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Authors
Frumkin, Madelyn R
Piccirillo, Marilyn L
Beck, Emorie D
et al.

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Feasibility and Utility of Idiographic Models in the Clinic: A Pilot Study

Madelyn R. Frumkin, **Marilyn L. Piccirillo**, **Emorie D. Beck**, **Jason T. Grossman**, **Thomas L. Rodebaugh**
Department of Psychological and Brain Sciences, Washington University in St. Louis

Abstract

Introduction: Idiographic, or individual-level, methodology has been touted for its potential clinical utility. Empirically modeling relationships between symptoms for a single individual may offer both the client and therapist information that is useful for case conceptualization and treatment planning. However, few studies have investigated the feasibility and utility of integrating idiographic models in a clinical setting.

Methods: Clients ($n = 12$) completed ecological momentary assessment regarding psychological symptoms five times per day for three weeks. Clients also generated predictions about the associative and directed relationships in their networks. Graphical vector autoregression was used to generate contemporaneous and directed networks from each client's data, and both clients and therapists completed self-report questionnaires regarding the feasibility and utility of these methods.

Results: Results indicated that the idiographic model structures varied widely across participants and differed markedly from the client's own predictions. Clients found the models useful, whereas their therapists demonstrated a more tempered response.

Discussion: These results echo previous findings suggesting that clients are willing to complete intensive data collection and are interested in the output, whereas therapists may be less open to idiographic methods. We provide recommendations for future implementation of personalized models in clinical settings.

Keywords

idiographic; network analysis; therapy; implementation

Researchers and clinicians alike have called for greater attention to idiographic, or single-subject, designs in psychological research (Wright & Woods, 2020). These calls have been motivated in part by numerous findings suggesting that what is true at the group level may not be true of many individuals in the group (Beck & Jackson, 2019; Beltz et al., 2016; Fisher et al., 2018; Molenaar, 2004). For example, Fisher and colleagues (2018) found that the average group-level correlation between depressed mood and worry ($r = .71$) was almost

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Correspondence regarding this article should be addressed to Madelyn R. Frumkin, Department of Psychological and Brain Sciences, Washington University in St. Louis, One Brookings Drive, Campus Box 1125, St. Louis, MO 63105. Phone: (314) 935-8627. mfrumkin@wustl.edu.

double that of the average individual-level correlation ($r = .40$, range −.11 to .89). Although we may expect a strong correlation based on the common co-occurrence of anxiety and depression, these results reflect heterogeneity in individual-level processes that may not be accurately characterized by group-level results.

Lack of group-to-individual generalizability may exist in part due to our current practice of assessing psychological disorders. The Diagnostic and Statistical Manual (DSM-5; American Psychiatric Association, 2013) defines disorders, in part, by the presence of a certain number of possible symptoms. Consequently, individuals diagnosed with the same disorder(s) can exhibit vastly different symptom profiles (Fried & Nesse, 2015). There is also overlap between diagnostic criteria that contributes to high rates of comorbidity (Kessler et al., 2005). Such heterogeneity and comorbidity seems to magnify the *therapist's dilemma* – the problem of treating a given individual using treatments developed from group-level research (Levine et al., 1992). Idiographic methods have the potential to help resolve the therapist's dilemma by providing empirical information about the relationships between symptoms for a single individual (Piccirillo & Rodebaugh, 2019). In response to the therapist's dilemma, clinical researchers have developed personalized case formulations to guide psychotherapy (Persons, 2006) and have promoted the use of client feedback in assessment (e.g., Collaborative/Therapeutic Assessment, Finn et al., 2012) and treatment (e.g., Collaborative Assessment and Management of Suicide Risk, Jobes, 2016). At their foundation, collaborative assessment techniques and therapeutic frameworks recognize the importance of incorporating client feedback to improve the utility and implementation of standard assessments and interventions. However, to our knowledge, no studies have collected or evaluated client predictions of their symptomatology and compared these predictions with clinical data. With the increased availability of ecological assessment and idiographic methods, incorporating client insight and awareness may improve the effectiveness and implementation of empirically-based assessments, treatment plans, and interventions.

Although results from idiographic methods have the potential to provide individual-level information that can be used in treatment planning, few researchers have examined the integration of idiographic models into clinical or applied settings (e.g., Kaiser & Laireiter, 2017; Schiepek et al., 2016). Even fewer researchers have examined the extent to which clients and therapists find idiographic methods useful and acceptable in understanding the individual's psychological experiences. Available data provide some indication that stakeholders find results from idiographic methods useful. For example, van der Krieke and colleagues (2015) found that community-based participants were generally positive about receiving results of idiographic networks related to their health and well-being. Similarly, Zimmerman and colleagues (2019) demonstrated that outpatient clients generally perceived idiographic models to be easy to understand and use; however, therapists reported that they gained little information from the individual-level results. Interestingly, the authors noted that many therapists expressed concern about burdening their clients with daily surveys, whereas clients ultimately reported low burden (Zimmermann et al., 2019). Results from these studies demonstrate modest support for the integration of idiographic methods into applied or clinical settings, although researchers have encountered considerably more skepticism for these methods among therapists than clients.

As the field of idiographic research grows, there is an increasing need to evaluate the application of these methods in clinical settings. Although researchers have begun to conduct clinical trials of idiographic interventions (Fisher et al., 2019), to our knowledge, Zimmerman and colleagues (2018) is the only study to have examined the perceived utility of idiographic methods in a clinical sample of treatment-seeking individuals and their therapists. Notably, Zimmerman and colleagues focused on personality pathology and behavior rather than psychological symptoms more generally. Additional research is needed to examine the utility of idiographic methods for a wider range of clinical symptomatology. The present study provides pilot data on the feasibility and utility of integrating idiographic methods into the assessment and treatment of clients seeking psychotherapy services. Importantly, we aim to take a critical view of our methods and provide clinicians and researchers with recommendations for collection and analysis of idiographic data in clinical settings.

Current Study

In the current study, we sought to construct idiographic models of client symptomatology and compare these models with the client's own predictions. We also sought to evaluate the feasibility, acceptability, and perceived utility of idiographic methods in a clinic setting. We recruited clients from the community who were seeking therapy services at the university's doctoral training clinic, as well as their student therapists. Clients completed ecological momentary assessment (EMA) of their psychological symptoms five times per day for three weeks. Consistent with a collaborative assessment framework, clients also generated predictions about the associative and directed relationships between their symptoms, and these predictions were compared to the empirical results. After completing EMA, both clients and their therapists received a copy of the client's idiographic models, along with a brief interpretation generated by the study researchers. Clients and therapists reported on their reactions to and perceptions of idiographic methods.

We hypothesized that idiographic models would differ across clients, reflecting the personalized nature of each client's symptomatology. Furthermore, we hypothesized that the clients' predictions would be largely congruent with empirical model results. Finally, we hypothesized that clients would have positive perceptions regarding the potential feasibility, acceptability, and clinical utility of these methods. In keeping with the previous literature (e.g., Zimmerman et al., 2018), we expected that therapists would have a more tempered response.

Method

Participants

Participants were clients and their graduate student therapists at a training clinic affiliated with the university's doctoral program. The training clinic provides low-cost psychotherapy on a sliding scale and does not accept insurance. Therapists were clinical science doctoral students supervised by licensed clinical psychologists. Psychotherapy was provided for psychological disorders (e.g., depression, anxiety), as well as more general concerns such as relationship issues. All clients were assessed by their therapists using a clinical diagnostic interview. As the clinic serves as an introductory practicum site for graduate students, individuals requiring a higher level of care (e.g., individuals who are acutely suicidal or engaging in high-risk substance use) are referred elsewhere.

Eligible clients were over the age of 18 and had access to a smartphone. We recruited clients who were about to begin psychotherapy or those who had already attended at least eight sessions. Timing of recruitment was designed to avoid potential violations to stationarity, as stability of the data structure (i.e., mean, variance, autocorrelation) over time is a key assumption of most time-series methods (Bringmann et al., 2017, 2018). Initial therapy sessions may produce rapid therapeutic change (Howard et al., 1986), potentially violating stationarity. Once a client was enrolled, his or her therapist was recruited and enrolled in the study.

Compensation was provided to clients either in the form of a mailed check or as a therapy credit. Clients could receive up to $45 for participating in this study. Clients received $5 for the first in-person visit and $10 for the second visit. Clients who completed at least 85% of the prompts each week during the EMA period received an additional $15. Clients were also provided an additional $15 if they completed at least 85% of the prompts during an optional second EMA period. Therapists were not compensated.

Measures

Clinical diagnoses.—The Structured Clinical Interview for DSM-5, Research Version was administered by graduate student therapists to assess for clinical diagnoses based on DSM-5 criteria (American Psychiatric Association, 2013). The clinical assessment procedure was supervised by licensed clinical psychologists and was administered as part of the standard intake for new clients, as opposed to being administered specifically for this research study.

Self-report measures.—Several self-report symptom measures were administered as part of this study. The Beck Depression Inventory (BDI-II; Beck et al., 1996) was used to assess severity of depressive symptoms. The BDI-II consists of 21 groups of statements, each corresponding to a symptom severity level from 0 (*Not present*) to 3 (*Severe*). The BDI-II has excellent internal consistency and good concurrent validity (Beck et al., 1996). Total scores on the BDI-II range from 0 to 63.

The Penn State Worry Questionnaire (PSWQ; Meyer et al., 1990) was administered to assess severity of generalized worry. The PSWQ consists of 16 items measured on a Likert-scale ranging from 1 (*Not at all typical of me*) to 5 (*Very typical of me*). Items focus on the respondent's reactions to worry as well as the pervasiveness and frequency of worry. The PSWQ has demonstrated high internal consistency and adequate-to-good test-retest reliability (Brown et al., 1992; Meyer et al., 1990). Total scores on this scale range from 16–80.

The self-report version of the Liebowitz Social Anxiety Scale (LSAS-SR; Cox et al., 1998) was administered to assess severity of social anxiety symptoms. This measure consists of 24 scenarios rated for fear or anxiety and avoidance of a given social situation. Scores on the

LSAS-SR are highly correlated with those of the clinician-administered version of the measure (*r*s = .81 to .85 among patients and .69 to .85 among non-anxious controls) and demonstrate excellent internal consistency (Fresco et al., 2001; Rytwinski et al., 2009). Total scores on this scale range from 0–144.

The Body Sensations Questionnaire (BSQ; Chambless et al., 1984) was administered to assess fear related to bodily sensations associated with panic attacks. The BSQ consists of items concerning 17 bodily sensations. Each item is rated on a 5-point Likert scale from 1 (*Not frightened or worried by this sensation*) to 5 (*Extremely frightened by this sensation*). The BSQ has high internal consistency and each item has demonstrated the ability to differentiate between normal controls and people with agoraphobia (Chambless et al., 1984). Total score was measured as mean score across items.

Ecological Momentary Assessment (EMA) Items.—All participants were administered eight core EMA items, which were selected based on the availability of an empirically-supported intervention for the symptom or experience. In addition, participants were given the option to personalize their EMA survey by including up to three items from a bank of six optional symptoms (see Table S1). For each item, clients rated their current experience on a scale from 1 (*Not at all*) to 10 (*A lot*). Participants were prompted to report on their present emotional experience at the time of the survey. Items were presented in random order at each prompt.

Client and Therapist Attitude Measures.—Self-report measures were developed for this study to assess client and therapist attitudes towards EMA and results from the personalized models. These items were designed to optimize face validity. Text and descriptive statistics for attitude measure items are presented in Table S2. The full measures and further details regarding these measures are included in the supplementary material (see Appendix A).

Procedure

Client procedure.—Individuals who called the clinic requesting psychotherapy between July 2018 and July 2019 received a short description of the study as part of the standard phone intake. Individuals accepted as new clients at the clinic were then contacted and enrolled by the first authors if they had expressed initial interest in the study. The first authors also shared information about the study with the graduate student therapists, who then shared a recruitment flyer with any clients who had been in therapy for at least eight sessions. Interested clients were then contacted and enrolled by the first authors.

There were two possible waves of data collection for each participant that took place at least three months apart. The first session of Wave 1 was conducted at the clinic. Informed consent was first obtained and the client selected the schedule to complete EMA. Next, clients reviewed the core EMA items and had the opportunity to select up to three additional items from a personalized bank of EMA items (see supplementary materials Table S1).

Clients then completed the model prediction procedure. Clients were shown an example of an associative and directed model and were given instructions regarding how to interpret the models. Clients first drew circles around any items they believed to be most strongly connected, representing predicted composites. Clients then selected up to three items they thought to be the most important to understanding their experience, as well as up to three items they believed to be the least important. These items represented the clients' predictions for items with the most and least strength centrality in the network. Lastly, clients drew associations between symptoms, as well as predicted causal pathways between symptoms over approximately three hours. Notably, therapists did not see the clients' predictions at any point in the study. Clients also completed a battery of self-report questionnaires and a survey regarding attitudes about EMA and idiographic models.

Clients then completed three weeks of EMA. EMA surveys were delivered via a smartphone application (LifeData) every three hours during a self-selected 12-hour period, for a total of five surveys per day. Surveys were available to complete for a period of 30 minutes and clients received up to two reminder notifications after the initial survey prompt. Clients were emailed periodic updates with regard to their EMA completion rates and were asked to share any technical issues or concerns that arose during the EMA period. Clients completed at least 21 days of EMA (maximum 24 days).

After completing the EMA period, clients then returned for a second in-person session, during which they were presented with a feedback report that featured their associative and directed models, as well as descriptions of significant paths and potential interpretations of the two models. Clients were debriefed on the limitations of the study and were given an opportunity to ask questions or share concerns about the models. Clients then completed self-report questionnaires about their current levels of symptoms, as well as a self-report measure assessing their attitudes towards the EMA and their idiographic models (see Supplementary material, Appendix A).

Approximately three months after completion of Wave 1, clients were invited to complete a second EMA protocol using similar methods. A second idiographic model was created and shared with the client and therapist. Clients completed self-report questionnaires about their current levels of symptoms, and both clients and their therapists completed self-report measures regarding their reactions to the results of the client's models.

Therapist procedure.—After a client enrolled in the study, one of the first authors invited the therapist of the client to participate in the study. Interested therapists provided informed consent and completed a brief questionnaire assessing attitudes towards the potential utility of idiographic models. After a client completed Wave 1 EMA, their therapist was given an identical copy of the feedback report to review. The therapist then completed a brief self-report measure assessing their attitudes regarding the utility of their client's models (see Supplementary material, Appendix A).

Data Analytic Plan

Idiographic models.—All data preparation was conducted in R using several packages (details available in supplementary material). Idiographic models were constructed using graphical vector autoregression (GVAR) in the graphicalVAR package (version 0.2.3; Epskamp, 2018). GVAR uses a network analytic framework to model both associative (i.e., contemporaneous) and partial directed (i.e., regressive) pathways between all items in the network, which are all depicted as partial correlations (Wild et al., 2010). GVAR uses a graphical least absolute shrinkage and selection operator (LASSO) approach that combines regularizing tuning parameters with a selection procedure to reduce relationships and prevent overfitting (Epskamp & Fried, 2018; Wild et al., 2010). This approach has been demonstrated to provide good specificity and sensitivity for effects in individuals when the number of time points is similar to those in the present study (Epskamp, 2016). Missing data were handled by specifying day and survey variables within the graphicalVAR() function in the graphicalVAR package in R. Doing so inserts rows for missing surveys within days and for overnight periods, which restricts lagged associations to the observed lag length (e.g., 3 hours). The layout of the idiographic models was based on the Fruchterman-Reingold algorithm, such that the length of an edge corresponds to its absolute weight (Epskamp et al., 2012; Fruchterman & Reingold, 1991).

Before GVAR analyses, a zero-order correlational analysis was conducted for each individual to evaluate whether there were items that exhibited large correlations ($r > .65$). To reduce concerns regarding multicollinearity, which may suppress or change inter-item relationships, items with large correlations were composited using equally-weighted averages at each time point and the composite variable was entered into the GVAR model. Additionally, we assessed zero-order correlations between study items and day and survey number to test for day and survey effects. If any variable exhibited a correlation with day or survey of $r > .30$, then day, survey, or day and survey (depending on the pattern of correlations) were regressed on each item and the residuals were extracted. The residualized data were used in the GVAR analysis to account for systematic effects of time. Potential for composites and residuals was examined for both waves of EMA data. Thus, it is possible that items presented in an individual's models differed across the two waves.

For centrality of symptoms, we report standardized (z) centrality estimates to allow for comparison across participants and waves of data. Strength estimates (i.e. the sum of edges for a focal node) were standardized within-person separately for each wave, such that a standardized score of zero indicates the average node strength for that wave and positive and negative scores indicate a higher or lower than average strength, respectively, in standard deviation units for that wave and person.

Agreement between predicted and empirical models.—Correlational analyses were conducted to determine the level of congruence between the participant's predicted models and his or her GVAR models. As the participants were asked to predict the presence or absence of pathways (rather than predict values for edge weights), we first converted the weighted edges of the empirical GVAR networks to −1 (negative relationship between two symptoms), 0 (no relationship between two symptoms), and 1 (positive relationship between two symptoms). Predicted models were coded in the same way to allow for direct comparison of the two networks. We then computed profile correlations between the GVAR and predicted networks to assess the degree to which each participant's predictions matched his or her GVAR model. A positive correlation would suggest concordance in predicting both the presence and direction of relationships, a negative correlation would suggest some concordance in predicting the presence but not direction of relationships, and a correlation near zero would suggest general discordance in predicting relationships. These correlations were also averaged across the group to assess group-level concordance in predictions. In addition to profile correlations, we also examined similarities in the items that clients identified as being the most and least important symptoms in their network and the items that were identified in the empirical networks as having the most and least strength centrality.

Feasibility and utility.—Self-report measures of client and therapist attitudes towards EMA and idiographic results were assessed using descriptive statistics, including frequencies and measures of central tendency and dispersion (i.e., mean, standard deviation).

Results

Participant Characteristics

A total of 17 clients initially enrolled in the study, and 12 clients completed Wave 1 EMA (see Figure 1). Selected client demographic and diagnostic information is presented in Table 1. Of the five clients who did not complete Wave 1 EMA, two clients were not able to download the EMA app, two withdrew from the study prior to completing EMA, and one withdrew from the study during the EMA period due to termination of treatment. Clients who completed EMA did not appear to differ systematically from those who did not complete EMA. However, full demographic and clinical characteristics were not available for some clients who did not complete the study.

The majority of clients who completed EMA were female (n = 7, 58.33%) and White (n = 10, 83.33%). The average age was 33.67 (SD = 12.13). The average session fee among participants was $25.67, corresponding with an average annual income ranging from $26,000 to $32,000. Most clients (91.67%) met criteria for multiple clinical diagnoses (M = 2.83, SD = 1.59, range: 0 to 5). Depressive disorders (n = 9) and generalized anxiety disorder (n = 5) were the most frequently diagnosed, although personality disorders (n = 4) were also common. Overall EMA compliance rates were good, with participants completing 84.9% of surveys on average. Participants completed an average of 94 surveys (range 69 – 117).

Model Prediction

Descriptive statistics for the individual EMA items can be found in Table S1 of the supplementary material. The profile correlation between predicted and empirical edges for each participant ranged from −.18 to .36 (M = .05, SD = .17) for the contemporaneous networks and from −.05 to .12 (M = −.01, SD = .06) for the lagged networks. On average, the very low correlations for the contemporaneous and lagged networks suggest that participants’ expectations about relationships between symptoms within and across time did not match the empirical networks. However, there was also substantial range in the size and valence of these correlations suggesting considerable interindividual variability, particularly for contemporaneous networks. Profile correlations are presented in Table S2 in supplementary material.

Attitudes towards EMA and Personalized Models

Wave 1, Session 1 Attitude Surveys.—All 17 clients completed Wave 1, Session 1 Attitude self-report measures prior to beginning EMA. Most clients (*n* = 12, 70.59%) agreed or strongly agreed that sharing the results of their personalized models would help their therapist understand and work on their problems. Most clients (*n* = 15, 88.24%) agreed or strongly agreed that the EMA surveys would make them more aware of their mood and symptoms, and three clients (17.65%) thought that being more aware of their symptoms would make them feel worse. Nearly half (*n* = 7, 47.06%) reported that they thought answering the EMA surveys would be burdensome[1]. Additionally, approximately half (*n* = 9, 52.94%) said that they thought their symptoms changed every three hours, whereas the remaining clients (*n* = 8, 47.06%) reported that they thought their symptoms changed every six hours.

All therapists of clients in the study completed the Wave 1, Session 1 EMA measures, with the exception of two therapists whose clients dropped out prior to completing the EMA protocol. A total of 12 therapists participated in the study, three of whom completed the study on behalf of two different clients. Of the 12 therapists, nearly all (*n* = 11, 91.67%) agreed or strongly agreed that individualized models could be helpful for treatment planning. Half of the therapists also reported that they were familiar with idiographic methodology (*n* = 6, 50%). Of note, the fourth author was also a therapist in this study but did not assist in the collection of the data. Results remained similar after removing his data from this analysis.

Wave 1, Session 2 Attitude Surveys.—Of the 12 clients who completed Wave 1 EMA, 11 completed Session 2 Attitude surveys. Most clients (*n* = 9, 81.82%) reported that completing EMA made them more aware of their mood and symptoms. There were three clients (27.27%) who reported that they felt worse when they were more aware of their symptoms. Similarly, three clients (27.27%) reported that completing the daily surveys was burdensome. After receiving a copy of their GVAR models, most clients (*n* = 7, 70%)[2] agreed that their model accurately described their symptoms. Most clients (*n* = 8, 80%) also agreed or strongly agreed that sharing these results would help their therapist understand and work on their problems, and half (*n* = 5, 50%) agreed that they would be able to use the results from these models to make changes on their own to improve their mental health.

All therapists of clients who completed Wave 1 EMA also completed the Wave 1, Session 2 Attitude survey (*n* = 12). Notably, this includes one therapist who completed the post-EMA survey on behalf of two separate clients. Most therapists (*n* = 8, 66.67%) agreed or strongly agreed that their client's models were easy to understand. Over half of therapists (*n* = 7, 58.33%) also agreed or strongly agreed that the results of the models matched their conceptualization of their client. There was no clear consensus on whether the models provided additional information about their client that they did not already know – four

[1]There was an error in the wording of this item such that participants responded to the burdensomeness of answering EMA surveys seven times per day, instead of five times a day (which corresponds to the five daily prompts). Thus, it is possible that the level of projected burden endorsed here is artificially higher.

[2]One client missed the back page of the survey, so this and the following two percentages are out of 10 participants.

therapists disagreed, four were neutral, and four agreed that the model provided additional information. Half ($n = 6$, 50.00%) agreed that they were likely to use their client's model in case conceptualization and/or treatment planning, whereas others ($n = 5$, 41.67%) were neutral. However, less than half ($n = 4$, 33.33%) agreed that the results of the model would inform their clinical work with their client. Others ($n = 5$, 41.67%) provided a neutral opinion and two therapists disagreed that the model would inform their clinical work with their client going forward. Descriptive statistics from attitude measures is presented in Table S3 in the supplementary material.

Idiographic GVAR Models

Results of the GVAR models varied widely across participants. Out of the four initial participants who provided data for both Wave 1 and Wave 2, we selected two exemplar participants who differed from each other based on length of time in therapy and number of psychiatric diagnoses. Descriptive statistics of EMA items for both participants are available in Table S4. Models for all participants from both time points are available in the supplementary materials and at https://emoriebeck.shinyapps.io/PSCEMA/). For the two exemplar patients, we provide a brief background on their clinical history and present results from their predicted and empirical GVAR models.

Participant 009.—Participant 009 was recruited for the study before beginning therapy. His presenting concern was relationship problems, and he did not meet criteria for any current diagnoses. In addition to the core EMA items, he chose to report on feeling dissatisfied with his appearance, feeling dissatisfied with his relationships, and thinking about a past trauma[3]. At Wave 1, this participant reported mild depressive symptoms and moderate levels of worry.

Participant 009 predicted that the most important items in his network would be feeling worried, feeling dissatisfied with relationships, and experiencing physical pain or discomfort; in contrast, his contemporaneous empirical model suggested that thinking about past trauma ($z = 1.58$) and difficulty concentrating ($z = .96$) were the strongest items in his network. Similarly, he predicted that feeling drowsy, feeling lonely, and having difficulty concentrating would be the least important items in his network, whereas his contemporaneous empirical model suggested that feeling drowsy ($z = -1.27$), feeling dissatisfied with appearance ($z = -.87$), and a loneliness ($z = -.37$) were the three weakest items in his network. Participant 009 also predicted several composites among his symptoms, many of which included worrying about the future. Indeed, worry was strongly correlated with feeling down, ruminating, feeling dissatisfied with relationships, and pain or discomfort (rs = .64 to .82). Therefore, these five items were composited into one item labeled negative affect.

Participant 009's predicted and raw empirical network can be visually compared in Figure 2. For the empirical results, we will focus on the composited and residualized networks, as these networks account for concerns regarding multi-collinearity and systematic effects of

[3]The client labeled his previous divorce as a past trauma, although further assessment suggested that this event could not be classified as an event that would be relevant to post traumatic stress disorder.

time. Specifically, the highly correlated items are composited into one item labeled negative affect. For this participant, some symptoms also tended to improve over the course of the day (i.e., difficulty concentrating, $r = -.33$) and worsen over the course of the study (i.e., drowsiness, $r = .38$). To account for systematic effects of time, day and survey were regressed onto all EMA items and the residuals were entered into the GVAR model.

Participant 009 predicted several contemporaneous relationships between rumination and worry, difficulty regulating emotions, physical pain, and feeling dissatisfied with his relationships. Thus, the creation of the negative affect composite was congruent with many of these predictions. However, when examining this composite in the contemporaneous model, there were some relationships that were not congruent with his predictions. For example, the strongest contemporaneous relationships were between thinking about past trauma and difficulty concentrating ($r = .11$), feeling lonely ($r = .10$), and dissatisfaction with appearance ($r = .06$). Notably, some of these items also displayed a restricted range (i.e., 1 to 5), suggesting that data for these variables may violate the normal distribution assumption of these analyses (see Table S4).

Participant 009's predicted directed paths largely involved predictors of physical pain (i.e., ruminating about the past, worrying about the future, and feeling dissatisfied with relationships). In his empirical model, however, all of these symptoms were included in a negative affect composite variable. In contrast to his prediction that trauma and dissatisfaction with relationships would prospectively predict rumination, his empirical model showed that the negative affect composite, which includes rumination and dissatisfaction with relationships, prospectively predicted thinking about a past trauma ($r = .13$). His empirical directed network also suggested several additional autoregressive and directed relationships that he did not predict. Negative affect ($r = .47$), dissatisfaction with appearance ($r = .46$), difficulty concentrating ($r = .09$), loneliness ($r = .22$), feeling drowsy ($r = .05$), and thinking about trauma ($r = .04$) all predicted themselves over time, suggesting that his symptoms tended to persist over the three-hour lags. There were also several potential feedback loops among his symptoms. For example, dissatisfaction with appearance predicted negative affect ($r = .14$), negative affect predicted difficulty concentrating ($r = .10$), and difficulty concentrating predicted negative affect ($r = .14$). Negative affect also predicted difficulty managing emotions over the three-hour lag ($r = .14$). Overall, his predicted model exhibited minimal overlap with his empirical model.

Participant 009 also completed Wave 2 of the study approximately three months later after completing a total of 18 sessions of therapy. Participant 009's Wave 2 model showed fewer directed relationships than his Wave 1 model. Negative affect predicted dissatisfaction with appearance ($r = .13$; different from Wave 1). Negative affect also exhibited a strong autocorrelation ($r = .42$), or persistence over time. Notably, Participant 009 utilized a larger range on most items at Wave 2 as compared to Wave 1 (see supplementary materials Table S4), suggesting that his Wave 2 data better met the assumptions of multivariate normality.

Participant 006.—Participant 006 was recruited for the study after completing 14 weekly therapy sessions focused on cognitive-behavioral treatment for generalized anxiety disorder. In addition to the core EMA items, she chose to report on feeling dissatisfied with her appearance, feeling dissatisfied with relationships, and experiencing an urge to complete a ritual. At the time of the study, this participant was reporting mild depressive symptoms and moderate levels of worry.

Participant 006 predicted that the most important items in her network would be rumination, feeling worried, and feeling dissatisfied with her relationships, and the least important items would be experiencing the urge to complete a ritual, experiencing physical pain or discomfort, and feeling drowsy. In contrast, her contemporaneous empirical network demonstrated that the strongest items were rumination ($z = 2.02$) and feeling drowsy ($z = 2.02$). All other items were unconnected, making them the weakest items in her empirical network. She also predicted several composites that were not demonstrated in her empirical model.

Participant 006's predicted and raw empirical network can be visually compared in Figure 3. For the empirical results, we will focus on the residualized networks that account for systematic effects of time. For this participant, some of her symptoms worsened over the course of the study, including dissatisfaction with appearance ($r = .44$), physical pain ($r = .36$), and rumination ($r = .31$), whereas dissatisfaction with relationships improved over the course of the study ($r = -.46$). Participant 006 predicted several contemporaneous pathways, including relationships between worry, difficulty concentrating, feeling down, and ruminating about the past. However, her empirical model showed only one contemporaneous relationship between feeling drowsy and rumination ($r = -.01$). Additionally, she predicted that worry would lead to increases in several variables later on, including greater rumination, difficulty regulating her emotions, and feeling dissatisfied with her appearance and relationships; however, her empirical model did not demonstrate any directed pathways.

Participant 006 began Wave 2 of the study approximately seven months after finishing Wave 1. During this time she had continued to receive weekly therapy, and she successfully terminated therapy shortly after completing Wave 2. In contrast to Wave 1, her Wave 2 model contained several pathways. The composite of feeling dissatisfied with her appearance and feeling worried was associated with greater physical pain ($r = .09$) and greater difficulty concentrating ($r = .11$). Difficulty concentrating was positively associated with difficulty managing emotions ($r = .16$) and increased rumination ($r = .17$), which was positively associated with feeling down ($r = .004$). Her directed model demonstrated that when she was having difficulty regulating her emotions, she was more likely to feel dissatisfied with her relationships three hours later ($r = .18$). Similarly, when she was feeling down, she was more likely to feel lonely later on ($r = .36$). In contrast, experiencing the urge to engage in a ritual predicted feeling less lonely later ($r = -.07$). Physical pain also predicted itself over time ($r = .17$). In summary, this participant's empirical models displayed little relationship to her predicted models and her empirical models differed from Wave 1 to Wave 2.

Discussion

Idiographic methods are cited as promising analytic tools for building personalized directives for psychological treatment (Fisher et al., 2019; Fried et al., 2017; Hofmann et al., 2016; Piccirillo et al., 2019). To date, there is limited research that has examined the integration of these methods into clinical settings. In the current study, we constructed idiographic models from a treatment-seeking sample and examined client and therapist attitudes towards idiographic methodology.

Clients' reactions to EMA and resulting idiographic models were largely positive. Prior to completing EMA, seven clients reported that answering the EMA surveys would be burdensome, whereas only three clients continued to hold this opinion after completing EMA. Those who completed the EMA period were highly compliant and there was only one client who discontinued the study during the EMA period as a result of their decision to seek treatment elsewhere. Some clients reported that the EMA made them more aware of their symptoms and that they felt worse when they were more aware of their symptoms. Importantly, given the phrasing of these items, we cannot conclude that EMA completion was directly related to clients feeling worse. With one exception, the individuals who predicted that completing EMA would be effortful and would make them more aware of their symptoms were not the same individuals who reported that completing EMA was burdensome or made them more aware of their symptoms. Most clients agreed that the idiographic models accurately described their symptoms and that these models could help their therapist understand and work on their problems.

Overall, therapists were also optimistic that the results from idiographic models would be useful prior to receiving their clients' models. Most therapists agreed that the models they received were easy to understand and matched their conceptualization of the client; however, therapists were split as to whether the model provided additional information that would be useful in therapy going forward. Thus, on the whole, both clients and therapists found these personalized methods to be acceptable, but clients tended to perceive more utility from these methods than therapists. These results echo findings from Zimmerman and colleagues (2019), in which therapists were ultimately more skeptical than clients regarding the potential utility of idiographic models. Importantly, given the sparseness of the models, it is possible that therapists in the current study remained optimistic about idiographic models but did not find their clients' models to be particularly useful.

Counter to our hypotheses, most clients did not predict paths that were ultimately demonstrated in their empirical models. Based on this finding, it is possible that clients have limited insight into the relationships among their symptoms, suggesting that empirical models may assist with treatment planning. However, we are cautious about this conclusion and offer alternative explanations for consideration. First, clients typically did not predict autoregressive pathways, despite such pathways being present for the majority of clients. This may reflect a lack of client understanding regarding autoregressive paths, possibly due to insufficient instruction regarding autoregressive paths during the model prediction protocol. However, our experience even among researchers familiar with idiographic models is that it may be more difficult to conceptually understand the implications of autoregressive paths compared to cross-lagged pathways. That is, even among researchers familiar with this area of research, there may be a bias towards prioritizing cross-lagged pathways. Secondly, we considered the possibility that agreement between predicted and empirical networks was low because the empirical networks were based on partial correlations. Partial correlations may be more difficult for participants to conceptualize and, thus, comparing their predicted model to an associative network may be a more fair comparison. However, upon further examination, agreement was similarly low when considering associative networks (these models are available for comparison at https://emoriebeck.shinyapps.io/PSCEMA/).

An additional possible explanation of the low concordance between predicted and empirical models is that the empirical models generated may be inaccurate depictions of clients' true underlying models. Empirical models are susceptible to error from numerous sources, including self-report bias, influence of unmeasured variables, and non-optimal timing of assessments. Although we collected a large sample of observations compared to previous studies, it is also possible that we were underpowered to uncover small effects, which would limit the accuracy of the empirical models. Thus, we cannot conclude that the empirical models are a reasonably accurate representation of the client's symptomatology without future tests of validity of such models. Consequently, our comparison can only determine the level of concordance, rather than the accuracy of either the clients' expectations or the empirical models. Further research is needed to understand how accurately idiographic models capture what is true for a given individual.

In this study, we offered potential interpretations of the idiographic models for two clients. Participant 009's empirical model showed many contemporaneous and directed paths, including a potential feedback loop between dissatisfaction with his appearance, negative affect, and difficulty concentrating. It is possible that therapy targeting these symptoms would ultimately be useful, especially in the absence of diagnostic information to guide treatment planning. In contrast, Participant 006's Wave 1 empirical model did not exhibit any directed pathways. In our experience, this sparseness in idiographic networks is not uncommon; however, the implications are unclear. At the group level, it has been suggested that individuals with more densely connected symptom networks are likely to experience more severe psychopathology, as network density may imply resistance to change in negative emotions (Pe et al., 2015). This proposition would suggest that the participants in our study, many of whom met criteria for multiple psychological disorders, should exhibit dense networks. However, we observed more sparse than dense networks among our participants overall. For example, Participant 006's model did not contain any directed pathways at Wave 1, despite meeting diagnostic criteria for GAD and reporting high levels of worry on the PSWQ. Furthermore, Participant 006 demonstrated clear decreases in depression and worry between Waves 1 and 2, yet her Wave 2 directed model was considerably denser than her Wave 1 model. Thus, this study provides no clear guidance regarding the relationship between symptom levels and network density, except to suggest that reductions in symptoms do not invariably result in less-dense networks. Further research at both the group and individual level is necessary to improve understanding of the relationship between network density and symptom severity.

The current study used minimal selection criteria, increasing our ability to examine the effectiveness of these methods in a clinically heterogeneous sample of individuals. However, the sample was primarily White and female, limiting our ability to generalize outside of this population. Feasibility and acceptability of EMA and idiographic methods should be examined in larger samples that are more representative of the entire population of therapy-seeking individuals. Additionally, clients in the current study were provided modest financial compensation for completing the first wave and additional compensation for completing the second wave (total possible compensation was $45 across both waves). Future research is needed to determine whether EMA and idiographic methods are feasible and acceptable in purely clinical contexts in which compensation is not provided. In these contexts, clients may be more willing to participate if their therapists view these methods as valuable to treatment planning. Notably, many existing empirically supported treatments (e.g., behavioral activation, cognitive behavioral therapy, dialectical behavior therapy) ask clients to complete daily monitoring of symptoms. This monitoring could be completed through EMA or electronic daily diary methods and used for both treatment and assessment purposes.

Furthermore, we recruited both clients and their therapists, allowing for a more holistic assessment of attitudes towards idiographic methods from relevant stakeholders. However, it should be noted that the therapists in the current study reported some familiarity with idiographic methodology and most therapists in this study maintained personal and professional relationships with the authors. Despite this degree of familiarity, therapists remained less optimistic than clients about the potential utility of idiographic models. Without this familiarity bias, we may expect therapists to have more negative reactions to idiographic methods. Thus, further research is needed to understand the challenges of integrating idiographic methodology into clinical settings while accounting for provider's attitudes.

We present several methodological considerations that pose challenges to future implementation research. For example, some participants did not utilize the full scale of some items, resulting in a categorical rather than continuous variable structure that violates the assumptions of our time series analytic methods. However, simulation data suggests that the sensitivity and specificity of paths identified in a network are similar across both continuous and ordinal data (Epskamp, 2016). Regardless, sufficient variability is needed to determine directed effects of symptoms. In our ongoing data collection efforts, we use a 0–100 response scale to potentially increase the likelihood of obtaining multivariate normality and a more continuous variable structure. Furthermore, the appropriate timescale for EMA items remains an empirical question as standardized guidelines are not currently extant. We administered assessments every three hours; however, preliminary simulation evidence suggests that assessments completed every few hours are unable to capture true symptom dynamics when the system is fluctuating on the order of seconds (Haslbeck & Ryan, 2019). This may help to explain why directed networks rarely matched an individual's predictions. That is, predicted prospective relationships among variables may have existed, but over a shorter time scale than was assessed here. Empirical methods are being developed to assist in selecting the appropriate lags for time series data (e.g., Differential Time-Varying Effect Model; Jacobson et al., 2019). Given that the appropriate timescale might differ between individuals, further research is needed to understand how to best design a study that captures personalized fluctuations in symptoms of interest.

Finally, it would be ideal to use an analysis method that directly models time. In the current study, we regressed out significant effects of time in order to best satisfy stationarity requirements, and we prevented the models from regressing across improper lag lengths (e.g. missing data and overnight periods). Alternative methods are able to directly model time, such as time-varying VAR (Bringmann et al., 2018), time-varying mixed VAR (Haslbeck & Waldorp, 2015), and, to a lesser extent, dynamic structural equation modeling (DSEM; Asparouhov et al., 2018). However, TV-VAR and TV-mVAR require many more time points and limit the number of variables that can be examined at one time. DSEM could be conducted in the current data. However, in idiographic models, DSEM can only model trends (e.g., in mean levels) and not changes in how variables relate over time. A thorough comparison of these different methods using appropriate data would be highly useful to the field.

Despite these limitations, we believe that this study provides initial information regarding the feasibility and challenges of integrating idiographic methods into clinical settings. Although assessment burden remains a concern, this study importantly adds to a growing body of evidence that clients are interested in the results of EMA and other forms of intensive longitudinal data collection (Bos et al., 2019). However, therapists in the present study reported more skepticism than clients, echoing prior work (Zimmerman et al., 2019). Ultimately, future implementation research is necessary to determine how and to what extent idiographic methods can be useful to both clients and therapists.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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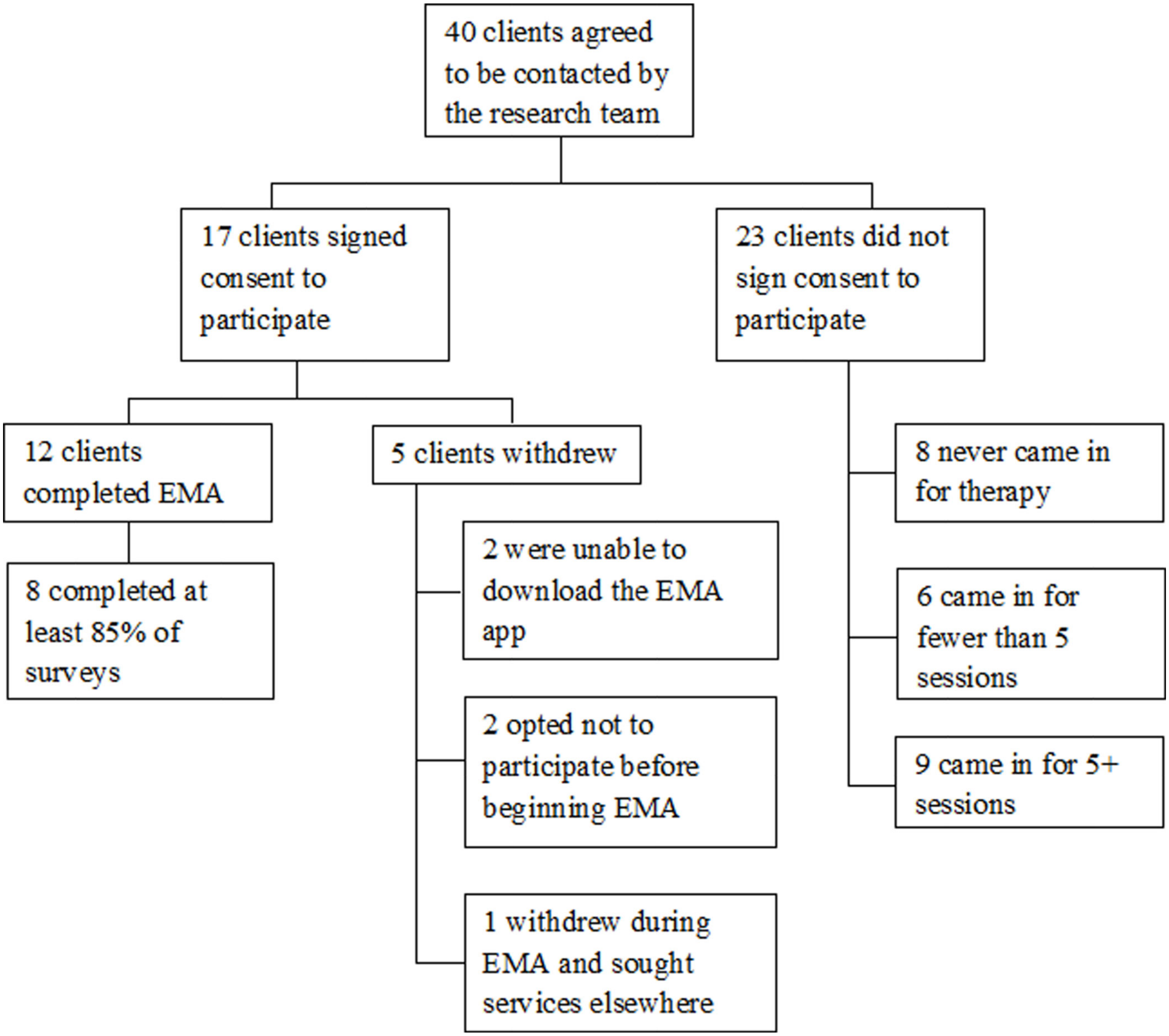

Figure 1.
Flow chart of study participation. EMA = ecological momentary assessment.

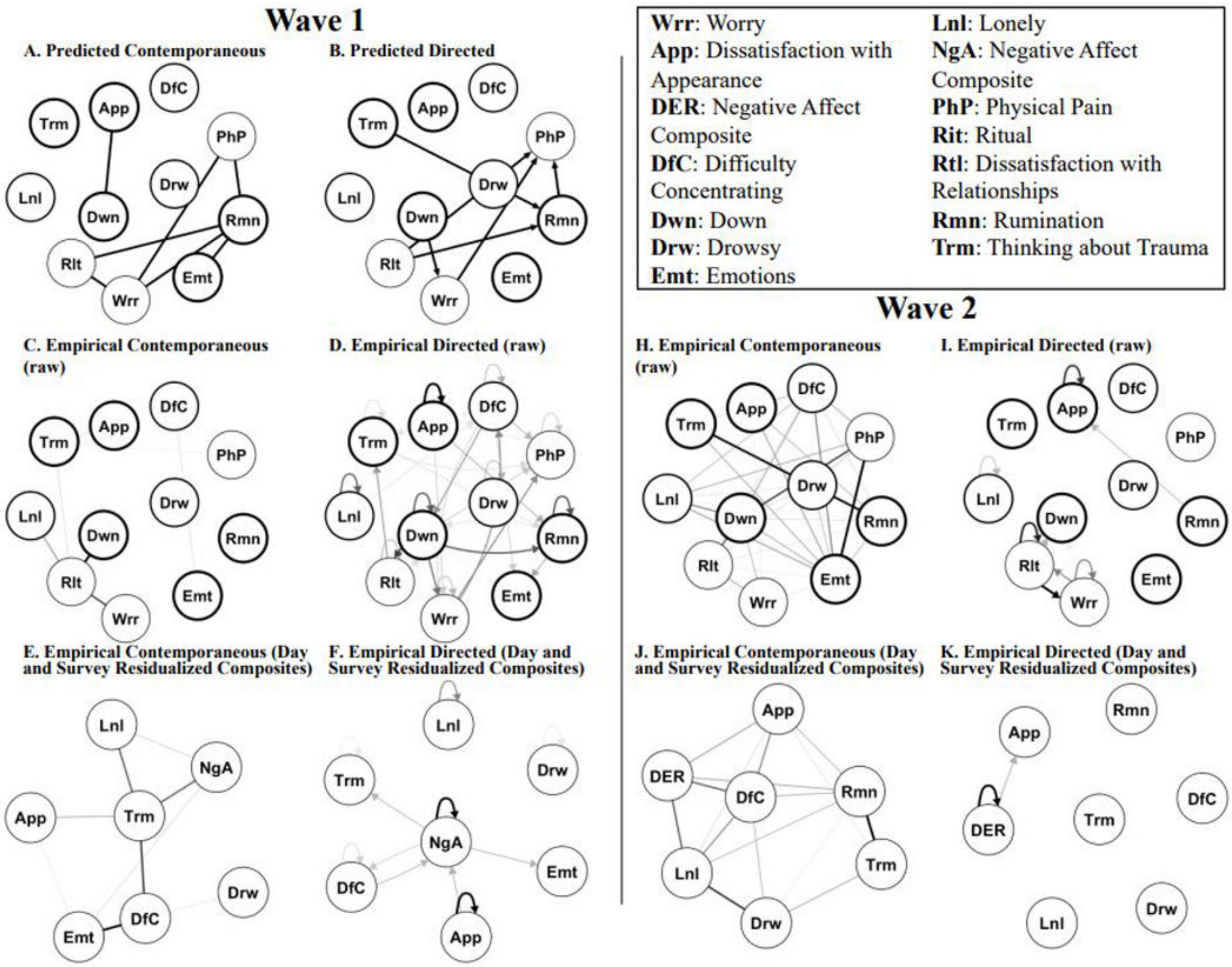

Figure 2.

Wave 1 and Wave 2 Networks for Participant 009. The top row represents Participant 009's predicted networks, the middle row represents raw empirical results (no composites or residualizing), and the bottom row represents the results that clients and therapists were shown. Solid lines indicate positive relationships, dotted lines indicate negative relationships, and thicker lines indicate stronger relationships. The arrangement of the nodes in the top two rows is based on the spring-based Fruchterman-Reingold algorithm of the Empirical Contemporaneous (raw) results in Wave 1. The layout of each model in the bottom row was allowed to vary freely using the spring-based Fruchterman-Reingold algorithm.

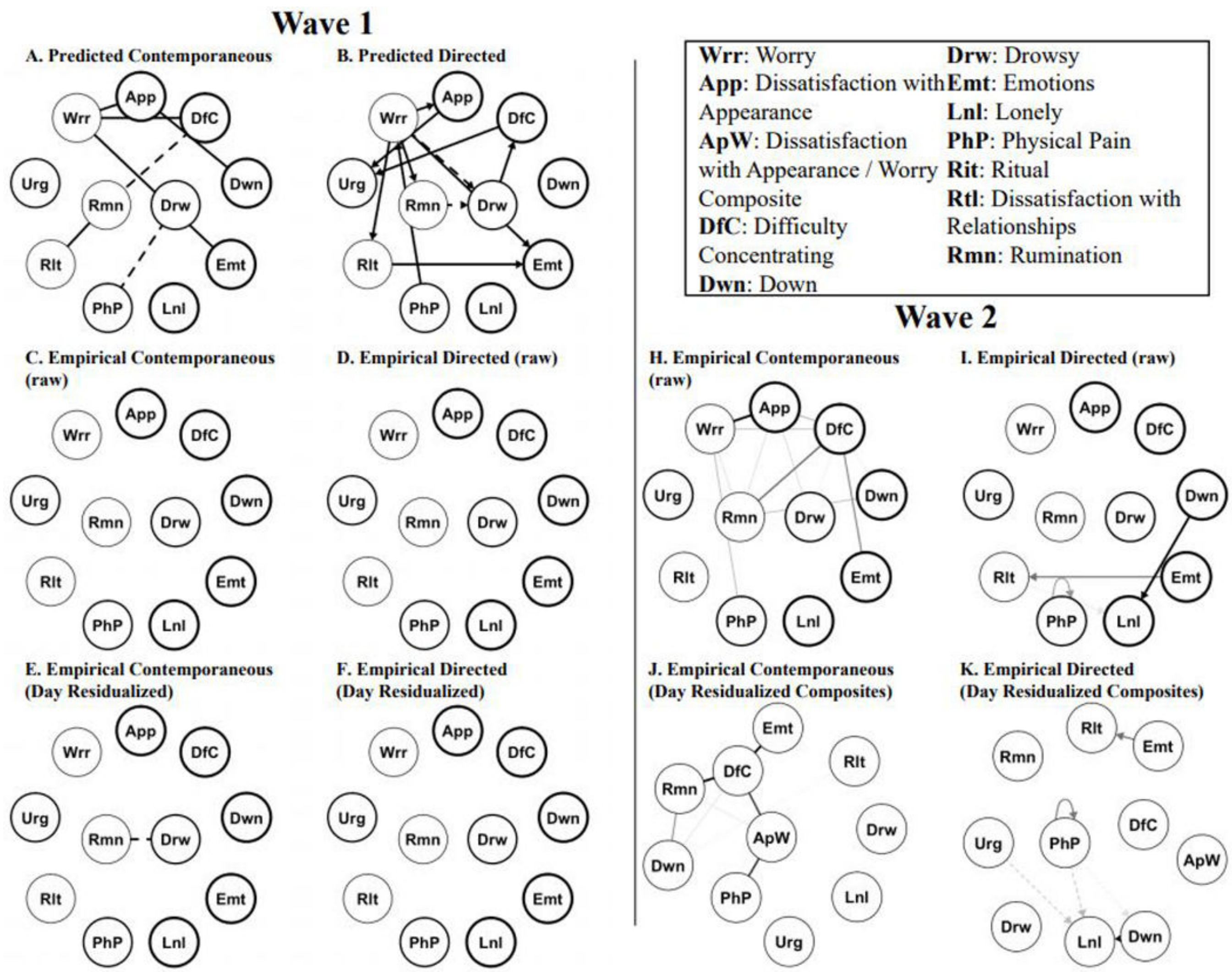

Figure 3.

Wave 1 and Wave 2 Networks for Participant 006. The top row represents Participant 006's predicted networks, the middle row represents raw empirical results (no composites or residualizing), and the bottom row represents the results that clients and therapists were shown. Solid lines indicate positive relationships, dotted lines indicate negative relationships, and thicker lines indicate stronger relationships. The arrangement of the nodes in the top two rows is based on the spring-based Fruchterman-Reingold algorithm of the Empirical Contemporaneous (raw) results in Wave 1. The layout of each model in the bottom row was allowed to vary freely using the spring-based Fruchterman-Reingold algorithm.

Table 1.

Demographics and baseline symptom measures

ID	Sex	Age (years)	Ethnicity	Session fee	Current Diagnoses	BDI-II	PSWQ	LSAS	BSQ
001	F	60's	White	$46,000	MDD, GAD, PD	37	35	72	40
002	NB	20's	White	$0 – $18,000	PDD, SAD, GAD, CUD, AVPD	26	70	69	64
003	F	20's	White	$28,000 – $34,000	AD	14	66	14	39
004*	M	60's	White	$0 – $18,000	Recurrent MDD, in partial remission, GAD	N/A	N/A	N/A	N/A
005	M	20's	White	$0 – $18,000	PDD, SAD, GAD, DPD, OCPD, OCD	10 (15)	72 (69)	49 (58)	39 (51)
006	F	20's	White	$26,000 – $30,000	GAD	10 (4)	72 (56)	7 (23)	47 (47)
007*	F	20's	White	$22,000 – $26,000	BD I, SAD, GAD, OCD, CUD, ADHD, Other specified TSRD	1	45	15	23
008	M	30's	Biracial	$36,000 – $42,000	MDD, AUD, CUD, OCPD	27	67	59	39
009	M	40's	White	$46,000 +	N/A	19 (14)	57 (54)	25 (25)	34 (31)
010	F	30's	Black	$0 – $18,000	MDD, PD	28	54	25	39
011	M	20's	White	$30,000 – $32,000	PTSD, PDD, SAD	8 (6)	49 (58)	37 (35)	35 (37)
012*	M	20's	White	$0 – $18,000	SAD, PD, GAD, OCD, PDD/MDE, ADHD	20	58	75	38
013*	N/A	N/A	N/A	N/A	N/A	40	59	99	19
014	F	40's	White	$0 – $18,000	ID, Other Specified DD, Other Specified AD	43	53	69	61
015	F	30's	White	$38,000 – $46,000	Recurrent MDD, GAD, OCD, PTSD	14	69	37	23
016*	N/A	N/A	N/A	N/A	N/A	19	28	52	24
017	F	20's	White	$0 – $18,000	PDD, BPD, DPD	23	63	81	48

Note.

* Denotes participants who did not complete EMA. Scores in parentheses indicate Wave 2 values. N/A = not available; MDD = Major depressive disorder; GAD = Generalized anxiety disorder; PD = Panic disorder; NB = Non-binary gender; PDD = Persistent depressive disorder; SAD = Social anxiety disorder; CUD = Cannabis use disorder; AVPD = Avoidant personality disorder; AD = Adjustment disorder; DPD = Dependent personality disorder; OCPD = Obsessive-compulsive personality disorder; OCD = Obsessive-compulsive disorder; BD = Bipolar disorder; ADHD = Attention Deficit Hyperactivity disorder; TSRD = Trauma and stressor-related disorder; AUD = Alcohol use disorder; PTSD = Post-traumatic stress disorder; MDE = Major depressive episode; PDD/MDE = Persistent depressive disorder with intermittent MDE, in current episode; ID = Insomnia disorder; DD = Depressive disorder; AD = Anxiety disorder; BPD = Borderline personality disorder; BDI-II = Beck Depression Inventory, 2nd edition; PSWQ = Penn State Worry Questionnaire; LSAS = Liebowitz Social Anxiety Scale; BSQ = Body Sensations Questionnaire.