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Developing an item pool to assess processes of change in psychological interventions: The Process-Based Assessment Tool (PBAT)[☆]

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ABSTRACT

Process-based therapy (PBT) focuses on treatment elements that target biopsychosocial processes of relevance to individual treatment goals. This 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 a machine-learning algorithm appropriate for the evaluation of individual items, we administered the PBAT online to a sample of 598 participants (290 male; 302 female; 6 unidentified. $M_{age} = 32.6$). 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.

The ultimate scientific purpose of diagnosing psychiatric syndromes is to identify their aetiology, 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, Lengel, & DeShong, 2016). Etiological and process knowledge linked to syndromes is similarly weak, leading even the developers of syndromal diagnosis (Kupfer, First, & Regier, 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 conceptual cost. Meta-analyses suggest that the effectiveness of psychotherapy interventions is not improving (Ljótsson, Hedman, Mattsson, & Andersson, 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 an increased emphasis on 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

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interventions" (Borsboom, Cramer, & Kalis, 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).

1. 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 et al., 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 et al., 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 statistical problem reveals itself.

2. The ergodic error

Assessing processes of change in groups and applying these processes to individuals requires sensitivity to changes within individual people. The traditional psychometric approach 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 Holzmann 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 Birkhoff (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, Medaglia, & Jeronimus, 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).

3. 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 syndrome-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 et al., 2020a). The model is *extended* in that it applies evolutionary concepts beyond the typical domains of genetics and cultural development, to include overt and private behavior (e.g., symbolic thought). The model is *meta* in that it is meant to be a model of models. The EEMM it's not based on a specific theoretical or intervention orientation with its specific terms (e.g., such as those drawn from CBT, ACT, psychodynamic approaches and so on), but rather is meant to describe areas of coverage and principles of change that specific clinical theories need to address when humans are viewed as evolving systems.

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). The present paper is designed to identity a pool of items that can be used in future empirical analysis. Ultimately, for a process item to be empirically valid, it will need to be shown to be useful in guiding the practitioner to intervene on the process and affect clinical outcomes. Researchers will need to address the question: Does providing information about the process over time improve therapeutic outcomes? Those studies are yet to be done, but identifying an assessment approach is crucial to such tests.

4. 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. We need an idionomic method, a systematic approach that models individual behaviour before making inferences about groups behavior. No one has yet worked out the best way to do this. 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, Curtiss, & Hayes, 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, Reeves, Lawyer, Medaglia, & Rubel, 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 evaluation is "preliminary" in that it begins by vetting items using a cross-sectional design and identifying items that fail to link to clinically relevant criterion and outcome variables. To take the next step and fully evaluate the PBAT, longitudinal research is needed to evaluate the utility of the vetted PBAT items in assessing and predicting clinically-relevant change (for an example, see Sanford, 2021; Sanford et al., under submission). 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 et al., 2020a), with the goal of staying sufficiently close to multi-dimensional and multi-level evolutionary concepts, such that items would be transtheoretical and useable by practitioners of any therapeutic orientation who 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 a supervised machine learning algorithm that is similar to an evolutionary process (Kursa, Rudnicki, & Others, 2010). Items and outcomes were randomly sampled from the data set (producing variation), and these samples then competed for success in predicting outcomes (the selection criteria). Items were retained if they successfully predicted outcomes across multiple iterations.

We tested three hypotheses. In keeping with research that enhancing and thwarting underlying psychological purposes are distinct processes (Bartholomew, Ntoumanis, Ryan, Bosch, & Thøgersen-Ntoumani, 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 also expected the PBAT to link to clinically relevant outcomes of sadness, anger, anxiety, stress, lack of social support, vitality, and health (Hypothesis 2). Finally, we expected PBAT items to link in theoretically coherent ways to the satisfaction or thwarting of underlying purposes (Hypothesis 3). That is, in keeping with the demonstrated distinctiveness between need satisfaction and need frustration (Chen et al., 2015), positive PBAT behaviours are expected to predict need satisfaction more than need frustration, and negative behaviours are expected to predict need frustration more than need satisfaction. Further, to demonstrate content validity, the selection items focused on connection, challenge, and motivation should relate moderately to the need for connection, competence and autonomy, respectively.

5. Method

5.1. Participants and design

We purchased a Qualtrics sample that was intended to be representative of key U.S. demographics. Participants completed an on-line, cross-sectional, anonymous survey in exchange for points they received from the survey company, which they could redeem for merchandise (directly from the company). The sample consisted of 598 participants (290 males; 302 females; 6 unidentified) with an average age of 32.57 (SD = 10.32). Key demographics including marital status (33% single; 39% married; 24% dating or in a relationship; 4% other), education (10% some high school; 19% high school degree; 32% some college or college diploma; 38% Some graduate/professional school training or degree), ethnicity (3% African American; 4% Hispanic; 43% European/European American; 10% Asian American; 8% South Indian/ Indian Subcontinent; and 32% other). We designed the survey so that participants were required to enter responses to the questions, resulting in a 100% completion rate.

5.2. Measures

5.2.1. 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). Ciarrochi presented an initial pool of items to the panel, and the panel then suggested revisions and improvements. The core goal was simplicity and theoretical clarity. We also revised items that were ambiguous in terms of their dimensions or evolutionary targets. After approximately 10 revisions, the final item pool was 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 digital-analogue scale, 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 idionomic 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. While one potential downside of this approach is that some participants may have difficulty using the slider consistently across items, potentially producing measurement error, some research suggests that digital-analogue response systems have performed well in web or smart phone based assessment as compared to traditional Likert style systems (e.g., Funke & Reips, 2012). A practitioner-friendly version of the scale is available in the Appendix.

5.2.2. Criterion-variables

Clinically relevant outcomes. We used the five STOP-D items to measure sadness, anxiety, stress, anger, and lack of social support (Young, Ignaszewski, Fofonoff, & Kaan, 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 ($\alpha = 0.89$).

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 (Chen et al., 2015) of need satisfaction and need frustration in the domains of autonomy (*I feel that my decisions reflect what I really want*; *I feel forced to do many things I wouldn't choose to do*), competence (*I feel I can successfully complete difficult tasks; I feel insecure about my abilities*) and connection (*I feel connected with people who care for me, and for whom I care; I feel the people who are important to me are cold and distant towards me)*. Participants were asked, "During the past week, to what extent is each statement true or false for you "and then rated the items on a 100-point slider scale from "Definitely False" to "Definitely True". Like PBAT, the need scale seeks to be transdiagnostic. i.e., every evidence-based therapy would be expected to increase need satisfaction (Vanteenkiste & Ryan, 2013). The need satisfaction and frustration construct has been widely used and validated in many contexts such as health, education, work, sport, and mental health (Longo, Gunz, Curtis, & Farsides, 2016; Warburton, Wang, Bartholomew, Tuff, & Bishop, 2020; Benita, Benish-Weisman, Matos, & Torres, 2020; Heissel et al., 2018; Rodrigues et al., 2021). It has also been validated across multiple age groups and cultures (Phuoc, 2020; Chen et al., 2015).

5.3. 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 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. We did not have repeated measure data for this initial study, so we analyzed across all subjects, thus focusing on processes that were of general importance to the group.

The machine learning algorithm selected was the Boruta algorithm (Kursa et al., 2010), which builds on the random forest classification approach (Breiman, 2001). First, it extends the data set by creating randomly shuffled copies of all features, or shadow features, which are uncorrelated with responses. 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

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		
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
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
Attention/Yearning to be Oriented	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/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
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
Overt Behavior/Need for Competence	I did not find a meaningful way to challenge myself	I found personally important ways to challenge myself
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
Excluded items	I changed my environment, to improve my life (examples: removing temptation; reducing distractions; surrounding myself with positive influences);	I stuck to what I cared about, even in the face of difficulties; I've used what I've learned in everyday life.

Note: As will be discussed below, the three excluded items were tested and ultimately removed yielding 18 items.

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. (Please see appendix B for a detailed description of this procedure).

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.

6. Results

6.1. 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 (Table 3). Males and females were not significantly different in sadness, anger, anxiety, stress, lack of support, or any form of need satisfaction. However, males were significantly more likely than females to report feeling more vital and healthy.

Table 3
Means, standard deviations, and sex differences for Need Satisfaction and outcome variables.

Scale	Female		Male		t_{diff}
	M	SD	M	SD	
Sad	50.84	31.05	52.54	29.52	0.68
Anxious	54.37	29.73	54.42	27.78	0.02
Stressed	57.23	28.92	55.84	28.46	−0.59
Angry	45.3	29.12	48.56	29.54	1.34
NoSupp	49.39	30.56	49.86	28.97	0.19
Health	2.93	0.98	3.13	1.11	2.34**
Vital	56.1	22.94	60.53	21.37	2.23**
Autonomy Satisfaction	63.12	19.51	64.48	19.57	0.85
Autonomy Frustration	48.99	24.08	50.93	24.1	0.98
Connection Satisfaction	65.57	22.36	67.04	18.46	0.87
Connection Frustration	50.05	25.81	46.24	26.88	−1.76
Competence Satisfaction	66.92	19.03	64.47	20.01	1.52
Competence Frustration	52.68	27.05	51.22	26.88	0.66

Note: $^*p < .05$, $^{**}p < .01$, $^{***}p <> 001$; People rated the extent they felt sadness, anxious, stressed, angry and unsupported on a 100-point scale ranging from “Not at all” to “a great deal”. Health ratings ranged form 1(poor) to 5 (excellent). Vitality ratings ranged from not at all true (0) to very true (100).

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.

6.2. Structural validity

Hypothesis 1. suggested that positive and negative PBAT behaviors would be distinctive and not mere opposite sides of the same continuum. Tables 4 and 5 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

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

PBAT item	Female		Male		t_{diff}
	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
	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
	Excluded items				
Changed my environment to improve life	63.05	22.6	60.48	24.8	1.32
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).

Table 4
Link between positive and negative selection 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 5
Relationship between variation and retention items.

	2	3	4
Variation			
1. Stuck, unable to change	−0.02	0.53	−0.06
2. Able to change Behavior	–	0.08	0.42
Retention			
3. Struggled to keep doing important		–	−0.02
4. Stuck to working strategies			

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.

6.3. 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 6, 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 6
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						
PersonalImpor	**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***
Negative selection						
Complying	−0.06	**0.48*** **	−0.10*	0.42***	−0.11**	0.41***
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***
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**
Excluded items						
ChangedEnvironment	0.34***	0.10*	0.24***	0.17***	0.30***	0.02
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***

Note: Bolded items are cases where PBAT items are expected to closely match the content of the validated need measure.

Table 7
Link between PBAT and clinically relevant outcome.

	Sad	Anxious	Stressed	Angry	NoSupp	Health	Vital
Positive Selection							
PersonalImpor	−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***
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***
Excluded items							
ChangedEnvironment	0.02	0.02	0.03	0.02	0.12**	0.16***	0.29***
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***

Finally, Hypothesis 3 suggested that the PBAT items should link to clinically relevant outcomes. Table 7 supports this prediction. Positive items predicted health and vitality best (mean = +0.25; range = +0.05 to +0.43) as compared to negative items (mean = −0.12; range = 0.00 to −0.25), whereas negative items predicted sadness, anxiety, stress, anxiety, and lack of support (mean = +0.42; range = +0.31 to +0.52) more so than positive items (mean = −0.07; range = +0.12 to −0.20). None of the correlations were so high as to suggest the PBAT was redundant with outcome measures.

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 8 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

Table 8
Ranked relative importance of PBAT items for six clinically relevant outcomes.

	Sad	Anxious	Stressed	Angry	NoSup	Vitality	Health
Positive Selection							
ConnectToPeople	10	16	19	10	10	18	NA
ExperienceRangeEmotions	18	15	13	NA	18	21	NA
HelpHealth	13	10	10	NA	17	1	1
ImportantChallenge	16	11	20	15	14	2	11
PaidAttToImportant	NA	13	15	12	13	6	16
PersonalImpor	11	NA	NA	14	15	10	NA
ThinkingHelpedLife	14	17	12	13	12	3	8
Negative Selection							
Complying	5	9	7	7	7	14	13
HurtConnect	9	8	6	4	4	19	NA
NoMeaningfulChallenge	6	7	8	8	8	8	5
NoOutletForFeelings	2	2	4	3	2	16	15
StruggleToConnectMoments	1	1	1	1	3	7	12
ThinkingGotInWay	4	4	3	6	5	9	10
HurtHealth	8	6	9	5	9	20	6
Positive Variation/Retention							
AbleToChangeBehavior	NA	18	11	NA	NA	4	3
StuckToStrategies	15	12	14	NA	19	11	4
Negative Variation/Retention							
StuckUnableChange	3	3	2	2	1	13	2
StruggledToKeepDoing	7	5	5	9	6	12	9
Excluded items							
UsedWhatLearned	12	NA	16	11	11	15	14
StuckToWhatCared	17	14	17	17	16	17	NA
ChangedEnvironment	NA	NA	18	16	NA	5	7

Note: Lower numbers and darker shading indicates higher importance

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

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".

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.

7. 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 PBAT was linked to the theoretically relevant constructs of need satisfaction and frustration and to clinically-relevant outcomes. These findings provide initial evidence for construct and criterion related validity. Future research is now needed to evaluate how the items work in a longitudinal context and/or a clinical context.

Note that while the final PBAT measure was 18 items, these items were 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 8) can be used to guide item selection, but so too can theoretical case conceptualization (Hofmann, Hayes, & Lorscheid, 2021) or guidance by subsequent empirical idionomic analyses since the data in this study are not longitudinal. Studies of that kind are already being done using the PBAT, and have shown that changes in PBAT items are linked to changes in clinically-relevant outcomes (Sanford, 2021).

Processes of change are defined as theory-based, dynamic, progressive, contextually bound, modifiable, and multilevel sequences linked to important outcomes (Hayes et al., 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 Broek, Deutz, Schoneveld, Burk, & Cillessen, 2016; Tang, Wang, & 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.

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, Chapman, Forman, & Beck, 2006; Hofmann, Asnaani, Vonk, Sawyer, & Fang, 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, Strosahl, & Wilson, 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, Ertekin, & Demir, 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, de Jesus Mari, Bacaltchuk, Verdeli, & Neugebauer, 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, Arendt, Ornbøl, Fink, & Walach, 2011), DBT (Neacsiu, Rizvi, & Linehan, 2010), ACT (Hayes et al., 1999) or Metacognitive 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, Van Liew, & Arch, 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. It has been argued previously (Hayes et al., 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 yearning's framework undergirding psychological flexibility (Hayes, 2019) added useful items beyond the competence, connectedness, and autonomy focus of SDT. All selection behaviors linked to the yearning's 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.

8. PBAT and the self

We found it difficult to construct behavioral items that directly tap into sense of self. However, we believe the PBAT items indirectly measure a sense of self that is autonomous, worthy, and competent. Concerning the "autonomous self", SDT theory suggests that the self is experienced as autonomous when a person feels like they are behaving according to their personal values and not merely due to external influence, guilt, or pressure (Ryan & Deci, 2017). The PBAT assesses behavior that is personally important versus behavior that is driven by compliance, and both items correlate moderately to the SDT measure of Autonomy Satisfaction and Autonomy Frustration.

Concerning the "competent self", the PBAT variation items correlated moderately with SDT competence, as do items related to being able to take on meaningful challenges. 36% of the variance in competence frustration is predicted by the single PBAT item, *I felt stuck and unable to change my ineffective behavior.* The SDT competence scale clearly focuses on self, with items like, "I feel capable at what I do", "I feel insecure about my abilities", and "I feel like a failure …. ".

Finally, concerning the "worthy self", the PBAT connection items are likely to link to the extent a person feels worthy of respect and love. PBAT connection items correlate with SDT items that focus on the extent people report they are connected to people who care for them (connection satisfaction) and/or feel disconnected and uncared for (connection frustration). Future research is needed to examine the extent that SDT interventions (Ryan & Deci, 2017) and self-concept interventions (Niveau, New, & Beaudoin, 2021) influence PBAT behaviors and vice versa.

9. 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. However, this study was cross-sectional and does not itself address the ergodic error. Future research using idionomic methods (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 (e.g., see Sanford, 2021; Sanford et al., under submission). Research will also be needed to examine if specific intervention kernels move specific PBAT-assessed processes, within different people and within different contexts and cultures. 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.

Declaration of conflicts of interest

None.

Acknowledgments

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Appendix A. PBAT

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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 respones on how you have been acting ____________________(time frame). Remember, there are no right or wrong answers

	Strongly Disagree 0	10	20	30	40	50	60	70	80	90	Strongly Agree 100
1. I was able to change my behavior, when changing helped my life											
2. I did things that hurt my connection with people who are important to me											
3. I was able to experience a range of emotions appropriate to the moment											
4. I struggled to keep doing something that was good for me											
5. I did not find a meaningful way to challenge myself											
6. I acted in ways that helped my physical health											
7. My thinking got in the way of things that were important to me											
8. I paid attention to important things in my daily life											
9. I did things only because I was complying with what others wanted me to do											
10. I stuck to strategies that seemed to have worked											
11. I found personally important ways to challenge myself											
12. I felt stuck and unable to change my ineffective behavior.											
13. I used my thinking in ways that helped me live better											
14. I struggled to connect with the moments in my day-to-day life											
15. I did things to connect with people who are important to me											
16. I chose to do things that were personally important to me											
17. I acted in ways that hurt my physical health											
18. I did not find an appropriate outlet for my emotions											

Appendix B. Burota algorithm

See Kursa, M. B, Rudnicki, W. R, & Others. (2010). Feature selection with the Boruta package. *Journal of Statistical Software*, *36* (11), 1–13.

1) Extend the information system by adding copies of all variables.
2) Shuffle values of added features to remove their correlation with responses. These values are called shadow features and represent what might be expected by chance.

New data set

Original features + Shadow features

PBAT1	PBAT2	PBAT3	PBAT4	S1	S2	S3	S4
23	41	76	88	37	56	3	99
37	11	89	99	23	11	76	88
89	56	3	67	89	41	89	67

3) Run a random forest classifier on the dataset to get mean decrease accuracy (MDA) for each feature in predicting the outcome. The higher the score, the more *important.* MDA refers to how much accuracy the model loses by excluding the variable.

The random forest is built up from decision trees, like the one illustrated below. We have pruned the lower branches of the tree to simplify presentation.

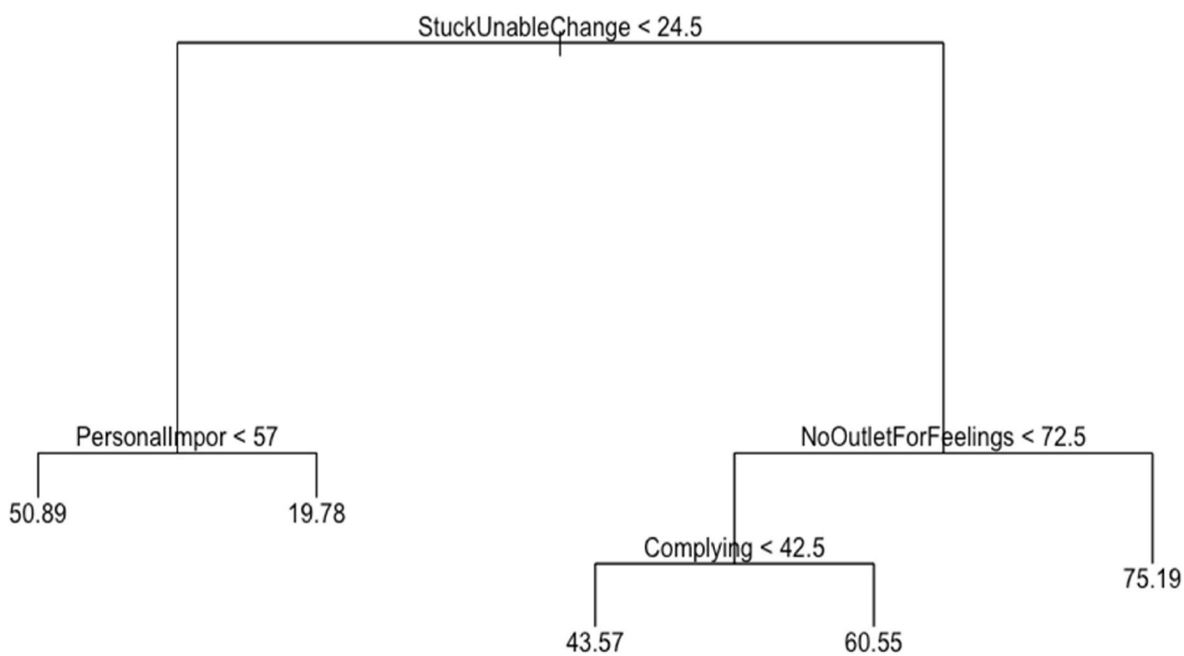

Fig. 1. A decision tree for PBAT items predicting sadness scores

Decision trees are a type of supervised machine learning (input and output are identified). With each node in the decision tree, we ask, "What feature will allow me to split the observations such that the resulting groups are as different from each other as possible (and the members in each subgroup are as similar as possible). In Fig. 1, above, people who *do not feel stuck and unable to change* (<24.5) and who *chose to do activities that were personally important* (>57) had the lowest sadness in the tree (19.78). Those who were stuck and had no outlet for feelings had the highest sadness (75.19.)

Random forest allows each individual tree to be based on a randomly sample from the dataset with replacement, resulting in different trees. 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 reduces the correlation or similarity between trees. 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.

4) Find the maximum Z score among shadow features (MZSF) and then assign a hit if the PBAT item scored better than the MZSF. The idea is that the feature is useful only if it does better than the best randomized feature. See table below for an example.

	PBAT1	PBAT2	PBAT3	PBAT4	S1	S2	S3	S4
MDA	.20	.06	.15	.09	.02	.03	.10	.07
HIT	1	0	1	0	–	–	MZSF	–

Note: MDA = Mean decrease in accuracy. Hit = PBAT item has higher MDA than highest shadow feature (S3). 1 = classified as important; 0 = classified as unimportant.

5) For each attribute with undetermined importance (e.g., perhaps PBAT 4 above), perform a two-sided test of quality with MZSF.
6) Classify attributes significantly lower that the MZSF as unimportant and remove them from consideration
7) Deem the attributes which have importance significantly higher that the MZSF as "Important". Attributes that are neither classified as important or unimportant are "tentative".
8) Remove all shadow attributes.
9) Repeat the procedure until the importance is assigned to all the attributions, or the algorithm reaches the set limit of random forest runs.
10) Confirm or reject any remaining tentative attributes by comparing the mean Z score of the attribute to the median Z score of the best shadow attribute.

Appendix C. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jcbs.2022.02.001.

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