AMERICAN PSYCHOLOGICAL ASSOCIATION

Rehabilitation Psychology

ISSN: 0090-5550

2024, Vol. 69, No. 4, 347–356
https://doi.org/10.1037/rep0000576

Psychometric Network Analysis in Rehabilitation Research: A Methodological Demonstration in Depression Symptoms of Veterans and Service Members at 1 and 2 Years After Traumatic Brain Injury

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Purpose/Objective: Psychometric network analysis (PNA) is an application of dynamic systems theory that can inform measurement of complex rehabilitation phenomena such as depressive symptom patterns in veterans and service members (V/SMs) after traumatic brain injury (TBI). This study applied PNA to the Patient Health Questionnaire-9 (PHQ-9), a common measure of depressive symptoms, in a sample of V/SMs with TBI at Years 1 and 2 (Y1–2) postinjury. ***Research Method/Design:*** A sample of 808 V/SMs with TBI participated, 594 contributing PHQ-9 data at Y1 and 585 at Y2. Participants were recruited while or after receiving inpatient postacute rehabilitation from one of five Veterans Affairs Polytrauma Rehabilitation Centers. ***Results:*** The networks were stable and invariant over time. At both times, network structure revealed the cardinal depressive symptom "feeling down, depressed, or hopeless," as evidenced

This article was published Online First August 29, 2024.

Aaron P. Turner served as action editor.

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The contents of this publication were developed under grants from the National Institute on Disability, Independent Living, and Rehabilitation Research (NIDILRR) to: TIRR Memorial Hermann (90DPTB0025), Icahn School of Medicine at Mount Sinai (90DPTB0028), Virginia Commonwealth University (90DPTB0021), University of Washington (90DPTB0024), and Moss Rehabilitation Research Institute (90DPTB0019). NIDILRR is a center within the Administration for Community Living (ACL) and the Department of Health and Human Services (HHS). The contents of this publication do not necessarily represent the policy of NIDILRR, ACL, and HHS and are not necessarily endorsed by the Federal Government. This material is based upon work supported in part by the Department of Veterans Affairs, Veterans Health Administration, Office of Research and Development. The authors have no conflicts of interest to declare. The views expressed in this article are those of the authors and do not necessarily represent the official policy or position of the Defense Health Agency (DHA), Department of Defense, or any other U.S. government agency. This work was prepared under Contract HT0014-22-C-0016 with DHA Contracting Office HT0014 and, therefore, is defined as U.S. Government work under Title 17 U.S.C.§101. Per Title 17 U.S.C.§105, copyright protection is not available for any work of the U.S. Government. For more information, please contact dha.TBICOEinfo@health.mil.

Paul B. Perrin served as lead for conceptualization, investigation, methodology, project administration, writing–original draft, and writing–review and editing and served in a supporting role for formal analysis. Samuel J. West served as lead for formal analysis and visualization, contributed equally to writing–original draft, and served in a supporting role for conceptualization, investigation, and writing–review and editing. Daniel W. Klyce served as lead for funding acquisition, contributed equally to investigation and project administration, and served in a supporting role for conceptualization, supervision, writing–original draft, and writing–review and editing. Sarah W. Clark, Tiffanie A. Vargas, Alexander J. Gates, Teague R. Henry, Mia E. Dini, Stephanie D. Agtarap, CB Eagye, Jacob A. Finn, Shannon B. Juengst, Kristen Dams-O'Connor, and Charles H. Bombardier served in a supporting role for writing–original draft and writing–review and editing. Samuel J. West and Daniel W. Klyce contributed equally to methodology.

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by its strength centrality. In the Y1 network, the suicidal ideation node was connected exclusively to the network through the guilt node, and in the Y2 network, the suicidal ideation node formed a second connection through the low mood node. The guilt node was the second most influential node at Y1 but was replaced by anhedonia node at Y2. ***Conclusions/Implications:*** This study demonstrated the potential of PNA in rehabilitation research and identified the primacy of feeling down, depressed, and hopeless after TBI at both Y1 and Y2, with guilt being the second most influential symptom at Y1, but replaced by anhedonia at Y2, providing supportive evidence that the relationships among depressive symptoms after TBI are dynamic over time.

Impact and Implications

Psychometric network analysis (PNA) represents a promising avenue for understanding how key rehabilitation variables influence one another, making it a valuable tool for unraveling the complexities of depressive symptoms after traumatic brain injury (TBI) and other psychological phenomena. This study demonstrated the application of PNA by modeling the structure of depression and the relationships among depressive symptoms over time in veterans and service members at 1 and 2 years post-TBI. Findings demonstrated the potential of PNA in rehabilitation research and identified the main symptom of depression after TBI at both time points to be feeling down, depressed, and hopeless, with secondary symptoms that change over time.

Keywords: psychometric network analysis, traumatic brain injury, veterans and service members, depressive symptoms, PHQ-9

Supplemental materials: https://doi.org/10.1037/rep0000576.supp

Depression in Veterans and Service Members (V/SMs) With Traumatic Brain Injury

Traumatic brain injury (TBI) has been recognized as the "signature injury" (Okie, 2005) of recent military conflicts, ushering in increased attention and research (Arango-Lasprilla et al., 2007; Brickell et al., 2019; Lamberty et al., 2014; Ropacki et al., 2018; Sayer et al., 2009). Nearly half a million TBIs have been sustained by active duty service members since 2000 (Defense Health Agency, 2023). The Departments of Defense and Veterans Affairs have focused on creating a comprehensive lifelong care plan for V/SMs with TBI (Armstrong et al., 2019; Darkins et al., 2008; Pogoda et al., 2017; Sayer et al., 2009). A foundation of specialized TBI care is the acknowledgment that V/SMs have high rates of mental health comorbidities (Chan et al., 2017; Finn et al., 2018; Pogoda et al., 2016; Pugh et al., 2018) that may influence care needs and service delivery.

Prevalence rates of major depressive disorder (MDD) after TBI range from 17% to 61% (Kreutzer et al., 2001; Rapoport, 2012; Scholten, et al., 2016). However, differences in diagnostic criteria, measures used, time since injury, and injury severity all contribute to variability in prevalence rates. Osborn et al.'s (2014) meta-analysis reported the prevalence of MDD or dysthymia following TBI was 27%, whereas the prevalence of clinically significant depressive symptoms was 38%. Depression symptoms are associated with reduced quality of life, greater disability, and restricted community participation (Hart et al., 2011).

The Patient Health Questionnaire-9 (PHQ-9) has been commonly used to evaluate depressive symptoms in people with TBI. Items on this measure correspond to the criteria outlined in the Diagnostic and Statistical Manual of Mental Disorders, 4th and 5th editions (American Psychiatric Association, 1994, 2013) for MDD. The PHQ-9 has adequate sensitivity and specificity for MDD (Fann et al., 2005) and functions similarly in TBI and non-TBI populations, generally loading on a single factor (Cook et al., 2011) and requiring few modifications for individuals with TBI (Dyer et al., 2016); research has suggested that TBI-related somatic factors do not inflate scores or overdiagnose depression (Cook et al., 2011).

Psychometric Network Analysis (PNA)

PNA represents an integrative approach to understanding the relationships between psychological variables, especially in the context of issues like TBI in V/SMs. Psychometric network analyses are rapidly gaining popularity for examining clusters of related symptoms as a connected system. For example, Klyce et al. (2021) applied PNA to help disentangle the complex associations between neurobehavioral symptoms and PTSD symptoms in V/SMs with TBI, finding that the arousal symptom bridged the two disorders. Traditional psychometric models often treat psychological item responses as indicators of an underlying latent variable, assuming that these variables are influenced by a single common cause. However, PNA takes a complex systems perspective, viewing these item responses as individual elements or nodes in a network, where the edges or lines between them represent statistical relationships (Borsboom et al., 2021). For instance, sleep problems may interact with loss of energy, low self-esteem, and rumination, creating a network of reinforcing factors. PNA has gained traction across various psychological fields, from clinical psychology and psychiatry to personality research and quality of life studies (Van Borkulo et al., 2014). Its success stems in large part from its generalizability; PNA offers a way to capture the relationships between observed variables without making assumptions about latent constructs, thereby providing fresh insights into the intricate interplay of symptoms and their importance within a network (Robinaugh et al., 2020).

The conceptualization of psychological factors as networks also facilitates the application of quantitative tools from complex network analysis. Here, node degree measures the number of connections and node strength captures the intensity of connections with which each node participates. The neighborhood of a node refers to the set of other nodes to which it is directly connected. Local network structures, known as motifs, capture regular patterns of interactions in the network (Letina et al., 2019). A path refers to a sequence of nodes connected by edges that allows for the traversal from one node to another (Golino & Epskamp, 2017). The extent to which a node plays a central or influential role in the network's structure and functioning is measured by the node's centrality (Opsahl et al., 2010). There are several different centrality metrics frequently used in PNA, including:

- Degree centrality is based on the number of direct connections (edges) a node has in the network used to highlight the well-connected network hubs.
- Betweenness centrality quantifies the extent to which a node lies on the shortest paths between other nodes in the network capturing the bridges in the network.
- Closeness centrality measures how quickly a node can reach all other nodes in the network. Nodes with high closeness centrality are typically central in terms of accessibility and information flow.
- Eigenvector centrality operationalizes the idea that a central node should be connected to other central nodes.
- Strength centrality measures the overall influence of a node within a network by considering both the number and weight of connections between nodes.

A very accessible comparison of these indices of centrality and other topological constructs of networks is presented in Landherr et al. (2010). The choice of centrality metric may depend on the specific characteristics and goals of the network analysis (Hallquist et al., 2021).

In psychometric networks, sets of many connected nodes reveal distinct communities (a.k.a. clusters) or subnetworks of related nodes. While many potential algorithms exist for extracting this community structure from general complex networks (e.g., modularity maximization, infomap, stochastic block models), the most commonly applied algorithm in PNA is the Walktrap community detection algorithm. The Walktrap algorithm assesses both the number and composition of communities within a psychometric network by utilizing random walks to integrate over the network structure (Pons & Latapy, 2006). These random walks jump from node to node along the network's neighboring edges, with greater edge weights denoting stronger connections such as partial correlations, serving as more likely paths to be followed. Communities are found by applying hierarchical agglomerative clustering to feature vectors capturing the probability that a random walk, starting at a source node, eventually lands on a target node. The Walktrap algorithm has several advantages, including its sensitivity to edge (e.g., partial correlation) strengths and the fact that it estimates the number and composition of communities without requiring explicit researcher guidance. Furthermore, it has been observed that these communities align with the latent factors found in factor models. Finally, the Walktrap algorithm has been shown to perform better at identifying community structure on constructed networks, such as correlation networks typically used in PNA, than other community detection methods (K. M. Gates et al., 2016).

Network comparison methods are valuable tools in PNA, as they allow researchers to assess and compare structural characteristics between groups (e.g., normal personality and psychopathology), or across time (e.g., before and after an intervention). The simplest comparison methods employ correlation measures, such as Pearson or Spearman correlation, and assess the overall similarity between properties of two networks (Costantini et al., 2019). Network alignment scoring evaluates the similar topological roles played by individual nodes or subnetworks. Bootstrapping is used to assess the stability and reliability of network comparisons through a process which generates multiple samples from the data and computes a distribution of network statistics (e.g., correlation coefficients) to estimate confidence intervals and test hypotheses about network differences (Christensen & Golino, 2021). Comparisons between the community structure of two networks using clustering similarity metrics, such as the adjusted rand index or normalized mutual information, reveal the consistency of community detection results across different datasets or conditions (A. J. Gates & Ahn, 2019; A. J. Gates et al., 2019).

Current Study

PNA represents a promising avenue for understanding intricate relationships among variables, making it a valuable tool for unraveling the complexities of TBI and various other psychological phenomena. Applications of PNA can provide new interpretative insights regarding how symptoms relate to each other when assessing complex phenomena in rehabilitation research and practice. PNA can therefore contribute to a deeper understanding of precisely how symptoms interrelate, which symptoms are mathematically the most important in the network, and which symptoms might be targeted through clinical intervention to fracture the network and reduce symptomology. As a result, the purpose of the current study was to demonstrate the application of PNA to the PHQ-9 in a sample of V/SMs with TBI at 1 and 2 years postinjury.

Method

Transparency and Openness

We report how we determined our sample size, all data exclusions, all manipulations, and all measures in the study, and we follow JARS (Kazak, 2018). All data analysis syntax and outputs, as well as research materials are available via request to the corresponding author. The data are not publicly available due to the privacy of data generated by the Veterans Affairs (VA). Data were analyzed using R Version 4.1.1. The study's design and its analysis were not preregistered.

Participants

The current study used data from the Department of Veterans Affairs TBI Model Systems (VA TBIMS) national database. Participants were recruited from one of five VA Polytrauma Rehabilitation Centers (PRCs). The inclusion criteria for the parent study were: (a) diagnosis of TBI per case definition (i.e., a traumatically induced structural brain injury or physiological disruption of brain function due to external force evidenced by onset or worsening of loss of and/or decreased consciousness, mental state alteration, memory loss for events immediately before or after injury, transient or stable neurological deficits, or intracranial lesion); (b) age 16 years or older at time of TBI; (c) admission to a PRC for TBI rehabilitation; and (d) informed consent by the participant or legally authorized representative. An additional inclusion criterion for the current study was that data were collected during follow-up assessments directly from the participant with TBI rather than a surrogate informant. Finally, participants were excluded if they did not have complete PHQ-9 data at either 1 or 2 years after injury. Although the overall sample consisted of 808 unique participants, 594 participants had data at Year 1 (Y1) and 585 at Year 2

Table 1
Sample Characteristics

Variable	*M* (*SD*) or *n* (%)
Sex	
Male	755 (93.4%)
Female	50 (6.2%)
Unknown/missing	3 (.4%)
Race/ethnicity[a]	
Hispanic/Latino/Spanish	103 (12.7%)
White	614 (76.0%)
Black or African American	99 (12.3%)
Asian	38 (4.7%)
American Indian or Alaskan Native	37 (4.6%)
Native Hawaiian or other Pacific Islander	18 (2.2%)
Injury severity (GCS score)	
Mild (14–15)	219 (27.1%)
Moderate (9–13)	92 (11.4%)
Severe (3–8)	190 (23.5%)
No acute hospitalization	48 (5.9%)
Chemically sedated	70 (8.7%)
Intubated	88 (10.9%)
Unknown	101 (12.5%)
Age at injury	36.99 (15.65)
Time to follow commands (days)	10.47 (21.32)
Posttraumatic amnesia (days)	33.33 (54.45)
Cause of injury	
Vehicular	400 (49.5%)
Gunshot wound	32 (4.0%)
Assaults with blunt instrument	33 (4.1%)
Other violence	120 (14.9%)
Sports	17 (2.1%)
Fall	149 (18.4%)
Hit by falling/flying object	10 (1.2%)
Pedestrian	29 (3.6%)
Other	10 (1.2%)
Unknown	8 (1.0%)

Note. GCS = Glasgow Coma Scale.
[a] For race/ethnicity, participants selected all categories that applied.

(Y2); 371 participants had data at both time points. A Little's Missing Completely at Random test was run comparing missingness across the two time points, which was just statistically significant, $\chi^2(18) = 29.01$, $p = .048$, suggesting an expected amount of nonrandom missingness, likely due either to differential attrition or to the PHQ-9 only being completed by V/SMs whose injury severity did not prevent the ability to do so. Table 1 presents participant demographics. Additional participant demographic information and descriptive findings of the VA TBIMS cohort can be found in Ropacki et al. (2018).

Procedure

Study procedures were approved by the Institutional Review Boards at each PRC. After informed consent, team members abstracted sociodemographic (i.e., sex) and injury-related (i.e., Glasgow Coma Scale [GCS] scores, time to follow commands, posttraumatic amnesia [PTA] duration, cause of injury) variables from participants' electronic medical record. Participants (or their surrogate informant) were either interviewed or completed a questionnaire asking about additional sociodemographic information (i.e., race/ethnicity and birthdate for age calculation). Follow-up assessments included the PHQ-9 and were conducted at 1 year (± 2 months) and 2 years (± 3 months) after injury. Data for follow-up assessments were collected via telephone interviews and/or mail-in questionnaires. PHQ-9 data could be collected by either method.

Measures

PHQ-9

The PHQ-9 is a patient-report measure of depression symptoms that parallel the nine symptoms comprising the *Diagnostic and Statistical Manual of Mental Disorders*, fourth and fifth editions of diagnostic criteria for MDD (American Psychiatric Association, 1994, 2013). Individuals rate how often they have been bothered by symptoms over the past 2 weeks with four response options (0 = *not at all*, 1 = *several days*, 2 = *more than half the days*, and 3 = *nearly every day*). The PHQ-9 was developed and validated for use among medical patients with high rates of physical illnesses and is widely used in health outcomes research (Kroenke et al., 2001). In people with TBI, the PHQ-9 is generally unidimensional with some exceptions, has excellent diagnostic sensitivity (0.93) and specificity (0.89), and has good convergent validity and test–retest reliability (0.76; Fann et al., 2005). The PHQ-9 items demonstrate similar functioning in people with TBI relative to primary care patients (Cook et al., 2011). The PHQ-9 exhibited appropriate internal consistency at both time points in the current sample (Y1 $\alpha = 0.85$; Y2 $\alpha = 0.86$).

Sociodemographic and Injury-Related Variables

Sociodemographic variables included sex, race/ethnicity, and age at injury. Sex and age at injury were abstracted from the medical record. Race/ethnicity was coded based on the participant's (or their proxy's) self-report after study enrollment on two variables: race and ethnicity. Racial categories included White, Black/African American, Asian, American Indian/Alaskan Native, and Native Hawaiian/Pacific Islander. Ethnicity was coded dichotomously (i.e., yes/no) based on Hispanic, Latino, or Spanish origin. The aggregated race/ethnicity variable classified participants as Hispanic/Latino/Spanish if they responded "yes" to the ethnicity variable, and those participants who responded "no" to the ethnicity variable were coded based on their racial category response. Participants were able to choose all categories that apply across both race and ethnicity. TBI-related variables were abstracted from participants' medical records and included GCS score at admission to the emergency department after TBI, cause of injury, time to follow commands in days, and duration of PTA in days. Time to follow commands is the first date post-TBI that the participant has been able to successfully follow commands at two consecutive assessments during a 24-hr period. Duration of PTA is the first date post-TBI that the participant demonstrates full orientation in two consecutive assessments with no more than 2 full days between them.

Statistical Analyses

Initial descriptive statistics were calculated to summarize the mean PHQ-9 score at each time point and the percentage of participants meeting or surpassing the traditional clinical cutoff score of 10. We then applied PNA to participants' item-level responses on the PHQ-9. In the current work, nodes represented cross-sectional variables (i.e., individual scale items or symptoms) and edges represented the regularized partial correlation between any two nodes. Regularized partial correlation is a technique that allows for the determination of the relationship between two variables while controlling for the effects of other variables (Epskamp et al., 2018). We also calculated the strength centrality of each node in our networks. Strength centrality is calculated as the sum of the absolute values of all edges connecting to a given node and can be interpreted as a measure of the overall influence of a node within a network. Using strength centrality, as opposed to other centrality measures, allows for an understanding of both the number of connections that a node has and their weight within the network. This makes it particularly useful in networks where the strength or intensity of connection matters, such as with PNA, where the frequency and intensity of symptoms or item responses matters more than just the presence of connections. In the current study, the use of strength centrality provides an indication of which items are the most important to the structure of depression.

The prevailing technique for estimating a psychometric network—used in the current study—is the graphical least absolute shrinkage and selection operator (GLASSO) (Friedman et al., 2008). The GLASSO estimates a Gaussian graphical model, in which the edges capture the partial correlations between two nodes while considering all other nodes in the network (Epskamp et al., 2018). Sparse networks are inferred by GLASSO penalizing and shrinking coefficients via the least absolute shrinkage and selection operator (LASSO), causing small coefficients to be set to zero via a penalized maximum likelihood (Ravikumar et al., 2011; Tibshirani, 1996). Ultimately, the GLASSO results in more concise outcomes and reduces the potential for spurious relationships, allowing researchers to create clear and concise maps of the complex web of factors that influence psychometrics and complex rehabilitation phenomena. At the most basic level, PNA enables the creation of network visualizations for psychometric variables, allowing practitioners to gain insight into the underlying structure of these statistical relationships (Jones et al., 2018). These visualizations unveil patterns, clusters, and anomalies that may be challenging to identify in raw data, thereby enhancing the ability to detect trends and irregularities.

We estimated our networks using the estimateNetwork function in the bootnet package for R Version 4.1.1 (Epskamp et al., 2018). We used the EBICglasso estimation routine with the default gamma parameter of 0.50 which applies the LASSO. The EBICglasso repeatedly applies LASSO at differing regularization strengths, selecting the regularization strength that maximizes the Extended Bayesian Information Criterion (EBIC) (Epskamp & Fried, 2018). This estimate process yields relatively stable networks that are easier to interpret and are less likely to contain spurious edges. Network stability and accuracy were examined by two 1,000-sample bootstraps (i.e., case-dropping and nonparametric, respectively) using the bootnet function from the bootnet package (Epskamp et al., 2018). Full information regarding our bootstrap procedures is available in Supplemental Document 1 in the online supplemental materials. Listwise deletion was used for missing values. The average network layout was computed using the averageLayout function from the qgraph package prior to visualization to aid in visual comparison (Epskamp et al., 2012).

Results

Descriptive Statistics

At Y1, participants' mean PHQ-9 score was 7.23 ($SD = 6.21$) with 32.8% meeting or surpassing the clinical cutoff score of 10. At Y2, participants' mean PHQ-9 score was 7.77 ($SD = 6.45$) with 35.0% meeting or surpassing the clinical cutoff.

Network Analysis

Inspection of the distributions of each item across both time points revealed severe skew in the suicidal ideation (SI) nodes at both time points (i.e., skew values > 3.00) due to a preponderance of "0" responses. Because such skew in psychometric networks can bias estimates of centrality, we applied the nonparanormal distribution to this item from both time points prior to estimation (Liu et al., 2009). Following network visualization (Figure 1) we proceeded with our bootstrap procedures. Per the standards recommended by Epskamp et al. (2018), correlation stability (CS) coefficients were ideal for edge weights (CS = 0.67) and strength centrality estimates (CS = 0.59) in the Y1 network. Similar stability values were found in the Y2 network for edges (CS = 0.60) and strength centrality (CS = 0.52). The edge weight estimates from our networks and their bootstrapped values are available in Tables S1 and S2 in the online supplemental materials.

Network Comparison

To examine the temporal stability of our resultant network structures we subjected our networks to invariance testing using the NetworkComparisonTest package for R (van Borkulo et al., 2023). This analysis revealed that the structure (distributions of edge weights) of the PHQ-9 network was invariant over time, $M = 0.23$, $p = .202$, as was the global strength of the networks, $S = 0.08$, $p = .690$. To further quantify the similarity of networks across time points we examined Spearman's rank-order coefficients examining the magnitude of edges and strength centrality in both networks. These analyses revealed that our networks largely agreed with one another in terms of edge weights, $r_s = 0.57$, $p < .001$, and centrality, $r_s = 0.72$, $p < .001$, but there was some variation between them. Thus, despite the network comparison not yielding a significant omnibus result (i.e., no differences) we were still able to examine rank-order differences in centrality.

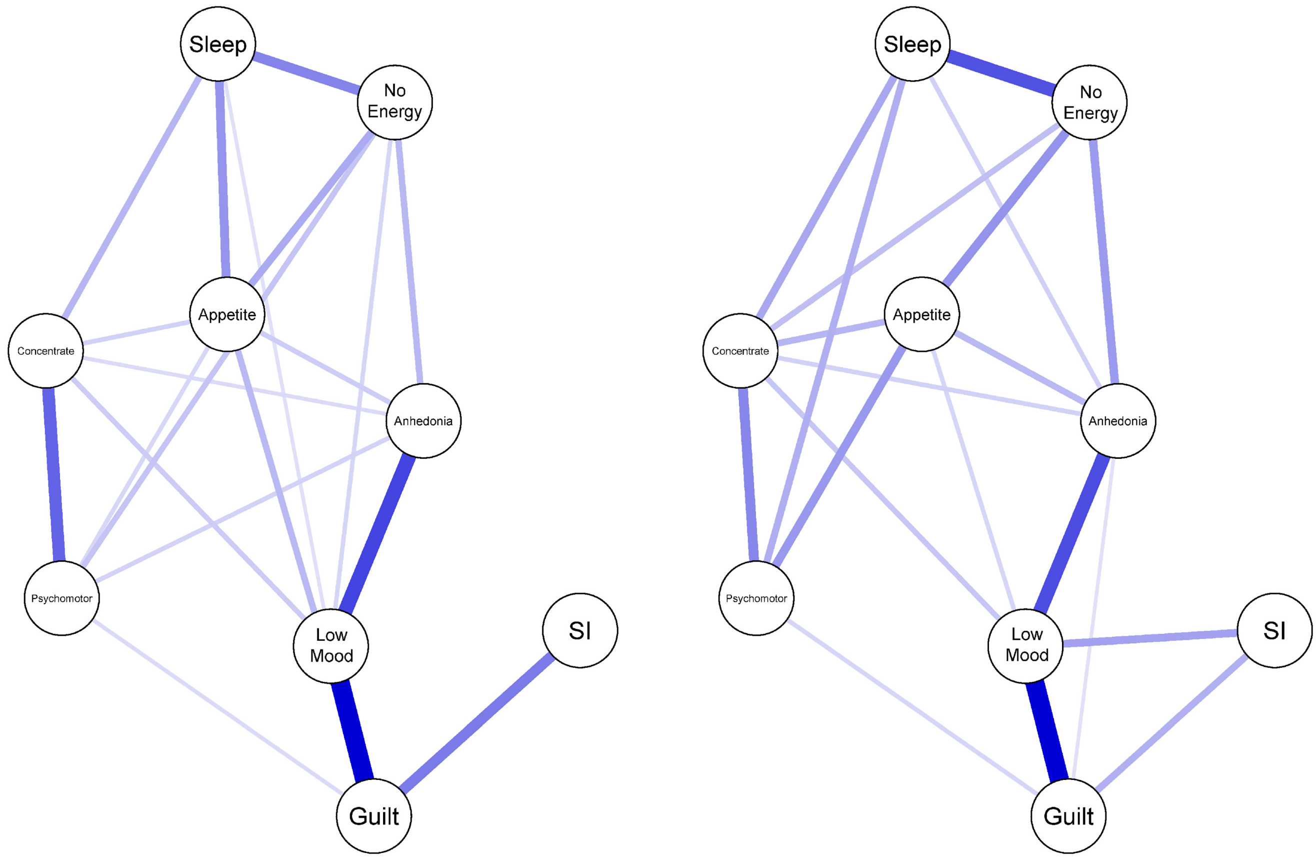
Centrality Estimates

As suggested in Table 2, in both networks the low mood node ("feeling down, depressed, or hopeless") emerged as the most central item from the PHQ-9. This node shared edges with guilt, anhedonia, and concentrate at both time points that were effectively identical in direction and strength. Guilt ("Feeling bad about yourself—or that you are a failure or have let yourself or family down") emerged as the second-most central node at Y1 but was supplanted by anhedonia ("Little interest or pleasure in doing things") at Y2.

Discussion

To demonstrate the utility of PNA in rehabilitation research, the current study applied the analysis to the PHQ-9, a common measure of depressive symptoms, in a sample of V/SMs with TBI at 1- and 2-year postinjury. The networks produced by PNA were stable and invariant over time. At both Y1 and Y2, network structure revealed the cardinal symptom of depression was represented by the "feeling down, depressed, or hopeless" item, as evidenced by the magnitude of the strength centrality estimates. The strength of the edges between nodes (depressive symptoms) suggested strong associations among psychological symptoms such as anhedonia, concentration, and poor mood and—to a lesser extent—among physiological symptoms such as low energy and poor sleep, as well. The strong

Figure 1
Time 1 (Left) and Time 2 (Right) PHQ-9 Networks



Note. Edge width and depth of color reflect the strength of partial correlation observed between any pair of nodes. All edges are positively valued. PHQ-9 = Patient Health Questionnaire-9; SI = suicidal ideation. See the online article for the color version of this figure.

association between "feeling down, depressed, or hopeless" and difficulty concentrating is consistent with prior research that found concentration difficulties to be a central node when examining the network structure of PTSD and depression symptoms in a sample of veterans with mild TBI (Shi et al., 2023). Although the networks were invariant, there were subtle differences. In the Y1 network, the SI node was connected exclusively to the network through guilt, and in the Y2 network, the SI node formed a second connection through low mood. The guilt node was the second most influential node at Y1 but was replaced by the anhedonia node at Y2. While the cardinal symptom remained the same, this change in the second most influential symptom provides support that the relationships among depressive symptoms after TBI are dynamic over time. Clinically, these findings may inform rehabilitation clinicians and other providers about the most salient depressive symptoms an individual may be experiencing as recovery progresses after TBI, which can be used to guide rehabilitation treatment planning. These findings contribute both to our understanding of depression as a construct among V/SMs with a history of TBI and to the field's understanding of how PNA can be used to assess interrelationships among impairments and symptoms after TBI and other acquired disabilities.

The general pattern of associations among nodes related to somatic (e.g., sleep, psychomotor changes) versus nonsomatic (e.g., feeling down, depressed, or hopeless) symptoms of depression is consistent with psychometric work on the PHQ-9 conducted in veterans with spinal cord injury. Elhai et al. (2012) compared four models for the PHQ-9—one single-factor model and three different

Table 2
Standardized Strength Centrality Values From the Y1 and Y2 Networks

Node	Abbreviated item content	Y1 (rank)	Y2 (rank)
Anhedonia	Little interest or pleasure in doing things	0.10 (4)	0.50 (2)
Appetite	Poor appetite or overeating	0.17 (3)	−0.14 (6)
Concentrate	Trouble concentrating on things…	−0.12 (6)	0.31 (3)
Guilt	Feeling bad about yourself or that you are a failure…	0.98 (2)	−0.04 (5)
Low mood	Feeling down, depressed, or hopeless	1.59 (1)	1.80 (1)
No energy	Feeling tired or having little energy	0.02 (5)	0.29 (4)
Psychomotor	Moving or speaking so slowly that others notice…	−0.34 (7)	−0.55 (8)
SI	Thoughts that you would be better off dead…	−2.05 (9)	−1.99 (9)
Sleep	Trouble falling or staying asleep or sleeping too much	−0.36 (8)	−0.19 (7)

Note. Numbers in parentheses indicate the centrality ranking of each node. Y1 = Year 1; Y2 = Year 2; SI = suicidal ideation.

two-factor models—concluding that the strongest fit was for the two-factor models differentiating somatic and nonsomatic symptoms. The two-factor model characterized sleep and appetite changes, low energy, poor concentration, and psychomotor changes as somatic, and feeling down, depressed, or hopeless, feeling worthless or guilty, and thoughts of death as nonsomatic (Krause et al., 2010). Our network structure similarly suggested strong connections within the cognitive/affective and somatic symptom domains, though also many overall connections throughout the network, similarly consistent with research identifying a unidimensional structure of the PHQ-9 (Fann et al., 2005). Indeed, our analyses did not provide any evidence to suggest there may be more than one node community among the PHQ-9 items.

The centrality of feeling down, depressed, or hopeless at both time points supports its primacy over the more somatic symptoms of depression, despite the lack of somatic symptoms measurement bias in depressive symptoms after TBI (Cook et al., 2011; Seel et al., 2010). The invariance in the network over the first 2 years after injury suggests a relatively stable depressive symptom structure. However, the second-highest centrality estimates of the guilt node at Y1 being supplanted by the anhedonia node at Y2 may suggest that the pattern of depressive symptoms evolves somewhat with changing abilities, adjustment, and circumstances over this postacute injury period. The higher centrality for guilt at Y1 than Y2 may reflect early feelings of guilt about the cause of injury itself (e.g., car accident) and/or practical consequences of postinjury loss (e.g., loss of employment) that include feelings of failure or feeling of having let family down (Chhuom & Thompson, 2021; Seel et al., 2010). Seel et al. (2010), in a review of the literature on depression after TBI, concluded that guilt and self-criticism best differentiated those who were depressed post-TBI. Self-esteem, changes in sense of identity, and feeling like a burden to family may be more central earlier after TBI while individuals and their family members are still adjusting to their new postinjury reality. As time goes on and rehabilitation gains may plateau, more affective symptoms like little interest or pleasure in doing things may take on greater importance.

Implications for Network Analysis in Rehabilitation Research

When applied to cross-sectional data, as shown in this study, PNA provides a powerful tool for exploring the measurement structure of the constructs under study. By describing the dependency structure as a network of relations among observed variables, rather than the more traditional approach of taking those observed variables as measurements of an underlying latent variable, researchers are better able to identify specific variables or clusters of variables that are highly central to the overall system. Applied to rehabilitation research, PNA of cross-sectional data has the potential to enhance the field's understanding of the measures used and help identify potential intervention targets to improve rehabilitation outcomes.

While PNA applied to cross-sectional data extends the field's understanding of measurement, PNA's real strength comes when it is applied to the analysis of longitudinal data. Psychometric network approaches to repeated measures data allow researchers to model their data as a dynamical system. This provides a powerful set of methods for identifying intervention targets, quantifying the expected effect of an intervention, and even simulating different intervention strategies in silico (Henry et al., 2022). With the rise of different data collection protocols that result in intensive longitudinal data, such as ecological momentary assessment methods deployed on smartphones (Shiffman et al., 2008), rich temporal data can be collected about the rehabilitation process, which in turn is amenable to a PNA approach. From this approach, rehabilitation researchers can better understand the causal drivers of recovery in aggregate, and even develop personalized models of recovery that aid in treatment planning. Furthermore, by integrating these models with modern machine learning algorithms, there is potential to create predictive analytics that proactively guide rehabilitation strategies. As researchers continue to collect vast amounts of data on the rehabilitation process, the application of PNA will have the potential to become a cornerstone of effective and efficient rehabilitation research.

Limitations and Future Directions

While network analysis as derived from mathematical graph theory has found application in diverse fields, there are important limitations to consider for both PNA as a method and its application to psychometric rehabilitation and TBI research which is relatively new and its limitations only begun to be explored (Borsboom & Cramer, 2013). One known limitation is that network analysis applied to cross-sectional data, such as the two time points in the current study cannot provide evidence of causal links. Additionally, while networks of larger sample sizes can be more stably and accurately estimated, the exploratory nature of network analysis makes it difficult to hypothesize expected network structure or edge weights to provide evidence for making a priori power analyses (Epskamp et al., 2018). As such, we caution readers that our networks are meant to provide an exploratory basis for the generation and testing of novel hypotheses (Peters et al., 2021). Another known limitation of the PNA approach is that static associations modeled between cross-sectional items, as in our study, hamper the assessment of dynamic changes that are likely to occur (Iverson, 2019). However, the current analysis utilized iterative Y1 and Y2 data to compare changes in the structure of depression, providing temporal insights into the diminishing and strengthening associations.

Results may be affected from bias through the listwise deletion procedure's requiring only subjects with complete PHQ-9 data within a time point. Similarly, while the Y1 and Y2 networks each had data from a majority of participants who had contributed data at both time points, there were a large number of participants who had data from only one time point. The Y1 and Y2 network models did not differ in omnibus comparisons, but nonetheless, a stronger test of invariance would have occurred with a larger proportion of the sample contributing data at both time points. Another limitation is the potential lack of generalizability of results from our mostly homogenous sample (all V/SMs) to TBI populations at large (Ropacki et al., 2018). Future studies could consider a more heterogeneous sample, to include more women, nonmilitary personnel, and individuals with mild TBI. Despite some observed changes in centrality estimates, our network comparison test did not suggest significant omnibus differences between the networks. However, according to findings from a simulation study (van Borkulo et al., 2023), a single edge missing in one network is typically enough to render them significantly different, and the sample size being less than $N = 750$ can produce a false negative on comparison. In addition to including a larger sample size, future studies could investigate the change of strength between central nodes within our model and the extent to which these changes drive experience of depression over the course of recovery.

Finally, network associations may have differed among people with symptoms consistent with MDD versus in persons for whom the symptoms were not suggestive of a depressive disorder. Symptoms within a subgroup of people who are "depressed" might hang together in ways that would be theoretically and therapeutically informative. In contrast, the interrelationships of symptoms among a subgroup of people not "depressed" might be less prominent or perhaps related to TBI. Unfortunately, the current study was underpowered to compare people at or above the traditional PHQ-9 cutoff score of 10 for clinically significant depressive symptoms to participants who scored below it. Future research with larger sample sizes should look at invariance by depressive threshold, as well as other potentially important variables like injury severity.

Conclusions

PNA provides rehabilitation researchers with an integrative approach to understanding the complex relationships between critical rehabilitation variables and the ways they interact to influence a network. To our knowledge, this is the first application of PNA to investigate the structure of depressive symptoms over time in a sample of V/SMs with TBI and provides a framework for the examination of other rehabilitation constructs over time. Results indicated the sustained centrality of low mood over the first 2 years postinjury, representing a high-priority treatment target given its apparent role in maintaining depressive symptoms and perhaps perpetuating or increasing SI 2 years after TBI. Feelings of guilt at Y1 were reflective of self-blame, only to be replaced in centrality by anhedonia at Y2 when rehabilitation gains may plateau. These findings provide a nuanced characterization of how depressive symptoms interact with each other over time in a sample at elevated risk and in great need of effective treatments.

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Received November 17, 2023
Revision received May 8, 2024
Accepted May 29, 2024 ■