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Empirical Research

Toward empirical process-based case conceptualization: An idionomic network examination of the process-based assessment tool

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ABSTRACT

Background: Syndromal classification has failed to produce a progressive science of case conceptualization for mental and behavioral health issues. An idiographic application of processes of change can provide a viable empirical functional analytic alternative if it could be linked to an *idionomic approach*, modeling idiographic effects first, and retaining nomothetic findings if they improve idiographic fit. Method: The present study examined this possibility by using the Process-Based Assessment Tool (PBAT), a new assessment tool linked to the Extended Evolutionary Meta-Model (EEMM) of Process-Based Therapy. The PBAT and items assessing common clinical outcomes were assessed repeatedly in 50 individuals in an experience sampling format over a 35 day period yielding at least 60 measurement occasions per person. These data were then analyzed in an idionomic fashion using Group Iterative Multiple Model Estimation (GIMME). Results: Analyses showed that the PBAT related to common clinical outcomes for virtually all participants in the individual complex networks identified by GIMME. Data showed that relationships had to be studied using an idionomic approach because participants' responses violated the ergodic assumptions underlying classical normative statistics. No overall group patterns were found. Subgroup relations did emerge for three common outcomes (sadness, anxiety, and life satisfaction) but most process to outcome relationships were idiographic. Idiographic networks were interpretable, however, using the broadened psychological flexibility approach of the EEMM. Conclusion: Idionomic network analysis of processes of change may provide a replicable form of empirical functional analysis and process-based case conceptualization.

It is important for practitioners to have ways of understanding and speaking about their clients' lives, goals, and difficulties that improve clinical intervention outcomes and foster the rapid development of clinical science itself (Hayes, Nelson, & Jarrett, 1987; Nelson-Gray, 2003). For the last half of a century syndromal approaches to these tasks, such as through the Diagnostic and Statistical Manual of Mental Disorders (DSM; American Psychiatric Association, 2013) or the International Classification of Diseases (ICD; WHO, 2018) have been the dominant approach. As a practical avenue toward case conceptualization with known treatment and conceptual utility, syndromal approaches have a number of known weaknesses, however, including poor specificity (Fried & Nesse, 2015; Galatzer-Levy & Bryant, 2013; Galatzer-Levy & Bryant, 2013, 2013; Watson, 2005; Widiger & Clark, 2000), a high degree of comorbidity (Brown, Campell, Lehman, Grisham, & Mancill, 2001; Kessler, Tat Chiu, & Demler, 2005; Lenzenweger, Lane, Loranger, & Kesslerand, 2007), and excessively broad treatment implications (Glick, Murray, Vasudevan, Marder, & Hu, 2001; López-Muñoz et al., 2003). Over a decade ago, the National Institute of Mental Health responded to this lack of empirical progress by launching the Research Domain Criteria (RDoC) project. The RDoC was conceptualized as a research agenda that seeks to formulate a dimensional approach based on the biological and behavioral processes underpinnings of mental illness with an emphasis on "genomics and neuroscience, which ultimately will inform future classification schemes" (Insel et al., 2010).

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While a reorientation toward processes of change could be progressive, the premature commitment to focus on issues in neurodevelopment (Insel & Cuthbert, 2015) undermined progress. Neurodevelopment is part of a dynamical system involving environment and behavior, but predetermining which elements are most important in such networks in the absence of clear data is scientifically unwise. It is quite possible, for example, that multiple genetic and biological pathways may produce the same outcomes (e.g., behaviors or symptoms), what has been termed the problem of "degeneracy" (Edelman & Gally, 2001; Tononi, Sporns, & Edelman, 1999). 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" (Borsboom, Cramer, & Kalis, 2019, p. 2). A new way forward toward case conceptualization systems with high levels of treatment and conceptual validity is needed.

1. Empirical functional analysis

One appealing alternative to syndromal classification is functional analysis, in which "behaviors and sets of behaviors are organized by the functional processes that are thought to have produced and maintained them" (Hayes, Wilson, Gifford, Follette, & Strosahl, 1996, p. 1153). As deployed in early behavior therapy, however, this approach failed because it was vague, excessively focused on direct contingencies, and difficult to replicate or generalize (Hayes & Follette, 1992). In children with several developmental disabilities empirical forms of functional analysis emerged that are widely used and known to be useful (Iwata, Dorsey, Slifer, Bauman, & Richman, 1982) but these methods no longer apply once clients develop even minimal language functions (Belisle, Stanley, & Dixon, 2017). In modified form and with an expanded set of processes it persisted as a conceptual system in clinical psychology (e.g., Haynes & O'Brien, 2000) but it never developed into a robust and widely adopted empirical case conceptualization alternative.

New empirical forms of functional analysis now seem possible, however, for three major reasons. First, a great deal has been learned empirically about processes of change, especially in the form of the identification of mediators of change in randomized trials. A variable is said to be a mediator when it accounts in whole or in part 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, controlling for treatment. Mediational variables are sometimes painted as causal (Imai, Keele, & Tingley, 2010; Kenny, 2008), but they are better conceptualized as functionally important pathways that can be further examined causally through experimental analysis (Kazdin, 2007; Nock, 2007). This approach to study treatment change processes based on only one or a few variables that are assumed to form linear and unidirectional relationships with the dependent and independent variables is highly problematic both from a conceptual and methodological approach (Hofmann, Curtiss, & Hayes, 2020). Despite these limitations, existing mediation studies may provide some clues about treatment change processes.

A wide variety of mediators are found with regularity, such as psychological flexibility (Stockton et al., 2019 for a review), mindfulness (Gu et al., 2015; Han, 2021), or cognitive reappraisal (Seeley et al., 2019; van den Akker et al., 2018). Mediators often impact treatments outside of a given treatment model. For example, experiential avoidance, one's attempts to suppress or change unwanted private events such as thoughts, emotions, memories, or urges (Hayes et al., 1996), mediates outcomes both in its "home base" of Acceptance and Commitment Therapy and in, say, Applied Relaxation (Eustis, Hayes-Skelton, Roemer, & Orsillo, 2016). Such overlapping mechanisms of change speak to the importance of a case conceptualization system that characterizes the interaction of processes of change and intervention elements in an empirical, rather than merely theoretical fashion.

A second reason that new forms of empirical functional analysis seem possible is that new statistical approaches have emerged that can approach mental and behavioral health problems as networks of interacting elements (Fried & Cramer, 2017). From a complex network perspective heterogeneity between persons is conceptualized as differing patterns of functional links between features of a disorder (Hofmann, Curtiss, & McNally, 2016) and comorbidity is conceptualized as the activation of processes that bridge specific domains (Borsboom & Cramer, 2013). The existence of new methods of assessment and analysis linked to complex networks arguably provides the statistical tools needed for a new empirical form of functional analysis to evolve.

Finally, conceptual and measurement advances in Process-Based Therapy (PBT; Hayes & Hofmann, 2018; Hofmann & Hayes, 2019) create a new concept for empirical functional analysis. In a PBT approach, the focus of intervention is no longer the signs and symptoms of psychiatric disorders but on the biopsychosocial processes of change that lead to clinically relevant outcomes. Such processes are defined as theoretically coherent, dynamic, progressive, contextually-bound, and modifiable evidence-based sequences of biopsychosocial events in the client and their interaction with their environment that can be changed in order to obtain desired outcomes.

Detection of such processes and their interrelationships is in essence a form of functional analysis. 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), in PBT, processes of change are conceptualized within an extended evolutionary meta-model (or "EEMM"; pronounced as in "team"). In line with recent efforts that have been undertaken to better embed behavioral science within the modern extended evolutionary synthesis (e.g., Wilson, Hayes, Biglan, & Embry, 2014a; Wilson, Hayes, Biglan, & Embry, 2014b; Hayes, Sanford, & Chin, 2017; Hayes & Sanford, 2015), PBT argues that evolutionary processes of variation, selection, and retention play out in a specific context across a variety of dimensions and at multiple levels of organization and time frames.

The EEMM draws loose heuristic distinctions between the six psychological dimensions of affect, cognition, attention, self, motivation, and overt behavior, in addition to processes that occur within the sociocultural and biophysiological levels of analysis. The resulting meta-model is shown in Fig. 1. 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 that explicitly furthers this synthesis (Hayes et al., 2017).

The EEMM is important to empirical functional analysis in part because of its linkage to new forms of assessment. Recently, Process-Based Assessment Tool (PBAT; Ciarrochi, Sahdra, Hofmann, & Hayes, 2022) has been developed to apply the EEMM to high temporal density measurement, utilizing only one or two items per EEMM domain. It 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, using psychological flexibility theory (Hayes, 2019) and self-determination theory (Ryan & Deci, 2017) to guide the selection criteria, or the behavior that is likely to promote a person's psychological and physical well-being. The content of the PBAT focuses on behavior linked to self-direction and autonomy, experiencing a range of feeling, developing social connection or belonging, developing competence, having a flexible attentional orientation to the present moment, and verbal coherence. Items regarding physical health behavior were also included given their importance to overall well-being (Ciarrochi, Bailey, & Harris, 2014) and their relevance to the sociocultural and biophysiological level of analysis of the EEMM. Additional items were also added that specifically targeted adaptive and maladaptive forms of variation and retention.

It is the purpose of the present study to pilot the PBAT as a tool for empirical case conceptualization and functional analysis. The statistical analytic approach used is unique, however, and requires a brief explanation.

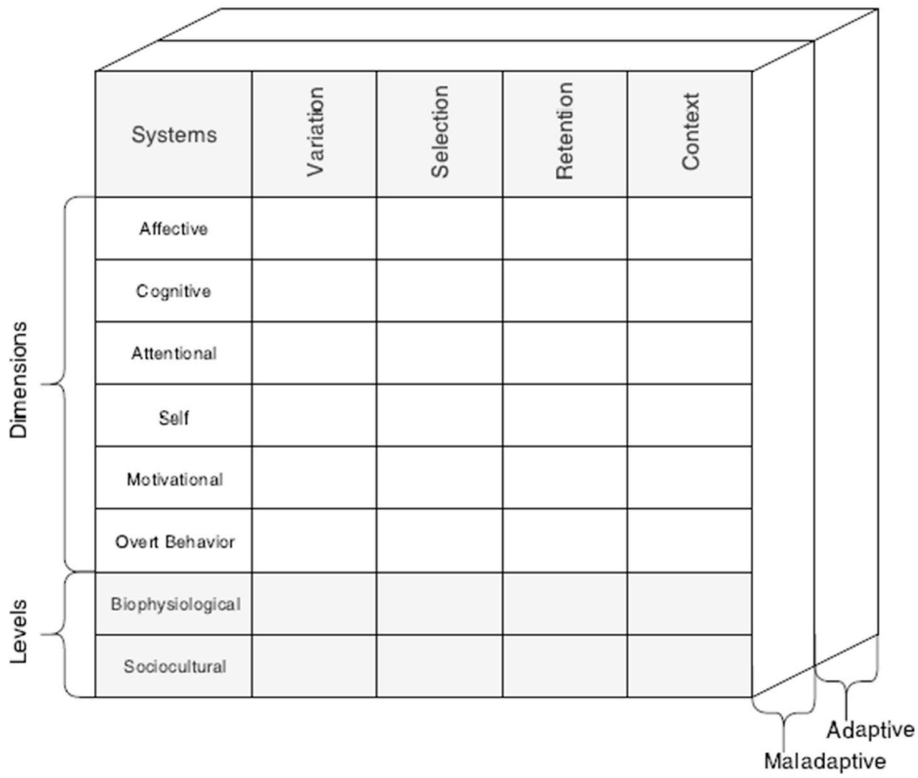

Fig. 1. The Extended Evolutionary Meta-Model (EEMM), Copyright Steven C. Hayes and Stefan G. Hofmann. Used by permission.

An Idionomic Approach to Processes of Change.

Calls for a more idiographic approach are not new (Sidman, 1952; Skinner, 1956), as it has been long known that processes of change cannot be adequately examined using purely nomothetic methods. Group averages can easily obscure clinically relevant individual differences (Barlow, Nock, & Hersen, 2009). This idea has emerged with renewed force (Grice, Barrett, Schlimgen, & Abramson, 2012; Molenaar, 2004; Hayes and Hofmann, 2018), as it has become clear that classical statistical analysis in behavioral science relies on the untenable assumption of ergodicity (Molenaar, 2004). In statistical physics, it has long been proven (Birkhoff, 1931) that only ergodic phenomena (Boltzmann, 1874) permit spatial samples to represent temporal samples. Ergodic events need to be stationary, with the same dynamic model applying to all elements (Molenaar, 2013). Applying that bit of accepted physical science to human psychological studies, suggests cross-sectional (between-person) results will apply to within-person temporally extended data only if the analyzed events are both stationary and the "main features of a statistical model describing the data are invariant across subjects" (Molenaar & Campbell, 2009, p. 113). In the case of processes of change this would be impossible because, by definition, change is not stationary, and furthermore between participant differences are the rule, not the exception. Thus, "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).

This is not just a theoretical concern. Fisher, Medaglia, and Jeronimus (2018) set out to test the ergodicity of data collected in six previously published studies with extensive intra-individual data collected via repeated measures with samples ranging from 43 to 535 participants. The ergodic assumption was violated across all measures and samples examined in the study. Variance within individuals was two to four times larger than variance within groups, a tell-tale fingerprint of a lack of ergodicity.

The solution pursued in the present study was to model data idiographically first and then to add information on nomothetic subpopulations and overall population parameters if and only if they improved idiographic model fit for most individuals. This "idionomic" approach (Hayes & Hofmann, 2021) was accomplished in the present study using Group Iterative Multiple Model Estimation (GIMME; Gates, Lane, Varangis, Giovanello, & Guiskewicz, 2017; Gates & Molenaar, 2012), which was specifically designed to bridge the gap between idiographic and nomothetic levels of analysis. GIMME relies on a unified structural equation modeling (uSEM; Kim, Zhu, Chang, Bentler, & Ernst, 2007) framework which combines SEM and Structural Vector Autoregressive (VAR) approaches to calculate both contemporaneous and lagged relationships (Piccirillo & Rodebaugh, 2019). GIMME identifies relationships present in individual longitudinal networks in the context of within-person variability assessed person by person. In an iterative fashion, it then seeks out pathways applicable at the sub-group and group level, only retaining them if they improve fit at the individual level. No assumption of ergodicity is ever made in this analytic approach. The individual data structure is treated as primary, weighing each individual's data contribution equally with no assumption of homogeneity. No sub-group or group-level pathways (or "edges" as they are discussed in network analysis, a term we will use throughout) are required, but if any are retained because they improve idiographic model fit, a final idiographic analysis is then recalculated after sub-group and group edges are modeled. Thus, relationships identified at the group level do not treat individuals as error terms. Rather, the focus is on how individuals may vary from one another.

Purpose of the Present Study.

The purpose of this study is to use high temporal density experience sampling and idionomic analysis to assess the relation of processes of change as measured by the PBAT to a variety of common clinical outcomes in the areas of psychological distress (sadness, anxiety, anger, lack of support, and stress), life satisfaction, and burnout. Specifically, the aims were to:

1) Quantify the degree to which ergodicity was supported or violated in assessing process to outcome relationships;

2) Specify the relative frequency and degree to which PBAT items were central to individual networks with reference to common clinical outcomes. Centrality was assessed by "out-strength" (the frequency and weight of edges that emerge from a given process node directed toward outcomes of interest), which is a measure of centrality of known stability (Fried, Epskamp, Nesse, Tuerlinckx, & Borsboom, 2016);
3) Document the extent to which meaningful subgroups arise and, if they occur, the degree to which subgroups are defined by shared pathways between elements that fit with the underlying theory of the PBAT;
4) Examine the degree to which edges emerge at the group level; and
5) 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.

2. Method

2.1. Participants

This study was approved by the institutional review board at [redacted]. Participants were recruited using Amazon's Mechanical Turk ("mTurk") service, both to maximize the potential pool of eligible participants and to secure a diverse sample in terms of age, gender, and nationality. 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. Because participants were familiar with this terminology, we will refer to the completion of tasks within this study that were verified by mTurk as "HIT tasks." 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 to prevent the collection of low-quality data, only those users with a verified acceptable HIT rate above 80% of previously completed tasks 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.

2.2. Procedure

Data Collection. The data collection period lasted 35 days, and respondents were asked to fill out the questionnaire twice daily, with a requirement that each participant respond to at least 60 of the bi-daily assessments to be included in the analysis. In order to incentivize engagement in the study, a completion bonus was given to individuals who met the latter criteria. 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, Gates, Pike, Beltz, & Wright, 2019; Wright et al., 2019). Data were gathered using *Nudge Learning*, a smartphone app. Surveys were distributed twice daily using the app, which notified users via push notifications, and stored time-stamped data locally for later transmission if the internet is not currently available. All items were presented using 0–100 visual analog "finger swipe" scales in order to discourage anchoring.

Upon agreement to participate in the study and completing informed consent, subjects were presented with detailed instructions on 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 responses per day. *Nudge Learning* notifications occurred twice a day: once between 10:30am and 12:30pm and once between 6pm and 8pm. The exact time of notifications varied randomly within this 2-h range. To maintain their participation, participants were permitted to miss no more than ten total assessment periods across the 35 days of data collection. If at any point they exceeded ten missed surveys, they were removed from the study. Participants were given clear instructions regarding the total duration of the data collection period, and amount of permitted missing data.

Participants were compensated monetarily for their participation in the study. Participants submitted the completion of their first survey as an initial HIT, which provided them a completion code within the app, which was then reimbursed $2. 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 a maximum of $150 for their time and effort over the course of the study. 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 et al., 2022) is an 18-item set of statements focused on variation, selection, and retention processes. 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; these items pairs also had one positively and one negatively valanced item. Items were retained based on an evolutionary machine learning algorithm that, unlike traditional psychometric analysis, is modeling the importance of individual items (see Ciarrochi et al. under submission).

The PBAT items testing in this study are shown in Table 1. The stem for each item was "Over the past 12 h" and the anchors were 0 = Strongly Disagree and 100 = Strongly Agree.

Screening Tool for Psychological Distress (Stop-D; Young, Ignaszewski, Fofonoff, & Kaan, 2007; Young, Nguyen, Roth, Broadberry, & Mackay, 2015; Appendix B) is comprised of five items addressing distress related

Table 1
Items of the process-based assessment tool (PBAT).

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 did things only because I was complying with what others wanted me to do	I chose to do things that were personally important to me
Overt Behavior/ Competence	I did not find a meaningful way to challenge myself	I found personally important ways to challenge myself
Health	I acted in ways that hurt my physical health	I acted in ways that helped 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 struggled to keep doing something that was good for me	I stuck to strategies that seemed to have worked

to sadness, anxiety, stress, anger, and perceived lack of social support. The specific items asked over the last time period "how much have you been bothered by": Sadness - "Feeling sad, down, or uninterested in life? " Anxiety - "Feeling anxious or nervous? "Stress - "Feeling stressed? " Anger - "Feeling angry? "Perceived lack of social support - "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 good criterion validity in that it produces similar observed correlations with a well-validated life satisfaction scale on self-reported happiness, physical health, and mental health.

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 subscale of the Maslach Burnout Inventory (MBI; Maslach, Jackson, Leiter, Schaufeli, & Schwab, 1986) across four large samples of medical professionals.

2.3. Data analytic approach

Ergodicity. If the relationship of process to outcome is ergodic that would mean that all individuals have the same intercept and slope coefficients (Molenaar, 2004). A multi-level model that assumes only random intercepts as compared to one that assumes both random intercepts and slopes should not differ significantly if the slope estimates are similar across individuals. To the extent that these models diverge, it means that slopes between process and outcome differ between people. Thus, the individuals' processes would violate the assumption of ergodicity both in terms of mean levels (intercepts) and of most interest here, relations among variables (slopes).

GIMME Analyses. Data were analyzed using the Subgrouping Group Iterative Multiple Model Estimation statistical package (S-GIMME; Gates, Lane, Varangis, & Giovanello, 2017) following the step in the published tutorial (Beltz & Gates, 2017) and reference manual (https://cran.r-project.org/web/packages/gimme/gimme.pdf) for S-GIMME. S-GIMME relies on a unified structural equation model (uSEM) framework which conducts SEM analysis of VAR models to estimate contemporaneous and temporally lagged relationships (Beltz, Beekman, Molenaar, & Buss, 2013; Gates, Molenaar, Hillary, Ram, & Rovine, 2010). In the uSEM approach, directionality is assessed from a Granger causality perspective, relying on VAR. Specifically, if Y(t) explains a significant amount of variability in X(t) after controlling for the auto-regressive influence of X (t-1) on X(t), it is included. The opposite relation is also tested. Contemporaneous directed relations emerge if, after controlling for other variables in the model (including autoregressive effects), X(t) explains greater variability in Y(t) than Y(t) does in X(t). Despite their directionality, these relations are functional in a statistical sense and should not be seen as causal, absent an experimental analysis. The use of directed contemporaneous relations assumes that the variables in the system can (at least partly) explain one another, which is presumed to hold true in the present case since the EEMM is deliberately designed to subsume known processes of change (Hayes, Hofmann, & Ciarrochi, 2020).

The GIMME approach does not assume that participants are homogeneous, meaning they are not expected to share the same structure of relations while exhibiting different strengths, in contrast with multilevel modeling techniques (Piccirillo, 2019). S-GIMME improves upon the original GIMME program by attempting to create functionally similar subgroups using shared characteristics of individuals' temporal processes before final idiographic modeling takes place. While S-GIMME does not assume homogeneity, it does assume that the idiographic data structure does not change over time (Lane et al., 2019). Thus, detrending the data and other analytic adjustments may at times be 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). In the event that stationarity is violated by significant linear trends in the data, data are regressed against time and the residuals are entered into GIMME. Analyses also require within person variability across all items. In the case that an individual's data is invariant across time for one or more items, a model cannot be computed and that person is removed from analysis.

Program Operation. GIMME is fully automated. All code can be found at: https://cran.r-project.org/web/packages/gimme (Lane et al., 2017). No exogenous effects were modeled, and data-driven subgroupings were sought. Standard group- and individual-level significance criteria ($a = .05$) were used.

S-GIMME clusters individuals into subgroups based on similarities in their network patterns following the group-level search. 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% or more of participant models. No sub-group level edges need be found in order to establish subgroups; subgroups are defined by similarities in their patterns of effects and weights of group-level edges. The default "walktrap" (Pons & Latapy, 2006) community detection method was utilized in the current study.

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-driven forward selection that iteratively adds paths one at a time. The search space for paths includes both contemporaneous and lagged relations in the same step, which offers a benefit over traditional VAR approaches that first identify lagged relations and in a next step models contemporaneous relations among residuals (Gates et al., 2010). The program analyzes data in five steps. First, a null model is fit for each individual which includes only autoregressive relations (i.e., how a given variable explains itself at the next time point). 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 for each individual if it is added. A strict Bonferoni correction is used to account for the multiple tests conducted. If a parameter would increase the fit for the largest "majority" of participants (the default of at least 75% was used here), 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 75% of the individuals in the sample. If, during this iterative process, an edge falls below the criterion for improving the majority of individuals' model fits, it is pruned. Next, subgrouping is performed using the weights from the group-level edges as well as the individual-level estimates for edges. The process of detecting and adding edges that are significant for the majority of individuals in the subgroup is repeated to search and add subgroup edges. Fourth, individual models are identified. After group-level and subgroup-level models are estimated for everyone, 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 no paths would significantly improve the model or an excellent fit is obtained via 2 of 4 commonly accepted fit indices (Brown, 2006): comparative fit index (CFI) $\geq$ 0.95; non-normed fit index (NNFI; also known as the Tucker- Lewis index) $\geq$ 0.95; root mean squared error of approximation (RMSEA) $\leq$ 0.05; standardized root mean residual (SRMR) $\leq$ 0.05. Finally, a confirmatory model that includes all group and individual level edges is fit.

Item Refinement. 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. Prior work has found that positively and negatively framed items contribute uniquely to life satisfaction and dissatisfaction outcomes (e.g., Chen et al., 2015). An iterative item refinement approach was undertaken to eliminate poorly performing elements from the model for 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 out-degree of each item was calculated by totaling the number of significant edges across final individual models from that item to the specified outcome. The worst performing elements of the PBAT in each such analysis (operationalized as processes that demonstrated a total out-degree of contemporaneous and lagged edges directed toward the outcome that was below the median split of all total edges from process to outcome in the initial models) were removed. The positive and negative items at the median or above in these two separate analyses (positively and negatively worded items) were then combined, and a final model was computed.

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. 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 were the presence or absence of directed contemporaneous or time-lagged edges between nodes at the individual, sub-group, and group-level. Of particular interest are the presence of directed edges emerging from process nodes toward outcome nodes, and the degree to which these pathways are shared at the group and subgroup levels.

Methods evaluation. We evaluated the use of these methods in light of the ergodocity assumption using simulated data, so as to ensure that evidence of a violation of ergodicity using these statistical methods were reliable. Specifically, we investigated if MLM results suggest ergodic data by reporting significant variation of coefficient estimates across individuals and if GIMME failed to recover the paths that exist for all individuals. For this analysis we simulated $N = 50$ "individuals", each with $T = 60$ time points, who have the identical data-generating coefficients. The coefficients were based on one individuals' parameter estimates as obtained from GIMME. In generating data where each individual is known to have identical population-level coefficients we can ascertain the extent to which the methods we used are able to confirm that the data do or do not meet the ergodic assumption. Data were simulated using equations discussed in detail previously (Gates et al., 2017; Lane et al., 2019; Ye et al., 2021).

3. Results

3.1. Participants

A total of 57 participants were recruited and completed at least one assessment. Participants who completed data collection (criteria are described below) were evenly represented with respect to gender ($n_{female} = 24$), ranged in age from 19 to 71 ($m_{age} = 38.5$) and resided predominantly in the United States (n = 42). Those residing internationally were located in Brazil (n = 8), India (n = 4), Italy (n = 2), and Canada (n = 1). Of the 57 original participants, 7 were lost to due to attrition, having missed more than 10 assessment periods in the first 35 days. These participants averaged 17.4 assessments out of the target of 60 and were not considered in any further analysis. A total of 5 of the 50 completers exhibited no variability on one or more assessment items, making analysis with GIMME impossible. These participants were removed from the analyses as their data was incompatible with our item refinement procedure.

3.2. Aim 1: tests of ergodicity

Ergodicity was examined based on the extent to which relationships between PBAT items and outcomes significantly varied within person across all outcomes. Multi-level analyses were calculated using the lme4 package (Bates et al. 2014), nesting all observations within person. For every link between process and outcome, we compared a multi-level model that assumed random intercepts (allowing people to differ on the DV) with one that assumed both random intercepts and slopes. A significant difference indicates that slopes between process and outcome differed between people. As seen in Tables 1 and 2, the tests of varying slopes were all greater than a critical chi-square value of 14 (df = 2), $p < .001$, indicating that slopes significantly varied from person to person for every process to outcome relationship.

In Tables 2 and 3, we present the 10 and 90 percentile of the distribution of betas between each process and outcome pairing. In general, processes ranged in the expected direction from neutral or inert to positive or negative betas, depending on the items. For example, the link between *struggling to connect to moments of day to day life* and *life satisfaction* ranged from −0.31 to 0, indicating that while it was generally a negative item, for some people there was no within person association between these two variables.

In a few cases, relationships ranged from positive to negative. For example, consider the relationship between *stuck to strategies* and *stress*. It would be incorrect to conclude that there was no relationship between these two variables merely because the average relationship approximated zero. Given the significance of the "varying slopes" ergodicity test, understanding this relationship must begin with idiographic analysis. As an example of the implications of a lack of ergodicity, this relationship is illustrated in Fig. 2. A significant negative link between *sticking to strategies* and *stress* ("significant" meaning that 95% confidence intervals do not overlap with zero) were found for seven participants, while five participants have a significant positive link, indicating that on days that they stuck to their workable strategies, they experienced higher stress. The average intercept was zero but, as shown in the caterpillar plot of intercepts, only two participants would be considered as having average stress (i.e., not significantly differing from the average) based on idiographic analyses. Similarly, the "average" fixed effect for the link between sticking to strategies and stress was −.01 (Table 2), but the right panel of Fig. 2 illustrate that for a subset of people, the relationship was significantly positive (error bars do not overlap with 0), and for another subset, it was significantly negative.

Nearly all the fixed effects (average) were significant and in the expected direction, indicating that the positive processes assessed by the PBAT were generally beneficial. Only the fixed effects for *thinking interfered* and *stuck to strategies* were not significant. However, interpretations of all fixed effects, or a lack thereof, should be done cautiously. Given the failure of meeting the ergodicity assumption, these fixed effects should be assumed to depend on the person and the overall dynamical system they reveal, and not interpreted as a homogenous, group-level finding.

The MLM results conducted on the simulated, non-ergodic data confirmed that these significant findings are likely not spurious. Specifically, for the 21 ergodicity/varying slope tests in the simulated data, none of them came up as significant using our strict criteria ($p < .001$). 5 slopes were found to have significant variability using the traditional p-value cutoff of < 0.05. The chi-squares for the simulated data ranged from 0 to 10.52, which is notably smaller than the chi-squares in the observed data, which ranged from 18.38 to 253.08, with many observed values well over 100 (Tables 2 and 3).

3.3. Aim 2: overall ability of the PBAT to link to outcomes in complex idionomic networks

The multi-level analyses above characterized the simple within and group relationships between PBAT processes and outcomes. GIMME analyses examined these relationships within complex idionomic networks containing multiple PBAT processes and given outcomes interacting over time. It is worth noting that nothing in the current structure of GIMME prioritizes process to outcome edges, so the present set of analyses is a kind of "risky test" of both the PBAT and the use of GIMME for case conceptualization purposes. It is possible here that outcomes can explain variability in processes and the reverse - that processes can explain variability in outcomes, which might be of most interest to clinicians.

Table 2
Betas and range of within person associations between negative processes and outcomes.

	Statistic	Selection							Variation and Retention	
		Helped Connection	Paid Attention	Personally Important	Exp Range Emotions	Thinking Helped	Important Challenge	Helped Health	Able to Change	Stuck to Strategies
Life Satisfaction	10%	0.05	0.01	0.02	−0.02	0.02	0.03	0	0.02	−0.11
	Average	0.14	0.15	0.15	0.11	0.16	0.12	0.13	0.14	0.04
	90%	0.22	0.28	0.24	0.21	0.28	0.24	0.26	0.24	0.18
	Slopes vary	25.32	115.97	73.36	37.41	96.65	63.65	76.99	82.81	152.08
Sadness	10%	−0.29	−0.4	−0.34	−0.34	−0.39	−0.36	−0.39	−0.36	−0.27
	Average	−0.16	−0.19	−0.18	−0.14	−0.18	−0.14	−0.15	−0.16	−0.04
	90%	−0.04	−0.04	−0.05	−0.05	0	0.02	−0.01	−0.01	0.11
	Slopes vary	81.59	94.62	79.92	37.41	137.6	72.44	115.26	133.54	96.1
Anxious	10%	−0.21	−0.33	−0.29	−0.28	−0.36	−0.24	−0.28	−0.32	−0.2
	Average	−0.11	−0.11	−0.12	−0.12	−0.12	−0.08	−0.11	−0.11	−0.03
	90%	0.03	0.04	0.02	0.07	0.04	0.08	0.01	0.04	0.17
	Slopes vary	110.09	86.81	135.52	116.94	191.75	92.58	103.53	148.48	112.69
No support	10%	−0.3	−0.33	−0.33	−0.27	−0.29	−0.31	−0.28	−0.34	−0.28
	Average	−0.14	−0.13	−0.14	−0.11	−0.15	−0.12	−0.12	−0.14	−0.05
	90%	0.07	0.08	−0.03	0	0	0.02	0	0.01	0.11
	Slopes vary	156.26	126.88	85.9	65.9	159.85	86.54	111.45	140.78	187.5
Anger	10%	−0.23	−0.24	−0.2	−0.27	−0.22	−0.19	−0.17	−0.26	−0.1
	Average	−0.09	−0.11	−0.11	−0.09	−0.11	−0.07	−0.09	−0.1	0.01
	90%	0.03	0	−0.05	0.04	−0.04	0.03	−0.03	0.01	0.16
	Slopes vary	50.09	43.65	34.48	65.9	25.14	18.38	21.31	58.91	36.37
Stress	10%	−0.33	−0.39	−0.35	−0.33	−0.51	−0.3	−0.28	−0.41	−0.25
	Average	−0.1	−0.12	−0.15	−0.11	−0.16	−0.11	−0.14	−0.16	−0.01
	90%	0.05	0.1	0.02	0.11	0.03	0.03	−0.01	0.04	0.11
	Slopes vary	110.57	150.34	139.98	99.15	168.95	64.15	79.03	140.03	170.34

Note: $^{*}p < .05$; $^{**}p < .01$. Average = Fixed effect, Beta relationship between process and outcome. All chi-square tests of varying slopes were highly significant (df = 2), indicating that individual slopes differ from the fixed effect, group estimate in all cases.

Table 3
Betas and range of within person associations between positive processes and outcomes.

	Statistic	Selection							Variation and Retention	
		Hurt Connection	No Challenge	No Outlet Feeling	Complying	Thinking interfered	Hurt Health	Struggled Connect	Unable to Change	Struggled to Keep Doing
Life Satisfaction	10%	−0.27	−0.23	−0.3	−0.23	−0.24	−0.25	−0.31	−0.29	−0.25
	Average	−0.11	−0.1	−0.15	−0.15	−0.03	−0.12	−0.13	−0.16	−0.11
	90%	0	0.01	−0.05	0.01	0.15	0	0	−0.01	0.03
	Slopes vary	70.92	72.85	79.03	57.01	115.05	70.63	95.34	95.22	103.13
Sadness	10%	−0.01	0	0.06	0.02	−0.16	−0.01	0.03	0.05	0
	Average	0.17	0.15	0.23	0.23	0.1	0.16	0.22	0.23	0.18
	90%	0.36	0.41	0.43	0.3	0.41	0.38	0.42	0.48	0.38
	Slopes vary	91.23	87.28	133.63	69.23	167.92	114.4	150	242.63	137.02
Anxious	10%	−0.01	−0.07	−0.01	−0.01	−0.27	−0.06	−0.04	−0.03	−0.01
	Average	0.13	0.07	0.18	0.18	0.02	0.1	0.16	0.16	0.11
	90%	0.33	0.26	0.44	0.35	0.29	0.32	0.49	0.36	0.29
	Slopes vary	101.23	77.96	253.08	128.9	244.97	101.49	242.04	242.22	101.83
No support	10%	−0.01	−0.01	0.02	−0.01	−0.09	−0.01	−0.02	0.04	−0.01
	Average	0.19	0.11	0.23	0.23	0.07	0.17	0.2	0.2	0.16
	90%	0.45	0.29	0.47	0.29	0.32	0.36	0.48	0.51	0.41
	Slopes vary	124.5	55.33	143.51	78.41	161.89	107.7	165.64	165.28	123.64
Anger	10%	0.01	−0.04	0.02	0.01	−0.12	0	0	0.02	0
	Average	0.19	0.09	0.2	0.2	0.06	0.18	0.15	0.15	0.13
	90%	0.46	0.36	0.48	0.28	0.31	0.43	0.41	0.34	0.34
	Slopes vary	93.35	47.71	71.61	42.15	69.01	119.56	64.71	45.31	55.77
Stress	10%	0	−0.06	−0.01	−0.02	−0.29	−0.01	−0.06	−0.02	−0.01
	Average	0.17	0.11	0.25	0.25	0.02	0.16	0.19	0.19	0.18
	90%	0.39	0.37	0.53	0.43	0.25	0.41	0.52	0.4	0.38
	Slopes vary	95.48	95.86	225.77	146.92	219.13	140.81	213.79	222.26	99.41

Note: $^*p < .05$; $^{**}p < .01$. Average = Fixed effect, Beta relationship between process and outcome. All chi-square tests of varying slopes were highly significant (df = 2, $p < .001$), indicating that individual slopes differ from the fixed effect, group estimate.

GIMME analyses described below found no group level edges that met the a priori criterion for inclusion for any outcome, namely improved fit for 75% or more of the participants. Of the 45 participants who had analyzable data, the number of significant contemporaneous or lagged PBAT item-to-outcome edges across the seven outcomes ranged from 19 to 34 (median value = 30).

Fig. 3 shows a heatmap of the out-degree of PBAT processes directed toward outcomes. The number in each cell represents the number of individual models that contained a directed edge from the process to the outcome, either contemporaneous or lagged. To visualize the relative importance of processes we have combined the findings across negatively and positively framed items for each domain, since we will examine these in detail later. It should be noted that in all cases a zero value here represents a process that was not present in the final model for an outcome. Each process that was actually included in a final GIMME analysis resulted in an out-degree of at least two.

A few trends are highlighted by this matrix. Process variables overall exhibited a consistent amount of out-degree with respect to the outcomes (obtained range: 36–57; possible range 0–90) with the notable exception of distress related to burnout (19). This may indicate burnout was a less salient outcomes across members of the sample. Models also reflect a sizeable role for attentional processes with respect to anxiety, life satisfaction, and sadness.

The processes of the PBAT are also broadly represented across at least some outcome domains, except for health behavior, which showed an out-degree with respect to anger but was not present in any other final model.

In sum, the multilevel and GIMME analysis converge to suggest that PBAT processes are broadly applicable to outcomes of interest, as measured by the fixed effects in Tables 2 and 3 and out-degree across individual network models in Fig. 3.

3.4. Aims 3, 4, and 5: complex idionomic network structure by individual outcome

The processes of change in the PBAT can be examined in the context of the overall idionomic network for each person and each outcome to assess their role in patterns of distress or life satisfaction for the person. No process is always positive or negative in a functional sense – it depends on context. A powerful way to illustrate this is to examine the idionomic networks directly and to use examples to show how processes combined to lead to clinical outcomes.

In what follows we indicate the items included in the final analysis for each outcome, as ranked by out-degree across individuals, and including the data showing the combined out-strength of all edges in the final idiographic analyses. Subgroups that improved model fit for half or more of the members of that subgroup for analyses related to each outcome are described in the Appendix. All 360 individual models across all eight outcomes converged normally indicating that at least two of four fit indices were considered "excellent." Because of the conservative approach taken by GIMME we do not report the fit indices here but see Gates et al., 2017.

For three of the eight outcomes (anxiety, sadness, and life satisfaction), subgroups included one or more out-edges from PBAT items to outcomes (sadness had two such subgroups). These four subgroups contained a total of 50 idiographic models spread across 29 unique individuals. To characterize how idionomic networks can lead to functional analyses, a final idiographic network from each of those four subgroups was randomly selected and examined graphically and via discussion for a person with relatively poor outcomes in this area. Randomization was conducted using the program at randomizer.org. Randomly selecting case examples was done from subgroups because the significant process to outcome subgroup edges ensure relevance to the outcome focus of empirical case conceptualization and functional

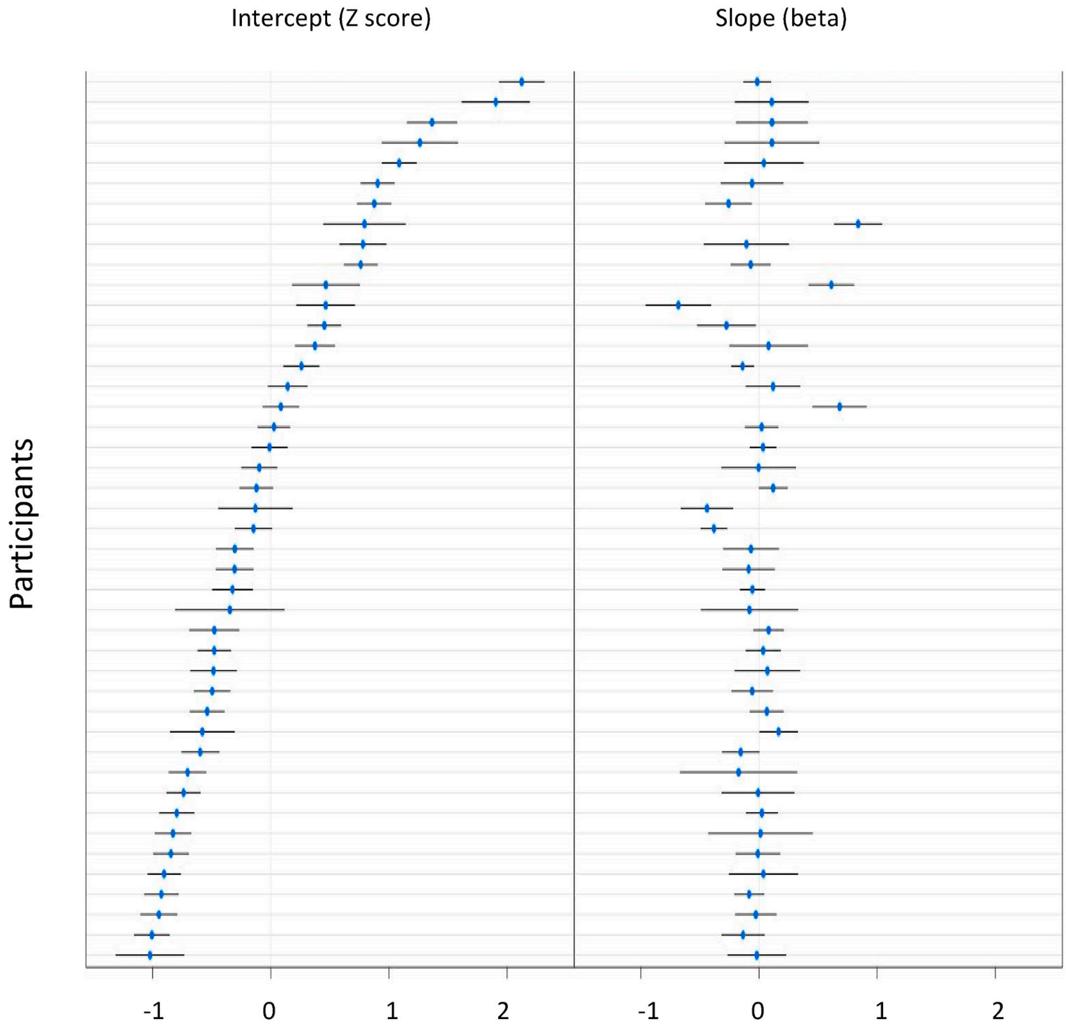

Fig. 2. Within person intercepts and the link (beta) between *sticking to strategies* and stress. Individual participants are depicted on the Y-axis, while the X-axis shows the Z score for each individual's intercept on the left and their slope between *sticking to strategies* and *stress* on the right.

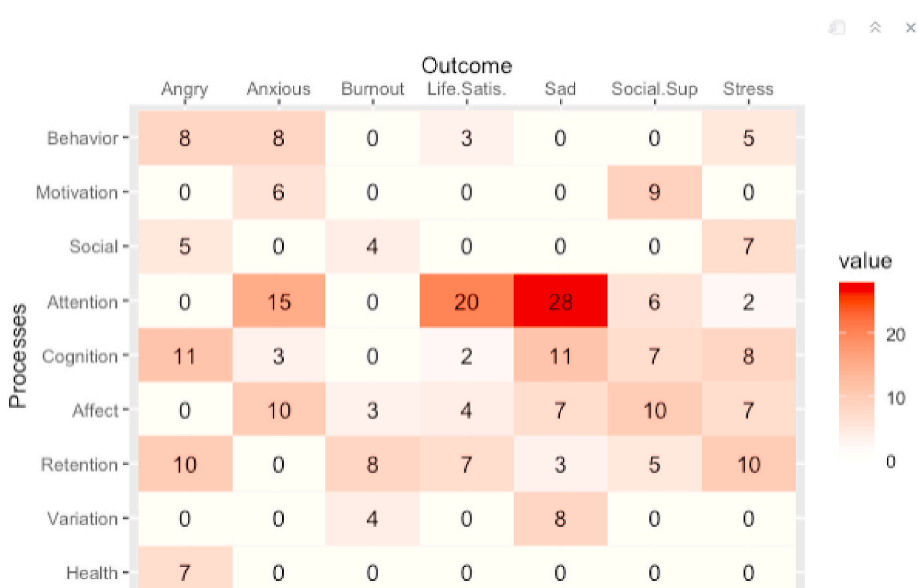

Fig. 3. Heatmap of the number of out-edges from PBAT domains to outcomes across all outcome by outcome GIMME analyses.

analysis, and because the models discussed were known to occur with some frequency within the overall population.

The results to follow can be interpreted as suggesting a large degree of heterogeneity exists in dynamic processes relating PBAT process items to outcomes. It's important to note that the heterogeneity is likely true and not spurious. GIMME and S-GIMME algorithms have a low rate of false positives, and a high rate of detecting paths that are consistently found in the sample (Gates et al., 2017; Gates & Molenaar, 2012). In the simulated data generated for this paper, S-GIMME recovered all of the paths used to generate the individuals' data as group-level paths. Subgroups were found in this data despite being generated to be ergodic, due to GIMME's conservative testing procedure and which could lead to clustering of individuals with similar patterns of non-significance into a subgroup. However, no subgroup-specific paths were found, further emphasizing that the subgroup-level paths found in the observed data truly do capture aspects of the processes that are consistently found across individuals and thus meeting the ergodic assumption for those sub-groups. The lack of group-level paths in the results to follow suggest a high level of heterogeneity.

Anxious. Items in the final model targeting distress related to anxiousness can be seen in Table 4.

Four subgroups were identified, three with subgroup-level edges. A subgroup without subgroup edges is possible when individual models share sufficient characteristics to be meaningfully grouped, despite no edges being present frequently enough to comprise a subgroup edge. Subgroup 3 ($n = 10$) will be characterized by the case example, since the network for each member of the subgroup contains the significant subgroup process to outcome edges. An additional 21 participants demonstrated an idiographic edge directed from a PBAT item to distress over anxiety. Thus, all totaled, 31 of the 45 participants with analyzable data (71%) showed a process to outcome edge in the area of anxiety. The set of subgroup edges for Subgroup 2 will be evident in the case example of an idiographic network below.

Case example. A case example was randomly drawn from Subgroup 3 members with anxiety levels that were above the median for the study. The network for participant #24 is shown in Fig. 4 (each node also had an auto-regressive relation, which are not shown). Closed arrowheads indicate positive relations; open arrowheads indicate negative relations. Arrowhead size indicates the strength of the edge as determined by the beta weight of the relationship. Precise person by person coefficients are generated by GIMME for each individual but while this might be relevant for clinical use, they are not central to the current paper and are not reported here.

Because this network is the first final idiographic network to be interpreted, we will make general comments regarding our approach, in addition to addressing specifics. Future idiographic interpretations will be more declarative, without reiterating the logical sequence.

Table 4
Network Elements and Out-Degree and Out-Strength in the Final Model for Anxious.

PBAT Item	Out Degree	Out Strength
I struggled to connect with the moments in my day to day life	15	3.88
I did things only because I was complying with what others wanted me to do	6	1.77
I did not find an appropriate outlet for my emotions	5	1.94
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

*Note: Out-degree and out-strength values shown here are the count of times a path occurred across individuals and the sum of that path weight across individuals, respectively.

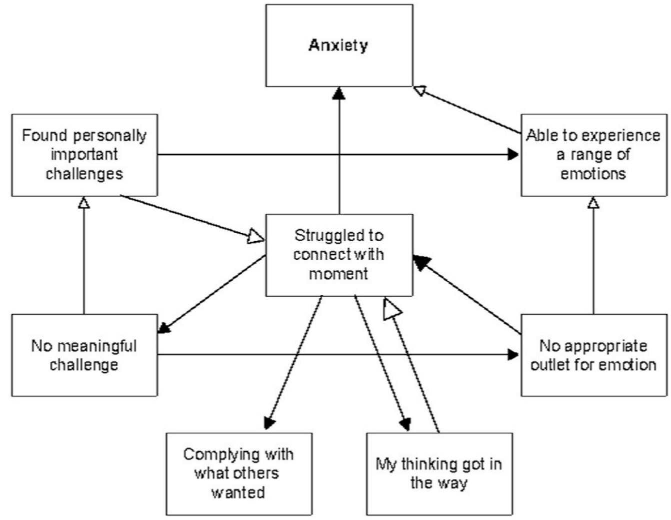

Fig. 4. A GIMME network for Participant #24.

This network is made up of contemporaneous directional relations. All of the edges were also characteristic of Subgroup 3, with the exception of these three relations, which were idiographic for Participant #24: *I was able to experience a range of emotions appropriate to the moment* → anxiety; *I struggled to connect with the moments in my day to day life* → *I did not find a meaningful way to challenge myself*; *I found personally important ways to challenge myself* → *I was able to experience a range of emotions appropriate to the moment.*

The edges in the network should not be thought of as mere correlations because they are directional given that relations go above and beyond the auto-regressive temporal relations of the relevant measure, as was explained earlier. That being said, they should not be thought of as causal in an experimental sense, nor as lagged relations unless the arrows are dashed (which none are in this network). Edges are statistical functions. To avoid both errors, we will use the term "is related to" in creating a functional analytic interpretation of the network.

A functional analysis needs to begin with the end point of interest, in this case, distress regarding anxiety. Experiencing a range of emotions is negatively related to distress over anxiety and struggling to connect to moments is positively related to it. Thus, in seeking a process-based empirical functional interpretation, these are the two key processes and those that are related to them are of special interest. Particular attention needs to be paid, however, to those features of the network that may suggest possible self-maintaining sub-networks involving these two processes, should they exist. Subnetworks of that kind can assume a life of their own and thus can be key targets of intervention in order to undermine resistance to change.

We can begin for participant #24 with the most dominant node in the network as indicated by the number of edges related to it, namely, *struggling to connect to moments*. *Not having an outlet for feelings* is positively related to *struggling to connect to moments*, while *having important challenges* is negatively related. Unexpectedly, *thinking getting in the way* is also negatively related, suggesting that this person feels *less* disconnected from the present when they become focused on interfering thoughts that are occurring. Indirect effects between these variables and *anxiety* exist through their relation to *struggling to connect to moments.*

Not having meaningful challenges is positively related to not having an outlet for feelings and negatively related to important challenges. This pattern means that a potentially self-amplifying loop is completed by the positive relation of struggling to connect to moments and not having meaningful challenges. A core subnetwork emerges for participant #24 (*Struggled to connect with moment* → *No meaningful challenge* → *No appropriate outlet for emotions*) that could easily become self-organizing, with branches that negatively relate to experiencing a range of emotions as well, the other node with an out-edge to anxiety.

Stated in other words, if this person were a clinical client presenting with distress about their feelings of anxiety, the empirical functional analysis might be said to indicate that the person may lose attentional focus on the present, becoming less motivated and more emotionally isolated, and even less focused on the present and more distressed by anxiety. That pattern spills over into a loss of contact with what is personally important (which is has a negative relation to losing attentional focus) and a diminished ability to experience a range of emotions, which is then directly related to distress over anxiety.

In terms of treatment targets, the two nodes with out-edges to anxiety could be directly targeted with, say, mindfulness training for struggling to connect to moments, or emotional exposure, emotional deepening, acceptance, or other emotion focused interventions designed to encourage experiencing a wider range of emotion. It could be ineffective, however, to target experiencing a wider range of emotions alone since it could leave in place a harmful potentially self-amplifying subnetwork (*Struggled to connect with moment → No meaningful challenge → No appropriate outlet for emotions*). Thus, if inputs into the two processes directly related to anxiety are to be targeted, kernels that address a lack of meaningful challenges and a lack of outlets for feelings loom large, in addition to mindfulness. Examples of evidence-based kernels that might address these process patterns include values work and developing emotional expression skills in relationships, respectively. An interesting option might be to combine these and then in the context of values-based relationship enhancement work, to work on mindful awareness of the present moment and broadening the felt emotion. Work that focused on the therapeutic relationship as a context for intervention might fit this functional analytic opportunity.

Angry. Items in the final model targeting distress related to anger can be seen in Table 5 and subgroups are shown in Table 5.

Three subgroups were identified, two with subgroup edges. Subgroup 2 had two positive edges *from* the STOP-D item Angry to PBAT items (to *I acted in ways that hurt my physical health* and to *I struggled to keep doing something that was good for me*) but no subgroup edges directed toward "Angry" and thus no case example is presented. All totaled, 26 participants (58% of the final sample) demonstrated an idiographic edge directed from a PBAT item to Angry.

Burnout. Items in the final model targeting distress related to anger can be seen in Table 6.

A total of 5 subgroups were discovered encompassing 35 participants but no subgroup level edges emerged in relation to burnout. Nineteen participants exhibited an idiographic network with a directed edge from a PBAT item to the burnout outcome (42% of the total sample). This was the lowest idiographic relation to outcome in the study and may be due to the nature of the sample, as participants may not have been traditionally employed in job leading to burnout at rates comparable to the general population.

Table 5
Network Elements and Out-Degree and Out-Strength in the Final Model for Angry.

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

*Note: Out-degree and out-strength values shown here are the count of times a path occurred across individuals and the sum of that path weight across individuals, respectively.

Table 6
Network Elements and Out-Degree and Out-Strength in the Final Model for Burnout.

PBAT Item	Out Degree	Out Strength
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

*Note: Out-degree and out-strength values shown here are the count of times a path occurred across individuals and the sum of that path weight across individuals, respectively.

Life Satisfaction. Items in the final model targeting life satisfaction can be seen in Table 7.

A total of 3 subgroups were discovered, encompassing 34 participants. The set of edges for Subgroup 1 ($n = 18$), will be shown in the case example. An additional 16 participants demonstrated an edge directed from a PBAT item to life satisfaction, for a total of 34 (76% of the final sample).

Case **example.** A case example was randomly drawn from Subgroup 1 members with life satisfaction levels that were below the median for the study. The network for participant #5 is shown in Fig. 5 (each node also had an auto-regressive relation, which are not shown).

All of but three of the relations shown were characteristic of Subgroup 1. The three that were idiographic for Participant #5 were *I paid attention to important things in my daily life → I stuck to strategies that seemed to have worked*; *I struggled to keep doing something that was good for me → I paid attention to important things in my daily life*; *I paid attention to important things in my daily life → I found personally important ways to challenge myself*.

This network shows clearly how important overall networks can be. The two nodes with the most edges are *I paid attention to important things in my daily life,* and *I used my thinking in ways that helped me live better.* There is a potentially self-amplifying loop between thinking, paying attention, and *I stuck to strategies that seemed to have worked*, but paying attention to important things is negatively related to life satisfaction. There are two indications in the network to explain this unexpected disconnect between what looks like an otherwise healthy and potentially self-amplifying loop and life satisfaction itself. One is that *I found personally important ways to challenge myself* is negatively related to paying attention and to helpful thinking. That suggests that personal importance is just not the same thing as "important things." The other is that the struggling to keep doing something good is positively related *I did not find an appropriate outlet for my emotions.* It is as if personal choices of importance and opportunities to feel have been walled off

Table 7
Network Elements and Out-Degree and Out-Strength in the Final Model for Life Satisfaction.

PBAT Item	Out Degree	Out Strength
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

*Note: Out-degree and out-strength values shown here are the count of times a path occurred across individuals and the sum of that path weight across individuals, respectively.

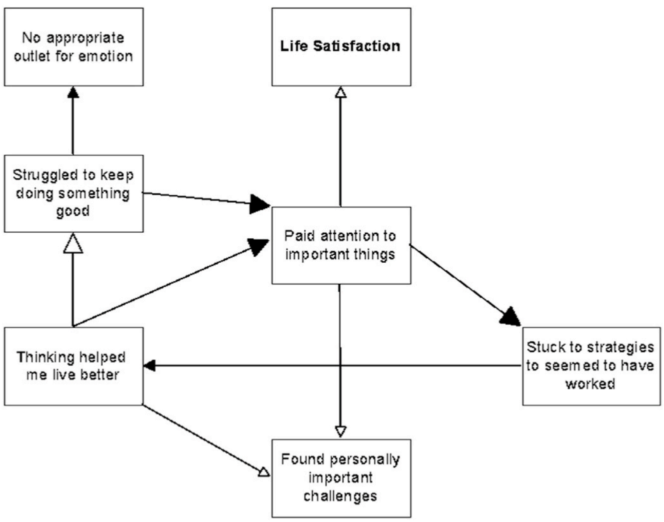

Fig. 5. A GIMME network for Participant #5 of life satisfaction relevant PBAT items and life satisfaction.

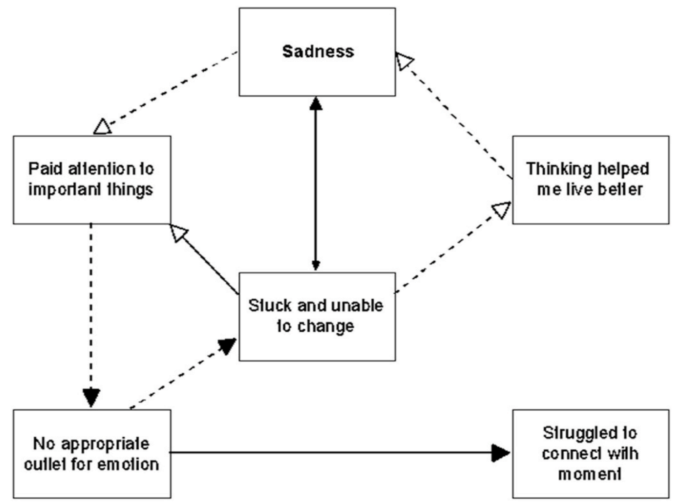

Fig. 6. A GIMME network for Participant #35 of a culled set of sadness relevant PBAT items and sadness.

from normally positive cognitive, attentional, and retention strategies, which are self-amplifying at the cost of life satisfaction. Workaholism, emotional restriction, and an externally focused motivational mind set could produce such a pattern. Were this person a client with increased life satisfaction as a goal, examination of more intrinsic values and of opportunities for emotional growth might help perturbate the system and give this person's skills more positive outlets. In essence there many need to be a re-examination of what is being said to be important when this person pays attention to "important things" in daily life.

Sadness. Items in the final model targeting distress related to sadness can be seen in Table 8.

A total of 3 subgroups were discovered which encompass 37 participants. Two subgroups (2, $n = 5$; 3, $n = 17$) had edges directed from PBAT items toward distress over sadness distress and will be characterized by case examples below. In addition to the 22 participants in these two subgroup 12 participants had idiographic edges from PBAT items to sadness (76% of the total sample).

Case **example 1.** One case example was randomly drawn from each of the subgroups with out-edges to sadness. The network for participant #35 from Subgroup 2 is shown in Fig. 6 (each node also had an auto-regressive relation, which are not shown). Dashed lines indicate Granger causal relations.

Only one relation was characteristic of Subgroup 1 – that from *being stuck and unable to change* to sadness. The inverse relation and all other relations shown were idiographic for Participant #5.

Table 8
Network Elements and Out-Degree and Out-Strength in the Final Model for Sadness.

PBAT Item	Out Degree	Out Strength
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 used my thinking in ways that helped me live better	8	3.02
I did not find an appropriate outlet for my emotions	7	3.20
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

*Note: Out-degree and out-strength values shown here are the count of times a path occurred across individuals and the sum of that path weight across individuals, respectively.

Working backward from distress over sadness, feeling *stuck and unable to change ineffective behavior* is in a potentially self-amplifying relationship with sadness, the only such relation or subnetwork in this network. Feeling stuck is also the most central node in the network, which suggests that healthy variation or behavioral activation might be important if this case were clinical. The only other input into sadness is a negative relationship from helpful thinking but feeling stuck is also in a negative relationship with helpful thinking so without that node continues to be central.

A possible clue about how feeling stuck might be modified is that it is exacerbated over time by not having appropriate outlets for emotions (which in turn is positively related to struggling to connect with moments). Paying attention to important things seems to increase the problem of not having emotional outlets, which suggest that behavioral activation alone might not be successful unless that relation can be changed.

If this were a client with the goal of dealing with sadness a possible focus for perturbating this network might be work on emotional flexibility and deepening, perhaps seeking out greater opportunities for emotion expression and experiencing. It might also help bring the person more into the present moment as well as reducing a sense of being stuck. Modifying the impact of feeling stuck on thinking might also be helpful.

Case **example 2.** A second case example for sadness was randomly drawn from Subgroup 3. The network for Participant #14 from Subgroup 2 is shown in Fig. 7 (each node also had an auto-regressive relation, which are not shown). Dashed lines indicate Granger causal relations. This is a complex network with 14 significant edges. Seven of the displayed relations are subgroup edges; seven are purely idiographic, namely, paid attention → struggled to connect; thinking helped → no outlet; struggled to connect → thinking helped; unable to change → thinking got in the way; unable to change → thinking helped; stuck to strategies → unable to change; no outlet for feedings → sad.

By chance, Participant #14 was the participant most distressed by sadness overall in the study. Working backward from sadness *struggled to connect with* and *I did not find an appropriate outlet for my emotions* were both positively related to sadness and struggling to connect to the moment was also positively related to the lack of an outlet for emotion. There were no simple self-amplifying loops related to any of these nodes. Sadness was however positively related to feeling stuck and unable to change, which was negatively related to the most central node of the network as measured by out-degree, thinking that helped. Thus, while was not evident why distress of sadness built up over time, there were some features of the network that might explain why it was hard to alleviate that distress.

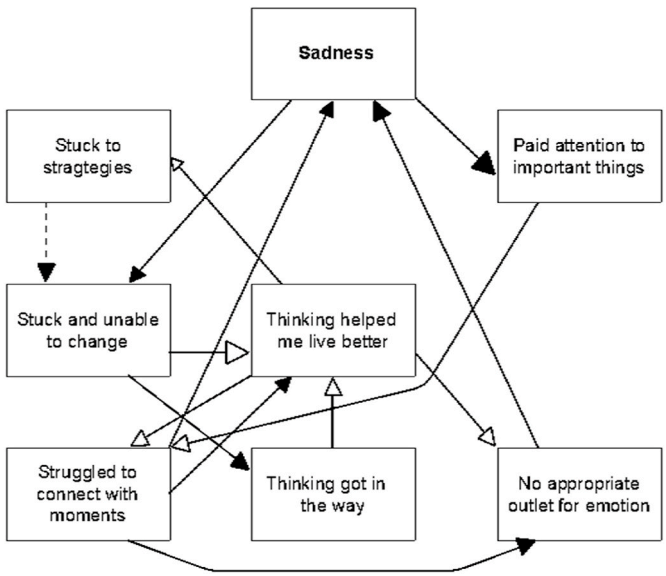

Fig. 7. A GIMME network for Participant #14 sadness relevant PBAT items and sadness.

If this were a client with the goal of dealing with sadness a possible focus for perturbating this network might be mindfulness training that is linked to greater attention to this person's emotional needs. The fact that helpful thinking is already negatively related to the processes that are positively related to sadness suggest also that fostering great cognitive flexibility would constitute a helpful treatment target.

Social Support. Items in the final model targeting distress related to perceived lack of social support can be seen in Table 9.

A total of 3 subgroups were discovered encompassing 39 participants but none had subgroup edges to the outcome. 27 of the idiographic models did have significant edges from the PBAT to social support (60% of the total sample).

Stress. Items in the final model targeting distress related to sadness can be seen in Table 10.

A total of 4 subgroups were discovered encompassing 38 participants but none had subgroup edges to the outcome. 30 of the idiographic models did have significant edges from the PBAT to social support (67% of the total sample).

4. Discussion

In this study, we applied an idionomic approach to examine processes of change using GIMME. Even though nothing in GIMME ensures this outcome, virtually all participants revealed edges from PBAT items to one or more common clinical outcomes in the 4–5 weeks of idiographic assessment. Such edges were most common in sadness and life-satisfaction (76% of the sample) and least common in burnout (42%). Understanding the role of given processes of change require appreciation of idionomic networks, as was shown in the four case examples drawn from subgroups with out-edges from processes to outcomes. Even such positive sounding item as "I paid attention to important things in my daily life" could play a negative role in the context of a particular network (see Subgroup 1, Life Satisfaction).

Table 9
Network Elements and Out-Degree and Out-Strength in the Final Model for Social Support.

PBAT Item	Out Degree	Out Strength
I did not find an appropriate outlet for my emotions	10	4.93
I did things only because I was complying with what others wanted me to do	8	3.02
I used my thinking in ways that helped me live better	7	2.51
I paid attention to important things in my daily life	6	2.76
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

*Note: Out-degree and out-strength values shown here are the count of times a path occurred across individuals and the sum of that path weight across individuals, respectively.

Table 10
Network elements and out-degree and out-strength in the final model for stress.

PBAT Item	Out Degree	Out Strength
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

*Note: Out-degree and out-strength values shown here are the count of times a path occurred across individuals and the sum of that path weight across individuals, respectively.

In contrast to these broad and contextually bound idionomic findings, the failure to find equivalent slopes across any process to outcome relationship demonstrates that if normative statistical approaches had been utilized, results would have applied only to a tiny fraction of participants. Categorical statements based on such analyses would simply be false if readers thought they applied even to a significant minority of actual persons. The present study adds to a body of work that strongly questions the applicability of the ergodic assumption to normative statistics as applied to processes of change, and underlines the practical cost of that failure.

This is not an unusual outcome. We are unaware of *any* clinical studies containing high temporal density data that have found that the ergodic assumption applies to human phenomena.

Practitioners are used to the idea that norms and averages do not accurately represent individuals, but they still believe that group statistics apply probabilistically to individuals. That idea is precisely what the ergodic theorem questions. Human lives unfold in idiographic ways that are dynamically sensitive to a wide range of situational, psychological, biophysiological, and sociocultural processes. As the present study shows, these can be modeled for most common clinical outcomes, and in some cases nomothetic generalizations may found that improve idiographic fit, but this conclusion does not apply to concepts examined through occasional assessment of a collection of individuals and the derivation of empirical relations tested against between-participant variability.

That may sound like a bitter pill to swallow given the enormous dominance of normative approaches in psychology, but decades of diagnostic and case conceptualization failure is a bitter pill as well, and there appears to be wide agreement that it is time to turn in a new direction. The recent *Report of the ACBS Task Force on the strategies and tactics of contextual behavioral science research* (Hayes et al., 2021) recommended that applied behavioral science needs more "idiographic and longitudinal, dynamic network-based research, especially in conjunction with high temporal density behavioral and biophysiological measures", using "measures that are idiographically useful" (p. 177; both quotes). The present study clearly fits with these Task Force recommendations.

This is the first study to examine the performance of a process-based item set specifically designed for idionomic research, using an idionomic data-analytic approach to case formulation and empirical functional analysis. The hopeful message of the present study is that new measurement and analytic alternatives exist within a PBT approach that can generate sensible empirical case conceptualizations, that seem readily testable within intervention research.

Results suggested that GIMME consistently yielded interpretable idionomic statistical models based on the PBAT that did not require the assumption of ergodicity. This raises the realistic probability that experience sampling of processes of change and of key outcomes can provide a way toward a new, empirical, and replicable form of case conceptualization that is built in a consciously idionomic fashion. Providing some support for that possible implication, coherent functional analyses of idiographic results appeared to emerge regularly from the networks of randomly selected participants with negative outcomes for this sample. If augmented by assessment of various contextual features of particular cases (e.g., problem behaviors, such as excessive drinking; information about social or work setting; physiological information from wearables), an idionomic approach to case conceptualization and functional analysis seems within reach from the current approach. These analyses, linked to coherent treatment models nested within the Extended Evolutionary Meta-Model (EEMM) of Process-Based Therapy and combined with treatment kernels focused on key processes of change, could lead to a diagnostic approach treatment utility – the holy grail of diagnostic research for more than half a century.

Process-based therapeutic work is based on the idea that "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 et al., 2019, p. 43). This is not a new idea. In humanistic and person focused (e.g., Greenberg, 1986) and behavior therapy traditions (e.g., Goldfried, 1980; Rosen & Davison, 2003), there has long been concern over a technological rather than process focus in psychotherapy research.

The approach to measurement and intervention that is reflected in the PBAT and its idionomic strategy is linked to long standing 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). In the behavioral and cognitive therapy tradition, methodological texts have emphasized the need for repeated measurement in practical work and "the separation of measurement error, extraneous variability, and intervention-related variability at the level of the individual" (Hayes, Barlow, & Nelson-Gray, 1999, p. 109). Nevertheless, a top-down normative approach has long dominated evidence-based therapy and its philosophical and methodological underpinnings, even in the behavioral and cognitive community.

These long-standing concerns within evidence-based therapy traditions have grown markedly more intense in recent years, with the growing recognition of the central importance of the ergodic assumption to classical normative statistics (e.g., Hayes et al., 2020). Researchers and practitioners are beginning to take seriously the possibility, even the probability, that case conceptualization systems based on normative concepts such as syndromes, personality types, and the like cannot succeed because they are based on a mathematical error. This startling outcome is difficult to avoid once it is agreed that ergodicity is indeed a necessary assumption of classical normative statistics, and that ergodicity is rare or even absent in human biopsychosocial phenomena.

Several alternative empirical nosological efforts are underway such as RDoC or the Hierarchical Taxonomy of Psychopathology (HiTOP; Kotov et al., 2017) but to our knowledge, all are still based on latent diseases and top-down normative categories that require ergodicity to succeed. We believe a truly new way forward is needed.

The relatively low attrition rate of the final sample indicates the PBAT is suitable for high temporal density longitudinal research and the GIMME-based requirement of at least 60 data points is not an insurmountable obstacle to its use. Whether this will apply to clinical contexts remains to be determined. On the one hand, individuals actively seeking treatment for psychological distress may be more motivated to participate in frequent assessment activities than healthy controls (e.g., Porras-Segovia et al., 2020; Shiffman, Stone, & Hufford, 2008), especially if the purpose of assessment is closely aligned to clinical goals. For example, clients might be provided with a meaningful interpretation of their baseline data such as describing the processes of change that are the top drivers of their well-being in day to day life; or following treatment, if changes in idiographic networks that indicate stable progress were well characterized. On other hand, some clients will be unwilling or unable to follow through with a regimen of frequent assessment. As the database of longitudinal PBAT responses grows, however, it may be possible to use pre-existing knowledge and Baysian analysis (Bolstad & Curran, 2016) to identify likely patterns of behavior from a relatively small number of measurement points, and passive high frequency data from wearables and smartphones may further reduce the assessment burden.

Characterizing treatment response will likewise initially require the comparison of stable idiographic networks pre and post intervention, and the assessment burden that entails. Over time, however, the combination of passive data, the efficient use of a growing database, and the development of efficient means of detrending data may narrow the temporal window needed to detect how intervention perturbates idiographic networks.

In the present study, the collection of at least 60 data points proved to provide reasonable power, with individual models converging normally for the overwhelming majority of participants and most participants showing PBAT to outcome edges. Thus, the combination of the PBAT and S-GIMME was shown to be a robust analytical measurement approach that was able to accommodate individual differences and link processes of change to common clinical outcome using a reasonably practical experience sampling approach.

This appears to be true even though no group level edges were discovered between nodes in any network considered for this analysis. The lack of group edges speaks both to the heterogeneity of the participants and of the processes assessed. The present results thus show that the EEMM itself may help lead toward a diagnostic and case conceptualization approach that is bottom-up and idionomic. However, this does bring up a meaningful limitation in the GIMME analysis, as though the approach does not assume ergodicity, it does assume weak stationarity - that is, that relationships between variables remain constant across time. Though some violations of stationarity can be accounted for statistically, it may be the case that during active treatment, relationships between variables may be dynamic and unstable (e.g. "sudden gains" in treatment). At this time, the present approach may best be utilized as a baseline assessment, perhaps while clients are on a waitlist for treatment. Further research is needed in order to assess how idionomic networks interact with ongoing treatment, and could present a way forward in evaluating not only baseline case conceptualization but also treatment response in an idiographic, data-driven manner.

Another possible problem with GIMME in a clinical context is that honest answers can produce invariant items will not allow the model to run. This can be addressed by entering a single invariant data point at a random time for the offending variables or by dropping invariant items, but the impact on case conceptualization results will need to be examined empirically.

Additional research is also needed on the methodological details of high temporal density phone-based measurement. For example, some variation in responses on the 100 point slider is due to measurement error, which would increase the noise to signal ratio and potentially lead to an underestimate of effects. Some research suggests that digital-analog response systems perform well in web or smart phone based assessment as compared to traditional Likert style systems (e.g., Funke & Reips, 2012), but issues of anchoring and avoiding excessive use of visual poles requires increased research attention.

The case conceptualizations that emerge from GIMME analyses must be tested experimentally to warrant the full meaning of the term "functional analysis", but it is important not to confuse "contemporaneous" relations in GIMME outputs with such relations from classical group statistics. The contemporaneous relations shown in the idiographic diagrams in the current study are contemporaneous between variables but are longitudinal within the predicted variable since they first account for longitudinal auto-regressive relations. This not only allows directionality to be determined, it also makes it more likely that within the temporal window examined, contemporary relations point to functional relations that can be manipulated. That prediction itself will need to be tested over time as GIMME-based case conceptualizations such as the ones presented here are tested in the context of intervention. To the degree to which that prediction is upheld, the present approach will be able to form the basis of an empirical system of functional analysis and a diagnostic approach with known treatment utility.

Empirical case conceptualization and evidence-based therapy are clearly at a crossroads. Systems that retain the false assumption of ergodicity cannot fully address the fundamental weaknesses of current approaches. Purely conceptual forms of functional analysis cannot adequately fill the resulting void. The present study is a promissory note suggesting that a process-based idionomic approach may be a scientifically and clinically viable alternative. Empirical process-based case conceptualization linked to a new statistical method of functional analysis is a clinically and scientifically sound alternative worth pursuing.

Declaration of competing interest

None.

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