Assessing Processes of Change in Psychological Interventions: The Process-Based Assessment Tool (PBAT)

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Abstract

The “protocols for syndromes” approach to evidence-based psychological intervention has failed the test of scientific progressivity. Process-based therapy provides an alternative model that is focused on treatment elements that target biopsychosocial processes of relevance to individual treatment goals. That shift in focus requires new, more integrative and idionomic models that identify key processes of change, using high temporal density measurement applied at the level of the person. Standard measurement validation approaches are inadequate to this challenge. The present study develops and provides a preliminary validation of a process-based assessment tool (PBAT) -- an item pool meant for intensive longitudinal clinical assessment. Developed using the Extended-Evolutionary Meta-Model of PBT and evaluated using an evolutionary algorithm appropriate for the evaluation of individual items, we administered the PBAT online to a representative sample of 598 participants (290 male; 302 female; 6 unidentified. $M_{\text{age}} = 32.6$). Analyses revealed that the PBAT distinguishes between positive and negative processes, links in theoretically coherent ways to need satisfaction and thwarting, and links to clinically relevant outcomes of sadness, anger, anxiety, stress, lack of social support, vitality, and health. The PBAT provides a beginning step towards developing a process-based tool that allows clinicians and researchers to select individual items or sets of items for individual-focused idionomic research and practice.

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The ultimate scientific purpose of diagnosing psychiatric syndromes is to identify their etiology, to understand the course of pathological processes, and to identify and understand clinically meaningful responses to intervention.

Unfortunately, there is wide agreement that little progress is being made on these issues. Despite its importance, research suggests the utility of traditional diagnosis in improving clinical outcomes is still minimal (Mullins-Sweatt et al., 2016). Etiological and process knowledge linked to syndromes is similarly weak, leading even the developers of syndromal diagnosis (Kupfer et al., 2002) to worry that research on the current diagnostic system in this area may “never be successful” (p. xix).

These weaknesses have a practical, not merely a conceptual cost. The rate of mental and behavioral health problems has remained persistently high (Moffitt et al., 2010; Richter et al., 2019), despite over a half century of research on clinical interventions linked to psychiatric syndromes. Indeed, meta-analyses suggest that the effectiveness of psychotherapy interventions is not improving (Ljótsson et al., 2017). Researchers commonly evaluate interventions in a “horse race” model, where they pit one package against another in a randomized-control trial. Many therapies receive moderate evidence of support with differences between therapies being absent or small (Cuijpers et al., 2013). Nevertheless, complex treatment packages have proliferated, often with unknown, unclear, or vastly overlapping targeted processes of change. It has become impossible to be expert at even a small subset of methods that claim to be evidence-based.

In acknowledgement of this palpable lack of progress, in the last decade there has been a sharp turn toward the direct examination of processes of change that are

linked to the goals of intervention (Hayes, Hofmann, & Ciarrochi, 2020a, 2020b; Hofmann & Hayes, 2019). The National Institute of Mental Health reoriented its research portfolio toward Research Domain Criteria (RDoC; Insel et al., 2010) -- studying processes that may help explain the neurodevelopmental features presumed to be the underlying mechanisms of mental health problems. Unfortunately the strong pre-commitment of RDoC to the role of biophysiological mechanisms (Vaidyanathan et al., 2020) undermined this program both scientifically and practically since there was and still 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 et al., 2018, p. 2).

Psychological science task forces have also sought to build consensus for a process focus (Hayes et al., 2021). For example, the report of the Inter-Organizational Task Force on Cognitive and Behavioral Psychology Doctoral Education (Klepac et al. 2012) called for more focus on “understanding the processes that determine behavior maintenance and change” (p. 693). Similarly, the Association for Contextual Behavioral Science (ACBS) Task Force on Strategies and Tactics of Contextual Behavioral Science Research (Hayes et al. 2021) called for more “research to identify processes of change” (p. 176) and “more longitudinal measurement that situates a psychological event in a behavioral stream and the context in which that stream occurs” (p. 175).

From Trademarked Packages to Evidence-based Process

Process-based therapy (PBT; Hayes & Hofmann, 2018) reflects these same trends. Not a new therapy, but a new approach to describing evidence-based therapy, PBT can be defined as the “contextually specific use of evidence-based processes linked to evidence-based procedures to help solve the problems and promote the prosperity of particular people” (Hofmann & Hayes, 2019, p. 38). We define processes of change as theory-based, dynamic, progressive, contextually bound, modifiable, and multilevel changes or mechanisms that occur in predictable empirically established sequences oriented toward desirable outcomes (Hayes, Hofmann, Ciarrochi, 2020a; Hofmann & Hayes, 2019). Said in another way, processes of change are biopsychosocial sequences that researchers have shown to be functionally important pathways toward meeting the goals of those receiving an intervention.

Unlike a syndromal approach, which starts with topographical features and hopes to find functionally important features, a process-based approach starts from the end and works backwards, constructing measurement and case analysis from elements known to be functionally important. This process-based approach could lead rapidly to greater clinical utility in the form of greater efficiency and effectiveness (Hayes, Hofmann, & Ciarrochi, 2020a, 2020b).

To explore these opportunities fully, however, we need new ways of measuring and analysing processes. Current approaches to the assessment of processes of change have emphasized self-report scales that are said to measure latent theoretical constructs and are validated using classical psychometrics. A change in tactics is essential because when classic psychometrics are applied to the practical world of treating a specific client in a specific context a lethal statistical problem reveals itself.

The Ergodic Error

Assessing processes of change in groups and applying these processes to individuals requires sensitivity to changes within individual people. The traditional psychometrician uses normative statistical assumptions to examine consistencies among collections of individuals, intending to apply findings from the group to everyone. Mathematically, these two approaches can be contradictory because the set of restrictive conditions under which inter-subject variability can properly model intra-subject variability are impossible to meet in clinical behavioral science.

Physicists have long known that the assessment of collections of elements in space correspond to the measurement of these elements over time only under certain “ergodic” conditions. Ludwig Boltzmann developed the concept in his work in statistical mechanics in the 1870’s (Ashley, 2015), but it did not become universally accepted in the physical sciences until Birkoff (1931) and von Neumann (1932) provided independent mathematical proof of the ergodic theorem. It has been accepted science over the near century since.

Molenaar (2004) realized that if different spatial locations are mathematically analogous to different people and temporal measurement applies to changes within a person then the ergodic theorem also dramatically limits the conditions under which we can apply normative assumptions to individual concepts tested using classic statistics in psychology. Specifically, the ergodic theorem demands that for such applications to be mathematically valid, there must first be no mean or variance changes within persons over time and secondly, each person in the population must obey the same dynamic model (Molenaar, 2013). Said more concretely, to be ergodic the mean and variance of a feature must be identical both for all cross-sectional collections of persons, and for each person over time (Gates, Chow, & Molenaar, in

press). These severe stationarity and homogeneity assumptions automatically eliminate processes of change as legitimate topics to be tested using classical normative statistics, if the goal is to apply that knowledge, even probabilistically, to particular people (Fisher et al., 2018; Rabinowitz & Fisher, 2020).

While this realization disrupts applied psychology, we can avoid the ergodic error by an “idionomic” approach (Hayes & Hofmann, 2021) that first validates concepts idiographically based on relationships established against the background of intrasubject variability alone, and then gathers these relations into nomothetic generalizations, provided doing so illuminates idiographic information without distortion (Gates & Molenaar, 2012).

Creating a Model of Processes of Change

There are other difficulties to be overcome beyond avoidance of the ergodic error when developing measures with a PBT focus. Unlike syndromally focused measures, measures of broadly focused processes of change need to be linked to a wide range of outcomes that are relevant to individual goals. Furthermore, because a wide range of processes could apply to a particular goal for a particular purpose, there must be a way to constrain these to a manageable problem space and to find an agreeable descriptive approach to promote consilience of findings across studies.

One proposed solution to this second set of difficulties has been to nest models of processes of change under the best-established theory available within life science, namely, evolutionary theory. Process-based therapy has embraced this approach with its “Extended Evolutionary Meta-Model” (EEMM) of processes of change (Hayes et al., 2019; Hayes, Hofmann, & Ciarrochi, 2020a). The EEMM proposes that models of broadly applicable processes of change should specify how positive or negative features of variation, selection, retention, and contextual fit are

reflected in key processes of change, approached in a multi-dimensional and multi-level evolutionary fashion. “Variation” refers to the degree of needed breadth and flexibility of processes that can be deployed to accomplish individual purposes; “selection” refers to the detection of relatively successful or unsuccessful deployment of skills or processes; “retention” refers to the maintenance of specific variants of processes; “context” refers to sensitivity to the internal and external situational and historical features that are predictive of success or failure for a given instance.

The EEMM suggests that we can apply these four essential and readily definable features of evolving systems to existing processes of change, organized into overall models by considering a broad set of psychological dimensions including affect, cognition, attention, self, motivation, and overt behavior and by examining additional dimensions occurring at the sociocultural and biophysiological levels of analysis. Because the defining nature of specific dimensions and levels of selection are empirical matters, the EEMM does not propose to establish hard dimensional or level of analysis boundaries, but adds these additional concepts based on their common occurrence in the literature on processes of change (Hayes, Hofmann, Ciarrochi, Chin, & Baljinder, 2020), to promote breadth of application and analysis.

The EEMM suggests that “each identified dimension can be functionally measured, using multiple methods, and in a way that fosters successful functional analysis”, cautioning that measures need to be “valid at the individual level”; and that it be empirically known “the extent to which intervention outcomes are due to various change dimensions at the idiographic level” (Hayes et al., 2021, all quotes are p. 179).

Creating Idionomic Process Measures

The final key area of practical difficulty is resolving how to develop and evaluate measures that fit these statistical and practical constraints once we acknowledge that classical psychometrics and group comparative approaches contain an irresolvable ergodic error. While we may use idionomic methods to develop such measures, no one has yet worked out precisely how to do so. In part the immediate barrier is practical. It seems possible to generate, say, self-report items that would be tested in high-density longitudinal idiographic networks of processes of change that target common outcomes (Hofmann et al., 2020), retaining items that appear frequently and prominently in clinical work both before and after intervention when evaluated using idionomic methods. However, these methods often require 40 or more longitudinal assessments in each phase typically spread out over several weeks (Fisher et al., 2017; Gates & Molenaar, 2012). Thus the assessment burden is considerable and grows as possible new items are added.

The present study attempted to address that problem by developing and providing a preliminary evaluation of the Process-Based Assessment Tool (PBAT). The PBAT is not a scale -- it is an item pool meant for idionomic use. The end goal of the study was to create and validate preliminary items that could then be used to study within-person processes of change, such as in daily diary studies or clinical studies using intensive repeated measures.

We derived PBAT items from the EEMM (Hayes, Hofmann, & Ciarrochi, 2020a), with the goal of staying sufficiently close to multi-dimensional and multi-level evolutionary concepts that items would transtheoretical and usable by practitioners of any therapeutic orientation that is willing to see behavioral and psychological science through the lens of evolution. Because processes of change are functionally defined, we linked items to the “selection” column of the EEMM by considering evidence on

human needs or yearnings, such as those suggested by self-determination theory (Ryan & Deci, 2017) or psychological flexibility (Hayes, 2019). To address the biophysiological level, we added health items. We also added items specifically focused on variation and retention. Positively and negatively worded items were used for each modelled dimension because satisfying and thwarting goals or needs are distinguishable (Chen et al., 2015). In line with existing practice in EMA approach (Nezlek, 2012), we focused items on behavior, rather than content of traits, beliefs, thoughts, schemas, or aspects of character, as is common in many process measures. The focus on clinically relevant psychological actions was intended to make the measure relevant across theoretical orientations and to help focus the therapist on clear targets for intervention.

There is no well agreed up method for vetting single items for experience sampling methods. A traditional psychometric approach, such as factor analysis or reliability analysis, is poorly suited for this task because such methods assess the quality of items in terms of item consistency with an inferred latent construct based on inter-item correlations. To test a set of individual items, we need methods that allow items to succeed in competition with other items. In the present study, we used an evolutionary algorithm that allowed specific items to compete for success in predicting outcomes (Kursa et al., 2010) and then retained specific items based on overall success in multiple iterations of the evolutionary algorithm.

We tested three hypotheses. In keeping with research that enhancing and thwarting underlying psychological purposes are distinct processes (Bartholomew et al., 2011; Ryan & Deci, 2017), we expected positive items would correlate moderately with other positive items, as would negative items, but positive and negative items would correlate less well (Hypothesis 1). We further expected PBAT

items to link in theoretically coherent ways to the satisfaction or thwarting of underlying purposes (Hypothesis 2), as well as to clinically relevant outcomes of sadness, anger, anxiety, stress, lack of social support, vitality, and health (Hypothesis 3).

Method

Participants and design

We purchased a nationally representative American sample of 598 participants (290 males; 302 females; 6 unidentified) from Qualtrics. Participants completed an on-line, anonymous survey in exchange for points they received from the survey company, which they could redeem for merchandise (directly from the company). We designed the survey so that participants were required to enter responses to the questions, resulting in a 100% completion rate. The mean age of the sample was 32.6 (SD = 10.32).

Measures

Process-Based Assessment Tool measure

To develop the content of the items, we formed a theoretically diverse expert panel. This panel included Steven C. Hayes (expert in Acceptance and Commitment Therapy), Stefan G. Hofmann (expert in Cognitive Behavioral Therapy), Louise Hayes (expert in youth and adolescence), Baljinder Sahdra (expert in methodology and social psychology), Joseph Ciarrochi (expert in Positive Psychology and Acceptance and Commitment Therapy), Ann Bailey (expert in Psychodynamic Therapy), Frank Deane (Expert in Cognitive and Behavioral Therapy), and Robert Brockman (Expert in Schema Therapy). The panel worked through several revisions of the measure. The core goal was simplicity and theoretical clarity. We revised items

that were ambiguous in terms of their dimensions or evolutionary targets. In the end, all items were approved by every member of the team.

Participants were presented with 21 statements. Items were designed to permit use with a specific temporal focus. In the present study, “During the last week,” was added to items. A sample item was “During the last week, I struggled to connect with the moments in my day-to-day life.” The full item pool is shown in Table 1. All items were rated on a 100-point touch-based slider, ranging from 0 (strongly disagree) to 100 (strongly agree). We chose a physical scale with such a wide range, in contrast to typical 5 or 7 point numerical scales, because we assumed that even small changes to clinically-relevant behaviour can be significant and because subsequent use of the items in idiomorphic research would depend on within respondent variability, which would be enhanced by a slider but needlessly reduced by a numerical scale, in which participants could easily remember past responses and potentially respond based on consistency rather than on current behavior. A practitioner-friendly version of the scale is available in the Appendix.

Table 1: Items in the PBAT

Process Target	Negative Behavior	Positive behavior
Variation	I felt stuck and unable to change my ineffective behavior.	I was able to change my behavior, when changing helped my life
Selection of Affect / Yearning to Feel	I did not find an appropriate outlet for my emotions	I was able to experience a range of emotions appropriate to the moment
Selection of Cognition / Yearning for Coherence	My thinking got in the way of things that were important to me	I used my thinking in ways that helped me live better
Selection of Attention /	I struggled to connect with the	I paid attention to important things

Yearning to be Oriented	moments in my day-to-day life	in my daily life;
Selection of Social Connection / Need for 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
Selection of Motivation / Need for 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
Selection of Overt Behavior / Need for Competence	I did not find a meaningful way to challenge myself	I found personally important ways to challenge myself
Selection of Physical Health Behaviors	I acted in ways that hurt my physical health	I acted in ways that helped my physical health
Retention	I struggled to keep doing something that was good for me	I stuck to strategies that seemed to have worked

Note: As will be discussed below, three additional items were tested and ultimately removed yielding these 18 items. The items removed were a negative variation item: *I changed my environment, to improve my life (examples: removing temptation; reducing distractions; surrounding myself with positive influences)*; and two negative retention items: *I stuck to what I cared about, even in the face of difficulties* and *I've used what I've learned in everyday life*. See text.

Criterion-variables

Clinically relevant outcomes. We used the five STOP-D items to measure sadness, anxiety, stress, anger, and lack of social support (Young et al., 2007, 2015). People rated the extent they felt each state, during the last week, on a 100-point scale ranging from “Not at all” to “a great deal”. We utilized the single item health measure (Ware & Sherbourne, 1992) to assess health in the past week. Responses ranged from 1 (poor) to 5 (excellent). Finally, to assess vitality, we used three positive items from the vitality scale (Ryan & Frederick, 1997), including “during the last week, I felt energized”, “vital and alive”, and “nearly always felt alert and awake”.. Responses ranged from not at all true (0) to very true (100). This scale demonstrated strong internal consistency ($\alpha = .89$)

Need satisfaction. Because the approach we took to “selection” in given dimensional areas is close to the concepts tested in needs psychology (Ryan & Deci, 2017), we selected two items with strong factor loadings from existing subscales of the need satisfaction and need frustration scale related to autonomy, competence, and connection (Chen et al., 2015). Participants rated the items on a 100-point slider scale from “Definitely False” to “Definitely True”.

Statistical procedure

Our main statistical approach to evaluating the PBAT contrasts with a traditional psychometric approach, in which the researcher seeks to identify latent variables that influence responses on scale items based on inter-item consistency. This approach is not applicable to single items. Our main analyses instead utilized a machine learning “evolutionary” algorithm to test the competitive ability of individual PBAT items to relate to each of our outcome variables. Focusing on the individual item level allows identification of high performing single items for use in intensive repeated-measures designs.

The machine learning algorithm selected was the Boruta algorithm, which builds on the random forest classification approach (Kursa et al., 2010). First, it extends the data set by creating randomly shuffled copies of all features, or shadow features, which are uncorrelated with responses. The data set is extended by at least five shadow features. Second, it runs a random forest classifier on the extended data set and gathers Z scores, or an index of how much information is lost if that item is not included in prediction. Third, it finds the maximum Z score among shadow attributes (the “MZSA”), and then assigns a hit to every item that scores better than MZSA. Fourth, it classifies every attribute or item that has importance significantly lower than the MSZA as “unimportant”, and the attributes that have importance

significantly higher than the MZSA as “important.” Finally, it repeats this entire procedure multiple times to get statistically robust results. Over iterations the algorithm estimates the importance of each item via the mean decrease in accuracy of prediction if the item is not in the model.

The core building block for a random forest analysis is a decision tree, which is like an evolutionary process. To build a decision tree, the algorithm starts by randomly using one of the 21 PBAT items or “features” to predict an outcome. If that item predicts significant variance, it is considered a useful feature and it is selected. An additional feature (item) is then selected randomly and is retained if it predicts additional outcome variance given the selected feature and the best (i.e., the luckiest) shadow feature. The algorithm keeps adding features in this way, as long as the new feature adds significant value to prediction as defined above. When features no longer improve fit, the algorithm stops.

Because any one single decision tree may be inadequate to judge fitness, a full random forest analysis generates many different trees, each one considering only a random subset of features (i.e., items) and only having access to a random set of the training points. This process of inducing variation before selection and retention leads to more robust predictions, just as would happen in any evolutionary process. Each individual tree provides only an imperfect understanding of what items are likely to be best and retained but in the random forest the many decision trees are then combined into a single model.

Returning to the Boruta algorithm, we used the 100-default number of maximum runs and a confidence level/pvalue of .01. At the end of 100 runs, attributes that were still tentative were confirmed or rejected by comparing the median Z score of the attributes with the median Z score of the best shadow

attribute. Features were retained that were most consistently predictive across all iterations. The Boruta multiple adjustment parameter was set to true, which forces the algorithm to use the Bonferroni method to adjust for multiple comparisons.

Results

Descriptives

We present the means and standard deviations of the PBAT Table 2. Concerning positive behavior, participants felt least successful at finding meaningful challenges and most successful at paying attention to important things in daily life and choosing to do personally important things. Concerning negative behaviors, participants felt that problems with unhelpful thinking were most common, whereas hurting social connection was least common. There were also sex differences, with males more likely than females to report not experiencing a range of emotions appropriate to the moment, not paying attention to important things in daily life, complying with others, hurting their health and social connections, and not using what they learned in everyday life.

In contrast to sex differences on the PBAT, there were few sex differences in outcomes or need satisfaction measures. Males and females were not significantly different in sadness, anger, anxiety, stress, lack of support, or any form of need satisfaction, all $t_s < 1.96$, all $p_s > .05$. Males were significantly more likely than females to report feeling more vital ($M_{\text{male}} = 60.5$, $SD = 21.4$; $M_{\text{female}} = 56.1$, $SD = 22.9$) and healthy ($M_{\text{male}} = 3.1$, $SD = 1.1$; $M_{\text{female}} = 2.9$, $SD = .98$), $t_s > 2$, $p_s < .05$.

Taken together, these results suggest that males report feeling better than females, despite reporting less positive behavior than females. Indeed, males are

more likely than females to report engaging in behavior that hurts their health but are more likely to report feeling healthy.

Table 2: Means, standard deviations, and sex differences for PBAT items.

	Female		Male		t _{diff}
PBAT item	M	SD	M	SD	
Positive Selection behavior					
Chose to do personally important things	73.54	20.3	71.17	20.0	1.4
Helped My Health	64.28	22.9	65.21	21.7	-.5
Paid attention to important things in daily life	74.53	18.1	71.44	19.5	2.0*
Connected with important people	67.7	22.4	66.0	22.5	.92
Experience range emotions approp. to moment	68.87	20.4	62.88	23.1	3.3***
Found ways to challenge self	63.3	21.9	63.62	22.4	-.17
Used thinking to live better	64.91	22.2	65.01	21.9	-.05
Negative Selection Behavior					
Did things only to comply to others	48.11	27.7	54.39	27.9	-2.7**
Hurt my health	40.63	31.1	47.1	29.2	-2.6**
Struggled to connect with moments of day	48.78	27.6	52.96	27.0	-1.9
Hurt social connections	37.08	30.4	47.01	29.6	-4.0**
Found no appropriate outlet for feelings	45.29	28.3	50.01	28.2	-2.0*
Found no meaningful challenge	48.09	28.5	52.58	27.5	-1.9
My thinking got in the way of important things	55.16	26.1	55.76	26.6	-.27
Variation					
Stuck & unable to change ineffective behavior	49.31	29.4	50.36	29.2	-.44
Able to change behavior, when changing helped	62.98	20.9	63.32	22.2	-.19
Changed my environment to improve life	63.05	22.6	60.48	24.8	1.32
Retention					
Struggled to keep doing what was important	53.28	27.6	55.94	27.4	-1.2
Stuck to Strategies that worked	62.93	22.9	64.55	21.3	-.89
Used what i learned in everyday life	72.23	18.5	68.81	21.0	2.1*
Stuck to what cared about, even in difficulties	69.26	20.6	68.93	20.4	.20

Note: * $p < .05$, ** $p < .01$, *** $p < .001$; Scale ranges from 0 (strongly disagree) to 100 (strongly agree).

Structural validity

Hypothesis 1 suggested that positive and negative variation, selection, and retention behaviors would be distinctive and not mere opposite sides of the same continuum. Tables 3 and 4 support this hypothesis. All such seven positive items correlated significantly with the other positive items (mean = $+.38$; range = $+.28$ to $+.58$) and generally moderately with one small and one large correlation among the 21 calculated, using typical cut-offs of $.3$ and $.5$ for those categories. Similarly, all such seven negative items correlated significantly with each other (mean = $+.49$; range = $+.38$ to $+.63$), also generally in the moderate range. Positive and negative items showed smaller and inconsistent relationships (mean = $-.05$; range = $+.28$ to $-.18$). Only 18 of the 49 relationships were statistically significant (range = $-.08$ to $-.18$) while 31 were not (range = $+.06$ to $-.07$) and all significant relationships were small. This suggests that people are engaging in both positive and negative behavior during the week. It is also worth noting that the correlations within positive and negative items do not suggest item redundancy. The strongest link ($r = .63$) was between *no outlet for feelings* and *struggled to connect with the moments in day-to-day life*.

Table 3: Link between positive and negative behavior

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. PersonalImpor	-												
2. HelpHealth	0.32***	-											
3. PaidAttToImportant	0.47***	0.33***	-										
4. ConnectToPeople	0.37***	0.35***	0.39***	-									
5. ExperienceRangeEmotions	0.38***	0.28***	0.33***	0.39***	-								
6. ImportantChallenge	0.33***	0.45***	0.37***	0.40***	0.30***	-							
7. ThinkingHelpedLife	0.38***	0.45***	0.32***	0.50***	0.32***	0.58***	-						
8. Complying	-0.03	0.02	-0.03	-0.04	0.06	0	-0.05	-					
9. HurtHealth	-0.07	-0.08*	-0.18***	-0.10*	0.05	-0.02	-0.05	0.38***	-				
10. StruggleConnectMoments	-0.08*	-0.04	-0.10*	-0.09*	-0.06	-0.04	-0.08*	0.47***	0.44***	-			
11. HurtConnect	-0.14***	0	-0.12**	-0.16***	-0.11**	0.05	-0.06	0.47***	0.51***	0.52***	-		
12. NoOutletForFeelings	-0.07	-0.05	-0.12**	-0.15***	-0.03	0	-0.07	0.48***	0.51***	0.63***	0.58***	-	
13. NoMeaningfulChallenge	-0.04	-0.01	-0.15***	-0.15***	0.03	-0.10*	-0.10*	0.45***	0.46***	0.55***	0.48***	0.58***	-
14. ThinkingGotInWay	0.04	-0.02	-0.07	-0.11**	0.05	0.05	-0.01	0.45***	0.45***	0.47***	0.45***	0.53***	0.46***

Note: shaded area is relationship between positive and negative behavior

Table 4: Relationship between variation and retention items

	1	2	3	4	5	6
1. StruggledToKeepDoing	-					
2. StuckUnableChange	0.53***	-				
3. StuckToStrategies	-0.02	-0.06	-			
4. StuckToWhatCared	0.05	-0.06	0.31***	-		
5. AbleToChangeBehavior	0.08*	-0.02	0.42***	0.35***	-	
6. UsedWhatLearned	0.01	-0.11**	0.34***	0.46***	0.46***	-
7. ChangedEnvironment	0.08	0.06	0.39***	0.23***	0.41***	0.36***

Criterion validity

Hypothesis 2 suggested that PBAT 21-items should link to the theoretically related measures of need satisfaction. In other words, engaging in effective variation, selection, and retention should help satisfy the need for connection, competence, and autonomy. Consistent with this hypothesis, as is shown in Table 5, positive behaviors were moderately linked to all three forms of need satisfaction (mean = +.38; range = +.24 to +.52), but not need frustration (mean = -.06; range = -.17 to -.19). Conversely, negative behaviors were moderately to strongly linked to all three forms of need frustration (mean = +.48; range = +.40 to +.62), but not need satisfaction (mean = -.13; range = -.01 to -.25).

Table 5: Link of PBAT items to satisfaction and frustration of the need for autonomy competence, and connection.

	Autonomy Satisfaction	Autonomy Frustration	Connection Satisfaction	Connection Frustration	Competence Satisfaction	Competence Frustration
Positive selection						
Personallmpor	0.44***	-0.07	0.36***	-0.11**	0.34***	-0.12**
HelpHealth	0.40***	-0.06	0.36***	-0.03	0.40***	-0.12**
PaidAttToImportant	0.37***	-0.10*	0.42***	-0.10*	0.36***	-0.18***
ConnectToPeople	0.33***	-0.10*	0.42***	-0.19***	0.42***	-0.19***
ExperienceRangeEmotions	0.29***	-0.01	0.34***	-0.05	0.27***	-0.10*
ImportantChallenge	0.52***	0	0.39***	0.04	0.47***	-0.13**
ThinkingHelpedLife	0.44***	-0.08	0.45***	-0.08*	0.51***	-0.17***
Complying	-0.06	0.48***	-0.10*	0.42***	-0.11**	0.41***
Negative selection						
HurtHealth	-0.06	0.42***	-0.12**	0.40***	-0.14***	0.41***
StruggleConnectMoments	-0.07	0.53***	-0.21***	0.52***	-0.20***	0.54***
HurtConnect	-0.04	0.45***	-0.18***	0.54***	-0.14***	0.42***
NoOutletForFeelings	-0.05	0.51***	-0.21***	0.51***	-0.21***	0.55***
NoMeaningfulChallenge	-0.06	0.40***	-0.17***	0.46***	-0.18***	0.53***
ThinkingGotInWay	0	0.42***	-0.15***	0.50***	-0.20***	0.50***
Variation						
AbleToChangeBehavior	0.40***	0	0.33***	0.07	0.42***	-0.09*
StuckUnableChange	-0.11**	0.51***	-0.23***	0.54***	-0.25***	0.62***
ChangedEnvironment	0.34***	0.10*	0.24***	0.17***	0.30***	0.02
Retention						
StruggledToKeepDoing	0.01	0.42***	-0.15***	0.44***	-0.16***	0.46***
StuckToStrategies	0.35***	-0.02	0.34***	-0.04	0.40***	-0.12**
StuckToWhatCared	0.36***	0.01	0.26***	-0.01	0.38***	-0.07
UsedWhatLearned	0.41***	-0.08	0.33***	-0.08	0.44***	-0.16***

Finally, *Hypothesis 3* suggested that the PBAT items should link to clinically relevant outcomes. Table 6 supports this prediction. Positive items predicted health and vitality best (mean = +.25; range = +.05 to +.43) as compared to negative items (mean = -.12; range = .00 to -.25), whereas negative items predicted sadness, anxiety, stress, anxiety, and lack of support (mean = +.42; range = +.31 to +.52) more so than positive items (mean = -.07; range = +.12 to -.20). None of the correlations were so high as to suggest the PBAT was redundant with outcome measures.

Table 6: Link between PBAT and clinically relevant outcomes

	Sad	Anxious	Stressed	Angry	NoSupp	Health	Vital
Positive Selection							
Personallmpor	-0.17***	-0.09*	-0.09*	-0.17***	-0.11**	0.18***	0.30***
HelpHealth	-0.15***	-0.13**	-0.11**	-0.04	-0.04	0.29***	0.42***
PaidAttToImportant	-0.14***	-0.08*	-0.08*	-0.16***	-0.11**	0.19***	0.33***
ConnectToPeople	-0.18***	-0.14***	-0.12**	-0.20***	-0.13**	0.14***	0.29***
ExperienceRangeEmotions	-0.07	0.03	0	-0.02	0	0.05	0.20***
ImportantChallenge	-0.10*	-0.12**	-0.07	-0.09*	0.02	0.19***	0.43***
ThinkingHelpedLife	-0.17***	-0.12**	-0.12**	-0.16***	-0.07	0.20***	0.43***
Negative Selection							
Complying	0.37***	0.35***	0.37***	0.39***	0.37***	-0.13**	-0.10*
HurtHealth	0.36***	0.35***	0.31***	0.38***	0.38***	-0.16***	-0.12**
StruggleToConnectMoments	0.52***	0.51***	0.47***	0.48***	0.48***	-0.15***	-0.12**
HurtConnect	0.36***	0.35***	0.37***	0.44***	0.45***	-0.03	0
NoOutletForFeelings	0.52***	0.50***	0.44***	0.48***	0.51***	-0.16***	-0.13**
NoMeaningfulChallenge	0.42***	0.36***	0.34***	0.38***	0.41***	-0.16***	-0.11*
ThinkingGotInWay	0.43***	0.42***	0.44***	0.39***	0.45***	-0.09*	-0.09*
Variation							
AbleToChangeBehavior	-0.12**	-0.06	-0.07	-0.06	0.03	0.24***	0.40***
ChangedEnvironment	0.02	0.02	0.03	0.02	0.12**	0.16***	0.29***

StuckUnableChange	0.51***	0.47***	0.48***	0.47***	0.51***	-0.25***	-0.19***
Retention							
StruggledToKeepDoing	0.39***	0.40***	0.39***	0.37***	0.43***	-0.12**	-0.10*
StuckToStrategies	-0.10*	-0.10*	-0.03	-0.08	0	0.20***	0.26***
StuckToWhatCared	-0.08	0.04	-0.01	-0.04	-0.04	0.07	0.17***
UsedWhatLearned	-0.14***	-0.03	-0.07	-0.16***	-0.07	0.19***	0.32***

Our final analysis utilized machine learning to identify the most important predictors of each clinically relevant outcome (see statistical procedure section). The analyses are fully reported in supplementary materials. Table 7 shows the item rank relative to the specified outcome (1 = top ranked).

All PBAT items were significant predictors of at least three clinically relevant outcomes. Able to change behavior was unranked three times but still was a top 5 predictor of vitality and health. In general, the negative items tended to link to the negative outcomes, and positive items linked to positive outcomes. The top predictor of all negative states was *struggled to connect to day-to-day moments of life*; the top predictor of health and vitality was *I acted in ways that helped my physical health*.

Table 7: Ranked relative importance of PBAT items for six clinically relevant outcomes

			Sad	Anxious	Stress	Anger	No Support	Vital	Health
Positive Selection	PersonalImpor		11	Unranked	Unranked	14	15	10	Unranked
	HelpHealth		13	10	10	Unranked	17	1	1
	PaidAttToImportant		Unranked	13	15	12	13	6	Unranked
	ConnectToPeople		10	16	19	10	10	18	Unranked
	ExperienceRangeEmotions		18	15	13	Unranked	18	21	Unranked
	ImportantChallenge		16	11	20	15	14	2	11
	ThinkingHelpedLife		14	17	12	13	12	3	8
Negative Selection	Complying		5	9	7	7	7	14	13
	HurtHealth		8	6	9	5	9	20	6
	StruggleToConnectMomen		1	1	1	1	3	7	12
	HurtConnect		9	8	6	4	4	19	Unranked
	NoOutletForFeelings		2	2	4	3	2	16	15
	NoMeaningfulChallenge		6	7	8	8	8	8	5
	ThinkingGotInWay		4	4	3	6	5	9	10
Neg V/R	StruggledToKeepDoing		7	5	5	9	6	12	9
	StuckUnableChange		3	3	2	2	1	13	2
Pos V/R	StuckToStrategies		15	12	14	Unranked	19	11	4
	AbleToChangeBehavior		Unranked	18	11	Unranked	Unranked	4	3
Dropped Items	StuckToWhatCared		17	14	17	17	16	17	Unranked
	UsedWhatLearned		12	Unranked	16	11	11	15	14
	ChangedEnvironment		Unranked	Unranked	18	16	Unranked	5	7

Note: V/R = Variation and retention items

Note: Unranked = Feature was a non-significant predictor (see supplemental section for full results of machine learning analyses).

Some PBAT items were top ten predictors of all negative outcomes, including *compliance, hurting connection, hurting health, having no meaningful challenge, having no outlet for feelings, struggling to keep doing something important, struggling to connect to moments, stuck and unable to change, and thinking getting in the way*. Concerning positive outcomes, positive variation (*able to change behavior, changed environment*) most clearly linked to vitality and health, and did not tend to link to negative outcomes. Vitality was most closely linked to *Helping health, having a meaningful challenge, and thinking helped*. Health was most strongly linked to *helping health, ability to change behavior, and stuck and unable to change*.

Based on these ratings, we created a recommended measure that includes one positive and negative item for each of the key elements of the Extended Evolutionary Meta model (see Table 1). Items excluded from the final recommended list included two retention items that were not a top ten predictor of any outcome (*I stuck to what I cared about, even in the face of difficulties*, and *I've used what I've learned in everyday life*). In addition, *changed environment* was a slightly worse predictor than *changed behavior*, so the latter was preferred. However, *changed environment* was ranked in the top 5 for vitality and top 10 for health and thus readers may wish to use the item when those goals are key. Unlike a traditional psychometric evaluation, individual item choices like that have no impact on the other items, since the PBAT is an item collection, not a scale.

Figure 1 shows the mean importance score for each of the retained item after 100 iterations of the algorithm. If the overall importance score fell below significance as measured against the best performing shadow variable, no value is shown in the figure. Specific numerical values for both Table 7 and Figure 1 can be found in the supplementary materials.

Note that while there are 18 items, items were in essence evaluated individually albeit competitively, and thus researchers or practitioners should use these items as a tool drawer and should feel free to use fewer or more items, depending on the purpose. The overall item importance to specific outcomes (see Table 7) can be used to guide item selection, but so too can theoretical case conceptualization (Hofmann et al., 2021) or guidance by subsequent empirical idionomic analyses since these the data in this study are not longitudinal. Studies of that kind are already being done using the PBAT (Sanford, 2021).

Note: Var./Ret. = variation and retention items

Discussion

The goal of the PBAT is to give researchers and practitioners a guide to a minimal, viable set of process-based items they can use to model and predict important processes of change that may interact to foster clinical outcomes. The results suggest that the PBAT may provide a useful beginning pool of items for research involving intensive, repeated measures of processes of change in individual clients.

Processes of change are defined as theory-based, dynamic, progressive, contextually bound, modifiable, and multilevel sequences linked to important

outcomes (Hayes, Hofmann, & Ciarrochi, 2020a). In the development of the PBAT item set, the EEMM and evolutionary theory was used most heavily to help generate items and to make predictions about item performance.

Items were designed to be contextually bound and focused on modifiable sequences by specifying actions focused on dimensions or level of responding in particular contexts. Items were designed to be multi-level in that sociocultural and biophysiological features were included, not just psychological items.

One area that was more difficult to address is that of “selection” since any action that leads to valued ends could be selected on that basis. In that area we relied on self-determination theory (Ryan & Deci, 2017), with its emphasis on the desire to connect and belong, to be competent, and to be able to choose what is most meaningful, relatively free of coercion and constraint. This framework has been extensively evaluated, and actions that promote these ends have been shown to promote well-being and positive life outcomes (Donald et al. 2020; Ng et al. 2012; Vasconcellos et al. 2020; Van den Broeck et al. 2016; Tang, Wang, and Guerrien 2020). These also line up with the EEMM areas of sense of self, overt behavior, and motivation well, but it leaves unclear what might be of proximal importance in the areas of affect, attention, and cognition. In this area we relied on psychological flexibility theory (Hayes, 2019), which suggests that people yearn for opportunities to feel, to be oriented, to find coherence and understanding in these three areas respectively.

We also found it difficult to construct items directly around sense of self, but by linking that area to a motivation to belong and connect, while still having a sense of autonomy and the ability to say what is of personal importance, it seems as though the social and cognitive areas could cover that dimension reasonably well.

The EEMM is not meant to have processes of change be sorted into boxes in a grid. Often variation, selection, retention, and context sensitivity areas blend across several rows of the EEMM. That was one reason we added items in the areas of variation and retention, leaving to additional research the process of adding and subtracting items within the EEMM structure. The PBAT as it is a “proof of concept” designed to allow idionomic research in PBT to proceed.

In accord with theoretical expectations, positive and negative PBAT behaviors were found to be distinctive (Hypothesis 1) and linked in coherent ways to established measures of need satisfaction (Hypothesis 2). Furthermore, all items were selected based on their competitive ability to relate to common positive and negative clinical outcomes, which they all did (Hypothesis 3). The real proof of concept, however, will follow only as the PBAT is applied to idionomic research itself. One reason that is true is that there are features of processes of change that could not be tested in this study. Processes of change are *dynamic*, because they may involve feedback loops and non-linear relationships, and *progressive*, because they may need to be arranged in sequences to reach the treatment goal (or speaking in terms of maladaptation, they may occur in self-sustaining problematic sequences). These features can only be detected in longitudinal studies using high density temporal measurement. Creating an item pool for such use was a purpose of the present study but the utility of the PBAT for that purpose is only now being evaluated (Sanford, 2021).

The top identified predictors of outcomes correspond to processes that are typically emphasized in a wide variety of major therapy types, as should be expected given its catholic purposes. For example, most forms of cognitive behavioral therapy (Butler et al., 2006; Hofmann et al., 2012) focus on problematic cognition, and the

two PBAT cognition items (thinking helped, thinking got in the way) were top predictors of positive and negative outcomes, respectively. Some forms of evidence-based therapy such as acceptance and commitment therapy (Hayes et al., 1999) or emotional-focused therapy (Greenberg, 2010) focus on restricted experience of emotions, and it was notable that an absence of appropriate ways to contact affect (*I did not find an appropriate outlet for emotions*) was a top predictor of negative outcomes. More behaviorally focused methods of intervention, such as behavioral activation (Dimidjian et al., 2006; Kanter et al., 2010) and problem-solving therapy (Eskin et al., 2008; Nezu & Nezu, 2001) would be supported by findings that behavioral rigidity (*stuck unable to change strategies*) strongly predicted negative outcomes while behavioral flexibility (*I was able to change my behavior*) predicted positive outcomes. Consistent with interpersonal therapies (de Mello et al., 2005; Maitland, 2015; Tsai et al., 2009), the social process item, *Hurt my connection with people that are important to me*, was a top predictor of negative outcomes, especially of anger and lack of social support. Mindfulness or attentional training methods such as MBCT (Fjorback et al., 2011), DBT (Neacsiu et al., 2010), ACT (Hayes et al., 1999) or Meta-cognitive therapy (Wells, 2008; Wells & Colbear, 2012) would be supported by the importance of the attention item, *I struggled to connect to the moments of my day to day life*. More bodily focused or wellness focused approaches (Dindo et al., 2017; Kini & Ho, 2018) would find support in the link between acting in ways to help health and positive outcomes.

From a Process-Based Therapy perspective, however, it is important to notice that all these processes can be important in some situations, for some clients, with reference to some goals. It makes little sense to develop myriad forms of intervention defined by treatment topographies, specific techniques, or narrow populations if

clients present with a much wider variety of challenges in biopsychosocial processes of change. Furthermore, absent a clear connection to processes of change it makes little sense to continue to develop treatment method after overlapping treatment method. We have argued previously (Hayes, Hofmann, & Ciarrochi, 2020a) that one value of the EEMM is that it raises the theoretical bar on *all* forms of evidence-based therapy, challenging them to show that their approaches can apply in a comprehensive way to contextually sensitive variation and selective retention issues across all major dimensions and levels of human functioning. Once evidence-based therapy is reconceptualized as an intervention that modifies processes of change that are of known importance, it is an open question whether and when syndromally focused methods might add values to more comprehensive methods that can be modularized to target specific biopsychosocial processes based on client need as identified, for example, by the PBAT.

Whilst the PBAT has clear theoretical links to psychological needs and clinically relevant outcomes, its value lies in its ability to function as an item toolkit that is distinct from these constructs. If, for example, the PBAT was just another measure of psychological needs, there would be no need to prefer it to the currently established needs measure. PBAT items correlated only modestly with outcomes and needs, suggesting they are not redundant. Furthermore, the inclusion of the yearnings framework undergirding psychological flexibility (Hayes 2019) added useful items beyond the competence, connectedness, and autonomy focus of SDT. All selection behaviors linked to the yearnings framework predicted significant variance in clinically relevant outcomes, and all made significant contributions to need satisfaction.

Variation and retention items were also important predictors of needs and outcomes. PBAT items focused on changing behavior or changing the environment were particularly good predictors of vitality. This finding could link to Fredrickson's broaden and build approach (Fredrickson, 2001; Fredrickson & Joiner, 2018), which suggests that positive affect prompts people to be exploratory, playful, curious, and experimental. This behavioral variation is expected to result in the development of new social resources and skills. Future process research is needed to examine if positive affect drives positive variation in the PBAT, or positive variation drives positive affect, or both.

A specific and unexpected finding was that relative to females, males reported engaging in less positive behavior and more negative behavior but did not report worse well-being or lower need satisfaction. For example, males reported doing more to hurt their relationships, and yet reported experiencing the same relationship need satisfaction as females. Males reported doing more to hurt their health, and yet report feeling healthier than females. More research linked to objective outcomes will be needed to interpret these differences.

Conclusions and future directions

This study was meant as a beginning step toward developing a process-based assessment tool that allows clinicians and researchers the freedom to select individual items or sets of items for use in idionomic research and practice. Future research using idionomic methods such as GIMME (Gates & Molenaar, 2012) will be needed to establish how the PBAT items interact over time in a dynamic and progressive way to predict changes in outcome, an essential feature of a process variable. Research will also be needed to examine if specific intervention kernels move specific PBAT-assessed processes. Those are precisely the empirical

challenges of process-based therapy more generally. The PBAT does not provide a solution to these challenges -- only a beginning method for assessing whether they can be met.

Appendix

To use the form, please enter your preferred time frame and context in the blank. Examples might be, “During the last week”, “During this day”, “During the second half of this day,” “During the last hour”, and “While at work today”.

PBAT

Please mark on the line how much you agree with each statement. Base these responses on how you have been acting in the last week. Remember, there are no right or wrong answers.

[illegible]

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Supplementary materials: Full output from Baruta machine learning analysis

Table S1: Ratings of importance for predictors of sadness

Item	Mean Import	Median Import	Min Import	Max Import	Hits	Decision
StruggleToConnectMoments	20.17	20.22	18.03	22.34	1	Confirmed
NoOutletForFeelings	18.76	18.66	16.84	20.57	1	Confirmed
StuckUnableChange	18.49	18.54	15.91	21.24	1	Confirmed
ThinkingGotInWay	13.83	13.76	10.28	16.06	1	Confirmed
Complying	8.7	8.61	6.82	10.57	1	Confirmed
NoMeaningfulChallenge	8.56	8.51	6.04	10.65	1	Confirmed
StruggledToKeepDoing	8.44	8.5	6.42	10.77	1	Confirmed
HurtHealth	7.87	7.84	5.65	9.97	1	Confirmed
HurtConnect	7.73	7.76	5.52	9.65	1	Confirmed
ConnectToPeople	6.72	6.71	4.35	8.77	0.99	Confirmed
Personallmpor	5.38	5.39	2.77	7.63	0.96	Confirmed
UsedWhatLearned	5.37	5.41	2.85	7.5	0.96	Confirmed
HelpHealth	5.21	5.3	2.9	7.99	0.94	Confirmed
ThinkingHelpedLife	3.59	3.62	1.58	5.37	0.73	Confirmed
StuckToStrategies	3.5	3.63	0.46	5.93	0.77	Confirmed
ImportantChallenge	2.92	3.02	0.4	5.98	0.57	Confirmed
PaidAttToImportant	2.75	2.73	0.8	4.53	0.59	Rejected
AbleToChangeBehavior	2.6	2.66	-0.3	4.76	0.47	Rejected
StuckToWhatCared	2.52	2.55	-0.08	4.77	0.47	Confirmed
ExperienceRangeEmotions	2.27	2.2	0.38	4.42	0.43	Confirmed
ChangedEnvironment	1.51	1.61	-0.8	3.38	0.15	Rejected

Note: Importance ratings varied across a maximum of 100 runs, due to variation in shadow(randomized) features and order of variable entry into each decision tree. *Hit* = Percentage of times item recorded higher importance than the highest shadow feature. *Confirmed* features are considered to be predictive of the outcome.

Table S2: Ratings of importance for predictors of anxiety

Item	Mean Import	Median Import	Min Import	Max Import	Hits	Decision
StruggleToConnectMoments	21.92	21.92	20.15	24.36	1	Confirmed
NoOutletForFeelings	18.2	18.25	16.08	20.26	1	Confirmed
StuckUnableChange	15.94	15.88	13.33	18.04	1	Confirmed
ThinkingGotInWay	12.73	12.71	10.72	15.5	1	Confirmed
StruggledToKeepDoing	10.46	10.45	7.93	12.79	1	Confirmed
HurtHealth	9.63	9.66	6.46	11.75	1	Confirmed
NoMeaningfulChallenge	7.92	7.94	5.74	9.85	1	Confirmed
HurtConnect	7.86	7.99	5.09	10.06	1	Confirmed
Complying	7.56	7.52	4.02	9.71	1	Confirmed
HelpHealth	6.08	6.13	3.18	7.96	1	Confirmed
ImportantChallenge	5.04	5.03	2.95	6.9	0.96	Confirmed
StuckToStrategies	4.17	4.19	1.48	6.3	0.91	Confirmed
PaidAttToImportant	4.1	4.07	0.65	6.38	0.89	Confirmed
StuckToWhatCared	3.91	3.86	1.67	6.36	0.84	Confirmed
ExperienceRangeEmotions	3.81	3.84	1.2	5.95	0.85	Confirmed
ConnectToPeople	3.39	3.35	0.34	5.64	0.75	Confirmed
ThinkingHelpedLife	3.3	3.37	0.87	6.46	0.73	Confirmed
Personallmpor	2.8	2.89	0.42	5.24	0.55	Rejected
UsedWhatLearned	2.74	2.71	0.23	5.31	0.6	Rejected
AbleToChangeBehavior	2.67	2.7	0.13	4.86	0.59	Confirmed
ChangedEnvironment	2.52	2.51	-0.31	5.07	0.51	Rejected

Note: Importance ratings varied across a maximum of 100 runs, due to variation in shadow(randomized) features and order of variable entry into each decision tree. *Hit* = Percentage of times item recorded higher importance than the highest shadow feature. *Confirmed* features are considered to be predictive of the outcome.

Table S3: Ratings of importance for predictors of anger

Item	Mean Import	Median Import	Min Import	Max Import	Hits	Decision
StruggleToConnectMoments	19.32	19.28	17.28	21.23	1	Confirmed
StuckUnableChange	17.16	17.16	15.15	19.44	1	Confirmed
NoOutletForFeelings	16.85	16.94	14.29	18.45	1	Confirmed
HurtConnect	12.62	12.62	10.16	14.97	1	Confirmed
HurtHealth	10.02	9.95	8.53	12.03	1	Confirmed
ThinkingGotInWay	9.47	9.51	7.13	11.97	1	Confirmed
Complying	8.95	8.97	6.35	11.88	1	Confirmed
NoMeaningfulChallenge	8.42	8.39	5.97	10.56	1	Confirmed
StruggledToKeepDoing	7.23	7.24	4.44	9.8	1	Confirmed
ConnectToPeople	6.34	6.37	3.69	8.64	0.99	Confirmed
UsedWhatLearned	6.09	5.99	3.3	8.19	0.99	Confirmed
PaidAttToImportant	4.53	4.63	1.81	7.9	0.87	Confirmed
ThinkingHelpedLife	4.48	4.59	1.46	6.27	0.88	Confirmed
Personallmpor	3.99	3.95	1.41	6.57	0.84	Confirmed
ImportantChallenge	3.51	3.56	1.31	5.99	0.7	Confirmed
ChangedEnvironment	2.72	2.78	0.34	5.66	0.54	Confirmed
AbleToChangeBehavior	2.63	2.71	0.25	5.07	0.51	Rejected
StuckToWhatCared	2.5	2.45	-0.98	5.55	0.44	Confirmed
HelpHealth	2.49	2.52	0.11	4.8	0.44	Rejected
ExperienceRangeEmotions	1.96	2.11	-1.07	4.36	0.39	Rejected
StuckToStrategies	1.57	1.72	-1.78	3.44	0.11	Rejected

Note: Importance ratings varied across a maximum of 100 runs, due to variation in shadow(randomized) features and order of variable entry into each decision tree. *Hit* = Percentage of times item recorded higher importance than the highest shadow feature. *Confirmed* features are considered to be predictive of the outcome.

Table S4. Ratings of importance for predictors of stress

Item	Mean Import	Median Import	Min Import	Max Import	Hits	Decision
StruggleToConnectMoments	19.44	19.45	17.74	21.81	1	Confirmed
StuckUnableChange	16.35	16.43	14.09	18.57	1	Confirmed
ThinkingGotInWay	15.78	15.77	13.78	18.29	1	Confirmed
NoOutletForFeelings	14.36	14.41	12.58	15.6	1	Confirmed
StruggledToKeepDoing	12.16	12.03	9.52	15.29	1	Confirmed
HurtConnect	9.78	9.75	7.05	11.51	1	Confirmed
Complying	9.49	9.55	7.34	11.66	1	Confirmed
NoMeaningfulChallenge	7.89	7.81	6.32	9.68	1	Confirmed
HurtHealth	7.04	7.07	4.81	9.55	1	Confirmed
HelpHealth	5.91	5.86	3.63	9.52	1	Confirmed
AbleToChangeBehavior	4.64	4.65	2.43	6.8	0.96	Confirmed
ThinkingHelpedLife	4.1	4	1.59	6.12	0.94	Confirmed
ExperienceRangeEmotions	4.06	3.93	2.03	6.69	0.92	Confirmed
StuckToStrategies	3.78	3.87	0.89	6.61	0.85	Confirmed
PaidAttToImportant	3.7	3.82	0.16	5.7	0.88	Confirmed
UsedWhatLearned	3.49	3.47	1.66	5.64	0.82	Confirmed
StuckToWhatCared	3.32	3.33	0.5	6.03	0.83	Confirmed
ChangedEnvironment	3.14	3.11	0.67	6	0.79	Confirmed
ConnectToPeople	3.02	3.1	1.11	5.54	0.7	Confirmed
ImportantChallenge	2.69	2.68	0.33	5.03	0.62	Confirmed
Personallmpor	2.19	2.29	-0.94	4.93	0.47	Rejected

Note: Importance ratings varied across a maximum of 100 runs, due to variation in shadow(randomized) features and order of variable entry into each decision tree. *Hit* = Percentage of times item recorded higher importance than the highest shadow feature. *Confirmed* features are considered to be predictive of the outcome.

Table S5. Ratings of importance for predictors for lack of support

Item	Mean Import	Median Import	Min Import	Max Import	Hits	Decision
StuckUnableChange	20	20	17.71	22.02	1	Confirmed
NoOutletForFeelings	16.98	16.94	15.21	19.09	1	Confirmed
StruggleToConnectMoments	15.11	15.09	12.53	17.02	1	Confirmed
HurtConnect	14.99	14.99	13.14	16.76	1	Confirmed
ThinkingGotInWay	14.83	14.93	12.91	17.3	1	Confirmed
StruggledToKeepDoing	11.86	11.83	9.89	13.98	1	Confirmed
Complying	9.56	9.6	7.29	11.47	1	Confirmed
NoMeaningfulChallenge	8.99	9.07	6.67	11.34	1	Confirmed
HurtHealth	8.8	8.81	6.68	11.2	1	Confirmed
ConnectToPeople	8.48	8.44	5.83	10.89	1	Confirmed
UsedWhatLearned	7.32	7.21	5.33	9.23	1	Confirmed
ThinkingHelpedLife	5.44	5.43	2.97	7.32	0.98	Confirmed
PaidAttToImportant	4.54	4.59	2.36	6.69	0.95	Confirmed
ImportantChallenge	4.24	4.34	2.16	6.58	0.95	Confirmed
Personallmpor	4.21	4.23	2.51	6.45	0.9	Confirmed
StuckToWhatCared	3.83	3.94	0.42	6.77	0.84	Confirmed
HelpHealth	3.59	3.65	1.07	6.17	0.76	Confirmed
ExperienceRangeEmotions	3.57	3.45	0.93	5.94	0.8	Confirmed
ChangedEnvironment	3.31	3.29	0.29	6.32	0.66	Rejected
StuckToStrategies	2.88	2.88	0.24	5.53	0.58	Confirmed
AbleToChangeBehavior	2.03	2.24	-0.8	4.03	0.27	Rejected

Note: Importance ratings varied across a maximum of 100 runs, due to variation in shadow(randomized) features and order of variable entry into each decision tree. *Hit* = Percentage of times item recorded higher importance than the highest shadow feature. *Confirmed* features are considered to be predictive of the outcome.

Table S6: Ratings of importance for predictors of vitality

Item	Mean Import	Median Import	Min Import	Max Import	Hits	Decision
HelpHealth	14.64	14.6	13.25	16.2	1	Confirmed
ImportantChallenge	13.29	13.48	11.71	14.64	1	Confirmed
ThinkingHelpedLife	12.4	12.44	10.56	14.51	1	Confirmed
AbleToChangeBehavior	11.7	11.62	10.61	13.81	1	Confirmed
ChangedEnvironment	10.1	10.18	8.18	11.55	1	Confirmed
PaidAttToImportant	8.07	8	6.55	9.35	1	Confirmed
StruggleToConnectMoments	7.7	7.59	5.62	9.65	1	Confirmed
NoMeaningfulChallenge	7.53	7.54	4.81	9.55	1	Confirmed
ThinkingGotInWay	7.07	6.98	5.67	9.89	1	Confirmed
PersonalImpor	7.04	7.16	4.83	8.55	1	Confirmed
StuckToStrategies	6.48	6.53	3.89	8.41	1	Confirmed
StruggledToKeepDoing	6.31	6.39	3.62	7.83	1	Confirmed
StuckUnableChange	6.24	6.28	4.52	8.71	1	Confirmed
Complying	5.82	5.7	3.58	8.22	1	Confirmed
UsedWhatLearned	5.68	5.76	3.24	7.41	0.97	Confirmed
NoOutletForFeelings	5.28	5.12	3.35	6.76	1	Confirmed
StuckToWhatCared	5	5.03	3.33	6.59	0.97	Confirmed
ConnectToPeople	4.5	4.55	2.4	6.47	0.95	Confirmed
HurtConnect	3.8	3.97	0.9	5.1	0.86	Confirmed
HurtHealth	3.53	3.42	1.31	5.82	0.78	Confirmed
ExperienceRangeEmotions	3.42	3.62	1.68	5.05	0.81	Confirmed

Note: Importance ratings varied across a maximum of 100 runs, due to variation in shadow(randomized) features and order of variable entry into each decision tree. *Hit* = Percentage of times item recorded higher importance than the highest shadow feature. *Confirmed* features are considered to be predictive of the outcome.

Table S7: Ratings of importance for predictors of health

Item	Mean Import	Median Import	Min Import	Max Import	Hits	Decision
HelpHealth	13.22	13.21	11.53	15.59	1	Confirmed
StuckUnableChange	13.2	13.13	10.98	15.7	1	Confirmed
AbleToChangeBehavior	8.41	8.34	6.29	11.02	0.99	Confirmed
StuckToStrategies	5.99	5.98	3.66	8.14	0.97	Confirmed
NoMeaningfulChallenge	5.7	5.75	3.49	7.76	0.99	Confirmed
HurtHealth	5.69	5.71	3.85	8.52	0.98	Confirmed
ChangedEnvironment	5.66	5.7	3.04	8.37	0.99	Confirmed
ThinkingHelpedLife	5.47	5.53	3.52	8.18	0.98	Confirmed
StruggledToKeepDoing	4.86	4.72	3.1	6.89	0.96	Confirmed
ThinkingGotInWay	4.71	4.73	2.53	6.47	0.93	Confirmed
ImportantChallenge	4.54	4.53	1.9	6.39	0.96	Confirmed
StruggleToConnectMoments	4.07	4.05	1.86	6.5	0.88	Confirmed
Complying	3.59	3.57	1.22	5.83	0.86	Confirmed
UsedWhatLearned	3.16	3.12	1.1	6.06	0.69	Confirmed
NoOutletForFeelings	3.15	3.03	0.99	4.93	0.78	Confirmed
ExperienceRangeEmotions	2.62	2.79	-0.76	5.34	0.59	Rejected
HurtConnect	2.61	2.7	-0.08	5.19	0.53	Rejected
PaidAttToImportant	2.51	2.47	-0.09	4.89	0.56	Confirmed
StuckToWhatCared	2.39	2.52	-0.48	5.04	0.56	Rejected
ConnectToPeople	1.46	1.46	-0.46	3.64	0.04	Rejected
Personallmpor	1.26	1.25	-0.04	2.94	0.02	Rejected

Note: Importance ratings varied across a maximum of 100 runs, due to variation in shadow(randomized) features and order of variable entry into each decision tree. *Hit* = Percentage of times item recorded higher importance than the highest shadow feature. *Confirmed* features are considered to be predictive of the outcome.