Working Memory Bridges Cognition, Emotion, and Brain Structure: A Multilayer Network Analysis of the Human Connectome Project-Young Adult

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Abstract

Multilayer network analyses allow for the exploration of complex relationships across different modalities. Specifically, this study employed a novel method that integrates psychometric networks with structural covariance networks to explore the relationships between cognition, emotion and the brain. Psychological (NIH Toolbox Cognition Battery and NIH Toolbox Emotion Battery) and anatomical MRI (cortical volume) data were extracted from the Human Connectome Project Young Adult dataset (n=1113). Partial correlation networks with graphical lasso regularisation and extended Bayesian information criterion tuning were used to model a psychometric bi-layer network consisting of seven cognitive nodes and four emotion nodes, as well as a neuro-psychometric tri-layer network consisting of these same nodes in addition to 24 brain nodes from the central executive and salience networks. Bridge strength centrality was used to identify nodes that bridged between layers. For the bi-layer network, it was found that stress was the most central bridge node. For the tri-layer network, it was found that working memory was the most central bridge node and that the right inferior parietal gyrus was the most central brain bridge node. The findings demonstrate the utility of multilayer networks in integrating multiple modalities of data for the potential identification of targets to improve psychological wellbeing.

1. Introduction

The symptomatology of many clinical conditions includes changes to cognition and emotion. For example, in neurological conditions such as following from a stroke or traumatic brain injury, individuals suffer from memory impairments, as well as low mood and anxiety (Konrad et al., 2011; Terrill et al., 2018). Similarly, psychological conditions such as Major Depressive Disorder, Generalised Anxiety Disorder, and schizophrenia involve both cognitive and emotional symptoms (American Psychiatric Association [APA], 2013; Diener et al., 2012). The relationships between cognition and emotion in these conditions are often complex and bi-directional. For example, after a stroke, individuals may have cognitive impairments, such as limited attention and working memory capacity that cause difficulties with daily tasks, leading to negative emotions, such as sadness and fear (Terrill et al., 2018). Conversely, these negative emotions may in turn exacerbate attention difficulties, as is often seen in Major Depressive Disorder (APA, 2013; Wang et al., 2020).

Network science has demonstrated utility in understanding how psychological constructs such as cognition and mental health are subserved by complex relationships between components (Ferguson, 2021; Giles et al., 2022; Kan et al., 2019; Kenny et al., 2021). Psychometric networks often use partial correlation networks (Epskamp & Fried, 2018) to analyse the conditional dependencies of psychological variables such as cognitive abilities (e.g., working memory, attention, etc.) or mental health symptoms (e.g., anxiety, depression, etc.). The variables (nodes) in these networks are connected to other nodes by edges, which represent the statistical relationships between them (i.e., partial correlations). The importance of nodes in the network can then be quantified by centrality metrics, such as strength centrality, which sums the absolute weight of the edges from each node to all other nodes in the network (Epskamp & Fried, 2018). Bridge strength centrality specifically

identifies nodes that are central to connecting different constructs, such as between comorbid conditions (Jones et al., 2021).

Psychometric networks have been used to better understand the relationships between the cognitive abilities involved in intelligence (Kan et al., 2019; Schmank et al., 2019), the relationships between symptoms within a number of mental health conditions, such as depression (Kenny et al., 2021), eating disorders (Giles et al., 2022), borderline personality disorder (De Paoli et al., 2020), and obsessive-compulsive disorder (Giles et al.). The approach has also been used in neurodegenerative conditions such as Alzheimer's Disease (Ferguson, 2021) where, for example, researchers identified processing speed as the most central node in the network for those with Alzheimer's Disease, and episodic memory as the most central node for controls (Ferguson, 2021). These findings suggest that psychometric networks can both identify cognitive abilities important to normal functioning and detect how these cognitive functions are altered in disease.

Psychometric networks are therefore a suitable framework to look at the complex and dynamic relationships between cognition and emotion. However, to truly understand the link between cognition and emotion, it is also necessary to identify the brain regions that are involved in both. It has been argued by some researchers that cognitive and emotional processes arise from often overlapping neurophysiological functions, and therefore, there are likely brain regions responsible for both cognitive abilities and emotions (Barrett, 2016; Kraljević et al., 2021; Pessoa, 2008). Brain regions within the central executive and salience networks have previously been found to be associated with a mixture of cognitive abilities and emotional states (Cromheeke & Mueller, 2014; Diener et al., 2012; Kraljević et al., 2021; Metzler-Baddeley et al., 2016). Furthermore, disruptions to these brain networks have been implicated in the cognitive or emotional symptoms of numerous psychopathological conditions (Menon, 2011). As neuroimaging studies typically focus on the neural corelates of

either cognition or emotion, few neuroimaging studies focus on identifying brain regions involved in both (Diener et al., 2012; Kraljević et al., 2021). However, one such study by Kraljević et al. (2021) used multiple linear regression models with data from the Human Connectome Project and found that the superior frontal cortex is significantly associated with both cognition and emotion. This discovery highlights the potential for further exploration of the relationship between cognition, emotion, and the brain.

A small number of studies have begun to model networks with both psychometric and neuroimaging data (Bathelt et al., 2022; Blanken et al., 2021; Hilland et al., 2020; Simpson-Kent et al., 2021). One approach is to integrate psychometric networks with structural covariance networks in a multilayer network (Hilland et al., 2020; Simpson-Kent et al., 2021). For example, Simpson-Kent et al. (2021) used multilayer partial correlation networks with a range of cognitive and neuroimaging measures from a sample of 805 students (ages 5-18 years) with learning difficulties. Specifically, the authors looked at the relationships between cognitive abilities, cortical volume, and fractional anisotropy. Reading ability was found to be the most central node, suggesting that for those with learning difficulties, interventions that focus on improving reading may lead to improvements in other cognitive abilities. Additionally, the superior frontal gyrus was found to be a bridge node, which suggests this region may be a target for intervention through non-invasive brain stimulation or cognitive training tasks that activate this area (Simpson-Kent et al., 2021).

Although a small number of studies have begun to explore the integration of psychological and neuroscientfic data together within a unified network framework (Bathelt et al., 2022; Blanken et al., 2021; Hilland et al., 2020; Simpson-Kent et al., 2021), no study has yet explored the integration of a psychometric network consisting of both cognitive and emotional variables with a brain network. Such an exploration of the relationship between cognition and emotion allows for a greater understanding of the complex relationships often

seen in clinical populations but also in non-clincial and sub-clinical contexts. Furthermore, establishing a multilayer network framework of psychometric and brain structural relationships with a large sample from a non-clinical young adult population can provide a baseline for comparison in future studies involving clinical samples and other age groups.

Using a large sample of healthy young adults from the Human Connectome Project, the present study therefore aims to explore the relationships between general cognitive abilities (Diener et al., 2012; Konrad et al., 2011) and the negative emotions often impacted in psychopathology (Diener et al., 2012; Salsman et al., 2013; Terrill et al., 2018), as well as their associated brain regions. To achieve this aim, we will first analyse a bi-layer network of cognitive abilities and negative emotions to determine the nodes that are most central in bridging cognition and negative emotion. Secondly, we will analyse a tri-layer network, consisting of cognitive abilities, negative emotions, and cortical brain regions from the central executive and salience networks (Cromheeke & Mueller, 2014; Diener et al., 2012; Kraljević et al., 2021; Metzler-Baddeley et al., 2016), to determine the nodes that are most central in bridging cognition, emotion and the brain.

2. Methods

2.1. Participants

The present study utilised pre-existing data from the Human Connectome Project (http://www.humanconnectome.org), specifically the Young Adult cohort (HCP-YA; publicly available since February 2017). The data acquisition for HCP-YA was led by Washington University and the University of Minnesota (Van Essen et al., 2012). Processed data was accessed for the 1206 HCP-YA participants. Ninety-three participants were excluded as they did not have anatomical MRI data. The remaining 1113 participants were aged between 22 and 35 years. There were 507 males (45.55%) and 606 females (54.45%). The participants included in HCP-YA were considered healthy, with no history of significant psychiatric or neurological conditions (Van Essen et al., 2012). Furthermore, the age range of participants was chosen to include adults during a period of relatively minimal neurological change, i.e., past the age of major neurodevelopmental changes and before the age of neurodegeneration (Van Essen et al., 2012). As this study only used pre-existing data, ethics exemption was granted through the Deakin University Human Research Ethics Committee.

2.2. Psychometric Measures

Cognition and emotion data in HCP-YA were acquired with the National Institute of Health (NIH) Toolbox for Assessment of Neurological and Behavioral Function® (NIH Toolbox; neuroscienceblueprint.nih.gov), a well-validated and reliable battery of measures (Salsman et al., 2013; Weintraub et al., 2013) that can be used with healthy and clinical populations. The NIH Toolbox can also be used to examine relationships between psychological functions and brain structure (Barch et al., 2013). The present study used data obtained with two of the NIH Toolbox's modular batteries: the NIH Toolbox Cognition Battery and the NIH Toolbox Emotion Battery.

2.2.1. Cognition

All seven of the cognitive tasks from the NIH Toolbox Cognition Battery (Weintraub et al., 2013) were included in analyses (Table 1) to capture a broad range of general cognitive abilities that vary in both healthy populations and in psychopathology (Al-Qazzaz et al., 2014; Cassetta et al., 2020; Diener et al., 2012). The tasks included the Picture Sequence Memory Test (episodic memory), Dimensional Change Card Sort Test (executive functioning), Flanker Task (attention), Oral Reading Recognition Test (reading), Picture Vocabulary Test (vocabulary), Pattern Comparison Processing Speed Test (processing speed), and List Sorting Working Memory Test (working memory). Scores for each variable were converted to *t*-scores, with higher scores indicating better performance.

Table 1

Cognitive variables as measured by the NIH Toolbox Cognition Battery.

Cognitive variable	NIH Task	Task Description	Scoring
Episodic memory (The ability to acquire, store and retrieve new information.)	NIH Toolbox Picture Sequence Memory Test	Participants are required to recall a sequence of pictures in the same order as originally presented, over two trials.	Scoring is based on the number of pictures recalled in the correct sequence, with higher scores indicating better episodic memory.
Executive function (The ability to plan, organise and monitor the execution of behaviours to achieve a goal.)	NIH Toolbox Dimensional Change Card Sort Test	Participants are required to match a picture to one of two pictures, according to either colour or shape. The dimension for matching alternates between trials.	Scoring is based on a combination of accuracy and reaction time, with greater scores indicating better executive control.
Attention (The ability to selectively attend to the appropriate stimuli amidst an abundance of stimuli.)	NIH Toolbox Flanker Inhibitory Control and Attention Test	Participants are required to respond in the direction of a middle arrow, that is flanked by additional arrows that are pointing in either the congruent or incongruent direction of the middle arrow.	Scoring is based on a combination of accuracy and reaction time, with greater scores indicating better attention.
Reading (The ability to accurately read and pronounce words.)	NIH Toolbox Oral Reading Recognition Test	Participants are required to read aloud the word on the screen.	Scoring is based on correctly reading and pronouncing the word, with greater scores indicating better reading ability.

Vocabulary (The ability to recall the meaning of words based on previous learning.)	NIH Toolbox Picture Vocabulary Test	Participants hear a word and are required to select, from four images, the image that most closely represents the heard word.	Scoring is based on selecting the correct image, with greater scores indicating better vocabulary.
Processing speed (The speed at which one is able to process and respond to information.)	NIH Toolbox Pattern Comparison Processing Speed Test	Participants are required to identify whether two images are identical.	Scoring is based on the number of items correctly answered in 90 seconds, with greater scores indicating faster processing speed.
Working memory (The ability to temporarily hold information in memory so that it can be utilised.)	NIH Toolbox List Sorting Working Memory Test	Participants are first required to sequence either food or animals in order of size based on remembering an unordered sequence of images. A second series of trials involves remembering both food and animals.	Scoring is based on the number of correctly ordered items in both series, with greater scores indicating better working memory.

2.2.2. Emotion

Four negative emotion scales were selected from the NIH Toolbox Emotion Battery (Salsman et al., 2013), i.e., the Anger-Affect Survey (anger), Fear-Affect Survey (fear), Sadness Survey (sadness), and Perceived Stress Survey (stress). Scales for negative emotion were included because they are able to capture variations in mental health in non-clinical contexts and are able to translate to clinical contexts as representations of symptoms (Salsman et al., 2013). For example, items within the Sadness Survey have been used to assess depression and items within the Fear-Affect Survey have been used to assess anxiety (Salsman et al., 2013). Scores for each emotion variable were converted to *t*-scores, with higher scores indicating more frequent experiences of that emotion.

Table 2

Emotion variables as measured by the NIH Toolbox Emotion Battery.

Emotion variable	NIH Survey	Item Description	Scoring

Anger (An affect involving hostility and cynicism, which often involves frustration at goal-directed behaviour being impeded.)	NIH Toolbox Anger-Affect Survey	Rated on a five-point Likert scale, each item begins with 'in the past 7 days…' followed by a prompt relating to experiences of anger, e.g., 'when I was frustrated, I let it show'.	Higher scores indicate more frequently experienced anger.
Fear (An affect characterised by autonomic arousal in response to perceived threat, which is considered to be an experience of anxiety when the response is disproportionate to the threat.)	NIH Toolbox Fear-Affect Survey	Rated on a five-point Likert scale, each item begins with 'in the past 7 days…' followed by a prompt relating to experiences of fear or anxiety, e.g., ' I felt anxious'.	Higher scores indicate more frequently experienced fear/ anxiety.
Sadness (An affect characterised by low mood, as well as negative self-perceptions and pessimism, which can be indicators for depression.)	NIH Toolbox Sadness Survey	Rated on a five-point Likert scale, each item begins with 'in the past 7 days…' followed by a prompt relating to experiences of sadness, e.g., 'I felt worthless'.	Higher scores indicate more frequently experienced sadness.
Stress (Stress is an individual's perception of being overwhelmed by life's demands, without sufficient resources to meet the demands or effectively cope with the pressure.)	NIH Toolbox Perceived Stress Survey	Rated on a five-point Likert scale, each item begins with 'in the past month…' followed by a question relating to experiences of stress, e.g., 'How often have you been upset by something that happened unexpectedly?'	Higher scores indicate more frequently experienced stress.

Note. All surveys use computer adaptive testing so there is no set number of items.

2.3. Neuroimaging Measures

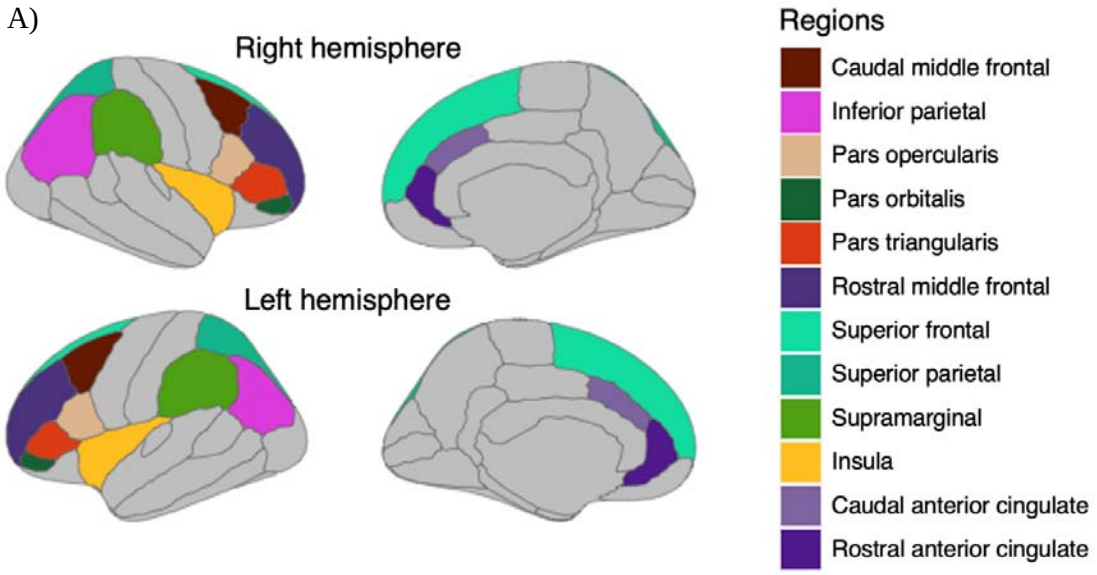
2.3.1. MRI Acquisition and Pre-Processing

The acquisition parameters and processing steps of the HCP-YA are described in detail in Glasser et al., (2013). In brief, the HCP structural imaging protocol used a 3T Siemens Skyra scanner with a 32-channel head coil to acquire T1 and T2-weighted images. T1-weighted images were acquired with a 3D Magnetisation Prepared Rapid Acquisition Gradient Echo (3D MPRAGE) sequence, with 0.7mm isotropic voxels, repetition time (TR) of 2400ms, echo time (TE) of 2.14ms, a field of view of 224 by 224mm^2, 256 sagittal slices, and an acquisition time of 7.40 minutes (Glasser et al., 2013). T2-weighted images were acquired with a 3D T2-SPACE sequence with the same geometry as the T1-weighted images but a TR of 3200ms, TE of 565ms, and an acquisition time of 8.24 minutes. To calculate the cortical volume of

each region, the HCP-YA team used FreeSurfer 5.3-HCP (Fischl, 2012; Glasser et al., 2013). The FreeSurfer pipeline, as detailed in Glasser et al. (2013), included co-registering and averaging T1 and T2-weighted images to improve pial surface quality, bias field correction, and segmentation and surface reconstruction.

2.3.2. Regions of Interest

Regions of interest (ROIs) were derived from the Desikan-Killiany atlas (Desikan et al., 2006). Based on previous research that identified brain regions involved in cognition and/or emotion (Cromheeke & Mueller, 2014; Diener et al., 2012; Kraljević et al., 2021; Menon, 2011; Metzler-Baddeley et al., 2016), the cortical volume of 12 ROIs were extracted from the central executive and salience networks (as depicted in Figure 1). Nine ROIs are from the central executive network and include the superior frontal gyrus (SF), caudal middle frontal gyrus (CMF), rostral middle frontal gyrus (RMF), pars orbitalis (POr), pars triangularis (PT), pars opercularis (POp), superior parietal gyrus (SP), inferior parietal gyrus (IP), and supramarginal gyrus (SM). Three ROIs are from the salience network and include the insula (I), rostral anterior cingulate gyrus (RAC), and the caudal anterior cingulate gyrus (CAC).



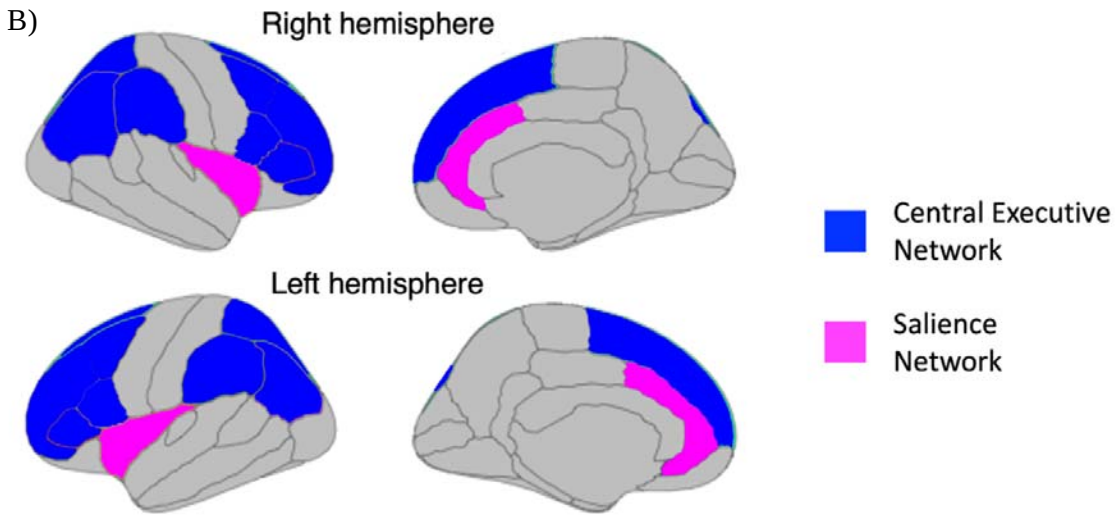


Figure 1. *(A) Grey Matter ROIs Based on the Desikan-Killiany Atlas, Depicted Bilaterally. (B) ROIs according to their network.*

2.4. Statistical Analysis

2.4.1. Network Estimation

Figure 2 depicts the analysis pipeline used to conduct the multilayer network analyses. All network analyses and visualisations were completed using the *bootnet* wraparound package (Epskamp et al., 2018; version 1.5) in R (R Core Team, 2020; version 4.1.2) and the code to run these analyses can be found on the Open Science Framework website (https://osf.io/fj68r/). A psychometric bi-layer network was modelled for cognition and emotion variables, including seven cognitive nodes and four emotion nodes. This network used (Pearson) partial correlation networks with model selection via graphical lasso regularisation (Friedman et al., 2008) and tuning of the extended Bayesian information criterion (EBIC; J. Chen & Chen, 2008). Partial correlation networks include undirected edges between nodes that are weighted by the strength of the partial correlation between the two nodes, after controlling for all other nodes in the network. Pearson correlations were used because the data are continuous. Graphical lasso regularisation was used because it is the

most conservative regularisation method for reducing the inclusion of spurious correlations in the network model. The EBIC hyperparameter was set to 0.5, to further reduce the likelihood of spurious correlations (Epskamp & Fried, 2018). Networks were visualised using the *qgraph* package (Epskamp et al., 2012; version 1.9.2), with node positioning determined by the Fruchterman-Reingold algorithm, which arranges strongly connected nodes near each other (Fruchterman & Reingold, 1991).

A neuro-psychometric tri-layer network was then modelled to include the 12 ROIs in addition to the cognitive and emotion variables. Each ROI included two nodes in the network, one for the cortical volume of each hemisphere i.e., 24 brain nodes in total. The tri-layer network was calculated in the same manner as the bi-layer network.

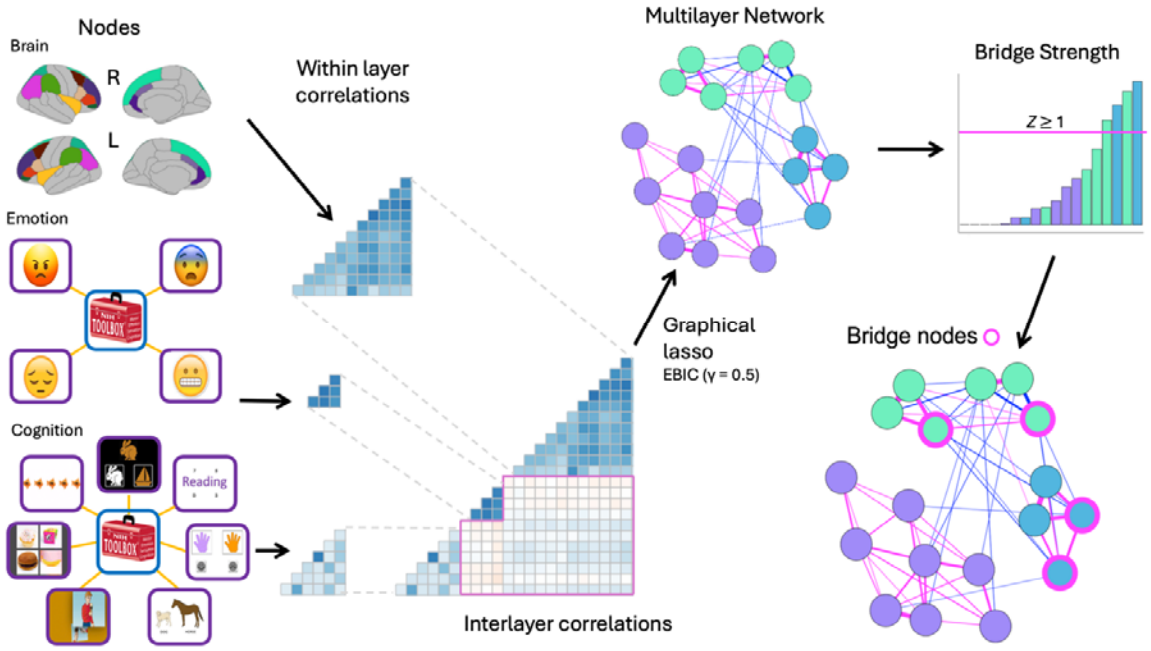


Figure 2. Overview of the analysis steps to generate multilayer networks and identify bridge nodes. First, individual variables for each layer (i.e., cognition, emotion and brain) were entered into a single correlation matrix. Graphical lasso model selection was then applied to generate the multilayer network from this matrix. Bridge strength was subsequently used to determine nodes that were important bridges between layers. “R” = right hemisphere, “L” =

left hemisphere. "*Z*" = *z*-score. Note: This figure pertains specifically to the neuro-psychometric tri-layer network, while the psychometric bi-layer network followed the same steps but did not include the brain data.

2.4.2. Network Description

To describe the density of the networks, we calculated the percentage of edges present in the network from the total possible number of edges. Based on previous network descriptions, a network with <30% of possible edges would be considered low density, 30-70% of possible edges would be considered moderate density, and >70% would be considered high density (Carmichael et al., 2023; Johal & Rhemtulla, 2023).

Bridge strength centrality was calculated to identify nodes that serve as bridges between layers (Jones et al., 2021). The *bridge* function of the *bootnet* package was used to calculate bridge centrality, after assigning nodes to pre-defined communities based on their layer, i.e., emotion, cognition, or brain layer. Bridge strength centrality was calculated for each node by summing the absolute edge weights between that node and nodes in different layers. In addition, normalisation was used to control for differences in community size, by dividing each node's bridge strength value by the node's maximum possible bridge strength value. Finally, bridge strength was calculated as a centrality coefficient and then standardised into a *z*-score. In line with previous work, bridge nodes were defined as those with a positive bridge strength centrality *z*-score equal to or greater than one (Simpson-Kent et al., 2021).

2.4.3. Inspection of Edge Weights

For both networks, a spreadsheet was generated for the post-hoc inspection of edge weight magnitudes. This spreadsheet aided in the description of the network models and quantifying the relative strength of edges. In addition, inspection of edge weights was conducted for bridge nodes to determine the number and weight of their edges. This information was used

to aid in the interpretation of how a bridge node connects between layers. For the tri-layer network, bridge nodes in the brain layer were inspected to determine if they contain edges with both cognition and emotion layers.

2.4.4. Edge Weight and Bridge Strength Stability

To determine the reliability of edge weight and centrality estimates in both the bi-layer and tri-layer networks, non-parametric bootstrapping was implemented using *bootnet*, as described in Epskamp et al. (2018), with 2000 bootstraps. Edges that occurred in less than 50% of the bootstrapped samples require caution when being interpreted (Carmichael et al., 2023). For bridge strength estimates, correlation stability (CS) coefficients were calculated (Epskamp et al., 2018) to determine the maximum proportion of the sample that can be dropped to retain a correlation of 0.7 with 95% probability. Simulation studies conducted by Epskamp et al. (2018) suggest that CS coefficients below 0.25 indicate that the rank order of centrality indices is not stable, and for CS coefficients between 0.25 and 0.5, differences between the centrality of nodes should be interpreted with caution.

3. Results

3.1. Psychometric Bi-layer Network: Description and Edge Weight Stability

The bi-layer network (Figure 3) was moderately dense as it included 28 edges out of a possible 55 (43%), with a mean edge weight of 0.137 (median: 0.081). The majority (24/28) of the edges were positive and ranged from 0.005 (between episodic memory and vocabulary) to 0.592 (between reading and vocabulary). The strongest edges were between nodes within the same layer, i.e., between reading and vocabulary (0.592), attention and executive function (0.381), and fear and sadness (0.362). During inspection of edges across layers, it was found that the strongest edges were all negative edges with stress. Specifically, these edges were between stress and episodic memory (-0.043), working memory (-0.029), executive function (-0.026) and vocabulary (-0.011). The remaining interlayer edges were positive and included

reading, i.e., reading was connected to anger (0.008) and fear (0.007). However, the edge between reading and fear should be interpreted with caution, as it was found in less than 50% of the 2000 bootstrapped samples (45.8%). All of the other edges in the bi-layer network can be considered stable, as they were found in more than 50% of the bootstrapped samples.

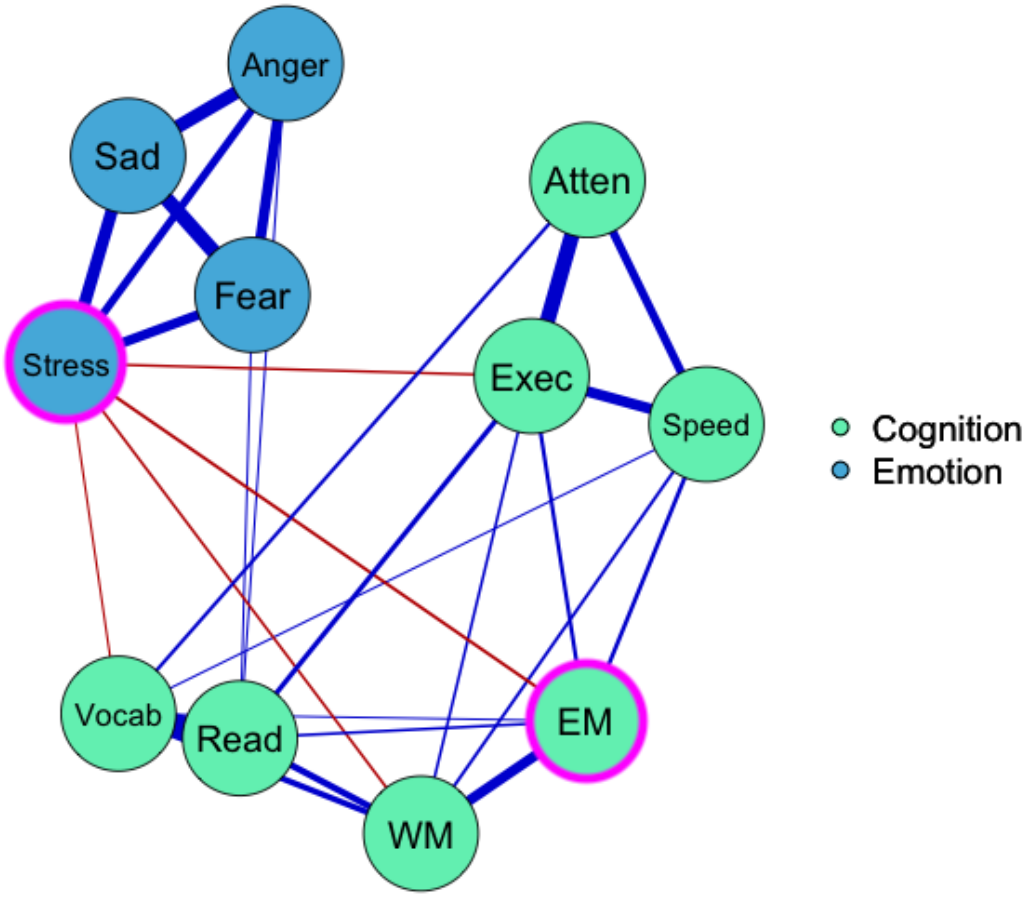


Figure 3. Bi-layer network (*n* = 1113). Note: Visualisation of the network uses the Fruchterman-Reingold algorithm to determine the placement of nodes. Nodes (circles) are variables from the NIH Toolbox Cognition Battery (cognition; colour coded green) and NIH Toolbox Emotion Battery (emotion; colour coded blue). Undirected edges (lines between nodes) represent partial correlations between variables, after controlling for all other variables, with thicker lines representing stronger relationships. Blue edges represent positive

relationships, whereas red edges represent negative relationships. Pink circles around nodes indicate that the node has a bridge centrality *z*-score ≥ 1. “EM” = episodic memory, “exec” = executive function, “atten” = attention, “read” = reading, “vocab” = vocabulary, “speed” = processing speed, “WM” = working memory, “anger” = anger, “fear” = fear, “sad” = sadness, “stress” = stress.

3.2. Psychometric Bi-layer Network: Bridge Strength Centrality

For the bi-layer network, bridge strength had a CS of 0.361. According to Epskamp et al. (2018) this CS suggests that the rank-order of bridge centrality has some degree of stability, however, the order should be interpreted with caution. Nonetheless, two bridge nodes were identified, having *z*-scores greater than one standard deviation (Figure 4). Stress ($z = 2.182$) was the most central bridge node, followed by episodic memory ($z = 1.242$). Supplementary Table 1 contains standardised (*z*-score) and unstandardised (raw centrality coefficient) centrality values for all nodes. In addition, Supplementary Figure 1 depicts the unstandardised scores in a bar graph.

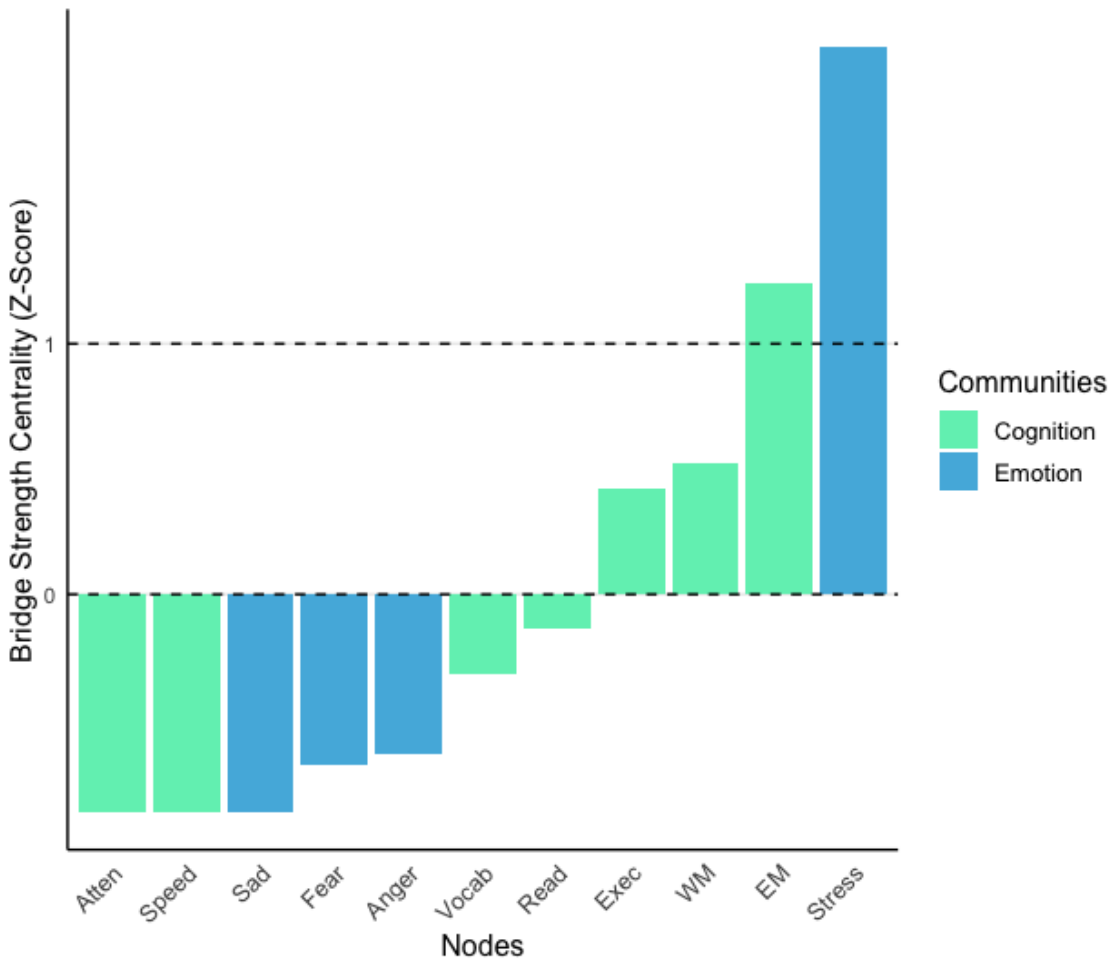


Figure 4. Bar graph of bridge strength centrality scores (*n* =1113). Note: The dashed line indicates a *z*-score of 1, nodes at or above this line are interpreted as bridge nodes. “EM” = episodic memory, “exec” = executive function, “atten” = attention, “read” = reading, “vocab” = vocabulary, “speed” = processing speed, “WM” = working memory, “anger” = anger, “fear” = fear, “sad” = sadness, “stress” = stress.

3.3. Neuro-Psychometric Tri-layer Network: Description and Edge Weight Stability

The tri-layer network (Figure 5) was low in density as it included 215 edges out of a possible 595 (36.13%), with a mean edge weight of 0.069 (median: 0.035). As with the bi-layer network, the majority of edge weights were positive (201/ 215), the strongest edges were within layers and the strongest edge was still between reading and vocabulary (0.579). This was followed by the edges between the left and right hemispheres of each of the following,

the insula (0.572), superior parietal gyrus (0.513), rostral middle frontal gyrus (0.482), inferior parietal gyrus (0.440), and superior frontal gyrus (0.411). There was also a moderately strong edge between the right rostral anterior cingulate and the right caudal anterior cingulate (0.388), and between the left rostral anterior cingulate and the left caudal anterior cingulate (0.385). The strongest edge between emotion nodes was between fear and sadness (0.361). The strongest positive edge between layers was between working memory and the right pars orbitalis (0.039), followed by the edge between vocabulary and the left insula (0.038), and the edge between working memory and the inferior parietal gyrus (0.037). The majority of negative edge weights were across layers (11/14), the strongest of which was between episodic memory and stress (-0.042), followed by episodic memory and the right rostral middle frontal gyrus (-0.030), working memory and stress (-0.025), executive function and stress (-0.023), and stress and the right superior frontal gyrus (-0.015). The three negative edges within layers were between the left caudal anterior cingulate and the left superior frontal gyrus (-0.173), the edge between the right caudal anterior cingulate and the right superior frontal gyrus (-0.125), and the edge between the right inferior parietal gyrus and the right supramarginal gyrus (-0.029). The majority of edge weights in the tri-layer network were stable when comparing edge weights across 2000 bootstrapped samples. However, 17 (7.92%) of the 215 edges were included in less than 50% of the bootstrapped samples and should be interpreted with caution (these edges are listed in Supplementary Table 2).

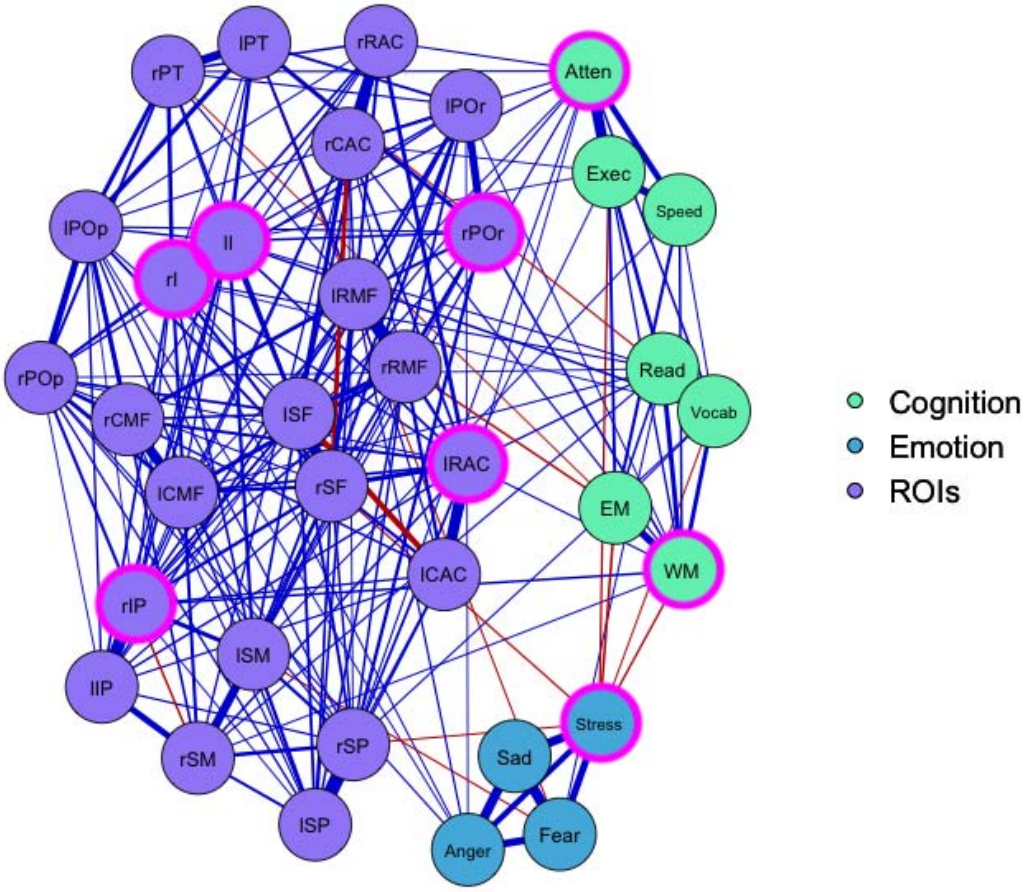


Figure 5. Tri-layer network (*n* = 1113). Note: Visualisation of the network uses the Fruchterman-Reingold algorithm to determine the placement of nodes. Nodes (circles) are variables from the NIH Toolbox Cognition Battery (cognition; colour coded green), NIH Toolbox Emotion Battery (emotion; colour coded blue), and the cortical volume of ROIs from the central executive and salience networks (ROIs; colour coded purple). Undirected edges (lines between nodes) represent partial correlations between variables, after controlling for all other variables, with thicker lines representing stronger relationships. Blue edges represent positive relationships, whereas red edges represent negative relationships. Pink circles around nodes indicate that the node has a bridge centrality *z*-score ≥ 1. “EM” = episodic memory, “exec” = executive function, “atten” = attention, “read” = reading, “vocab”

= vocabulary, “speed” = processing speed, “WM” = working memory, “anger” = anger, “fear” = fear, “sad” = sadness, “stress” = stress, “l” before a ROI indicates the left hemisphere, “r” before a ROI indicates the right hemisphere, “SF” = superior frontal gyrus, “CMF” = caudal middle frontal gyrus, “RMF” = rostral middle frontal gyrus, “POr" = pars orbitalis, “PT” = pars triangularis, “POp” = pars opercularis, “SP” = superior parietal gyrus, “IP” = inferior parietal gyrus, “SM” = supramarginal gyrus, “I” = insula, “RAC” = rostral anterior cingulate, “CAC” = caudal anterior cingulate.

3.4. Neuro-Psychometric Tri-layer Network: Bridge Strength Centrality

For the tri-layer network, bridge strength had a CS of 0.438, suggesting that the rank-order of bridge centrality has some degree of stability, however, the order should be interpreted with caution. Nonetheless, there were eight bridge nodes, having *z*-scores greater than one standard deviation (Figure 6). Five of these nodes were brain nodes, two were cognitive nodes and one was an emotion node. In descending order, the bridge nodes were working memory (z = 1.978), right inferior parietal gyrus (z = 1.831), left insula (z = 1.770), attention (z = 1.373), stress (z = 1.226), right insula (z = 1.164), left rostral anterior cingulate (z = 1.099), and right pars orbitalis (z = 1.039). Supplementary Table 3 contains standardised (z-score) and unstandardised (raw centrality coefficient) centrality values for all nodes. In addition, Supplementary Figure 2 depicts the unstandardised scores in a bar graph.

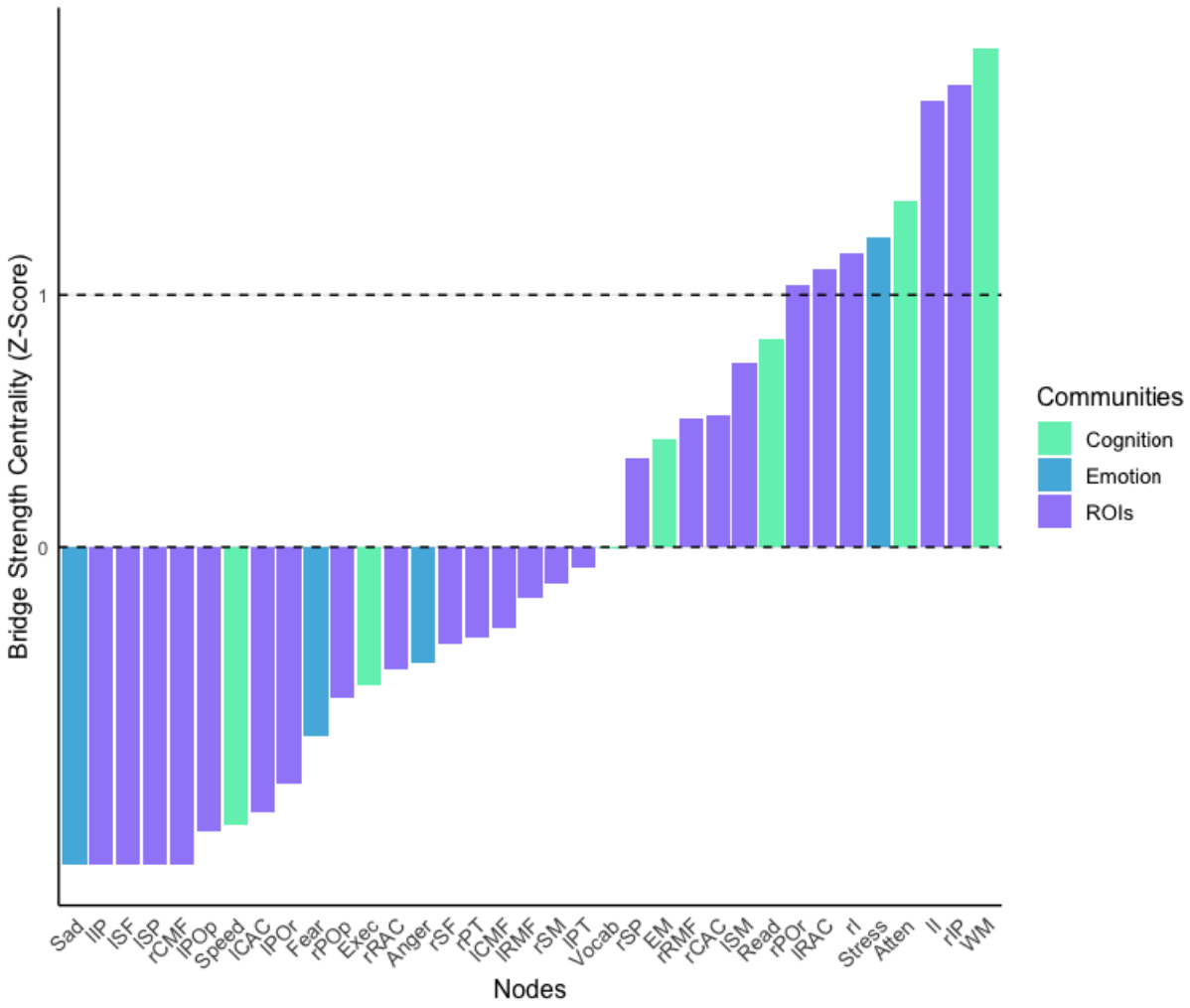


Figure 6. Bar graph of bridge strength centrality scores (*n* =1113). Note: The dashed line indicates a *z*-score of 1, nodes at or above this line are interpreted as bridge nodes. “EM” = episodic memory, “exec” = executive function, “atten” = attention, “read” = reading, “vocab” = vocabulary, “speed” = processing speed, “WM” = working memory, “anger” = anger, “fear” = fear, “sad” = sadness, “stress” = stress, “l” before a ROI indicates the left hemisphere, “r” before a ROI indicates the right hemisphere, “SF” = superior frontal gyrus, “CMF” = caudal middle frontal gyrus, “RMF” = rostral middle frontal gyrus, “POr" = pars orbitalis, “PT” = pars triangularis, “POp” = pars opercularis, “SP” = superior parietal gyrus, “IP” = inferior parietal gyrus, “SM” = supramarginal gyrus, “I” = insula, “RAC” = rostral anterior cingulate, “CAC” = caudal anterior cingulate.

3.5. Post-Hoc Analysis of Bridge Node Edges in the Neuro-Psychometric Network

The most central bridge node in the tri-layer network was working memory (z = 1.98). Working memory had six positive edges with brain nodes, i.e., right pars orbitalis (0.039), right inferior parietal gyrus (0.037), right caudal anterior cingulate (0.016), left rostral anterior cingulate (0.013), right supramarginal gyrus (0.006), and left pars orbitalis (0.005), as well as a negative edge with stress (-0.025). The second most central cognition bridge node was attention, which had nine positive edges with brain nodes, i.e., right insula (0.019), left supramarginal gyrus (0.017), right inferior parietal gyrus (0.015), right pars triangularis (0.014), right rostral anterior cingulate (0.013), right caudal anterior cingulate (0.013), right superior parietal gyrus (0.010), left caudal middle frontal gyrus (0.006), and caudal anterior cingulate (0.004). The only emotion bridge node was stress, which had four negative edges with cognition, i.e., episodic memory (-0.042), working memory (-0.025), executive function (-0.023), and vocabulary (-0.005), as well as two negative edges with brain nodes, i.e., the right superior frontal gyrus (-0.015), and right superior parietal gyrus (-0.008).

To investigate whether any of the brain nodes that emerged as bridge nodes act as bridges between cognition and emotion, their edges were inspected to see if they have edges with both cognition and emotion layers, or if they have edges with only one of these layers. It was found that the most central bridge brain node, the right inferior parietal gyrus, has two interlayer edges, both connecting to cognition nodes: working memory (0.037) and attention (0.016). The third most central bridge brain node, the right insula, is the only bridge brain node that bridges between the brain layer and both the cognition and emotion layers. The right insula has four edges, with attention (0.020), reading (0.014), anger (0.006), and vocabulary (0.001).

4. Discussion

The present study aimed to explore the complex relationships between cognition, emotion, and brain structure in healthy young adults, utilising a novel analytic framework. Specifically, the aim was to use a multilayer network approach to identify nodes that are central to the relationship between cognition and emotion, both in a purely psychometric context, as well as when integrating neuroscientific data. In the psychometric bi-layer network of cognitive abilities and emotional states, it was found that stress is the most central bridge node, followed by episodic memory. Furthermore, in the neuro-psychometric tri-layer network consisting of cognitive abilities, emotional states and brain regions, it was found that working memory was the most central bridge node overall, the right inferior parietal gyrus was the most central brain region bridge node, and stress was the most central emotion bridge node.

The most central bridge node in the bi-layer network was stress. Stress was negatively related to episodic memory, working memory, executive function, and vocabulary. This finding is in alignment with an extensive body of research on stress and cognition (Calvo & Gutiérrez-García, 2016; Sandi, 2013; Zaheed et al., 2021). For example, Zaheed et al. (2021) found that stress was associated with worse episodic memory in healthy older adults (aged 60 to 95 years). This result is congruent with the present study, whereby it was found that the strongest edge across layers is between episodic memory and stress.

Similar to the findings of Ferguson (2021) in healthy older adults, it was found that episodic memory was a central node in the psychometric bi-layer network. While Ferguson's psychometric network only included cognitive abilities, our findings show that episodic memory is not only important in the network of cognitive abilities, but it also bridges cognition with emotion. Furthermore, the participants in Ferguson's study had a mean age of 76 years, therefore, the present study's results in a young adult sample suggest that episodic

memory's centrality may be stable across the lifespan in those without a neurodegenerative condition. As Ferguson compared the healthy network to an Alzheimer's Disease network and found that processing speed became more central in the Alzheimer's Disease network, future research could compare the present findings to a network of cognition and emotion in neurodegenerative conditions. Such comparisons may reveal different patterns of edges and centralities than the present study's network of healthy young adults.

In the tri-layer network, working memory was the most central bridge node. Similar to the bi-layer network, working memory was negatively associated with stress. However, the increased importance of working memory in the tri-layer network compared to the bi-layer network is due to its many edges with brain region nodes. Working memory had edges with six brain region nodes, specifically the right pars orbitalis, right inferior parietal gyrus, right caudal anterior cingulate, left rostral anterior cingulate, right supramarginal gyrus, and left pars orbitalis. Many of these regions have been found to be associated with brain changes resulting from working memory training (Metzler-Baddeley et al., 2016). As working memory was only found to be central in the tri-layer network and not the bi-layer network, our findings support the notion that it is beneficial to include neuroscientific data when aiming to identify important psychometric variables in a network (Bathelt et al., 2022; Blanken et al., 2021; Hilland et al., 2020; Simpson-Kent et al., 2021). This approach may therefore allow researchers to identify more appropriate targets for intervention than when analysing psychometric variables alone. Furthermore, a working memory training program, such as is implemented in Metzler-Baddeley et al. (2016), may provide benefit to not only working memory but may have downstream benefits for other cognitive abilities, such as episodic memory and reading ability, while also decreasing negative emotions.

The right inferior parietal gyrus was the most central bridge node of the brain regions, with interlayer edges to working memory and attention. This finding aligns with previous

research examining the inferior parietal gyrus' involvement in cognitive tasks (Cao et al., 2021; Ren et al., 2019). For example, Cao et al. found that the inferior parietal gyrus was activated during a 2-back task in both healthy controls and individuals with major depressive disorder. They suggested that the inferior parietal gyrus is involved in focusing attention on external stimuli, which in turn facilitates working memory. Similarly, a relationship between the right inferior parietal gyrus and attention has been found in virtual lesion studies using Transcranial Magnetic Stimulation (TMS; Bareham et al., 2018; Karhson et al., 2015). Our findings suggest that the right inferior parietal gyrus may be the most impactful brain region to target for intervention. For example, stimulation of the right inferior parietal gyrus through therapeutic TMS may improve working memory and attention. Enhancing cognitive function in this way could potentially contribute to better stress management, as these cognitive and emotional processes were also found to be intertwined.

A notable absence from the bridge nodes in the tri-layer network was the superior frontal gyrus. The left superior frontal gyrus was found to be associated with both cognition and emotion in the study of Kraljević et al., (2021) using HCP-YA data. Furthermore, Simpson-Kent at al. (2021) found the bilateral superior frontal gyrus to be central to their network of cognition and cortical volume. However, Simpson-Kent et al. used community-based bridge centrality, in which there was more than one community that included brain regions. This approach may have elevated the importance of brain regions that bridge to other brain regions rather than those specifically connected to cognition. Furthermore, although Kraljević et al., (2021) extracted similar cognition, emotion and brain imaging data as the present study, they used multiple linear regression models, suggesting that the present study's use of partial correlation networks may have revealed that the superior frontal gyrus' relationship to cognition and emotion is mediated by its relationship to other brain regions, indicating a more indirect role.

As the present study was interested in identifying brain regions that bridge between cognition and emotion, it is worth noting that the right inferior parietal gyrus did not have edges with any emotion nodes. The only bridge node from the brain layer in the present study that was found to be directly associated with both emotion and cognition was the right insula. The right insula was connected to anger as well as attention, reading and vocabulary. This finding is consistent with previous findings on the role of the insula in both emotion and cognition (Gasquoine, 2014). It has been found that the insula is crucial to interoception, which in turn gives rise to emotional feeling (Damasio, 2003). The insula's role in cognition is likely more indirect. While the insula has been implicated in cognitive impairments, these have been suggested to result from diaschisis or disconnection, rather than the insula having a direct role in the affected cognitive abilities (Gasquoine, 2014). Supporting the insula's more direct involvement in emotion and more downstream involvement in cognition is a brain network model proposed by Menon and Uddin (2010), who suggest that the insula is activated in relation to salient events and then signals to other brain regions to facilitate working memory and attention, while generating the emotional feelings appropriate to that event. Therefore, the insula may be a target for intervention when attempting to improve cognition and emotion, such as through mindfulness meditation (Sharp et al., 2018).

The findings of the present study should be considered cautiously in light of the exploratory and novel nature of the analysis and its limitations. Firstly, the centrality indices of both networks were found to have some degree of stability; however, according to CS cut-off values recommended by Epskamp et al. (2018), they should be interpreted with caution. The level of stability in the present study may be inherent to the use of bridge strength centrality in multilayer networks that include both psychometric and neuroscientific data. Bridge strength centrality only includes edge weights between layers, and these edge weights tended to be weaker and less stable than edges within layers. As the present study had a large

sample size, future multilayer networks likely need to have similar or larger sample sizes to detect bridge nodes with sufficient stability.

Partial correlation networks using cross-sectional data cannot identify within-subject dynamics, but rather a tendency towards certain patterns between-subjects (Borsboom et al., 2021; Simpson-Kent et al., 2021). We suggest that future research could use longitudinal designs to capture within-subject network relationships. For example, ecological momentary assessment (EMA) could be used to repeatedly record emotional or cognitive data. Psychometric network research has developed techniques to analyse networks from EMA data (Kroeze et al., 2017; Mansueto et al., 2022; Rabinowitz & Fisher, 2020; van der Velden et al., 2018; for a review, see Wright & Woods, 2020), however, such approaches are yet to incorporate neuroscientific data. Furthermore, partial correlation networks cannot detect causality or the directionality of the relationships between nodes. While these models allow for data exploration and hypothesis generation, they should not be used to draw causal inferences. Alternative multivariate analytic approaches, such as structural equation modelling, or networks with directed edges (e.g., directed acyclic graphs; Bathelt et al., 2022), may be useful for validating and building upon the exploratory findings of multilayer partial correlation networks.

To conclude, this is the first study to integrate a psychometric network of both cognition and emotion with a structural covariance network of cortical brain regions. Specifically, this multilayer network approach used a large sample of healthy young adults to reveal that working memory may be central to the relationship between the brain, cognition, and emotion. Furthermore, the right inferior parietal gyrus and the right insula may be important brain regions when considering cognition and emotion in this population. Further advancement of this analytic approach may allow for comprehensive and targeted treatment

strategies, as well as a greater understanding of the complex and dynamic relationship between the brain and the mind.

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References

American Psychiatric Association. (2013). *Diagnostic and statistical manual of mental disorders* (5th ed.). https://doi.org/10.1176/appi.books.9780890425596

Al-Qazzaz, N., Ali, S., Ahmad, S. A., Islam, S., & Mohamad, K. (2014). Cognitive impairment and memory dysfunction after a stroke diagnosis: A post-stroke memory assessment. *Neuropsychiatric Disease and Treatment*, 1677. https://doi.org/10.2147/NDT.S67184

Barch, D. M., Burgess, G. C., Harms, M. P., Petersen, S. E., Schlaggar, B. L., Corbetta, M., Glasser, M. F., Curtiss, S., Dixit, S., Feldt, C., Nolan, D., Bryant, E., Hartley, T., Footer, O., Bjork, J. M., Poldrack, R., Smith, S., Johansen-Berg, H., Snyder, A. Z., & Van Essen, D. C. (2013). Function in the human connectome: Task-fMRI and individual differences in behavior. *NeuroImage*, *80*, 169–189. https://doi.org/10.1016/j.neuroimage.2013.05.033

Bareham, C. A., Georgieva, S. D., Kamke, M. R., Lloyd, D., Bekinschtein, T. A., & Mattingley, J. B. (2018). Role of the right inferior parietal cortex in auditory selective attention: An rTMS study. *Cortex*, *99*, 30–38. https://doi.org/10.1016/j.cortex.2017.10.003

Barrett, L. F. (2016). The theory of constructed emotion: An active inference account of interoception and categorization. *Social Cognitive and Affective Neuroscience*, nsw154. https://doi.org/10.1093/scan/nsw154

Bathelt, J., Geurts, H. M., & Borsboom, D. (2022). More than the sum of its parts: Merging network psychometrics and network neuroscience with application in autism. *Network Neuroscience*, 1–22. https://doi.org/10.1162/netn_a_00222

Blanken, T. F., Bathelt, J., Deserno, M. K., Voge, L., Borsboom, D., & Douw, L. (2021). Connecting brain and behavior in clinical neuroscience: A network approach.

Neuroscience & Biobehavioral Reviews, *130*, 81–90. https://doi.org/10.1016/j.neubiorev.2021.07.027

Borsboom, D., Deserno, M. K., Rhemtulla, M., Epskamp, S., Fried, E. I., McNally, R. J., Robinaugh, D. J., Perugini, M., Dalege, J., Costantini, G., Isvoranu, A.-M., Wysocki, A. C., van Borkulo, C. D., van Bork, R., & Waldorp, L. J. (2021). Network analysis of multivariate data in psychological science. *Nature Reviews Methods Primers*, *1*(1), 58. https://doi.org/10.1038/s43586-021-00055-w

Calvo, M. G., & Gutiérrez-García, A. (2016). Cognition and Stress. In *Stress: Concepts, Cognition, Emotion, and Behavior* (pp. 139–144). Elsevier. https://doi.org/10.1016/B978-0-12-800951-2.00016-9

Cao, W., Liao, H., Cai, S., Peng, W., Liu, Z., Zheng, K., Liu, J., Zhong, M., Tan, C., & Yi, J. (2021). Increased functional interaction within frontoparietal network during working memory task in major depressive disorder. *Human Brain Mapping*, *42*(16), 5217–5229. https://doi.org/10.1002/hbm.25611

Carmichael, J., Hicks, A. J., Gould, K. R., Spitz, G., & Ponsford, J. (2023). Network analysis of anxiety and depressive symptoms one year after traumatic brain injury. *Psychiatry Research*, 115310. https://doi.org/10.1016/j.psychres.2023.115310

Cassetta, B. D., Menon, M., Carrion, P. B., Pearce, H., DeGraaf, A., Leonova, O., White, R. F., Stowe, R. M., Honer, W. G., Woodward, T. S., & Torres, I. J. (2020). Preliminary examination of the validity of the NIH toolbox cognition battery in treatment-resistant psychosis. *The Clinical Neuropsychologist*, *34*(5), 981–1003. https://doi.org/10.1080/13854046.2019.1694072

Chen, J., & Chen, Z. (2008). Extended Bayesian information criteria for model selection with large model spaces. *Biometrika*, *95*(3), 759–771. https://doi.org/10.1093/biomet/asn034

Cromheeke, S., & Mueller, S. C. (2014). Probing emotional influences on cognitive control: An ALE meta-analysis of cognition emotion interactions. *Brain Structure and Function*, *219*(3), 995–1008. https://doi.org/10.1007/s00429-013-0549-z

Damasio, A. (2003). Feelings of Emotion and the Self. *Annals of the New York Academy of Sciences*, *1001*(1), 253–261. https://doi.org/10.1196/annals.1279.014

De Paoli, T., Fuller Tyszkiewicz, M., Huang, C., & Krug, I. (2020). A network analysis of borderline personality disorder symptoms and disordered eating. *Journal of Clinical Psychology*, *76*(4), 787–800. https://doi.org/10.1002/jclp.22916

Desikan, R. S., Ségonne, F., Fischl, B., Quinn, B. T., Dickerson, B. C., Blacker, D., Buckner, R. L., Dale, A. M., Maguire, R. P., Hyman, B. T., Albert, M. S., & Killiany, R. J. (2006). An automated labeling system for subdividing the human cerebral cortex on MRI scans into gyral based regions of interest. *NeuroImage*, *31*(3), 968–980. https://doi.org/10.1016/j.neuroimage.2006.01.021

Diener, C., Kuehner, C., Brusniak, W., Ubl, B., Wessa, M., & Flor, H. (2012). A meta-analysis of neurofunctional imaging studies of emotion and cognition in major depression. *NeuroImage*, *61*(3), 677–685. https://doi.org/10.1016/j.neuroimage.2012.04.005

Epskamp, S., Borsboom, D., & Fried, E. I. (2018). Estimating psychological networks and their accuracy: A tutorial paper. *Behavior Research Methods*, *50*(1), 195–212. https://doi.org/10.3758/s13428-017-0862-1

Epskamp, S., Cramer, A. O. J., Waldorp, L. J., Schmittmann, V. D., & Borsboom, D. (2012). **qgraph**: Network Visualizations of Relationships in Psychometric Data. *Journal of Statistical Software*, *48*(4). https://doi.org/10.18637/jss.v048.i04

Epskamp, S., & Fried, E. I. (2018). A tutorial on regularized partial correlation networks. *Psychological Methods*, *23*(4), 617–634. https://doi.org/10.1037/met0000167

Ferguson, C. (2021). A network psychometric approach to neurocognition in early Alzheimer's disease. *Cortex*, *137*, 61–73. https://doi.org/10.1016/j.cortex.2021.01.002

Fischl, B. (2012). FreeSurfer. *20 YEARS OF fMRI*, *62*(2), 774–781. https://doi.org/10.1016/j.neuroimage.2012.01.021

Friedman, J., Hastie, T., & Tibshirani, R. (2008). Sparse inverse covariance estimation with the graphical lasso. *Biostatistics*, *9*(3), 432–441. https://doi.org/10.1093/biostatistics/kxm045

Fruchterman, T. M. J., & Reingold, E. M. (1991). Graph drawing by force directed placement. *Software: Practice and Experience*, *21*(11), 1129–1164. https://doi.org/10.1002/spe.4380211102

Gasquoine, P. G. (2014). Contributions of the Insula to Cognition and Emotion. *Neuropsychology Review*, *24*(2), 77–87. https://doi.org/10.1007/s11065-014-9246-9

Giles, S., Hughes, E. K., Fuller-Tyszkiewicz, M., Treasure, J., Fernandez-Aranda, F., Karwautz, A. F. K., Wagner, G., Anderluh, M., Collier, D. A., & Krug, I. (2022). Bridging of childhood obsessive-compulsive personality disorder traits and adult eating disorder symptoms: A network analysis approach. *European Eating Disorders Review*, *30*(2), 110–123. https://doi.org/10.1002/erv.2885

Glasser, M. F., Sotiropoulos, S. N., Wilson, J. A., Coalson, T. S., Fischl, B., Andersson, J. L., Xu, J., Jbabdi, S., Webster, M., Polimeni, J. R., Van Essen, D. C., & Jenkinson, M. (2013). The minimal preprocessing pipelines for the Human Connectome Project. *NeuroImage*, *80*, 105–124. https://doi.org/10.1016/j.neuroimage.2013.04.127

Hilland, E., Landrø, N. I., Kraft, B., Tamnes, C. K., Fried, E. I., Maglanoc, L. A., & Jonassen, R. (2020). Exploring the links between specific depression symptoms and brain structure: A network study. *Psychiatry and Clinical Neurosciences*, *74*(3), 220–221. https://doi.org/10.1111/pcn.12969

Johal, S. K., & Rhemtulla, M. (2023). Comparing estimation methods for psychometric networks with ordinal data. *Psychological Methods*, *28*(6), 1251–1272. https://doi.org/10.1037/met0000449

Jones, P. J., Ma, R., & McNally, R. J. (2021). Bridge Centrality: A Network Approach to Understanding Comorbidity. *Multivariate Behavioral Research*, *56*(2), 353–367. https://doi.org/10.1080/00273171.2019.1614898

Kan, K.-J., van der Maas, H. L. J., & Levine, S. Z. (2019). Extending psychometric network analysis: Empirical evidence against g in favor of mutualism? *Intelligence*, *73*, 52–62. https://doi.org/10.1016/j.intell.2018.12.004

Karhson, D. S., Mock, J. R., & Golob, E. J. (2015). The Role of Right Inferior Parietal Cortex in Auditory Spatial Attention: A Repetitive Transcranial Magnetic Stimulation Study. *PLOS ONE*, *10*(12), e0144221. https://doi.org/10.1371/journal.pone.0144221

Kenny, B., Orellana, L., Fuller Tyszkiewicz, M., Moodie, M., Brown, V., & Williams, J. (2021). Depression and eating disorders in early adolescence: A network analysis approach. *International Journal of Eating Disorders*, *54*(12), 2143–2154. https://doi.org/10.1002/eat.23627

Konrad, C., Geburek, A. J., Rist, F., Blumenroth, H., Fischer, B., Husstedt, I., Arolt, V., Schiffbauer, H., & Lohmann, H. (2011). Long-term cognitive and emotional consequences of mild traumatic brain injury. *Psychological Medicine*, *41*(6), 1197–1211. https://doi.org/10.1017/S0033291710001728

Kraljević, N., Schaare, H. L., Eickhoff, S. B., Kochunov, P., Yeo, B. T. T., Kharabian Masouleh, S., & Valk, S. L. (2021). Behavioral, Anatomical and Heritable Convergence of Affect and Cognition in Superior Frontal Cortex. *NeuroImage*, *243*, 118561. https://doi.org/10.1016/j.neuroimage.2021.118561

Kroeze, R., van der Veen, D. C., Servaas, M. N., Bastiaansen, J. A., Oude Voshaar, R. C., Borsboom, D., Ruhe, H. G., Schoevers, R. A., & Riese, H. (2017). Personalized Feedback on Symptom Dynamics of Psychopathology: A Proof-of-Principle Study. *Journal for Person-Oriented Research*, *3*(1), 1–10. PubMed. https://doi.org/10.17505/jpor.2017.01

Mansueto, A. C., Wiers, R. W., van Weert, J. C. M., Schouten, B. C., & Epskamp, S. (2022). Investigating the feasibility of idiographic network models. *Psychological Methods*. https://doi.org/10.1037/met0000466

Menon, V. (2011). Large-scale brain networks and psychopathology: A unifying triple network model. *Trends in Cognitive Sciences*, *15*(10), 483–506. https://doi.org/10.1016/j.tics.2011.08.003

Menon, V., & Uddin, L. Q. (2010). Saliency, switching, attention and control: A network model of insula function. *Brain Structure and Function*, *214*(5–6), 655–667. https://doi.org/10.1007/s00429-010-0262-0

Metzler-Baddeley, C., Caeyenberghs, K., Foley, S., & Jones, D. K. (2016). Task complexity and location specific changes of cortical thickness in executive and salience networks after working memory training. *NeuroImage*, *130*, 48–62. https://doi.org/10.1016/j.neuroimage.2016.01.007

Pessoa, L. (2008). On the relationship between emotion and cognition. *Nature Reviews Neuroscience*, *9*(2), 148–158. https://doi.org/10.1038/nrn2317

Rabinowitz, A. R., & Fisher, A. J. (2020). Person-Specific Methods for Characterizing the Course and Temporal Dynamics of Concussion Symptomatology: A Pilot Study. *Sci Rep*, *10*(1), 1248. https://doi.org/10.1038/s41598-019-57220-1

Ren, Z., Zhang, Y., He, H., Feng, Q., Bi, T., & Qiu, J. (2019). The Different Brain Mechanisms of Object and Spatial Working Memory: Voxel-Based Morphometry and

Resting-State Functional Connectivity. *Frontiers in Human Neuroscience*, *13*, 248. https://doi.org/10.3389/fnhum.2019.00248

Salsman, J. M., Butt, Z., Pilkonis, P. A., Cyranowski, J. M., Zill, N., Hendrie, H. C., Kupst, M. J., Kelly, M. A. R., Bode, R. K., Choi, S. W., Lai, J.-S., Griffith, J. W., Stoney, C. M., Brouwers, P., Knox, S. S., & Cella, D. (2013). Emotion assessment using the NIH Toolbox. *Neurology*, *80*(Issue 11, Supplement 3), S76–S86. https://doi.org/10.1212/WNL.0b013e3182872e11

Sandi, C. (2013). Stress and cognition. *WIREs Cognitive Science*, *4*(3), 245–261. https://doi.org/10.1002/wcs.1222

Schmank, C. J., Goring, S. A., Kovacs, K., & Conway, A. R. A. (2019). Psychometric Network Analysis of the Hungarian WAIS. *Journal of Intelligence*, *7*(3), 21. https://doi.org/10.3390/jintelligence7030021

Sharp, P. B., Sutton, B. P., Paul, E. J., Sherepa, N., Hillman, C. H., Cohen, N. J., Kramer, A. F., Prakash, R. S., Heller, W., Telzer, E. H., & Barbey, A. K. (2018). Mindfulness training induces structural connectome changes in insula networks. *Scientific Reports*, *8*(1), 7929. https://doi.org/10.1038/s41598-018-26268-w

Simpson-Kent, I. L., Fried, E. I., Akarca, D., Mareva, S., Bullmore, E. T., the CALM Team the CALM Team, & Kievit, R. A. (2021). Bridging Brain and Cognition: A Multilayer Network Analysis of Brain Structural Covariance and General Intelligence in a Developmental Sample of Struggling Learners. *Journal of Intelligence*, *9*(2), 32. https://doi.org/10.3390/jintelligence9020032

Terrill, A. L., Schwartz, J. K., & Belagaje, S. R. (2018). Best Practices for The Interdisciplinary Rehabilitation Team: A Review of Mental Health Issues in Mild Stroke Survivors. *Stroke Research and Treatment*, *2018*, 1–8. https://doi.org/10.1155/2018/6187328

van der Velden, R. M. J., Mulders, A. E. P., Drukker, M., Kuijf, M. L., & Leentjens, A. F. G. (2018). Network analysis of symptoms in a Parkinson patient using experience sampling data: An n = 1 study: Symptom Network Analysis in Parkinson's Disease. *Movement Disorders*, *33*(12), 1938–1944. https://doi.org/10.1002/mds.93

Van Essen, D. C., Ugurbil, K., Auerbach, E., Barch, D., Behrens, T. E. J., Bucholz, R., Chang, A., Chen, L., Corbetta, M., Curtiss, S. W., Della Penna, S., Feinberg, D., Glasser, M. F., Harel, N., Heath, A. C., Larson-Prior, L., Marcus, D., Michalareas, G., Moeller, S., … Yacoub, E. (2012). The Human Connectome Project: A data acquisition perspective. *NeuroImage*, *62*(4), 2222–2231. https://doi.org/10.1016/j.neuroimage.2012.02.018

Wang, X., Zhou, H., & Zhu, X. (2020). Attention deficits in adults with Major depressive disorder: A systematic review and meta-analysis. *Asian Journal of Psychiatry*, *53*, 102359. https://doi.org/10.1016/j.ajp.2020.102359

Weintraub, S., Dikmen, S. S., Heaton, R. K., Tulsky, D. S., Zelazo, P. D., Bauer, P. J., Carlozzi, N. E., Slotkin, J., Blitz, D., Wallner-Allen, K., Fox, N. A., Beaumont, J. L., Mungas, D., Nowinski, C. J., Richler, J., Deocampo, J. A., Anderson, J. E., Manly, J. J., Borosh, B., … Gershon, R. C. (2013). Cognition assessment using the NIH Toolbox. *Neurology*, *80*(Issue 11, Supplement 3), S54–S64. https://doi.org/10.1212/WNL.0b013e3182872ded

Wright, A. G. C., & Woods, W. C. (2020). Personalized Models of Psychopathology. *Annual Review of Clinical Psychology*, *16*(1), 49–74. https://doi.org/10.1146/annurev-clinpsy-102419-125032

Zaheed, A. B., Sharifian, N., Kraal, A. Z., Sol, K., Manly, J. J., Schupf, N., Brickman, A. M., & Zahodne, L. B. (2021). Mediators and Moderators of the Association Between Perceived Stress and Episodic Memory in Diverse Older Adults. *Journal of the*

International Neuropsychological Society, *27*(9), 883–895.

https://doi.org/10.1017/S1355617720001253