Inferring Causality Using a Network Analysis Approach

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Abstract

The present study utilized intraindividual time-series data from a comorbid case to examine idiosyncratic relations among symptoms via a network analysis (NA) approach. Relations among depression and anxiety symptoms were examined through four networks. The networks build upon each other by determining symptom covariation, establishing temporal precedence, controlling for other possible causal variables, and examining the identified causal mechanisms. These steps are crucial for determining causality (Haynes et al., 2011) and the ability to make inferences based on the available information changes with each step of analysis. Determining causality is a crucial component for treatment intervention as it guides the clinician towards specific variables or symptoms that may be most impactful in an individual's symptom network.

Introduction

- A dynamical systems or network analysis (NA) approach defines symptoms as mutually interacting components of a multifaceted network (Borsboom & Cramer, 2013).
- NA can be used to visually examine an individual's unique presentation of symptoms and how they are related, including the direction and magnitude of the relations and what symptoms appear to cluster together (or not) over time.
- The current study describes how each of three intraindividual NAs relates to the requirements for inferring causality outlined by Haynes et al. (2011).
- The concurrent association network (Figure 1) provides a basic map of the presentation and relation between symptoms at any single point in time (step 1 in inferring causality: determining covariation).
- The lead-lag association network (Figure 2) establishes temporal precedence by modeling day-to-day dynamical processes occurring within and between symptoms (step 2 in inferring causality: establishing temporal precedence).
- The lead-lag relative importance network (Figure 3) models the day-to-day dynamic processes occurring within and between the person's symptoms, over and above other symptoms within the network (step 3 of inferring causality: controlling for other variables).

Method

PARTICIPANTS

- Single individual, female, 44 years old, diagnosed with major depressive disorder, dysthymia, social phobia, and anxiety disorder NOS.

PROCEDURE

- Over the course of 122 days, she completed 90 daily ratings, at ~the same time each day.
- Ratings of items were based on the Mood and Anxiety Symptoms Questionnaire (MASQ) & assessed depression, anxiety, and mixed distress (depression + anxiety).
- 3 networks (Figures 1- 3), and their corresponding centrality indices, were created from concurrent and lagged bivariate correlation matrixes utilizing the Fruchterman-Reingold algorithm in R qgraph.
- Only edges representing at least a small effect size ($r \leq 0.10$; Cohen, 1988) were included.
- Networks show direction (green arrows indicate positive, red arrows indicate negative relations) and strength of relations between items (thickness of the arrow).

Centrality Indices (Table 1):

- Indegree: estimates how much information a symptom receives directly from other symptoms.
- Outdegree: estimates how much information a symptom sends directly to other symptoms.
- Betweenness: quantifies how much information passes through a given symptom by calculating the number of times it lies on the shortest path between two nodes.

Results

Figure 1. Intraindividual Concurrent Association Network

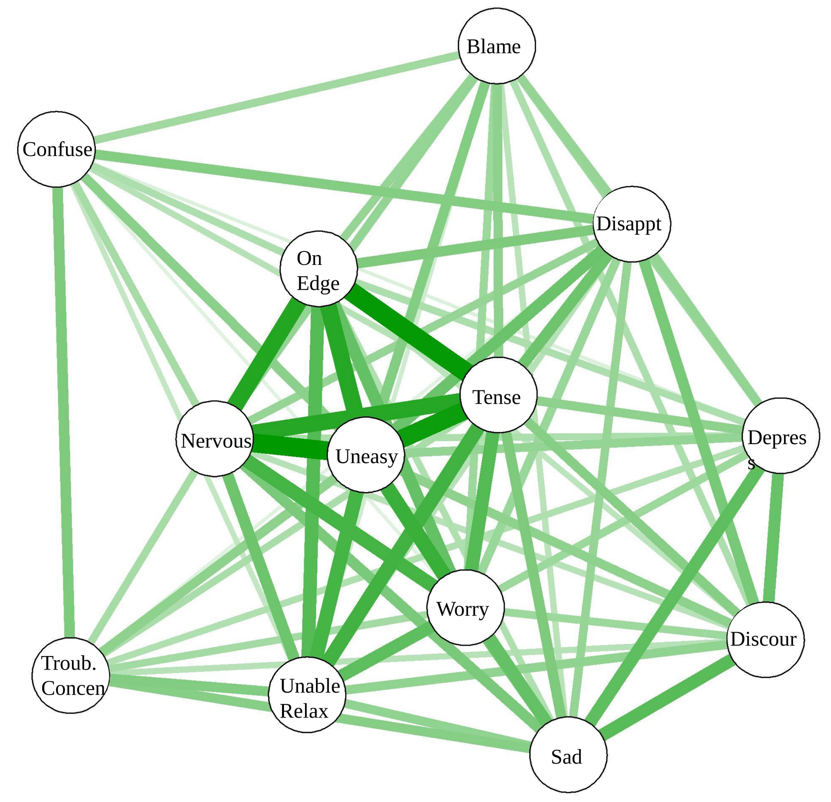

Figure 2. Intraindividual Lead-Lag Association (Bivariate) Network

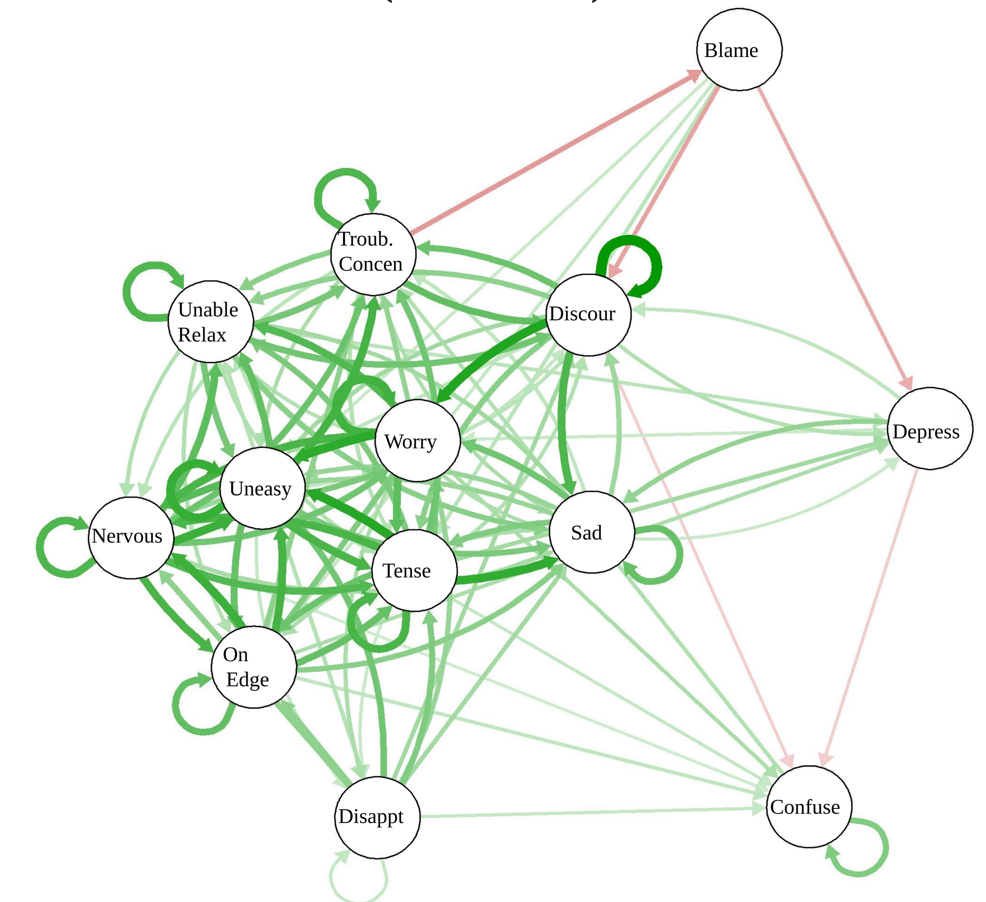

Figure 3. Intraindividual Lead-Lag Relative Importance Network

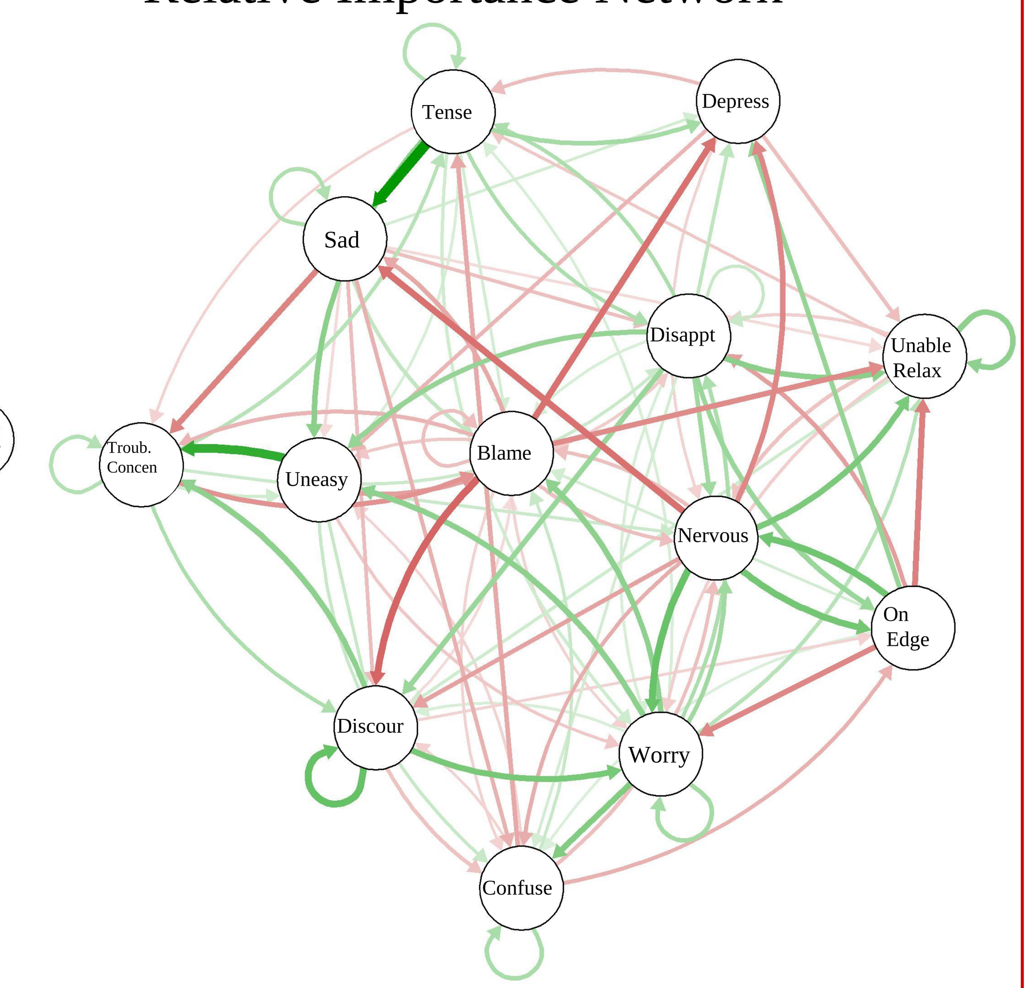

Table 1. Centrality Indices

Distress Symptoms	Concurrent Bivariate In/OutDegree	Concurrent Bivariate Betweenness	Lead Lag Bivariate InDegree	Lead Lag Bivariate OutDegree	Lead Lag Bivariate Betweenness	Lead Lag Partialed InDegree	Lead Lag Partialed OutDegree	Lead Lag Partialed Betweenness
Depression								
1. Sad	4.36	2	2.46	1.77	7	1.29	1.37	5
2. Depressed	3.75	0	0.94	0.56	0	1.51	0.67	2
3. Discour	3.77	0	1.74	2.16	18	1.84	1.04	7
4. Disappt	4.14	4	0.40	1.87	0	1.28	2.11	8
5. Blame	3.31	0	0.21	0.73	0	1.78	2.23	10
Anxiety								
1. Nervous	5.39	0	2.35	2.32	2	1.64	2.46	11
2. Tense	5.87	2	2.57	2.82	9	1.19	1.82	10
3. Uneasy	6.27	2	2.9	2.62	6	1.59	1.51	9
4. Unable Relax	4.68	0	2.22	1.86	1	1.77	0.70	0
5. On Edge	5.18	0	1.92	2.00	0	0.97	1.80	5
Mixed								
1. Worry	4.77	0	2.04	2.61	18	1.72	1.81	18
2. Troub. Concen.	3.21	0	2.29	1.40	24	1.50	0.97	4
3. Confused	2.64	0	0.84	0.16	0	1.41	1.00	2

Note. A higher score on each of the three centrality indices (i.e. InDegree, OutDegree, Betweenness) indicates the symptom is more central to the network. Symptom labels are those used in the figures.

Example "Feeling Uneasy"

- Determining Covariation using the Concurrent Association NA (Fig. 1): Feeling Uneasy covaries with other symptoms on a typical day and is highly central to the network.
- Establishing Temporal Precedence using the Lead-Lag Association NA (Fig. 2): For today predicting tomorrow, feeling uneasy is strongly predicted by other symptoms yesterday (InDegree) and its level today relatively strongly predicts level of other symptoms tomorrow (Outdegree).
- Controlling for Other Symptoms in the Network using the Lead-Lag Relative Importance NA (Fig. 3): Even after controlling for time and other symptoms, feeling uneasy remains an influential and central symptom in the network.

Conclusions

- These intraindividual NA results from time series data of a single comorbid case present a detailed visualization of those symptoms that affect other symptoms the most, and how they symptoms differentially relate at each level of analysis, thereby indicating which symptoms are associated with the most distress.
- Each level of analysis builds upon each other, providing more information in inferring causality (Haynes et al., 2011).
- Once information is gathered from each network and causality is assessed, intervention can be tailored to address the most prominent and highly intercorrelated symptoms, thus potentially increasing treatment efficacy.
- Please feel free to contact Emma Evanovich at emma.evanovich@ttu.edu or Gregory H. Mumma, Ph.D. at g.mumma@ttu.edu with any questions.

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