An affective space view on depression and anxiety

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Abstract

The circumplex model for core affect is among the most prominent characterizations of emotion and has received extensive empirical support. However, no prior study exists that connects the measurement of depression and anxiety with the core affect structure and the bipolar dimensions of arousal and valence it includes.

Objectives: This study aims to investigate the reconcilability between a continuous model based on Russell's core affect system and a discrete entity view on depression and anxiety.

Methods: The data were drawn from the anxiety and depression short forms in the Patient-Reported Outcomes Measurement Information System ($N = 763$). It consists of 15 items with a 5-point Likert scale. Ratings of the items in terms of distress and arousal were obtained from experts in emotion research. An approach based on Russell's core affect theory was compared with the common type of factor models in which the items are lined up on clearly separated depression and anxiety dimensions with an empty space in between, as if they are separate and discrete entities. Our alternative model works with a continuous space instead.

Results: The core affect theory-based method exhibits a goodness of fit that is comparable with the conventional models.

Conclusions: Depression and anxiety can be understood in terms of Russell's bipolar core affect model; the core affect-based model leaves room for symptoms in the space between dimensions.

KEYWORDS

affective disorders, Bayesian approach, measurement, patient reported outcome

1 | INTRODUCTION

Depression and anxiety disorders are common mental health conditions with high lifetime prevalence. They are affecting nearly 10% of the population with an increasing trend worldwide (WHO, 2016). The symptoms are associated with increased risk behaviors, diseases, and impairment in social and physical functioning, largely worsening the quality of life (Jaycox et al., 2009). The availability of measurement instruments is of vital importance for screening and treatment. A recent trend is to move from a categorical view to a dimensional view and from discrete to continuous, but the result has actually been a hybrid, with a continuum for each category, a depression dimension, and a correlated anxiety dimension but with

an empty space in between. This allows for subjects to be spread in the two-dimensional space, and because the dimensions are correlated, the dimensional structure can also account for comorbidity. However, such a dimensional structure is still categorical in terms of items, in that separate clusters of items are used per dimension. We want to go one step further and also allow continuity for the items, without forcing the items to locate on discrete lines, one for depression and one for anxiety. This is consistent with a more fully dimensional approach, and it also allows for symptoms in between depression and anxiety and not just for comorbidity among patients. Even more importantly for our purpose, it would fit well with Russell's (1980) core affect system. The model we will investigate is an affective space model.

1.1 | Two major approaches

In understanding emotions, there exist two major approaches, discrete and dimensional. The discrete theory posits that humans share a series of basic emotions such as anger, fear, sadness, and happiness, each linked with distinctive neural systems, antecedents, and physiological reactions (Ekman, 1999), even though the intensity of these dimensions can vary. Notwithstanding these quantitative intensity differences, the system is basically categorical but with heterogeneity within the categories captured by within-category dimensions (De Boeck, Wilson, & Acton, 2005). Levels within a category do not undo the categorical nature of a category. All categories have exemplars with different degrees in which they represent the category. In contrast, the kind of dimensional approach that is represented by the circumplex model (Russell, 1980; Schlosberg, 1952) considers emotions to fall along a space defined by two orthogonal dimensions, valence and arousal. Both dimensions are bipolar: pleasure versus displeasure and high versus low activation (Russell, 1980), and the space between the dimensions is filled with affect terms. The circumplex model is among the most prominent characterizations of emotion and has received emerging consensus (Rubin & Talarico, 2009), based on empirical support from studies involving self-report of mood, judgements of semantic similarity between affect terms, and ratings of facial emotion expressions (Kring, Feldman-Barrett, & Gard, 2003; Russell, 1980; Russell, Lewicka, & Niit, 1989), as well as from neurophysiological experiments (e.g., Colibazzi et al., 2010; Delaney-Busch, Wilkie, & Kuperberg, 2016). Factor analysis studies using principal components analysis or exploratory factor analysis have revealed the circumplex structure based on self-reported mood (Feldman, 1995a, 1995b; Lorr, Shi, & Youniss, 1989; Russell, 1980). However, no prior studies exist that seek a reconciliation between the core affect system and models with discrete dimensions and thus an empty space in between the dimensions (Note: The Browne, 1992 CIRCUM software assumes a perfect circular shape of emotions, which is not intended by Russell, 1980.).

Mounting evidence from neurophysiological experiments support both a discrete and a dimensional emotion representation in the brain. For example, in a meta-analysis with neuroimaging studies, Vytal and Hamann (2010) found that basic emotions are associated with distinct neural correlates, upholding a discrete theory. Other studies reported distinct neural systems for valence and arousal, advocating a dimensional theory (Colibazzi et al., 2010; Sieger et al., 2015). Given that there is clinical evidence for both theoretical views on (human perceptions of) emotions, a major question of interest is whether from a measurement point of view, the two approaches can be reconciled for depression and anxiety: one with depression and anxiety as separate categories of items with a dimension per category and another with a more continuous dimensional space based on valence and arousal. An interesting potential of the latter is that depression and anxiety as affective disorders can be mapped into the affect core system as described by Russell (1980) for the general population.

1.2 | Factor structures

Extensive efforts have been made investigating the factor structure of scales for depression and anxiety. For example, either a multidimensional

or bi-factor structure has been proposed with the Symptom Checklist-90, the Depression Anxiety Stress Scales, the Hospital Anxiety and Depression Scale, and the Inventory of Depression and Anxiety Symptoms, to name a few (e.g., Bjelland, Dahl, Haug, & Neckelmann, 2002; Henry & Crawford, 2005; Ryttilä-Manninen et al., 2016; Simms, Grös, Watson, & O'Hara, 2008). In a highly prominent approach, the tripartite model, depression and anxiety are located in a three-dimensional space, with a shared dimension of general affective distress for both depression and anxiety and a specific dimension for each of the two—low positive affect for depression and high physiological arousal for anxiety (Clark & Watson, 1991; Watson, Clark, et al., 1995; Watson, Weber, et al., 1995).

Among the recently developed measurement approaches is the Patient-Reported Outcomes Measurement Information System (PROMIS), which is a National Institutes of Health initiative to develop item banks and short forms for health outcomes across several domains, featuring state-of-the-art techniques such as item response theory (IRT) for measurement in the domain of health issues (Pilkonis et al., 2011). Using IRT, evidence has been found for a two-dimensional structure (anxiety and depression), though with high correlations between the two dimensions ($r > 0.75$; Liu et al., 2015). A bi-factor solution has also been investigated, with a general negative factor and two specific factors, one for anxiety and one for depression (e.g., Irwin et al., 2010; Stucky & Edelen, 2014).

However, these are models with category-based dimensions, one for depression and another for anxiety, which does not allow a structure such as Russell's (1980) circumplex structure based on the dimensions of arousal and valence. Neither do the established measurement models allow cross-loadings unless with the general factor as in the bi-factor model. We believe that the confirmatory factor model drives the result. Our research question is whether a more continuous model based on a general psychological theory such as the circumplex can also explain the data, so that the continuous view can be reconciled with the more discrete view on depression and anxiety. We will use a new model in line with Russell's theory so that the position of the items is in line with their position on the valence and arousal dimensions, to test whether the circumplex also applies to a clinical instrument to measure depression and anxiety. The test is successful if the new model fits the data equally well or better than the earlier discussed models.

Our study can also be seen as filling a gap that is mentioned by Kemp and Felmingham (2008). These authors describe three models for depression and anxiety: one that is based on self-report data (the tripartite model; Clark & Watson, 1991) and two neurobiological models—the approach avoidance model (Davidson & Irwin, 1999) and the valence-arousal model (Heller & Nitschke, 1998). Kemp and Felmingham mention a major issue with the valence-arousal model that it has not been investigated with self-report data. This is a gap we hope to fill with our alternative approach.

1.3 | An alternative

In the typical confirmatory factor models and IRT models, the confirmatory nature refers to the zero loadings or discriminations so that items load on only one dimension and each dimension represents a category of items (and possibly the general dimension if a bi-factor

model is used). All models we will use are IRT models but equivalent with factor models (e.g., Wirth & Edwards, 2007).

The crux of our alternative for confirmatory factor analysis (CFA) and corresponding IRT models is to model the item discriminations (loadings in a factor model) as a function of the coordinates in the circumplex. Because predictions are never perfect, we allow a residual term. Item discriminations are defined as follows:

$$\alpha_{jd} = g_d X_{jd} + \varepsilon_{jd}$$

where α_{jd} is the discrimination of item j for dimension d ; X_{jd} is an external covariate, not derived from the item responses but from expert ratings of item j in terms of dimension d ; g_d is the weight for the link of X_{jd} with α_{jd} ; and ε_{jd} is a residual with zero mean and normal distribution to account for imperfect prediction of the discrimination based on the circumplex coordinates. In line with the core affect theory, two orthogonal dimensions will be used.

The random residual can also account for possible unreliability of the covariates that represent the coordinates of the circumplex. Random terms for item parameters in the presence of item covariates have been discussed and used in the literature before (Cho, De Boeck, Embretson, & Rabe-Hesketh, 2014; De Boeck, 2008; De Jong, Steenkamp, Fox, & Baumgartner, 2008) but never for a multidimensional model. An important feature of the model is that it is more confirmatory than CFA in one way and less confirmatory than CFA in another way. It is more confirmatory because all discriminations are estimated on the basis of externally derived circumplex coordinates (rather than just constraining some of the loadings to zero); it is less confirmatory because of the residual term.

We will compare four models: a unidimensional model, a traditional correlated two-dimensional CFA model, a bi-factor model, and our affective space model, which is a confirmatory bipolar model.

2 | METHODS AND MATERIALS

2.1 | Data source

The data were drawn from the anxiety and depression short forms in the PROMIS, which is a publicly available database concerning the assessment of various aspects of the health profile in a community sample. The short form consists of 15 items: seven anxiety items and eight depression items. Respondents were asked to indicate how often they experienced the emotional symptoms in the past 7 days based on a 5-point scale (1 = *never*, 2 = *rarely*, 3 = *sometimes*, 4 = *often*, 5 = *always*; Pilkonis et al., 2011).

The data are from a large sample ($N = 21,133$) described in Cella et al. (2010), subdivided into a clinical sample ($N = 7,080$) and a general population sample ($N = 14,053$) with very similar demographic characteristics as in the U.S. Census of 2000. For a more detailed description and recruitment procedures, see Cella et al. (2010). The 15-item form we are using was presented to 925 participants from the general population sample. Of these participants, 839 answered at least one item, and 809 of those were considered valid respondents based on the PROMIS criterion that responses were not provided in less than 1 s. Finally, complete data are available for 763 of the 809, which means

that for 5.7%, at least one item response is missing. In demographic terms, 52% are female; 80% White, 10% Black, and 10% other; 78% have a high school degree or higher; and the mean age is 51, $SD = 18.9$. These demographic characteristics are very similar to those of the full general population sample. On the basis of 10 self-rated mental and physical health items from the same survey, the sample with complete responses ($N = 763$) has highly similar means and standard deviation for all 10 items compared with the total sample of valid respondents ($N = 809$). For all these reasons, we decided to continue with the sample of 763 respondents instead of considering imputation, which is in line with a preliminary analysis by Farouni (2014).

Experts from the field of emotion research were asked to rate the 15 items in terms of degree of distress ($n = 8$) and a bipolar degree of arousal ($n = 12$), respectively, and the averaged ratings were labeled as X_1 (for distress ratings) and X_2 (for arousal ratings) hereafter. All raters were active researchers from another university than the authors of this study, either senior graduate students working on their dissertations (5/8 and 8/12) or researchers with a PhD degree; half were male, and half were female, all from a research group with a prominent international publication record in the domain of affect and emotion. The ratings were made in a strictly independent way. The inter-rater reliability of the two kinds of ratings are 0.75 and 0.96. The lower reliability of the former reflects the smaller differences between the items regarding the degree of distress expressed in the items.

2.2 | Model specifications

The unidimensional model, the correlated two-dimensional CFA model, and the bi-factor model are well known, but the bipolar confirmatory model that we use based on the core affect system may need some further explanation. All items load on both dimensions: the distress dimension and the arousal dimension. For item discriminations, a regression approach is used (not as a separate step but as part of the model estimation) with a dimension-specific residual variance for the item discriminations denoted as $\sigma_{\varepsilon_1}^2$ and $\sigma_{\varepsilon_2}^2$. The regressions are expressed as $\alpha_{j1} = g_1 X_{j1} + \varepsilon_{j1}$ and $\alpha_{j2} = g_2 X_{j2} + \varepsilon_{j2}$ (for a graphical illustration, please see the Supporting Information).

2.3 | Parameter estimation

Graded response models were run using the R2jags (Su & Yajima, 2012) package in R (R Core Team, 2017) to interface with JAGS 4.0 (Plummer, 2015). Prior distributions for the parameters were specified, and model convergence was diagnosed by relevant statistics and plots. For the details of the Bayesian estimation approach, see the Supporting Information. Model comparison was performed by using the deviance information criterion (DIC; Spiegelhalter, Best, Carlin, & van der Linde, 2002), a Bayesian alternative for the Akaike information criterion and Bayesian information criterion. Smaller values of DIC indicate better model fit.

3 | RESULTS

As a first step, we have checked the convergence of the model estimations. For the method and results of the convergence checks, see the Supporting Information. Next, the four models are compared in terms

of goodness of fit to the data. The model comparison results show that two of the three multidimensional models are better than the unidimensional model ($DIC = 16852$). Among the multidimensional models, the bipolar model displays comparable model fit ($DIC = 16,142^1$) with the two-dimensional CFA ($DIC = 16,161$) and a better fit than the bi-factor model ($DIC = 16,968$). Although without a penalty for model complexity, the bi-factor model does better than the unidimensional model, the DIC values show that it does not when model complexity is taken into account.

For a closer evaluation of the rather small difference between the best two fitting models, we have used five analysis runs for each. When the 10 results are ranked from 1 to 10 (from best to worst), the average rank orders are 5.2 for the bipolar model and 5.8 for the two-dimensional CFA. The corresponding average DIC values are 16,112.2 (bipolar) and 16,128.8 (two-dimensional CFA). This performance of the bipolar model is confirmed by the deviance values (without a penalty for model complexity), which are always smaller for the bipolar model, even though the discrimination parameters in the bipolar model are replaced with just two regression weights and two residual variances to explain the discrimination parameters. In sum, for our data, the bipolar model is a clearly competitive model and can be considered as a useful alternative for the two-dimensional confirmatory model and the bi-factor model, which are the two conventional measurement models.

Table 1 shows the mean, standard deviations, and average ratings of distress and arousal expressed in each item. In terms of the descriptive statistics, people reported low degrees of distress for all the items, which could be expected from a community sample as in the current dataset. Table 1 also shows the ratings of distress, which are all positive, and the ratings of arousal after subtracting the midpoint score so that the means are positive for all the anxiety items and negative for depression items, which is consistent with the bipolar nature of the arousal rating.

The expected item discriminations for the bipolar model (not counting the residual term) are also shown in Table 1 and graphically represented in Figure 1. We will first discuss Table 1 and the corresponding orthogonal affective space structure presented in Figure 1 before moving to the correlated factor solution for a comparison, based on the Figures 2 and 3. Table 1 shows that all discrimination values are positive for the distress dimension (α_1 values) and positive for items 1–7 (anxiety items) and negative for items 8–15 (depression items) for the arousal dimension (α_2 values). These discriminations echo the theoretical rationale—positive discriminations on the distress dimension and the arousal dimension represent anxiety-related feelings, and positive discriminations on the distress dimension combined with negative discriminations on the arousal dimension represent depression-related feelings.

The x-axis of Figure 1 represents the arousal dimension, whereas the y-axis represents the valence (distress) dimension. Only the distress range of the y-axis is displayed because all items express distress. The right-hand side of the x-axis corresponds to higher level of

arousal, as expressed with terms such as “nervous,” “anxious,” and “worried,” and the left-hand side represents the items with lower arousal ratings. All seven items in the quadrant to the right are from the anxiety short form, whereas all eight items in the quadrant to the left belong to the depression short form. As for the relationship between the items, the more similar items are closer to each other. The position of the items is not circular, which is consistent with the report by Feldman (1995b) and Kring et al. (2003) that a loading-defined circumplex does not have to conform to a circle but flexibly reflects emotional experiences across various samples and contexts. The position of the items also reflects some of the continuity in the space in that the items do not align on just two lines as enforced by the two-dimensional CFA model.

In regard to the model-based regression of the item discriminations on the coordinate ratings from experts, these ratings have an estimated effect of 0.501 (g_1) for the distress dimension, with a 95% credible interval of [0.436, 0.570]. For the arousal dimension discriminations, the estimated effect of the coordinate ratings is 0.467 (g_2g_1), credible interval = [0.350, 0.578]. The standard deviation of the residuals of the distress discriminations is 0.901, and the corresponding values for the arousal dimension are 0.427. These results show that the discriminations are clearly related to the coordinate ratings. It is worthwhile to note that the discrimination indices for the distress (valence) dimension are consistently larger than those of the arousal dimension. This result echoes Feldman's (1995a) findings that people give more weight to the valence dimension than to the arousal dimension when it comes to self-report emotions.

On the basis of the goodness-of-fit results, the two-dimensional CFA is a competitive model. Its mapping of emotions is depicted in Figure 2. The location of items is again defined by their discrimination parameter estimates. All items fall along the two axes of anxiety and depression, as a reflection of the hybrid emotion theory, with a dimension per category (which is why we use the term “hybrid”). The dimensions are discrete in terms of items because the space between and beyond the dimensions is empty. The angle (32°) between the two axes depicts the inter-factor correlation ($r = 0.849$). All items are forced into a single line defined by anxiety or depression. The distances between the items are thus compressed to be narrower. For example, “depressed,” “helpless,” “worthless,” “failure,” and “sad” are located very near to each other on the depression axis, whereas “failure” and “worthless” have a rather different position in the bipolar mapping compared with the tight cluster of the other three, “helpless,” “sad,” and “depressed” (see Figure 1). Compared with the CFA approach, the bipolar model avoids forcing items to be located right on the same two lines without any room in between the lines so that the similarity and differences among the items may be artificially constrained in line with a discrete view on depression and anxiety. For a more direct comparison, please refer to a rotated version of the bipolar model in Figure 3 and the CFA solution of Figure 2. The rotation is established using the CEFA program (Browne, Cudeck, Tateneni, & Mels, 2008).

It is reassuring for our approach that the homogeneity of the items as reflected in the traditional CFA approach and as intended by the authors of the scale still leaves room for some continuity in the space, as shown in Figures 1 and 3, instead of a concentration on just two

¹The goodness-of-fit values vary to some extent depending on the run, which is not unusual for Bayesian model estimation, so we conclude that the DIC of the bipolar model is similar to the two-dimensional CFA model.

TABLE 1 Descriptive statistics, emotion ratings, and bipolar parameter estimates for the items

Item	Description	M	SD	X ₁	X ₂	α_1	α_2
Anx 1	I felt fearful	1.49	0.84	8.75	3.17	3.045	0.723
Anx 2	I felt anxious	1.86	1.03	7.75	2.58	3.424	1.053
Anx 3	I felt worried	2.03	1.05	6.00	0.92	3.094	0.876
Anx 4	I found it hard to focus on anything other than my anxiety	1.39	0.75	4.25	0.42	2.884	0.747
Anx 5	I felt nervous	1.79	0.93	4.50	2.25	3.487	1.134
Anx 6	I felt uneasy	1.82	0.97	4.50	0.50	3.635	0.820
Anx 7	I felt tense	2.05	1.06	5.00	0.83	2.720	0.816
Dep 1	I felt worthless	1.51	0.94	8.25	-2.25	3.698	-1.308
Dep 2	I felt that I had nothing to look forward to	1.61	0.98	6.25	-2.50	3.129	-1.239
Dep 3	I felt helpless	1.56	0.93	6.50	-2.00	3.453	-0.806
Dep 4	I felt sad	2.07	1.03	7.75	-1.33	3.364	-0.741
Dep 5	I felt like a failure	1.68	1.01	8.25	-2.58	3.568	-1.193
Dep 6	I felt depressed	1.86	1.06	5.00	-1.58	3.454	-0.721
Dep 7	I felt unhappy	2.04	1.06	7.50	-2.08	3.846	-0.936
Dep 8	I felt hopeless	1.53	0.93	6.25	-1.83	3.986	-1.231
Regression coefficients							
$g_1 = 0.501$ [0.436, 0.570]							
$g_2 = 0.467$ [0.298, 0.642]							
Random effects							
$\sigma_{\epsilon_1}^2 = 0.812$							
$\sigma_{\epsilon_2}^2 = 0.182$							

Note. X₁: ratings of distress; X₂: ratings of arousal. α_1 : valence; α_2 : arousal. All the item discrimination estimates have a 95% credible interval that does not include zero. $\sigma_{\epsilon_1}^2$ and $\sigma_{\epsilon_2}^2$: residual variance of discriminations for dimensions 1 and 2, respectively.

lines as in Figure 2. The larger flexibility is not at the cost of more parameters. For discriminations, the number of parameters of the bipolar model is largely reduced to the two weights (g_1 and g_2) and two residual variances ($\sigma_{\epsilon_1}^2$ and $\sigma_{\epsilon_2}^2$) instead of 15 discriminations (loadings).

4 | DISCUSSION

On the basis of the PROMIS data, supportive evidence was found for a more continuous model of depression and anxiety as an alternative

FIGURE 1 Bipolar mapping of the circumplex model. The y-axis in the circumplex starts from 2.25

FIGURE 2 Two-dimensional confirmatory factor analysis mapping for discrete emotions

FIGURE 3 Target rotation of bipolar solution to the confirmatory factor analysis solution

for the more traditional discrete dimensional view based on categories of items, one category for depressive and another for anxiety disorder symptoms. On the basis of the goodness-of-fit results, the new and more continuous affective space approach offers an alternative to the more discrete conventional approach. Hence, on the basis of our results, depression and anxiety can also be understood in terms of Russell's (1980) bipolar core affect model.

In terms of methodology, the study sheds light on a new way to test theories about the underlying dimensional structure of data. Using item covariates for discriminations in a multidimensional model is a new confirmatory development beyond CFA and the bi-factor model. The latter two models divide the loadings or discriminations into two categories: zero versus free parameters. Our approach is more fine-grained, with item discriminations as a function of theoretically meaningful covariates. This is a step beyond the dichotomous treatment of discriminations/loadings as fixed to zero versus freely estimated. Additionally, it extends the Cho et al. (2014) study to multidimensional models with a latent regression for discrimination indices per dimension. This will enhance theoretically relevant interpretations of multidimensional models. The random residuals are necessary because like in all regression models, a perfect explanation is impossible.

We see important clinical implications of our work. Evidence for the bipolar model suggests that anxiety and depression can now be connected to a well-known general theory of core affect in terms of valence and (bipolar) arousal, providing a rival model that accounts

for both normal variation in affect as well as symptoms of mood and anxiety disorders. In line with the bipolar model, symptoms of depression and anxiety can be viewed as more extreme positions on these two affect dimensions, with arousal not needing to be seen as primarily somatic and physiological as in the tripartite model. In addition, an examination of the rotated dimensional plot in Figure 3 shows considerable room between depression and anxiety. We suspect that this room likely stems from selecting items so as to reflect discrete categories. With a model that allows cross-loaded items, there is no need to limit questionnaires to dimensionally homogeneous sets of items. Thus, the bipolar model should encourage researchers to examine items that could provide a broader and more comprehensive characterization of the experiences that characterize these conditions. Finally, we believe that distinctions among the models we examined ultimately have the potential to inform treatment development and approaches to personalized care. Both in recognition of the potential for targeting transdiagnostic processes to improve treatment efficacy and in light of the impractical training burden imposed on therapists tasked with mastering many different disorder-specific treatments, there has been a great deal of interest in developing transdiagnostic approaches for the treatment of mood and anxiety disorders (e.g., Barlow, Allen, & Choate, 2016). A different structural model of psychopathology has the potential to lead to substantive differences in the way that treatment targets are framed and engaged. Recognition of key symptoms that are not addressed by available treatments has already

served as the basis for some novel interventions (Carl, Gallagher, & Barlow, 2017). In addition, there has been interest in using symptom presentations as a basis for personalizing treatments for mood and anxiety disorders (e.g., Fisher, 2015). Better understanding the structure of mood and anxiety symptoms could inform those working to personalize treatments by providing promising measurement models for capturing individual differences in symptom presentations.

Our study is not without limitations. Most of these limitations are at the same time suggestions for further study. First, the study concerns a community sample so that the average degree of depression and anxiety is rather low. Although community samples are of interest in themselves, clinical samples may have more practical relevance and may reveal interesting additional aspects of the structure of depression and anxiety. For example, the results of a study with clinical samples and different scales in a longitudinal design suggest that the structure is more complex when the severity of depression is higher (Fried et al., 2016). In itself, this does not contradict the affective space. For example, extra dimensions can arise with increasing severity; for example, because of local dependency, clusters can originate in the affective space based on symptoms influencing each other, as suggested in the same article by Fried et al. (2016).

To further test the model, it would be beneficial to work with more than one depression and anxiety scale. This may be a way to integrate a multitude of assessment tools for depression and anxiety. Further, it would also be interesting to include more items than the ones which figure in existing scales, because the existing scales are all inspired by a conception of depression and anxiety as within-category dimensions and not by an affective space view. The set of items from existing scales can be extended with a wider range of affects in an attempt to better cover the affective space, including positive affect. For the item covariates, which are necessary to estimate the model, we have used ratings by experts, and hence, they are subjective to some extent. A better solution may be to rely on established affective space coordinates from earlier studies for items that are added as markers to fill the affect space. As a final note on the validity of the bipolar affect space model, the model has been compared with three common and popular models: the unidimensional model, the correlated dimensions model, and the bifactor model. In principle, also other models could be considered, for example, based on an exploratory dimensional analysis.

A cautionary note is in order regarding the missing responses. We do not know why only 839 of the 925 subjects have responded to any of the 15 items or why not all responding subjects have responded to all items (5.7% did not). However, the missingness was without apparent consequences for the demographic and health characteristics of the sample. Because this is certainly not always the case for missing data, one may wonder how to deal with missing data when the present approach is used. Possible solutions are data imputation or an estimation method without bias (e.g., maximum likelihood and Bayesian estimation) if the missingness is at random, although it may result in some reduction of power.

Although our study is not without limitations, the approach and the result seem promising and throw new light on depression and anxiety, for how to measure and for how to interpret symptoms in terms of the affect space. With additional research, this more nuanced and continuous view of symptoms may lead to more personalized forms of treatment.

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CONFLICT OF INTEREST

This study has not received any financial support, and the authors declare no conflicts of interest.

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REFERENCES

- Barlow, D. H., Allen, L. B., & Choate, M. L. (2016). Toward a unified treatment for emotional disorders – Republished article. *Behavior Therapy*, 47, 838–853. <https://doi.org/10.1016/j.beth.2016.11.005>
- Bjelland, I., Dahl, A. A., Haug, T. T., & Neckelmann, D. (2002). The validity of the Hospital Anxiety and Depression Scale. An updated literature review. *Journal of Psychosomatic Research*, 52, 69–77. [https://doi.org/10.1016/S0022-3999\(01\)00296-3](https://doi.org/10.1016/S0022-3999(01)00296-3)
- Browne, M. W. (1992). Circumplex models for correlation matrices. *Psychometrika*, 57, 469–497. <https://doi.org/10.1007/BF02294416>
- Browne, M. W., Cudeck, R., Tateneni, K., & Mels, G. (2008). CEFA: Comprehensive exploratory factor analysis, version 3.03 [computer software and manual]. Retrieved from <http://faculty.psy.ohio-state.edu/browne/>
- Carl, J. R., Gallagher, M. W., & Barlow, D. H. (2017). Development and preliminary evaluation of a positive emotion regulation augmentation module for anxiety and depression. *Behavior Therapy*. <https://doi.org/10.1016/j.beth.2017.11.008>
- Cella, D., Riley, W., Stone, A., Rothrock, N., Reeve, B., Yount, S., ... PROMIS Cooperative Group (2010). The Patient-Reported Outcomes Measurement Information System (PROMIS) developed and tested its first wave of adult self-reported health outcome item banks: 2005–2008. *Journal of Clinical Epidemiology*, 63, 1179–1194.
- Cho, S. J., De Boeck, P., Embretson, S., & Rabe-Hesketh, S. (2014). Additive multilevel item structure models with random residuals: Item modeling for explanation and item generation. *Psychometrika*, 79, 84–104. <https://doi.org/10.1007/s11336-013-9360-2>
- Clark, L. A., & Watson, D. (1991). Tripartite model of anxiety and depression: Psychometric evidence and taxonomic implications. *Journal of Abnormal Psychology*, 100, 316–336. <https://doi.org/10.1037/0021-843X.100.3.316>
- Colibazzi, T., Posner, J., Wang, Z., Gorman, D., Gerber, A., Yu, S., ... Peterson, B. S. (2010). Neural systems subserving valence and arousal during the experience of induced emotions. *Emotion*, 10, 377–389. <https://doi.org/10.1037/a0018484>
- Davidson, R. J., & Irwin, W. (1999). The functional neuroanatomy of emotion and affective style. *Trends in Cognitive Sciences*, 3, 11–21. [https://doi.org/10.1016/S1364-6613\(98\)01265-0](https://doi.org/10.1016/S1364-6613(98)01265-0)
- De Boeck, P. (2008). Random item IRT models. *Psychometrika*, 73, 533–559. <https://doi.org/10.1007/s11336-008-9092-x>
- De Boeck, P., Wilson, M., & Acton, G. S. (2005). Conceptual and psychometric framework for distinguishing categories and dimensions. *Psychological Review*, 112, 129–158. <https://doi.org/10.1037/0033-295X.112.1.129>
- De Jong, M. G., Steenkamp, J. B. E. M., Fox, J.-P., & Baumgartner, H. (2008). Using item response theory to measure extreme response style in marketing research: A global investigation. *Journal of Marketing Research*, 45, 104–115. <https://doi.org/10.1509/jmkr.45.1.104>
- Delaney-Busch, N., Wilkie, G., & Kuperberg, G. (2016). Vivid: How valence and arousal influence word processing under different task demands. *Cognitive, Affective, & Behavioral Neuroscience*, 16, 415–432. <https://doi.org/10.3758/s13415-016-0402-y>

- Ekman, P. (1999). Basic emotions. In T. Dalgleish, & T. Power (Eds.), *Handbook of cognition and emotion* (pp. 45–60). New York: Wiley.
- Farouni, N. S. (2014). Latent variable models of categorical responses in the Bayesian and frequentist frameworks. Unpublished master thesis of the Ohio State University. Columbus, OH.
- Feldman, L. A. (1995a). Valence focus and arousal focus: Individual differences in the structure of affective experience. *Journal of Personality and Social Psychology*, 69, 153–166. <https://doi.org/10.1037/0022-3514.69.1.153>
- Feldman, L. A. (1995b). Variations in the circumplex structure of mood. *Personality and Social Psychology Bulletin*, 21, 806–817. <https://doi.org/10.1177/0146167295218003>
- Fisher, A. J. (2015). Toward a dynamic model of psychological assessment: Implications for personalized care. *Journal of Consulting and Clinical Psychology*, 83, 825–836. <https://doi.org/10.1037/ccp0000026>
- Fried, E. I., van Borkulo, C. D., Epskamp, S., Schoevers, R. A., Tuerlinckx, F., & Borsboom, D. (2016). Measuring depression over time ... or not? Lack of unidimensionality and longitudinal measurement invariance in four common rating scales of depression. *Psychological Assessment*, 28, 1354–1367. <https://doi.org/10.1037/pas0000275>
- Heller, W., & Nitsche, J. B. (1998). The puzzle of regional brain activity in depression and anxiety: The importance of subtypes and comorbidity. *Cognition and Emotion*, 12, 421–447.
- Henry, J. D., & Crawford, J. R. (2005). The short-form version of the Depression Anxiety Stress Scales (DASS-21): Construct validity and normative data in a large non-clinical sample. *British Journal of Clinical Psychology*, 44, 227–239. <https://doi.org/10.1348/014466505X29657>
- Irwin, D. E., Stucky, B. D., Langer, M. M., Thissen, D., DeWitt, E. M., Lai, J. S., ... DeWalt, D. A. (2010). An item response analysis of the pediatric PROMIS anxiety and depressive symptoms scales. *Quality of Life Research*, 19, 595–607. <https://doi.org/10.1007/s11136-010-9619-3>
- Jaycox, L. H., Stein, B. D., Paddock, S., Miles, J. N., Chandra, A., Meredith, L. S., ... Burnam, M. A. (2009). Impact of teen depression on academic, social, and physical functioning. *Pediatrics*, 124, 596–605.
- Kemp, A., & Felmingham, K. (2008). The psychology and neuroscience of depression and anxiety: Towards an integrative model of emotion disorders. *Psychology & Neuroscience*, 1, 177–181. <https://doi.org/10.3922/j.psns.2008.2.010>
- Kring, A. M., Feldman-Barrett, L., & Gard, D. E. (2003). On the broad applicability of the affective circumplex. *Psychological Science*, 14, 207–214. <https://doi.org/10.1111/1467-9280.02433>
- Liu, Y., Wang, J., Hinds, P. S., Wang, J., Shen, N., Zhao, X., ... Yuan, C. (2015). The emotional distress of children with cancer in China: An item response analysis of C-Ped-PROMIS anxiety and depression short forms. *Quality of Life Research*, 24, 1491–1501. <https://doi.org/10.1007/s11136-014-0870-x>
- Lorr, M., Shi, A. Q., & Youniss, R. P. (1989). A bipolar multifactor conception of mood states. *Personality and Individual Differences*, 10, 155–159. [https://doi.org/10.1016/0191-8869\(89\)90199-2](https://doi.org/10.1016/0191-8869(89)90199-2)
- Pilkonis, P. A., Choi, S. W., Reise, S. P., Stover, A. M., Riley, W. T., & Cella, D. (2011). Item banks for measuring emotional distress from the Patient-Reported Outcomes Measurement Information System (PROMIS®): Depression, anxiety, and anger. *Assessment*, 18, 263–283. <https://doi.org/10.1177/1073191111411667>
- Plummer, M. (2015). JAGS version 4.0. User manual. Retrieved from <http://www.uvm.edu/~bbeckage/Teaching/DataAnalysis/Manuals/manual.jags.pdf>
- R Core Team (2017). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing, Vienna, Austria. <https://www.R-project.org/>
- Rubin, D. C., & Talarico, J. M. (2009). A comparison of dimensional models of emotion. *Memory*, 17, 802–808. <https://doi.org/10.1080/09658210903130764>
- Russell, J. A. (1980). A circumplex model of affect. *Journal of Personality and Social Psychology*, 39, 1161–1178. <https://doi.org/10.1037/h0077714>
- Russell, J. A., Lewicka, M., & Niit, T. (1989). A cross-cultural study of a circumplex model of affect. *Journal of Personality and Social Psychology*, 57, 848–856. <https://doi.org/10.1037/0022-3514.57.5.848>
- Ryttilä-Manninen, M., Frojd, S., Haravuori, H., Lindberg, N., Marttunen, M., Kettunen, K., & Therman, S. (2016). Psychometric properties of the Symptom Checklist-90 in adolescent psychiatric inpatients and age- and gender-matched community youth. *Child and Adolescent Psychiatry and Mental Health*, 10(23), 23. <https://doi.org/10.1186/s13034-016-0111-x>
- Schlosberg, H. (1952). The description of facial expression in terms of two dimensions. *Journal of Experimental Psychology*, 44, 229–237. <https://doi.org/10.1037/h0055778>
- Sieger, T., Serranová, T., Ruzicka, F., Vostatek, P., Wild, J., Štastná, D., ... Jech, R. (2015). Distinct populations of neurons respond to emotional valence and arousal in the human subthalamic nucleus. *Proceedings of the National Academy of Sciences of the United States of America*, 112(10), 3116–3121. <https://doi.org/10.1073/pnas.1410709112>
- Simms, L. J., Grös, D. F., Watson, D., & O'Hara, M. W. (2008). Parsing the general and specific components of depression and anxiety with bifactor modeling. *Depression and Anxiety*, 25, 34–46.
- Spiegelhalter, D., Best, N., Carlin, B., & van der Linde, A. (2002). Bayesian measures of model complexity and fit. *Journal of the Royal Statistical Society*, 64, 583–639. <https://doi.org/10.1111/1467-9868.00353>
- Stucky, B. D., & Edelen, M. O. (2014). Using hierarchical IRT models to create unidimensional measures from multidimensional data. In S. P. Reise, & D. A. Revicki (Eds.), *Handbook of item response theory modeling: Applications to typical performance assessment*. Multivariate applications series. (pp. 183–206). New York, NY, US: Routledge/Taylor & Francis Group.
- Su, Y. S., & Yajima, M. (2012). R2jags: A package for running jags from R. R package version 0.03–08. Available from: <http://CRAN.R-project.org/package=R2jags>.
- Vytal, K., & Hamann, S. (2010). Neuroimaging support for discrete neural correlates of basic emotions: A voxel-based meta-analysis. *Journal of Cognitive Neuroscience*, 22, 2864–2885. <https://doi.org/10.1162/jocn.2009.21366>
- Watson, D., Clark, L. A., Weber, K., Assenheimer, J. S., Strauss, M. E., & McCormick, R. A. (1995). Testing a tripartite model: II. Exploring the symptom structure of anxiety and depression in student, adult, and patient samples. *Journal of Abnormal Psychology*, 104, 15–25. <https://doi.org/10.1037/0021-843X.104.1.15>
- Watson, D., Weber, K., Assenheimer, J. S., Clark, L. A., Strauss, M. E., & McCormick, R. A. (1995). Testing a tripartite model: I. Evaluating the convergent and discriminant validity of anxiety and depression symptom scales. *Journal of Abnormal Psychology*, 104, 3–14. <https://doi.org/10.1037/0021-843X.104.1.3>
- WHO. WHO statistics (2016). Available at: <http://www.who.int/mediacentre/news/releases/2016/depression-anxiety-treatment/en.2016>.
- Wirth, R. J., & Edwards, M. C. (2007). Item factor analysis: Current approaches and future directions. *Psychological Methods*, 12, 58–79. <https://doi.org/10.1037/1082-989X.12.1.58>

SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

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