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Personality traits vary in their association with brain activity across situations

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Human cognition supports complex behaviour across a range of situations, and traits (e.g. personality) influence how we react in these different contexts. Although viewing traits as situationally grounded is common in social sciences, often studies attempting to link brain activity to human traits examine brain-trait associations in a single task, or, under passive conditions like wakeful rest. These studies, often referred to as brain wide association studies (BWAS) have recently become the subject of controversy because results are often unreliable even with large sample sizes. Although there are important statistical reasons why BWAS yield inconsistent results, we hypothesised that the situation in which brain activity is measured will impact the power in detecting a reliable link to specific traits. We performed a state-space analysis where tasks from the Human Connectome Project (HCP) were organized into a low-dimensional space based on how they activated different large-scale neural systems. We examined how individuals' observed brain activity across these different contexts related to their personality. We found that for multiple personality traits, stronger associations with brain activity emerge in some tasks than others. These data highlight the importance of context-bound views for understanding how brain activity links to trait variation in human behaviour.

Adaptive behaviour depends on efficiently meeting the demands imposed by specific environmental conditions, and humans function successfully in a wide range of situations. For example, situations can vary on the need for sustained attention[1], skilled performance acquired through learning[2], or on our knowledge of the world[3]. In any specific situation, therefore, optimal performance corresponds to a specific balance of input from different cognitive systems. Consistent with this perspective, contemporary work in psychology has established that how individuals respond to environmental demands provides a useful way to understand trait variation within our species[4]. For example, personality dimensions can be conceptualised as "if-then" rules where a given trait is most likely to lead to a type of behaviour when the individual is in a situation with a specific set of features[5].

Although this context-dependent view of human behaviour has made important contributions to the social sciences[6] it has played a less important role in neuroscience[7]. For example, studies that link brain activity to traits, often referred to as Brain Wide Association Studies (BWAS), focus on differences in brain activity that emerge during tasks or often at rest. However, the BWAS paradigm has recently become the subject of controversy due to concerns that without sample sizes in excess of several thousand individuals, the results may be prone to false positives (i.e. Type I error[8], although see ref. 9 for an alternative perspective). Our study set out to

explore whether BWAS focusing on an "if-then" view of personality provides an alternative way of estimating the brain basis of different human traits.

Results

In order to determine how brain responses under different situations relate to personality traits, we leveraged the task and resting state functional Magnetic Resonance Imaging (fMRI) data and the self-reported personality measures from the Human Connectome Project (HCP, 10). As descriptions of personality traits we focused on the so called Big 5 personality traits[10] since these traits are replicable[11] and show well described links to real-world behaviour[12,13]. In order to compare how different personality traits vary with brain activity across multiple task situations we constructed a state space using the first three dimensions of brain variation from a previous decomposition of group level resting state data of the HCP[14]. These dimensions of brain variation, often referred to as "gradients"[15] describe functional differences between activity in different brain systems. We focused on the first three dimensions, which correspond to differences between primary and association cortex (Dimension 1, D1), visual and somato-motor cortex (Dimension 2, D2) and variation between the two large scale systems embedded within association cortex, namely the default

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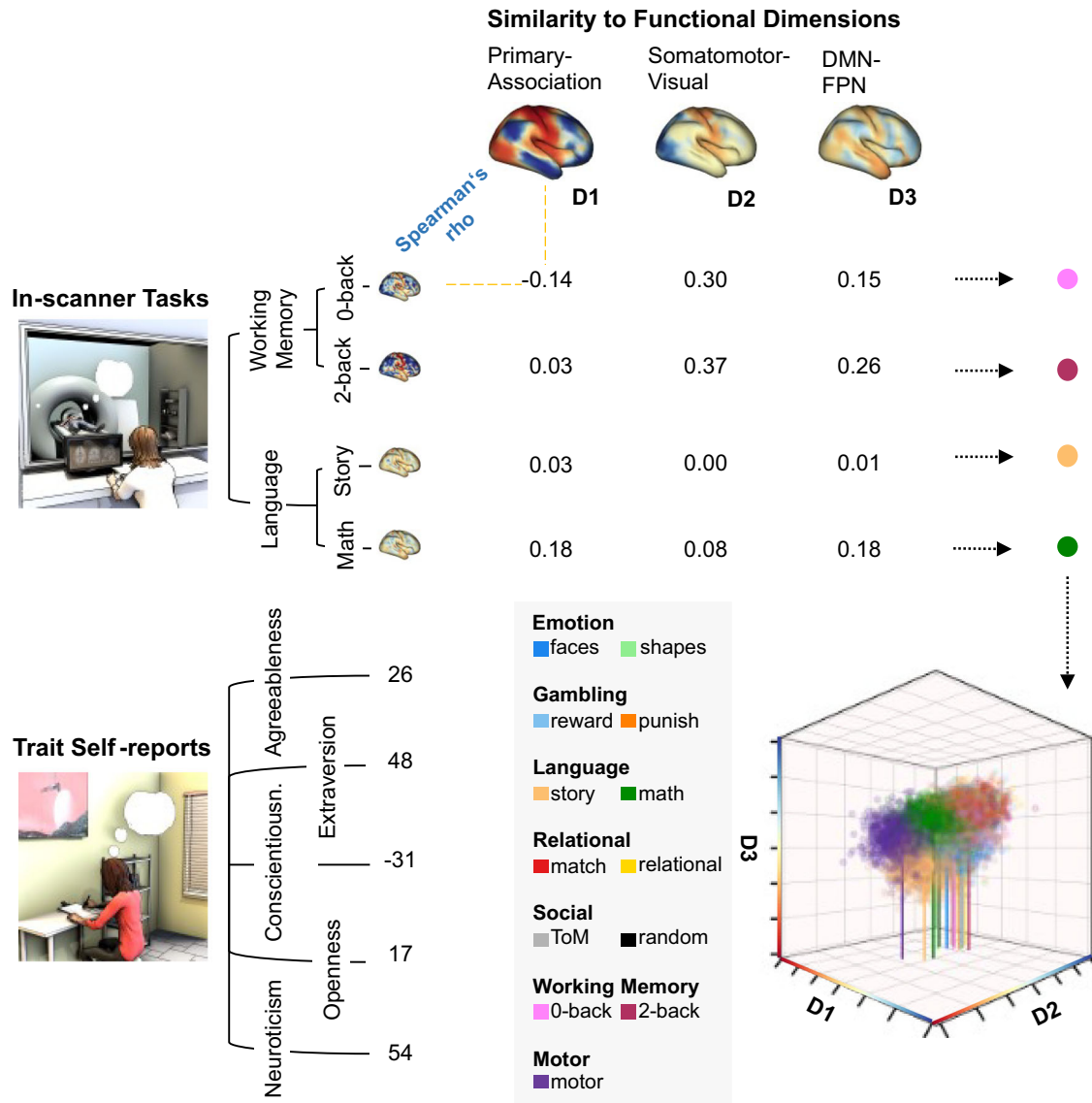
Fig. 1 | Generation of a 'state-space' to understand how the neural correlates of personality traits are differentially expressed across task situations. To simultaneously map neural activity across individuals and situations we utilised a state-space approach[19–21] in which we calculated the correlation between the whole brain map of an individual's brain activity in a specific task condition (contrasted with the respective baseline) with each of the three dimensions of brain variation generated by the decomposition of brain activity at rest[14]. This results in a series of values which can be considered to be co-ordinates in a 3-dimensional space upon which we can conduct inferential statistics to understand how neural activity changes across situations and individuals and how these two influences on brain activity interact. (See Supplementary Fig. 1 for the distribution of all individuals' maps within the space and Supplementary Fig. 2 for the group average of each task condition within the state space). The location on a dimension in this analysis describes the degree of fit between an observed brain map and the relative levels of activity described by the specific gradient. Thus, if one map is higher on gradient 3 than another map, the first map would have higher activity in the fronto-parietal system than in the DMN, compared to the second map.

mode network, (DMN) and fronto-parietal networks (FPN) (Dimension 3, D3). Note that in our study we only use resting-state data to describe brain organisation (e.g. Glasser et al.[16]), and so avoid the hypothesised problems in using this method for ascertaining brain-trait associations[8]. We used this 'state space' to organise the macro-scale patterns of each individual's brain activity in the seven tasks (13 conditions) measured in the HCP by correlating each spatial map for each task condition (contrasted with the implicit baseline of each condition) with each of the group-level dimensions of brain variation (see Methods). This process yielded a set of x, y, z co-ordinates for describing the observed brain activity for each individual in each task context (Fig. 1). We also calculated the pair-wise similarities in the whole brain maps (see Supplementary Fig. 2). Our analytic approach uses no group averaging and preserves the unique functional topography of each individual during task performance as this is argued to be important for accurately

describing brain organisation[17,18]. Instead of averaging individual maps, we compared the unthresholded map for each task for each individual against the first three group-level gradients describing how each individuals brain resembled these well-documented dimensions of brain variation. This state-space approach allows trait-related variation in brain activity, contextual differences in brain activity, and their interaction, to be differentiated along one or more of the independent dimensions of brain variation focused on in our study (See[19–21] for prior demonstrations of this approach). One advantage of our state-space method is that it provides a simple low-dimensional manifold in which the impact of traits and situations can both be simultaneously assessed. In other words, it provides a way of assessing the possibility that brain-trait relationships are situationally dependent, that is analytically and computationally simpler than more concrete regional approaches to understanding brain function.

We used linear mixed models, as used the lmerTest package[22] in R[23], to perform inferential statistics on the co-ordinates of each brain map to understand whether they supported a situationally bound account of how brain activity maps onto dimensions of personality (see Methods for details of the models). We performed these analyses once for each dimension of brain variation, and in each analysis modelled (i) the main effect of task conditions, (ii) the main effect of each dimension of personality (Neuroticism, Openness to Experience, Conscientiousness Extraversion and Agreeableness) and (iii) the interactions between each trait dimension and task condition. Subject ID and family ID were modelled as random effects, and age, gender, and mean framewise displacement were added as covariates of no interest. We included family ID as a random effect to control for the fact that the HCP data set includes individuals who are biological siblings.

In these analyses, a main effect of condition indicates a difference between the location of task conditions on the dimension of brain variation of interest. A main effect of a personality trait indicates a similar association between that trait and brain activity across each task context. Finally, a trait-by-condition interaction indicates that the association between trait and brain activity follows an "if-then" rule, because the strength and/or direction of the association between trait and brain activity is variable across the task conditions sampled in our study. To control for family-wise error in these analyses we controlled for the 78 pairwise comparisons between tasks, the five traits that make up the Big 5 and the three dimensions of brain variation ($78 \times 5 \times 3 = 1170$). Using the Bonferroni correction method this led to an alpha value of $0.05/1170 = 0.00004$. Although the Bonferroni method may be considered to be too conservative, we chose this method because we do not have a holdout sample and are addressing a broad question about the landscape of brain trait associations. In this context, using a stringent threshold ensures that we identify only the most robust results.

In each of these three models we identified a significant main effect of task condition (D1: $F_{(12, 11964)} = 5.92$, $p < 0.00001$; D2: $F_{(12, 972)} = 51.05$, $p < 0.00001$; D3: $F_{(12, 11992)} = 10.83$, $p < 0.00001$). This indicates that brain activity recorded in the specific task conditions measured in the HCP significantly varies along each of the three dimensions of brain variation that make up our state space (see Supplementary Table 2 for complete results and Supplementary Fig. 2 for mean locations of all conditions in the state space) establishing that across the set of tasks included in the HCP there was significant variation in the average balance of different neural systems engaged during task completion.

In addition, for two out of three dimensions of brain variation studied we identified at least one example where the association between a trait and brain activity was explained by an "if-then" relationship (Fig. 3). For the second dimension of brain variation (D2, differentiation between visual and somato-motor cortex), a significant interaction was observed for Agreeableness ($F_{(12, 11958)} = 3.82$, $p < 0.00001$). The condition with the most positive association (i.e., towards visual cortex) was the "2-back" working memory ($t = 2.17$) while the task with the strongest negative association (towards somato-motor cortex) was "motor" ($t = -3.35$).

For D3 (the dissociation between the default mode network and the fronto-parietal network) we found significant interactions for both Openness to Experience ($F_{(12, 11979)} = 4.40$, $p < 0.00001$) and Conscientiousness ($F_{(12, 11984)} = 3.57$, $p < 0.00003$). For Openness to Experience the task with the most negative association (i.e., towards the default mode network) was "story" ($t = -3.60$) and the most positive was the "reward" condition in the gambling task ($t = 2.12$). For Conscientiousness, the task with the most negative association was with the "motor" task ($t = -2.78$) and the "0-back" working memory condition had the strongest positive association ($t = 2.66$).

It is important to note that in all three models none of the main effects of traits passed our correction for family-wise error; the strongest association was in D2 for Neuroticism ($p = 0.033$ uncorrected, complete results of all linear models can be found under Supplementary Tables 3–9). Together, therefore, our analysis indicates only weak support for the hypothesis that traits will show a general association with brain activity across tasks, and substantial support for the view that these associations are modulated by the task context. Overall, therefore, our data is consistent with the view that traits lead to situationally specific changes in brain activity and inconsistent with the implicit assumptions behind many BWAS that attempt to link traits to a single condition.

Next, we examined the sample size needed to infer associations between traits and brain activity across situations in our analysis. One criticism of BWAS is that the magnitude of associations between activity within regions or sets of regions and traits are often higher with smaller numbers of participants and decline with larger sample sizes: a pattern that is indicative of false positives with underpowered designs[8]. For each of the significant interaction effects, therefore, we repeatedly sampled individuals from our population to create samples-sizes ranging from 25 to 950 in 16 log-spaced steps. We created 1000 examples of each sample size. We examined how these relationships changed with increasing power (bottom row, Fig. 3). It can be seen that with smaller sample sizes the task-trait relationships begin to stabilise, i.e., generate > 95% estimates that all have the same direction, for samples that are between 222 and 459. Relative to those observed in BWAS that focus on brain activity at rest, these estimates tend to stabilise with equivalent, if not smaller, samples. Lastly, as the full HCP dataset contains pairs of individuals who are siblings, we repeated the reproducibility analysis, generating bootstrapped samples which only contained singletons in each resampling iteration, yielding broadly similar results (Supplementary Fig. 4).

Discussion

Using a state-space created from dimensions of brain variation observed at rest we established that different tasks employed in the HCP vary in the whole brain patterns of brain activity they engender. This analysis confirms that these situations provoke different challenges to the brain. Consistent with psychological models of cognition and behaviour that emphasise trait variation as a set of "if-then" rules, different tasks systematically varied in their utility to capture the brain activity associated with different traits. Openness to Experience, for example, was most strongly associated with increased activity within the default mode network during the "story" task condition and increased activity in the fronto-parietal network during the "reward" condition. Agreeableness was linked to relatively greater activity in somato-motor cortex in the "motor" task and with relatively greater visual activity during "2-back" working memory. In contrast, Conscientiousness was linked to greater engagement of the fronto-parietal system than the default mode network during the "0-back" working memory compared to the "motor" task.

Together these data illustrate that associations between brain activity and trait variation cannot be mapped equally in a single situation. Consistent with psychological perspectives that traits can be conceived of as stable responses to specific environmental challenges ("if-then" rules) our analysis establishes that brain activity correlates of traits vary substantially across situations. For instance, the association we find between Openness to Experience and activity in the default mode network during the "story" and "ToM" tasks sit in line with the previously reported role of the default mode network in tasks that require narrative engagement and comprehension[24,25] and theory of mind ability[26,27]. While the link between DMN and Openness to Experience has been established in brain activity at rest[28], we find that this effect is strongest during task contexts that require narrative comprehension ("story") and theory of mind ("ToM") and shows the opposite direction in the condition that requires reward-based decision making ("reward"). This suggests that regardless of sample size[8], or analytic approach[9], studies seeking associations between brain-activity and traits will likely have greater success in detecting accurate associations by tailoring the situations in which brain activity is measured to challenge the brain in an appropriate manner. Our study, therefore, establishes that one reason why BWAS may yield inconsistent results is that because the resting-state context is only one of many situations the brain can be placed within, so may not be the best way to understand the complete landscape of brain-trait associations. This is likely because at least some traits are likely to be linked to how the individual responds to cognitive challenges that rest does not provoke. While it

continues to be important to employ well powered designs, and better analytic approaches, BWAS will become more useful following the development of better theoretical models which include situations (including rest) in which brain-traits are most likely to emerge (e.g.[29]). We note that recent work has used approaches that combine resting-state and hypothesis-driven task paradigms to gain insight into the organisation of specific functions in the brain and individual differences[30–33], and a trend for estimating trait associations in appropriate contexts is also emerging in population studies of genetics[34].

At the same time as illustrating that trait associations with brain activity are at least partially situationally bound, our approach highlights important new avenues of inquiry for understanding how human variation is linked to patterns of brain activity. For example, what are the best situations for mapping the neural correlates of specific traits, and how many situations are needed to efficiently map the bulk of human traits? We utilised the HCP task data because it is the largest existing dataset to sample a wide range of tasks along with trait measures. However, the selection of tasks for the HCP was not designed to test "if-then" relationships between personality and brain activity. It is likely, therefore, that there are better batteries of tasks with which to distinguish the neural correlates of different traits. Fortunately, techniques such as neuroadaptive Bayesian optimisation, which uses machine learning to efficiently identify correlations between brain activity and behaviour, can be used to identify situations in which a specific trait maps onto specific patterns of brain activity efficiently[35]. Iteratively, this process will enable the detection of situations where specific brain-trait associations can be mapped in an optimal manner and which in turn will improve the efficiency with which the neural correlates of different features of human behaviour can be understood.

Our analyses also highlight specific analytic questions that will need to be resolved to properly determine how the correlations between neural activity and traits vary across situations. For example, our study used a state-space based on patterns of brain variation at rest as a low-dimensional space; allowing us to preserve individual topography while simultaneously modelling task and individual differences in brain function. It has been shown that using broad-scale activations as a measure of brain function can offer more statistical power compared to regional effects, with a relatively moderate decrease in specificity[29]. In our study we used functional gradients because they are a convenient tool for organising brain-wide activity[19–21]. However, there are likely better ways to characterise the dimensions of brain variation and organisation in order to perform state-space analyses like the one we report here. For example, contemporary work in neuroscience has identified dimensions of brain variation that combine information related to brain structure with functional behaviour (e.g., ref. 36). Fortunately, machine learning can be used to perform multiverse analyses that optimise how different features of brain organisation can be best analysed to maximise their links with phenotypes[37]. It is likely that optimising the dimensions of brain variation will generate state spaces that allow BWAS to estimate trait-related patterns of brain activity in a more effective manner. For example, we found a relationship between greater activity within the DMN during the ToM task with greater agreeableness, which did not pass our correction for multiple comparisons, but was seen in a prior study[38]. It may be possible to optimise key features of this paradigm to increase its power to detect a possible relationship to Agreeableness. These more targeted analyses could also include the identification of parcellation schemes suitable for testing more nuanced models of brain function than are possible with macro-scale gradients. This could be helpful moving forward because our study design is optimised to detect macro-scale changes in brain activity and it is possible that certain trait features relate to more subtle differences in function than can be captured in our state space. It is also important to note that our study provides only an indirect comparison of the comparative power of tasks compared to rest (i.e. in the number of subjects required to reach a pattern that is unlikely to lead to Type I error, Fig. 3). The tasks data is clearly separated into different contexts, whereas resting state data is a continuous time series (that may contain a number of 'hidden' states). In the future it could be possible to separate resting state data into a sequence of

brain states (e.g. using Hidden Markov Models[39], or Co Activation Patterns[40]). The states could be projected onto low-dimensional manifold and would allow for a more direct comparison with task states. Finally, our study focused on trait descriptions of human behaviour that have well established features (i.e., the "Big 5"). Our analytic choice was motivated by the idea that BWAS should focus on traits that have real-world significance[41]. In this context, the "Big 5" have well established reliability[11] and are predictive of behaviour in real-world situations including academia[12] and the workplace[13] and are predictive of psychopathology[42]. However, it remains to be seen whether the same tasks which establish the situationally specific neural correlates of the "Big 5" can also discriminate the brain mechanisms which impact mental health, or physical illness, both of which are probably the most important outcomes from BWAS studies[41]. In the future, therefore, it is important to take seriously the goal of understanding how to tailor task conditions for acquiring brain activity that have better capacity to discriminate phenotypes linked to health, wellbeing, productivity and disease.

In conclusion, our state space analysis of the tasks in the HCP suggest that brain-trait associations are inextricably linked to the context in which brain activity is measured and this observation leads to two concrete suggestions for future studies. First, when examining specific brain-trait relationships it would be helpful to consider the most appropriate situations in which these association will emerge as out study shows that this intimately related to the sample size needed for these associations to stabilise. It is important to note that these conditions may include rest for some specific traits, since there are likely to be certain traits that express their associations most clearly in relatively unconstrained situations. Second, if in the future it is deemed important to generate large data sets similar to the HCP[43] or the Adolescent Brain Cognitive Development (ABCD)[44], project, then it is likely that the statistical power for detecting robust brain correlates for a range of different traits can be derived from a combination of both the amount of time spent acquiring data in a specific situation (enabling stable measurement) and the range of different cognitive and emotional features that data acquisition encompasses (which enables the testing battery to discriminate multiple different traits).

Methods
Data
We used task and resting state fMRI, and self-reported questionnaire data from the human Connectome Project[43] 1200 subjects release. Data acquisition protocols were approved under the Washington University institutional review board. All ethical regulations relevant to human research participants were followed and all participants provided written informed consent. The HCP dataset (N = 1206) includes multimodal MRI, behavioural, genetic, physiological and demographic data from adult twins and their non-twin siblings between 22- 37 years of age. From these, our analysis made use of the minimally preprocessed (2 mm smoothing)[45] task-fMRI maps and NEO-FFI personality measures[10] and summaries of the group-averaged functional connectivity matrix from the 900 subjects release[14]. Additionally, we used demographic information of subjects (age in years, gender), and head-movement parameters of each task-fMRI session as covariates. The final sample size of all HCP subjects with preprocessed task-fMRI data available for download is 1088 (590 women, mean age = 29.52 ± 3.59 years; 498 men, mean age = 27.92 ± 3.61 years). Supplementary Table 1 shows the number of subjects available in each task condition.

Neural state space
To create a neural state space, which describes maximal functional covariation of different neural systems, we used previously established low-dimensional summaries of the group-level whole-brain functional connectivity matrix[14]. These dimensions of brain variation, often referred to as "gradients", describe functional differences between brain systems. In our analysis, we created a three-dimensional "state space" from the first three gradients which correspond to differences between (i) primary and association cortex, (ii) visual and sensorimotor cortex and (iii) variation between
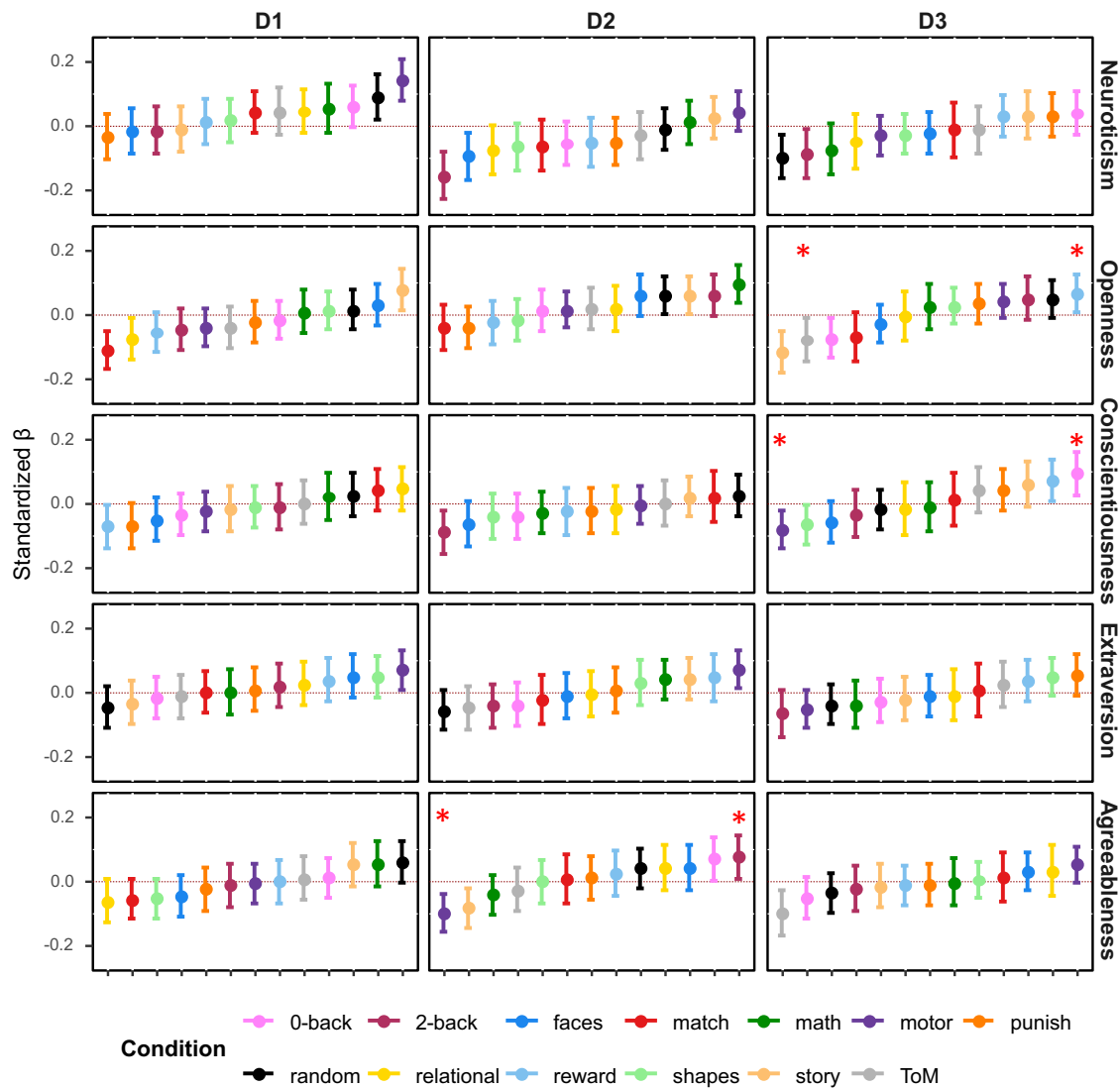
Fig. 2 | Associations between personality traits and state space location across all dimensions and task conditions. In this figure, each point reflects the estimate of the association between a trait of the "Big 5" and a single dimension of brain variation, under a single task condition, while controlling for all other variables in the model. Error bars indicate the 95% Confidence Intervals around this estimate. For ease of interpretation, tasks are ordered from the most negative to the most positive.

Significant interaction effects between conditions and traits are marked with asterisk (controlling for multiple comparisons, $p < 0.00004$). D1 reflects the dissociation from primary cortex (negative) to association cortex (positive). D2 reflects the dissociation between somato-motor (negative) and visual cortex (positive). D3 reflects the dissociation between the default mode network (negative) and fronto-parietal network (positive).

the two large scale systems embedded within association cortex (default mode network, DMN, and fronto-parietal networks, FPN).

To project each individual's brain activity across different contexts into the state space, we calculated spearman rank correlation between each of the three gradient maps and each individual's un-thresholded z-map from each task condition in grayordinate space. (Fig. 1). Only the main contrasts (each condition against the respective implicit baseline) were used for this purpose, resulting in 13 maps for each individual, namely, Motor: (1) average of all movements; Emotion: (1) faces (2) shapes; Language: (1) maths, (2) story; Social: (1) random interactions, (2) theory of mind (ToM); Working Memory: (1) 0-back, (2) 2-back; Gambling: (1) reward, (2) punish; and Relational: (1) match (2) relational. The correlation coefficient of each map with the three gradients served as the location of that map along the respective dimension of brain variation in the state space (Fig. 1)

Linear mixed models
To understand and quantify how locations of tasks in the state space varied with dimensions of personality, we performed regression using linear mixed

models once for each dimension of brain variation as the outcome variable, and the task context, each dimension of personality (Neuroticism, Openness to Experience, Conscientiousness, Extraversion and Agreeableness) and the interactions between each dimension and each task condition as predictors. Subject ID and family ID were added as random effects, and age, gender, and mean framewise displacement were used as covariates of no interest.

Example model for one dimension of variation:

$$
\begin{aligned}
Location = \beta_0 &+ \beta_1 \times condition + \beta_2 \times Neuroticism + \beta_3 \times Openness + \\
&\beta_4 \times Conscientiousness + \beta_5 \times Extraversion + \beta_6 \times Agreeableness + \\
&\beta_7 \times (condition \times Neuroticism) + \beta_8 \times (condition \times Openness) + \\
&\beta_9 \times (condition \times Conscientiousness) + \beta_{10} \times (condition \times Extraversion) + \\
&\beta_{11} \times (condition \times Agreeableness) + \beta_{12} \times age + \beta_{13} \times gender + \\
&\beta_{14} \times meanFD + usub + uFamily + \epsilon
\end{aligned}
$$

In these analyses, a main effect of task indicates a difference between the location of tasks on the dimension of interest. A main effect of personality trait indicates a similar association with brain activity with a trait
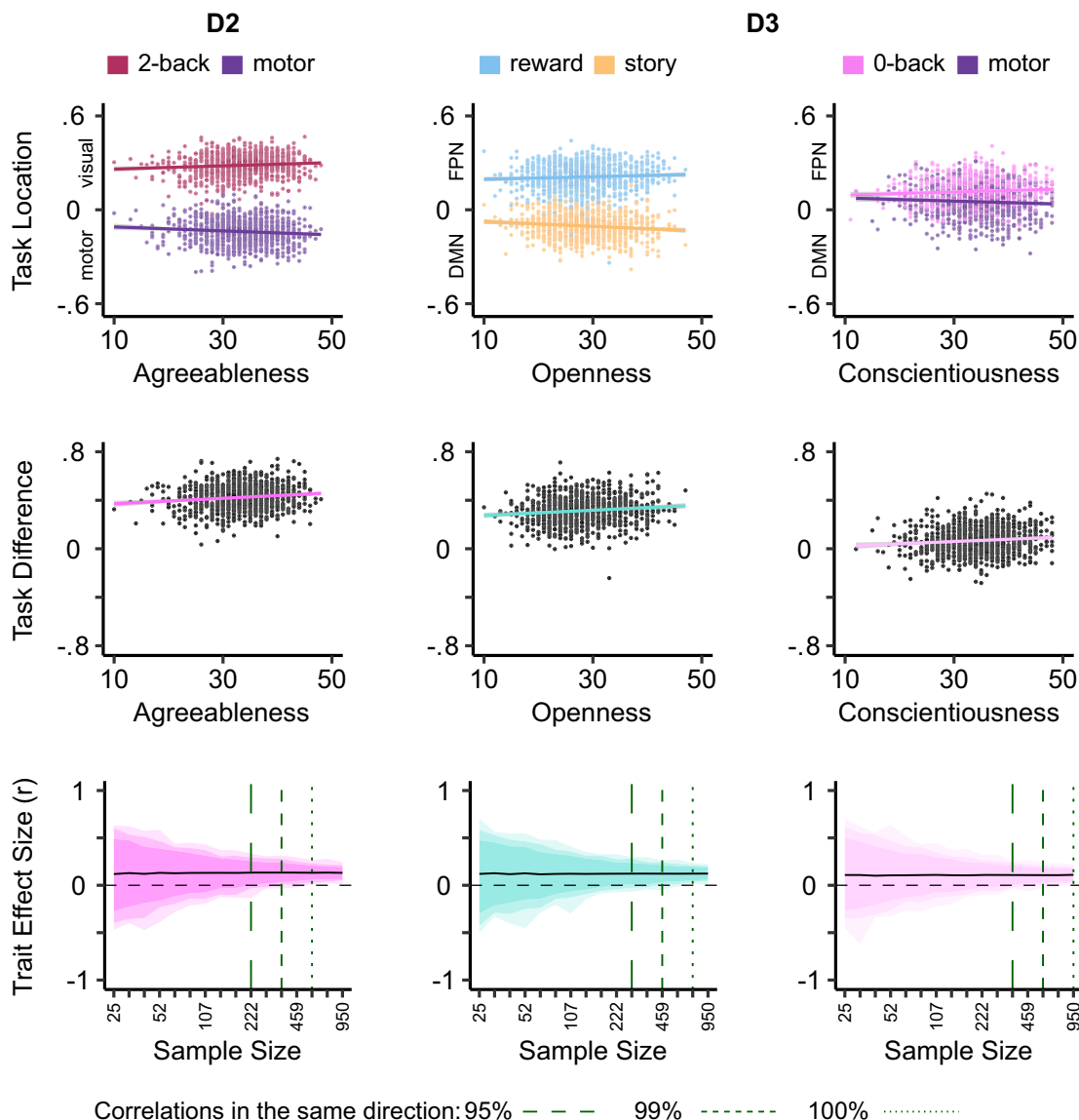
Fig. 3 | Trait associations with respect to variation between visual and sensorimotor systems (D2) and default mode and fronto-parietal networks (D3). This figure illustrates the strongest relationship between brain activity and trait for the three personality dimensions for which significant interactions were identified: Agreeableness, Openness to Experience and Conscientiousness. Scatter plots in the top row show the relationships between two conditions and the specific trait along the dimension of brain variation of interest. In these plots, x axis shows the trait score, and y axis shows the location of a specific task condition on the dimension of brain variation of interest, i.e. the Spearman correlation between the task condition map, and the respective gradient map. Each point represents one individual. Scatter plots in the middle row show the correlation between the trait and the divergence of two task-condition maps shown above on the dimension of brain variation interest. In these plots, y axis shows the pair-wise difference (e.g. 2back - motor) in the Spearman correlation score of the two task maps with the dimension of interest. Plots in the bottom row summarise the results of a bootstrapping analysis showing the distribution of the same correlations as a function of sample size. In these plots, the shaded regions show the distribution of 100%, 99%, and 95% of the effects (Pearson's R) derived from the bootstrapping and vertical dashed lines indicate the sample sizes required to consistently find effects in the same direction within the 95% and 99% confidence intervals, and in the whole range (100%).

across each task context. Finally, a trait-by-task interaction indicates that associations between traits and brain activity varied in their strength, direction, or both across different tasks. To control for family-wise error in these analyses we controlled for the 78 pairwise comparisons between tasks, the five traits which make up the "Big 5" and the three dimensions of brain variation ($78 \times 5 \times 3 = 1170$). Using the Bonferroni correction method this led to an alpha value of $0.05/1170 = 0.00004$. To illustrate the change in trait-brain associations depending on context, we followed up each significant trait*condition interaction, by comparing the strongest positive and negative associations of the respective trait and with task locations along dimensions of brain variation (Fig. 3). Linear models were fitted using the lmerTest[22] package in R[23]. We used the emmeans[46] package to derive the slope for each trait in the model at each level of the factor "condition",

resulting in an estimate for the association of each combination of trait and task condition and state-space location shown in Fig. 2.

Reproducibility of context-specific brain-wide associations
To examine the distribution of effects found in our analysis as a function of sample size, and to estimate the sample size required to reliably identify such effects, we calculated the bootstrapped (with 1000 iterations) bivariate correlation estimates and confidence intervals for all significant task-brain interactions (Fig. 3). Following Marek and colleagues[8] we focused on the strongest associations identified in our initial analyses. For each of these effects, we created 16 logarithmically spaced samples sizes from 25 to 950 subjects, by resampling subjects with replacement 1000 times at each sample size. Similar to the follow-up analysis for task × trait interactions in the

original sample, in each resampled dataset, we calculated the bivariate correlation between trait scores and the distance between two brain maps that show the strongest diverging associations with that trait along a dimension. (e.g., correlation between Openness and (D3 location of reward – D3 location of story). Figure 3 shows the distribution of these bootstrapped estimates with increasing sample sizes and indicates the 95% and 99% confidence intervals as well as full range of effect sizes derived from bootstrapping.

Finally, given that the HCP dataset is made up of sibling pairs and groups, to avoid inflated estimates resulting from resampling of closely related individuals, we repeated the bootstrapping analysis in a smaller subsample (n = 442) of "singletons" where, in each iteration, no more than one member of each family could be included at a time. For this analysis, we used 13 log-spaced sample sizes between 25 and 442. The results of this analysis are shown in Supplementary Fig. 4.

Reporting summary
Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

References
1. Parasuraman, R. *Handbook Of Perception And Human Performance, 2. Cognitive Processes And Performance* (eds. Boff, K. R., Kaufman, L. & Thomas, J. P.) 1–39 (John Wiley & Sons., 1986).
2. Chi, M. T. H., Glaser, R. & Farr, M. J. *The Nature Of Expertise.* (Lawrence Erlbaum Associates, Inc., 1988).
3. Lambon-Ralph, M. A., Jefferies, E., Patterson, K. & Rogers, T. T. The neural and computational bases of semantic cognition. *Nat. Rev. Neurosci.* **18**, 42–55 (2016).
4. Mischel, W. & Shoda, Y. A cognitive-affective system theory of personality: reconceptualizing situations, dispositions, dynamics, and invariance in personality structure. *Psychol. Rev.* **102**, 246–268 (1995).
5. Jackson, J. J. et al. What do conscientious people do? Development and validation of the Behavioral Indicators of Conscientiousness (BIC). *J. Res. Pers.* **44**, 501–511 (2010).
6. Ross, L. & Nisbett, R. E. *The Person And The Situation: Perspectives Of Social Psychology* (Pinter & Martin Publishers, 2011).
7. Shamay-Tsoory, S. G. & Mendelsohn, A. Real-life neuroscience: an ecological approach to brain and behavior research. *Perspect. Psychol. Sci.* **14**, 841–859 (2019).
8. Marek, S. et al. Reproducible brain-wide association studies require thousands of individuals. *Nature* **603**, 654 (2022).
9. Spisak, T., Bingel, U. & Wager, T. D. Multivariate BWAS can be replicable with moderate sample sizes. *Nature* **615**, E4–E7 (2023).
10. Costa, P. T. & McCrae, R. R. The revised NEO personality inventory (NEO-PI-R). *SAGE Handb. Personal. Theory Assess. Vol. 2 - Personal. Meas. Test.* p. 179–198 https://doi.org/10.4135/9781849200479.N9 (2008).
11. Cobb-Clark, D. A. & Schurer, S. The stability of big-five personality traits. *Econ. Lett.* **115**, 11–15 (2012).
12. Kappe, R. & van der Flier, H. Using multiple and specific criteria to assess the predictive validity of the Big Five personality factors on academic performance. *J. Res. Pers.* **44**, 142–145 (2010).
13. Judge, T. A. & Zapata, C. P. The person–situation debate revisited: effect of situation strength and trait activation on the validity of the big five personality traits in predicting job performance. *Acad. Manag. J.* **58**, 1149–1179 (2014).
14. Margulies, D. S. et al. Situating the default-mode network along a principal gradient of macroscale cortical organization. *Proc. Natl Acad. Sci. USA* **113**, 12574–12579 (2016).
15. Bernhardt, B. C., Smallwood, J., Keilholz, S. & Margulies, D. S. Gradients in brain organization. *Neuroimage* **251**, 118987 (2022).
16. Glasser, M. F. et al. A multi-modal parcellation of human cerebral cortex. *Nature* **536**, 171–178 (2016).
17. Braga, R. M. & Buckner, R. L. Parallel interdigitated distributed networks within the individual estimated by intrinsic functional connectivity. *Neuron* **95**, 457–471.e5 (2017).
18. Gordon, E. M., Laumann, T. O., Adeyemo, B. & Petersen, S. E. Individual variability of the system-level organization of the human brain. *Cereb. Cortex* **27**, 386–399 (2017).
19. Turnbull, A. et al. Reductions in task positive neural systems occur with the passage of time and are associated with changes in ongoing thought. *Sci. Rep.* **10**, 9912 (2020).
20. Song, H., Shim, W. M. & Rosenberg, M. D. Large-scale neural dynamics in a shared low-dimensional state space reflect cognitive and attentional dynamics. *Elife* **12**, e85487 (2023).
21. Karapanagiotidis, T. et al. The psychological correlates of distinct neural states occurring during wakeful rest. *Sci. Rep.* **10**, 21121 (2020).
22. Kuznetsova, A., Brockhoff, P. B. & Christensen, R. H. B. lmerTest package: tests in linear mixed effects models. *J. Stat. Softw.* **82**, 1–26 (2017).
23. R Core Team. *R: A Language And Environment For Statistical Computing* (2021).
24. Xu, J., Kemeny, S., Park, G., Frattali, C. & Braun, A. Language in context: emergent features of word, sentence, and narrative comprehension. *Neuroimage* **25**, 1002–1015 (2005).
25. Simony, E. et al. Dynamic reconfiguration of the default mode network during narrative comprehension. *Nat. Commun.* **7**, 12141 (2016).
26. Spreng, R. N., Mar, R. A. & Kim, A. S. N. The common neural basis of autobiographical memory, prospection, navigation, theory of mind, and the default mode: a quantitative meta-analysis. *J. Cogn. Neurosci.* **21**, 489–510 (2009).
27. Saxe, R. & Kanwisher, N. People thinking about thinking people: The role of the temporo-parietal junction in "theory of mind". *Neuroimage* **19**, 1835–1842 (2003).
28. Beaty, R. E. et al. Personality and complex brain networks: the role of openness to experience in default network efficiency. *Hum. Brain Mapp.* **37**, 773 (2016).
29. Greene, A. S., Gao, S., Scheinost, D. & Constable, R. T. Task-induced brain state manipulation improves prediction of individual traits. *Nat. Commun.* **9**, 2807 (2018).
30. Huber, L. et al. Sub-millimeter fMRI reveals multiple topographical digit representations that form action maps in human motor cortex. *Neuroimage* **208**, 116463 (2020).
31. Tobyne, S. M., Osher, D. E., Michalka, S. W. & Somers, D. C. Sensory-biased attention networks in human lateral frontal cortex revealed by intrinsic functional connectivity. *Neuroimage* **162**, 362 (2017).
32. Braga, R. M., DiNicola, L. M., Becker, H. C. & Buckner, R. L. Situating the left-lateralized language network in the broader organization of multiple specialized large-scale distributed networks. *J. Neurophysiol.* **124**, 1415–1448 (2020).
33. DiNicola, L. M., Braga, R. M. & Buckner, R. L. Parallel distributed networks dissociate episodic and social functions within the individual. *J. Neurophysiol.* **123**, 1144–1179 (2020).
34. Santure, A. W. & Garant, D. Wild GWAS—association mapping in natural populations. *Mol. Ecol. Resour.* **18**, 729–738 (2018).

35. Lorenz, R., Hampshire, A. & Leech, R. Neuroadaptive Bayesian optimization and hypothesis testing. *Trends Cogn. Sci.* **21**, 155–167 (2017).
36. Valk, S. L. et al. Genetic and phylogenetic uncoupling of structure and function in human transmodal cortex. *Nat. Commun.* **13**, 1–17 (2022).
37. Dafflon, J. et al. A guided multiverse study of neuroimaging analyses. *Nat. Commun.* **13**, 1–13 (2022).
38. Udochi, A. L. et al. Activation of the default network during a theory of mind task predicts individual differences in agreeableness and social cognitive ability. *Cogn. Affect. Behav. Neurosci.* **22**, 383–402 (2022).
39. Vidaurre, D., Smith, S. M. & Woolrich, M. W. Brain network dynamics are hierarchically organized in time. *Proc. Natl Acad. Sci. USA* **114**, 12827–12832 (2017).
40. Liu, X., Zhang, N., Chang, C. & Duyn, J. H. Co-activation patterns in resting-state fMRI signals. *Neuroimage* **180**, 485–494 (2018).
41. Tervo-Clemmens, B. et al. Reply to: multivariate BWAS can be replicable with moderate sample sizes. *Nature* **615**, E8–E12 (2023).
42. Widiger, T. A. et al. Personality in a hierarchical model of psychopathology. *Clin. Psychol. Sci.* **7**, 77–92 (2019).
43. Van Essen, D. C. et al. The WU-Minn Human Connectome Project: an overview. *Neuroimage* **80**, 62 (2013).
44. Casey, B. J. et al. The Adolescent Brain Cognitive Development (ABCD) study: Imaging acquisition across 21 sites. *Dev. Cogn. Neurosci.* **32**, 43–54 (2018).
45. Glasser, M. F. et al. The minimal preprocessing pipelines for the Human Connectome Project. *Neuroimage* **80**, 105–124 (2013).
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