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Reexamining the Circumplex Model of Affect

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The circumplex model of affect has been among the most widely studied representations of affect. Despite the considerable evidence cited in support of it, methods typically used to evaluate the model have substantial limitations. In this article, the authors attempt to correct past limitations by using a covariance structure model specifically designed to assess circumplex structure. This model was fit to 47 individual correlation matrices from published data sets. Analyses revealed that model fit was typically acceptable and that opposing affective states usually demonstrated strong negative correlations with one another. However, analyses also indicated substantial variability in both model fit and correlations among opposing affective states and suggested several characteristics of studies that partially accounted for this variability. Detailed examination of the locations of affective states for 10 of the correlation matrices with relatively optimal characteristics provided mixed support for the model.

At least since the pioneering work of Wundt (1912/1924), psychologists have been interested in exploring the underlying structure of affective experience (see Reisenzein, 1992). Of the various models to emerge over the years, one of the best known and most widely studied has been the circumplex model of affect (for reviews, see Larsen & Diener, 1992; Plutchik & Conte, 1997). The circumplex model of affect was originally proposed by Schlosberg (1941, 1952) and subsequently most extensively elaborated upon by Russell (1980). This model postulates that the underlying structure of affective experience can be characterized as an ordering of affective states on the circumference of a circle (see Figure 1). The similarity between any two affective states is presumed to be a function of their distance from one another on the perimeter of the circle with the dissimilarity between any two states increasing as the distance between them on the circle increases. More formally stated, the model implies that affective states should have decreasing positive correlations with one another as their separation from one another approaches 90°. At 90° separation, two affective states should be uncorrelated with one another. As the separation approaches 180°, affective states should have increasing negative correlations with one another.

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Most advocates of the circumplex model of affect also explicitly postulate two orthogonal psychological dimensions underlying this circular ordering. Some researchers (e.g., Russell, 1980; Larsen & Diener, 1992) have postulated an evaluation dimension and an arousal dimension (see solid arrows of Figure 1). Thus, this conceptualization postulates that the underlying dimensions of affective states are similar to two of the three dimensions of connotative meaning (i.e., evaluation and activity) found to underlie language more generally (Osgood, Suci, & Tannenbaum, 1957). Other researchers (e.g., Watson & Tellegen, 1985) have postulated a different set of dimensions rotated 45° from the hypothesized evaluation and arousal dimensions (see broken arrows of Figure 1). They have labeled these dimensions positive affect (i.e., high activation positive affect vs. low activation negative affect) and negative affect (i.e., high activation negative affect vs. low activation positive affect). Still others have offered somewhat different conceptualizations of the dimensions underlying affective states (e.g., Diener, Larsen, Levine, & Emmons, 1985; Thayer, 1989).

Substantial evidence has accumulated that is consistent with this model of affect. Principal-components analyses of self-reported affect and multidimensional-scaling analyses of similarity judgments of affective states have suggested that affective states form a circular pattern in two-dimensional space (e.g., Block, 1957; Bush, 1973; Feldman, 1995a, 1995b; Feldman Barrett & Russell, 1998; Howarth & Young, 1986; Meyer & Shack, 1989; Russell, 1978, 1980; Russell & Mehrabian, 1977; Russell & Pratt, 1980; Russell & Steiger, 1982; Rusting & Larsen, 1995; Watson & Tellegen, 1985; Zevon & Tellegen, 1982). Analyses of judgments of facial expressions of emotion have also suggested a circular structure (e.g., Abelson & Sermat, 1962; Cliff & Young, 1968; Dittmann, 1972; Fillenbaum & Rapoport, 1971; R. S. Green & Cliff, 1975; Shepard, 1962). Additionally, circular patterns generalize to children (Bullock & Russell, 1984, 1985; Russell & Bullock, 1985; Russell & Ridgeway, 1983) and to adults outside the North American cultural context (Almagor & Ben-Porath,

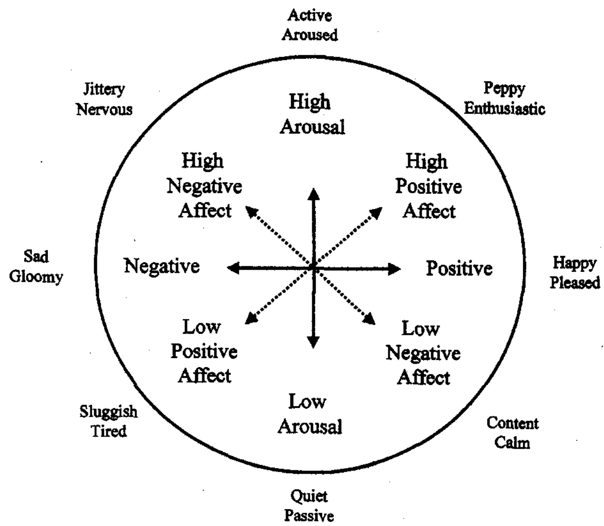

Figure 1. Circumplex model of affect. From "Promises and Problems With the Circumplex Model of Emotion," by R. J. Larson and E. Diener, in M. S. Clark (Ed.), 1992, *Review of Personality and Social Psychology: Emotion* (Vol. 13, p. 31), Newbury Park, CA: Sage. Copyright 1992 by Sage. Adapted with permission. From "A Circumplex Model of Affect," by J. A. Russell, 1980, *Journal of Personality and Social Psychology, 39,* p. 1164. Copyright 1980 by the American Psychological Association. Adapted by permission of the author. From "Toward a Consensual Structure of Mood," by D. Watson and A. Tellegen, 1985, *Psychological Bulletin, 98,* p. 221. Copyright 1985 by the American Psychological Association. Adapted by permission of the authors.

1989; Russell, 1983, 1991; Russell, Lewicka, & Niit, 1989; Sjoberg, Svensson, & Persson, 1979; Watson, Clark, & Tellegen, 1984).

Evaluating the Circumplex Model of Affect

As with any theory, limitations of the model have been noted. Some have criticized it on the basis of the argument that a two-dimensional representation fails to capture important aspects of emotional experience and therefore sometimes does not reflect crucial differences among some emotions. For instance, fear and anger are both negative-high-arousal emotions that are located in the same region of the circle yet these emotions are quite different from one another (see Larsen & Diener, 1992). Others have noted that different versions of the model sometimes postulate different locations for affective states and that empirically affective states are not always located in their predicted regions of the circle (see Watson, Wiese, Vaidya, & Tellegen, 1999). Still others have noted that the model was formulated on the basis of a selection of emotions that was not guided by systematic sampling or clear theoretical guidelines (Morgan & Heise, 1988).

Despite these and other limitations, the model has achieved broad acceptance as a useful representation of affect (see Larsen & Diener, 1992; Plutchik & Conte, 1997). However, consideration of the statistical methods by which circumplex structure has been assessed suggests that the data may not be as compelling as is believed. Typically, researchers have tested the model in one of two ways (see Fabrigar, Visser, & Browne, 1997). One approach has been to extract a set of factors or principal components from a correlation matrix of self-reported affect and then to construct a graphical representation of the solution by plotting each state in two-dimensional space with the factor loadings serving as coordinates. This representation is examined to determine if it produces a circular pattern. A second approach is the use of multidimensional scaling analysis (MDS) on similarity ratings among affective states or facial expressions of emotion. A two-dimensional plot of the locations of the states or expressions is constructed and the representation is examined to determine if it forms a circular pattern.

Fabrigar et al. (1997) noted that these approaches have serious limitations. Most notably, neither analysis provides a quantifiable method for assessing the circumplex structure of data. Both rely on a purely subjective judgment as to the extent of similarity between the obtained graphical representation and the hypothesized circular pattern. Obviously, these representations almost never perfectly match predictions, thereby making it difficult to reach clear conclusions about the structure of the data. Also, even if a circular pattern is found, affective states may not be located as expected. Once again, a purely subjective judgment as to the seriousness of these discrepancies must be made.

Importantly, model fit indices available in factor analysis and in MDS do not provide an index of circumplex structure (see Fabrigar et al., 1997). For instance, if more than two factors are extracted, as is frequently done, the model being fit in no way directly corresponds to a circumplex representation. This problem is not alleviated by using two-factor models. It has been shown that a two-factor model can fit the data poorly even when the data are circumplex (Browne, 1992; Fabrigar et al., 1997).[1] Likewise, fit measures in MDS are not informative, because they only assess the fit of a two-dimensional solution. No restriction is placed on the solution that affective states must be located along the perimeter of a circle. Therefore, fit could be excellent even when data are not circumplex.

Covariance Structure Modeling Tests of the Circumplex Model of Affect

Although traditional approaches to testing the model have serious limitations, developments in quantitative methodology have provided more precise methods of assessing circumplex structure. Perhaps the most promising of these methods is the circular stochastic process model with a Fourier series (CSPMF; Browne, 1992; see also Fabrigar et al., 1997). This approach is a nonstandard type of covariance structure model designed to assess circumplex structure. Like other covariance structure models, the CSPMF assumes that variance in people's responses can be divided into the common score variance and the unique score variance. However, unlike these traditional models, this model assumes that common

[1] Browne (1992) has found that a two-factor model corresponds to a very restricted form of circumplex structure. Thus, this model can fit quite poorly even when the data have circumplex structure (for more detailed discussion of these issues, see Browne, 1992; Fabrigar et al., 1997). In virtually all uses of principal-components/factor analysis to test the circumplex model of affect, researchers have not reported indices of model fit. Thus, it is impossible to know if these two factor models fit the data well. Given the highly restrictive form of circumplex structure tested by the two-factor model, it seems unlikely that the fit of the models was particularly good.

scores on variables (e.g., affective states) can be represented as points on the circumference of a circle, with one common score variable serving as the reference point and the other common score variables' locations being specified as polar angles from this reference variable. The model explicitly postulates that the correlation between any two common score variables should be a function of the angle of separation (i.e., the distance) between the common score variables located on the circle.

The CSPMF can be fit to data using standard covariance structure modeling parameter estimation methods to obtain information about the structure of the data. Indices of model fit can be computed, and because the CSPMF directly corresponds to the assumptions implied by a circumplex representation, the fit of the model provides a direct assessment of circumplex structure. The model also provides estimates (in the form of polar angles) and confidence intervals for the location of the common score variables on the circle. Estimates and confidence intervals for the communalities of the measured variables can also be obtained. The model also provides an estimate of the minimum common score correlation (MCSC; i.e., the correlation between common score variables that are 180° apart from one another on the circle). Finally, it provides an estimate of the mathematical relationship between distances on the circle and correlations among common scores (i.e., the correlation function).

Because of its relatively recent origin, there are only a few reported applications of the CSPMF to testing the circumplex model of affect. These applications have produced conflicting findings and detailed reports of results have generally been lacking. In a methodological article, Fabrigar et al. (1997) used affect data collected by Russell and Pratt (1980) to illustrate the use of the CSPMF. They found that the fit of the model was acceptable and that, as predicted, states at opposite sides of the circle had strong negative associations ($r = -.86$). They also found that the locations of all but one of the affective states were consistent with theoretical expectations. Watson et al. (1999) reported analyses of three data sets using the CSPMF. They found that model fit ranged from marginal to poor and that the locations of affective states were often discrepant with predictions. Confidence intervals for locations and correlations of opposing affective states were not reported. Yik, Russell, and Feldman Barrett (1999) reported analyses of two data sets. These analyses produced poor model fit and locations for affective states that were often, but not always, consistent with theoretical expectations. Confidence intervals and correlations between opposing affective states were not reported. Finally, Russell and Carroll (1999) used the CSPMF to obtain estimates of the locations of affective states and then used these locations to calculate the relation between distance on the circle and correlations between affective states (see also Carroll, Yik, Russell, & Feldman Barrett, 1999). They found that increased distance was associated with stronger negative correlations. However, detailed results of the CSPMF analyses were not reported.

Goals and Overview of the Present Research

When viewed in its entirety, the literature on the circumplex model of affect is somewhat ambiguous. Most past investigations have used statistical methods that do not provide clear tests of the model, and more refined tests have produced contradictory evidence.[2] The goal of the present research is to use the CSPMF to conduct a more precise, detailed, and comprehensive assessment of the model than has previously been attempted. Our first objective is to gauge the degree to which a circumplex representation provides a plausible characterization of the structure of affect. We do so by examining the fit of the CSPMF to 47 correlation matrices derived from self-reports of affective states. We also examine the degree to which the CSPMF indicates that affective states at opposing sides of the circle are negatively related to one another. Thus, unlike previous investigations, we assess how well the model performs over a large number of data sets that are relatively heterogeneous in their characteristics.

Our second objective is to assess the variability of the fit of the model and correlations among opposing affective states across data sets and to identify factors that contribute to this variability. We investigate three properties of measures that previous research suggests might influence the structure of self-reported affect. One such factor is the time frame specified in self-reports. In some studies participants have been asked to report their current affect, whereas in other studies they have been asked to report their affect over an extended period of time. A number of researchers have investigated the possibility that the bipolarity of positive and negative affect might be influenced by the time frame of judgments (e.g., Diener & Emmons, 1984; Diener & Iran-Nejad, 1986; Watson, 1988). We also explore the nature of the judgment specified in the self-report items. Self-reports of affect sometimes require respondents to report the intensity of their experience, whereas in other cases questionnaires require reports of the frequency of experiencing affective states. Research has suggested that intensity and frequency are separable components and that asking respondents to report one or the other can influence the structure of self-reported affect (e.g., see Diener et al., 1985; Watson, 1988; Schimmack & Diener, 1997). Additionally, we investigate how the use of multiple-item versus single-item measures of affective states influences the performance of the model. Numerous researchers have noted that the use of multi- versus single-item measures can influence both systematic and random error in measures and that this in turn can influence correlations among affective states (e.g., D. P. Green, Goldman, & Salovey, 1993; D. P. Green, Salovey, & Truax, 1999; Russell & Carroll, 1999).

We also explore two features of the affective states included in these data sets that might influence performance of the model. One feature is the extent to which the affective states sampled fully capture all regions of the circle or merely a subset of the regions. Researchers have suggested that the conclusions reached about the structure of affect can be influenced by the regions of the circle that have been sampled (e.g., Feldman Barrett & Russell, 1998; Russell & Carroll, 1999). A second feature that we examine is the extent to which data sets include terms that are ambiguous with respect to whether they comprise affective states. Obviously, if researchers include terms that do not belong within the domain of

[2] In their review of different methods of testing circumplex structure, Fabrigar et al. (1997) noted several analytical approaches to testing circumplex structure that have sometimes been used in addition to principal-components/factor analysis and multidimensional scaling. However, they also noted that the other approaches have many of the same limitations as more common approaches as well as some unique limitations. Use of these alternative approaches is also comparatively rare.

interest, the obtained structure of affective states is likely to be distorted.

Our third objective is to report a detailed assessment of the locations of affective states. When conditions exist that suggest that the model is not appropriate, one would not necessarily expect locations of affective states to be consistent with theory. However, under more optimal conditions, one would expect affective states to order themselves as predicted by theory. Thus, we examine the locations of affective states by focussing on a subset of matrices that our more comprehensive analyses suggest possess relatively optimal characteristics. We provide detailed reports of analyses of these matrices.

Comprehensive Analysis of Correlation Matrices

In our first set of analyses, we were interested in addressing three fundamental questions. First, is the circumplex model of affect a plausible description of the structure of affective experience across data sets involving ratings of a wide array of affective states drawn from a wide range of different samples? Second, what is the relationship between affective states at opposite sides of the circle across this wide array of data sets? Third, how do model fit and the MCSC vary as a function of characteristics of measures and affective states? To address these issues, we conducted comprehensive analyses of a large number of correlation matrices drawn from previously published data sets.

Method

Selection of data sets. We began the data set selection process by conducting a computer-based literature search of articles reporting tests of the circumplex model of affect. After locating these articles, we then examined their reference sections to find additional articles that reported tests of the structure of affect. These additional articles included both explicit tests of the circumplex structure of affect and tests of the structure of affect in which circumplex representations were not specifically examined. Once a final list was compiled, we examined each article to determine if it met two selection criteria: (a) the article reported data that was based on participants' self-reported affective experiences (as opposed to participants' judgments of the similarity of affective states or facial expressions of emotion) and (b) the article included ratings of multiple affective states (as opposed to ratings of only two or three affective states). The first selection criterion was necessary because the CSPMF is a covariance structure model and therefore is designed to be fit to a correlation (covariance) matrix of variables rather than matrices of similarity ratings between objects. The second selection criterion was necessary because a correlation matrix must have at least six variables for the CSPMF to be a falsifiable model. There were 78 correlation matrices from 32 articles that we identified as meeting the selection criteria.

Next, we attempted to obtain the identified correlation matrices. A total of 14 correlation matrices were reported in 6 of the 32 articles. One of these matrices (Block, 1957) was later found to be unanalyzable and thus was not included in the analyses reported in this article.[3] The authors of the remaining 26 articles were mailed requests for either the raw data or the correlation matrix (or matrices) examined in their articles. Authors were sent a reminder letter approximately 1 month after the initial request. Ultimately, a total of 34 correlation matrices from 9 journal articles were provided. Thus, our analyses were based on 47 correlation matrices drawn from 14 articles (Borgatta, 1961; Diener, Smith, & Fujita, 1995; Feldman, 1995b; Feldman Barrett, 1996; D. P. Green et al., 1993; Howarth & Young, 1986; Kercher, 1992; Mayer & Gaschke, 1988; Mayer, Mamberg, & Volanth, 1988; Russell & Mehrabian, 1977; Russell & Pratt, 1980; Rusting & Larsen, 1995; Sjoberg et al., 1979; Watson, 1988).

Analysis of individual correlation matrices. The circumplex model of affect was initially tested by fitting the CSPMF to each matrix using the program CIRCUM (see Browne, 1992; Fabrigar et al., 1997).[4] Maximum likelihood estimation was used to fit the model. To fit the CSPMF, it was necessary to specify one variable as the reference variable in the model. The location of this variable is fixed at 0°, and the locations of all other variables are estimated in the form of polar angles from this reference variable. Importantly, selection of the reference variable is essentially arbitrary in that it does not influence model fit, the ordering of variables on the circle, or the distances between variables on the circle. Choosing the reference variable simply determines the reference point on the circle. Because of the variability in affective states included in data sets, no single affective state could be selected as the reference variable for all matrices, so reference variables were arbitrarily selected.

Fitting the CSPMF also requires a researcher to specify how many free parameters will be included in the correlation function. The correlation function is the mathematical relationship between the distance of common score variables on the circle and the correlation among common score variables. There is virtually an infinite number of correlation functions that might be used to define this relationship. However, the CSPMF sets logical restrictions to ensure that the resulting function will be conceptually compatible with a circumplex representation. The CSPMF allows for determining which of this family of conceptually sensible functions best fits the data. The greater the number of free parameters specified in the function, the wider the range of possible functions that can be fit to the data.

Because circumplex theories of affect do not make precise predictions regarding shape of the correlation function, and because the CSPMF requires that the function be conceptually compatible with a circular representation, there are few, if any, theoretical implications to the exact shape of the correlation function. Thus, in our analyses, we empirically determined the optimal correlation function by fitting a series of models with differing numbers of free parameters in the correlation function. We selected the model with the number of free parameters in the correlation function that produced the best fit while not resulting in serious parameter estimation problems (see Browne, 1992; Fabrigar et al., 1997).

Classification of matrices. One primary goal of these analyses was to determine if study characteristics influenced the extent to which self-reported affect possessed circumplex structure and the magnitude of associations between opposing affective states. Thus, matrices were classified according to five characteristics. One characteristic was whether the correlation matrix was based on state judgments or trait judgments (i.e., the time frame of judgments). In some cases, participants were asked to report if they were currently experiencing various affective states (state judgments), whereas in other cases they were asked to report their past affective experiences over an extended period of time such as a week or a month

[3] Analyses of the correlation matrix reported in Block (1957) using the program CIRCUM (see Browne, 1992) failed to converge on a final set of parameter estimates. It is difficult to know for certain why this was the case. One possibility is that there may have been one or more errors in the matrix reported in the article. Such errors can sometimes result in difficulties in parameter estimation for covariance structure models. Additionally, it is possible that the matrix may have been based on pairwise (rather than listwise) deletion of missing data, which can also present problems for fitting covariance structure models to data. This correlation matrix was the only matrix for which we were unable to fit the CSPMF.

[4] The correlation matrices varied in size from 6 to 64 affective states. The current version of CIRCUM, however, does not allow for analysis of correlation matrices larger than 50 variables. Of the 47 correlation matrices, 13 contained more than 50 affective states. In these cases, lists of the variable names across the 13 data sets were compiled. Affective states that were unique to only one data set were eliminated. This allowed us to reduce these matrices to 50 variables or less so that they could be analyzed.

(trait judgments). Obviously, this distinction is somewhat blurry in that there is an infinite range of possible time frames that might be specified. We classified judgments of how participants were feeling that day or in a shorter time frame as state judgments and time frames longer than the current day as trait judgments. Of the 47 matrices, 30 involved state judgments and 17 involved trait judgments.

We also classified matrices according to whether they were based on frequency or intensity judgments. In some studies, participants reported the frequency with which they experienced affective states (e.g., "How *often* have you experienced feeling happy?"). Other times, participants reported the intensity of their experience of affective states (e.g., "To what extent do you feel happy?"). Of the 47 correlation matrices, 11 involved frequency judgments and 36 involved intensity judgments.

A third characteristic examined was whether the variables in the matrix were based on single-item or multiple-item measures. Respondents sometimes completed a single measure for each affective state, and scores on these individual items were the basis for the correlation matrix. In other cases, respondents completed multiple measures for each affective state that were combined to form a single score for that affective state. A correlation matrix was then based on the aggregate scores. Of the 47 matrices, 34 were based on single-item measures and 13 were based on multiple-item measures.

The fourth characteristic was the extent to which a matrix contained ambiguous terms. Some matrices included terms for which there was consensus that these terms constituted affective states relevant to the circumplex model, whereas other matrices included terms that were not clearly affective states and/or for which clear predictions had not been made. We coded the proportion of ambiguous terms in each matrix. A term was judged ambiguous if it had not been explicitly included in one of three affect circumplex formulations that we used for coding purposes (i.e., Larsen & Diener, 1992; Russell, 1980; Watson & Tellegen, 1985) and if it was not a synonym (as determined by a thesaurus) of a term included in one of these formulations. Thus, scores for matrices had a possible range of .00 to 1.00. For later comparisons, we also assigned matrices to high, medium, and low ambiguity categories. Because there was no conceptual rationale for precise values for inclusion in these categories, we used criteria to produce relatively equal sized groups of matrices. High ambiguity matrices (a total of 16) included matrices with scores of .29 or more. Medium ambiguity matrices (a total of 15) included matrices with scores from .19 to .28. Low ambiguity matrices (a total of 16) were matrices with scores of .18 or less.[5]

Correlation matrices were also coded for how completely they sampled affective states. In considering Figure 1, it is possible to think of the affect circle as consisting of eight conceptual regions (i.e., octants). One factor that might influence results is how adequately a matrix reflects the regions of the circle. Thus, matrices were coded for how many regions of the circle were represented. A matrix was judged as representing a region if at least one affective state belonging to that region was included in the matrix. We based our assignment of affective states to regions on three theoretical formulations (i.e., Larsen & Diener, 1992; Russell, 1980; Watson & Tellegen, 1985). When these perspectives differed on the location of an affective state, we used the location favored in two of the three formulations. If a term had never been explicitly assigned a region but was a synonym (as determined by a thesaurus) of a term that had been assigned a region, the new term was placed in the same region as its synonym. Ambiguous terms were not counted as representing any region. Thus, each matrix could receive a score ranging from 0 to 8. For later comparisons, we assigned matrices to high, medium, and low representation categories. High representation matrices (a total of 11) were those that included all eight regions. Medium representation matrices (a total of 24) were those that included at least half the regions (i.e., four) but not all of the regions. Low representation matrices (a total of 12) included less than half of the regions.[6]

Results

Analysis of all matrices. Because numerous matrices were examined, space constraints preclude a detailed description of the results for each matrix. Thus, we concentrate on two pieces of information from the analyses: model fit and the MCSC. Model fit can be assessed using a variety of indices. We assessed fit using the root mean squared error of approximation (RMSEA). RMSEA has been recommended by Browne and Cudeck (1992) because it is sensitive to model parsimony and is relatively insensitive to sample size. Additionally, evaluations of fit indices suggest it is one of the most effective in detecting misspecifications in complex models (Hu & Bentler, 1998). Browne and Cudeck suggested that RMSEA values of .050 or less constitute good fit, values of .051 to .080 constitute acceptable fit, values of .081 to .100 constitute marginal fit, and values greater than .100 constitute poor fit (see also MacCallum, Browne, & Sugawara, 1996).[7] The adequacy of the circumplex model of affect was also assessed by examining the estimate of the correlation between affective states that are 180° apart from one another on the circle (i.e., MCSC). The MCSC is the correlation among common score variables and, as such, has been corrected for random error. Circumplex theories have generally postulated that opposing affective states should have strong negative correlations (see Feldman Barrett & Russell, 1998).

[5] Because this procedure involved some measure of judgment on the part of the coder, we later had a second rater code each matrix for item ambiguity using the same procedure. The correlation in the scores across the two coders indicated that the coding procedure had high reliability ($r = .98$).

[6] As with the coding of ambiguity, we later had a second rater code how many regions of the circle were represented in each matrix. The correlations between coders of assignment of affective states to regions of the circle indicated high reliability (correlations ranged from .91 to .99). Additionally, it is worth noting that for exploratory purposes, a number of other features of data sets were also coded, including nature of the sample (e.g., student vs. nonstudent, North American vs. non-North American, male vs. female), whether a reference object was used in affective judgments (e.g., did participants rate how a reference object made them feel), and whether the affective states being evaluated were actual or desired. Unfortunately, for these characteristics, there was little variance across the data sets, thus precluding any meaningful analyses of the impact of these characteristics.

[7] In many articles reporting covariance structure modeling analyses, it is common to report the results of numerous model fit indices. On the other hand, we focus our analyses on a single index of model fit: RMSEA. We do so for several reasons. First, evaluations of model fit indices have demonstrated that there is substantial variability in the quality of performance of different fit indices. RMSEA has been found to be one of the most effective indices for detecting misspecifications in complex models (e.g., Hu & Bentler, 1998). Second, RMSEA provides a strong adjustment for model parsimony, whereas many of these other indices do not. This property is particularly pertinent in our analyses in which we are often comparing models that differ substantially in parsimony. Third, RMSEA is an absolute fit index and thus does not require the specification of a baseline model to serve as a comparison point. Therefore, this fit index avoids the conceptual ambiguity of determining what the most meaningful baseline model for comparison should be. Finally, guidelines for interpreting RMSEA have been well developed such that a range of values corresponding to different levels of fit have been established. For most other fit indices, guidelines have not been developed beyond simple dichotomous good or bad categories. Such dichotomous guidelines are overly simplistic

Analyses revealed substantial variation across data sets with regard to goodness of fit. Of the 47 correlation matrices, 9 had good model fit, 20 had acceptable model fit, 7 had marginal model fit, and 11 had poor model fit. RMSEA ranged from .000 to .242. The median fit was .073, which puts the fit of the model into the acceptable fit category. MCSC values also ranged greatly (i.e., from −1.00 to .266) across data sets. Despite the range, we found that almost all of the MCSC values were negative. In fact, the median MCSC of −.658 indicated a strong negative relationship between opposing affective states.

Impact of study characteristics on the structure of affect. Although a circumplex model generally provided acceptable fit and indicated a strong negative relationship between opposing affective states, there was substantial variance in both RMSEAs and MCSCs. To explore why this might have been the case, comparisons of RMSEA and MCSC across categories of study characteristics were made using two descriptive statistics. First, we compared the median values of RMSEA and MCSC across categories. One strength of using the median is that this value is relatively insensitive to the existence of outliers. However, one drawback is that this index does not allow us to isolate the effects of single study characteristic on RMSEA and MCSC. That is, because some study characteristics might be confounded (i.e., correlated) with one another across data sets, it is possible that some differences across levels of a particular study characteristic could be spurious. Therefore, we also compared the adjusted means for RMSEA and MCSC across categories. These adjusted means reflect differences across categories after having statistically partialed out the effects of the four other study characteristics. Additionally, because comparisons were sometimes confounded with model complexity and the size of the correlation matrices analyzed, comparisons also controlled for degrees of freedom in the model. To the extent that both types of comparisons provide results that are consistent with one another, one can be more confident in the conclusions drawn.

Table 1 provides the results for comparisons of state versus trait judgments. The first two columns of Row 1 indicate that although model fit was acceptable in both categories, there was a very weak tendency for fit to be better for state than trait judgments. This same pattern was more strongly evident for the adjusted means. When people were asked to make state judgments, model fit was acceptable. In contrast, when people made trait judgments, model fit was poor. Row 2 of Table 1 indicates that time frame was also related to the MCSC. For both medians and adjusted means, opposing affective states had stronger negative correlations for state judgments than for trait judgments.

Table 2 provides comparisons of medians and adjusted means for frequency versus intensity judgments. Row 1 of Table 2 shows that results were inconsistent across our two comparisons. The medians indicated a very slight tendency toward better model fit for frequency judgments than intensity judgments. However, a stronger difference in the opposite direction was obtained for the adjusted means. For MCSC, Row 2 of Table 2 shows that the medians indicated stronger negative correlations for intensity judgments than frequency judgments. However, this difference largely disappeared in the comparison of adjusted means. One explanation for this reduction is that the distinctions between state versus trait judgments and frequency versus intensity judgments were somewhat confounded. That is, state judgments almost always also involved intensity judgments, whereas trait judgments tended to also involve frequency judgments. The fact that the impact of time frame on MCSC was reduced less by controlling for frequency or intensity than the impact of frequency or intensity on MCSC was reduced by controlling for time frame suggests that time frame had the stronger influence on MCSCs. Nonetheless, a weak difference across frequency and intensity judgments did remain.

Table 1
Median and Adjusted Mean Root Mean Squared Error of Approximation (RMSEA) and Minimum Common Score Correlation (MCSC) as a Function of Time Frame of Judgment

	Median		Adjusted mean	
Measure	State	Trait	State	Trait
RMSEA	.072	.075	.078	.104
MCSC	−.764	−.393	−.641	−.453

Note. State and trait refer to time frame of judgment.

Table 3 presents the comparisons across matrices based on single-item versus multiple-item measures. Row 1 of Table 3 shows that both the medians and adjusted means suggested model fit was better when measures were based on single items rather than multiple items. The medians in Row 2 also suggested that the MCSC was substantially larger for single-item data sets than for multiple-item data sets. However, this difference largely disappeared in the comparison of adjusted means.

Table 4 provides the comparisons for affective state ambiguity. The medians presented mixed evidence regarding model fit. Data sets with a high percentage of ambiguous variables had a marginal fit, whereas both the moderate and low ambiguity matrices had acceptable fit. However, there was a tendency for the moderate ambiguity data sets to have slightly better fit than the low ambiguity data sets. Comparisons of the adjusted means were more consistent with a clear tendency for model fit to become poorer as the proportion of ambiguous affective states increased. For the MCSC, the medians suggested that negative correlations among opposing affective states were stronger in the low ambiguity data sets than in the other two categories. However, this difference was weakened and reversed in the adjusted means.

Table 5 presents the comparisons for levels of variable sampling of the affect circle. Medians suggested a slight tendency for improved model fit as representation of regions of the circle increased. However, a stronger reverse effect occurred for the adjusted means. For the MCSCs, both medians and adjusted means indicated strong negative correlations when half or more of the

in that it is far more sensible to conceptualize fit on a continuum ranging from very poor to very good. Thus, when considering all these factors, RMSEA seems to be the fit index that best meets all the requirements of our analyses. Stated another way, it seems more defensible to base conclusions on one good index rather than on one good index and a variety of poor ones. Nonetheless, in our analyses, we did compute two other indices of model fit: Tucker-Lewis Index (Tucker & Lewis, 1973) and Bollen-89 Index (Bollen, 1989). In Footnote 8, we report how the results of these indices are similar to and different from the results for RMSEA.

Table 2
Median and Adjusted Mean Root Mean Squared Error of Approximation (RMSEA) and Minimum Common Score Correlation (MCSC) as a Function of Type of Judgment

	Median		Adjusted mean	
Measure	Frequency	Intensity	Frequency	Intensity
RMSEA	.072	.076	.098	.084
MCSC	−.402	−.761	−.501	−.599

Note. Frequency and intensity refer to type of judgment.

Table 4
Median and Adjusted Mean Root Mean Squared Error of Approximation (RMSEA) and Minimum Common Score Correlation (MCSC) as a Function of Affect State Ambiguity

	Median			Adjusted mean		
Measure	Low	Medium	High	Low	Medium	High
RMSEA	.080	.066	.097	.055	.096	.111
MCSC	−.766	−.467	−.431	−.549	−.588	−.591

Note. Low, medium, and high refer to level of ambiguity.

regions were represented and weak negative correlations when less than half the circle was represented.

Discussion

The circumplex model provided a reasonable representation of affect with the median RMSEA for the 47 matrices reaching the acceptable level. Consistent with theory, the median MCSC indicated a strong negative correlation between opposing affective states. However, there was substantial variation in RMSEA and MCSC. Several factors were identified that appeared to contribute to this variation.

Model fit. Comparisons indicated that model fit was better for data sets with variables based on single-item measures than data sets with variables based on multiple-item measures. This finding appears puzzling given that one might expect multiple-item measures to be more reliable and (to the extent different response scales are used) less distorted by systematic measurement error. However, it is important to remember that our analyses involved a latent variable model in which the circumplex structure of common score variables was assessed. Thus, these analyses examined the structure of variables after having removed random error. Therefore, the gains of higher reliability in measures were likely to have been modest. Additionally, when examining multiple-item data sets, we noted that such measures often did not include items with different response scales, thereby making it unlikely that these measures were less distorted by systematic measurement error than the single-item measures. Of course, neither of these points explains why multiple-item measures produced worse fit than single-item measures. One explanation might have been the fact that in many of these data sets, decisions to combine items were inappropriate. When we examined these data sets, we found that researchers often combined items assessing different affective states into a single measure. Some of these aggregate measures even involved combining affective states that would be predicted to fall in different regions of the circle (e.g., the combination of fearful, blue, and shocked). One might expect such errors to distort the circumplex structure of the data.

Comparisons provided more modest evidence suggesting that the time frame of judgments and the ambiguity of affective states had an impact on model fit. These results seem sensible. One implicit assumption in the circumplex model of affect is that the experience of one affective state will tend to be positively associated with the experience of other states close to it on the circle and negatively associated with the experience of states far from it on the circle. Such interdependence of states might exist because the experience of an affective state facilitates similar affective states and inhibits dissimilar affective states. Alternatively, interdependence might be observed because external factors triggering particular affective states are likely to trigger similar states and to not trigger, or perhaps suppress, dissimilar states. Both rationales for interdependence among affective states seem most relevant to current affective experience (see Diener & Emmons, 1984; Diener & Iran-Nejad, 1986). For example, because affective experiences are often transitory, it is reasonable that an affective state (e.g., happiness) might facilitate or inhibit other affective states at the time it is experienced, but it is less likely that this effect would continue over an extended time. Likewise, because external factors influencing affect often change over time, it is reasonable to expect interdependence among current affective states but less interdependence among affective states experienced over extended time

Table 3
Median and Adjusted Mean Root Mean Squared Error of Approximation (RMSEA) and Minimum Common Score Correlation (MCSC) as a Function of Single-Item Versus Multiple-Item Measures

	Median		Adjusted mean	
Measure	Single	Multiple	Single	Multiple
RMSEA	.073	.103	.082	.102
MCSC	−.705	−.437	−.596	−.525

Note. Single = single-item measure; multiple = multiple-item measure.

Table 5
Median and Adjusted Mean Root Mean Squared Error of Approximation (RMSEA) and Minimum Common Score Correlation (MCSC) as a Function of Regions of the Circle Sampled

	Median			Adjusted mean		
Measure	Low	Medium	High	Low	Medium	High
RMSEA	.084	.073	.068	.038	.094	.125
MCSC	−.351	−.754	−.763	−.302	−.686	−.656

Note. Low, medium, and high refer to the number of octants of the circle sampled.

frames. Given these facts, it is not surprising that there was some tendency for state judgments to show better circumplex structure than trait judgments.

The results for affective state ambiguity are also sensible. In reviewing variables that were coded as ambiguous, we noticed that it was not clear whether some of these items should have been considered affective states at all. For example, many of these variables appeared to be personality traits rather than affective states (e.g., dominant, sociable). To the extent that measures that did not belong in the domain of interest were included, the underlying structure of affective states might have been distorted.

One final issue regarding model fit that merits comment concerns the size of the effects we observed. These differences may appear to be of small magnitude. However, it is important to keep in mind the metric of RMSEA. The widths of the different categories of fit for RMSEA (e.g., acceptable, marginal) are in the .020 to .030 range. Thus, differences of this magnitude reflect substantial shifts in fit. The differences we observed for some study characteristics were often of this magnitude or greater. Additionally, the cumulative impact of these features is likely to be even greater. For example, if we consider the differences in marginal means as estimates of the unique impact of each of the three primary characteristics found to influence model fit, the cumulative effect would be .102 in model fit. Such a difference would be sufficient to move model fit from excellent (e.g., .030) to very poor (e.g., .132).[8]

Minimum common score correlations. We obtained consistent evidence that negative correlations among opposing affective states were stronger for short time frames than for long time frames. We obtained more modest evidence that the use of single- versus multiple-item measures might also influence MCSC. The reasons for both of these factors influencing MCSC are similar to those discussed with respect to model fit. We also identified two other factors related to the MCSC that were not related to model fit in a consistent fashion. Relatively strong evidence was obtained that the sampling of affective states influenced MCSC. When fewer than half the eight regions were represented in the matrix, very weak negative correlations were obtained. If half or more of the regions were sampled, large negative correlations were obtained. This finding is probably more statistical than substantive. Specifically, when less than half the regions are represented, a matrix might include affective states that are all on the same side of the circle. In such cases, it is likely to be difficult for parameter estimation procedures to extrapolate what the correlation should be for variables on opposite sides.

Why MCSCs varied as a function of type of judgment is less obvious. It is sensible that the intensity of experiencing affective states should have a strong negative relationship with the intensity of experiencing opposing affective states. However, it is also sensible to expect strong negative associations for frequency judgments of opposing affective states (e.g., a person who reports feeling frequently nervous is unlikely to report feeling frequently calm). Thus, our results seem somewhat curious. However, as we noted earlier, one explanation is that these differences may have been driven by the fact that these two types of judgments were confounded with time frame. Consistent with this explanation, the effect of frequency versus intensity judgments was greatly reduced when the impact of time frame was controlled for in the adjusted means. Nonetheless, a modest difference still remained.

Analyses of Optimal Correlation Matrices

In our first set of analyses, we concentrated on assessing the viability of the circumplex model of affect by examining the goodness of fit of the CSPMF and the CSPMF's estimate of the correlation among opposing affective states across a wide range of data sets. We concentrated on these pieces of information, because the many data sets being analyzed made it impractical to report detailed results for each data set. Although this information is relevant to evaluating the model, it is not the only important information. Past formulations of the model have also made specific predictions about the locations of particular affective states on the circle. Thus, to fully evaluate the model, it is necessary to examine how well the locations of affective states on the circle conform to theoretical expectations.

The purpose of this second set of analyses was to examine the locations of affective states. Because our first set of analyses indicated substantial variability in the performance of the model as a function of study characteristics, we knew that there were some matrices for which the model was an inadequate representation of the data. Thus, there seemed little point to examining the locations of affective states in these data sets. However, our earlier set of analyses also provided us with information about study characteristics that could be used to identify a subset of matrices that should provide relatively optimal conditions for the circumplex model of affect. These matrices should presumably provide the context in which one would be most likely to obtain meaningful estimates of the locations of affective states. Therefore, we chose to focus our attention on these optimal matrices.

Method

Selection of data sets. Earlier analyses indicated that the model was most appropriate when data were based on judgments involving short time frames (i.e., state judgments), judgments involving intensity of affect, single-item measures, sampling of affective states from all regions of the circle, and data sets including few ambiguous affective states. Thus, we identified those matrices that included all of these optimal conditions. There were 10 such matrices. These matrices included three matrices (Ns = 72, 120, and 312) from Feldman (1995b), one matrix (N = 275) from Feldman Barrett (1996), two matrices (Ns = 549 and 566) from Mayer and Gaschke (1988), three matrices (Ns = 202, 155, and 206) from Mayer et al. (1988), and one matrix (N = 232) from Rusting and Larsen (1995).

Analyses of matrices. Matrices were analyzed using the same basic procedure of fitting the CSPMF to each matrix. The major difference in

[8] Although we considered RMSEA to be the most optimal model fit index for the types of analyses we were conducting, we also examined the Tucker-Lewis Index (TLI) and Bollen-89 Index (BL89). These two indices have been found to be two of the better performing incremental model fit indices (see Hu & Bentler, 1998). Differences in these indices produced somewhat weaker effects (when the metrics of these indices are taken into account) than the results for RMSEA. However, the patterns of results were generally the same. These indices produced similar patterns to RMSEA for comparisons of medians as a function of time frame and multiple- versus single-item measures. The pattern of medians was somewhat less consistent for ambiguity. The patterns for marginal means were similar to RMSEA patterns for all three comparisons. In all comparisons of RMSEA, TLI, and BL89, no statistical tests were conducted. No tests were conducted because the distributions of these indices are unlikely to satisfy the assumptions of standard statistical tests. Thus, we adopted a more descriptive approach.

these analyses was that "happy" was specified as the reference variable in each analysis. Happy was chosen because it was one of the few affective states that was common to all 10 matrices. By specifying happy as the reference variable in each matrix, cross-matrix comparisons in results were simplified. Happy has also been hypothesized in many formulations of the model to be located in the positive-evaluation/no-arousal region of the circle. In graphical representations, affective states of this type are usually placed at 0°. Thus, setting happy as the reference point produced solutions organized in a manner similar to how the model is typically depicted.[9]

Results

General information about the models. As one might expect given the optimal nature of the matrices, the RMSEAs and MCSCs indicted that a circumplex representation of affect usually provided a plausible representation of the data. The three matrices drawn from Feldman (1995b) produced RMSEA values of .091, .075, and .121, respectively. The MCSC values for these data sets were −.520, −.575, and −.763. The matrix drawn from Feldman Barrett (1996) produced an RMSEA of .085 and a MCSC of −.671. For the two Mayer and Gaschke (1988) matrices, the RMSEA values were .048 and .047 and the MCSC values were −.782 and −.771. The matrices drawn from Mayer et al. (1988) produced RMSEA values of .060, .065, and .053. The MCSC values for these models were −.765, −.767, and −.788. The matrix drawn from Rusting and Larsen (1995) produced an RMSEA of .072 and an MCSC of −.574.[10]

Locations of affective states. Table 6 presents the estimated locations of affective states. These locations are expressed in the form of polar angles on the circle and thus can range from 0° to 360°. The first column lists each affective state, the second column its most commonly predicted location (see Larsen & Diener, 1992; Russell, 1980; Watson & Tellegen, 1985), and the remaining columns the locations of affective states as estimated from each of the matrices.

When judging if the location of an affective state corresponds to its predicted location, it is unrealistic to expect it to fall at exactly the predicted location. These predictions are idealized locations in that they assume that the affective state is exactly at the center of that octant of the circle. For example, affective states predicted to be at 0° are assumed to have a strong positive evaluative component but little arousal component. However, these states would only fall exactly at 0 if there was a strong positive evaluative component and absolutely no presence of an arousal component. Obviously, even similar affective terms convey subtle differences in meaning and many of them would not be expected to fall at the exact center of the octant. Therefore, some variation in the locations of even highly similar affective states should occur, but these affective states should fall in the same general region near their predicted location. Therefore, it is more appropriate to view the model as predicting the octants where affective states should be located rather than exact locations. For purposes of evaluating the present results, we considered any affective state falling within 20° of its idealized location as consistent with theoretical expectations. Such a location indicates that this affective state is clearly closer to the center of its predicted region than it is to the center of either adjacent region.

The first group of affective states (Rows 1–11) in Table 6 present the estimated locations for those affective states, included in one or more of the matrices, expected to fall near 0° (i.e., the positive-evaluation/no-arousal octant). Because happy was always the reference variable, its location was always fixed at 0. The locations for all other terms in this group were estimated from the data. This group conformed well to theory. Eight of these terms (cheerful, content, delighted, glad, joyful, kindly, pleased, and warmhearted) were located in the expected region for every matrix that included them. "Satisfied" appeared in the expected region in all but one matrix (the matrix from Feldman Barrett, 1996), and this matrix was one of three matrices that tended to produce somewhat aberrant estimates. "Playful" appeared in the expected octant in every matrix but one (Matrix 2 of Mayer et al., 1988).

The second group of terms (Rows 12–17) in Table 6 are affective states that are expected to fall near 45° (i.e., the positive-evaluation/high-arousal region). None of these terms, except "elated" which appeared in only one matrix, consistently conformed to expectations. Although each term was sometimes located in the appropriate octant, there was a tendency for terms to be shifted toward the positive-evaluation/no-arousal region. In many cases, terms were actually in this region rather than their predicted region. Therefore, these terms seemed to reflect a much stronger positive-evaluation component and a somewhat weaker high-arousal component than one might expect.

The third group (Rows 18–25) in Table 6 are terms predicted to fall in the no-evaluation/high-arousal octant (near 90°). This group was highly discrepant with theory in that the terms almost never fell in their predicted region. Instead, these terms tended to be in the positive-evaluation/high-arousal octant and occasionally were even at the border of the positive-evaluation/no-arousal octant. Thus, contrary to expectations, these terms showed a substantial positive-evaluation component.

The fourth group of affective states (Rows 26–36) in Table 6 are those terms hypothesized to be located in the negative-evaluation/high-arousal region (near 135°). Many of the terms in this group are consistent with expectations. "Jittery" and "distressed" always fell in the predicted region (although distressed is only included in one matrix). "Afraid" and "nervous" were located in the appropriate region in all but two of the matrices and these were two (Matrix 3 of Feldman, 1995b, and the matrix from Feldman Barrett, 1996) of the three matrices that produced the most discrepant results. Still other terms (ashamed, annoyed, fearful, and

[9] When computing the locations of variables, the direction of the ordering (but not the order itself) of variables produced by the CSPMF is arbitrary. For example, imagine an analysis produced a solution in which happy was fixed at 0°, peppy was estimated at 45°, aroused was estimated at 90°, and so on. The direction of this ordering of affective states from the reference variable could be completely reversed such that peppy was at 315°, aroused at 270°, and so on. Such a reversal would not change any other aspect of the solution, including the fit of the model, the MCSC, the communalities, or the distances among variables on the circle. Thus, to aid in comparisons among solutions for our analyses, we present results in which all solutions are scaled to be in a consistent direction.

[10] For the matrices from Feldman (1995b), the optimal number of free parameters in the correlation functions for the models were 2, 3, and 1, respectively. For the matrix from Feldman Barrett (1996), there were 3 free parameters in the correlation function. For the two Mayer and Gaschke (1988) matrices, there were 6 and 7 free parameters in the correlation functions of the models. The models fit to the matrices from Mayer et al. (1988) had 6, 5, and 7 free parameters in the correlation functions. The model fit to the Rusting and Larsen (1995) matrix had 3 free parameters in the correlation function.

Table 6
Estimates of Affective State Locations (Ranging from 0° to 360°) From Optimal Correlation Matrices

Affective State	Commonly predicted location	Feldman (1995b)			Feldman Barrett (1996)	Mayer & Gaschke (1988)		Mayer et al. (1988)			Rusting & Larsen (1995)
		Matrix 1	Matrix 2	Matrix 3	Matrix 1	Matrix 1	Matrix 2	Matrix 1	Matrix 2	Matrix 3	Matrix 1
Happy	0	0	0	0	0	0	0	0	0	0	0
Cheerful	0						4	0	6	4	4
Content	0					347	353	359	350	349	348
Delighted	0						7	6	9	6	12
Glad	0										0
Joyful	0					6	7	6	10	5	
Kindly	0						6	354	15	9	
Playful	0						17	7	80	19	
Pleased	0					3	3	5	6	356	3
Satisfied	0	5	346	346	303	349	354	359	350	351	
Warmhearted	0						7	359	5	9	9
Enthusiastic	45	27	29	17	6						11
Elated	45										26
Excited	45										18
Full of Pep	45					25					
Lively	45					27	21	13	24	21	14
Peppy	45	26	40	18	2	23	24	19	24	26	18
Aroused	90	41	65	199	20	25					41
Activated	90					36	23	20	27	22	
Active	90					27	26	18	69	27	25
Astonished	90										29
Intense	90					108					57
Energetic	90					32	27	21	30	30	
Surprised	90	134	100	245	50						24
Wide awake	90					58	48	43	40	48	
Angry	135						166	171	158	164	83
Ashamed	135						157	164	157	157	139
Afraid	135	135	144	298	78						
Annoyed	135						168	168	170	151	86
Distressed	135										122
Fearful	135					149	158	161	150	160	141
Hostile	135										79
Irritable	135										88
Jittery	135					134	134	147	132	148	123
Nervous	135	140	118	288	89		147	150	142	145	131
Worried	135						158	163	149	158	
Blue	180					173	172	174	166	172	166
Disappointed	180	175	161	311	124						
Discontent	180					170	176	181	178	174	
Dissatisfied	180					165					
Gloomy	180					174	171	174	165	171	166
Grouchy	180						171	169	163	178	94
Joyless	180					183	181	178	183	180	
Miserable	180										164
Sad	180	162	174	311	144	170	170	172	170	169	164
Unhappy	180					167	173	175	173	170	162
Bored	225						188	186	197	197	106
Depressed	225					168					
Discouraged	225					166	168	173	163	166	
Drowsy	225					228	227	220	220	235	116
Half Asleep	225					233	221	225	228	221	
Sleepy	225	217	220	1	179	238	225	223	216	225	
Sluggish	225	213	223	349	178	213	213	207	235	218	117
Tired	225					229	224	213	220	225	115
Inactive	270					203	202	195	255	213	215
Quiet	270	266	261	36	207	287	200	196	246	193	224
Still	270	227	253	265	213						233
At Rest	315					326	340	349	339	335	256
At Ease	315										268
Calm	315	317	292	316	240	314	322	334	321	326	259
Relaxed	315	307	312	323	249		333	338	329	335	263
Serene	315										240
Confident	Am						354	1	349	349	310
Proud	Am						6	7	6	3	309
Alert	Am					37	37	27	49	38	
Vigorous	Am					22	26	22	27	29	
Clutched up	Am					146	173	172	168	172	
Disgusted	Am						166	169	164	163	
Guilty	Am						158	163	152	162	133
Slow	Am					202	206	201	240	211	
Leisurely	Am					315					

Note. Am = Terms that were ambiguous with respect to prior theory.

worried) were sometimes in the expected octant but also frequently were shifted closer than expected to the negative-evaluation/no-arousal octant. "Angry" also tended to be located in the negative-evaluation/no-arousal region of the circle. "Hostile" and "irritable" were actually in the no-evaluation/high-arousal octant, although these terms were in only one matrix (Rusting & Larsen, 1995) and this was one of the three matrices that produced the discrepant results.

The fifth group (Rows 37–46) in Table 6 are those terms predicted to be in the negative-evaluation/no-arousal region. These terms were consistent with expectations. With a few exceptions involving the three discrepant matrices, these terms fell in the predicted octant (near 180°).

The sixth group of terms (Rows 47–53) in Table 6 are affective states hypothesized to fall in the negative-evaluation/low-arousal octant (near 225°). This group provided a somewhat mixed picture. Some of the terms (drowsy, half asleep, sleepy, sluggish, and tired) were relatively consistent with theory. These states were in the expected octant in all but the three matrices that produced the most discrepant results. Other terms in this group (bored, depressed, and discouraged) were usually located in the negative-evaluation/no-arousal octant rather than in their predicted octant.

The seventh group (Rows 54–56) in Table 6 are terms predicted to be in the no-evaluation/low-arousal region (near 270°). These terms produced highly variable results. Each term appeared in the expected location for at least one matrix. However, these terms tended to be shifted into the negative-evaluation/low-arousal octant and sometimes even into the negative-evaluation/no-arousal region.

The eighth group of terms (Rows 57–61) in Table 6 are terms expected to reflect the positive-evaluation/low-arousal region (near 315°). Some of these terms conformed well to expectations, whereas others did not. "Calm" fell in the expected octant in all but the three discrepant matrices, and "relaxed" was located in the appropriate region in six of the matrices. In one matrix it fell just at the border of the appropriate region and the positive-evaluation/no-arousal region. "At rest" tended to fall near the border of these two octants as well. "At ease" and "serene" both fell outside their expected region, but these terms were in only one matrix and this was one of the more poorly performing matrices.

The final group (Rows 62–71) in Table 6 are terms that our coding indicated were ambiguous with respect to prior theory. "Confident" and "proud" were consistently located in the positive-evaluation/no-arousal octant. "Alert" and "vigorous" tended to fall in the positive-evaluation/high-arousal octant. "Clutched up" and "disgusted" tended to fall in the negative-evaluation/no-arousal region. "Guilty" was found to be located in either the negative-evaluation/high-arousal region or the negative-evaluation/no-arousal region. "Slow" was consistently located in the negative-evaluation/low-arousal octant. Finally, "leisurely" was found to be located in the positive-evaluation/low-arousal octant.

Discussion

Our second set of analyses provide mixed support for contemporary versions of the circumplex model of affect. As one might expect given the relatively optimal features of the data sets, model fit generally reached good or acceptable levels. Likewise, analyses produced MCSCs indicating strong negative correlations among opposing affective states. However, there was some variation in model fit and the MCSC. This finding is not surprising given that the characteristics identified in our first set of analyses are almost certainly not an exhaustive list of the many factors that influence the structure of self-reported affect.

Of primary interest in this second set of analyses were the locations of affective states. Affective states predicted to fall in the positive-evaluation/no-arousal octant or in the negative-evaluation/no-arousal octant consistently conformed to theoretical expectations. Affective states expected to be in the negative-evaluation/high-arousal region, the negative-evaluation/low-arousal region, or the positive-evaluation/low-arousal region of the circle often followed predictions. For all three octants, there were some affective states consistent with predictions. However, some affective states for each of these octants were also discrepant with expectations. These findings suggest that the model is correct in its assumption that affective states exist that reflect these octants. However, it also suggests that assumptions regarding some affective states predicted to be in these regions may have been in error. None of the terms postulated to be in the positive-evaluation/high-arousal, no-evaluation/high-arousal, or no-evaluation/low-arousal octants consistently fell in their predicted regions. The most consistent distortion that occurred was a tendency for the evaluative component to be stronger than expected. This finding is consistent with the work of Osgood et al. (1957) who found that evaluation was the most powerful dimension of connotative meaning in words. Furthermore, distortions of this sort in past circumplex research have been noted. Feldman (1995b) found that people tended to weigh the evaluative dimension more than the arousal dimension in self-reports of affect. What is less clear is why no affective states were consistently located in these three octants. One possibility is that the model is fundamentally wrong in that no affective states exist that fall in these regions. Alternatively, such states might exist but were not included in the matrices. Given that these matrices included terms traditionally assumed to be located in these octants, at the least, assumptions regarding many of these terms need to be revised.

General Discussion

Summary of Key Findings

In our first set of analyses, we tested the circumplex model for a wide array of affective states drawn from a wide range of data sets. These findings generally provided support for the model as a reasonable representation. The median value for model fit fell within the acceptable range and the median MCSC indicated that opposing affective states had strong negative associations with one another. The first set of analyses also suggests that characteristics of the data might have influenced the structure of self-reported affect. The time frame of judgments, the use of multiple-item measures versus single-item measures, and the number of theoretically ambiguous affective states included in the data set all influenced the extent to which data possessed circumplex structure. Additionally, the extent to which opposing affective states were negatively correlated was influenced by the time frame of judgments, the use of intensity versus frequency judgments, the use of multiple-item measures versus single-item measures, and the extent to which all octants of the circle were represented in the matrix. Therefore, although the circumplex model of affect was generally a reasonable representation of self-reported affect, the model was a more appropriate representation under some conditions than others.

Our second set of analyses assessed the locations of affective states relative to theoretical predictions of the circumplex model of affect. For five of the eight octants, at least some affective states consistently fell in their expected regions. However, some affective states expected to fall into these regions did not, thereby suggesting that assumptions about the nature of some affective states may need to be revised. More problematic was the fact that affective states could not be found that consistently fell in the other three regions of the circle. What is less clear is if this reflects something fundamental about the nature of affect or simply bias in the sampling of affective states.

Implications of Key Findings

As noted in the introduction, statistical methods typically used to test the circumplex model of affect have had significant limitations. In the few cases in which more precise covariance structure modeling methods have been applied, results have often been contradictory, and sometimes important details of these analyses have not been reported. The present study addressed some of these limitations by using a covariance structure model specifically designed to test circumplex structure. Thus, the fit of the model provided a clear numerical index of the extent to which data conformed to circumplex structure. In addition, this article reported formal tests of circumplex structure of affect across a wide range of data sets. Thus, the present research constitutes perhaps the most statistically rigorous and comprehensive evaluation of the circumplex structure of affect yet attempted.

A second way in which this article moves beyond previous work is the manner in which we have estimated the locations of affective states. In the past, locations have typically been determined by using component or factor loadings as coordinates in a graphical representation or by using the coordinates from MDS analyses to represent the location of the affective states. In the present analyses, we estimated locations using a model that explicitly postulated that affective states can be represented as an ordering of variables on the perimeter of a circle. There are several advantages to this approach. One advantage was that the location estimates in this latter approach were generated from a model that explicitly represented relations among affective states as an ordering of variables on a circle, whereas analyses from previous approaches derived estimates from models that did not directly correspond to a circumplex representation. Thus, there is a clearer rationale for the computation of the estimates reported in the present research than in previous research. Another benefit was that because we used a latent variable model, we were able to examine relations among affective states after having removed random error of measurement. Therefore, we were able to account for distortions in results due to random error. In contrast, approaches typically used in past research did not allow one to determine if discrepancies between predictions and results were as a result of measurement error or the fact that circumplex structure was not present in the data. Finally, we presented estimates of the locations of 71 affective states from 10 data sets. Thus, we were able to examine the consistency of the locations of a sizeable number of affective states across a much larger number of data sets than has typically been the case.

Our analyses also moved beyond previous research in that our approach allowed us to formally assess the nature of the relation between affective states at opposite sides of the circle (i.e., the MCSC). This assessment provided information that was not readily available in the methods previously used in the literature. Although researchers have often examined the correlations between affective states that differ in their evaluative nature (e.g., affective states with positive vs. negative evaluation components), researchers have much less often examined bipolarity in affective states that contained little evaluation component. In contrast, the MCSC assessed the bipolarity among opposing affective states at all points on the circle. Furthermore, these estimates of bipolarity were computed under logical restrictions implied by a circumplex representation (e.g., the magnitude of bipolarity among opposing affective states should be the same for any two opposing points on the circle). Thus, the present estimates of bipolarity in affective states are somewhat different from most previous studies.

Finally, we identified characteristics of the studies that influenced the extent to which self-reported affect possessed circumplex structure and the degree to which self-reports of affective states were negatively related to one another. The examination of how design features of studies influence the structure of affect is certainly not unique (e.g., see Feldman, 1995b; D. P. Green et al., 1993; Rusting & Larsen, 1995; Watson, 1988). Indeed, we selected the features we did in part because there was empirical and theoretical precedence for these features influencing the structure of self-reported affect. However, our comparisons also differed from many past studies. Most studies have tested whether study features influence the bipolarity of positive and negative affective states. Although such tests are certainly relevant to circumplex perspectives of affect, they are not tests of circumplex structure per se. Our analyses are the first attempt to identify factors that might influence the fit of circumplex models to affect data sets. Thus, the present research provides a more direct examination of the influence of study characteristics on circumplex structure. Likewise, our comparisons of the MCSC were comparisons of bipolarity that were more explicitly tied to circumplex perspectives than any comparisons that have previously been conducted.

Directions for Future Research

Although this research addressed a number of useful questions, it also highlighted a number of other interesting issues that remain to be addressed. First, although the fit of the model was generally reasonable, there was also tremendous variability in model fit and in the correlations among opposing affective states across data sets. Our analyses suggested several factors that were partially responsible for this variation. However, there are almost certainly other important factors that contribute to this variability and future research should attempt to identify these factors. Likewise, for those factors that have been identified, it would also be useful to explore the psychological mechanisms by which these factors influence circumplex structure.

Other promising directions for future research arise out of our focus on existing affect data sets. When examining the impact of study characteristics, we categorized a large number of existing data sets on the basis of whether they fell in one of these particular categories. The value of this approach is that it allowed us to examine the impact of a wider range of different features than would have been feasible within the context of a few data sets involving experimental manipulations. However, because our comparisons did not involve experimental manipulations, our comparisons may have been confounded with a variety of other study characteristics. Analyses involving adjusted means allowed us to statistically control for some potential confounds, but such analyses cannot account for all possible confounding effects. Future work should experimentally manipulate these characteristics to more precisely test their influence on the fit of circumplex models and the degree to which opposite affective states are negatively related.

Likewise, because our analyses involved existing data sets, we were limited by the design features of these past studies. For example, most of our data sets involved questions using a single response format. Thus, it was not possible to control for systematic measurement error due to measurement methods. The existence of this type of error should have resulted in an underestimation of the bipolarity of affective states (e.g., see D. P. Green et al., 1993, 1999). Therefore, it is possible that the strong negative MCSCs observed in our analyses should in reality be even stronger. Additionally, systematic measurement error would likely have only served to distort circumplex structure. Thus, the generally acceptable level of fit for circumplex models that we observed might in reality be even better. Research testing the present findings using multiple measurement methods would be a valuable direction for future inquiry.

Another consequence of our use of existing data sets was that our analyses relied solely on self-reports of affect, which has been the predominant method used in past work. Obviously there are limits in self-reported affect data (see Larsen & Diener, 1992) in that features of self-report measures can introduce response biases, people might not always be able to effectively express their affective experiences in verbal form, and people might sometimes be motivated to misreport their affective experiences. Given this fact, it is not clear if our results would generalize to affect assessed by other methodologies (e.g., facial EMG). Research investigating the robustness of the present findings using alternative methods of assessment is an important line of future inquiry.

Yet another consequence of the use of existing data sets is the specific sampling of affective states we examined. Our data sets were mostly data sets that included samples of affective states guided by circumplex perspectives. It is important to recognize that many of the terms included in these data sets would not be regarded as true emotions in other theories of affect (e.g., Ekman, 1972; Ortony, Clore, & Collins, 1988). It would be useful to test how well the circumplex model performs in the context of samples of emotions derived from other theoretical perspectives.

A fifth consequence of our use of existing data sets is that we were limited to exploring the impact of only those study features for which there was substantial variation across data sets. Obviously, there are a number of other features of measures and contexts that past research suggests might influence the structure of affect. Future studies investigating such study features would be useful.

Another direction for future research would be to understand factors influencing the locations of affective states. Our analyses revealed that although some affective state locations were theoretically sensible and reasonably stable across data sets, the locations of other affective states were much less ideal. It is not clear why such variability was observed or why some affective states, and in some cases entire conceptual groups of affective states, failed to conform to theoretical expectations. One explanation for the discrepancies between the results and existing theory is that it may be the case that some of the affective states that researchers have categorized as falling within certain regions of the circle do not correspond to people's actual perceptions of these affective states. If this is the case, additional sampling of affective states in future studies should ultimately result in identifying affective states that are good representations of each region of the circle. Alternatively, it is possible that the location of affective states may shift as a function of various contextual factors or characteristics of the person making the judgments (e.g., see Feldman, 1995b). For instance, it may be that some contexts lead an individual to stress one of the dimensions (e.g., arousal) over another (e.g., valence), whereas other contexts lead participants to emphasize both dimensions. Such variations in context might account for variability in the locations of affective states as well as why some affective states sometimes fail to conform with theoretical predictions. Of course, it is also possible that there may simply not be affective states falling in some regions of the circle. Further clarification of these issues seems essential to fully assessing the adequacy of circumplex representations of affect.

Finally, it should be noted that although we found the circumplex model of affect to be a reasonable representation of affect in many respects, our findings do not speak to the issue of whether alternative models might provide even better accounts of the data. Alternative structural models of affect have been proposed (e.g., see Tellegen, Watson, & Clark, 1999a, 1999b). In our data sets, direct comparisons of such models with the circumplex model were not feasible, because the heterogeneity in affective states included in our data sets made it difficult to specify a single conceptually similar alternative model to serve as a basis for comparison across all the data sets. However, future studies directly comparing circumplex models to these alternative models would be a valuable direction for future research (e.g., for a recent debate concerning one such alternate model, see D. P. Green & Salovey, 1999; Tellegen et al., 1999a, 1999b).

Taken together, our analyses indicate that the circumplex model remains a viable representation of the structure of affect in some respects. However, as previously outlined, a number of issues remain to be explored. By investigating these and other issues, researchers are likely to make substantial progress in arriving at a more complete understanding of the structure of affect.

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