# Personality Neuroscience

Subjects: Psychiatry
Contributor: Dora Brooks

It has long been understood that a multitude of biological systems, from genetics, to brain networks, to psychological factors, all play a role in personality. Understanding how these systems interact with each other to form both relatively stable patterns of behaviour, cognition and emotion, but also vast individual differences and psychiatric disorders, however, requires new methodological insight. Novel data-driven approaches, such as multilayer networks, may prove to be viable methods for explaining and predicting individual difference with greater veracity through incorporating data at more than one scale.

Keywords: Personality Neuroscience ; psychology ; multilayer networks ; symptom networks ; network neuroscience

## 1. Personality as a Complex System

Broadly speaking, the theory of emergence states that behaviour arises as a property of an organised system, where the parts of these systems alone do not give rise to the behavioural properties [1][2]. From genetics to molecular pathways, brain circuitry to environmental and social interactions, it can be hypothesised that multiple systems contribute to the emergence of unique human personalities in much the same way.

Current efforts to describe personality in psychology and neuroscience are predominantly carried out either at the level of individual systems, such as the behavioural or neural level alone, or through top-down approaches which link characteristics of one system, such as aggression, to characteristics of another, such as volume or activity of a brain region. More recently, top-down approaches have been used in combination with brain network measures [3][4], which unlike simple morphological studies which measure localised activity or volume alone, are capable of discerning complex structural and functional patterns across the whole neural level through incorporating interactions between multiple brain regions [5][6].

As we demonstrate using the example of the five-factor model (FFM), top-down approaches have consistently established a link between the neural and psychological levels of personality, indicating that there could indeed be neural components that contribute to the emergence of psychological characteristics. These methods, however, are still vastly constrained by a number of methodological simplifications which may be preventing the complex mechanisms of personality that exist across multiple levels, from being derived. These constraints predominantly rest upon (1) the latent variable model used to define personality traits at the psychological level whereby variation in psychological characteristics are explained by an underlying trait, and (2) the use of latent traits to identify the neural correlates of personality (NCPs) through what is known as a “top-down” approach. This is where a top-down approach infers that the NCPs may explain variation in the psychologically defined trait.

Recently, a body of research has advocated for the use of a network model of psychological characteristics, known as a symptom network, as an alternative to the latent variable approach [7][8]. Through this lens, psychological characteristics are seen in relation to each other and not in relation to a common cause. Using the analogy of aggression to compare the two approaches, a latent variable model would argue that an aggressive trait is causing behaviours such as hostility, being easily provoked, and being physically violent, whereas a symptom network model may find that feelings of hostility are strongly related to being easily provoked, which may in turn be linked to physically violent responses. In this way, aggressive behaviour could be seen as an emergent property of a symptom network composed of hostility, being easily provoked and being physically violent.

Unlike the top-down approach frequently used with the latent variable model, there is currently no defined manner by which to connect networked psychological characteristics of personality, at one level, to the networked characteristics of the brain, at another.

In order to explore this possibility, we discuss a number of novel approaches that allow multiple levels of networked characteristics to be connected, these approaches are broadly known as multilayer networks [9]. These methodologies are not only able to incorporate complexity through networking psychological and neural characteristics, but also allow the application of a variety of network analytical tools capable of deriving potentially relevant patterns that exist between the levels. Such an approach reduces the impact of a-priori statistical simplifications intrinsic to top-down and latent-variable approaches. If successful, the multilayer approach could precipitate a formulation of personality that more veraciously describes and predicts individual differences and changes that accompany psychiatric and neurological disease. Through exploring a preliminary methodology for such an approach, we find a strong basis for the idea that the study of a complex, emergent system such as personality, including neural and behavioural, cognitive and emotional characteristics (BCECs), would benefit from an integrated, multilayer network approach.

## 2. Multilayer Personality Neuroscience

The multilayer network approach refers to a number of methodologies endeavouring to combine two or more networks into a single 'multilayer' network [9]. By doing so, the resulting model provides further insight into the organisation and dynamics of a more complete system, potentially superseding the explanatory and predictive power of a single layer network alone.

The many formulations of multilayer networks have sparked interest in fields involved with deriving and predicting complex phenomena, such as biological, social, technical and transport systems [10][11][12][13][14][15]. This interest largely stems from the approach's capacity to incorporate multiple datasets that involve more than one modality, scale, or point in time, as is often the case in the study of complex systems. A general example of the use of a multilayer network can be seen by expanding the analogy of transport systems:

If one wished to understand why there were frequently traffic jams at the central station of a city, the problem may not be well explained by looking at the cars alone. Instead, an investigation into the interaction between cars, pedestrians, bicycles and trains may (1) yield a more complete model of the system (2) allow for more accurate prediction of the system and (3) allow interventions to be implemented which prevent traffic build-ups and make the system more efficient.

This analogy can be directly translated into the general framework of a multilayer network. Here, the transport modalities are defined as layers, the nodes are defined as geographical locations, the connections between the layers, known as interlayer edges, are defined on the basis that the geographical locations in each layer are identical and can therefore be connected. These identical nodes between layers have been termed 'replica nodes' [16]. The presence of replica nodes is fundamental to this formulation of the multilayer network as it allows the different layers to be connected.

Recently, this general formulation of the multilayer network has been used in studies of the brain [17][18][19]. Layers have often been defined on the basis of (1) differing imaging modalities [20], such as one level representing structural connectivity and the other functional connectivity, (2) differing scales within one modality as layers [19] or (3) with time-series data, where layers are represented as different moments in time [21].

This general formulation of the multilayer network which integrates different imaging modalities or time-series data, however, would not be directly applicable to the study of the relationship between brain and behaviour. This is because in these prior examples, interlayer connections are formed on the basis of replica nodes which would not exist across multiple scales such as in the neural and behavioural levels. In this way, the general multilayer method is not able to give an indication of the properties of a system that emerge across the micro and macro levels. The following section discusses a means by which to extend the use of the multilayer network across multiple scales, allowing for the aforementioned benefits to be harnessed in the study of the relationship between the neural and BCEC levels of personality.

### Constructing a Multilayer Network without Replica Nodes

The first step towards creating this multilayer network would involve both brain and BCEC data collection in a sample of individuals. First, for every participant, it would be necessary to collect scores for characteristics in a personality questionnaire such as the NEO PI-R. The normalised scores in each of these characteristics would then be used to create a group level BCEC network (Cramer et al., 2012), using partial correlation networks [22]. This network would represent the BCEC network layer within the multilayer. Second, it would be necessary to measure brain network data for every participant, using for instance rsfMRI. To create the brain network layer, both a normalised group level brain network, or individual level brain networks could be used, where the latter would give a greater indication of heterogeneity between individuals.

After creating the networks at the level of the brain and BCEC, it is then necessary to relate the normalised mean scores for each node in the BCEC network to each node in the brain network. This is done in order to create weighted interlayer connections, based on correlations between each brain node and each personality node. In order to do this, a quantifiable characteristic of the brain node must be selected, such as the node's overall connectivity or centrality. Both these measures would provide each node with a value, for each participant, within each layer. For example, at the individual level the FFM BCEC network node corresponding to warmth (E1) could have a score of 0.90 (Figure 1a) and the node corresponding to the medial prefrontal cortex (mPFC) could have a score of 5, which could be based on the node's degree (Figure 1b). Calculating group-level correlations between node pairs is then necessary to quantify the strength of the interlayer connections.

**Figure 1.** Methodology for multilayer approach without interlayer identities. (**a**) Normalised personality scores in every facet of a personality the FFM (Friendliness = Extraversion One (E1)) are collected from a sample of individuals and used to make a BCEC network by means of the Partial Correlation network methodology. This data is used to create the BCEC network layer in the multilayer network (**d**). (**b**) Brain network nodes are defined and network characteristics, such as degree, clustering and centrality, are quantified for the original sample of individuals. This is used to create a brain network layer in the multilayer network (**d**). (**c**) A matrix is created which quantifies the correlations between each node in the personality data and each node in the brain data, this matrix score is then used to define the weight of the intralayer connections ($X_{n,n}$).

In order to quantify the strength of the relationships between nodes across the two layers, a matrix could be devised using a normal correlation or a non-parametric correlation (Figure 1c). Further research into more rigorous statistical approaches for this step of the methodology is still required and may become clearer as more is learnt about the approach. In theory, however, the outputted matrix scores provided by such a statistical analysis, could then be used as the weighted interlayer connections between the BCEC network and the brain layer (Figure 1d). Together, this would give a multilayer BCEC-brain network (Figure 1d).

This multilayer model would allow network analyses to be carried out over both layers, in order to derive novel interactions between neural and psychological characteristics, and network communities and/or hierarchies that are biologically relevant to the emergence of personality. This may prove useful in first modelling brain-BCEC interactions in personality at a group level, and further in being able to form individual multilayer networks that could provide insight into differences between (sub)groups. An example could be the exploration of hypothesised subtypes of personalities and their possibly distinctive multilayer network topologies. Furthermore, the technique could involve a greater number of layers corresponding to additional networks which could be impacting upon personality trait and brain networks, such as environmental and genetic factors.

Overall, although in its infancy, this multilayer approach allows for personality to be viewed as a dynamic and multifaceted phenomenon, where individual phenotypes can be modelled as an accumulation of variable interactions between multiple layers.

## References


1. Lewes, G.H. Problems of Life and Mind; Trübner: London, UK, 1879.
2. Mill, J.S. A System of Logic, Ratiocinative and Inductive: Being a Connected View of the Princples of Evidence, and the Methods of Scientific Investigation; Cambridge Library Collection—Philosophy; Cambridge University Press: Cambridge, UK, 1843.
3. Markett, S.; Montag, C.; Reuter, M. Network Neuroscience and Personality. Pers. Neurosci. 2018, 1, e14.

4. Tompson, S.H.; Falk, E.B.; Vettel, J.M.; Bassett, D.S. Network Approaches to Understand Individual Differences in Brain Connectivity: Opportunities for Personality Neuroscience. Pers. Neurosci. 2018, 1.
5. Bassett, D.S.; Sporns, O. Network neuroscience. Nat. Neurosci. 2017, 20, 353–364.
6. Douw, L.; Van Dellen, E.; Gouw, A.A.; Griffa, A.; De Haan, W.; Heuvel, M.V.D.; Hillebrand, A.; Van Mieghem, P.; Nissen, I.A.; Otte, W.M.; et al. The road ahead in clinical network neuroscience. Netw. Neurosci. 2019, 3, 969–993.
7. Borsboom, D.; Cramer, A.O. Network Analysis: An Integrative Approach to the Structure of Psychopathology. Annu. Rev. Clin. Psychol. 2013, 9, 91–121.
8. Borsboom, D.; Cramer, A.; Kalis, A. Brain disorders? Not really… Why networkstructures block reductionism in psychopathology research. Behav. Brain Sci. 2018, 42, 1–54.
9. Kivelä, M.; Arenas, A.; Barthelemy, M.; Gleeson, J.P.; Moreno, Y.; Porter, M.A. Multilayer Networks. J. Complex Netw. 2014, 2, 203–271.
10. Boccaletti, S.; Bianconi, G.; Criado, R.; del Genio, C.I.; Gómez-Gardeñes, J.; Romance, M.; Sendiña-Nadal, I.; Wang, Z.; Zanin, M. The structure and dynamics of multilayer networks. Phys. Rep. 2014, 544, 1–122.
11. De Domenico, M.; Solé-Ribalta, A.; Gómez, S.; Arenas, A. Navigability of interconnected networks under random failures. Proc. Natl. Acad. Sci. USA 2014, 111, 8351–8356.
12. De Domenico, M.; Granell, C.; Porter, M.A.; Arenas, A. The physics of spreading processes in multilayer networks. Nat. Phys. 2016, 12, 901–906.
13. Gallotti, R.; Barthelemy, M. The multilayer temporal network of public transport in Great Britain. Sci. Data 2015, 2, 140056.
14. Gómez, S.; Díaz-Guilera, A.; Gómez-Gardeñes, J.; Pérez-Vicente, C.J.; Moreno, Y.; Arenas, A. Diffusion Dynamics on Multiplex Networks. Phys. Rev. Lett. 2013, 110, 028701.
15. Mucha, P.J.; Richardson, T.; Macon, K.; Porter, M.A.; Onnela, J.-P. Community structure in time-dependent, multiscale, and multiplex networks. Science 2010, 328, 876–878.
16. Bianconi, G. Multilayer Networks: Structure and Function; Oxford University Press: Oxford, UK, 2018.
17. De Domenico, M. Multilayer modeling and analysis of human brain networks. GigaScience 2017, 6, 1–8.
18. Mandke, K.; Meier, J.; Blanke, O.; O'Dea, R.D.; Van Mieghem, P.; Stam, C.J.; Hillebrand, A.; Tewarie, P.K. Comparing multilayer brain networks between groups: Introducing graph metrics and recommendations. NeuroImage 2018, 166, 371–384.
19. Tewarie, P.K.; Hillebrand, A.; Van Dijk, B.W.; Stam, C.J.; O'Neill, G.C.; Van Mieghem, P.; Meier, J.M.; Woolrich, M.W.; Morris, P.G.; Blanke, O. Integrating cross-frequency and within band functional networks in resting-state MEG: A multi-layer network approach. NeuroImage 2016, 142, 324–336.
20. Battiston, F.; Nicosia, V.; Chavez, M.; Latora, V. Multilayer motif analysis of brain networks. Chaos Interdiscip. J. Nonlinear Sci. 2017, 27, 047404.
21. Braun, U.; Schäfer, A.; Walter, H.; Erk, S.; Romanczuk-Seiferth, N.; Haddad, L.; Schweiger, J.I.; Grimm, O.; Heinz, A.; Tost, H.; et al. Dynamic reconfiguration of frontal brain networks during executive cognition in humans. Proc. Natl. Acad. Sci. USA 2015, 112, 11678–11683.
22. Epskamp, S.; Fried, E.I. A tutorial on regularized partial correlation networks. Psychol. Methods 2018, 23, 617–634.