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An Idionomic Network Analysis of Psychological Processes and Outcomes

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Abstract

Background: Clinical psychology research emphasizing treatment packages targeted at DSM defined problems obscures individual differences and violates statistical assumptions regarding its applicability to individuals in the sample. An alternative approach maps the relationship between psychological processes and outcomes at the individual level before aggregating results. This study represents the first effort to undertake such an approach using a novel measure, the Process Based Assessment Tool (PBAT), that assesses functionally defined psychological processes linked to intervention and based on modern evolution science.

Methods: Data on psychological variation, selection, and retention, domains of psychological distress, life satisfaction, and burnout, were collected twice daily for a 35-day period using a smartphone application. These data were analyzed using the S-GIMME statistical package to generate group, sub-group, and individual level network models.

Results: S-GIMME models successfully converged for all participants. Network models directed at each of 7 outcomes yielded interpretable subgroups. Elements of the PBAT reliably produced directed pathways impacting elements of psychological distress within the sample. 17 of 18 elements of the PBAT appear in final models which maximized directed pathways toward each of the 7 targeted outcomes.

Discussion: The PBAT demonstrated utility as a daily diary measure and reliably produced directed pathways impacting domains of psychological distress and well-being. Subgroup formation demonstrated consistency across outcomes directed models. Individual network models represent potential clinical utility.

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The prevailing strategy in clinical psychology for the past few decades has taken the form of a medical model, whereby the goal has been to amass a body of scientifically validated protocolized treatment packages targeted at specified syndromes, using the Diagnostic and Statistical Manual of Mental Disorders (DSM; American Psychiatric Association, 2013) or the International Classification of Diseases (ICD; WHO, 2018). While this approach has led to an array of empirically-supported treatments which have no doubt been of enormous help to patients (Barlow, 2004), the core assumptions of this strategy are now being questioned.

The problems are many. The DSM has been plagued by issues of underwhelming specificity (Fried, 2015; Watson, 2005; Widiger & Clark, 2000; Galatzer-Levy & Bryant, 2013) in diagnoses. For example, the diagnosis of PTSD famously can be made with any 1 of 636,120 symptom combinations (Galatzer-Levy & Bryant, 2013). That possibility is not merely logical – it has been shown to be empirical in a recent exploration of the heterogeneity of Major Depression as defined by the DSM-V, which found 1,030 unique depression symptom profiles in 3,703 depressed patients (Fried & Nesse, 2015). Data of this sort has led some to predict that the “entire notion of valid categories of mental disorder will collapse in self-contradiction” (McLaren, 2010).

A second major problem is comorbidity (Lenzenweger, Lane, Loranger, & Kesslerand, 2007; Grant & Harford, 1995; Brown, Campbell, Lehman, Grisham, & Mancill, 2001; Clark, Watson, & Reynolds, 1995). Across a large national survey, roughly a quarter of the population met the 12-month point-prevalence criteria for a psychiatric disorder, of those that did, a total of 45% met criteria for 2 or more diagnoses (Kessler, Tat Chiu, & Demler, 2005). For those diagnosed with a principal mood or anxiety diagnosis, 57% met criteria for an additional axis I diagnosis at the time of assessment, while 81% meet criteria for an additional axis I diagnosis at some point over their lifetime (Brown, Campell, Lehman, Grisham, & Mancill, 2001). Finally, a meta-analysis including 22 epidemiological studies examining the association between substance abuse disorders and mood and anxiety disorders, found that those who meet criteria for an illicit-substance use disorder are 3.8 times more likely to be diagnosed with major depression than the general population and 2.91 times more likely to be diagnosed with an anxiety disorder (Xiong Lai, Cleary, Sitharthan, & Hunt, 2015). This is a fundamental issue, as diagnoses can only be considered valid if they either (1) exhibit a zone of rarity, meaning that given the prevalence of any two disorders it is rare to find individuals who show a combination of symptomatology, or (2) exhibit unique physiological, anatomical, histological, chromosomal, or molecular abnormalities, as is the case for disorders such as Down's or fragile X syndromes (Kendell & Jablensky, 2003).

A third problem is that treatment developers have been unable to reliably link packages specifically to problems. This is especially evident and worrisome in the area of medications in which the trend over time has been to target more and more problems with the same pharmaceutical interventions. For example, in a bibliometric analysis of Selective Serotonin Reuptake Inhibitors (SSRIs) covering the years from 1980 to 2000, the number of trials per indicated problem was: depression (834), obsessive-compulsive disorder (171), panic disorder (75), social phobia (33), bulimia nervosa (31), generalized anxiety disorder (22), posttraumatic stress disorder (18), and premenstrual syndrome (30; Lopez-Munoz et al., 2003). Additionally, a number of trials were found for problems that are not yet officially indicated for SSRIs including schizophrenia (49), alcoholism (42), trichotillomania (14), aggresssivity (14), dementias (20), obesity (18), and headaches/migraines (10). Similarly, in addition to psychosis, atypical antipsychotic medications have been studied in association with a variety of problem areas including: tic disorders, bipolar disorder, pervasive developmental disorders, borderline personality disorder, obsessive-compulsive disorder, depression, substance abuse, posttraumatic stress disorder, stuttering, conduct disorder, and pedophilia (Glick, Murray, Vasudevan, Marder, & Hu, 2001). In psychosocial interventions, greater treatment specificity has emerged, but treatment protocols have done so within the same basic theoretical systems and targeting similar psychosocial mechanisms. This can be seen, for example, across the traditional CBT manuals for depression (Beck & Alford, 2009), anxiety disorders (Beck, Emery, & Greenberg, 2005), bipolar disorder (Newman, Leahy, Beck, Reilly-Harrington, & Gyulai, 2002), personality disorders (Beck, Davis, & Freeman, 2015), and substance abuse (Liese, Beck, & Friedman-Wheeler, 2012).

A fourth problem is that the main purpose of a syndromal strategy is showing no signs of being fulfilled. The strategic scientific reason behind the creation of systems of syndromes is that it might simplify and empower the search for consistent patterns of etiology, mechanistic course of pathological processes, and detailed, theoretically meaningful responses to intervention. When that happens, syndromes turn into known diseases. Diseases are functional entities and in some areas of medicine a syndromal strategy has led to their discovery, but not with psychiatric syndromes. In the history of the DSM not a single syndrome has been elevated to a disease.

In response to this state of affairs the National Institute of Mental Health undertook the Research Domain Criteria (RDoC) project which was put forth as a research agenda that seeks to formulate a dimensional diagnostic system based on the biological and behavioral underpinnings of mental illness with an emphasis on “genomics and neuroscience, which ultimately will inform future classification schemes” (Insel et al., 2010). RDoC sought to reconceptualize diagnosis from that of mental or behavioral health disorder to “brain disorders” or “neural circuit disorders” which may be treated by pharmacotherapy, psychotherapy, or methods such as deep brain stimulation or transcranial magnetic stimulation (Insel & Cuthbert, 2015). This initiative has been explicitly linked primarily to work looking for biomarkers of psychopathology such as neuroimaging derived neurophysiological brain signatures (Drysdale et al., 2016; Woo, Chang, Lindquist, & Wager, 2017; Nusslock & Alloy, 2017; Malhi et al., 2015), and genomic sequencing (Kaiser & Fang, 2015; Lueken et al., 2016; Goes, 2016). Unfortunately, to date “there is no compelling evidence for the viability of reducing mental disorders to unique biological abnormalities, both in terms of enhanced etiological understanding and of improving the effectiveness of interventions” (pg. 2, Borsboom, Cramer, & Kalis, 2019).

While the existing nosological systems of psychopathology have proven to be problematic, there remains a need for diagnostic systems. It is beneficial for clinicians to have a shorthand for particular presentations of those seeking treatment, however, this implies that such classifications will have treatment utility (Hayes, Nelson, & Jarrett, 1987; Nelson-Gray, 2003). That is to say, the information provided by a diagnostic distinction should lead to more beneficial outcomes. This is most obviously accomplished by a link to specific treatment indications. As we have seen, existing systems poorly identify the nature of the problem and do little to determine the approach likely to be taken in treating it.

Functionally Relevant Psychological Processes

One feature that is missing in a syndromal approach to diagnosis is an exploration of the role of theoretically derived, empirically demonstrated, and functionally important psychological processes in the development, maintenance, and treatment of psychopathology. A functional approach can be defined as one where the “the topographical characteristics of any particular individual's behavior is not the basis for classification; instead, behaviors and sets of behaviors are organized by the functional processes that are thought to have produced and maintained them” (pg. 1153, Hayes, Wilson, Gifford, Follette, & Strosahl, 1996). One way to accomplish this task is by functional analysis in which the patient’s behavior and the context in which it occurs is identified, organized into behavioral principles, and used to develop an intervention which is then subjected to analysis and modification. However, in its classical form, these analyses could be vague, too narrowly focused on direct contingencies, and difficult to replicate or generalize (Hayes & Follette, 1992).

It is possible that these known functional analytic problems could be ameliorated by repeating a number of functional analyses utilizing a broad set of dimensions, resulting commonalities might be collapsed into categories tied to assessment and clinical procedures, or into empirically precise models of case conceptualizations linked to treatment kernel selection. If the processes put into such a process were functional, evidence based, and theoretically coherent it might lead to a more testable approach enabling falsifiable predictions about changes that were more dynamic across time, and that interacted in a multi-level system (Hofmann & Hayes, 2019).

The search for functional processes has primarily been conducted in clinical trials via a search for mediators. A variable is said to be a mediator when it accounts for the relation between an intervention and outcome variable (Baron & Kenny, 1986). That is to say, the effect of independent variable X is transmitted through mediating variable M which impacts outcome variable Y. While mediational analyses have been painted as causal (Kenny, 2008; Imai, Keele, & Tingley, 2010), they are better conceptualized as establishing the basis of the relationship between the variables involved in the change process from which more functional and causal accounts may emerge through experimental analysis (Nock, 2007; Kazdin, 2007).

One of the key findings from the protocols for syndromes era was that the mediators of a particular treatment were often consistent across an array of psychopathological domains. Within traditional Cognitive Behavioral Therapy (CBT) the outcomes of treatment for panic, Multiple Sclerosis related fatigue, depression, insomnia, and pediatric bipolar disorder, have all been found to be mediated by cognitive restructuring (MacPherson, Weinstein, Henry, & West, 2016; Espie et al., 2014; Seeley et al., 2017; van den Akker et al., 2018). Clinical trials of Acceptance and Commitment Therapy (ACT; Hayes, Strosahl, & Wilson, 2011) have reliably found psychological flexibility to mediate outcomes across myriad problem areas (see Hayes, Luoma, Bond, Masuda, & Lillis, 2006; Stockton et al., 2019 for reviews).

Another key finding has been overlap in the therapeutic processes across treatments. For example, cognitive defusion, a process within the psychological flexibility model that involves one's ability to distance from and observe thoughts, has been shown to mediate the effect of both CBT and ACT for anxiety (Arch, Wolitzky-Taylor, Eifert, & Craske, 2012). Similarly, changes in experiential avoidance, one's attempts to suppress or change unwanted private events such as thoughts, emotions, memories, or urges (Hayes, Wilson, Gifford, Follette, & Strosahl, 1996), have been shown to mediate both ACT and Applied Relaxation (Eustis, Hayes-Skelton, Roemer, & Orsillo, 2016). Changes in experiential avoidance and threat perception were both demonstrated to be mediators of a group-based transdiagnostic CBT intervention (Espejo, Gorlick, & Castriotta, 2017). That therapeutic procedures from across schools of treatment show overlapping mechanisms of change speaks to the importance of a functional classification system. It also speaks to the need for a more complex way of conceptualizing the interaction of functionally defined psychopathology and therapeutic process. One step toward that end is to map the patterns of symptomatology outlined in currently existing diagnostic systems.

Contemporary Network Approaches to Psychopathology

The network approach to psychopathology has recently emerged as an alternative to the "common cause" medical disease model discussed above. Network approaches "[conceptualize] mental disorders as networks of [elements] that directly interact with one another" (pg. 999, Fried & Cramer, 2017). The term element is used here as opposed to the term symptoms, as the latter directly implies the common cause approach to which network approaches stand in opposition of (McNally, 2012; Robinaugh, Leblanc, Vuletich, & McNally, 2014; Snaith, 1993). Within a network approach, elements co-occur not because they are caused by the same underlying disorder, but because they are directly related to each other. For example, sleep disturbance, fatigue, and impaired concentration co-occur not because they are all symptoms of depression, but because a lack of consistent sleep is directly related to fatigue and impaired concentration. It should be noted, the use of the term “direct” here does not preclude the presence of intermediate processes that may not be directly observed (Cramer, Waldorp, van der Maas, Borsboom, 2010).

Network Theory has been stated to be comprised of 4 principles: (1) complexity, (2) symptom-component correspondence, (3) direct causal connections, and (4) mental disorders follow network structure (Borsboom, 2017). Complexity means psychological disorders are best characterized by the interactions of the various elements of the psychopathological network. Symptom-component correspondence refers to the idea that “the components in the psychopathology network correspond to the problems that have been codified as symptoms in the past century and appear as such in current diagnostic manuals” (pg. 7, Borsboom, 2017). “Direct causal connections” refers to the interventionist conceptualization of causal relationships meaning that an experimental or natural intervention which changes one elements of a network subsequently changes the probability distribution of other elements in the network. Finally, the fourth principle states that the topology of networks is significant in that some elements are more central than others and give rise to the phenomenological manifestation of mental disorders as clusters of elements which reliably co-occur. This means the emergence of psychopathology can be thought of as the activation of elements in a network that spreads to other directly related elements and/or results in feedback loops among elements.

One implication of network theory is that the particular structure of a network of elements is important. While the occurrence of any five depression symptoms are held to be indicative of the same underlying cause, a network approach meaningfully differentiates between models with differing presence and relation amongst elements. Elements such as loss of interest/pleasure, depressed mood, fatigue, and concentration problems have been shown to be more directly related or “central” to depression, than suicidal thoughts, hypersomnia and a decrease in weight/appetite, and those elements have demonstrated superior predictive validity with respect to future diagnosis (Boschloo, van Borkulo, Borsboom, & Schoevers, 2016). Thus, heterogeneity is conceptualized as differing patterns of causal links between features of a disorder (Hofmann, Curtiss, & McNally, 2016). Likewise, comorbidity can be conceptualized as the activation of elements which bridge psychopathological domains (Borsboom & Cramer, 2013; Cramer et al., 2010). For example, the presence of sleep problems, fatigue, and lack of concentration are present in the networks of both depression and anxiety. The activation of these bridge elements may, in turn, spread such that both networks are active.

The treatment implications of this approach are readily apparent. To the extent that the causal structure of networks can be determined, techniques can be brought to bear on the central elements of psychopathology. Effective intervention is then likely to spread down the causal stream, although continued assessment will provide direction for further clinical targets. However, it is worth noting the troubling reliance on existing clinical diagnostic categories as the content of psychopathological networks. Borsboom (2017) states:

> The assumption implies that psychopathology symptoms are defined at the right level of granularity, and successfully identify the important components in the psychopathology network. Insofar as factors not encoded in common diagnostic systems play a role (e.g., psychological processes not included in the symptomatology, neural conditions, genetic antecedents), they must do so by: a) constituting the symptom in question (e.g., the symptom of anxiety involves a neural realization in the brain, which partly constitutes that symptom), b) constituting a symptom-symptom connection (e.g., the biological clock is part of the system that generates the insomnia -> fatigue relation), or c) acting as a variable in the external field (e.g., chronic pain is likely to be an external factor that causes fatigue). (pg. 7).

At issue here is the success with which existing diagnostic categorization effectively captures all important components. Modern cognitive behavioral therapies specify theoretically driven psychopathological processes which do not constitute the element in question, do not neatly fit into an element-element connection, and are not external to the network. A discussion of how these theoretically important psychological processes may be integrated into, and better inform, network models is discussed below. For the time being, we adopt a softer stance toward the use of existing classificatory criteria: “for this paper, we understand mental disorders ... not as reliable and valid phenotypes but as reasonable starting points for clinical investigations of the network structure of [elements]” (pg. 1004, Fried & Cramer, 2017).

An Idionomic Approach to Diagnosis

While there appears to be wide agreement that an alternative to the DSM is needed, the present project is based on the idea that the best avenue forward requires a change in the level of analysis. Idiographic analyses linked to nomothetic generalizations (what has recently been called “idionomic” analysis, Hayes et al., 2021) is required in diagnosis and for theoretical, practical, and statistical reasons.

Take, for example, the existing research on experiential avoidance, which has generated robust findings demonstrating it to be a transdiagnostic factor in the etiology of psychopathology (Chowla & Ostafin, 2007; Ruiz, 2010). Mediational analyses of ACT in clinical trials have routinely shown reductions in experiential avoidance to be associated with improved outcomes. However, a recent study provides evidence that this may not always be the case. When comparing a native German sample and a Turkish immigrant sample results show that for the latter, use of emotional suppression and reappraisal do not demonstrate the expected correlation with psychopathology seen in the former (Voswinckel et al., 2019). The Turkish individuals demonstrated less emotional acceptance and more suppression, but these strategies did not significantly correlate with measures of depression. However, while the use of suppression and reappraisal strategies were not correlated in the Turkish sample, they were strongly associated in the German sample. While the findings here remain at the group level, they speak to the possibility that individuals within a group engage in psychological processes in fundamentally different and important way. Consider that while the omnibus correlation between engaging in experiential avoidance and indication of depressive elements within a population is strong (Mellick, Vanwoerden, & Sharp, 2017; Rueda & Valls, 2016), there may exist a small but meaningful sub-population of individuals who are engaging in suppression + reappraisal in a way that does not predict negative outcomes.

This kind of finding is not unique within the field. Grice, Cohn, Ramsey, and Chaney, (2015) re-examined data from Ramsey et al. (2013) which explored the mediational role of children's self-attribution on the relationship between parental distress and children's depressive symptomatology. While the original analysis showed full mediation (in accordance with best-practice statistical methodology), only 46% of the parent-child dyads demonstrated the expected patterns of data on re-analysis. This is not to discount the importance of the findings reported by the original trial, the mediational analysis revealed a significant pattern in the aggregate population data, however, the reanalysis reveals that any given population finding does not necessarily apply to any given individual or dyad in the study. This is troubling, as psychologists, and particularly clinical psychologists, are primarily interested in the behavior of individuals (or, as in this case, targeted dyads, not collections of different targeted units).

While calls for a more idiographic approach to psychology are hardly new (Sidman, 1952; Skinner, 1956), the idea has more recently resurfaced in new forms (Grice, Barrett, Schlimgen, & Abramson, 2012; Molenaar, 2004; Hayes et al., 2018). Specifically, what is meant by an idionomic approach, such as that tested in the present study, is the analysis of individuals prior to combining the data across individuals in ways that do not distort the analysis of individuals. In other words, an idionomic approach follows the advice to investigate then aggregate; never the other way around.

The discrepancies outlined above can be explained by the non-ergodicity of the data collected. It is well known from books that address single-case designs that group averages can easily obscure clinically relevant individual differences (Barlow, Nock, & Hersen, 2009), but it is not as widely known that mathematicians in the physical sciences have long agreed that analyses of collections of events can be assumed mathematically to apply to the behavior of individual events only under a highly-constrained set of circumstances (Birkhoff, 1931) that define phenomena as being “ergodic” when they are met.

The ergodic theorem applies to the relation of measurement in space and time, and although the theorem itself has been accepted science for over 90 years, Peter Molenaar (2004) was apparently the first behavioral scientist to realize that it applied to people and processes, not just space and time. He argued convincingly that only for ergodic data is the assumed relation between the structure of data collected at the group level and data of the individual valid (Molenaar, 2004). This assumption can be seen in methodology where data are pooled together and analyzed at the group level and findings are then meant to apply to, and inform interventions with, individuals. In order for this to be true, the data must meet two conditions: homogeneity and stationarity. Homogeneity means that the “main features of a statistical model describing the data are invariant across subjects” (pg. 113, Molenaar & Campbell, 2009). For example, for a given measure the factor structure and factor loadings obtained at the group level need by be true of the factor structure and loadings of each individual. This can be tested, for example, by comparing the standard inter-individual factor structure of a measure to the individual level factor structure (P-technique; Cattell, Cattell, & Rhymer, 1947) obtained by pooling across multiple administrations of the measure of each individual over time. Secondly, in order to demonstrate stationarity, the statistical qualities of the psychological process must be invariant across time. More concretely, for a behavioral phenomenon to be ergodic any cross sectional sample across people would have a mean and standard deviation that was identical to each person in the sample over time (Gates, Chow, & Molenaar, in press).

While ergodicity does exist in the non-living world (in a few noble gases for example; see Volkovysskii & Sinai, 1971) any developmental or change process will violate this requirement by definition because developmental or change processes shift overtime. Thus, it is impossible legitimately to study processes of change using standard methodologies or analyses if the purpose is to apply the results to individuals.

The approaches undertaken during the protocols for syndromes era relied heavily on an assumption of ergodicity. Samples were defined by their diagnostic group, which assumed a common cause for the problem and thus assumed a common response to treatment. Measures were largely designed using classical test theory, that is, based on true scores of latent constructs obtained at the group level by measuring inter-individual variability in a sample. Treatments were kept uniform using protocols with clinicians scored on their level of adherence. Data were collected and pooled into groups according to levels of the independent variable before being analyzed. Conclusions were then largely expected to be utilized by clinicians who were tasked with bringing these findings to bear on the treatment of a particular individual with a particular set of problems, referred to as the Therapist's Dilemma (Levine, Sandeen, & Murphy, 1992).

Testing the assumption of ergodicity is vital because if a psychological process is non-ergodic "the structures of [inter-individual variability] and [intra-individual variability] can differ to an arbitrary degree, up to being completely unrelated. Hence, claims based on classical test theory that a test is valid and reliable cannot be generalized to individual assessments of development, learning, or any other non-stationary process" (pg. 209. Molenaar, 2004). Fisher, Medaglia, and Jeronimus (2017) set out to test the ergodicity of data collected in six previously published studies with samples ranging from 43 to 535 participants which collected extensive intra-individual data via repeated measures. While data was mixed regarding the relation of group level and intra-individual central tendency, there was uniformly large discrepancies between the variance structures with intra-individual data demonstrating standard deviations approximately 3 to 13 times larger across the samples and measures. The ergodic assumption was violated uniformly across all measures and samples examined in the study, strongly suggesting the need to model psychological processes at the level of the individual in cases where inferences are to be made at that level.

A number of recent efforts have undertaken the task of modeling psychopathology at the level of the individual. A sample of 10 individuals diagnosed with Generalized Anxiety Disorder (GAD), measured daily via email delivered web-survey for a minimum of 60 responses (M = 69.1), collected single item measures of: 6 GAD symptoms, 4 related behavioral symptoms (avoidance, preparation for possible negative outcomes, procrastination, reassurance seeking), and 2 aspects of worry (distress, unpleasantness of content) using a 0-100 visual analog scale and subjected the data to p-technique intra-individual factor analysis and dynamic factor modeling (Fisher, 2015). Briefly, dynamic factor modeling is a multilevel vector autoregression (VAR) method which measures lagged and cross-lagged relationships among vectors at the inter and intra-individual level (Piccirillo & Rodebaugh, 2019). Results indicated that only 2 participants yielded factor structures consistent with DSM-defined GAD (i.e., worry and at least three other constituent elements) while the other 8 participants yielded factor structures that differed from each other and did not fit existing diagnostic criteria. Notably, 9 of the participants data yielded an avoidance related factor and 7 yielded a fatigue and worry factor, pointing to the central importance of these elements. Perhaps more importantly for the clinician, while one participant's dynamic factor model showed avoidance leading to subsequent reductions in distress, three other individuals demonstrated the inverse relationship, which may inform differential timing and form of exposure techniques used with these individuals.

Utilizing similar methods Fisher et al. (2017) examined the dynamic factor structures of 40 individuals with either primary Major Depressive Disorder (MDD) or GAD. Data were subjected to a network analysis and though the complexity of the results are beyond the scope of this paper, some key takeaways include the central importance of anger and irritability across individual models, the relatively modest role of worry, and mixed importance of depressed mood. The findings of this study are primarily important in their ability to both describe generalized patterns of relations found across the majority of individual networks with their notable exceptions. Results for this study were subsequently used in an open trial in which modularized CBT components were tailored to individuals based on their network structure (Fisher et al., 2019). Results indicate an observed effect size for treatment larger than the benchmarked effect size for CBT calculated via meta-analysis (Johnsen & Friborg, 2015). While it is important to interpret the results of open trials with caution, the latest finding in this line of research highlights the promise of dynamic assessment in improving clinical outcomes.

In a sample of 96 Israeli civilians exposed to rocket fire who responded twice daily over a 30 day period using a 20-item checklist of PTSD symptomology (Greene, Gelkopf, Epskamp, & Fried, 2018). Data were used to create three models, a contemporaneous network which displays relations among the PTSD elements (similar to a multilevel partial correlation network), a temporal network which measures if changes from an individual's mean at one time-point predicts changes in another variable at the next time point, making possible the establishment of Granger causality (Granger, 1969) and an inter-individual network. Key findings were the relative similarities between individual contemporaneous and inter-individual networks, but differences present in the patterns of temporal networks highlighting the importance of the latter. For example, while blame was positively associated with other elements in the contemporaneous models, it demonstrated the inverse association in the temporal model such that blame was associated with less severity at the following timepoint.

In another example of a more idiographic approach, Wright et al. (2016) utilized p-technique factor analysis on data collected contingently after interpersonal interactions over a 21-day period with a sample of 25 individuals diagnosed with Borderline Personality Disorder (BPD). Data collected after every interpersonal interaction that lasted longer than 10-minutes covered aspects of interpersonal behavior, affect, aggression, and substance use (50 total items). The authors highlight results from 5 unique intra-individual factor structures with a focus on their clinical implications. In a follow-up examining 94 individuals diagnosed with a personality disorder who provided a minimum of 60 daily data points, data on affect, interpersonal behavior, stress, functioning (22 total items). Data were subjected to a group iterative model estimation analysis (GIMME; Gates et al., 2017; Gates & Molenaar, 2012) which was specifically designed to bridge the gap between idiographic and nomothetic levels. GIMME relies on a unified structural equation modeling (uSEM; Kim, Zhu, Chang, Bentler, & Ernst, 2007) framework which combines SEM and VAR to calculate both contemporaneous and temporal relationships (Piccirillo & Rodebaugh, 2019). GIMME utilizes relationships present in individual networks and then selects additional pathways applicable at the group level only if they improve fit at the individual level (by default defined as being true in 75% of cases). This is important as the individual data structure is treated as primary, does not assume homogeneity while weighing each individual's data contribution equally, and is used to identify relationships generalizable at a group level, while simultaneously providing data on how individuals may vary. Additionally, patterns may be uncovered that hold for only a subgroup of individuals (set at default to apply to 50% of the sample) in a similar idionomic fashion. Results indicated group level patterns for all six auto-regressive paths meaning that the score for one day reliably predicted the next day's score for a given domain. Notably 3 individuals demonstrated a negative autoregressive path for 1 or 2 domains possibly indicating feedback loops (whereby high scores one day predict low scores the next). One other pathway met the cutoff criteria for the group level, the contemporaneous relationship between negative affect and stress (present in 92.5% of the sample). A total of 3 subgroups were revealed including 60, 23, and 11 individuals respectively, 2 individuals did not fit into any subgroup. Notably, for subgroup 1 there existed a shared pathway indicating a contemporaneous association from negative affect to social affiliation, suggesting that for this subgroup negative affect predicts social withdrawal. Subgroup 2 and 3 did not exhibit any unique shared pathways and were instead defined by the overall similarities across their models. This allows for between group comparisons that may be of interest.

Taken together, this methodology represents a bottom-up idionomic approach to dynamic assessment capable of yielding data that is generalizable across levels of interest. It a) provides heterogeneous idiographic profiles on the relationships between clinically relevant domains; b) parses individuals into subgroups with relatively similar profiles allowing study and recommendations to be made at this nomothetic level, and c) indicates patterns that hold true individually for nearly the entire sample which is more likely to be generalizable across the population of interest.

An Evolutionarily Informed Approach to Process-Based Therapy

While the emergence of methodology that makes possible the study of idiographic psychological networks holds a great deal of promise for clinical psychology, the extant literature on the subject to date is largely devoid of theoretically derived, functionally relevant, psychological processes, tightly linked to intervention. The existing research to date has instead opted largely to model the relationships between features outlined in existing psychopathological diagnostic manuals. Fisher (2015) acknowledges this, stating that while his study utilizes DSM nosology "future research need not be similarly delimited. As noted earlier, the proposed model could be applied to repeated measures of cognitive; behavioral; emotional; and even physiological, endocrinological, or brain-derived data" (pg. 834).

A focus on theoretically derived biopsychosocial processes of change linked to intervention strategy and goals of the individual is the stated purpose of Process-Based Therapy (PBT; Hayes & Hofmann, 2018; Hofmann & Hayes, 2019). Within the PBT literature a recent approach has been to use an extended evolutionary synthesis as a "model of models" to bring some degree of consilience to the search for coherent sets of change processes (e.g., Hayes et al., 2019; Hofmann, Hayes, & Lorscheid, 2021)

Using evolutionary theory to establish greater consilience among various models of human change avoid the narrow conflicts that exist among various approaches and schools within psychology. No responsible scientist disagrees that human animals are the product of natural selection, and embracing the principles of modern evolutionary science arguably allows processes of change to be explored and linked to the pantheon of credible clinical interventions in psychology without needless in-fighting. Dobzhansky famously said "nothing in biology makes sense except in the light of evolution" (1973) and in a similar way if our goal to increase the consilience of psychology (Wilson, 2012) perhaps it is more accurate to say that nothing in the life sciences makes sense except in light of evolution. Recent efforts have been undertaken to better embed behavioral science within the modern extended evolutionary synthesis (Wilson et al., 2014a; Wilson et al., 2014b; Hayes, Sanford, & Chin, 2017; Hayes & Sanford, 2015). The role of behavior and language (often referred to as symbolic behavior) are increasingly acknowledged for their roles in developmental plasticity, inclusive inheritance, and niche construction (Laland et al., 2015).

The evolutionary processes of variation, selection, and retention, play out in context across dimensions and at multiple levels, including within the lifetime of the individual. This has been well acknowledged within the behavioral tradition (Popa & McDowell, 2016), with Skinner (1981) referring to operant conditioning as both a product of evolution and as an evolutionary process of selection by consequences.

Symbolic behavior has been similarly nested as both a product of evolution and as an evolutionary process itself (Hayes & Sanford, 2014). Variability has been demonstrated to be a reinforceable dimension of behavior in non-human animal models (Doughty & Galizio, 2015; Galizio et al., 2018; Fonseca Júnior & Leite Hunziker, 2017). However, the interaction of the symbolic stream, in the form of rule-governed behavior, has yielded different results for humans and non-human animals (Maes & van der Goot, 2006; Doolan & Bizo, 2013). Language has been demonstrated to both be a source of and limiting factor in behavioral variation. Increases in variability occur in the context of novel verbal stimuli producing novel behavior (Hayes, Thompson, & Hayes, 1989; O'Hora, Barnes-Holmes, Roche, & Smeets, 2004). Rule-governance can inversely result in limited rigid repertoires (Wulfert, Greenway, Farkas, Hayes, & Dougher, 1994).

This has important implications for psychopathology. When daily variability of anxiety severity was measured four times daily for 20 weeks in 69 participants diagnosed with GAD currently undergoing psychological treatment, results indicate that anxiety symptoms which vary throughout the period of the day, but follow a rigid pattern day-to-day, predict severity of GAD symptomatology, and that increases in day-to-day variation of anxiety severity are associated with successful treatment (Fisher & Newman, 2016). Thus, expanding healthy variability in behavioral patterns appears to be a fundamental process in psychological treatments.

The role of selection is in some ways more obvious. The study of reinforcement itself can be taken to be the study of behavioral selection. "The product of operant conditioning is not a single coherent repertoire but thousands of smaller repertoires, conflicts among which must somehow be resolved" (pg. 579, Skinner, 1990). That resolution comes in the form of selection across the interwoven behavioral and symbolic streams. In non-human animal models, the magnitude of reinforcement has been shown to be inversely related to behavioral variability, suggesting it is functioning as a strong selection criterion for the pattern of responses emitted (Doughty, Giorno, & Miller, 2013). Symbolic behavior, however, creates more complicated selection pressures. For example, human animals may fail to make contact with natural reinforcers in following the socially mediated consequences of coherence with given rules (Hayes, Brownstein, Haas, & Greenway, 1986; Hayes, Brownstein, Zettle, Rosenfarb, & Korn, 1986). While this can be fantastically useful in cases where behavioral variation is dangerous (i.e., put on your coat because it’s below freezing outside), it can also result in pathological behavior such as when selection pressure is exerted toward reducing or eliminating contact with aversive private experiences (i.e., experiential avoidance). Values work within the psychological flexibility model can be conceptualized as a way of creating selection pressure for prosocial or functionally adaptive behavioral repertoires (Hayes & Sanford, 2015). While there has been substantial theoretical work to date in establishing the link between multi-dimensional multi-level evolutionary principles and psychological models, there has been a dearth of research which explicitly furthers the synthesis (Hayes, Sanford, & Chin, 2017).

Purpose of the Present Study

Making significant progress within the domain of knowledge development entails creating considerable upheaval. When familiar methods and approaches prove to be inadequate in answering questions of importance, the development of novel strategies must be undertaken. As the era of packages for problems ends, there has emerged a growing chorus of researchers calling for a renewed focus on the individual (Molenaar, 2004; Barlow & Nock, 2009; Hofmann & Curtiss, 2018). To increase the precision and scope of our scientific statements in clinical psychology we must undertake a modern approach to functional analysis such that we seek to specify "What core biopsychosocial processes should be targeted with this client given this goal in this situation, and how can they most efficiently and effectively be changed?" (pg. 38, Hayes & Hofmann, 2019). This emphasis on functionally defined psychological processes tightly linked to intervention represents a move away from trademarked treatment protocols and siloed schools of intervention and toward a more unified and coherent field. To that end, the investigation of psychological processes informed by modern multi-dimensional multi-level evolution, undertaken at the level of the individual, represents an opportunity to improve the depth of our understanding of psychopathology while paving the way toward functional links to our existing armory of cognitive behavioral techniques.

However, progress in this direction requires new assessment and analytic approaches. The purpose of this study is to test a new, idiographic measure that is explicitly designed to foster the PBT focus discussed by Hayes and Hofmann and to examine several predictions that emerge from that perspective. This approach is consistent with a recent Association of Contextual Behavioral Science task force report, which recommends research that examines relevant variables across levels of analysis within a broad evolutionary framework and emphasizes the importance of longitudinal and idionomic approaches, as well as the development of psychometric procedures to validate and ensure the utility of such assessment (Hayes et al., 2021).

Creation of an Idiographic Measure. The current study utilizes a novel measure, the Process-Based Assessment Tool (PBAT; Ciarrochi, Hayes, and Hofmann, in preparation) which has emerged from theory in PBT and modern evolution science. It is designed to measure functionally adaptive variation, selection, and retention in behavior. The goal in designing the measure was to create a clinical process measure capable of being useful across existing schools of intervention. It has been specifically designed with daily diary studies in mind utilizing only one or two items per domain and is separated into three main categories: variation, selection, and retention.

The measure examines selection across cognition, affect, overt behavior, self-concept, attentional control, and motivation as derived from Hayes et al. (2019). Items regarding social interaction and physical health behavior were also added given their importance to overall well-being (Ciarrochi, Bailey, & Harris, 2014) and their relevance to the bio-physiological and sociocultural levels of analysis that impacts on psychological dimensions in the Extended Evolutionary Meta-Model (EEMM) that underlies PBT (Hayes et al., 2019; Hofmann et al., 2021).

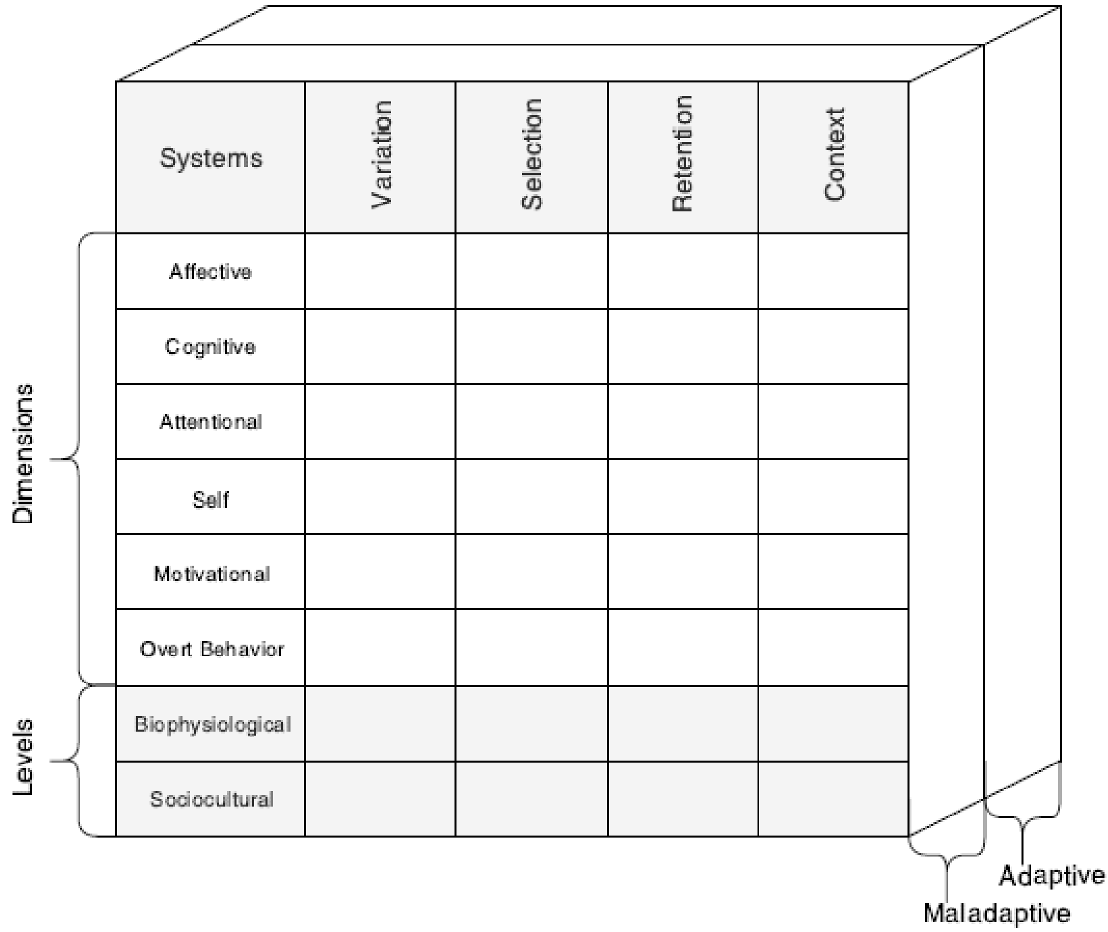

Figure 1. The Extended Evolutionary Meta-Model (EEMM)

Items on the PBAT were created based on a combination of self-determination theory (Ryan & Deci, 2017), and the yearnings framework that emerges from psychological flexibility (Hayes, 2019). These items measure selection pressure exerted by motivating operations focused on autonomous meaning, range of feeling, social connection or belonging, competence, orientation, and verbal coherence. Briefly, self-determination theory is a macro theory of motivation which has been used extensively to predict and interpret research on psychological well-being. This stands as an alternative to the somewhat arbitrary domains approach used in previous measures (Wilson, Sandoz, Kitchens, & Roberts, 2010; Lundgren, Dahl, & Hayes, 2008). Additionally, a physical health item was added as explained above.

Each domain includes a positively and negatively valanced item in order to better capture the nature of selection pressures. All items are framed regarding behavior or process as opposed to outcomes (i.e., *I did things to connect with people* vs. *I connected with people*). This is meant to better capture the individual's interactions in creating their niche in the environment. It is also designed to help orient clinicians to the modifiable aspects of a patient's behavior.

By examining the frequency with which processes relate to both each other and outcomes of interest, such as psychological distress and life satisfaction, we may further be able to develop our theoretical understanding of these processes. While the exact relationship amongst elements in an individual's network are likely to be unique, the identification of principles and models that may help explain the cascade of processes to outcomes may help advance case conceptualization and the selection of intervention components or kernels (Embry& Biglan, 2008) that have a great likelihood of success. Those advantages will depend on the degree to which these analytic methods apply across networks that involve elements both of well-being (e.g., life satisfaction) or of specific elements of psychological distress (anger, anxiety, sadness, lack of social support, and stress) or burnout that are commonly seen, targeted, or set as a goal in clinical work. In essence such an approach may inform what components of ongoing functional analyses within treatment are especially likely to be useful.

Testing the Adequacy of this Measure in an Idionomic Approach. It is the goal of this project to map the complex interactions between the elements of the PBAT, and seven psychological outcomes (anger, anxiety, sadness, lack of social support, stress, life satisfaction, and burnout), utilizing an idionomic dynamic assessment approach utilizing GIMME. What results will be a series of individual networks, which can be mined to create functionally similar sub-groups, and potentially uncover commonly shared patterns which can be meaningfully generalized at the population level provided they improve idiographic model fit. Specifically, this study has the following aims:

1) Establish the relative frequency and degree to which elements of the EEMM, as represented by PBAT items, are central to networks of five specific aspects of psychological distress, life satisfaction, and burnout. Centrality is traditionally established by (1) quantifying how well an element is connected to other elements, (2) quantifying how well an element is indirectly connected to other elements, and (3) quantifying how important an element is in the average path between two other elements (Epskamp, Borsboom, & Fried, 2018). The current project emphasizes a slightly different conception, namely, the out-strength (the frequency and weight of edges that emerge from a given node) directed toward outcomes of interest (i.e., elements of psychological distress, life satisfaction, and burnout). Node strength has been demonstrated to be more stable than other centrality measures such as connectedness and betweenness (Fried et al., 2016). Analyses will also establish the relative frequency with which elements derived from the EEMM exhibit granger causality with respect to elements of psychological distress, life satisfaction, and burnout.

2) Based on the idiographic networks established, explore the extent to which meaningful subgroups arise. In the case that such subgroups emerge, establish the degree to which subgroups are defined by shared pathways between elements that fit with the underlying theory of the PBAT. While it is difficult to specifically predict the emergence, quantity, or properties of sub-groups, if they are found they may be useful in the design of clinical interventions targeted at sub-populations.

3) Establish to what degree edges emerge at the group level. In particular, previous research has shown group-level findings for the autoregressive paths of elements of psychopathology (Wright et al., 2019), that was conceptualized as inertia (Kuppens, Allen, & Sheeber, 2010). This would be predicted for the elements of psychological distress in the current study as well if the population was clinically distressed, but it is less clear in a population of conveinece and the implications of elements of variation and selection are also less clear.

4) Based on the idiographic networks established after the identification of group and sub-group models, explore in a preliminary way whether the interrelationships among PBAT items and their relation to outcomes fit within the psychological flexibility model as extended by the EEMM.

Feasibility Pilot

A pilot project was undertaken in order to assess the relative feasibility and workability of the daily diary structure, a novel smartphone data collection tool, and the incentive structure for collecting idiographic data using the PBAT.

Participants. Participants were recruited across two venues of healthcare and behavior modification service providers, a school for children with special needs and a non-profit which provides applied behavior analysis for adults with disabilities. Participants were adults in possession of an iOS or Android smartphone and consisted of teachers, behavioral technicians, behavior analysts, and supervisors or administrative staff. Recruitment was conducted via email and included a full description of the study demands, incentives, and tutorial for the use of the data collection smartphone application.

Incentives. Subjects were offered several forms of compensation for completion of the experiment. Firstly, they were promised access to their idiographic psychological network with a description of how to read and make use of it. Secondly, each site was offered a workshop conducted by the lead author based on the findings of the study and targeted toward reducing burnout and improving psychological health. This workshop was also offered as an incentive for the organizations to allow the project to be undertaken with their employees. Third, participants were initially to be entered into a lottery to win 1 of 10 $25 Amazon gift cards. This was converted to a guaranteed $50 for completion midway through the study.

Smartphone Application. Data were gathered using a smartphone application, *Nudge Learning*, a free iOS and Android app. Surveys were distributed daily using the app, which notifies users via push notifications and stores time-stamped data locally for later transmission if internet is not currently available. All items were presented using 0-100 visual analog scales in order to best prevent anchoring and to ensure the within person variability critical to GIMME analyses. *Nudge Learning* notifications were randomized to occur during once per day in the evening between the hours of 6pm-8pm. This is to ensure some amount of variability in the timepoints that data were collected, but to also respect the assumption of relatively equidistance of timepoints. The data collection period was designed to last for 100 days, with a requirement that each participant respond to at least 60 of the daily assessments.

Recruitment, Attrition, and Software Performance. A total of 20 participants were recruited, with 10 coming from each site. Recruitment was conducted via two rounds of emails and coordination with administrative staff at each site. Of the 20 participants recruited, 11 completed 10 or fewer days of assessment, an additional 4 completed 10-25 days, and 5 participants completed the minimum 60 days of data collection. In sum, recruitment and attrition were both poorer than initially expected.

Errors were experienced with the smartphone app that helped explain the problems in retention. During the 4th week of data collection an updated version of *Nudge Learning* was pushed out for all users. Unfortunately, the update crashed the application, and it was inoperable for a two-week period. When an additional update was pushed out to correct the issue, it required participants to fully uninstall and re-install the application. The combination of problems resulted in a considerable spike in attrition, particularly among participants who were averaging 3-4 assessments per week.

Outside of this specific outage, the smartphone application behaved as expected. Notifications appeared to present themselves on time, provided the user allowed notifications on installation. The participant specific notifications created by the research team were received by participants and appeared to have a positive effect on survey completion. There were no reported errors with respect to assessment completion (e.g., participants unable to respond using sliders, surveys completed but not received by the research team).

Lessons Learned. This pilot was invaluable in shaping the current project and shed light on several potentials design pitfalls. Firstly, while there are potential advantages to data quality in collecting assessments once daily for 60-100 days, this proved to be too burdensome for most participants. While a certain degree of attrition over time was expected, the amount of missing data within active participants was surprising. For example, even among participants who went on to complete the minimum 60-day threshold, these participants averaged 4-5 assessments per week. For those who failed to complete, were often submitting 3-4 assessments per week before resulting in attrition. Two possible conclusions were reached: the incentives offered in the pilot were inadequate, and retention problems were likely exacerbated by the extended timeframe of data collection. Additionally, while designed to maximize completion rates, the allowance of 40 missed days over a 100-day period may have actually undermined consistent assessment completion.

In sum, results of the pilot strongly indicated the following: 1) recruiting a larger pool of participants was desirable, 2) a shorter data collection period with more regular assessments might maintain regular engagement and decrease both missing data and attrition, 3) incentives should be both greater in size and be delivered with more immediacy 4) *Nudge Learning* is a suitable platform with which to conduct this research. The present project implemented all of these lessons.

Method

Subjects

Participants were recruited using Amazon's Mechanical Turk service. This was chosen to both maximize the potential pool of eligible participants as well as maintaining as representative a sample as possible. The mTurk program is a marketplace in which employers or researchers post "Human Intelligence Tasks" or HITs for individuals to complete in exchange for payment. Tasks may range from simple image identification, transcription, or data entry to market or other forms of research. Within the field of psychology mTurk has become popular as it represents a more racially and socio-economically diverse sample than that of college students (Casler, Bickel, & Hackett, 2013; Bader, Baumeister, Berger, & Keuschnigg, 2019). Data quality collected through mTurk has been shown to be of equal quality to other data collected online or face-to-face, and mTurk participants have demonstrated superior performance on attention checks compared to college student samples (Hauser & Schwarz, 2016).

In accordance with best practice and in order to prevent the collection of low-quality data, only those with a verified acceptable HIT rate above 80% of previously completed task were permitted to participate (Aguinis, Villamor, & Ramani, 2021; Chmielewski & Kucker, 2020). In addition, recruited participants were required to 1) own a smartphone with reliable access to internet/data, and 2) be a native English speaker. There were no other inclusion or exclusion criteria.

Procedure

Data Collection. The data collection period lasted 35 days, with a requirement that each participant respond to at least 60 of the daily assessments in order to be included in the analysis and to receive a completion bonus. While formal power recommendations have yet to be established (Fried et al., 2017), 60 data points is a well-established sample size across network modeling studies (Fisher, 2015; Lane et al., 2019; Wright et al., 2019). Data were gathered using *Nudge Learning*. Surveys were distributed twice daily using the app, which notified users via push notifications and store time-stamped data locally for later transmission if internet is not currently available. All items were be presented using 0-100 visual analog scales in order to best prevent anchoring.

Upon agreement to participate in the study and completing informed consent, subjects were presented with detailed instructions as to how to download the *Nudge Learning* application, enable notifications, and complete daily surveys. Once the application was downloaded, the lead experimenter assigned them to the study within the application, at which point they were able to complete their first daily diary entry. Participants were instructed they would be asked to complete two daily responses per day. *Nudge Learning* notifications occurred once during day between 10:30am and 12:30pm and once during the evening between the hours of 6pm-8pm.The exact time notifications appeared was scheduled to vary within this 2 hour range. To maintain their participation, participants were permitted to miss no more than 10 total assessment periods across the 35 days of data collection. At any point if they exceeded 10 missed surveys they were removed from the study. Participants were given clear instructions as to the total duration of data collection, and amount of permitted missing data.

Data completion was monitored by the lead experimenter and a team of undergraduate research assistants. If a participant missed a day of data collection, they were prompted via a push notification from the application the following day to return to consistent assessment completion.

Participants were compensated monetarily for their participation in the study. Participants submitted an initial HIT task at the completion of their first survey, which provided them a completion code within the app. This HIT was reimbursed $2 for completion. Every additional complete day of assessment completion yielded an additional $2 which was paid as a “HIT Bonus” each Friday. Survey completion was assessed by the research team and bonuses were paid out without additional steps taken by participants. Upon the completion of their 60th daily diary survey, participants were reimbursed with a bonus of $90. Thus, in total participants were paid $5 a day for their time and effort including the completion bonus. This compensation strategy was designed in accordance with recent recommendations for researchers utilizing mTurk for smartphone-based longitudinal studies (Turner, Eberz, & Martinovic, 2021)

Measures. *Process Based Assessment Tool (PBAT;* Ciarrochi, Hayes & Hoffman, *in preparation*) is an 18-item measure of psychological variation, selection, and retention. The 14 selection items cover the domains of affect, cognitive processes, attention, social connection, motivation/autonomy, overt behavior/competence, and physical health with one positive and one negatively valanced item for each. Two items assess range of variation in behavior and two items assess behavioral retention across time. Items were created and refined by an expert panel with theoretically diverse backgrounds. The panel included (parentheses indicate area of expertise): Steven C Hayes (ACT); Stefan Hofmann (CBT); Baljinder Sahdra (methodology and social psychology); Joseph Ciarrochi (Positive Psychology & ACT); Ann Bailey (Psychodynamic Theory); Frank

Deane (CBT); Robert Brockman (Schema Therapy); and Louise Hayes (Child Clinical Psychology & ACT). Each domain includes a positively and negatively valanced item in order to account for the importance of need thwarting behavior and need supporting behavior (Bartholomew et al. 2011; Ryan & Deci 2017). The PBAT development panel created several revisions of the measure with the goal of simplicity, theoretical clarity, and use within daily diary studies in which participants may be easily overburdened. After the items were created, a blind rating was conducted to ensure that all items were rated as measuring what they were intended to, ambiguous items were further revised. Next the items were subjected to a machine learning evolutionary algorithm to capture important items with respect to a variety of positive and negative outcome variables, and to eliminate redundant or unimportant items. Specifically, a random forest Borunta algorithm (Kursa & Rudnicki, 2010) was utilized to identify the extent that the variation, retention, and selection items each linked to anxiety, sadness, anger, social support, vitality, and health. Boruta is a wrapper built around a random forest classification algorithm (Liaw & Wiener, 2002). In a random forest algorithm "the importance measure of an attribute is obtained as the loss of accuracy of classification caused by the random permutation of attribute values between objects" (pg. 3, Kursa & Rudnicki, 2010). That is to say, importance is derived by the extent to which a feature of a measure is discernable from random variation with respect to a given outcome. In order to do this, Borunta creates "shadow" features, or items, which are created by shuffling values across existing items. The importance of these shadow features can be due only to random fluctuations in the data. From here, the best performing shadow attribute is determined and all items are compared to this benchmark. Items that outperform this comparison are kept, those that do not are rejected. In this way, only items which successfully contribute to the prediction, beyond that of random variation, of a chosen outcome are maintained. For the PBAT this process was conducted with respect to 7 outcomes: sadness, anxiety, anger, stress, lack of support, vitality, and health. Items that consistently performed well across these outcomes were maintained in the final measure.

Table 1. PBAT items

Process Target	**Negative items**	**Positive items**
Affect	I did not find an appropriate outlet for my emotions	I was able to experience a range of emotions appropriate to the moment
Cognitive processes, including those related to self	My thinking got in the way of things that were important to me	I used my thinking in ways that helped me live better
Attention	I struggled to connect with the moments in my day to day life	I paid attention to important things in my daily life;
social/Connection	I did things that hurt my connection with people who are important to me	I did things to connect with people who are important to me
Motivation/Autonomy	I chose to do things that were personally important to me	I did things only because I was complying with what others wanted me to do
Overt Behavior/ competence	I found personally important ways to challenge myself	I did not find a meaningful way to challenge myself
Health	I acted in ways that helped my physical health	I acted in ways that hurt my physical health
Variation	I felt stuck and unable to change my ineffective behavior;	I was able to change my behavior, when changing helped my life
Retention	I stuck to strategies that	I struggled to keep doing something

	seemed to have worked	that was good for me

Screening Tool for Psychological Distress (Stop-D; Young, Ignaszewski, Fofonoff, & Kaan, 2007; Young, Nguyen, Roth, Broadberry, & Mackay, 2015; Appendix B) is a 5-item screen measuring sadness, anxiety, stress, anger, and perceived lack of social support. The STOP-D has demonstrated strong correlations with existing well-validated measures of anxiety and depression. Additionally, indicated severity on STOP-D items cohere with established severity cutoffs. These five items represented the primary outcomes of interest and was used to broadly represent the elements of psychopathology.

Stop-D items:

Over the past day, how much have you been bothered by:

Feeling sad, down, or uninterested in life?

Feeling anxious or nervous?

Feeling stressed?

Feeling angry?

Not having the social support you need?

Single-Item Life Satisfaction Measure (Cheung & Lucas, 2014). The single item “In general, how satisfied are you with your life?” has demonstrated strong criterion validity with a well validated life satisfaction scale and strong criterion validity as evidenced by similar observed correlations with SES, self-reported physical and mental health, and happiness between the single item measure and well validated scale.

Single-Item Measure of Emotional Exhaustion (West, Dyrbe, Sloan, & Shanafelt, 2009). The single item "I feel burned out from my work" has demonstrated strong correlations with the emotional exhaustion sub-scale of the Maslach Burnout Inventory (MBI; Maslach, Jackson, Leiter, Schaufeli, & Schwab, 1986) across 4 large samples of medical professionals.

Data Analytic Plan

Data were analyzed using the Subgrouping Group Iterative Multiple Model Estimation statistical package (S-GIMME; Gates, Lane, Varangis, & Giovanello, 2017) according to the recently published tutorial (Beltz & Gates, 2017) and reference manual (https://cran.r-project.org/web/packages/gimme/gimme.pdf). S-GIMME is run under the R statistical software (R Core Team, 2013). A data matrix was created for each participant. In this matrix, columns represent variables and rows represent timepoints. A separate data-file was created for each participant.

GIMME relies on the unified structural equation model (uSEM) framework which combines SEM with VAR to estimate contemporaneous and temporally lagged relationships (Beltz, Beekman, Molenaar, & Buss, 2013). uSEM is capable of conducting time-series analyses using an SEM framework, allowing for the construction of individual level models with directional relationships (Lane et al., 2019). VAR allows for the specification of the direction of a relationship, necessary to establish Granger causality. Granger causality applies when one variable, X, is able to explain future variance in variable Y above and beyond the autoregression of variable Y. This approach does not assume that participants are homogeneous, meaning they are not expected to share the same path model while exhibiting different strengths, as does multilevel modeling (Piccirillo, 2019). GIMME is capable of analyzing intensive longitudinal data for multiple individuals while allowing for individual-level heterogeneity and general patterning of the sample (Wright et al., 2019). Several simulation studies indicate that GIMME is consistently able to detect patterns of effects in heterogeneous samples at higher rates than competing models (Gates & Molenaar, 2012; Lanes, Gates, Pike, Beltz, & Wright, in press; Smith et al., 2011). Additionally, a strict stopping criterion is utilized that favors parsimony in order to prevent overfitting. S-GIMME improves upon the original GIMME program by creating functionally similar subgroups, defined using shared characteristics of individuals' temporal processes, and uncovering more widely generalizable group-level findings. While S-GIMME does not assume homogeneity, it does assume stationarity, meaning that the idiographic data structure does not change over time (Lane et al., 2019). Thus, detrending the data and other analytic adjustments are at times required. GIMME models have demonstrated reliability with models utilizing between 3 and 20 elements (Beltz & Gates, 2017).

Preprocessing. Though there is currently no consensus on the best way to handle missing data in person-specific time-series designs (Honaker & King, 2010), GIMME handles missing data using full information maximum likelihood (FIML). Meaning missing values are not replaced or imputed, but the missing data is handled within the analytic model, estimating population parameters that would most likely produce the estimates from the sample data that is analyzed. This method utilizes all available information and avoids list-wise deletion which negatively impacts network results. Secondly, GIMME assumes weak stationarity in the data (i.e., it does not model changes to a network over time).

Program Operation. GIMME is fully automated can be run using a graphic user interface. All code can be found at: https://cran.r-project.org/web/packages/gimme (Lane et al., 2017). Measurement interval were input as 12-hours, no exogenous effects were modeled, and thus a uSEM analysis was utilized, data-driven subgrouping was utilized. Standard, a=.05, group- and individual-level significance criteria was used.

Sub-grouping clusters individuals into subgroups, based on information available after the group-level search. Individuals are placed subgroup based on their network patterns. Subgroup level edges are derived in the same way as group-level edges. A sub-group level edge is added if it is found to be significant in 50% of participant models. No sub-group level edges need be found in order to establish subgroups, instead these subgroups are defined by the similarities of their patterns of effects. The default "walktrap" method was utilized here.

Upon running the program, a set of information is provided for the network estimate of each participant. GIMME networks are person-specific, there is a personalized result for each member of the sample which includes edges common across the sample and edges unique to the individual. GIMME is fit using data-drive forward selection. The uSEM analyses do not utilize "step-wise" model fitting, it models both contemporaneous and lagged relations in the same step, and thus does not rely on input order.

The program analyzes data in five steps. First, a null model is fit for each individual. Secondly, a group-level model is identified via Lagrange Multiplier tests (Sörbom, 1989), which analyze the extent to which a parameter will significantly improve model fit if added. If a parameter would increase the fit for a "majority" of participants (defined here as the default 75%), it is added to the model, and the model is re-estimated. The search-and-add procedure is continued until there is no longer an edge that would significantly improve model fit for the majority of the sample. If, during this iterative process, an edge falls below the criterion for significance across a majority of the sample, it is pruned. Next, this process is repeated to search and add subgroup edges if it improves model fit in 51% of the individuals. Fourth, individual models are identified. The group level model is first applied for each individual, then the same search-and-add Lagrange Multiplier tests are utilized to establish whether additional parameters would significantly improve the model fit. This process is continued until an excellent fit is obtained via 2 of 4 commonly accepted fit indices (Brown, 2006): comparative fit index (CFI) $\geqslant .95$; non-normed fit index (NNFI; also known as the Tucker- Lewis index) $\geqslant .95$; root mean squared error of approximation (RMSEA) $\leqslant .05$; standardized root mean residual (SRMR) $\leqslant .05$. Finally, a confirmatory model that includes all group and individual level edges is fit.

***A posteriori* Model Validation**. A posteriori model validation was conducted in order to ensure that the generated models are optimal representations of the data and satisfy model assumptions by verifying the white noise assumption for the standardized residuals output for each model (Lütkepohl, 2005). Residuals are considered white-noise when they have no auto- or cross-correlations. If this is the case, then the first order lagged model implemented by GIMME was successful in removing temporal dependencies in the data.

Linkage to aims. Data is given regarding the fit indices and estimates of the directed lagged and contemporaneous edges. Here the presence and absence of edges as well as the weight of edges is provided. This is the data utilized to determine Aim 1 regarding the degree to which nodes of PBAT processes interplay or establish granger causality with nodes of psychopathology, quality of life, and burnout. In order to maximize the out-strength centrality of relevant processes directed toward outcomes of interest, an iterative approach was undertaken to eliminate poorly performing elements from the model with regard to each outcome. In this approach, positively and negatively framed PBAT items were divided and entered into an S-GIMME model with one outcome of interest (i.e., an element of the STOP-D, life satisfaction, or burnout). The worst performing elements of the PBAT, defined as the process which demonstrated the least out-strength directed toward the outcome, across the sample, were eliminated. This process was based on a median split of all total edges from process to outcome from the initial models. At this point the positive and negative items were combined and a final model was computed. This approach was undertaken in order to distill the most important process elements in the context of a specific outcome of interest, while preserving a relative balance between positively and negatively framed items.

Within the final models, as derived from the process above, the data regarding group and subgroup level edges were examined for Aim 2 and Aim 3. Of particular note are the presence or absence of group-level auto-regressive pathways for variation and retention nodes. Network depictions were also produced for each individual network – these were considered in analyses that explored Aim 4. Thus, the primary data of interest used to test the specific aims of this study are the presence or absence of contemporaneous or directed time-lagged edges between nodes at the individual, sub-group, and group-level. The data analytic approach was designed to explore the conceptual and possible applied utility of this overall approach to empirical case conceptualization, bringing together as it does the psychological flexibility model as extended by the EEMM, the measure development strategy deployed in the development of the PBAT, and the idionomic data analytic strategy instantiated in S-GIMME.

RESULTS

Participants

A total of 57 participants were recruited and completed at least one assessment. Of these, 7 participants were lost to attrition having missed more than 10 assessment periods in the first 30 days. The eliminated participants averaged 17.43 assessments and were not considered in any further analysis. Participants who completed data collection were evenly represented with respect to gender (Female n = 24; Male n = 26), ranged in age from 19 to 71 (m = 38.5), and resided predominately in the United States (n = 38). A total of 6 participant exhibited no variability on one or more item which made further analysis impossible using GIMME. These participates were removed from the analysis, leaving 44.

Network Structure by Outcome

Anxious. Items in the final model targeting distress related to anxiousness can be seen in Table 1. All 44 individual models converged normally indicating that at least two of four fit indices were considered “excellent.” No group level edges were discovered. Auto-regressive pathways were found for all elements in the network. A total of 4 subgroups were discovered, encompassing 35 participants.

Table 2

Network Elements and Out-Strength in the Final Model for Anxious

PBAT Item	Edges	OS
I struggled to connect with the moments in my day to day life	15	3.88
I did not find an appropriate outlet for my emotions	5	1.94
I did things only because I was complying with what others wanted me to do	6	1.77
I was able to experience a range of emotions appropriate to the moment	5	1.51
I did not find a meaningful way to challenge myself	5	1.19
My thinking got in the way of things that were important to me	3	1.11
I found personally important ways to challenge myself	3	1.09

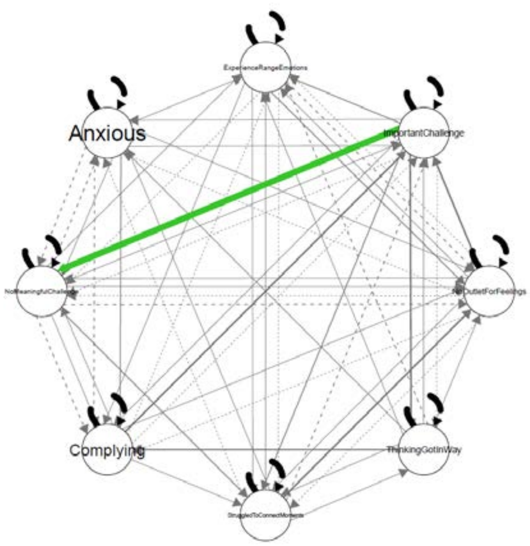

Figure 2. Anxious subgroup 1

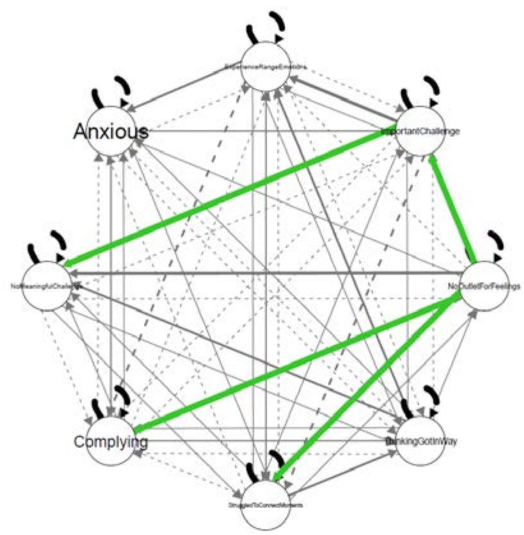

Figure 3. Anxious subgroup 2

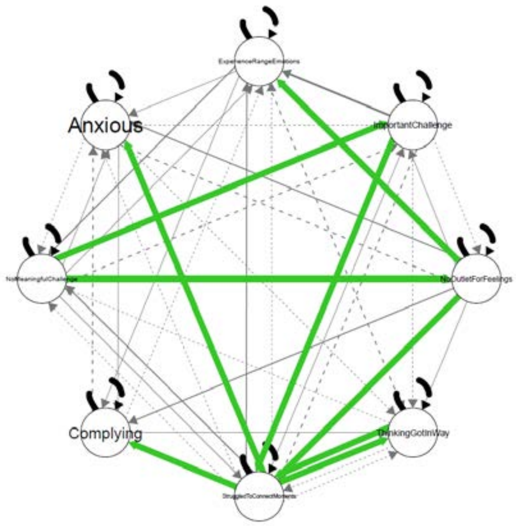

Figure 4. Anxious subgroup 3

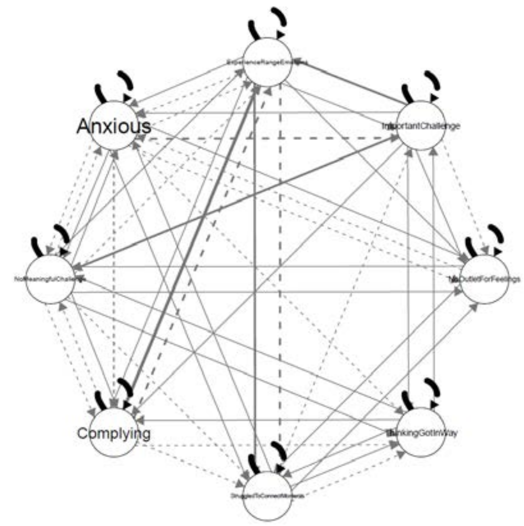

Figure 5. Anxious subgroup 4

Subgroup 1 included 12 participants and was characterized by a subgroup edge from the paired items assessing the presence of a personally important challenge over the past half day. Subgroup 2, *n*=6, exhibited this same group level edge, with the addition of contemporaneous edges from compliance to having no outlet for feelings to important challenge, and from having no outlet for feelings to struggling to connect to the moment. Subgroup 3, *n*=10, comprised 10 individuals and contains a group level edge directed toward anxiousness. At the subgroup level, struggling to connect to moments demonstrated the most out-strength with directed pathways toward anxiousness, thinking getting in the way, and compliance. This element also demonstrated in-strength with pathways directed toward it from personally important challenge, having no outlet for feelings and a self-amplifying loop with thinking getting in the way. The centrality of this node, within this subgroup, indicates it may represent a clinically meaningful sub-population for which inability to connect to personally important moments is especially important. Subgroup 4, *n*=6, illustrates the possibility that no subgroup level edges emerge with the formation of a subgroup. This is possible when individual models share sufficient characteristics to be meaningfully grouped, despite no edges being present frequently enough to comprise a subgroup edge.

Angry. Items in the final model targeting distress related to anger can be seen in Table 2. All 44 individual models converged normally indicating that at least two of four fit indices were considered "excellent." No group level edges were discovered. Auto-regressive pathways were found for all elements in the network. A total of 3 subgroups were discovered which encompass 34 participants.

Table 3

Network Elements and Out-Strength in the Final Model for Angry

PBAT Item	Edges	OS
I acted in ways that hurt my physical health	7	2.71
I did things that hurt my connection with people who are important to me	5	2.52
I struggled to keep doing something that was good for me	6	2.43
I stuck to strategies that seemed to have worked	4	2.10
My thinking got in the way of things that were important to me	6	1.71
I used my thinking in ways that helped me live better	5	1.70
I did not find a meaningful way to challenge myself	3	1.19
I chose to do things that were personally important to me	5	0.49

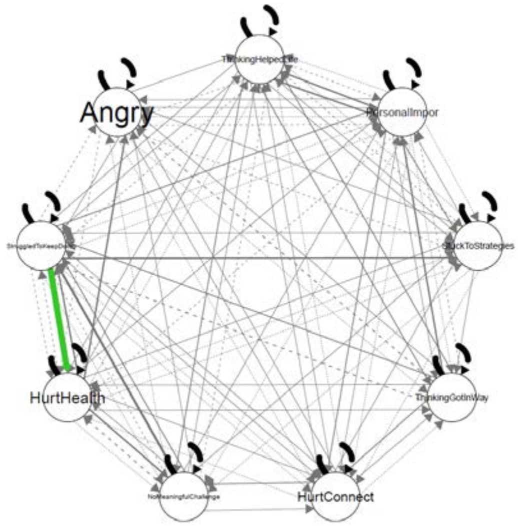

Figure 6. Anger subgroup 1

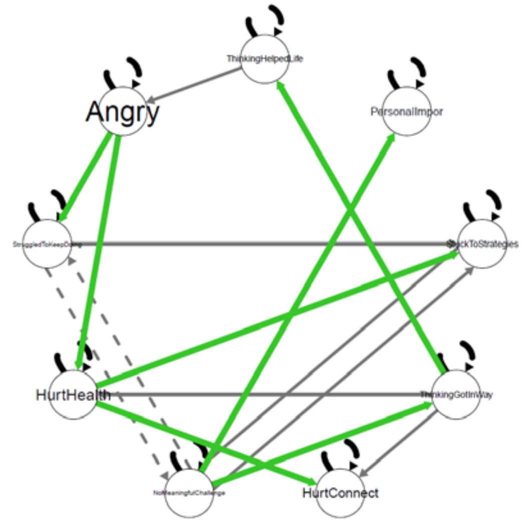

Figure 7. Anger subgroup 2

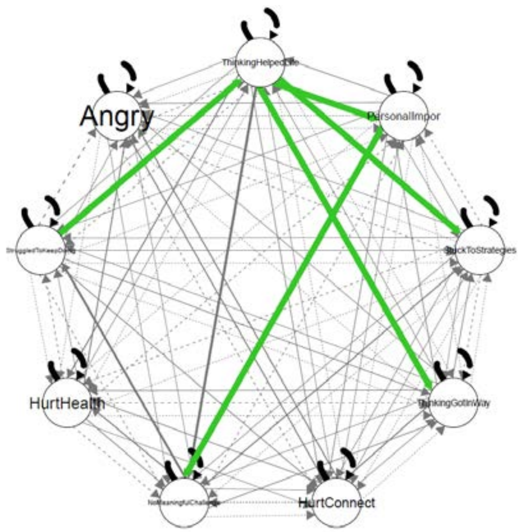

Figure 8. Anger subgroup 3

Subgroup 1, *n*=17, is characterized by a subgroup level pathway emerging from struggling to keep doing what works directed toward hurting health. Subgroup 2, *n*=2, similarly shows directed pathways from anger to both struggling to stick to workable strategies and to hurting health. Taken together, while these models were built to emphasize the out strength of elements directed toward anger, physical health behavior may represent the more generally applicable outcome. Subgroup 3, *n*=15, shows functionally adaptive thinking as the most central element with out-strength directed toward personally important activities, sticking to workable strategies, and thinking getting in the way. Additionally, in-strength is directed from struggling to keep doing what works.

Burnout. Items in the final model targeting distress related to anger can be seen in Table 3. All 44 individual models converged normally indicating that at least two of four fit indices were considered "excellent." No group level edges were discovered. Auto-regressive pathways were found for all elements in the network. A total of 5 subgroups were discovered which encompass 35 participants.

Table 4

Network Elements and Out-Strength in the Final Model for Burnout

PBAT Item	Edges	OS
I struggled to keep doing something that was good for me	8	2.68
I did things to connect with people who are important to me	4	1.91
I was able to change my behavior, when changing helped my life	4	1.88
I did not find an appropriate outlet for my emotions	3	1.11

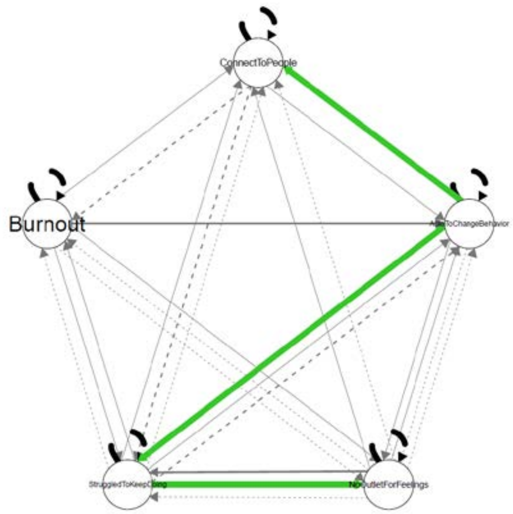

Figure 9. Burnout subgroup 1

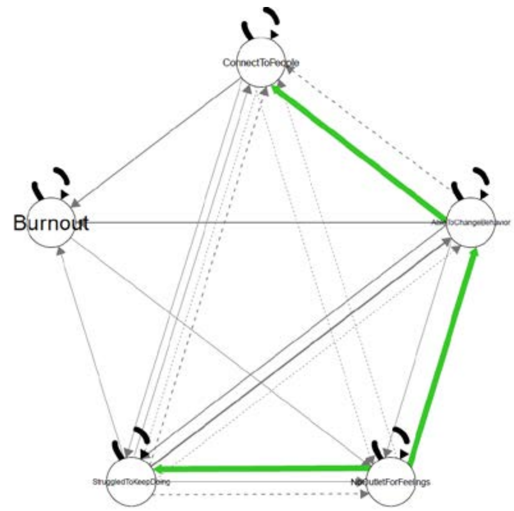

Figure 10. Burnout subgroup 2

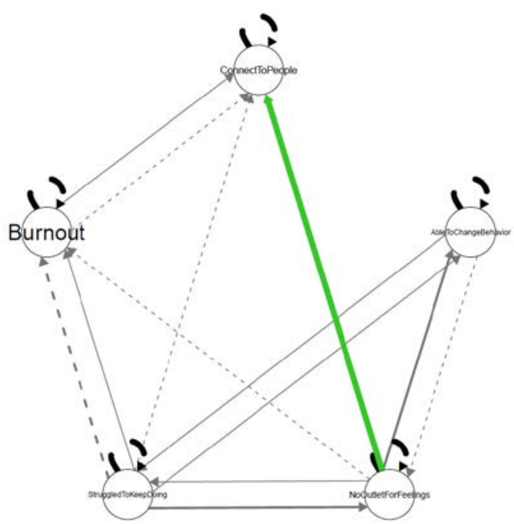

Figure 11. Burnout subgroup 3

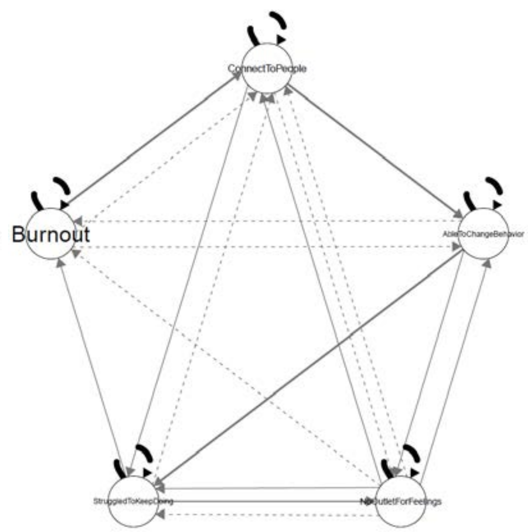

Figure 12. Burnout subgroup 4

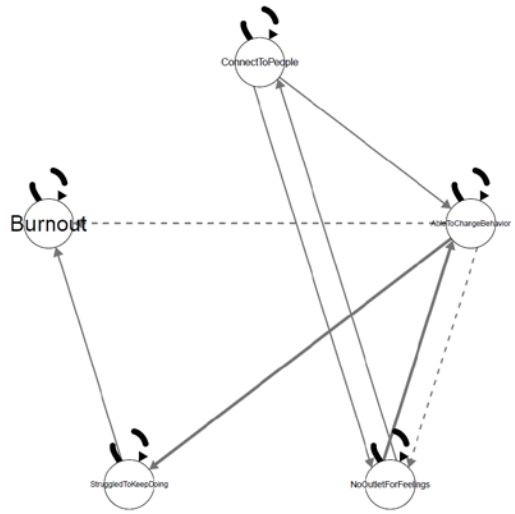

Figure 12. Burnout subgroup 5

Less PBAT out-strength was observed overall with respect to burnout resulting in less elements meeting criterion for inclusion in the final model. Additionally, no subgroup level edges emerged in relation to burnout. This may be due to the nature of the sample, as participants may not have been traditionally employed at rates comparable to the general population. Subgroup 1, *n*=9, includes subgroup edges from being able to change behavior in adaptive ways toward struggling to stick to effective strategies and improving connection to others. Struggling to maintain effective behavior also impacted on having an outlet for feelings. Subgroup 2, *n*=11, shows the same edge from being able to change and connecting to people, and an inverse edge from having and outlet for feelings to struggling to maintain adaptive strategies. Having an outlet for feelings shows a directed edge toward being able to change in this subgroup. Subgroup 3, *n*=5, shows a directed subgroup edge from having an outlet for feelings to doing things to connect to people. Subgroups 4, *n*=6, and Subgroup 5, *n*=4, were not characterized by any subgroup-level edges.

Life Satisfaction. Items in the final model targeting life satisfaction can be seen in Table 4. All 44 individual models converged normally indicating that at least two of four fit indices were considered "excellent." No group level edges were discovered. Auto-regressive pathways were found for all elements in the network. A total of 3 subgroups were discovered which encompass 34 participants.

Table 5

Network Elements and Out-Strength in the Final Model for Life Satisfaction

PBAT Item	Edges	OS
I paid attention to important things in my daily life	20	8.57
I stuck to strategies that seemed to have worked	5	2.22
I did not find an appropriate outlet for my emotions	4	1.47
I found personally important ways to challenge myself	3	1.44
I used my thinking in ways that helped me live better	2	1.44
I struggled to keep doing something that was good for me	2	0.71

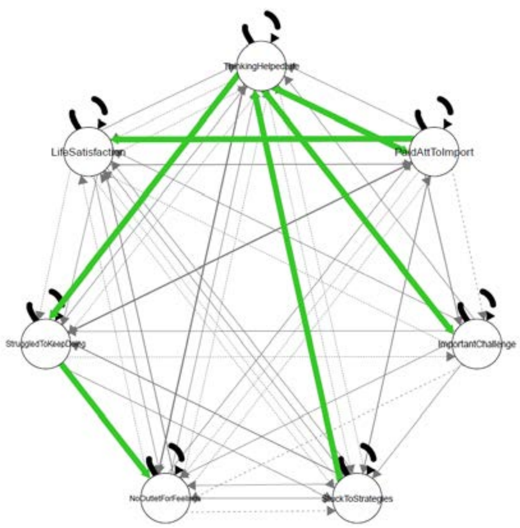

Figure 13. Life satisfaction subgroup 1

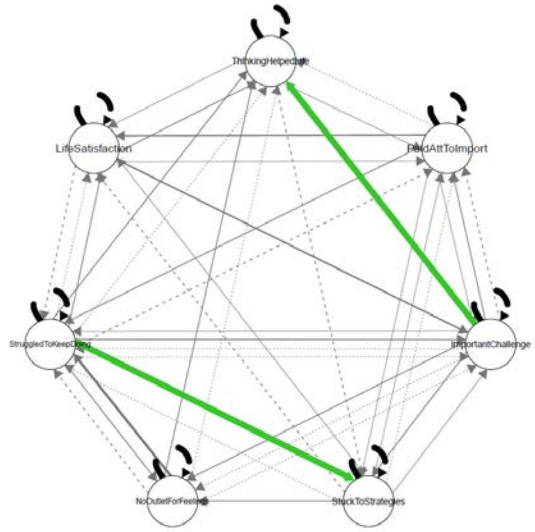

Figure 14. Life satisfaction subgroup 2

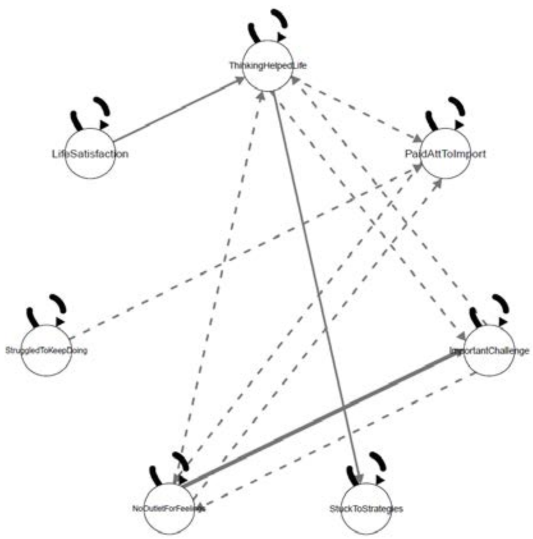

Figure 14. Life satisfaction subgroup 3

In subgroup 1, *n*=18, subgroup level edges emerged from thinking helping life to paying attention to important moments to life satisfaction. Subgroup edges also emerged from thinking helping life to having personally important challenge and struggling to keep doing what work, which was linked to having an outlet for feelings. Finally, an edge from sticking to strategies that work to thinking helping life is observed. Within this subgroup the level of adaptive cognition appears to be central to perceptions of life satisfaction. Within subgroup 2, *n*=13, no subgroup edges were found to be related to life satisfaction, but edges were found between personally important challenge toward thinking helping one's life, and between the item pair assessing retention of effective behavioral strategies. Subgroup 3, *n*=2, is small and did not include any subgroup level edges.

Sadness. Items in the final model targeting distress related to sadness can be seen in Table 5. All 44 individual models converged normally indicating that at least two of four fit indices were considered "excellent." No group level edges were discovered. Auto-regressive pathways were found for all elements in the network. A total of 3 subgroups were discovered which encompass 37 participants.

Table 6

Network Elements and Out-Strength in the Final Model for Sadness

PBAT Item	Edges	OS
I struggled to connect with the moments in my day to day life	22	9.93
I felt stuck and unable to change my ineffective behavior;	8	5.85
I did not find an appropriate outlet for my emotions	7	3.20
I used my thinking in ways that helped me live better	8	3.02
I paid attention to important things in my daily life	6	2.04
My thinking got in the way of things that were important to me	3	1.86
I stuck to strategies that seemed to have worked	3	1.12

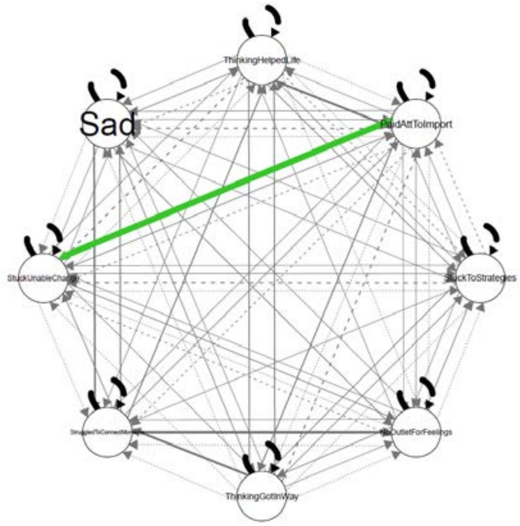

Figure 15. Sadness subgroup 1

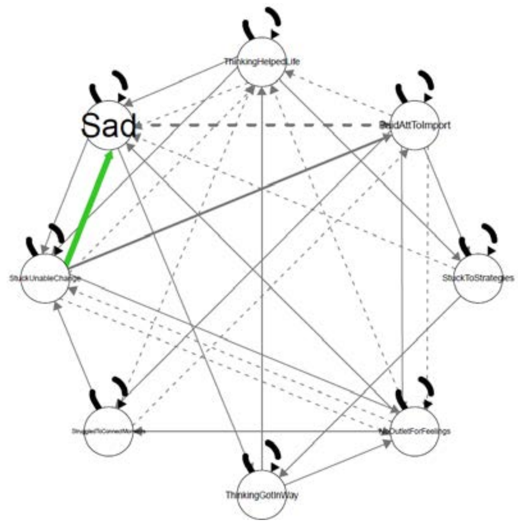

Figure 16. Sadness subgroup 2

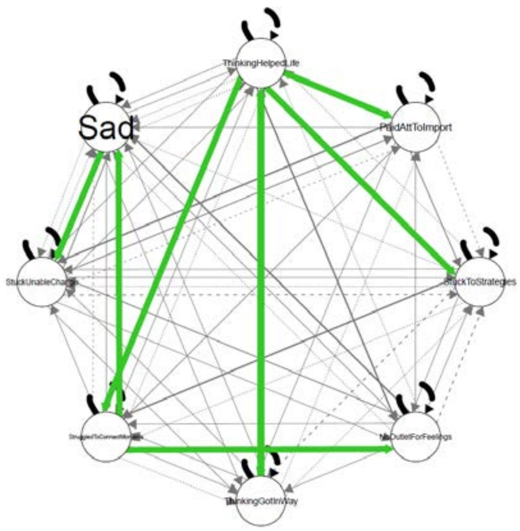

Figure 17. Sadness subgroup 3

Subgroup 1, *n*=15, shows a subgroup level edge emerging from paying attention to important moments toward being stuck and unable to change. Within subgroup 2, *n*=5, being stuck and unable to change is shown to impact contemporaneously on sadness. Subgroup 3, *n*=17, shows a total of 6 subgroup-level edges. This subgroup appears to be best characterized by the centrality of thinking helping life, with three outgoing pathways (paying attention to important moments, sticking to workable strategies, and struggling to connect to moments) and one incoming pathway from the negatively framed cognitive item. Additionally, an edge from struggling to connect to moments to sadness was discovered, with sadness impacting upon feeling stuck and unable to change.

Social Support. Items in the final model targeting distress related to perceived lack of social support can be seen in Table 6. All 44 individual models converged normally indicating that at least two of four fit indices were considered "excellent." No group level edges were discovered. Auto-regressive pathways were found for all elements in the network. A total of 3 subgroups were discovered which encompass 39 participants.

Table 7

Network Elements and Out-Strength in the Final Model for Social Support

PBAT Item	Edges	OS
I did not find an appropriate outlet for my emotions	10	4.93
I paid attention to important things in my daily life	6	2.76
I used my thinking in ways that helped me live better	7	2.51
I did things only because I was complying with what others wanted me to do	8	3.02
I stuck to strategies that seemed to have worked	5	1.60
I chose to do things that were personally important to me	1	0.54

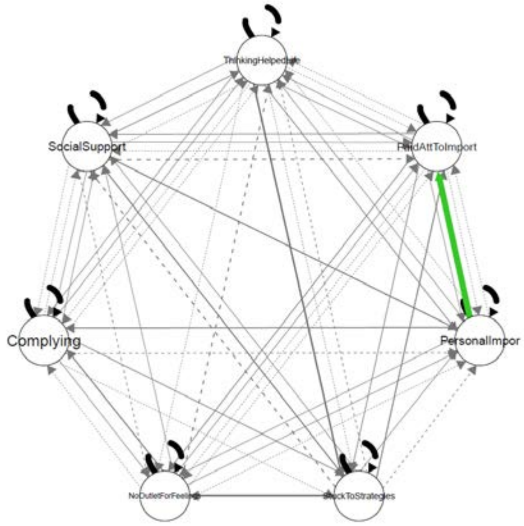

Figure 18. Social support subgroup 1

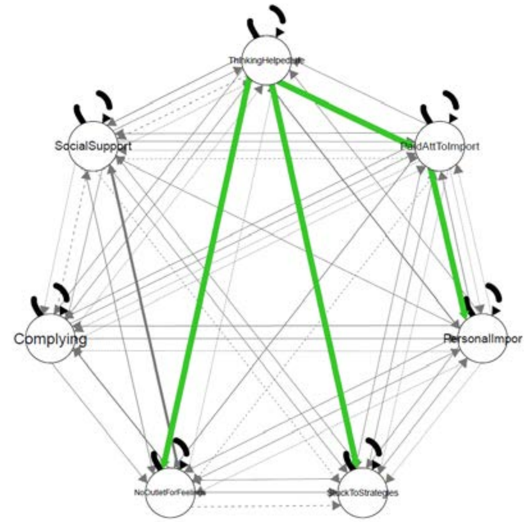

Figure 19. Social support subgroup 2

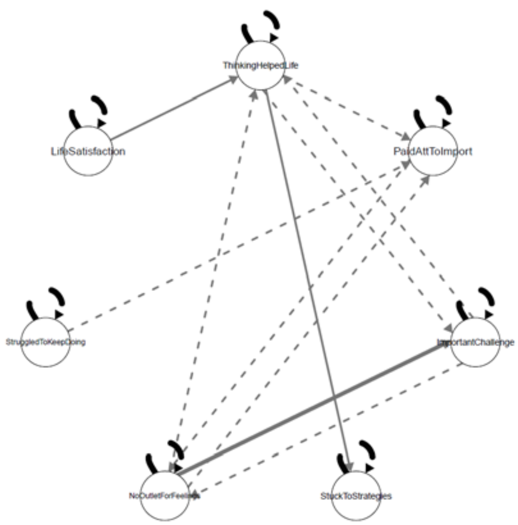

Figure 20. Social support subgroup 3

Social support subgroup 1, *n*=15, shows a subgroup pathway emerging from doing things that are personally important directed toward paying attention to important moments. Subgroup 2, *n*=21, is again characterized by thinking helping life as its most central node with out-strength pathways directed toward having no outlet for feelings, sticking to strategies that work, and paying attention to important moments which has a further cascading pathway toward doing things that are personally important. Subgroup 3, *n*=3, is relatively small and does not contain any subgroup-level edges.

Stress. Items in the final model targeting distress related to sadness can be seen in Table 7. All 44 individual models converged normally indicating that at least two of four fit indices were considered "excellent." No group level edges were discovered. Auto-regressive pathways were found for all elements in the network. A total of 4 subgroups were discovered which encompass 38 participants.

Table 8

Network Elements and Out-Strength in the Final Model for Stress

PBAT Item	Edges	OS
I used my thinking in ways that helped me live better	8	3.20
I did things to connect with people who are important to me	7	2.75
I did not find an appropriate outlet for my emotions	7	2.66
I stuck to strategies that seemed to have worked	5	2.6
I struggled to keep doing something that was good for me	5	1.75
I did not find a meaningful way to challenge myself	5	1.44
I paid attention to important things in my daily life	2	0.64

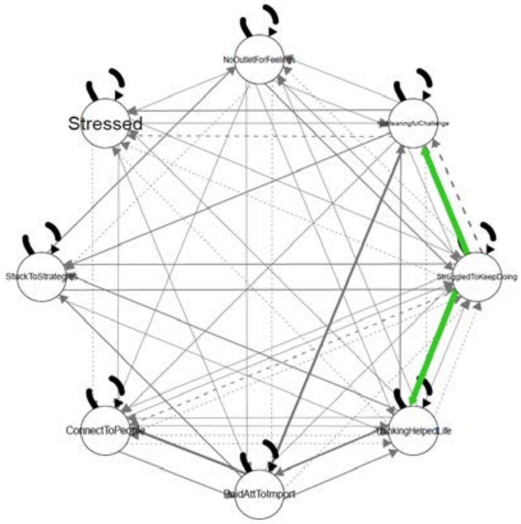

Figure 21. Stressed subgroup 1

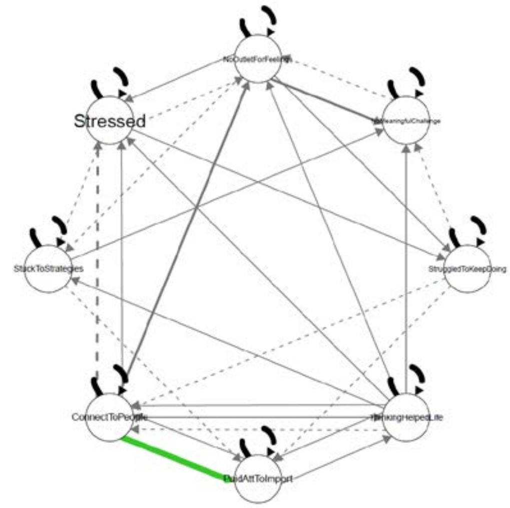

Figure 22. Stressed subgroup 2

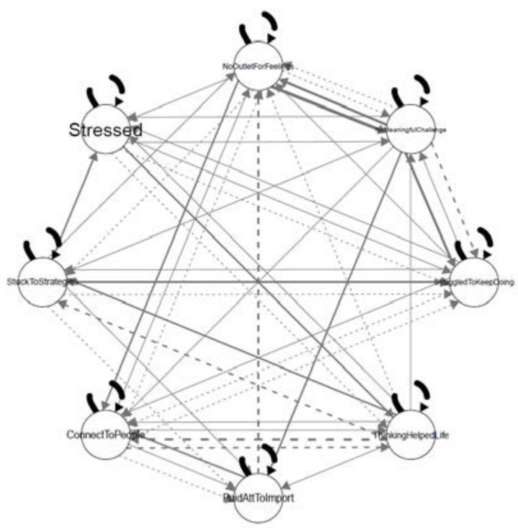

Figure 23. Stressed subgroup 3

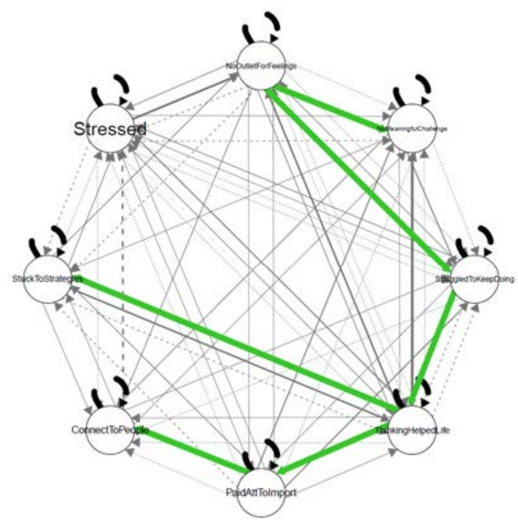

Figure 24. Stressed subgroup 4

Subgroup 1, *n*=10, contained 2 subgroup level edges, both emerging from struggling to keep doing what works and impacting reporting no meaningful challenge in like and having thinking help life. Subgroup 2, *n*=5, includes one subgroup-level edge from doing things to connect to people directed toward paying attention to important moments. There are no subgroup-level edges within the model for subgroup 3, *n*=8. The fourth subgroup, *n*=15, is again characterized by the centrality of thinking helping life with directed pathways toward sticking to effective strategies and paying attention to important moments, which has a directed path to connecting with people, and incoming paths from struggling to keep doing what works. Struggling to do what works has an incoming pathway from having no outlet for feeling which is further impacted by having no meaningful challenge in life.

Subgroup Consistency. A total of 5 subgroups across the above analyses share a structure characterized by the centrality of “I used my thinking in ways that helped me live better” (life satisfaction subgroup 1, sadness subgroup 3, anger subgroup 3, social support subgroup 2, and stress subgroup 4). While these models were built by selecting the items that showed the most out-strength directed toward the outcome of choice, it is telling that similar patterns emerged within a subgroup of participants across the models. This appears to be in part due to consistency in which items performed well and were included in each model. Thinking helped my life was found to have a directed subgroup-level pathway toward struggling to maintain effective strategies in 4 of the models, and a directed pathway toward paying attention to what is important in 4 models. However, this element was also found to have subgroup level pathways directed at 6 additional unique elements across the models and was found to have 4 unique incoming subgroup-level pathways. There is also evidence of consistency of which participants make-up this subgroup. A total of 29 subjects appeared in any one of these five subgroups, of those who appear once, 31% are included in all five subgroups, 17% appear in three or four subgroups, 31% appear in two subgroups, and 21% appear only once. Taken together, this speaks to both the consistency of network structures containing overlapping elements. Additionally, S-GIMME models and subgroup members can fluctuate given individual level differences in network structure as elements are replaced between models.

Discussion

Behavioral psychologists have long insisted that the need for repeated measurement in practical work comes with the requirement of “the separation of measurement error, extraneous variability, and intervention-related variability at the level of the individual” (Hayes, Barlow, & Nelson-Gray, 1999, p. 109). The approach to measurement and intervention that is reflected in the PBAT and idionomic strategy is linked to long standing behavioral skepticism about the mathematical assumptions of typical normative comparisons as they apply to individuals, namely that it is impossible to “apply the results to nonrandom samples even though these are the only kinds of samples clinicians ever treat” (Hayes, 1988, p. 117). Instead, “in order to understand why and how changes happen in an individual, we need to study the processes of change at the level of the individual, and then to gather nomothetic summaries based on collections of such patterns” (Hayes, Hofmann, Stanton, Carpenter, Sanford, Curtiss, & Ciarrochi, 2019, p. 43).

Some philosophers of science (e.g., Popper, 1997) have taken a dim view of inductive research since it admittedly contains the logical error of affirming the consequent. In his view and that of other falsificationists, although scientific theories can never fully be empirically verified, they can be shown to fail, and thus the logical principle of modus tollens should be the core rule of the empirical sciences. The problem with this idea is that empirical science requires auxiliaries and conditions to test hypotheses. For example, if a process is said to lead to an outcome in a population in some circumstances, these processes and outcomes much be measured, this population much be sampled, and these circumstances much be modeled. Because these auxiliaries and conditions are themselves not generally measured or tested precisely in behavioral science, it "makes it hard for us social scientists to fulfill a Popperian falsifiability requirement" (Meehl, 1978, p. 819).

Inductive behavioral science begins its different way forward by narrowing the gap between concepts and the auxiliaries and conditions involved in testing them. A functional and contextual approach to behavior:

> begins with careful behavioral observations: refined and precise descriptions of behavioral phenomena in well-characterized contexts. The functional relationship between behavioral phenomena and contextual events are organized into behavioral principles: ways of speaking about these relations that are precise and broad in scope, allowing behavioral phenomena to be both predicted and influenced. Specific complex phenomena are unpacked through functional analysis: the application of behavioral principles to a specific behavioral history and form. These are then organized into systematic and generally applicable sets of functional analyses of important classes of behavioral observations. When we have that level, we have a behavioral theory. Theories of this kind are "analytic-abstractive" in that they are inductive generalizations that sit atop

abstractions and analyses based on the observational level. (Hayes et al., 2007, p. 48).

Analytic-abstractive models or theories are not tested in a hypothetico-deductive fashion. Rather they are tested by systematic replication: the extension of high precision, high scope, measurement approaches, tightly linked to an underlying theorical model, and systematically varied across populations, domains, and conditions (Hayes, Barnes-Holmes, & Wilson, 2012). Said in another way, risky inductive tests are based first on creating a tight link between measures and the theoretical concepts or models they are said to quantify, and then examining them in systematic and theoretically coherent extensions across people and circumstances so as to make success or failure meaningful. Ironically, this is highly similar to Meehl's (1978) proposed solution to the difficulties of mounting Popper's falsification approach in psychology, but with a twist. Meehl argued it would be a "very strange coincidence" (p. 821) if there was correspondence between empirical observations and the "antecedently improbable observational patterns" (p. 821) suggested by a particular theory or model but he argued that was true, precisely because the auxiliaries and conditions are loosely linked to the theory. Said more loosely, since it is surprising to detect a signal through noise, it is thereby more surprising and "valuable to show approximate agreement of observations with a theoretically predicted numerical point value, rank order, or function form" (Meehl, 1978, p. 825; italics in the original). As Hayes (2004) points out, however, this is not falsification, it is verification. Furthermore, it is often not unlikely that poorly understood auxiliaries and conditions might produce outcomes that correspond to theoretical predictions. For example, if the conditions of measurement readily allow observer bias, theories that comport with that bias might be easily confirmed. Hayes argued that showing agreement of observations with a theoretically predicted numerical point value, rank order, or function form is simply the condition under which “verification provides a particularly useful guide to a research program” but for this to occur “there has to be a small gap between theory and the auxiliaries and conditions.” (Hayes, 2004, p. 36).

As this strategy applies to the present study, the PBAT refined its measurement procedures in a precise and highly specified and theoretically driven fashion. The performance of the PBAT items were then examined using data analytic procedures in a highly refined and specified idionomic way. GIMME itself allows statistical models to be generated and systematically tested with known and conservative principles. Said in another way, the PBT, the EEMM, PBAT and GIMME are all designed to narrowing the gap between concepts, auxiliaries, and conditions so that an inductive approach can be instructive.

Results from the present analysis are a promising step in this direction. Individual models converged normally for the overwhelming majority of participants. This indicates S-GIMME is a statistical procedure that is generally robust and able to accommodate novel measures of psychological processes. It is also further evidence that 60-data points provides reasonable power. Finally, the relatively low attrition rate of the final sample indicates the PBAT is suitable for daily diary research and is not overly burdensome to participants.

No group level edges were discovered between nodes in any network considered for this analysis. This speaks both to the heterogeneity of the participants and of the processes assessed. Strong auto-correlations emerged for all processes, including those of items measuring behavioral variability and retention. This suggests that like most psychological processes, reliable patterns emerge in individual patterns of variability and retention, or the lack thereof. While no group-level edges were found, subgroups emerged for each outcome oriented model. Multi-individual subgroups within these models varied between 2-5, with membership varying between 2-21 further speaking to the heterogeneity of the sample with respect to these psychological processes.

Perhaps most encouraging is the frequency of observed edges which emerged from elements of the PBAT directed toward specific elements of psychological distress. Both contemporaneous and time-lagged relations were observed for each element of psychological distress within this sample. The current analysis emphasized these relationships by selecting only the items that impacted most consistently on a chosen outcome and using these items to create a more parsimonious model. It is notable that 17 of a possible 18 PBAT items were included in at least one final model, speaking to the generally applicability of this measure to assess processes which directly bear on psychological functioning. The only item to not be included regards physical health: “I acted in ways that helped my physical health” while its negatively framed paired item “I acted in ways that hurt my physical health” only appeared in one final model. This may reflect that these items function more as an outcome variable than a functional process that is consistently related to psychological outcomes. Further analyses may investigate physical health behavior as an outcome in idiographic network studies using the PBAT.

Several elements of the PBAT emerged as consistently related to specific outcomes within this sample. The majority of participates (26) demonstrated a contemporaneous directed relationship from paying attention to important moments in life to overall life satisfaction. This is perhaps unsurprising given the literature linking mindful practice to quality of life (Han, 2021; Rayan & Ahmad, 2016; Lassander et al., 2021). This item appears to capture the functional process through which one attends to naturally occurring reinforcers in their environment influencing their perceived satisfaction with life. In the context of sadness, a majority of individual models (25) showed a directed pathway emerging from “I used my thinking in ways that helped me live better.” The negatively framed item assessing thinking getting in the way emerged as a directed edge for 7 participants. It is also important to note the framing of the outcome here -- participants were not merely asked about the presence of sadness as an emotion, but how much they were bothered by sadness. Taken together, this indicates the importance of maladaptive cognitive strategies in distress related to sadness. Furthermore, this element of the PBAT is also present in the final models for anger, life satisfaction, perceived social support, stress, and general psychological distress indicating a wide scope of applicability. Lastly, “I did not find an appropriate outlet for my emotions” was present in 7 of the 8 final network models, only being absent from anger, while representing the highest proportion of direct edges for perceived social support and stress. In these three top performing items we have an attentional component, a cognitive component, and an affective component, perhaps suggesting the conceptual utility of the EEMM as a “meta-model” that can be used to assess the comprehensiveness of process-based models (Hayes et al., 2019).

Items concerning interpersonal behavior, fostering stronger connections to other or impairing one’s connection to another were relatively unrepresented in most of the final models, most notably the model targeting perceived social support. While these items would be theorized to strongly impact social support, other items may have better captured shared variance. Additionally, it is unclear to what extent social distancing in the context of the ongoing COVID-19 pandemic has impacted social behavior and its relevance to psychological networks reported on a day to day basis.

In sum, there do appear to be theoretically coherent trends in which items are applicable to various specific domains of psychological suffering, however, it is important to note that the final model for each domain was unique. None of the outcomes had the exact same set of processes of change that were above the median frequency. Additionally, it should be stressed that individual networks within these models are unique with idiographic patterns amongst nodes. While may be tempting to simply specify the most generally useful items, across domains and across people, and advise the use of those items in a refined measure, it remains important to maintain as much idiographic variability as possible. Using a small set of psychological process and outcome items provides benefits both in the ease of daily assessment administration and in generally yielding more parsimonious and interpretable network. However, it appears clear from these data that process items should be selected that best fit a particular theoretically driven case conceptualization for the person and presenting problem. The data here alone are not enough to provide strong guidance to that end but are a first step in the process. With additional replications of this method utilizing overlapping assessments with novel populations, we seek to establish consistent functional patterns which can be used to make useful generalizations and treatment recommendations.

Clinical Implications

In order to illustrate the potential clinical utility of idiographic network models utilizing functional psychological processes directly tied to kernels of intervention, two models were selected from which a case conceptualization will be developed. Models were selected based on having at least one directed pathway toward the outcome of interest and at least two process to process. Approximately 70% of individual network models met this criteria, the examples below were chosen based on the variety of potentially clinically useful pathways they represented.

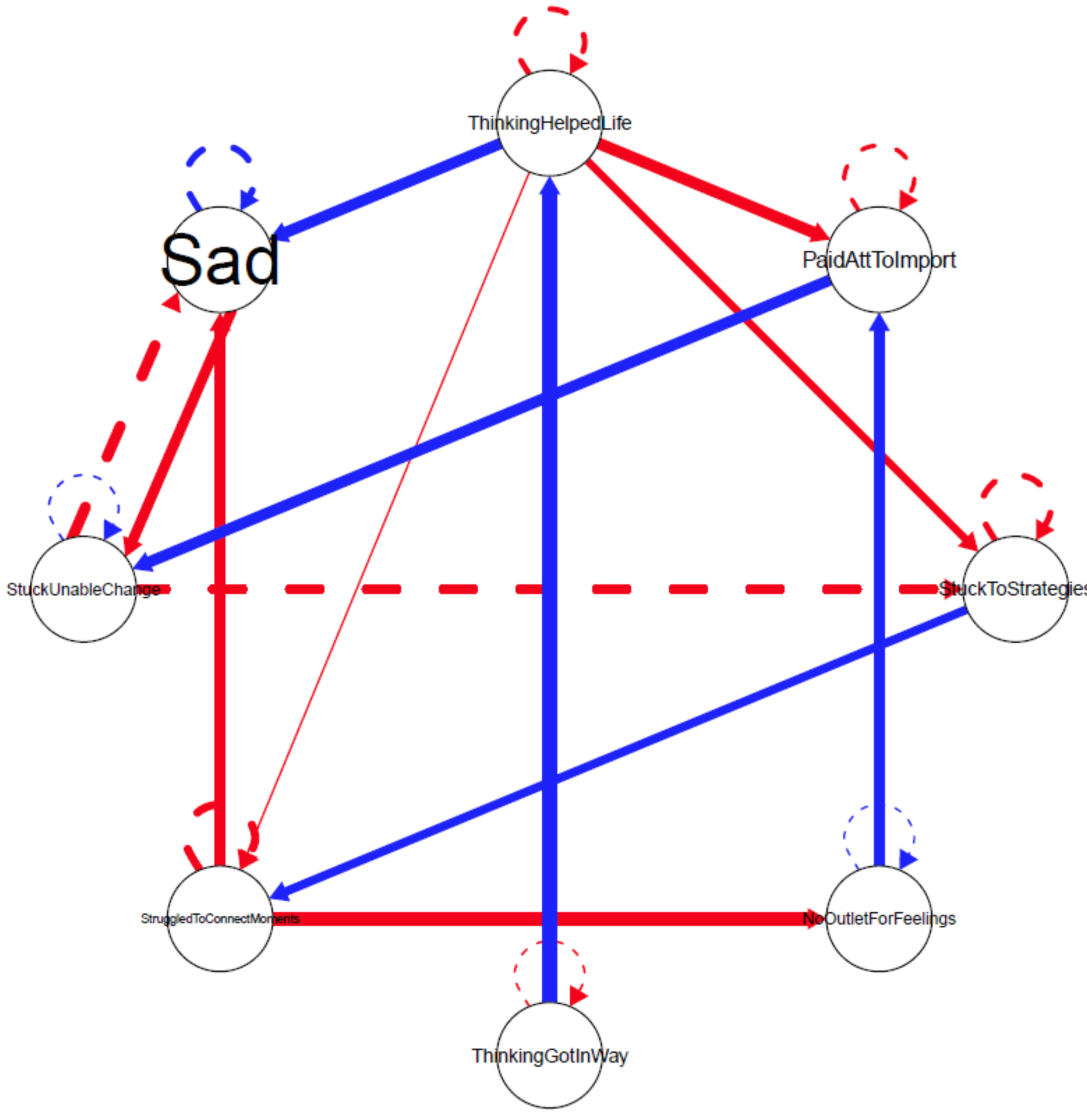

Figure 25. Idiographic Network Model for Subject 1

Figure 25 displays the individual network model for a participant targeting distress related to sadness. Perhaps most striking is the self-amplifying loop between sadness and feeling stuck or unable to change behavior. This fits a classic behavioral activation conceptualization whereby the less important and meaningful behavior a person engages in, the worse they feel. Here we see this illustrated by a contemporaneous relationship between sadness and feeling stuck, likely not engaging in valued activity. This, in turn, predicts increased sadness at the next time-point. Next, we see that the cognitive elements exhibit considerable out-strength (represented by the thickness of the lines in the model). The two cognitive items are strongly linked, as would be expected, and cascade into relationships with sadness, and paying attention to important moments, which in turn is inversely related to feeling stuck and predicts increased sadness. The network model for this person suggests that targeting a problematic relationship with cognition such that it impairs the person's ability to engage in a variety of valued behavior or attend to relevant natural reinforcers would be instrumental. Additionally, this person exhibits a self-correcting pattern whereby feeling struck also predicts an increased likelihood of returning to strategies that have worked for them in the past. When they return to these well-rehearsed adaptive strategies, they report less problems connecting to the moment and which in turn impacts on sadness. Within the context of treatment this self-correcting pattern should be emphasized and bolstered to more quickly ameliorate the self-amplifying loop of sadness and behavioral invariability.

A second network follows with a person experiencing distress related to anger. As the individual reports increased problematic anger, we see it predicts behaviors which hurt their health at the next time point, feeding a self-amplifying loop with struggling to keep doing what you know works. Both of these elements show inverse auto-correlations, which in this case, likely speaks to a pattern where higher and lower responses were reported in the midday as opposed to the evening assessment. The network also indicates that when the person does something that hurts their connection with others, it further feeds the pattern of deleterious health behavior. This pattern would fit a hypothetical substance abuse patient that, when they experience anger or interpersonal conflict it predicts a pattern of failing to stick to strategies they have used to maintain sobriety and engaging in substance use. In addition to the cognitive element represented by using thinking to help your life impacting on utilizing strategies that have worked, we find that engaging in personally important, or values consistent, behavior impacts on both anger and interpersonal functioning. Therefore, the clinician is oriented to emphasizing values clarification and valued behavior scheduling over the course of treatment.

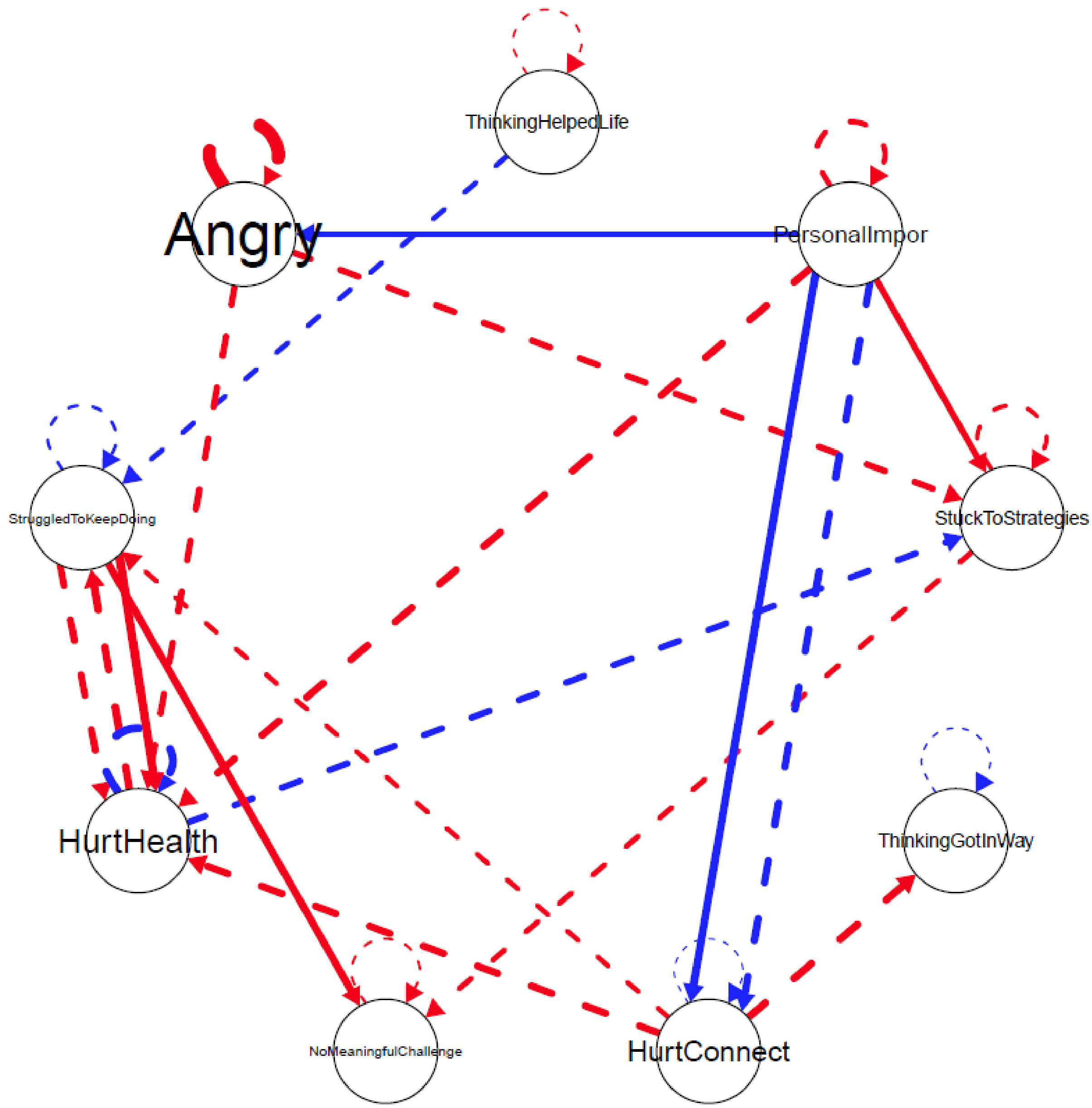

Figure 26. Idiographic Network Model for Subject 2

While it may sometimes be unrealistic or unethical for a clinician to delay treatment long enough to conduct daily diary assessment for a sufficient period to model their cases idiographically, when such conditions are appropriate network analyses such as these liked to a large data set of similar clients might provide meaningful clinical utility. This would need to be demonstrated empirically, but if the relationships between edges in process-based network models such are somewhat consistent in person with same process deficits and problem focus, clinicians may be able to make use of large reference samples in creating case conceptualizations. In this approach, the clinician would select the relevant intervention target(s) (e.g., sadness, anxiousness, stress) and a set of process variables that appear to be particularly relevant to the patient. An S-GIMME analysis could then be conducted on a large reference sample using this combination of elements. The product of this analysis would yield potentially useful subgroups and subgroup pathways as well as a list of commonly occurring edges. This could inform, though not substitute for, an ongoing functional analysis of the patient. For example, the practitioner may be warned of commonly occurring self-amplifying loops that could occur, and that could explain why problematic results have been resistant to change.

Conclusions. The theoretically coherent set of results found in this study support the ongoing work in creating idionomic analyses of processes of change. The PBAT held up in a way that supports the benefits of the EEMM. GIMME was able to yield consistently interpretable data, using datasets that may be possible to collect in clinical settings.

A variety of trends suggest that the day may not be far away in which top-down normative categories will be put away as the goal of mental and behavioral health diagnosis in favor of a measurement and data analytic strategy that gives voice to each and every individual cared for as part of the health care system. This is already occurring in some areas of personalized medicine and the day appears to be arriving in mental and behavioral health care. Process-based functional analysis seems far more likely to have treatment utility as a treatment guidance system since the processes that are fed into the approach are precisely those known to be related to functionally important pathways of change.

The days of “protocols for syndromes” appear to be on the wane and if it is true that syndromes violate mathematically established accepted science that is nearly a century old, that day cannot come soon enough. It is not yet clear what will replace the existing syndromal model, but this study suggests that the early steps that have been taken toward an idionomic, process-based approach are empirically progressive.

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