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Longitudinal and personalized networks of eating disorder cognitions and behaviors: Targets for precision intervention a proof of concept study

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Abstract

Introduction: Despite the high mortality and significant societal and personal costs associated with eating disorders (EDs) there are few evidence-based treatments. Part of the difficulty developing and implementing evidence-based treatments in EDs is due to the extremely high heterogeneity (e.g., variability in treatment outcome, symptom presentation etc) present.

Methods: To begin to identify specific symptom heterogeneity within persons, the current study used novel within and between group and intra-individual network analyses to create longitudinal and within-person networks of ED cognitions and behaviors (N = 66 individuals diagnosed with an ED). This article provides a proof of concept study for how to use between and within-person network analyses both for the EDs and other forms of psychopathology.

Results: We found that cognitions focused on desiring thinness played a likely maintaining role in ED pathology, across network type and across time. Furthermore, we showed that three individuals with the same diagnosis (anorexia nervosa) differed in which symptoms maintained the disorder. We use these participants to exemplify how to use intra-individual network analysis to personalize treatment focused on the primary maintaining symptoms. Finally, we found that amount of time (e.g., 4 hr vs. simultaneously) impacts how symptoms maintain each other.

Conclusions: These findings have implications for the development of novel personalized evidence-based treatments for EDs, as well as implications for how the field understands how psychopathology maintains itself. These data represent a first-step towards using intra-individual network analyses in the ED field, as well as for hypotheses generation in future research.

KEYWORDS

anorexia nervosa, eating disorders, network analysis, personalized treatment

1 | INTRODUCTION

Eating disorders (EDs) are serious mental illnesses, with the highest mortality rate of any psychiatric disorder (Klump, Bulik, Kaye, Treasure, & Tyson, 2009). Despite high levels of mortality, societal cost, and personal impairment, there are few empirically supported treatments for EDs (Linardon, Fairburn, Fitzsimmons-Craft, Wilfley, & Brennan, 2017). The most utilized and well-supported treatment for adults with EDs is Cognitive-Behavioral Therapy for Eating Disorders (CBT-E; Fairburn, 2008; Fairburn, Cooper, & Shafran, 2003). CBT-E is based on theory that proposes that EDs are primarily cognitive disorders characterized by overvaluation of weight and shape. This overvaluation of weight and shape maintains ED pathology through pathways between cognitive, behavioral, affective, and physiological symptoms. CBT-E is proposed to work by disrupting pathways between symptoms in these domains. For example, intervention on fear of weight gain (cognition) might then disrupt connections between fear of weight gain and excessive exercise, body checking, and restriction (behaviors), thereby weakening the disorder. However, CBT-E is ultimately only effective for approximately 50% of individuals with eating disorders (Fairburn et al., 2015). More research is needed to improve CBT-E to expand its effectiveness and to develop novel evidence-based treatments (e.g., Danielsen, Rekkedal, Frostad, & Kessler, 2016).

Part of the low response rates in CBT-E may be attributable to the significant symptom and treatment response heterogeneity that is seen in the EDs (Forbush et al., 2017), though it is possible this prior finding is accounted for by treatments that only produce modest response rates rather than heterogeneity per se. For example, other than age of onset and duration of illness, there are no reliable indicators of treatment outcomes (e.g., Murray, Loeb, & Le Grange, 2015). Some individuals with EDs recover rapidly and permanently, and others fall into a chronic illness course (Bardone-Cone et al., 2010). It is unclear why some individuals recover, while others do not. It is also unclear how cognitive-behavioral factors vary across individuals (e.g., Castellini, Montanelli, Faravelli, & Ricca, 2014). This heterogeneity makes it difficult for clinicians to pinpoint which maintaining symptoms should be targeted in treatment. In other words, personalized treatments that can target the heterogeneous maintaining symptoms of EDs are needed.

There is recent emphasis on using precision medicine to identify precise intervention targets, which should lead to more effective treatments (Insel, 2014). In the anxiety and depression literature, researchers are beginning to test data-driven techniques to personalize and direct clinicians to the use of modular treatments (Fernandez, Fisher, & Chi, 2017; Fisher, Reeves, Lawyer, Medaglia, & Rubel, 2017). This approach has been shown to outperform clinician judgment and shows how data-driven methods can be used to personalize treatment. For example, the development of the Dynamic Assessment Treatment Algorithm (please see Fernandez, Fisher & Chi, 2017 for information on its development) showed that this algorithm was more likely to adhere to data when determining which modules of the Unified Protocol to funnel patients into, whereas clinicians were more likely to approach treatment in an additive manner (module 1, then module 2 etc). These data fit with the substantial literature showing that clinician-judgment is often flawed in comparison to actuarial or data-based approaches (e.g., Dawes, Faust, & Meehl, 1989; Spengler et al., 2009) and point to the importance of developing data-driven approaches to personalize treatment.

To develop personalized interventions for EDs, we first need to identify the unique maintaining symptoms across and within individuals. Recent advances in network analysis allow for the creation of personalized, intra-individual networks that show how symptoms of disorders maintain themselves both between and *within* individuals (Bringmann et al., 2013, 2016; Epskamp et al., 2017). Network analysis is a methodology drawn from network theory and network science that allows for an unprecedented number of interacting factors to be considered at once within one statistical model (Borsboom & Cramer, 2013; Borsboom, 2017). Instead of identifying an underlying disease (as in latent variable modeling), network theory conceptualizes symptoms themselves as causal maintaining mechanisms of psychiatric illness (Boschloo et al., 2015; Fried et al., 2016, 2017; Kendler, Zachar, & Craver, 2011; McNally, 2016; Nelson et al., 2017). For example, instead of assuming that depression is caused by an underlying disease of 'depression', network theory assumes that symptoms of depression interact and cause each other (e.g., lack of sleep leads to fatigue, which then leads to low energy and then low mood), creating depression (Borsboom et al., 2011; Borsboom, 2017; Fried et al., 2016). Therefore, network analysis based on network theory allows for the examination of how cognitive-behavioral symptoms interact and become mutually reinforcing.

Until recently, cross-sectional network analyses have been used to identify possible intervention targets for ED treatments, such as fear of weight gain (Levinson et al., 2017; Debois et al., 2017) and body checking (Forbush et al., 2016). However, cross-sectional models are limited in that they cannot separate between-subjects relationships from short-term within-subjects relationships (Hamaker, 2012). Intraindividual network analysis moves beyond cross-sectional models that conceptualize maintaining symptoms of EDs across individuals to show what symptoms maintain EDs within individuals. Temporal group-level models (based on multiple observations in multiple individuals) allow for the examination of both intra-individual dynamics, between-subjects overlap, and differences between within- and between-subjects networks.

Specifically, we can estimate (1) temporal, (2) contemporaneous, and (3) between-subject networks, as well as (4) intraindividual networks within one person (Epskamp et al., 2016). Temporal models elucidate the dynamics of psychopathology, showing how one symptom may predict another at the next time point, which is essential in understanding maintaining cycles of psychopathology. Contemporaneous models show how the variables are related at the same time point while accounting for temporal relationships. Because temporal relationships may occur within seconds (e.g., affect impacting behavior and vice versa), contemporaneous models may uncover relationships that are missed in temporal networks (Epskamp et al., 2017). Finally, between-subjects models (cross-sectional between-person models) allow for the examination of between-mean relationships for all individuals under study (e.g., individuals who are more afraid to gain weight are, on average, also more likely to think about dieting). Intra-individual networks can be created for each individual that shows how one person's symptoms maintain their eating disorders. By constructing each of these networks, it is possible to begin to identify both between and within person the cognitive-behavioral symptoms that maintain EDs. Researchers can then identify what contributes to the high heterogeneity of cognitive-behavioral ED symptoms and which unique symptoms might be future targets of investigation for precision medicine interventions between and within individuals.

To create such models, we need intensive, longitudinal data across time (e.g., Epskamp et al., 2017c; Fisher et al., 2017). Thus, in the current pilot study, which can be considered an applied tutorial, we used ecological momentary assessment data (N = 66) to collect longitudinal data across 1 week (28 assessment points) on ED cognitions and behaviors. We then used both between (or traditional, cross-sectional between-person network analyses) and within (e.g., intra-individual) network analyses to model networks of ED cognitions and behaviors. We had three primary questions: First, what are the cognitive-behavioral relationships between individuals across time (e.g., temporal, contemporaneous, and between-subjects models); Second, are within-individuals models heterogeneous, despite similar diagnoses; Third, what are specific targets (e.g., symptoms) that might be used to generate hypotheses for future novel personalized treatment development research? We hypothesized that, (a) the between-person model would replicate prior cross-sectional between-person models showing that desire for thinness and fears of weight gain would be the primary central symptoms; and (b) given the high level of heterogeneity in ED symptom profiles, the intra-individual models would vary across individuals regardless of the same primary diagnosis.

2 | METHODS

2.1 | Participants

Participants were 66 individuals diagnosed with an ED. Participants were primarily female (*n* = 64; 97.0%); European American (*n* = 56; 86.2%); and had an average age of 24.98 (*SD* = 7.31; Range = 14–41). Other ethnicities reported were Asian (*n* = 3; 4.5%; Hispanic (*n* = 3; 4.5%); Black (*n* = 1; 1.5%) multiracial (*n* = 2; 3%) and one reported her ethnicity as not listed.

2.1.1 | Diagnoses and clinical characteristics

We used the Eating Disorder Diagnostic Scale (Stice, Telch, & Rizvi, 2000; see measures below) to determine diagnoses from DSM-5, which were made prior to beginning the ecological momentary assessment (EMA) protocol: AN (*n* = 40; 60.6%), atypical AN (*n* = 14; 21.2%), BN (*n* = 6; 9.1%), low frequency BN (*n* = 1; 1.5%), and other specified feeding and eating disorders (*n* = 3; 4.5%). The majority of participants reported that they were currently in treatment for an ED (*n* = 49; 74.2%), with an average of 2.5 hrs (*SD* = 4.53; Range = 0 to 30 hrs) of treatment per week. Median body mass index (BMI) was 20.66 (*SD* = 3.46; Range 13.89–32.28). Other self-reported current diagnoses were Anxiety Disorder (*n* = 41; 62.1%); Depressive Disorder (*n* = 38; 57.6%); OCD (*n* = 13; 19.7%); and PTSD (*n* = 7; 10.6%).

2.2 | Diagnostic inventory

2.2.1 | Eating disorder diagnostic scale

The EDDS is a brief self-report measure used to diagnose EDs, such as anorexia nervosa, bulimia nervosa, and binge eating disorder (EDDS; Stice, Telch, & Rizvi, 2000). The EDDS has demonstrated adequate internal consistency, as well as criterion and convergent validity (Stice, Fisher, & Martinez, 2004).

2.3 | EMA measures

The EMA survey assessed 11 items that were classified as either ED cognitions or ED behaviors. We drew items from the Eating Disorder Inventory-2 (EDI-2; Garner, Olmstead, & Polivy, 1983), the Eating Pathology Symptoms Inventory (EPSI; Forbush et al., 2013), and the Eating Disorder Examination-Questionnaire (EDE-Q; Fairburn & Beglin, 1994), because of their strong psychometric properties and as has been used in prior EMA research (e.g., Mason et al., 2016). Four items represented ED cognitions and were selected from the Eating Disorder Inventory-2 (Garner, Omstead, & Polivy, 1983): *I feel like I have overeaten; I am thinking about dieting; I am preoccupied with the desire to be thinner; I am terrified of gaining weight*. Participants were asked to rate how they felt "right now" and to rate each item on a 1 to 6 scale, where 1 = "not at all" and 6 = "extremely." Seven items described common ED behaviors drawn from the EDE-Q and EPSI: *Vomiting or other compensatory behaviors; Excessive exercise; Body-checking; I have weighed myself; Binge-eating; Restriction*. Participants were asked to rate how much they engaged in these behaviors since their last check in and to rate each item on a 1 to 6 scale, where 1 = "not at all" and 6 = "a lot."

2.4 | Procedures

All procedures were approved by the Washington University Institutional Review Board. Participants were recruited from an ED clinic after discharge from either a residential or partial hospitalization treatment program or from an ED alumni research registry. Participants were invited to participate in a study of daily habits. All procedures were completed either online or through a mobile application; participants living in any area of the country could participate. Participants provided informed consent and then completed the EDDS online. After completion of the online survey, participants were given instructions on how to download and access a mobile application measuring daily habits (please see http://www.christophermetts.com/status-post). This application notified participants four times a day for 1 week and asked participants to report on their ED cognitions and behaviors. Participants were compensated based on the number of times they responded to the mobile application questionnaires and could receive up to 25 dollars for participation.

2.5 | Data analytic procedure: Network analysis

Vector autoregressive (VAR) modeling was used for the analysis of time-series data, both within an individual and on a group level (Bringmann et al., 2013). These analyses are unique in that they statistically identify the most important symptoms both between and within individuals and across time. We used the multi-level vector autoregressive (mlVAR) package, version 0.4 in R to estimate three group-level networks: temporal, contemporaneous, and between-subject (between-subjects is analogous to the cross-sectional analyses that are generally presented in the network analyses field; Epskamp, Deserno, & Bringmann, 2017b). For a more detailed description of each model, see Epskamp et al. (2016). In all three networks, each symptom (or variable) is represented as a node, and links between nodes (i.e., edges) represent associations between symptoms. In a temporal network, edges with an arrowhead pointing from one node to another indicates that the first node predicts the other at the next time point. For example, if fear of weight gain has an arrow leading to thinking about dieting, then it indicates that fear of weight gain is predicting thinking about dieting at the next time point, while controlling for the previous time point (e.g., auto-regressive model). In a contemporaneous network, the edge represents partial correlations between variables, after controlling for all other variables in the same time point and also variables of the previous time point. In the between-subjects network, edges represent an average of two regression parameters: how well the mean of one variable predicts the mean of the other variable and vice versa. When the networks are plotted, only significant edges are shown using the "or" rule (see Epskamp et al., 2017 for more details).

TABLE 1 Descriptive information for individual items in overall sample

Item	Label	Mean (*SD*)	Range
I feel like I have overeaten	Feelovereat	3.16 (1.89)	1–6
I am thinking about dieting	Thinkdiet	3.75 (1.90)	1–6
I am preoccupied with the desire to be thinner	Desirethin	4.10 (1.84)	1–6
I am terrified of gaining weight	Feargain	4.47 (1.75)	1–6
Vomiting or other compensatory behaviors	Vomit	1.31 (.97)	1–6
Excessive exercise	Exercise	1.63 (1.29)	1–6
Body-checking	Bodycheck	3.02 (1.87)	1–6
I have weighed myself	Weighself	1.59 (1.45)	1–6
Binge eating	Binge	1.28 (1.00)	1–6
Restriction	Restrict	2.46 (1.71)	1–6

Next, we used the graphical VAR package in R to create intraindividual networks for three randomly selected individuals with AN (Wild et al., 2010). We created both temporal and contemporaneous networks for each of these individuals. This method allows us to determine on an individual level the hypothesized maintaining cognitions and behaviors.

The most central nodes were identified in all group-level networks (i.e., group-level temporal, contemporaneous, and between-subject networks) and in the contemporaneous intraindividual networks. Three commonly used indices of centrality are betweenness, closeness, and strength (McNally, 2016). For the group-level temporal and contemporaneous networks, we used the strength centrality to select the most central nodes because it is considered more stable than betweenness and closeness (Epskamp, Borsboom, & Fried, 2017a). Strength centrality refers to the sum of the edge weights between a focal node and all other nodes to which it is connected in the network. A node with high strength centrality would be highly correlated with many other nodes in the network (Borsboom & Cramer, 2013; McNally, 2016). For the temporal group-level network, inStrength and outStrength values were calculated. In inStrength centrality refers to a sum of connections pointing towards the node and indicates how many incoming arrows a symptom receives from the directly connected symptoms. In words, high inStrength represents that a symptom receives input from many other symptoms. OutStrength centrality refers to a sum of connections pointing from one node to the other nodes in the network and indicates how much information a symptom sends to other symptoms it is directly connected to (Bringmann et al., 2015). In words, outStrength represents that a symptom provides input to many other symptoms. For individual networks, centrality was calculated only for contemporaneous networks (Asparouhov, Hamaker and Muthén, 2018). The indices of centrality were calculated using the centrality Plot and centrality Table functions in q graph (Epskamp et al., 2012). Missing data were estimated using the Kalman filter as part of the estimation procedure (Haan-Rietdijk et al., 2017; Asparouhov, Hamaker, and Muther, 2018). Furthermore, over all we had a 73% compliance rate for EMA data, which is as high or higher than most EMA studies in eating disorders. Additionally, within our intra-individual networks calculated for the three individuals with AN, these participants had greater than 84% complete data.[1]

[1]Factors that contribute to power for these types of analyses are sample size, number of time points, and number of symptoms (parameters) included in the model (Schultzberg, M., & Muthén, B., 2018). With a sample size of 66 participants with 28 time points and 10 parameters we would achieve over .80 power for a small to moderate effect.

3 | RESULTS

3.1 | Compliance data

Average compliance was 73%. The average number of observations missed is 7.28 (*SD* = 6.97) out of 28 observations. Median number of observations missed is 5.00, range = 0–26. For individual networks, participant 1 did not miss any observations, participant 2 missed four observations, and participant 3 had 10 missing observations.

3.2 | Descriptive statistics and zero-order correlations

Average values and variance of individual items are reported in Table 1 for the group network and in Table 2 for the individual networks. Table 3 shows zero-order correlations between averages of each symptom assessed.

3.3 | Group level within-and between person networks: Temporal, contemporaneous, and between-subjects models (*n* > 1 networks)

Temporal, contemporaneous, and between-subject networks for the total sample are shown in Figure 1. As seen in Figure 2, in the group-level temporal network, the following nodes with the highest strength centrality were identified: desire to be thin (inStrength = 1.45), body checking (InStrength = 1.18), exercise (OutStrength = 1.82), and binge eating (OutStrength = 1.33). In the contemporaneous network, the following nodes with highest strength centrality were identified: desire to be thin (Strength = 1.62), thinking about dieting (Strength = 1.23), and fear of weight gain (Strength = 0.61). In the between-subject network, the following nodes with highest strength centrality were identified: desire to be thin (Strength = 2.13) and restriction (Strength = 1.04).

TABLE 2 Descriptive information for individual items for each participant included in intra-individual network analyses

Item	Label	Mean (*SD*)		
		Participant 1	Participant 2	Participant 3
I feel like I have overeaten	Feelovereat	2.61 (1.54)	2.25 (2.09)	2.33 (.84)
I am thinking about dieting	Thinkdiet	3.86 (.71)	4.79 (1.76)	2.39 (.92)
I am preoccupied with the desire to be thinner	Desirethin	4.82 (.72)	5.04 (1.63)	2.72 (.75)
I am terrified of gaining weight	Feargain	5.14 (.52)	5.46 (1.21)	5.50 (.62)
Vomiting or other compensatory behaviors	Vomit	0	1.96 (1.71)	1.11 (.32)
Excessive exercise	Exercise	0	4.29 (2.22)	3.11 (.47)
Body-checking	Bodycheck	2.93 (.86)	3.42 (2.04)	3.17 (.94)
I have weighed myself	Weighself	0	2.79 (2.06)	4.44 (.86)
Binge eating	Binge	0	1.13 (.61)	1.17 (.38)
Restriction	Restrict	2.18 (.95)	5.50 (1.14)	2.22 (.55)

TABLE 3 Zero-order correlations among symptoms included in network models

	1	2	3	4	5	6	7	8	9	10
1.Feelovereat	–									
2.Thinkdiet	.64**	–								
3.Desirethin	.58**	.73**	–							
4.Feargain	.53**	.76**	.74**	–						
5.Exercise	.18**	.24**	.23**	.19**	–					
6.Binge	.31**	.22**	.19**	.17**	.05	–				
7.Bodycheck	.33**	.54**	.59**	.56**	.35**	.28**	–			
8.Weighself	.24**	.27**	.25**	.26**	.48**	.14**	.32**	–		
9.Restrict	.52**	.58**	.50**	.51**	.16**	.10**	.13**	.13**	–	
10.Vomit	.24**	.25**	.24**	.22**	.22**	.30**	.23**	.37**	.04	–

Note. ***p* < .001; feelovereat = feel like I have overeaten; thinkdiet = thinking about dieting; desirethin = preoccupied with the desire to be thinner; feargain = terrified of gaining weight; exercise = excessive exercise; binge = binge eating; bodycheck = body checking; weighself = weighed myself; restrict = restriction; vomit = vomiting or other compensatory behaviors.

3.4 | Intraindividual networks (*n* = 1 networks)

Temporal and contemporaneous networks for three randomly selected individuals with anorexia nervosa are shown in Figure 3 (temporal and contemporaneous). As seen in Figure 4, for participant 1, thinking about dieting (Strength = 1.90) was the most central symptom; for participant 2, binge eating (Strength = 1.61) and exercise (Strength = 0.78) were the most central symptoms; for participant 3, restricting (Strength = 1.67) and thinking about overeating (Strength = 0.44) were the most central symptoms.

4 | DISCUSSION

We demonstrated how longitudinal between and within-person network analysis can be used to identify relationships between ED cognitions and behaviors both between and within individuals (at the group level), as well as within one person. These methods hold extreme promise for the development of precision medicine interventions for EDs. For example, identification of which cognitions and behaviors maintain EDs both between- and within-individuals provides a clearer picture on the structure of ED psychopathology both at the group and individual level of analysis, as well as across time. Identification of likely maintaining symptoms within one person might lead to interventions personalized to the individual by targeting their specific maintaining symptoms. Theoretically, intervention on core, maintaining symptoms should decrease all other symptoms within the network (McNally et al., 2016), though we should note there has not yet been empirical demonstration that intervention on core symptoms produces change, though central symptoms do predict ED treatment outcomes (Olatunji, Levinson, and Calebs, 2018). Theoretically, we can now identify possible maintaining symptoms not only across groups, but also within the individual. It is also possible that intra-individual network analysis might be used as one method to identify severe symptoms that need to be targeted in treatment. Overall, this manuscript shows how intra-individual network analyses could be used in the ED field and the psychopathology field at large. However, we should note that intraindividual network analysis is an extremely novel methodology, and thus, results should be interpreted cautiously. Future research should use these results for hypothesis generation for future larger scale research. We await future research with larger sample sizes and additional assessment points to make any firm conclusions.

4.1 | Overarching findings across model types

While the results here should still be considered tentative, there are two primary hypotheses to be tested in future research that arise

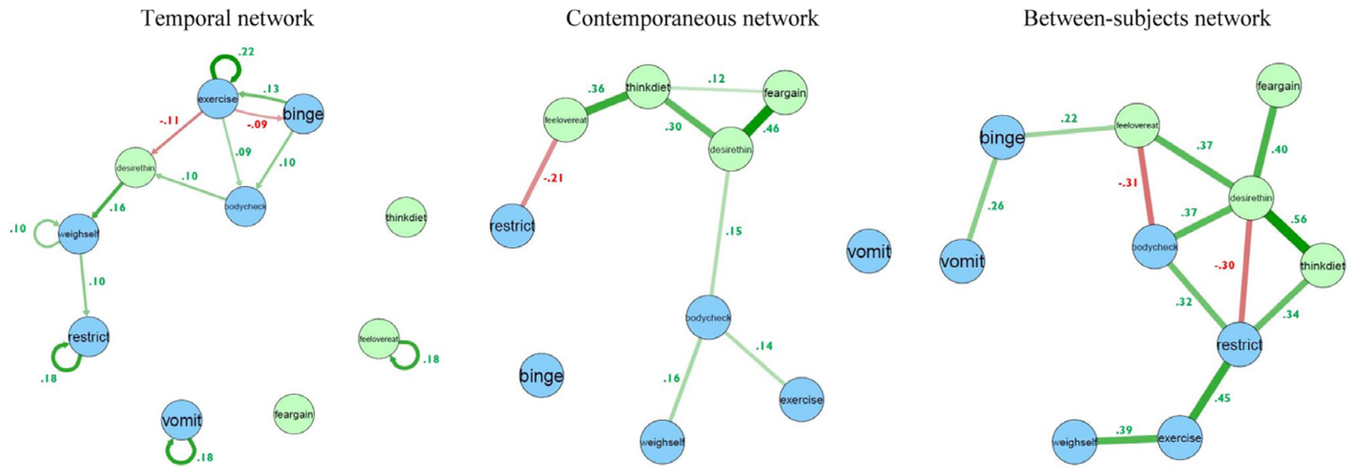

FIGURE 1 Group-level temporal, contemporaneous, and between-subject networks. *Note.* Green nodes indicate cognitions and blue nodes indicate behaviors. Green lines indicate positive relationship and red line indicate negative relationship between symptoms. Partial correlations are shown. Thicker lines between nodes represent stronger relationships. Edges that were not significantly different from zero were removed from the networks. Symptom label descriptions: Feelovereat = feel like I have overeaten; thinkdiet = thinking about dieting; desirethin = preoccupied with the desire to be thinner; feargain = terrified of gaining weight; exercise = excessive exercise; binge = binge eating; bodycheck = body checking; weighself = weighed myself; restrict = restriction; vomit = vomiting or other compensatory behaviors [Color figure can be viewed at wileyonlinelibrary.com]

from the networks presented. First, desire for thinness emerged as a central symptom across each of the group-level models (temporal, contemporaneous, and between-subject). These findings align with recent cross-sectional network analyses finding that overvaluation of weight and shape and fear of weight gain are central symptoms in BN pathology (DuBois et al., 2017; Forbush et al., 2016; Levinson et al., 2017). Indeed, the between-subjects network is a replication of these prior cross-sectional network models. Desire for thinness and

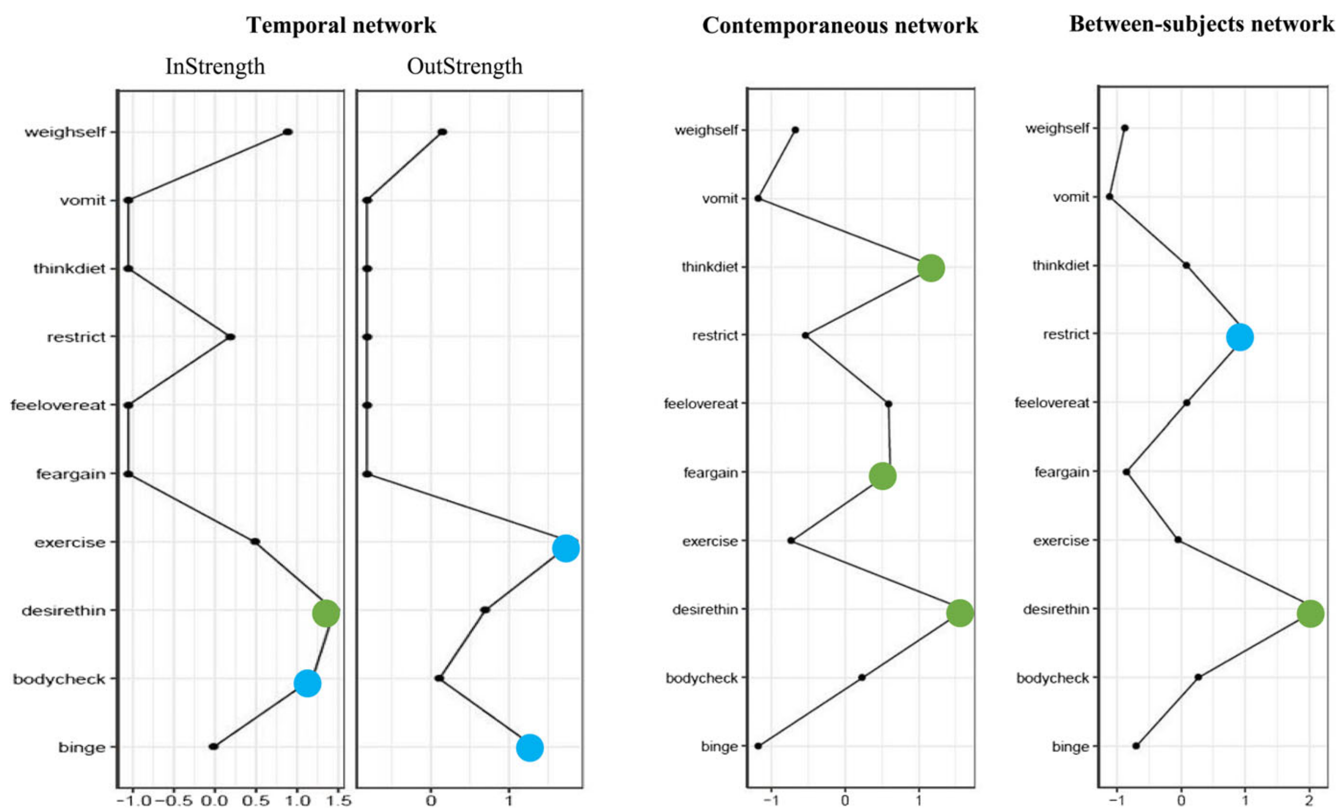

FIGURE 2 Strength centrality graphs for group-level network. *Note.* Higher values indicate that a node is more central to the network. Green dots indicate central cognitions and blue dots indicate central behaviors. Symptom label descriptions: Feelovereat = feel like I have overeaten; thinkdiet = thinking about dieting; desirethin = preoccupied with the desire to be thinner; feargain = terrified of gaining weight; exercise = excessive exercise; binge = binge eating; bodycheck = body checking; weighself = weighed myself; restrict = restriction; vomit = vomiting or other compensatory behaviors [Color figure can be viewed at wileyonlinelibrary.com]

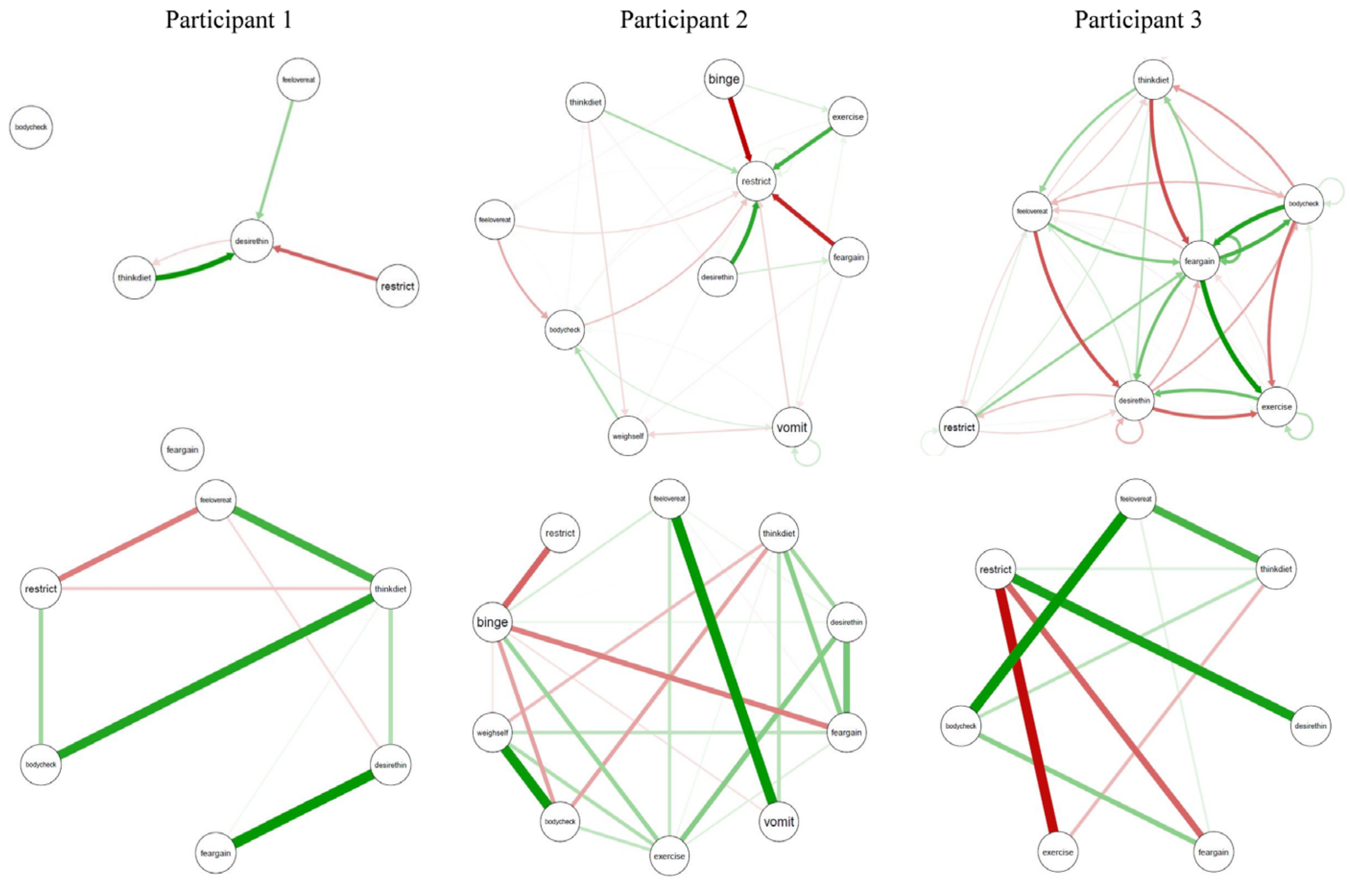

FIGURE 3 Temporal and contemporaneous networks for three individuals with AN. Temporal networks are on top; contemporaneous on bottom. *Note.* Green lines indicate positive relationship and red line indicate negative relationship. Thicker lines between nodes represent stronger relationships. Symptom label descriptions: Feelovereat = feel like I have overeaten; thinkdiet = thinking about dieting; desirethin = preoccupied with the desire to be thinner; feargain = terrified of gaining weight; exercise = excessive exercise; binge = binge eating; bodycheck = body checking; weighself = weighed myself; restrict = restriction; vomit = vomiting or other compensatory behaviors [Color figure can be viewed at wileyonlinelibrary.com]

overvaluation of weight and shape have long been considered core symptoms of ED pathology, both theoretically and empirically (e.g., Chernyak & Lowe, 2010; Dalley & Buunk, 2011; Fairburn, Shafran, & Cooper, 1999). These networks provide additional evidence that desire for thinness may play a possible maintaining role on average in ED pathology within-individuals and temporally across time.

Second, EDs are extremely heterogeneous in symptom presentation and in response to treatment. This statement is by no means a new idea in the ED literature, as much literature recognizes the heterogeneity present (e.g., Castellini et al., 2011; Eddy et al., 2008; Fairburn & Cooper, 2011; Fairweather-Schmidt & Wade, 2014; Forbush et al., 2017; Krug et al., 2013; Luo, Donnellan, & Klump, 2016; Stice, 2016; Stice, Marti, Shaw, & Jaconis, 2009; Sysko, Hildebrandt, Wilson, Wilfley, & Agras, 2010; Thomas, Vartanian, & Brownell, 2009; Tozzi et al., 2005). However, we found that even within three individuals with the same diagnosis (AN), the associations between ED pathology are vastly different. Furthermore, core symptoms that maintain AN pathology likely significantly differ across individuals. In other words, while our treatments are designed based on group-level averages and to target similar symptoms maintaining EDs across individuals, researchers need to recognize that maintaining symptoms are likely different for many, if not all, individuals who present for treatment. This extreme heterogeneity may partially explain why such high numbers of individuals do not respond to established treatments and establishes a method that researchers might use to improve existing treatments (Castellini et al., 2014; Sysko et al., 2010). Our treatments need to incorporate within-person differences in ED cognitions and behaviors and develop or tailor treatments based on these differences.

4.2 | Importance of time and type of model

While we await replication of the results presented here with additional data points and larger samples, there are some tentative fine-grained hypotheses that can be generated from the temporal, contemporaneous, between-subjects, and intra-individual network models. Each of these networks represents a different level of analysis, each holding unique insights for the ED field. Using averages (group average), we were able to parse out within and between-subjects relationships (see Figure 1). We found that weighing predicted restricting at the next time point (4 hr: temporal network), illustrating a possible causal relationship between these variables. However, there was no relationship between weighing and restricting at the same time point (contemporaneous network). This finding indicates that weighing and restriction are not occurring concurrently, but rather that weighing is leading to later restricting. Alternatively, weighing and body checking

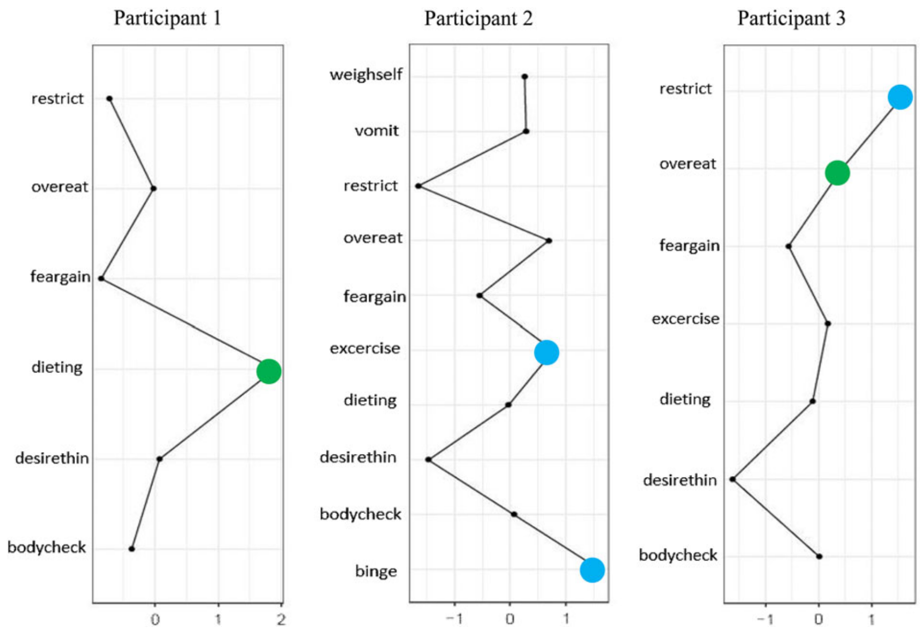

FIGURE 4 Strength centrality graphs for individual contemporaneous networks. *Note.* Higher values indicate that a node is more central to the network. Green dots indicate central cognitions and blue dots indicate central behaviors. Symptom label descriptions: Overeat = feel like I have overeaten; dieting = thinking about dieting; desirethin = preoccupied with the desire to be thinner; feargain = terrified of gaining weight; exercise = excessive exercise; binge = binge eating; bodycheck = body checking; weighself = weighed myself; restrict = restriction; vomit = vomiting or other compensatory behaviors [Color figure can be viewed at wileyonlinelibrary.com]

frequently co-occurred at the same time with a moderate relationship between these symptoms, suggesting that one may trigger another within a short time frame (contemporaneous network). Notably, there are also several negative relationships within each of these models, primarily between cognitions and behaviors. These edges might represent that cognitions are weakened by behaviors, functioning similarly to obsessions and compulsions in obsessive–compulsive disorder, which has also been supported by previous recent research (Levinson et al., 2018). These findings also show how both temporal and contemporaneous networks can offer unique insights into the structure of ED psychopathology. Finally, these results also show how understanding the time frame in the relationship between symptoms can allow us to target them more effectively and how time is important for the conceptualization of what maintains psychopathology.

4.3 | Temporal networks

A temporal network tests on average how within-individuals symptoms impact each other across time (Figure 1, model 1). This type of model allows researchers to identify longitudinal relationships among symptoms on average. In other words, on average restriction might lead to binge eating 4 hrs later. In this data, in the temporal network, which focuses on approximately a 4-hr time range, cognitions related to desire for thinness received input from exercise, binge eating, and body checking behaviors, whereas drive for thinness sent input to weighing oneself and restriction. In other words, future research should test if desire for thinness is at the crux of a complex illness pathway with several other ED cognitions and behaviors impacting themselves across time. Desire for thinness is linked to several symptoms in all three networks, which shows its importance in likely maintaining ED psychopathology for both shorter and longer time intervals, as well as demonstrating the utility of understanding how symptoms impact each other across specific time points on average across individuals (4 hr; temporal network).

4.4 | Contemporaneous networks

A contemporaneous network represents a snapshot in time (one time point), while controlling for the temporal relationships presented in the temporal network (Figure 1, model 2). This model allows researchers to identify how symptoms operate together at one time point (on average across individuals) while accounting for relationships between these symptoms in the previous measurement. Contemporaneous networks allow us to identify possible causal relationships between variables that occur faster than the measured time interval (i.e., 4 hr). For example, *feeling like one has overeaten* may trigger *thoughts about dieting* within several minutes. Such relationships would not be identified in the temporal and within-subjects network. In our data in the contemporaneous network, the four cognitions (desire for thinness, fears of weight gain, thinking about dieting, and feeling like one has overeaten) are very closely connected with the ED behaviors branching off from these closely connected cognitions. This relationship was also seen in the between-subjects network. We hypothesize that ED cognitions related to desire for thinness and fear of weight gain have a cascade effect that then impact behaviors (Arbuthnott, Lewis, & Bailey, 2015; Meeus, 2016; Selby, Anestis, & Joiner, 2008). In other words, when an individual begins thinking one ED cognition, these thoughts rapidly multiply and then influence ED behaviors. This idea is consistent with the proposition in CBT theory of a *downward spiral of thoughts* (e.g., Garner, Vitousek, & Pike, 1997). These data also show the utility of a contemporaneous network.

4.5 | Between-subjects network

A between-subjects network shows on average across individuals how symptoms relate to each other (without accounting for time) (Figure 1, model 3). To date, all network models of ED psychopathology (of which we are aware) have been cross-sectional between-subjects models. These models are important for identifying the structure of psychopathology and for how EDs operate on average. They provide a novel conceptualization of EDs (how symptoms interact and maintain themselves), which informs the fields understanding of psychopathology on average. Additionally, between-person data can inform treatment development specifically for treatments provided in group format and/or for treatment or prevention that is based on averages, signifying what targets will most likely on average be the optimal target. Our data replicate prior between-subjects networks, showing the central importance of desire for thinness/overvaluation of weight and shape (Dubois et al., 2017; Forbush et al., 2016; Levinson et al., 2017).

4.6 | Intraindividual networks

Intraindividual networks can be created within one person (Figure 3). These models show how one individuals' ED symptoms relate to each other. In the current data, in addition to demonstrating the high heterogeneity of ED cognitions and behaviors, the intra-individual networks show how network analysis might be used to funnel patients into personalized interventions and/or how to identify targets for novel personalized treatment development (see David et al., 2017; Fisher et al., 2017 for examples on how this method has been applied for treatment in the depression and anxiety literature). Thinking about dieting was the most central symptom for participant 1, formulating the hypothesis that this participant should start with treatment challenging thoughts around dieting. Binge eating and excessive exercise were the most central symptoms for participant 2, formulating the hypothesis that this participant should start treatment focused on changing behaviors. Finally, restriction and thinking about over-eating were the most central symptoms for participant 3, formulating the hypothesis that this third participant should be directed into an intervention that disrupts both behaviors (restriction) and cognitions (thinking about over-eating). Future research should test if CBT-E can be adapted into a modular format in which participants can be channeled into a unit that specifically focuses on the most central maintaining symptoms, as is being done in the anxiety disorder field with the Unified Protocol for Emotional Disorders (Fernandez et al., 2017; Fisher et al., 2017).

4.7 | Limitations and future research

We need to consider several limitations of this study. First and foremost, we had very few assessment points (28) and a small sample size. Though there are no formal recommendations or conclusions as of yet, but it has been suggested from simulation research for the mlVAR (average, within-person networks) that it is ideal to have a large sample size with many assessment points and fewer nodes, though no specific numeric guidelines exist (Epskamp, Waldorp, Mõttus, & Borsboom, 2016). More research is needed with intensive longitudinal data in a large sample of individuals with EDs. In directed networks, the issue of time-frame in which the observed processes unfolds is particularly important (Butts, 2009). If the measured interval (i.e., time between observations) is different from the time-frame in which the actual process unfolds, important relationships may not be observed. For example, if drive for thinness is followed by excessive exercising 1 hr later, a network based on measurements every 4 hr may not show this dynamic. Furthermore, our models are limited by the cognitions and behaviors we chose to include. Again, given that network analysis is a new methodology, there are no recommendations on how to choose appropriate symptoms to include in our models. We hope future researchers will consider this limitation and develop empirical recommendations for determining which symptoms to include. There are also currently no specific measures designed for use in EMA for network analysis, and therefore, we do not know the psychometric properties of the measure we used (although we did strive to utilize symptoms from existing, psychometrically strong measures that have previously been utilized in EMA protocols; Mason et al., 2017). Additionally, there has been no work yet on the replicability of within-person networks. We also do not know if these findings will replicate in larger more diagnostically diverse samples, such as those that include a larger proportion of binge eating disorder and/or bulimia nervosa. Specifically, in regard to our intra-individual networks, we need additional data to establish if within-person networks will replicate or if variations in networks are due to chance. Our results regarding the individual within-person networks should be considered with care, such that it is possible that the heterogeneity identified here could be due in part to instability in network structures. Regardless, this data shows how to apply network heterogeneity analyses to the eating disorders. We hope that future research will create stability indices to test the reliability of the networks. Finally, we should use caution when interpreting node centrality in these types of networks (Epskamp et al., 2017). We hope that future research will use psychometrically strong measures with large sample sizes and many measurement points to help elucidate strong conclusions to these questions.

Future research on heterogeneity should continue to assess heterogeneity using multiple types of models. For example, the Hierarchical Taxonomy Of Psychopathology (HiTOP) model (e.g., Kotov et al., 2017), which conceptualizes mental disorders based on dimensional taxomonies, the Research Domain Criteria approach (e.g., Insel et al., 2010), which classifies mental disorders based on underlying dimensions across multiple levels of analysis, as well as latent network models, an emerging methodology that combines latent variable and network models. These methodologies hold promise for our understanding of heterogeneity in psychopathology and we hypothesize that a combination of these methods will lead to the greatest breakthroughs.

5 | CONCLUSIONS

Despite these limitations, we think that both within- and between person network analysis and intraindividual network analysis holds significant promise for the ED field and the field of psychopathology as a whole. The data presented here can be used for generating hypotheses for future larger scale research, as well as for how to use intraindividual network analyses in ED research. Using group-level between and within person and intraindividual network analysis allows us to, for the first time, identify how ED pathology maintains itself both between and within individuals and to identify targets for novel personalized treatment development. We now have a method that can be used to address the extreme heterogeneity within EDs and to develop and adapt treatments that can more clearly address this complex form of psychopathology.

AUTHORSHIP

C.A.L. developed the concept for the study, collected data, oversaw analyses, and wrote the manuscripts. I.V. and L.B. ran analyses, assisted with conceptualization, and assisted with manuscript preparation.

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