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Explanatory personality science in the neuroimaging era: The map is not the territory

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Abstract

The recent rise of magnetic resonance imaging (MRI) has led to a proliferation of studies that seek to link individual differences in personality directly to their neural correlates. These studies function to describe personality at a lower level of analysis, but they do little to advance the field's understanding of the causal mechanisms that give rise to personality traits. To transition to a more explanatory personality neuroscience, researchers should strive to conduct theory-driven empirical studies that bridge multiple levels of analysis. Effectively doing so will require a continued reliance on rich description, strong theories, large samples, and careful behavioral experimentation. Integrating these components will lead to more robust and informative studies of personality neuroscience that help to move the field closer to explaining the causal sources of individual differences.

Keywords

personality; neuroimaging; description; explanation; theory

Having spent much of its youth describing how individuals differ from one another, personality neuroscience is now poised to begin interrogating mechanistic questions about the biological and cognitive underpinnings of personality traits. In this commentary, we highlight key challenges facing contemporary personality neuroscientists as they transition from *describing* individual differences to *explaining* them at new levels of analysis. We focus our discussion on neuroimaging research because of its current popularity, though many of our critiques and suggestions apply to other methods as well. Because our main goal is to discuss how personality neuroscience can move toward mechanistic accounts of

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traits, we do not review major empirical findings, instead referring interested readers to recent comprehensive reviews of the field [1–3].

Technological Innovations Alone are Insufficient for Explaining Personality Traits

The pace of personality neuroscience over the last two decades has been feverish. In particular, the widespread availability of MRI has facilitated a recent proliferation of *mapping studies* that use large publicly available datasets to explore neural correlates of self-report measures of personality. Mapping studies share several common characteristics. First, they are often atheoretical and exploratory in nature. Analyses are conducted across the whole brain and hypotheses about which neural correlates will be associated with which traits are either loosely specified or absent. Second, results from mapping studies are frequently nonspecific, with different traits exhibiting overlapping correlations with the same neural correlates. Third, mapping studies are typically void of experimentation; no attempt is made to manipulate behaviors that aggregate over time into a trait of interest [4]. As a result, discussion sections often rely on reverse inference [5] to suggest that the link between a trait and brain region is the product of some cognitive process that others have linked to the same region, even if that process was never actually measured in the study itself.

Mapping studies provide a well-powered means of describing personality at a lower level of analysis (the brain), but they are poorly suited to generating *explanations* of personality that are compatible across levels of analysis [6]. Instead, mapping studies rely on the technological sophistication of MRI to link traits with neural correlates even when we have little notion of the types of processes these correlates are responsible for [7]. In essence, MRI has done for personality neuroscience what fitness trackers have done for personal health. Fitness trackers provide users with new information, often at different levels of analysis (e.g., heart rate, metabolic rate, activity level), that are descriptive markers of one’s fitness level. But knowing one’s heart rate, and how it correlates with overall fitness, tells us very little if our goal is to understand how the cardiovascular system maintains health. Likewise, knowing the region, circuit, or network a trait is associated with can help to describe personality at the level of the brain, but it does little to explain how that region, circuit, or network supports trait behavior [8].

Explanation is Built from Theories that Bridge Multiple Levels of Analysis

Studying personality from different levels of analysis is a worthy goal because differing levels of analysis afford different types of explanations [9]. Nonetheless, transitioning from a descriptive science to an explanatory one requires personality neuroscientists to move beyond simply conducting empirical studies at different levels of analysis and toward theories that make specific predictions about how explanations at one level of analysis can explain observed data at another [10]. Reducing personality into its lower-level substrates yields decontextualized (though novel) information. In contrast, strong theories evoke higher-level explanatory concepts to synthesize this information into a coherent understanding of personality [11,12].

If theory is prerequisite to explanation, then what makes a good and useful theory? This question has led to considerable debate, with some researchers eschewing verbal theories that rely on folk psychological concepts in favor of formal computational models that explicitly define the relationship between variables in the form of mathematical equations [13–15]. Others consider this transition to be “wishing the impossible” given the complexity of personality traits [16]. In practice, verbal theories have directly precipitated many empirical advances in personality neuroscience, despite rarely being invoked by mapping studies [17,18].

The most productive personality theories make specific predictions about which variables are related, in what way, and at what magnitude [13,16]. Computational models are not well-suited to accomplishing this task for all of personality (or even a single broad trait), but they can help push researchers toward further specificity by translating verbal hypotheses into mathematical expressions that make concrete predictions about the latent processes that generate individual differences in trait-relevant behavior. Competing accounts of behavior can then be adjudicated by examining how variations in the form of the model or the parameters it includes influences the model’s ability to reproduce observed data [14]. Results can be used to refine, inform, and adjust broader verbal theories.

Computational models may be uniquely suited to facilitate the bridge-building *between* levels of analysis that is critical for moving from description to explanation. For example, high-level accounts of a trait’s function (e.g., that Extraversion represents variability in reward processing) can place constraints on the types of models best suited to represent behavior [11]. Conversely, adding resource or capacity constraints (e.g., memory or attentional constraints) that improve a model’s ability to capture observed behavior can add detail to verbal trait theories [10]. Likewise, discriminability in associations between model-based parameters and traits may help disentangle mechanisms involved in one trait from those involved in another [19]. Bridges can also be built across lower levels of analysis, as when neural activity is used to adjudicate between competing computational models, or model-based parameters are used to better interpret trial-to-trial variability in neural activity [20].

Personality Neuroscience Needs Experimentation

One reason for the proliferation of mapping studies may be that there is a high degree of difficulty involved in conducting reliable theory-driven personality neuroscience that yields causal insights. Because of their relatively stable nature, it is nearly impossible to manipulate personality traits and observe the downstream effects. Ethical considerations also limit our ability to manipulate brain structure and functioning (though, pharmacological manipulations can be useful; [21–24]) meaning that even the most rigorous studies of personality neuroscience are likely to be fundamentally correlational. As Krakauer and colleagues [8] have noted, these types of challenges lead researchers to substitute a difficult problem (explaining individual differences) with a simpler one (describing those differences at the neural level).

Personality psychologists do retain a high degree of experimental control over the contexts and stimuli that elicit the thoughts, emotions, and behaviors that comprise personality traits. Creatively varying experimental task conditions and stimuli can reveal the contextual variables that elicit trait variability and help to disentangle the cognitive processes that link a trait's neural instantiation to its behavioral outputs and psychometric indicators. Despite the many advantages afforded by experimental tasks however, studies of personality neuroscience rarely emphasize behavioral measures.

One reason for this may be the misconception that traits are *decontextualized*, or able to be independently observed regardless of the situation [25,26]. The idea of decontextualized traits runs counter to influential personality theories from the last half century, which posit that traits reflect predispositions toward specific patterns of thought, emotion, and behavior in response to particular types of stimuli – whether it be rewards, punishments, or conspecifics [12,17,27,28]. The ubiquitous nature of the stimuli to which traits respond can make it appear as though traits themselves are decontextualized, but this is unlikely to be the case [29]. In the absence of relevant stimuli, it may be difficult to observe individual differences in a trait, *regardless of whether measurements are taken at the behavioral or neural level.* Indeed, experimental designs that manipulate the presence or absence of trait-relevant stimuli can reveal associations between traits and neural activity that are not always present at rest [30–32].

Practical considerations make the full-scale integration of behavioral methods into personality neuroscience challenging. Classic cognitive tasks employ strong manipulations (e.g., the Stroop effect) intended to produce robust group-level effects while minimizing between-person individual differences (thought to be a source of noise), which attenuates the very interindividual variability in both behavior [33] and neural activity [34] that is of interest to personality researchers. Consequently, many common fMRI paradigms show poor test-retest reliability (a phenomenon known as "the reliability paradox"), which limits their utility for capturing stable individual differences [35,36].

Interestingly, the reliability paradox seems to be perpetuated in part by a tendency for researchers to aggregate behavioral performance on a task into person-level summary statistics (e.g., overall accuracy, mean reaction time). This can cause attenuated correlations with individual difference constructs for two reasons. First, trial-to-trial variability in performance is discarded during aggregation, meaning that performance is treated as though it were assessed free of measurement error [37]. Second, summary statistics reduce performance to simplified behavioral outputs, many of which are not flexible enough to capture the underlying cognitive processes that generate the data [38]. Moving forward, personality neuroscientists can avoid these difficulties by adopting (1) experimental manipulations that maintain (and explicitly elicit) individual differences for trait-relevant behaviors of interest (more trials per person may help in this regard) and (2) analytical approaches that preserve the hierarchical structure of task data (e.g., multilevel structural equation modeling) and better capture the latent processes presumed to generate the behavior of interest (e.g., computational models).

Balancing the Need for Adequate Power with the Need for Experimental Precision

Integrating behavioral experimentation into personality neuroscience is complicated by the need to attain large sample sizes to achieve adequate statistical power, which may itself be a major contributor to the trend toward mapping studies. Effect sizes in personality research are modest (the average effect size is $r = .19$; [39]), and therefore less likely to be reliably detected in small samples (Type II error). Conversely, as sample size goes down, sampling variability increases, leading to less precise estimates of correlations and greater influence of outliers [40]. Greater instability in correlations can lead to null effects appearing as though they are significant (Type I error), and true effects appearing larger in magnitude than they really are. In small sample MRI studies, estimates of an effect will vary across voxels, with only voxels that significantly inflate the size of an effect reaching significance. As a result, neural effects appear larger in magnitude but more spatially selective, when in fact they are both weaker and more spatially diffuse [41].

Personality neuroscience has tried to deal with the problem of small samples through an increased reliance on large, publicly available neuroimaging datasets that include hundreds or thousands of participants. Shared datasets represent an important resource going forward, but they rarely permit the kind of careful behavioral manipulation necessary to understand the ecological contexts and stimuli that elicit trait-relevant behavior. Most large-scale datasets include scans to assess anatomical structure and resting-state functional connectivity, but fewer include measures of task-based neural activity. In the absence of behavioral measures designed with a specific trait in mind, many researchers resort to mapping studies, linking multiple traits directly to their structural or resting state substrates. Even when large-scale datasets include task-based functional scans, they often do so in less-than-ideal conditions: only a few tasks can be added due to time and space constraints (prohibiting the use of latent variables from metrics derived across tasks), and the tasks that are added often feature generic manipulations in an effort to appease the large number of investigators who may be interested in using them. These kinds of generic manipulations can make it difficult to test theory-driven predictions about the types of stimuli that elicit individual differences and types of processing that occur in response to those stimuli.

The reality is that personality neuroscientists are in an unenviable position, needing to balance the desire to conduct theory-driven explanatory neuroscience with the need to achieve adequate statistical power [42]. Going forward, investigators may resolve these competing demands by forming smaller collaborations with like-minded researchers, which can facilitate larger samples while requiring less sacrifice to one's study design. Researchers should consider incorporating behavioral data into neuroscientific studies whenever possible, even if behavioral data was measured outside the scanner. Trial-by-trial performance indicators and model-derived parameters can then be used to predict structural or resting state indices, which may provide some traction on the cognitive processes that link neural circuitry to individual differences (e.g., there is convergence between task-based and resting state networks, and evidence that resting state activity contributes to task-evoked activity; [43]). Such findings can provide the foundation for subsequent studies in which behavior and neural activity are captured simultaneously. Finally, in some cases researchers may find success pivoting to less expensive modalities, such as electroencephalography (EEG) or psychophysiological measures. One intriguing possibility is to adopt study designs with planned missingness, combining cheaper measures with a more expensive one (in this case, MRI) to attain higher power than one would otherwise have [44]. Latent variables can be used to capture shared variance between the measures (e.g., combining a reward-related ERP component from different tasks with reward-related neural activity in the striatum; [45]), yielding a multimodal measure that 1) reduces measurement error, and 2) increases effective sample size at no additional cost. These latent variables can subsequently be related to other observed or latent variables reflecting model-based parameters derived from task performance and/or psychometric assessments, allowing one to effectively bridge different levels of analysis.

Rich Description is the Foundation of Explanation

Moving forward, empirical work on the structure of personality can inform and constrain studies of personality neuroscience that seek to bridge multiple levels of analysis in service of explanation. Indeed, good description is a prerequisite to explanation, and a flawed descriptive framework undermines the specificity and validity of findings at lower levels of analysis [14,46].

One of the most useful features of structural models of personality is that they can aide in hypothesis generation. For instance, trait dimensions included in most contemporary models of personality show strong continuity across species, making them more amenable to connections with phylogenetically conserved neural systems [47,48]. This allows personality neuroscientists to leverage findings from animal research, where stronger experimental manipulations are possible, to generate novel hypotheses about the cognitive and neural substrates of individual differences (e.g., [49]).

Novel hypotheses can also be derived from the relations between traits. Broader traits that reside at the top of the personality hierarchy account for patterns of covariation in narrow traits that reside lower in the hierarchy. At each level of the hierarchy, some set of mechanisms should explain why lower-order traits covary to form higher-order traits, whereas some other set of mechanisms should explain the unique variance that causes these traits to diverge from one another [7,16]. The goal of the modern-day personality neuroscientist is not to describe these patterns of covariation, but to generate hypotheses about the neurocognitive mechanisms that might explain them.

Careful phenotypic description can also push neuroscientific findings toward greater specificity. Too often in contemporary neuroscience, individual difference measures are haphazardly correlated with neural or cognitive correlates without any a priori predictions being made about the nature or specificity of these associations. This can lead to processes of interest being confusingly linked to multiple traits or disorders when the true association is due to shared variance between the constructs [50]. Alternatively, the same processes may be related to a single broad trait but unreliably so, because the association is actually better accounted for by some more narrow feature of the construct (e.g., a specific facet).

Structural models of personality can help avoid these difficulties by providing ready-made tests of specificity that burden the investigator to show that a given trait-brain or trait-behavior association does not generalize to other traits at the same level of the hierarchy and is not better accounted for by a related, but narrower construct. Where such specificity is not present, one's theory should be revised.

As it stands, nonspecificity is strikingly apparent in personality neuroscience, with many traits mapping on to the same neural correlate and many neural correlates mapping onto the same trait. This could indicate complexity in the neural systems contributing to a trait [51], or alternatively, signal that our search for the neural substrates of specific personality traits is playing out at the wrong level of resolution [52]. Structural models can help to address the latter problem because traits at the top of the hierarchy, which reflect a wider range of behavior than those lower in the hierarchy, should be tied to neural systems that are distributed more diffusely throughout the brain and therefore able to govern a broader swath of circuitry [53]. Likewise, studies seeking to understand the neural underpinnings of traits closer to the bottom of the hierarchy might focus their efforts on more narrow or specialized circuits that may have been coopted during the course of evolution to meet specific adaptive challenges [54].

Overall, understanding the structure and nature of personality traits is a prerequisite to explaining individual differences. This is not to say that priority must always be given to the Big Five, or to any other descriptive trait model. What matters far more than the number of trait constructs in one's model is understanding the breadth and scope of those traits, how they are related to one another, and whether they are well-suited to one's specific theoretical questions [55,56].

Conclusion

The advent of neuroimaging brought with it promises of a new, explanatory personality science, but the interim two decades have yielded studies that present correlations between traits and neural tissue with little explication of the cognitive mechanisms that could produce such correlations. Conducting neuroscientific studies that generate explanatory insights into personality requires rich description, strong theory, large samples, careful behavioral experimentation, and most importantly, an ability to bridge multiple levels of analysis. By embracing these lessons from the last twenty years of personality neuroscience, the field will finally be able to transition into a new era of explanation.

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References

1. Kennis M, Rademaker AR, Geuze E: Neural correlates of personality: An integrative review. Neurosci Biobehav Rev 2013, 37:73–95. [PubMed: 23142157]

2. Allen TA, DeYoung CG: Personality neuroscience and the five factor model. In The Oxford Handbook of the Five Factor Model. Edited by Widiger TA. Oxford; 2017:1–63.*A recent review of the major methodological issues and empirical findings, particularly from mapping studies, in personality neuroscience.
3. DeYoung CG, Allen TA: Personality Neuroscience A Developmental Perspective. 2018.
4. Fleeson W, Jayawickreme E: Whole trait theory. J Res Pers 2015, 56:82–92. [PubMed: 26097268]
5. Poldrack RA: Inferring mental states from neuroimaging data: From reverse inference to large-scale decoding. Neuron 2011, 72:692–697. [PubMed: 22153367]
6. McNaughton N, Smillie LD: Some metatheoretical principles for personality neuroscience. Personal Neurosci 2018, 1.
7. Allen TA, Schreiber AM, Hall NT, Hallquist MN: From description to explanation: Integrating across multiple levels of analysis to inform neuroscientific accounts of dimensional personality pathology. J Pers Disord 2020, 34:650–676. [PubMed: 33074057] * An earlier commentary from these same authors that extends the logic of the current argument to the domain of personality pathology, highlighting the role of dimensional models of psychopathology in personality neuroscience and reviewing recent empirical work that has helped to generate stronger mechanistic insights into the nature of maladaptive traits.
8. Krakauer JW, Ghazanfar AA, Gomez-Marin A, MacIver MA, Poeppel D: Neuroscience needs behavior: Correcting a reductionist bias. Neuron 2017, 93:480–490. [PubMed: 28182904] * A recent commentary in which the authors argue that careful description and manipulation is necessary for identifying the component processes and algorithms that underlie behavior. Only after such behavioral work is carried out should one begin investigating the neural instantiation of these component processes.
9. Lilienfeld SO: Cognitive neuroscience and depression: Legitimate versus illegitimate reductionism and five challenges. Cognit Ther Res 2007, 31:263–272.
10. Love BC: The algorithmic level is the bridge between computation and brain. Top Cogn Sci 2015, 7:230–242. [PubMed: 25823496] * A recent commentary in which the author argues that building bridges across levels of analysis is key to generating mechanistic insights. In particular, Marr's algorithmic level (the level at which computation occurs) is highlighted as a useful intermediate for building bridges to higher-level accounts of a construct (e.g., it's function) as well as its neural implementation.
11. Love BC: Levels of biological plausibility. Philos Trans R Soc B 2021, 376:20190632.
12. Trofimova I, Reviews TR-N& B, 2016 undefined: Temperament and arousal systems: a new synthesis of differential psychology and functional neurochemistry. Elsevier [date unknown],
13. Fried EI: Lack of theory building and testing impedes progress in the factor and network literature. Psychol Inq 2020, 31:271–288.
14. Patzelt EH, Hartley CA, Gershman SJ: Computational phenotyping: Using models to understand individual differences in personality, development, and mental illness. 2019, doi:10.1017/pen.2018.14.* A recent commentary in which the authors discuss the role of computational modeling in personality and psychopathology. The focus is on how computational models can be used to generate mechanistic predictions about future behaviors and underlying neural activity. Recent empirical applications of computational models are reviewed.
15. Guest O, Martin AE: How computational modeling can force theory building in psychological science, https://doi.org/101177/1745691620970585 2021, 16:789–802.
16. DeYoung CG, Krueger RF: To wish impossible things: On the ontological status of latent variables and the prospects for theory in psychology. Psychol Inq 2020, 31:289–296.
17. Depue RA, Collins PF: Neurobiology of the structure of personality: Dopamine, facilitation of incentive motivation, and extraversion. Behav Brain Sci 1999, 22:491–517. [PubMed: 11301519]
18. Gray JA, McNaughton N: The neuropsychology of anxiety: An enquiry into the functions of the septo-hippocampal system. Oxford; 2000.
19. Hall NT, Schreiber AM, Hallquist MN, Allen TA: Disentangling cognitive processes in externalizing psychopathology using drift diffusion modeling : Antagonism , but not disinhibition , is associated with poor cognitive control. 2021, doi:10.1111/jopy.12628.

20. Brown VM, Zhu L, Solway A, Wang JM, McCurry KL, King-Casas B, Chiu PH: Reinforcement Learning Disruptions in Individuals With Depression and Sensitivity to Symptom Change Following Cognitive Behavioral Therapy. JAMA Psychiatry 2021, doi:10.1001/jamapsychiatry.2021.1844.
21. Wacker J, Smillie LD: Trait extraversion and dopamine function. Soc Personal Psychol Compass 2015, 9:225–238.
22. Wright AGC, Creswell KG, Flory JD, Muldoon MF, Manuck SB: Neurobiological functioning and the personality-trait hierarchy: Central serotonergic responsivity and the stability metatrait. Psychol Sci 2019, 30:1413–1423. [PubMed: 31487227]
23. Robbins TW: Opinion on monoaminergic contributions to traits and temperament. Philos Trans R Soc B Biol Sci 2018, 373.
24. Kanen JW, Robbins TW, Trofimova IN: Harnessing temperament to elucidate the complexities of serotonin function, [date unknown], doi:10.31234/OSF.IO/GVMUY.
25. Mõttus R, Wood D, Condon DM, Back MD, Baumert A, Costantini G, Epskamp S, Greiff S, Johnson W, Lukaszewski A, et al. : Descriptive, Predictive and Explanatory Personality Research: Different Goals, Different Approaches, but a Shared Need to Move Beyond the Big Few Traits. Eur J Pers 2020, 34:1175–1201.
26. McAdams DP, Pals JL: A new Big Five: Fundamental principles for an integrative science of personality. Am Psychol 2006, 61:204–217. [PubMed: 16594837]
27. DeYoung CG, Krueger RF: A cybernetic theory of psychopathology. Psychol Inq 2018, 29:117–138.
28. Gray JA: Causal theories of personality and how to test them. In Multivariate analysis and psychological theory. Edited by Royce J. Academic Press; 1973:409–463.
29. DeYoung CG: Cybernetic big five theory. J Res Pers 2015, 56:33–58.
30. Kuper N, Käckenmester W, Wacker J: Resting frontal EEG asymmetry and personality traits: A meta-analysis. Eur J Pers 2019, 33:154–175.
31. Wacker J: Effects of positive emotion, extraversion, and dopamine on cognitive stability-flexibility and frontal EEG asymmetry. Psychophysiology 2018, 55.
32. Greene AS, Gao S, Scheinost D, Constable RT: Task-induced brain state manipulation improves prediction of individual traits. Nat Commun 2018, 9.
33. Cooper SR, Gonthier C, Barch DM, Braver TS: The Role of Psychometrics in Individual Differences Research in Cognition: A Case Study of the AX-CPT. Front Psychol 2017, 0:1482.
34. Infantolino ZP, Luking KR, Sauder CL, Curtin JJ, Hajcak G: Robust is not necessarily reliable: From within-subjects fMRI contrasts to between-subjects comparisons. Neuroimage 2018, 173:146–152. [PubMed: 29458188]
35. Hedge C, Powell G, Sumner P: The reliability paradox: Why robust cognitive tasks do not produce reliable individual differences. Behav Res Methods 2018, 50:1166–1186. [PubMed: 28726177] *A recent empirical study in which the authors show that strong task manipulations can produce robust effects that also limit interindividual variability. As a result, performance on such tasks can be difficult to reliably link to individual difference constructs.
36. Elliott ML, Knodt AR, Ireland D, Morris ML, Poulton R, Ramrakha S, Sison ML, Moffitt TE, Caspi A, Hariri AR: What Is the test-retest reliability of common task-functional MRI measures? New empirical evidence and a meta-analysis https://doi.org/101177/0956797620916786 2020, 31:792–806.
37. Rouder IN, Haaf JM: A psychometrics of individual differences in experimental tasks. Psychon Bull Rev 2019 262 2019, 26:452–467. [PubMed: 30911907]
38. Haines N, Kvam P, Irving L, Smith C: Learning from the reliability paradox: How theoretically informed generative models can advance the social, behavioral, and brain sciences. psyarxiv.com 2021.
39. Gignac GE, Szodorai ET: Effect size guidelines for individual differences researchers. Pers Individ Dif 2016, 102:74–78.
40. Schönbrodt FD, Perugini M: At what sample size do correlations stabilize? J Res Pers 2013, 47:609–612.

41. Grady CL, Rieck JR, Nichol D, Rodrigue KM, Kennedy KM: Influence of sample size and analytic approach on stability and interpretation of brain-behavior correlations in task-related fMRI data. Hum Brain Mapp 2021, 42:204–219. [PubMed: 32996635]
42. Poldrack RA: The Costs of Reproducibility. Neuron 2019, 101:11–14. [PubMed: 30605654]
43. Pezzulo G, Zorzi M, Corbetta M: The secret life of predictive brains: what's spontaneous activity for? Trends Cogn Sci 2021, 25:730–743. [PubMed: 34144895]
44. Graham J, Taylor B, Olchowski A, Cumsille P: Planned missing data designs in psychological research. Psychol Methods 2006, 11:323–343. [PubMed: 17154750]
45. Proudfit GH: The reward positivity: From basic research on reward to a biomarker for depression. Psychophysiology 2015, 52:449–459. [PubMed: 25327938]
46. Kotov R, Krueger RF, Watson D, Achenbach TM, Althoff RR, Bagby RM, Brown TA, Carpenter WT, Caspi A, Clark LA, et al. : The Hierarchical Taxonomy of Psychopathology (HiTOP): A dimensional alternative to traditional nosologies. J Abnorm Psychol 2017, 126:454–477. [PubMed: 28333488]
47. Gosling SD: Personality in non-human animals. Soc Personal Psychol Compass 2008, 2:985–1001.
48. Latzman RD, Hecht LK, Freeman HD, Schapiro SJ, Hopkins WD: Neuroanatomical correlates of personality in chimpanzees (Pan troglodytes): Associations between personality and frontal cortex. Neuroimage 2015, 123:63–71. [PubMed: 26311604]
49. Robbins TW, Gillan CM, Smith DG, de Wit S, Ersche KD: Neurocognitive endophenotypes of impulsivity and compulsivity: towards dimensional psychiatry. Trends Cogn Sci 2012, 16:81–91. [PubMed: 22155014]
50. Abram SV, DeYoung CG: Using personality neuroscience to study personality disorder. Personal Disord 2017, 8:2–13. [PubMed: 28045302]
51. Trofimova I: Contingent Tunes of Neurochemical Ensembles in the Norm and Pathology: Can We See the Patterns? Neuropsychobiology 2021, 80:101–133. [PubMed: 33721867]
52. Poldrack RA: Mapping mental function to brain Structure: How can cognitive Neuroimaging Succeed? Perspect Psychol Sci 2010, 5:753–761. [PubMed: 25076977]
53. Depue RA, Lenzenweger MF: Toward a developmental psychopathology of personality disturbances: A neurobehavioral dimensional model. In Developmental psychopathology (Vol. 2): Developmental neuroscience. Edited by Cicchetti D, Cohen DJ. Wiley; 2015:762–796.
54. DeYoung CG: The neuromodulator of exploration: A unifying theory of the role of dopamine in personality. Front Hum Neurosci 2013, 7:1–26. [PubMed: 23355817]
55. Wiernik B, Yarkoni T, Giordano C, Raghavan M: Two, five, six, eight (thousand): Time to end the dimension reduction debate! 2020, doi:10.31234/osf.io/d7jye.
56. Bainbridge TF, Ludeke S, Smillie L: Evaluating the Big Five as an Organizing Framework for Commonly Used Psychological Trait Scales. J Pers Soc Psychol 2021, doi: 10.31234/OSF.IO/VEBTM.

Highlights

- The rise of functional neuroimaging has led to increasing attempts to link personality traits directly to neural correlates.
- Knowing the neural correlates of personality traits helps to describe traits at a lower level of analysis but does little to explain individual differences.
- Transitioning to an explanatory personality neuroscience will require empirical work that bridges multiples levels of analysis and integrates careful behavioral experimentation into large samples.