Journal of Contextual Behavioral Science 41 (2026) 101021

Contents lists available at ScienceDirect

Journal of Contextual Behavioral Science

journal homepage: www.elsevier.com/locate/jcbs

Spanish validation of the PBAT and cross-country mapping of process-outcome networks using link community analysis

Carmen Goicoechea [a,b,*], Amie Wallman-Jones [c], Joseph Ciarrochi [d], Steven C. Hayes [e], Stefan G. Hofmann [f], Pandelis Perakakis [a,**]

[a] Department of Social, Work and Differential Psychology, Complutense University of Madrid, Madrid, Spain
[b] Department of Educational Sciences, University of La Rioja, Logroño, Spain
[c] Department of Neurology, University of California, San Francisco, CA, USA
[d] Institute of Positive Psychology and Education, Australian Catholic University, Sydney, Australia
[e] Department of Psychology, University of Nevada, Reno, USA
[f] Department of Psychology, Philipps-University of Marburg, Marburg, Germany

ARTICLE INFO

Keywords:
Process-based therapy
PBAT
Network analysis
Link communities
Psychological processes
Cross-country comparison

ABSTRACT

The Process-Based Assessment Tool (PBAT) was developed within the framework of process-based therapy, an alternative to symptom-focused diagnostic models, to monitor biopsychosocial change processes and support personalized therapeutic interventions. This cross-sectional study validated the Spanish PBAT by replicating the original U.S. study protocol in 602 Spanish adults. We also aimed to compare predictive process-outcome networks across Spain, the U.S., Sweden, and Poland using link community network analysis. Structural validity was assessed through inter-item correlations, and criterion validity through associations between PBAT items and clinical outcomes and need satisfaction/frustration. The Boruta algorithm identified the most predictive items for each outcome. Results confirmed the structural and criterion validity of the Spanish PBAT. Link community network analysis revealed country-specific differences in which processes most strongly predicted distress: difficulties finding appropriate emotional outlets were most central in Spain, perceived inability to change ineffective behavior was relatively prominent in the U.S., and cognitive interference and attentional difficulties were most prominent in Sweden, while Poland showed a more distributed pattern across these three processes. Future research could extend this approach to individual longitudinal data, potentially enabling clinicians to identify and target core psychological processes based on a person's unique profile.

1. Introduction

One of the pressing challenges in psychotherapy today is the persistent gap between expected and actual results in clinical practice. The widespread adoption of symptom-based diagnostic systems, such as the Diagnostic and Statistical Manual of Mental Disorders (DSM; American Psychiatric Association, 2013) or the International Classification of Diseases (ICD; World Health Organization, 2019), has led to evidence-based therapies with demonstrated efficacy in controlled trials. However, the clinical utility of syndromal diagnosis remains limited: diagnostic categories show weak links to underlying etiology, high rates of comorbidity suggest shared rather than distinct processes across disorders, and treatment effect sizes have not substantially improved over decades of research (Mullins-Sweatt et al., 2016). The Marburg Declaration (Rief et al., 2024), resulting from a meeting of leading clinical psychology researchers in 2022, synthesizes these concerns and proposes a shift from syndrome-focused protocols toward identifying and targeting the processes that link to lasting changes in relevant clinical outcomes. This is the fundamental premise of Process-Based Therapy (PBT; Hofmann & Hayes, 2019), an emerging

The study was approved by the ethics committee of the Complutense University of Madrid (Ref. CE_20240208_11_SOC).
The data and software code can be accessed on the project website in the OSF repository: https://doi.org/10.17605/OSF.IO/UJ65Z.
* Corresponding author. Department of Educational Sciences, Faculty of Letters and Education, University of La Rioja, Juan Luis Vives Building, 26004, Logroño, La Rioja, Spain.
** Corresponding author. Department of Social, Work and Differential Psychology, Faculty of Psychology, Complutense University of Madrid, Campus de Somosaguas, Pozuelo de Alarcón, 28223, Madrid, Spain.
E-mail addresses: carmen.goicoechea@unirioja.es (C. Goicoechea), pperakakis@ucm.es (P. Perakakis).

https://doi.org/10.1016/j.jcbs.2026.101021
Received 13 May 2025; Received in revised form 22 July 2026; Accepted 28 July 2026
Available online 1 August 2026

person-centered approach for guiding evidence-based clinical intervention.

Unlike traditional approaches that classify patients within diagnostic categories, PBT focuses on identifying and directly addressing the specific biopsychosocial processes related to personalized therapeutic goals. To delineate these processes, PBT is based on the extended evolutionary meta-model (EEMM), which conceptualizes individuals as evolving systems and integrates various therapeutic models to understand and organize psychological processes of change in a multidimensional and multilevel framework. Accordingly, this model identifies four core elements in the evolution of change: variation (the flexibility and range of responses), selection (the identification of effective strategies), retention (the maintenance of beneficial changes), and context (internal and external factors influencing success). The EEMM examines these processes across multiple dimensions, both psychological (such as affect, cognition, motivation, attention, self, overt behavior) as well as biophysiological and sociocultural aspects (Ciarrochi et al., 2022; Hayes et al., 2020). Ciarrochi et al. (2022) developed the Process-Based Assessment Tool (PBAT) to facilitate the assessment of these change processes and monitor progress in psychological interventions. In the EEMM framework, *processes* refer to the overarching dimensions of variation, selection, and retention operating across psychological domains such as affect, cognition, attention, and social behavior. The PBAT operationalizes these processes through concrete, self-reportable behaviors — specific actions or experiences that instantiate the underlying processes in daily life. Each PBAT item captures either a positive behavior (one that contributes to well-being and adaptive functioning, e.g., "I paid attention to important things in my daily life") or a negative behavior (one that contributes to difficulties and potential psychopathology, e.g., "My thinking got in the way of things that were important to me"). Importantly, positive and negative are not used here as evaluative labels for the processes themselves, but to describe the functional direction of the behavior: positive behaviors promote effective variation, selection, and retention, while negative behaviors reflect difficulties in these same processes (Cyniak-Cieciura et al., 2024). These designations serve as a rough guide for group-level assessment; whether a specific behavior is adaptive or maladaptive for a given individual ultimately depends on contextual and idiographic factors that cross-sectional data cannot capture (Hayes et al., 2020). The PBAT is therefore designed as an item pool for intensive longitudinal clinical assessment, although its structural and criterion validity must first be established cross-sectionally — an approach taken by all existing PBAT validation studies. The original U.S. validation (Ciarrochi et al., 2022) showed that PBAT items distinguish between positive and negative behaviors, align with constructs of need satisfaction and frustration, and correlate with clinically relevant outcomes including sadness, anger, anxiety, stress, lack of social support, vitality, and health. Subsequent validations in Swedish (Larsson & Sundström, 2024) and Polish (Cyniak-Cieciura et al., 2024) populations replicated these findings. All three studies used the Boruta machine learning algorithm (Kursa & Rudnicki, 2010) to identify which PBAT items are the most important predictors of each clinical outcome, providing cross-country evidence of the PBAT's predictive structure.

The Boruta algorithm was chosen for this purpose because, unlike traditional regression approaches, it evaluates each item's predictive importance through a competitive process against random permutations of the data, retaining only those items that consistently outperform chance across repeated iterations (see Method for details). Applying this same procedure independently in each country sample allows a direct comparison of which behaviors emerge as the most important predictors of each outcome.

The present study both validates and extends prior research on the PBAT. First, we confirm the measure's robustness in a Spanish population, a critical step toward ensuring its applicability in Spanish-speaking clinical and research settings. We replicated validation procedures consistent with earlier studies using a Spanish sample recruited through quota-based sampling stratified by sex, age, and geographical region. Second, we extend this work by introducing a novel network analysis approach, applying link community detection to Boruta-selected PBAT items. Network analysis is particularly suited to the PBT framework, which conceptualizes clinical outcomes as shaped by constellations of interacting processes rather than isolated predictors. Link community detection (Ahn et al., 2010) captures this by identifying clusters of co-predictive processes and outcomes while allowing individual items to belong to multiple communities — reflecting the PBT assumption that a single process can contribute to multiple outcomes simultaneously. While the Boruta algorithm identifies which items predict which outcomes, the network approach reveals how these predictive relationships are structurally organized: which processes share predictive roles, which outcomes cluster together, and which items bridge multiple outcome domains. Based on prior findings, we hypothesized that: (1) positive and negative PBAT behaviors would emerge as distinct constructs; (2) positive behaviors would be associated with need satisfaction and positive clinical outcomes, while negative behaviors would be associated with need frustration and negative clinical outcomes; and (3) the network analysis would reveal both shared and country-specific patterns in the predictive relationships between PBAT processes and clinical outcomes.

2. Method

2.1. Participants

2.1.1. Spanish dataset

Participant recruitment was conducted by the market research institute SONDEA S.L., which maintains an online panel and uses a proprietary web-based application for data collection. The target sample size of 602 was selected to match the original U.S. validation study (Ciarrochi et al., 2022), enabling direct comparison of results. Participants were recruited from the panel using a quota-based sampling strategy, with quotas for sex, age group, and geographical region set according to the municipal register of the Spanish National Institute of Statistics (INE, 2022). This approach ensures that the sample approximates the demographic composition of the general Spanish adult population along these dimensions, though it does not constitute probability-based sampling and may be subject to self-selection biases inherent in online panel research (see Limitations). The only inclusion criterion was being a registered panel member aged 18 or older. No exclusion criteria were applied. The final sample consisted of 602 participants (49% female), aged 18–75 years. Participants completed the survey online in their own settings using the SONDEA platform and were financially compensated for their participation through the panel's standard reward system. The survey included the PBAT, the STOP-D, the vitality items, the single-item health measure, and the need satisfaction/frustration items (see Measures). The study was approved by the ethics committee of the Complutense University of Madrid (Ref. CE_20240208_11_SOC). All participants provided informed consent before completing the questionnaires. Data collection took place on March 12th and 13th, 2024.

2.1.2. International datasets

Detailed information about the international datasets used in comparing link communities is provided in the respective publications. In brief, the U.S. sample consisted of 598 participants (290 males; 302 females; 6 unidentified) with an average age of 32.57 ($SD = 10.32$) (Ciarrochi et al., 2022), the Swedish sample included a total of 427 participants with an average age of 48, (female mean age = 49.40, $SD = 16.34$ and male mean age = 46.24, $SD = 17.69$) (Larsson & Sundström, 2024), and the Polish dataset comprised of 602 participants with an average age of 50.36 ($SD = 16.36$) (Cyniak-Cieciura et al., 2024). The Boruta importance rankings for the U.S. and Polish samples were extracted from the published validation studies (Ciarrochi et al., 2022; Cyniak-Cieciura et al., 2024). Item-level data for the Swedish sample were publicly available as part of the published study materials (Larsson & Sundström, 2024) and were additionally used for measurement invariance testing (see Data Analysis).

2.2. Measures

2.2.1. Process-Based Assessment Tool (PBAT)

The Process-Based Assessment Tool (PBAT; Ciarrochi et al., 2022) is an 18-item self-report measure utilizing a 100-point response scale, ranging from 0 ("strongly disagree") to 100 ("strongly agree"). To ensure an accurate translation of the PBAT into Spanish, a back-translation approach was employed, as recommended in the literature (Muñiz et al., 2013). The process involved three independent translations by a bilingual translator and two English-speaking psychologists. A panel of psychologists with expertise in behavioral case conceptualization within contextual behavioral science reviewed the translated items and reached a consensus on the preliminary Spanish version (Back Translation 1). This version was then back-translated into English and reviewed by another expert group, including an author of the original PBAT, to ensure translation equivalence (Back Translation 2). After incorporating suggested revisions, the final Spanish version (Back Translation 3) was established. The original PBAT items with their Spanish translation are shown in Table 1. A practitioner-friendly version of the Spanish version of the scale is available in the Appendix.

2.2.2. Outcome variables

Clinically relevant outcomes. Psychological distress was assessed using the STOP-D questionnaire (Young et al., 2007, 2015), where participants rated the intensity of sadness, anxiety, stress, anger, and lack of social support experienced during the past week on a sliding scale from 0 ("not at all") to 100 ("a great deal"). Health status in the past week was measured via a five-point scale (Ware & Sherbourne, 1992), with responses ranging from 1 ("poor") to 5 ("excellent"). Additionally, three items from the Subjective Vitality Scale (Ryan & Frederick, 1997) were included, instructing participants to evaluate their experiences from the past week using a slider scale from 0 ("not at all true") to 100 ("very true"). These three items were selected by Ciarrochi et al. (2022) from the original seven-item Subjective Vitality Scale to reduce participant burden while retaining the core construct. The same three items have been used in all subsequent PBAT validation studies. In the present sample, the vitality items showed good internal consistency ($\alpha = .87$, $\omega = 0.87$), comparable to previous validations (U.S.: $\alpha = .89$; Sweden: $\alpha = .91$).

Need satisfaction. Following the reasoning of the original PBAT validation study (Ciarrochi et al., 2022), which aligns some of the dimensions proposed in the PBAT with constructs utilized in needs psychology (Ryan & Deci, 2017), we included items of needs satisfaction and frustration across three domains: autonomy, competence, and connection (Chen et al., 2015). Participants responded to these items, specifying their experiences over the past week using a slider scale from 0 ("definitely false") to 100 ("definitely true"). In the present sample, the need satisfaction items showed acceptable internal consistency ($\alpha = .79$) and the need frustration items likewise ($\alpha = .75$).

The STOP-D items, vitality items, and need satisfaction/frustration items were translated into Spanish as part of the present study using the same back-translation procedure described above for the PBAT. To our knowledge, no prior Spanish-language validation of the STOP-D or the specific need satisfaction/frustration items used here (Chen et al., 2015) has been published. The single-item health measure (Ware & Sherbourne, 1992) has been widely used in Spanish-language research. All questionnaire items were presented in a randomized order. Response markers were centrally positioned: 50 for scales ranging from 0 to 100 and 3 for the five-point health scale ranging from 1 to 5.

Table 1
Items in the PBAT and their Spanish translation.

Process Target		PBAT items	Spanish translation
Selection			
Affect/Yearning to Feel	+	I was able to experience a range of emotions appropriate to the moment	Fui capaz de sentir una variedad de emociones apropiadas para el memento
	-	I did not find an appropriate outlet for my emotions	No encontré una salida apropiada para mis emociones
Cognition/ Yearning for Coherence	+	I used my thinking in ways that helped me live better	Utilicé mi pensamiento de maneras que me ayudaron a vivir mejor
	-	My thinking got in the way of things that were important to me	Mi pensamiento se interpuso en cosas que eran importantes para mí
Attention/ Yearning to be Oriented	+	I paid attention to important things in my daily life	Presté atención a cosas importantes en mi vida diaria
	-	I struggled to connect with the moments in my day-to-day life	Me costó conectar con los momentos de mi día a día
Social Connection/ Need for Connection	+	I did things to connect with people who are important to me	Hice cosas para estar más cerca de las personas que son importantes para mí
	-	I did things that hurt my connection with people who are important to me	Hice cosas que dañaron mi relación con personas que son importantes para mí
Motivation/Need for Autonomy	+	I chose to do things that were personally important to me	Elegí hacer cosas que eran personalmente importantes para mí
	-	I did things only because I was complying with what others wanted me to do	Hice cosas solo por cumplir con lo que otros querían que hiciera
Overt Behavior/ Need for Competence	+	I found personally important ways to challenge myself	Encontré maneras personalmente importantes de desafiarme a mí mismo/a
	-	I did not find a meaningful way to challenge myself	No encontré una manera significativa de desafiarme a mí mismo/a
Physical Health Behaviors	+	I acted in ways that helped my physical health	Actué de forma que ayudó a mi salud física
	-	I acted in ways that hurt my physical health	Actué de forma que perjudicó mi salud física
Variation	+	I was able to change my behavior, when changing helped my life	Fui capaz de cambiar mi comportamiento, cuando cambiar ayudaba a mi vida
	-	I felt stuck and unable to change my ineffective behavior	Me sentí atascado/a e incapaz de cambiar mi comportamiento ineficaz
Retention	+	I stuck to strategies that seemed to have worked	Me ceñí a estrategias que parecían haber funcionado
	-	I struggled to keep doing something that was good for me	Me costó continuar haciendo algo que era bueno para mí

2.3. Data analysis

The study employed a cross-sectional, between-subjects design. All analyses reported below examine between-person associations in a single measurement occasion.

2.3.1. Replication protocol

Our initial analyses closely followed the protocol used by all three previous validation studies (Ciarrochi et al., 2022; Cyniak-Cieciura et al., 2024; Larsson & Sundström, 2024). Pearson correlations were used to explore links between positive and negative PBAT items, and the relation of PBAT items with clinically relevant outcomes and need satisfaction/frustration items. Welch's t-tests were used for establishing sex differences in descriptive statistics. We used the Boruta algorithm (Kursa & Rudnicki, 2010), a machine learning feature selection algorithm, to identify the most important PBAT items for each clinically relevant outcome. The algorithm initially creates shadow features by randomly shuffling original features, establishing importance benchmarks unrelated to the outcome. A random forest classification is then applied to this extended dataset, generating Z scores that quantify information loss when features are excluded from prediction. The maximum Z score among shadow attributes (MZSA) serves as a reference threshold against which all original features are evaluated. Features performing significantly better than the MZSA are classified as "important", while those performing worse are deemed "unimportant". To ensure statistical robustness, this entire procedure is repeated across multiple iterations. The algorithm ultimately quantifies and ranks each item's importance through the mean decrease in prediction accuracy observed when that item is removed from the model. We used the 100-default number of maximum runs, a confidence level p value of 0.01, and a Bonferroni correction for multiple comparisons. Following 100 algorithm runs, tentative attributes were resolved by comparing their median Z scores with the median Z score of the top-performing shadow attribute. Only those features that demonstrated consistent predictive power across iterations were retained, while the rest were discarded. More detailed information on the specific implementation of the algorithm is provided in Ciarrochi et al. (2022). All analyses were performed using R Statistical Software (v4.4.2; R Core Team, 2024). The Boruta algorithm was implemented via the *Boruta* R package (v8.0.0; Kursa & Rudnicki, 2010).

2.3.2. Link communities

To visualize relationships between PBAT items and clinical outcomes identified by the Boruta algorithm, we employed the link community detection method (Ahn et al., 2010). This approach is particularly suited for establishing meaningful groupings when individual nodes (in this case, PBAT items and clinically relevant outcomes) may participate in multiple communities simultaneously.

For each of the four datasets (Spanish, U.S., Swedish, Polish), we initially constructed an undirected graph from the Boruta feature selection results. In these graphs, *nodes* represented either PBAT items or clinically relevant outcomes measured by the STOP-D, health, and vital scales, *links* (edges) connected PBAT items to the clinical outcomes they predicted, and *link weights* were assigned based on the importance rank of each predictor from the Boruta algorithm, with higher weights indicating stronger predictive relationships. To focus on the most robust relationships, we only included the three most important predictors for each outcome, thereby sparsifying the networks while retaining the most relevant connections. This threshold balances parsimony with informativeness: including fewer predictors risks omitting relevant relationships, while including more produces denser networks that obscure community structure. A sensitivity analysis using the top five predictors for the Spanish dataset confirmed that the core network structure was robust to this choice (see Supplementary Fig. S1).

Link communities were subsequently detected using the *linkcomm* R package (v.1.0.14; Kalinka & Tomancak, 2011). The algorithm starts by comparing the Jaccard similarity between pairs of links with a common node. For example, for links e_{ik} and e_{jk}, where i and j are PBAT items and k is a shared outcome (e.g., "SAD"), their Jaccard similarity is calculated as:

$$S(e_{ik}, e_{jk}) = \frac{|n^{+}(i) \cap n^{+}(i)|}{|n^{+}(i) \cup n^{+}(i)|}, \tag{1}$$

where $n+(i)$ refers to all nodes directly connected to node i, which is also known as the first-order neighborhood of node i. As an example, if the neighborhood of i is the set of outcomes *n+(i) = {"SAD", "ANGRY", "STRESSED"}* and the neighborhood of j is *n+(j) = {"SAD", "ANGRY", "ANXIOUS"}*, then the intersection $|n^{+}(i) \cap n^{+}(i)|$ is *{"SAD", "ANGRY"}* and the union $|n^{+}(i) \cup n^{+}(i)|$ is *{"SAD", "ANGRY", "STRESSED", "ANXIOUS"}*. From equation (1), we calculate a Jaccard similarity between the two edges of $2/4 = 0.5$.

After calculating pairwise similarities for all links in the network, the algorithm performs hierarchical clustering using average linkage, producing a dendrogram of link relationships. Optimal community detection is then performed by cutting the dendrogram at the point that maximizes the partition density, which represents the density of links within clusters normalized against the theoretical maximum and minimum number of possible links. For our bi-partite networks with two distinct categories of nodes (PBAT items and outcomes), the partition density is calculated as:

$$D_c = \frac{2}{M}\sum_{c} m_c \frac{m_c + 1 - n_c}{2n_{c0}n_{c1} - 2(n_c - 1)}, \tag{2}$$

where M is the total number of edges, m_c is the number of edges in subset c, n_c is the number of nodes in subset c, n_{c0} is the number of nodes in partition 0 (PBAT items), and n_{c1} is the number of nodes in partition 1 (outcomes).

After establishing the relevant communities, we produced network visualizations where nodes represent either PBAT items or outcomes, edges indicate predictive relationships, nodes participating in multiple communities appear as pie charts, and segment sizes in these pie charts represent the node's membership to each community based on the number of edges they have in each community. This approach illustrates how specific PBAT items relate to multiple communities of outcomes, highlighting clusters of PBAT items and outcomes that share predictive relationships across different EEMM dimensions — for instance, a single community may include items from the affect, attention, and variation domains alongside multiple distress outcomes, indicating that these processes co-predict the same set of outcomes. More details on the implementation of the algorithm and the R code used for its implementation are provided in the additional online material (https://doi.org/10.17605/OSF.IO/UJ65Z).

2.4. Measurement invariance

To evaluate the cross-country comparability of the PBAT, we tested measurement invariance of a two-factor model (positive and negative selection items) across the Spanish and Swedish samples — the two countries for which item-level data were available. Variation and retention items were excluded as they represent theoretically distinct evolutionary processes rather than additional indicators of the selection constructs. Multi-group confirmatory factor analysis was conducted using the lavaan R package (Rosseel, 2012) with robust maximum likelihood estimation (MLR) to account for non-normality. Configural, metric, and scalar invariance were tested sequentially, with model comparison evaluated using ΔCFI $\leq$ 0.010 and ΔRMSEA $\leq$ 0.015 as criteria (Chen, 2007). When full scalar invariance was not achieved, modification indices were inspected to identify non-invariant intercepts, and a partial scalar invariance model was tested with those intercepts freed.

3. Results

Distributional properties of all variables were examined prior to analysis. Skewness values ranged from −0.83 to 0.30 and kurtosis values from −1.21 to 1.21 across PBAT items and outcome variables, within conventional thresholds for the analyses employed (|skewness| < 2, |kurtosis| < 7; Curran et al., 1996). Mardia's test indicated a departure from multivariate normality for the PBAT selection items (multivariate skewness = 24.81, $p < .001$; multivariate kurtosis = 325.22, $p < .001$); robust maximum likelihood estimation (MLR) was therefore used in the measurement invariance analysis to account for this. Sex differences were tested using Welch's t-test, which does not assume equal variances.

3.1. Descriptives

Tables 2 and 3 show descriptive statistics and sex differences of PBAT items and outcome variables, respectively. Regarding positive behavior, female participants felt most successful in "paying attention to important things in daily life" (Attention+).[1] In contrast, male participants felt most successful in "experiencing a range of emotions appropriate to the moment" (Affect+). Both female and male participants felt least capable of "finding ways to challenge themselves" (Challenge+).[2] Regarding negative behaviors, "my thinking got in the way of important things" (Attention-) received the highest score and "hurting social connections" (Social-) the lowest.

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

PBAT item	Female		Male		t_{diff}	p value
	M	SD	M	SD		
Positive Selection						
Chose to do personally important things	70.417	18.981	70.814	20.747	−0.244	0.807
Helped My Health	64.726	22.525	66.451	23.277	−0.923	0.356
Paid attention to important things in daily life	70.889	21.052	71.183	20.597	−0.173	0.863
Connected with important people	68.886	21.088	71.898	21.630	−1.729	0.084
Experience range emotions approp. to moment	68.570	19.112	72.447	19.354	−2.472	0.014
Found ways to challenge self	57.798	22.304	57.681	23.939	0.062	0.951
Used thinking to live better	65.107	20.261	66.654	21.364	−0.911	0.363
Negative Selection						
Did things only to comply to others	50.570	27.427	53.308	29.490	−1.179	0.239
Hurt my health	37.801	27.485	40.122	28.363	−1.019	0.309
Struggled to connect with moments of day	44.664	27.392	46.546	27.649	−0.838	0.402
Hurt social connections	36.726	29.939	39.458	31.259	−1.094	0.274
Found no appropriate outlet for feelings	42.534	27.869	44.108	29.175	−0.677	0.499
Found no meaningful challenge	46.678	24.562	47.258	26.722	−0.277	0.782
My thinking got in the way of important things	53.313	26.701	56.390	27.348	−1.396	0.163
Variation						
Stuck & unable to change ineffective behavior	43.573	27.831	48.536	28.546	−2.158	0.031
Able to change behavior, when changing helped	69.026	19.735	71.142	21.502	−1.257	0.209
Retention						
Struggled to keep doing what was important	47.114	28.062	54.444	28.778	−3.162	0.002
Stuck to Strategies that worked	60.277	21.140	58.407	21.871	1.066	0.287

Note. Scales range from 0 (strongly disagree) to 100 (strongly agree).

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

Scale	Female		Male		t_{diff}	p value
	M	SD	M	SD		
Sad	43.410	30.135	45.810	31.079	−0.961	0.337
Anxious	45.850	28.498	52.831	30.313	−2.908	0.004
Stressed	49.202	29.253	55.268	29.159	−2.547	0.011
Angry	44.375	27.505	48.407	29.675	−1.727	0.085
NoSupp	42.436	30.126	46.247	30.943	−1.530	0.126
Vital	62.243	20.022	58.688	21.816	2.081	0.038
Health	3.000	0.878	2.810	0.876	2.655	0.008
Autonomy Satisfaction	64.941	20.858	62.983	23.125	1.090	0.276
Autonomy Frustration	42.805	27.392	45.217	28.320	−1.062	0.289
Connection Satisfaction	69.326	21.068	67.769	23.479	0.855	0.393
Connection Frustration	36.879	28.745	38.163	29.945	−0.536	0.592
Competence Satisfaction	65.042	21.903	64.919	23.068	0.067	0.946
Competence Frustration	42.710	28.443	45.827	29.605	−1.316	0.189

Note. People rated the extent to which they felt sad, anxious, stressed, angry and unsupported on a scale from 0 (not at all) to 100 (a great deal). Health ratings ranged from 1(poor) to 5 (excellent). Vitality ratings ranged from 0 (not at all true) to 100 (very true).

Concerning sex differences, male participants gave on average higher scores to "experiencing a range of appropriate emotions to the moment" (Affect+; $p = .014$), "feeling stuck and unable to change their ineffective behavior" (Variation-; $p = .031$), and "struggling to keep doing what was important" (Retention-; $p = .002$). There were also sex differences in the outcome variables, with male participants scoring higher in feeling anxious ($p = .004$) and stressed ($p = .011$). In contrast, female participants scored higher in feeling more vital ($p = .038$) and healthy ($p = .008$). This pattern of sex differences is consistent with the original U.S. validation (Ciarrochi et al., 2022), where males similarly reported less positive behavior but better subjective outcomes, providing additional replication evidence across validation studies.

Altogether, these results suggest that female participants report feeling better than male participants. Despite male participants reporting positive behavior related to affect selection more frequently, they were also more likely to report having difficulty changing their ineffective behavior and retaining behaviors that were good for them.

3.2. Reliability and measurement invariance

The positive and negative PBAT selection items showed good internal consistency in the Spanish and Swedish samples ($\alpha = .85$ and $\alpha = .82$, respectively). These values should be interpreted descriptively, as the PBAT is an item pool assessing distinct processes rather than a unidimensional scale.

Configural invariance was supported (CFI = 0.936, RMSEA = 0.062), indicating that the two-factor structure holds in both countries. Metric invariance was also supported (ΔCFI = −0.009, ΔRMSEA = 0.002), confirming equivalent factor loadings and warranting comparisons of predictive relationships across samples. Full scalar invariance was not

[1] Throughout the manuscript, PBAT items will be referred to using intuitive labels, accompanied by a positive or negative sign depending on the type of behavior they represent. See Table 1 for the correspondences.

[2] "Challenge" is the label used to refer to the target process of overt behavior (see Table 1).

achieved (ΔCFI = −0.018), but partial scalar invariance was established after freeing the intercepts of five items: Social+, Challenge+, Health+, Social−, and Cognition− (ΔCFI = −0.001, ΔRMSEA = −0.001). Item-level data for the U.S. and Polish samples were not available, so measurement invariance was tested for these two countries only.

3.3. Structural and criterion validity

Tables 4 and 5 show the correlation coefficients between PBAT items. Correlations between selection items were positive (mean positive items = 0.46; mean negative items = 0.39), while correlations between positive and negative items were predominantly negative and weak (mean = – 0.13). These results suggest that positive and negative selection behaviors on the PBAT are different. Although the majority of the relationships (33 out of 49) reached statistical significance, they showed considerable variability in both strength and direction (range = – 0.35 to 0.11), suggesting that while positive and negative behaviors are related, they are not opposite ends of a single continuum. Following conventional benchmarks (Cohen, 1988), we interpret correlations below 0.30 as weak, 0.30–0.50 as moderate, and above 0.50 as strong throughout. Notably, the positive retention item ('Stuck to strategies that worked') was significantly positively correlated with the negative variation item (0.12) and with the negative retention item (0.19). As we discuss below, this pattern is consistent with the "equisyncratic" nature of retention processes (Ciarrochi et al., 2024).

Table 6 shows the relationship between PBAT items and the satisfaction or frustration of needs. As expected, positive behaviors were moderately associated with needs satisfaction (mean = 0.40) and more weakly with needs frustration (mean = −0.16). In contrast, negative behaviors showed a moderate association with needs frustration (mean = 0.42) and a weaker, though significant, negative association with needs satisfaction (mean = −0.21). The positive retention item ("Stuck to strategies that worked") correlated positively and significantly with frustration in autonomy (0.12).

Lastly, the results on the relation between PBAT items and clinically relevant outcomes are shown in Table 7. Positive items better predicted health and vitality (mean = 0.32) compared to negative items (mean = – 0.21). In contrast, negative items better predicted sadness, anxiety, stress, anger, and lack of support (mean = 0.41) than positive items (mean = 0.16). Similarly to the original study, none of the correlations were high enough to suggest that the PBAT was redundant with the outcome measures. Once again, the positive retention item ("Stuck to strategies that worked") showed positive, although weak, correlations with the outcomes of sadness (0.04), anxiety (0.02), stress (0.06), anger (0.03), and lack of support (0.04).

3.4. Relative importance

The Boruta machine learning algorithm was utilized to identify the most critical predictors of each clinically relevant outcome. Table 8 shows the ranking of items related to each outcome. Negative PBAT items tended to be better predictors of negative outcomes, and positive items of positive outcomes. The network visualizations afford more specific insights about the relations between concrete PBAT items and outcomes (see next section).

3.5. Link community networks

Network graphs facilitate the visualization of predictive relationships between specific PBAT items and outcomes assessed by the STOP-D questionnaire and items related to vitality and health. Additionally, link communities group nodes based on shared neighbors, clustering those with greater overlap—such as outcomes tied to the same processes—into cohesive units. Importantly, nodes can belong to multiple communities if their connections span distinct clusters. Fig. 1 shows the network derived from the Boruta results on the Spanish

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	0.38***	–											
3. PaidAttToImportant	0.52***	0.47***	–										
4. ConnectToPeople	0.48***	0.39***	0.55***	–									
5. ExperienceRangeEmotions	0.40***	0.40***	0.51***	0.47***	–								
6. ImportantChallenge	0.38***	0.40***	0.38***	0.36***	0.39***	–							
7. ThinkingHelpedLife	0.55***	0.53***	0.60***	0.47***	0.45***	0.52***	–						
8. Complying	−0.15***	−0.11**	−0.15***	0.00	0.01	0.02	−0.10*	–					
9. HurtHealth	−0.16***	−0.31***	−0.32***	−0.21***	−0.17***	−0.02	−0.21***	0.36***	–				
10. StruggleConnectMoments	−0.23***	−0.19***	−0.29***	−0.17***	−0.16***	−0.02	−0.25***	0.45***	0.43***	–			
11. HurtConnect	−0.16***	−0.15***	−0.21***	−0.12**	−0.06	0.11**	−0.16***	0.41***	0.45***	0.52***	–		
12. NoOutletForFeelings	−0.27***	−0.22***	−0.35***	−0.25***	−0.17***	−0.04	−0.30***	0.35***	0.52***	0.54***	0.50***	–	
13. NoMeaningfulChallenge	−0.18***	−0.08	−0.22***	−0.12**	−0.05	0.04	−0.11**	0.29***	0.26***	0.40***	0.28***	0.42***	–
14. ThinkingGotInWay	−0.02	−0.04	−0.12**	−0.07	−0.04	0.03	−0.08	0.32***	0.28***	0.44***	0.38***	0.38***	0.27***

Note. Shaded area is the relationship between positive and negative behavior.

Table 5
Relationship between variation and retention items.

	1	2	3
Variation			
1. Stuck, unable to change	–		
2. Able to change behavior	−0.14***	–	
Retention			
3. Struggled to keep doing important	0.50***	−0.03	–
4. Stuck to working strategies	0.12**	0.26***	0.19***

dataset, with outcome nodes in bold capitals and process nodes in regular lowercase. Node size reflects degree (number of connections), while edge thickness indicates Boruta ranking, the thickest edges marking the highest-ranked predictors.

We observe three distinct link communities emerging. The first (orange), includes the links connecting the "VITAL" outcome to its three predictors: "Challenge+", "Health+", "Cognition+". These links form a community because "Challenge+" and "Health+" share "VITAL" as their only neighbor, yielding identical links to it, while "Cognition+" connects similarly, sharing "VITAL" among its two neighbors ("VITAL", "HEALTH"). A second community (green) includes multiple links between outcomes — "HEALTH", "ANGRY", "ANXIOUS", "NOSUPP", "STRESSED", "SAD"— and their predictors. Notably, "NOSUPP" and "ANGRY" share identical processes ("Affect-", "Variation-", and "Social-"), resulting in highly similar links that cluster together. The process nodes "Affect-" and "Variation-" also exhibit substantial neighborhood overlap: "Affect-" connects to all six outcomes, while "Variation-" links to a significant subset ("HEALTH", "ANGRY", "NOSUPP", and "SAD"). This shared connectivity drives their grouping in hierarchical clustering.

A third community (blue) arises from links between "SAD", "ANXIOUS", and "STRESSED" and the process node "Attention-", where two-thirds of their neighbors overlap. This strong similarity distinguishes these links from those tied to "Affect-", which shares only 50% of its neighbors with "Attention-". The same cluster also includes the

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	**0.54******	−0.25***	0.43***	−0.26***	0.46***	−0.26***
HelpHealth	0.39***	−0.24***	0.44***	−0.16***	0.39***	−0.19***
PaidAttToImportant	0.45***	−0.32***	0.46***	−0.34***	0.40***	−0.31***
ConnectToPeople	0.40***	−0.16***	**0.49******	−0.25***	0.46***	−0.18***
ExperienceRangeEmotions	0.43***	−0.16***	0.37***	−0.14***	0.41***	−0.14***
ImportantChallenge	0.41***	−0.07	0.28***	0.05	**0.42******	−0.08
ThinkingHelpedLife	0.50***	−0.25***	0.46***	−0.22***	0.50***	−0.26***
Negative Selection						
Complying	−0.22***	**0.43******	−0.17***	0.39***	−0.10*	0.34***
HurtHealth	−0.21***	0.44***	−0.31***	0.46***	−0.19***	0.40***
StruggledConnectMoments	−0.30***	0.46***	−0.29***	0.50***	−0.16***	0.44***
HurtConnect	−0.20***	0.37***	−0.27***	**0.52******	−0.15***	0.38***
NoOutletForFeelings	−0.34***	0.49***	−0.37***	0.53***	−0.23***	0.46***
NoMeaningfulChallenge	−0.19***	0.29***	−0.15***	0.38***	−0.02	**0.32******
ThinkingGotInWay	−0.19***	0.31***	−0.17***	0.35***	−0.09*	0.40***
Variation						
StuckUnableChange	−0.32***	0.47***	−0.31***	0.50***	−0.21***	0.50***
AbleToChangeBehavior	0.40***	−0.18***	0.32***	−0.08	0.38***	−0.07
Retention						
StruggledToKeepDoing	−0.21***	0.39***	−0.20***	0.34***	−0.15***	0.37***
StuckToWorkingStrategies	0.21***	0.12**	0.18***	0.03	0.20***	0.06

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 outcomes.

	Sad	Anxious	Stressed	Angry	NoSupp	Health	Vital
Positive Selection							
PersonalImpor	−0.31***	−0.27***	−0.19***	−0.24***	−0.23***	0.29***	0.41***
HelpHealth	−0.28***	−0.25***	−0.18***	−0.17***	−0.18***	0.30***	0.46***
PaidAttToImportant	−0.34***	−0.24***	−0.23***	−0.22***	−0.30***	0.30***	0.41***
ConnectToPeople	−0.28***	−0.20***	−0.15***	−0.17***	−0.21***	0.22***	0.38***
ExperienceRangeEmotions	−0.18***	−0.13**	−0.10*	−0.07	−0.17***	0.22***	0.36***
ImportantChallenge	−0.14***	−0.09*	−0.05	0.00	−0.02	0.24***	0.43***
ThinkingHelpedLife	−0.37***	−0.27***	−0.22***	−0.20***	−0.25***	0.33***	0.51***
Negative Selection							
Complying	0.41***	0.34***	0.33***	0.36***	0.33***	−0.20***	−0.17***
HurtHealth	0.41***	0.35***	0.31***	0.40***	0.40***	−0.25***	−0.27***
StruggledConnectMoments	0.50***	0.46***	0.45***	0.49***	0.45***	−0.20***	−0.25***
HurtConnect	0.44***	0.41***	0.39***	0.53***	0.44***	−0.16***	−0.13**
NoOutletForFeelings	0.58***	0.45***	0.43***	0.49***	0.52***	−0.28***	−0.28***
NoMeaningfulChallenge	0.35***	0.28***	0.27***	0.29***	0.38***	−0.13**	−0.09*
ThinkingGotInWay	0.43***	0.37***	0.35***	0.36***	0.36***	−0.18***	−0.15***
Variation							
StuckUnableChange	0.58***	0.48***	0.45***	0.49***	0.50***	−0.28***	−0.32***
AbleToChangeBehavior	−0.21***	−0.14***	−0.10*	−0.10*	−0.10*	0.26***	0.39***
Retention							
StruggledToKeepDoing	0.44***	0.43***	0.37***	0.41***	0.40***	−0.23***	−0.27***
StuckToStrategies	0.04	0.02	0.06	0.03	0.04	0.09*	0.15***

Table 8
Boruta feature importance rankings for PBAT items across outcome variables.

	Emotional Symptoms (STOP-D)					Well-being	
PBAT Item	Sad	Anxious	Stressed	Angry	No Support	Vitality	Health
Chose to do personally important things	10	9	13	9	13	10	4
Helped My Health	14	11	—	15	15	3	5
Paid attention to important things in daily life	13	14	11	11	10	4	6
Connected with important people	12	12	10	13	14	9	12
Experience range emotions approp. to moment	15	15	—	14	12	7	13
Found ways to challenge self	18	16	14	16	—	2	11
Used thinking to live better	7	8	9	12	11	1	3
Did things only to comply to others	6	7	7	8	9	16	15
Hurt my health	9	10	12	7	8	11	9
Struggled to connect with moments of day	3	3	1	4	4	12	8
Hurt social connections	8	6	3	1	3	—	—
Found no appropriate outlet for feelings	1	2	2	2	1	6	1
Found no meaningful challenge	11	13	8	10	7	14	16
My thinking got in the way of important things	4	5	5	6	5	15	7
Stuck & unable to change ineffective behavior	2	4	4	3	2	8	2
Able to change behavior, when changing helped	16	18	—	—	—	13	14
Struggled to keep doing what was important	5	1	6	5	6	5	10
Stuck to Strategies that worked	17	17	—	—	—	17	17

Note. Cell shading reflects Boruta importance rank: darker grey = lower rank (stronger predictor), white = item not selected (—). STOP-D = Symptom Tracking of Psychological Disorders.

"Retention-" to "ANXIOUS" link. Thus, "Attention-" emerges as a key process node, selectively influencing three of the six nearby outcome nodes. This pattern defines a cluster of clinically relevant outcomes primarily driven by attentional processes.

Fig. 2 presents the link community networks across all four datasets, including the Spanish network (Fig. 1), facilitating a comparison of network structures across countries. Focusing on similarities, we note that the outcome node "VITAL" is consistently predicted by the same three processes: "Challenge+", "Cognition+", and "Health+". In the U.S. network, however, "Health+" connects the vitality subnetwork—previously isolated in the Spanish network—to the "HEALTH" node and the broader network. As "VITAL" and "HEALTH" belong to distinct link communities, "Health+" is depicted as a pie, highlighting its dual relevance to both communities.

Interestingly, in the U.S. network, all negative outcomes—"ANXIOUS", "STRESSED", "ANGRY", "NOSUPP", and "SAD"—cluster within a single community, as they share three common predictors: "Affect-", "Variation-", and "Attention-". With connections to five outcomes, "Variation-" is the most connected process in the U.S. network, whereas "Affect-" was the most connected process in the Spanish network. In addition, "Variation-" is relevant for two distinct outcome groups, as shown by its depiction as a pie.

The Sweden and Poland networks, as depicted in Fig. 2, further illustrate country-level variations in the predictive relationships between PBAT processes and STOP-D outcomes. In the Sweden network, two distinct link communities emerge. The first community (orange) centers on the "VITAL" outcome, which is predicted by the same three processes observed in prior networks: "Challenge+", "Cognition+", and "Health+". Notably, "Health+" connects "VITAL" to the "HEALTH" outcome, mirroring the U.S. network's structure, but here "HEALTH" remains more isolated, with fewer connections to the broader network. The second community (green) clusters all negative outcomes—"ANXIOUS", "ANGRY", "SAD", "NOSUPP", and "STRESSED"—along with their predictors: "Attention-", "Cognition-", and "Affect-". Within this community, "Attention-" and "Cognition-" exhibit the highest degree, as indicated by their larger size, connecting to all five negative outcomes. This contrasts with the Spain and U.S. networks, where the highest degree was held by "Affect-" and "Variation-", respectively.

The Poland network also reveals two link communities, but with distinct structural differences. The first community (orange) again includes "VITAL", predicted by "Challenge+", "Health+", and "Social+", a slight variation from other networks where "Cognition+" typically appears instead of "Social+". Here, "Health+" links "VITAL" to "HEALTH", and an additional process, "Health-", connects to "HEALTH", forming a small subnetwork. The second community (green) groups the negative outcomes—"SAD", "ANXIOUS", "NOSUPP", "ANGRY", and "STRESSED"—with their predictors: "Affect-", "Variation-", and "Attention-". Similar to the U.S. and Sweden networks, these negative outcomes are predicted by only three processes, while Spain presents a more diverse structure with five different processes relating to negative outcomes.

4. Discussion

The primary objective of this study was to validate the Process-Based Assessment Tool (PBAT) for use in a Spanish-speaking population and to extend its application through network analysis. We translated the English PBAT items into Spanish using a back-translation procedure to ensure linguistic and conceptual equivalence. Structural and criterion validity were assessed, following the methodologies of the original U.S. validation (Ciarrochi et al., 2022) and subsequent validations in Sweden (Larsson & Sundström, 2024) and Poland (Cyniak-Cieciura et al., 2024). Our results aligned with prior findings: positive and negative PBAT behaviors emerged as distinct constructs, with positive items correlating positively with each other and negatively with negative items, and vice versa. Criterion validity was evidenced by theoretically consistent associations—positive behaviors correlated with need satisfaction,

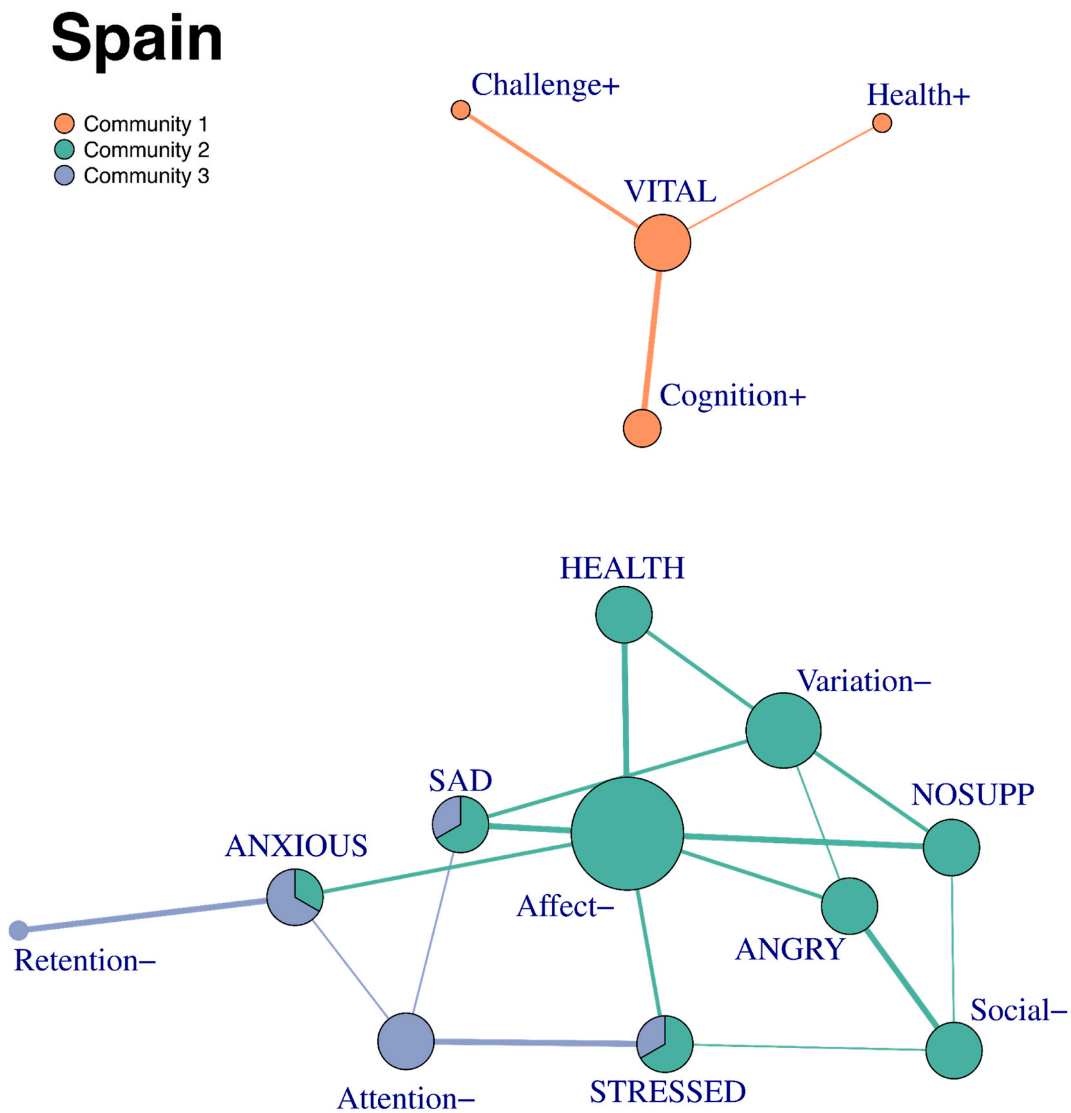

Fig. 1. Link community network for the Spanish dataset
Note. The network displays predictive relationships between PBAT items and STOP-D, vitality, and health outcomes using Boruta results. Outcome nodes are labeled in bold capital letters (e.g., "VITAL", "ANXIOUS"), while process nodes are in regular lowercase (e.g., "Challenge+", "Affect-"). Node size reflects degree (number of connections), and edge thickness indicates Boruta ranking, with thicker edges representing higher-ranked predictors. Three link communities are identified: Community 1 (orange) includes "VITAL" and its predictors; Community 2 (green) groups "HEALTH", "ANGRY", "ANXIOUS", "NOSUPP", "SAD", and their predictors; and Community 3 (blue) comprises "SAD", "ANXIOUS", "STRESSED", and their connections to "Attention-" and "Retention-". Nodes spanning multiple communities (e.g., "SAD", "ANXIOUS", "STRESSED") are depicted as pies, with segments colored according to their community memberships. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

while negative behaviors linked to need frustration. In addition, positive items strongly predicted health and vitality, whereas negative items better predicted sadness, anxiety, stress, anger, and lack of support. A notable exception to this pattern of results was the positive retention item "Stuck to strategies that worked" ("Me ceñí a estrategias que parecían haber funcionado"), which showed near-zero or weakly positive correlations with negative behaviors, need frustration, and distress indicators. Rather than indicating a problem with the item, this pattern is consistent with what recent longitudinal idionomic research has shown for retention processes more broadly. Using within-person modeling, Ciarrochi et al. (2024) found that the pooled cross-sectional effect of retention on negative affect is essentially zero, but masks substantial individual heterogeneity: 28% of individuals showed a negative association between retention and distress — for whom sticking to strategies was protective — while 14% showed a positive association — for whom it was harmful. This is the signature of an equisyncratic construct: adaptive for some individuals, maladaptive for others, depending on whether the retained behavior still fits the current context. Group-level pooling across individuals who differ in the direction of the effect necessarily produces a near-zero average. The cross-sectional null we observe in the Spanish data — along with the variable behavior of this item reported in the Swedish (Larsson & Sundström, 2024) and Polish (Cyniak-Cieciura et al., 2024) validations — is therefore not evidence that the item is problematic, but rather what would be predicted for a retention behavior at the group level. This interpretation also illustrates the broader rationale for the PBAT's idiographic design: items whose group-level effects are weak or inconsistent may nonetheless be highly informative at the individual level, and the clinical utility of such items can only be properly evaluated within persons over time.

The reliability and measurement invariance analyses reported in the Results provide further support for the validity of the Spanish PBAT and the comparability of findings across validation samples. The internal consistency of the positive and negative selection item sets was good, despite the items tapping distinct psychological domains — a pattern

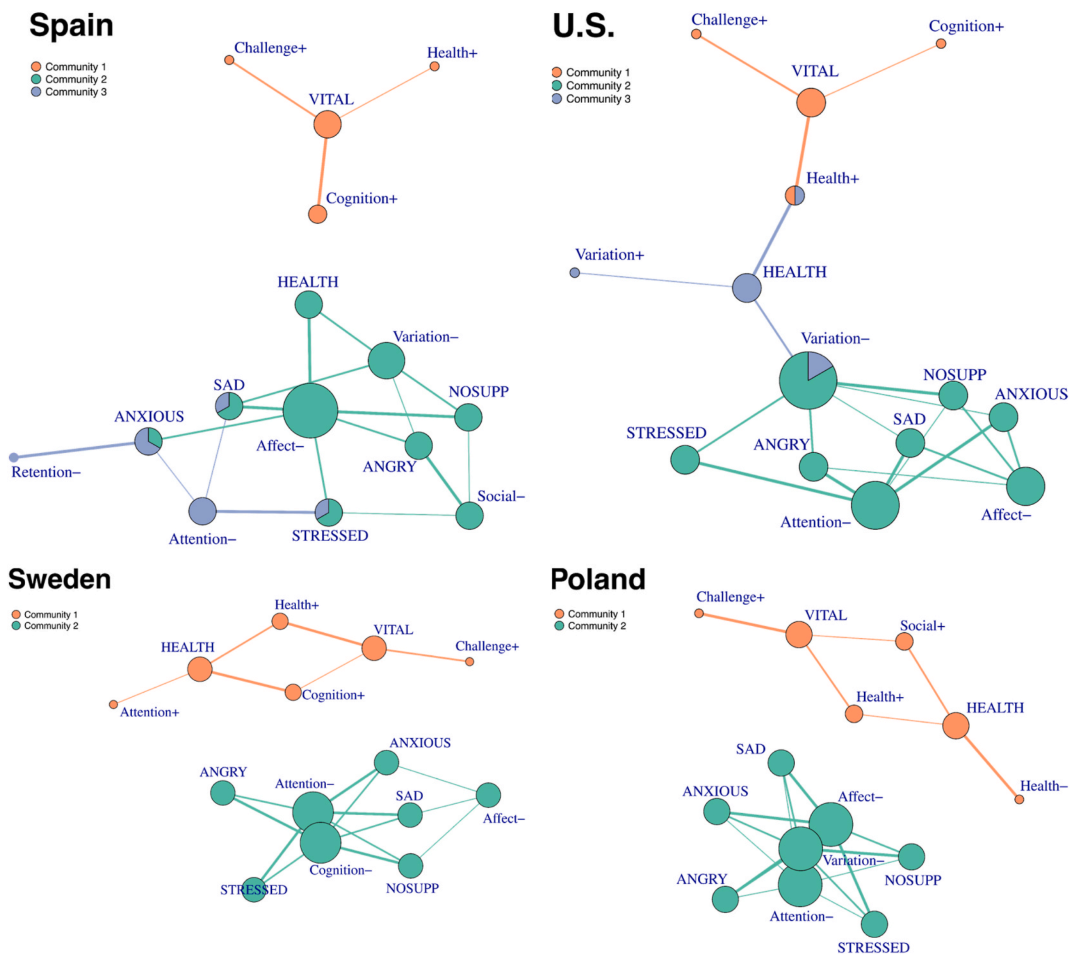

Fig. 2. Link Community Networks Across Four Datasets (Spain, U.S., Sweden, Poland)
Note. Each panel displays predictive relationships between PBAT items and STOP-D, vitality, and health outcomes using Boruta results for the respective dataset. Outcome nodes are labeled in bold capital letters (e.g., "VITAL", "ANXIOUS"), while process nodes are in regular lowercase (e.g., "Challenge+", "Affect-"). Node size reflects degree (number of connections), and edge thickness indicates Boruta ranking, with thicker edges representing higher-ranked predictors. Nodes spanning multiple communities (e.g., "Health+" and "Variation-" in the U.S., "SAD" and "ANXIOUS" in Spain) are depicted as pies, with segments colored according to their community memberships. The absence of pie representations in Sweden and Poland indicates that all nodes are exclusively tied to single communities in those networks.

consistent with the moderate inter-item correlations observed across all validation studies. The measurement invariance analysis between Spain and Sweden confirmed that the two-factor structure and factor loadings are equivalent, supporting the comparability of predictive relationships across these two samples. The five items with non-invariant intercepts (Social+, Challenge+, Health+, Social−, Cognition−) suggest that baseline endorsement of social and cognitive behaviors differs across countries, which is consistent with the country-level differences in network structure described below, where social and cognitive processes play varying roles. Item-level data for the U.S. and Polish samples were not available for invariance testing; the consistent structural validity patterns across all four studies provide indirect support for comparability, though this remains a limitation.

Our second aim was to introduce a network visualization approach to afford an intuitive illustration of the relationships between biopsychosocial processes and clinical outcomes. Using results from the Boruta machine learning algorithm—applied across all four validation studies (Spain, U.S., Sweden, Poland)—we constructed network graphs where nodes represent PBAT items and outcomes, and edges indicate predictive relationships. A link similarity-based community detection method (Ahn et al., 2010) was then applied, clustering nodes based on shared connection patterns and allowing overlapping community memberships. This approach groups processes and outcomes that share predictive relationships while identifying nodes that bridge multiple communities, revealing how specific processes relate to multiple outcome domains simultaneously.

Applying these network visualizations to datasets from Spain, the U.S., Sweden, and Poland revealed distinct country-level patterns. In Spain, negative affect behavior ("Affect-") was central, predicting all distress outcomes ("SAD", "ANXIOUS", "STRESSED", "NO SUPPORT", "ANGRY") and "HEALTH", indicating that difficulties with emotional expression were the strongest predictor of distress in this sample. In contrast, in the U.S., negative variation behavior ("Variation-") played a dominant role, indicating that perceived inability to change ineffective behavior was the strongest predictor of distress in this sample. In Poland, "Affect-", "Attention-", and "Variation-" shared equal roles, with these three processes sharing similar levels of predictive importance. Conversely, the Swedish network uniquely emphasized negative cognition ("My thinking got in the way …") and attention ("I struggled to connect …"), with negative affect playing a less prominent role and cognitive interference and attentional difficulties emerging as the strongest predictors of distress. These country-level differences in network structure are descriptive and may reflect variations across countries in how psychological processes relate to distress, but could also be influenced by differences in sample characteristics, recruitment methods, or translation across studies.

Regarding vitality, the networks in Spain, the U.S., and Sweden consistently linked the "VITAL" outcome to three positive behaviors: "Cognition+" (using thinking to enhance life), "Challenge+" (pursuing meaningful challenges), and "Health+" (acting to improve physical health). In Poland, however, "Cognition+" was replaced by "Social+" (connecting with important people), with social connection replacing cognitive processes as a predictor of vitality in this sample.

The network structures further highlighted country-level differences. The U.S. network was fully connected, with "HEALTH" and "VITAL" forming distinct yet linked communities via "Health+", and all negative outcomes clustering in a single community tied to positive outcomes through "Variation-". This overall pattern suggests an interplay between well-being and distress processes. In contrast, the Swedish and Polish networks featured two isolated communities—one for positive outcomes, one for negative—indicating a clearer separation of these processes. The Spanish network was more complex, with negative outcomes split into two communities driven by five predictors (versus three in other countries), with negative outcomes predicted by a larger set of processes than in other samples. Notably, "HEALTH" in Spain uniquely appeared in the distress community, predicted by negative behaviors, linking physical health closely to psychological distress.

These network visualizations offer an intuitive way to examine the predictive relationships between PBAT items and clinical outcomes. It is important to note, however, that the present analyses are based on cross-sectional, between-person data from four country samples. The networks therefore reflect group-level predictive patterns (which items tend to co-predict which outcomes across individuals) and cannot be interpreted as representing within-person processes or causal relationships. Our analysis showed that only a subset of the 18 PBAT items (three in the U.S., Sweden, and Poland, and five in Spain) were central to predicting negative outcomes at the between-person level. While identifying consistent group-level predictors is valuable for informing population-wide screening and assessment priorities, it risks overlooking important within-person variability. As shown in Ciarrochi et al. (2024), processes with weak average effects across individuals can have strong but opposing effects within individuals, which cancel each other out in group-level analyses. A critical next step for future research is therefore to apply the link community network approach to individual longitudinal data collected through ecological momentary assessment. Within-person networks could reveal which specific processes drive a given individual's distress, potentially enabling more targeted clinical interventions. The present cross-sectional findings provide a foundation for such work by identifying which processes and outcomes cluster together at the group level and by demonstrating the feasibility of the network visualization approach.

4.1. Limitations

Several additional limitations should be noted. Participants were recruited through a commercial online research panel using quota-based sampling. Although this ensured demographic balance on key variables, panel members may differ from the general population in ways that affect response patterns — a limitation shared with other PBAT validation studies that used similar recruitment approaches (Cyniak-Cieciura et al., 2024; Larsson & Sundström, 2024). The wide age range (18–75) encompasses different developmental stages across which psychological processes may operate differently; future research could examine age-moderated effects or validate the PBAT within specific age groups. Measurement invariance was tested only between Spain and Sweden, as item-level data were not available for the U.S. and Polish samples; the consistent structural validity patterns across all four studies provide indirect support for comparability, but this remains a constraint on the cross-country comparisons. Finally, the STOP-D and need satisfaction/frustration items were translated into Spanish as part of this study and have not been independently validated in Spanish-speaking populations.

4.2. Conclusions and future directions

This study validated the Spanish version of the PBAT, confirming its structural and criterion validity in a new country and language. Additionally, we introduced a link community network analysis approach that visualizes the predictive relationships between PBAT items and clinical outcomes. Applying this approach to data from Spain, the U.S., Sweden, and Poland revealed country-specific patterns in network structure, including differences in which processes were most central to predicting negative outcomes. These observed differences should be interpreted with caution, as they may reflect variations in sample composition or methodology across studies in addition to, or instead of, cultural factors (see Limitations).

The practical potential of this network approach lies in its future application to individual longitudinal data. By constructing personalized networks from repeated assessments, clinicians could identify the PBAT items most relevant to each patient's unique psychological profile, moving beyond group-level assumptions toward person-centered assessment. Testing this application in clinical and ecological momentary assessment settings is an important direction for future research.

Funding information

This research was supported by grant PID2022-138249NB-I00 from the Spanish Ministry of Science and Innovation. Dr. Hofmann receives financial support by the Alexander von Humboldt Foundation (as part of the Alexander von Humboldt Professur), the Hessische Ministerium für Wissenschaft und Kunst (as part of the LOEWE Spitzenprofessur), the DYNAMIC center, funded by the LOEWE program of the Hessian Ministry of Science and Arts (Grant Number: LOEWE1/16/519/03/09.001 (0009)/98), the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) – Project-ID 521379614 – TRR 393SFB/Transregio 393 and the Excellence Cluster EXC3066 "The Adaptive Mind". He also receives compensation for his work as editor from the American Psychological Association and royalties and payments for his work from various publishers.

CRediT authorship contribution statement

Carmen Goicoechea: Conceptualization, Formal analysis, Methodology, Writing – original draft. **Amie Wallman-Jones:** Writing – review & editing. **Joseph Ciarrochi:** Writing – review & editing. **Steven C. Hayes:** Writing – review & editing. **Stefan G. Hofmann:** Writing – review & editing. **Pandelis Perakakis:** Conceptualization, Formal analysis, Funding acquisition, Methodology, Project administration, Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

We thank Carmen Luciano and members of the Madrid Institute of Contextual Psychology (MICPSY) for assisting in the translation of the original PBAT.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jcbs.2026.101021.

Appendix

PBAT

Instrucciones: Marca en la línea el grado de acuerdo con cada afirmación. Basa tus respuestas en cómo has estado actuando durante la última semana*. Recuerda que no hay respuestas correctas o incorrectas.

Escala de respuesta

Totalmente en desacuerdo — Totalmente de acuerdo

0 — 100

1. Fui capaz de cambiar mi comportamiento, cuando cambiar ayudaba a mi vida
2. Hice cosas que dañaron mi relación con personas que son importantes para mí
3. Fui capaz de sentir una variedad de emociones apropiadas para el memento
4. Me costó continuar haciendo algo que era bueno para mí
5. No encontré una manera significativa de desafiarme a mí mismo/a
6. Actué de forma que ayudó a mi salud física
7. Mi pensamiento se interpuso en cosas que eran importantes para mí
8. Presté atención a cosas importantes en mi vida diaria
9. Hice cosas solo por cumplir con lo que otros querían que hiciera
10. Me ceñí a estrategias que parecían haber funcionado
11. Encontré maneras personalmente importantes de desafiarme a mí mismo/a
12. Me sentí atascado/a e incapaz de cambiar mi comportamiento ineficaz
13. Utilicé mi pensamiento de maneras que me ayudaron a vivir mejor
14. Me costó conectar con los momentos de mi día a día
15. Hice cosas para estar más cerca de las personas que son importantes para mí
16. Elegí hacer cosas que eran personalmente importantes para mí
17. Actué de forma que perjudicó mi salud física
18. No encontré una salida apropiada para mis emociones

References

Ahn, Y.-Y., Bagrow, J. P., & Lehmann, S. (2010). Link communities reveal multiscale complexity in networks. *Nature, 466*(7307), 761–764. https://doi.org/10.1038/nature09182

American Psychiatric Association. (2013). *Diagnostic and statistical manual of mental disorders* (5th ed.) Washington, DC: Author.

Chen, B., Vansteenkiste, M., Beyers, W., Boone, L., Deci, E. L., Van der Kaap-Deeder, J., Duriez, B., Lens, W., Matos, L., Mouratidis, A., Ryan, R. M., Sheldon, K. M., Soenens, B., Van Petegem, S., & Verstuyf, J. (2015). Basic psychological need satisfaction, need frustration, and need strength across four cultures. *Motivation and Emotion, 39*(2), 216–236. https://doi.org/10.1007/s11031-014-9450-1

Chen, F. F. (2007). Sensitivity of goodness of fit indexes to lack of measurement invariance. *Structural Equation Modeling, 14*(3), 464–504. https://doi.org/10.1080/10705510701301834

Ciarrochi, J., Sahdra, B., Hayes, S. C., Hofmann, S. G., Sanford, B., Stanton, C., Yap, K., Fraser, M. I., Gates, K., & Gloster, A. T. (2024). A personalised approach to identifying important determinants of well-being. *Cognitive Therapy and Research, 48*(4), 1–22. https://doi.org/10.1007/s10608-024-10486-w

Ciarrochi, J., Sahdra, B., Hofmann, S. G., & Hayes, S. C. (2022). Developing an item pool to assess processes of change in psychological interventions: The Process-Based Assessment Tool (PBAT). *Journal of Contextual Behavioral Science, 23*, 200–213. https://doi.org/10.1016/j.jcbs.2022.02.001

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates.

Curran, P. J., West, S. G., & Finch, J. F. (1996). The robustness of test statistics to nonnormality and specification error in confirmatory factor analysis. *Psychological Methods, 1*(1), 16–29. https://doi.org/10.1037/1082-989X.1.1.16

Cyniak-Cieciura, M., Dudek, J., & Ostaszewski, P. (2024). The Polish version of the Process-Based Assessment Tool (PBAT)—The measure of processes of change in psychological interventions. *PLoS One, 19*(6), Article e0304661. https://doi.org/10.1371/journal.pone.0304661

Hayes, S. C., Hofmann, S. G., & Ciarrochi, J. (2020). A process-based approach to psychological diagnosis and treatment:the conceptual and treatment utility of an extended evolutionary meta model. *Clinical Psychology Review, 82*, Article 101908. https://doi.org/10.1016/j.cpr.2020.101908

Hofmann, S. G., & Hayes, S. C. (2019). The future of intervention science: Process-based therapy. *Clinical Psychological Science, 7*(1), 37–50. https://doi.org/10.1177/2167702618772296

Instituto Nacional de Estadística. (2022). Avance de la Estadística del Padrón Continuo a 1 de enero de 2022. https://www.ine.es/prensa/pad_2022_p.pdf.

Kalinka, A. T., & Tomancak, P. (2011). Linkcomm: An R package for the generation, visualization, and analysis of link communities in networks of arbitrary size and type. *Bioinformatics, 27*(14), 2011–2012. https://doi.org/10.1093/bioinformatics/btr311

Kursa, M. B., & Rudnicki, W. R. (2010). Feature selection with the boruta package. *Journal of Statistical Software, 36*(11). https://doi.org/10.18637/jss.v036.i11

Larsson, A. B., & Sundström, F. T. A. (2024). Optimizing process-based therapy: A boruta-driven approach to identifying key clinical outcomes in a Swedish validation of the process-based assessment tool (PBAT). *Journal of Contextual Behavioral Science, 33*, Article 100794. https://doi.org/10.1016/j.jcbs.2024.100794

Mullins-Sweatt, S. N., Lengel, G. J., & DeShong, H. L. (2016). The importance of considering clinical utility in the construction of a diagnostic manual. *Annual Review of Clinical Psychology, 12*, 133–155. https://doi.org/10.1146/annurev-clinpsy-021815-092954

Muñiz, J., Elosua, P., & Hambleton, R. (2013). Directrices para la traducción y adaptación de los tests: Segunda edición. *Psicothema, 25*(2), 151–157. https://doi.org/10.7334/psicothema2013.24

R Core Team. (2024). *R: A Language and environment for statistical computing*. R Foundation for Statistical Computing. https://www.R-project.org/.

Rief, W., Asmundson, G. J. G., Bryant, R. A., Clark, D. M., Ehlers, A., Holmes, E. A., McNally, R. J., Neufeld, C. B., Wilhelm, S., Jaroszewski, A. C., Berg, M., Haberkamp, A., & Hofmann, S. G. (2024). The future of psychological treatments: The Marburg Declaration. *Clinical Psychology Review, 110*, Article 102417. https://doi.org/10.1016/j.cpr.2024.102417

Rosseel, Y. (2012). Lavaan: An R package for structural equation modeling. *Journal of Statistical Software, 48*(2), 1–36. https://doi.org/10.18637/jss.v048.i02

Ryan, R. M., & Deci, E. L. (2017). *Self-determination theory: Basic psychological needs in motivation, development, and wellness*. The Guilford Press. https://doi.org/10.1521/978.14625/28806

Ryan, R. M., & Frederick, C. (1997). On energy, personality, and health: Subjective vitality as a dynamic reflection of well-being. *Journal of Personality, 65*(3), 529–565. https://doi.org/10.1111/j.1467-6494.1997.tb00326.x

Ware, J. E., & Sherbourne, C. D. (1992). The MOS 36-item short-form health survey (SF-36). I. Conceptual framework and item selection. *Medical Care, 30*(6), 473–483.

World Health Organization. (2019). *International statistical classification of diseases and related health problems* (11th ed.) https://icd.who.int/.

Young, Q.-R., Ignaszewski, A., Fofonoff, D., & Kaan, A. (2007). Brief screen to identify 5 of the most common forms of psychosocial distress in cardiac patients: Validation of the screening tool for psychological distress. *Journal of Cardiovascular Nursing, 22*(6), 525–534. https://doi.org/10.1097/01.JCN.0000297383.29250.14

Young, Q.-R., Nguyen, M., Roth, S., Broadberry, A., & Mackay, M. H. (2015). Single-item measures for depression and anxiety: Validation of the screening tool for psychological distress in an inpatient cardiology setting. *European Journal of Cardiovascular Nursing, 14*(6), 544–551. https://doi.org/10.1177/1474515114548649