functional neuroimaging studies. *Cerebral Cortex*, *19*(12), 2767–2796. http://doi.org/10.1093/cercor/bhp055

Buckner, R. L., Andrews-Hanna, J. R., & Schacter, D. L. (2008). The brain's default network: Anatomy, function, and relevance to disease. *Annals of the New York Academy of Sciences*, *1124*(1), 1–38. http://doi.org/10.1196/annals.1440.011

Bzdok, D., Eickenberg, M., Grisel, O., & Thirion, B. (2015). Semi-Supervised Factored Logistic Regression for High-Dimensional Neuroimaging Data. Retrieved from https://hal.archives-ouvertes.fr/hal-01211248

Bzdok, D., Langner, R., Schilbach, L., Jakobs, O., Roski, C., Caspers, S., … Eickhoff, S. B. (2013). Characterization of the temporo-parietal junction by combining data-driven parcellation, complementary connectivity analyses, and functional decoding. *NeuroImage*, *81*(1), 381–392. http://doi.org/10.1016/j.neuroimage.2013.05.046

Bzdok, D., Varoquaux, G., Grisel, O., Eickenberg, M., Poupon, C., & Thirion, B. (2016). Formal Models of the Network Co-occurrence Underlying Mental Operations. *PLoS Computational Biology*, *12*(6), e1004994. http://doi.org/10.1371/journal.pcbi.1004994

Christoff, K., Gordon, A. M., Smallwood, J., Smith, R., & Schooler, J. W. (2009). Experience sampling during fMRI reveals default network and executive system contributions to mind wandering. *Proceedings of the National Academy of Sciences of the United States of America*, *106*(21), 8719–24. http://doi.org/10.1073/pnas.0900234106

Christoff, K., Irving, Z. C., Fox, K. C. R., Spreng, R. N., & Andrews-Hanna, J. R. (2016). Mind-wandering as spontaneous thought: a dynamic framework. *Nature Reviews Neuroscience*, *17*(11), 718–731. http://doi.org/10.1038/nrn.2016.113

Eickhoff, S. B., Laird, A. R., Fox, P. T., Bzdok, D., & Hensel, L. (2016). Functional Segregation of the Human Dorsomedial Prefrontal Cortex. *Cerebral Cortex*, *26*(1), 304–321. http://doi.org/10.1093/cercor/bhu250

Eickhoff, S. B., Thirion, B., Varoquaux, G., & Bzdok, D. (2015). Connectivity-based parcellation: Critique and implications. *Human Brain Mapping*, *36*(12), 4771–4792. http://doi.org/10.1002/hbm.22933

Ellamil, M., Fox, K. C. R., Dixon, M. L., Pritchard, S., Todd, R. M., Thompson, E., & Christoff, K. (2016). Dynamics of neural recruitment surrounding the spontaneous arising of thoughts in experienced mindfulness practitioners. *NeuroImage*. http://doi.org/10.1016/j.neuroimage.2016.04.034

Fox, K. C. R., Spreng, R. N., Ellamil, M., Andrews-Hanna, J. R., & Christoff, K. (2015). The wandering brain: Meta-analysis of functional neuroimaging studies of mind-wandering and related spontaneous thought processes. *NeuroImage*, *111*(1), 611–621. http://doi.org/10.1016/j.neuroimage.2015.02.039

Franklin, M. S., Mrazek, M. D., Anderson, C. L., Johnston, C., Smallwood, J., Kingstone, A., & Schooler, J. W. (2014). Tracking Distraction: The Relationship Between Mind-Wandering, Meta-Awareness, and ADHD Symptomatology. *Journal of Attention Disorders*, 1–12. http://doi.org/10.1177/1087054714543494

Gilbert, S. J., Dumontheil, I., Simons, J. S., Frith, C. D., & Burgess, P. W. (2007). Comment on

"Wandering minds: the default network and stimulus-independent thought." *Science*, *317*(5834), 43. http://doi.org/10.1126/science.1140801

Golchert, J., Smallwood, J., Jefferies, E., Seli, P., Huntenburg, J. M., Liem, F., … Margulies, D. S. (2017). Individual variation in intentionality in the mind-wandering state is reflected in the integration of the default-mode, fronto-parietal, and limbic networks. *NeuroImage*, *146*(1), 226–235. http://doi.org/10.1016/j.neuroimage.2016.11.025

Hardoon, D. R., Szedmak, S., & Shawe-Taylor, J. (2004). Canonical correlation analysis: an overview with application to learning methods. *Neural Computation*, *16*(12), 2639–2664. http://doi.org/10.1162/0899766042321814

Hastie, T., Tibshirani, R., & Wainwright, M. (2015). *Statistical Learning with Sparsity: The Lasso and Generalizations*. *CRC Press*. http://doi.org/10.1201/b18401-1

Hemphill, J. F. (2003). Interpreting the magnitudes of correlation coefficients. *The American Psychologist*, *58*(1), 78–9. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/12674822

Jenkinson, M., Bannister, P., Brady, M., & Smith, S. (2002). Improved optimization for the robust and accurate linear registration and motion correction of brain images. *NeuroImage*, *17*(2), 825–841. http://doi.org/10.1016/S1053-8119(02)91132-8

Karapanagiotidis, T., Bernhardt, B. C., Jefferies, E., & Smallwood, J. (2017). Tracking thoughts: Exploring the neural architecture of mental time travel during mind-wandering. *NeuroImage*, *147*, 272–281. http://doi.org/10.1016/j.neuroimage.2016.12.031

Killingsworth, M. A., & Gilbert, D. T. (2010). A Wandering Mind Is an Unhappy Mind. *Science*, *330*(6006), 932–932. http://doi.org/10.1126/science.1192439

Konishi, M., McLaren, D. G., Engen, H., & Smallwood, J. (2015). Shaped by the past: the default mode network supports cognition that is independent of immediate perceptual input. *PloS One*, *10*(6), e0132209. http://doi.org/10.1371/journal.pone.0132209

Margulies, D. S., Ghosh, S. S., Goulas, A., Falkiewicz, M., Huntenburg, J. M., Langs, G., … Smallwood, J. (2016). Situating the default-mode network along a principal gradient of macroscale cortical organization. *Proceedings of the National Academy of Sciences of the United States of America*, *113*(44), 12574–12579. http://doi.org/10.1073/pnas.1608282113

McVay, J. C., & Kane, M. J. (2009). Conducting the train of thought: Working memory capacity, goal neglect, and mind wandering in an executive-control task. *Journal of Experimental Psychology. Learning, Memory, and Cognition*, *35*(1), 196–204. http://doi.org/10.1037/a0014104

McVay, J. C., Kane, M. J., & Kwapil, T. R. (2009). Tracking the train of thought from the laboratory into everyday life: An experience-sampling study of mind wandering across controlled and ecological contexts. *Psychonomic Bulletin & Review*, *16*(5), 857–63. http://doi.org/10.3758/PBR.16.5.857

Medea, B., Karapanagiotidis, T., Konishi, M., Ottaviani, C., Margulies, D., Bernasconi, A., … Smallwood, J. (2016). How do we decide what to do? Resting-state connectivity patterns and components of self-generated thought linked to the development of more concrete personal goals. *Experimental Brain Research*, 1–13. http://doi.org/10.1007/s00221-016-4729-y

Mittner, M., Hawkins, G. E., Boekel, W., & Forstmann, B. U. (2016). A neural model of mind wandering. *Trends in Cognitive Sciences*, *20*(8), 570–578. http://doi.org/10.1016/j.tics.2016.06.004

Mrazek, M. D., Smallwood, J., Franklin, M. S., Chin, J. M., Baird, B., & Schooler, J. W. (2012).

The role of mind-wandering in measurements of general aptitude. *Journal of Experimental Psychology: General*, *141*(4), 788–798. http://doi.org/10.1037/a0027968

Poerio, G. L., Totterdell, P., Emerson, L.-M., & Miles, E. (2016). Helping the heart grow fonder during absence: Daydreaming about significant others replenishes connectedness after induced loneliness. *Cognition and Emotion*, *30*(6), 1197–1207. http://doi.org/10.1080/02699931.2015.1049516

Power, J. D., Mitra, A., Laumann, T. O., Snyder, A. Z., Schlaggar, B. L., & Petersen, S. E. (2014). Methods to detect, characterize, and remove motion artifact in resting state fMRI. *NeuroImage*, *84*, 320–341. http://doi.org/10.1016/j.neuroimage.2013.08.048

Roy, M., Shohamy, D., & Wager, T. D. (2012, March). Ventromedial prefrontal-subcortical systems and the generation of affective meaning. *Trends in Cognitive Sciences*. NIH Public Access. http://doi.org/10.1016/j.tics.2012.01.005

Ruby, F. J. M., Smallwood, J., Engen, H., & Singer, T. (2013). How self-generated thought shapes mood-the relation between mind-wandering and mood depends on the socio-temporal content of thoughts. *PLoS ONE*, *8*(10), e77554. http://doi.org/10.1371/journal.pone.0077554

Schacter, D. L., Addis, D. R., & Buckner, R. L. (2007). Remembering the past to imagine the future: the prospective brain. *Nature Reviews Neuroscience*, *8*(9), 657–661. http://doi.org/10.1038/nrn2213

Seli, P., Risko, E. F., Smilek, D., & Schacter, D. L. (2016). Mind-wandering with and without intention. *Trends in Cognitive Sciences*, *20*(8), 605–617. http://doi.org/10.1016/j.tics.2016.05.010

Smallwood, J., & Andrews-Hanna, J. (2013). Not all minds that wander are lost: The importance of a balanced perspective on the mind-wandering state. *Frontiers in*

Psychology, *4*, 441. http://doi.org/10.3389/fpsyg.2013.00441

Smallwood, J., Karapanagiotidis, T., Ruby, F., Medea, B., de Caso, I., Konishi, M., … Jefferies, E. (2016). Representing representation: Integration between the temporal lobe and the posterior cingulate influences the content and form of spontaneous thought. *PLOS ONE*, *11*(4), e0152272. http://doi.org/10.1371/journal.pone.0152272

Smeekens, B. A., & Kane, M. J. (2016). Working Memory Capacity, Mind Wandering, and Creative Cognition: An Individual-Differences Investigation Into the Benefits of Controlled Versus Spontaneous Thought. *Psychology of Aesthetics, Creativity, and the Arts*, *10*(4), 389–415. http://doi.org/10.1037/aca0000046

Stawarczyk, D., & D'Argembeau, A. (2015). Neural correlates of personal goal processing during episodic future thinking and mind-wandering: An ALE meta-analysis. *Human Brain Mapping*, *36*(8), 2928–2947. http://doi.org/10.1002/hbm.22818

Stawarczyk, D., Majerus, S., Maquet, P., & D'Argembeau, A. (2011). Neural correlates of ongoing conscious experience: Both task-unrelatedness and stimulus-independence are related to default network activity. *PLoS ONE*, *6*(2), e16997. http://doi.org/10.1371/journal.pone.0016997