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Cognitive Vulnerability to Depression: A Taxometric Analysis

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Although there is increasing support for the hypothesis that negative cognitive styles contribute vulnerability to depression, it remains unclear how best to conceptualize the heterogeneity in cognitive vulnerability to depression. Specifically, does this heterogeneity reflect quantitative or qualitative differences among individuals? The goal of this study was to address this question by examining whether the underlying structure of cognitive vulnerability to depression is best conceptualized as dimensional or categorical. Taxometric analyses provided consistent support for the dimensional nature of negative cognitive styles. It appears, therefore, that cognitive vulnerability to depression is best conceptualized as a dimensional construct, present to a greater or lesser extent in all individuals. Despite this, the strength of the relationship between negative cognitive styles and depressive symptoms does appear to vary as a function of where along the cognitive style continuum one falls.

According to cognitive theories of depression (e.g., Abramson, Metalsky, & Alloy, 1989; Beck, 1967, 1987; Clark, Beck, & Alford, 1999), individuals' characteristic ways of interpreting negative events in their lives may leave them vulnerable to developing depression following the occurrence of these events. There is accumulating evidence that these negative cognitive styles do indeed contribute vulnerability to future symptoms and diagnoses of depression (for reviews, see Abramson et al., 2002; Alloy et al., 1999; Clark et al., 1999; Ingram, Miranda, & Segal, 1998; Joiner & Wagner, 1995; Peterson & Seligman, 1984). Despite this, however, there is some disagreement regarding how to best conceptualize cognitive vulnerability to depression. Specifically, although it is clear that individuals differ in terms of the negativity of their cognitive styles, what remains unclear is whether this heterogeneity reflects quantitative versus qualitative differences among individuals. That is, is cognitive vulnerability to depression best conceptualized as a dimensional construct, with differences between individuals simply reflecting quantitative differences along a continuum (cf. Abramson et al., 1989)? Or, on the other hand, is cognitive vulnerability to depression best conceptualized categorically, with qualitative differences reflecting distinct high and low cognitive dysfunction subgroups of the population (cf. Miller & Norman, 1986)?

There is some support for the existence of distinct subgroups in terms of cognitive vulnerability to depression. For example, researchers have identified subgroups of depressed patients whose cognitive styles are significantly more negative than those of other depressed patients. These high and low cognitive dysfunction groups have been found to differ on a variety of clinical characteristics, as well as in their response to treatment (see Hamilton & Abramson, 1983; Miller & Norman, 1986; Miller, Norman, & Keitner, 1990; Norman, Miller, & Dow, 1988; Norman, Miller, & Klee, 1983). In addition, there is some evidence that the cognitive styles of the high cognitive dysfunction group remain negative following clinical improvement of their depressive symptoms, supporting the idea that negative cognitive styles may be a stable vulnerability factor only for this subset of depressed patients (Miller & Norman, 1986; but see also Hamilton & Abramson, 1983).

A limitation of these studies is that the high cognitive dysfunction subgroups were identified as simply those participants who scored above established norms on common measures of cognitive styles (e.g., one standard deviation above the mean). Thus, although high and low cognitive dysfunction subgroups have been found to differ on a number of variables, no study has explicitly examined whether the differences in negative cognitive styles between groups are truly qualitative rather than simply quantitative. In the current study, therefore, taxometric analyses were conducted to determine whether the latent structure of cognitive vulnerability to depression is best conceptualized as dimensional or categorical.

The indicators chosen for these analyses were based on two of the leading cognitive theories of depression—Beck's (1987; Clark et al., 1999) theory and the hopelessness theory (Abramson et al.,

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1989). Specifically, Beck has proposed two forms of cognitive vulnerability to depression, sociotropy and autonomy, which contribute vulnerability to depression following stressors in the interpersonal and achievement domains, respectively. The hopelessness theory outlines three forms of cognitive vulnerability—negative inferential styles about causes, consequences, and self-characteristics following the occurrence of negative life events—each of which is hypothesized to contribute incremental risk to the development of depression. Important for conducting a taxometric analysis, factor analytic studies have supported the hypothesis that these vulnerability factors represent distinct yet related constructs (e.g., Cane, Olinger, Gotlib, & Kuiper, 1986; Hankin, Carter, & Abela, 2003; Joiner & Rudd, 1996).

Taxometric Analyses

Meehl and his colleagues (Meehl, 1995, 1999; Meehl & Yonce, 1994, 1996; Waller & Meehl, 1998; see also Joiner & Schmidt, 2002) have developed a set of taxometric procedures used to determine whether the construct examined is best considered as dimensional or categorical (i.e., taxonic). The validity and robustness of these procedures have been established in a number of studies (see Waller & Meehl, 1998). Rather than relying on traditional significance testing, evidence of taxonicity is provided by replication across analytic approaches. Three taxometric procedures, mean above minus below a cut (MAMBAC; Meehl & Yonce, 1994), maximum eigenvalue (MAXEIG; Waller & Meehl, 1998), and latent mode (L-MODE; Waller & Meehl, 1998), were used in this study.[1] Evidence for taxonicity was gathered in two ways. First, taxonicity was evaluated within each analysis by examining the shape of the output graph (as described below). Second, given that a true taxon should produce similar base-rate estimates across different taxometric analyses, the different base-rate estimates were also compared.

In MAMBAC (Meehl & Yonce, 1994), indicators are examined two at a time, with one variable serving as the input and the other serving as the output. Cases are sorted from lowest to highest on the input variable, with a cut between each case. Then the average score on the output indicator of cases falling below this cut is subtracted from the average score of cases falling above the cut. This is repeated for every cut along the input indicator, and the results are plotted on a graph. In MAMBAC, each indicator serves as both an input and an output variable in every possible pairwise combination, yielding $k(k - 1)$ curves, where k represents the number of indicators included in the analysis. Whereas taxonic data yield peaked distributions, dimensional data yield dish-shaped distributions, with the highest elevations at either end of the distribution.

In MAXEIG (Waller & Meehl, 1998), one of the indicator variables is sorted in ascending order, and the remaining variables are used as output variables. The first eigenvalue of the covariance matrix of output variables is then plotted across overlapping windows of the indicator variable. With 90% overlap (the default setting suggested by Waller & Meehl, 1998), the first sliding window plots the eigenvalue of the output variable for the first 100 cases, for example, of the indicator. In the next sliding window, the first 10 cases of the indicator are replaced with the next 10 cases not included in the first sliding window. This is repeated until the eigenvalues for the specified number of sliding windows (e.g., 50) have been plotted (cf. A. M. Ruscio & Ruscio, 2002). A separate graph is produced for each input variable. Evidence of taxonicity is obtained when there is a distinct peak in the plot of eigenvalues, whereas a dimensional construct yields a relatively smooth plot (Waller & Meehl, 1998). This is because if the data are taxonic, the covariance among indicators should be relatively lower at the ends of the distribution, due to the concentration of either taxon or complement (nontaxon) group members, than at the more heterogeneous middle of the distribution. One benefit of MAXEIG is that it has a built-in procedure for clarifying the existence of a low base rate taxon, the *inchworm consistency test* (Waller & Meehl, 1998). In conducting this test, a series of MAXEIG analyses are performed with an increasing number of sliding windows (e.g., 100, 150, 200, 250). Data indicative of a low base rate taxon yield graphs that become increasingly peaked as more windows are added, whereas dimensional data yield graphs that remain relatively flat despite the addition of additional sliding windows.

In L-MODE, the indicators are factor analyzed, and then the distribution of estimated true factor scores on the first principal factor is plotted (Waller & Meehl, 1998). Evidence of taxonicity is obtained by a bimodal distribution, whereas dimensionality is evidenced by a unimodal distribution. Four base-rate estimates are derived from L-MODE analyses: Two are derived from factor scores representing the upper and lower modes of the latent distribution (P_U and P_L), the third is the average of these two estimates (P_{AVG}), and the fourth is derived empirically from the classification of participants into taxon and complement classes (P_{EMP}; Waller & Meehl, 1998). Whereas a taxonic structure within the data tends to produce a relatively small discrepancy between P_U and P_L, a dimensional structure tends to produce a large discrepancy and yield P_{AVG} and P_{EMP} estimates near .50.

Previous studies have used these techniques to examine the latent structure of a number of constructs (for a review, see Haslam & Kim, 2002). Of relevance to the current study, several studies have also examined the latent structure of depression, with some studies supporting the dimensional nature of depression (e.g., Franklin, Strong, & Greene, 2002; A. M. Ruscio & Ruscio, 2002; J. Ruscio & Ruscio, 2000) and others finding evidence of taxonicity, at least among some sets of symptoms (e.g., Ambrosini, Bennett, Cleland, & Haslam, 2002; Beach & Amir, 2003; Haslam & Beck, 1994; but see also J. Ruscio, Ruscio, & Keane, in press). This is the first study, however, to examine whether cognitive vulnerability to depression exhibits taxonicity.

Method

Participants

Participants were a subset of those participating in the first phase of screening for the Temple–Wisconsin Cognitive Vulnerability to Depression (CVD) Project (Alloy & Abramson, 1999). In the first phase of screening for the CVD Project, an unselected sample of university undergraduates was administered the Cognitive Style Questionnaire (CSQ; Alloy et al., 2000) and the Dysfunctional Attitudes Scale (DAS; Weissman & Beck, 1978). The current study focused on 2,117 participants from the Temple University site and 2,885 participants from the University of Wisconsin site with complete data (N = 5,002). Participants included in

[1] John Ruscio's taxometric package was used for all analyses. This program can be downloaded for free at www.etown.edu/psychology/faculty/ruscio.htm.

Table 1
Descriptive Statistics for Each Site

Variable	TU	UW	χ^2 or t	$r_{\text{effect size}}$
Gender (% women)	57.3	60.7	5.98*	.03
Ethnicity (% Caucasian)	59.7	89.6	563.99**	.34
Age (years)	19.63 (3.61)	18.16 (0.86)	21.07**	.29
CSQ–Generality	4.09 (0.87)	4.21 (0.77)	5.15**	.07
CSQ–Consequences	3.76 (1.02)	3.95 (0.92)	7.04**	.10
CSQ–Self-Characteristics	3.47 (1.19)	3.54 (1.10)	2.05*	.03
DAS–PE	39.99 (14.16)	40.83 (13.33)	2.14*	.03
DAS–AO	37.87 (10.07)	41.03 (9.28)	11.49**	.16
BDI	9.40 (8.03)	6.98 (6.28)	11.99**	.17

Note. TU and UW data for gender and ethnicity are percentages; remaining TU and UW data are means (with standard deviations). Chi-square analyses were used to test for site differences in gender and ethnicity ($df = 1$; $N = 5{,}000$ and 4,834 for gender and ethnicity, respectively), and independent samples t tests ($df = 5000$) were used to test for site differences in participants' age, cognitive style variables, and depressive symptoms. TU = Temple University; UW = University of Wisconsin—Madison; CSQ = Cognitive Style Questionnaire; DAS–PE = Dysfunctional Attitudes Scale—Performance Evaluation subscale; DAS–AO = Dysfunctional Attitudes Scale–Approval by Others Subscale; BDI = Beck Depression Inventory.
* $p < .05$. ** $p < .01$.

this study were compared with those excluded because of missing data ($n = 202$) in terms of demographic characteristics, negative cognitive styles, and depressive symptoms. Although three significant differences emerged, each reflected a small effect. Participants in this study were significantly more likely to be Caucasian than were excluded students (77.6% vs. 53.3%, respectively), $\chi^2(1, N = 5{,}129) = 61.94$, $p < .001$, $r_{effect\ size} = .11$. In addition, participants in this study had significantly more negative cognitive styles as assessed by the CSQ–Generality subscale ($M = 5.45$ [$SD = 0.64$] vs. $M = 5.39$ [$SD = 0.70$], respectively), $t(5202) = 3.47$, $p < .001$, $r_{effect\ size} = .05$, and significantly lower depressive symptom levels ($M = 8.00$ [$SD = 7.17$] vs. $M = 9.50$ [$SD = 9.38$], respectively), $t(5202) = 2.86$, $p = .004$, $r_{effect\ size} = .04$, than did excluded students. Descriptive statistics for participants included in this study from each site are presented in Table 1. As can be seen in the table, there were site differences on each of the variables. With the exception of ethnicity and age, however, the sizes of the effects were fairly small. Given these differences, data from the two sites were initially analyzed separately. Because the results were virtually identical across both sites, only results from the entire sample are presented (to conserve space).

Measures

The CSQ, a revised version of the Attributional Style Questionnaire (Peterson et al., 1982), was used to assess individuals' tendency to make stable and global attributions and to infer negative consequences and negative self-characteristics following the occurrence of negative life events. The CSQ contains 24 hypothetical events (12 positive and 12 negative). In the current study, only the negative events were used because previous studies have shown that inferences for negative events are more strongly related to depressive episodes than are inferences for positive events (e.g., Alloy et al., 2000). In response to each of the hypothetical events (e.g., "You want to be in an intimate, romantic relationship, but aren't."), the participant is asked to indicate what she or he believes would be the major cause of the event if it happened to her or him. In addition, the participant is asked to answer a series of questions about the cause and consequences of each event, as well as what the occurrence of the event would mean for his or her self-concept. Consistent with research suggesting that the causal attributional dimensions of stability and globality load onto a common factor (Joiner & Rudd, 1996), a composite score was created by averaging participants' responses on both dimensions, forming the CSQ–Generality subscale. Responses to the consequences and self-characteristics dimensions were also averaged to form their respective subscales. Scores on each subscale range from 1 to 7, with higher scores indicating more negative cognitive styles. In this study, each of the subscales exhibited good internal consistency (αs = .85, .83, and .87 for the Generality, Consequences, and Self-Characteristics subscales, respectively).

The DAS, a 40-item self-report inventory, was used to assess participants' maladaptive attitudes, including sensitivity to social criticism, perfectionistic performance standards, expectations of control, and rigid ideas about the world. Response options to each of the questions range, on a 7-point Likert-type scale, from *totally agree* to *totally disagree.* For this study, we used the two DAS subscales, Performance Evaluation and

Table 2
Correlations and Descriptive Statistics for the Total Sample

Variable	1	2	3	4	5	M	SD	Range
1. CSQ–Generality	—					4.16	0.82	1.21–6.95
2. CSQ–Consequences	.71**	—				3.87	0.97	1.00–6.92
3. CSQ–Self-Characteristics	.51**	.66**	—			3.51	1.14	1.00–7.00
4. DAS–PE	.27**	.37**	.44**	—		40.48	13.70	15.00–101.00
5. DAS–AO	.28**	.39**	.40**	.50**	—	39.69	9.75	10.00–70.00
6. BDI	.26**	.29**	.33**	.43**	.29**	8.00	7.17	0.00–56.00

Note. CSQ = Cognitive Style Questionnaire; DAS–PE = Dysfunctional Attitudes Scale—Performance Evaluation subscale; DAS–AO = Dysfunctional Attitudes Scale—Approval by Others subscale; BDI = Beck Depression Inventory.
** $p < .01$.

Table 3
Base-Rate Estimates Obtained From the Taxometric Analyses

Data set	MAMBAC Range	MAMBAC *M*	MAMBAC *SD*	MAXEIG Range	MAXEIG *M*	MAXEIG *SD*	L-MODE P_L	L-MODE P_U	L-MODE P_{AVG}	L-MODE P_{EMP}
Research	.38–.57	.45	.07	.16–.75	.33	.28	.08	1.00	.54	.53
Simulated taxonic	.27–.59	.43	.09	.32–.44	.38	.05	.33	.83	.58	.52
Simulated dimensional	.33–.51	.44	.06	.28–.72	.48	.23	.03	1.00	.51	.51

Note. MAMBAC = mean above minus below a cut; MAXEIG = maximum eigenvalue; L-MODE = latent mode; P_L = base-rate estimate based on the lower mode of the latent distribution; P_U = base-rate estimate derived from the upper mode of the latent distribution; P_{AVG} = average of P_U and P_L; P_{EMP} = base-rate estimate empirically derived from the classification of participants into taxon and complement classes.

Approval by Others (DAS–PE and DAS–AO, respectively; see Cane et al., 1986), which tap Beck's (1987; Clark et al., 1999) cognitive styles of autonomy and sociotropy, respectively. Studies have suggested that scores on these subscales may be a better measure of cognitive vulnerability to depression than the total scale score (see Clark et al., 1999). Scores on the DAS–PE subscale range from 15 to 105, and scores on the DAS–AO subscale range from 10 to 70, with higher scores indicating more dysfunctional attitudes. Both subscales exhibited good internal consistency (αs = .87 and .78 for DAS–PE and DAS–AO, respectively).

The Beck Depression Inventory (BDI; Beck, Rush, Shaw, & Emery, 1979) was used to assess participants' depressive symptom levels. Total scores on the BDI range from 0 to 63, with higher scores indicating more severe levels of depressive symptoms. Numerous studies have established the validity and reliability of the BDI (Beck, Steer, & Garbin, 1988). In this study, the BDI exhibited good internal consistency (α = .87).

Procedure

Recruitment for this study occurred in freshman classrooms, dormitories, and campus activities, as well as by handing out questionnaire packets on campus. Participants completed the packets either individually or in groups. They received either course credits (if recruited from introductory psychology classes) or $5 for completing the questionnaires.

Results

Given that taxometric analyses are limited by the construct indicators chosen (Widiger, 2001; see also Beach & Amir, 2003), analyses were first conducted to determine whether the indicators chosen exhibited sufficient validity for taxometric analysis. The first step of this process was to examine the interindicator correlations and eliminate any variables correlating less than .30 with the other indicators. As can be seen in Table 2, the correlations between the CSQ–Generality composite and the DAS–PE and DAS–AO subscales fell below our threshold. Specifically, the CSQ–Generality subscale shared only 7% and 8% variance with the DAS–PE and DAS–AO, respectively. Therefore, the CSQ–Generality subscale was excluded from the taxometric analyses.[2] Next, we evaluated the validity of the four remaining cognitive style indicators using the procedure outlined by Meehl and Yonce (1994). Specifically, we created a composite cognitive style variable by averaging participants' standardized scores on each of the four remaining indicators. We then calculated the average interindicator correlation (nuisance covariance) among participants scoring in the upper and lower quartiles on this composite (r_{avg} = .01 and .06 for the lower and upper quartiles, respectively; overall r_{avg} = .03). To provide a conservative estimate of indicator validity, we assumed a moderate base rate taxon (P = .25). Substituting this value, as well as the nuisance covariance calculated above and the average interindicator correlation in the full sample (r_{avg} = .46), into the formula provided by Meehl and Yonce yielded an average estimated separation of 2.07σ. This result supports the suitability of the four cognitive style indicators for taxometric analysis.

However, as a further test, we conducted MAMBAC analyses. The primary goal in this set of analyses was to ensure that the indicators were capable of distinguishing a taxonic from a dimensional structure in the data. The results obtained from the 12 curves generated with the research data were compared with those obtained with simulated taxonic and dimensional data.[3] Although the base-rate estimates were fairly similar across the research, simulated taxonic, and simulated dimensional data sets (see Table 3), the curves generated for the research data were virtually identical to those created with the simulated dimensional data, with both sets producing consistent dish-shaped curves. Further, each was clearly distinguishable from the set of graphs produced with the simulated taxonic data. Representative curves (i.e., every third curve from each series) from the MAMBAC analyses are presented in Figure 1.

Having supported the suitability of the four negative cognitive style indicators for taxometric analyses, MAXEIG analyses were conducted with each of the four cognitive variables serving, in turn, as the input variable. We ran these analyses using 100 sliding windows with 90% overlap, yielding 459 participants per window. As can be seen in Figure 2, the distributions produced by the research data were relatively flat, closely matching those produced

[2] An alternative to omitting the CSQ–Generality scale would have been to eliminate the two DAS scales, but this would have resulted in fewer indicators for the taxometric analyses. This said, however, taxometric analyses were conducted with only the three CSQ indicators, and the results from these analyses were virtually identical to those reported in the article. Details from these analyses are available from Brandon E. Gibb.

[3] In this study, simulated data sets matching the distributions and correlations of indicators in the research data were created using John Ruscio's taxometric package. The only difference was that these data sets were created so as to have either a taxonic or dimensional latent structure. The taxon base rate in the simulated taxonic data set was calculated by the program and was based on the characteristics of the research data rather than being supplied a priori. Although the use of sample-specific simulated data sets has only recently been introduced for use in taxometric analyses (J. Ruscio, Ruscio, & Meron, 2003), it is useful for evaluating the validity of proposed indicators as well as for clarifying the presence of a taxonic versus dimensional structure in the data.

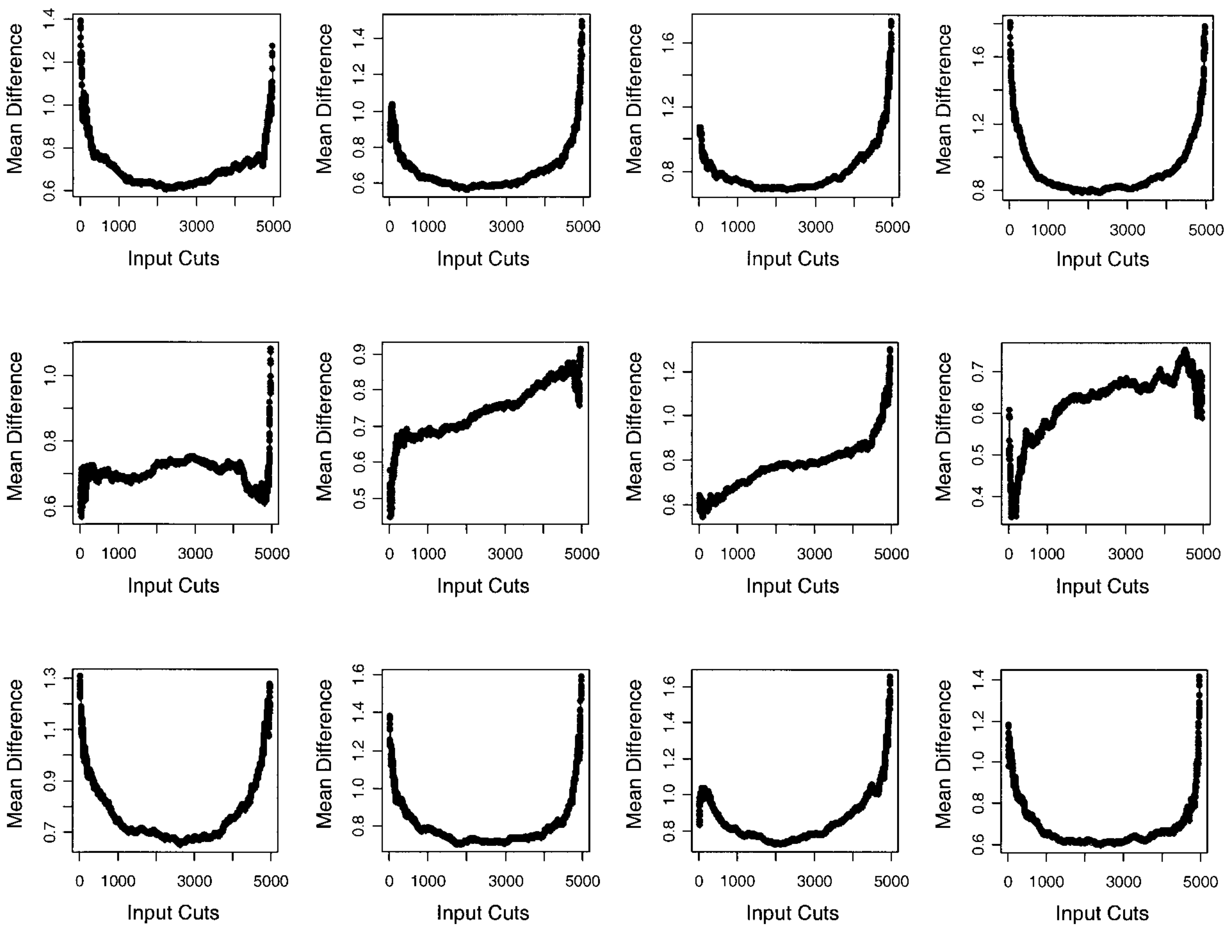

Figure 1. Results of MAMBAC analyses for the research (top row), simulated taxonic (middle row), and simulated dimensional (bottom row) samples. Within each row, graphs represent every third curve from each series. MAMBAC = mean above minus below a cut.

by the simulated dimensional data. In contrast, the simulated taxonic data produced curves with distinct peaks. In addition, the base-rate estimates obtained for the research data varied considerably, providing further support for the dimensional structure of the data (see Table 3). Inspecting the graphs from the research data, however, it could be argued that there is a slight elevation at the right end, suggesting the possibility of a low base rate taxon. Two lines of evidence argue against this conclusion. First, the simulated taxonic data yielded peaks toward the middle of the distribution. Second, the inchworm consistency test revealed a flat distribution across increasing numbers of sliding windows (see Figure 3). Because analyses of each indicator produced virtually identical series of graphs, only the graphs produced for one of the indicators are provided (to conserve space).

Finally, L-MODE analyses were conducted. As can be seen in Figure 4, both the research and the simulated dimensional data yielded unimodal distributions. In contrast, the simulated taxonic data yielded a bimodal distribution. Further evidence for the dimensional nature of the data is provided by the absolute difference between the base-rate estimates from the upper and lower modes, which was virtually identical to that obtained using the simulated dimensional data and almost twice that obtained using the simulated taxonic data (see Table 3).

Despite these consistent results, one could argue that the dimensional results were due to the focus on undergraduates with relatively low levels of depressive symptoms. Specifically, researchers have suggested that depressogenic schemata may remain latent until primed by either negative life events or a negative mood (for reviews, see Clark et al., 1999; Ingram et al., 1998). To address this, we reconducted the analyses, focusing on participants scoring in the highest 10% on the BDI ($n = 515$; mean BDI score = 23.94, $SD = 5.98$). Taxometric analyses with this subsample also yielded results that were almost identical to those obtained in the full sample, providing further support for the dimensional nature of cognitive vulnerability to depression.[4] Therefore, it does not appear that the full sample results were due to the relatively low average levels of depressive symptoms among those participants.

Each of the taxometric procedures, therefore, provided clear support for the dimensional nature of the data. However, they do not speak to the relation between negative cognitive styles and depressive symptoms. Specifically, conceptualizing cognitive vulnerability to depression dimensionally does not imply that the relationship between negative cognitive styles and depression

[4] Details of these analyses are available from Brandon E. Gibb.

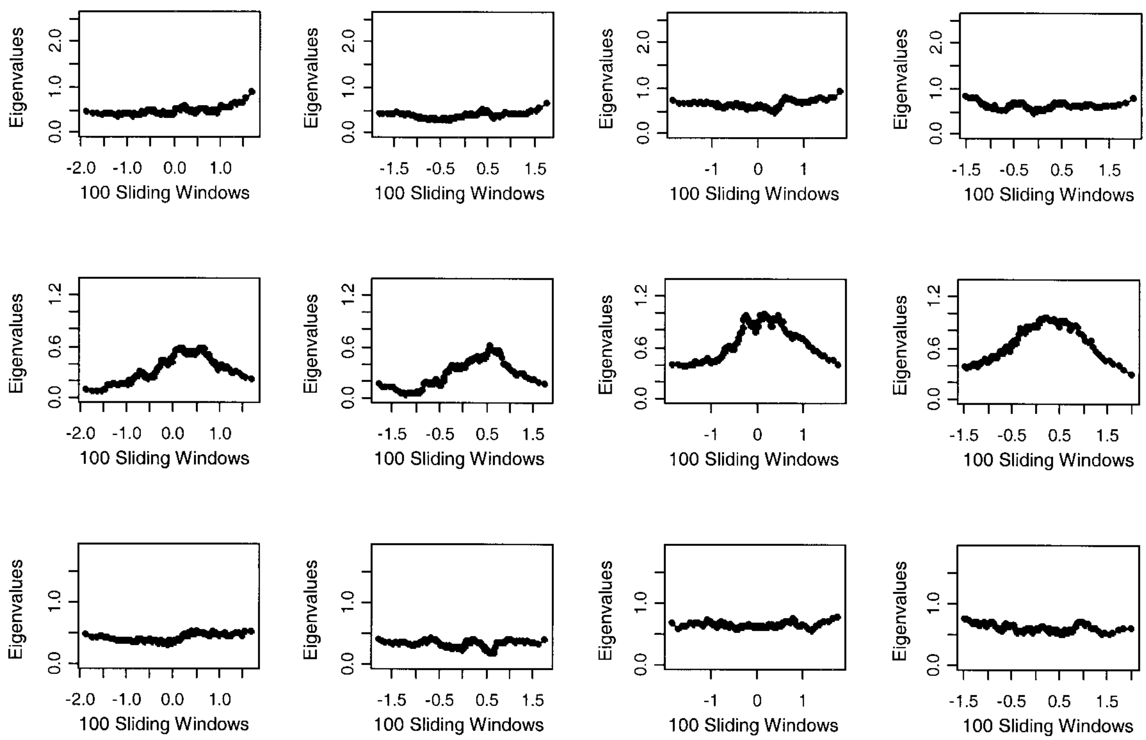

Figure 2. Results of MAXEIG analyses for the research (top row), simulated taxonic (middle row), and simulated dimensional (bottom row) samples. Within each row, graphs represent results for CSQ–Consequences, CSQ–Self-Characteristics, DAS–PE, and DAS–AO, respectively, serving as indicators. CSQ = Cognitive Style Questionnaire; DAS–PE = Dysfunctional Attitudes Scale—Performance Evaluation Subscale; DAS–AO = Dysfunctional Attitudes Scale—Approval by Others subscale; MAXEIG = maximum eigenvalue.

should necessarily be equivalent at each point along the cognitive style continuum. That is, negative cognitive styles may have nonlinear (e.g., quadratic or cubic) effects on depression. To date, however, investigations have been limited to the search for linear effects. Therefore, analyses were conducted to determine whether higher order trends in the relationship between negative cognitive styles and depressive symptoms existed. Given the number of studies examining the attributional component of the hopelessness theory, the CSQ–Generality dimension was included in these analyses along with the other four cognitive style indicators. The results of the trend analyses are presented in Table 4 and are depicted visually in Figure 5. For ease of presentation, only the cubic trends are presented in the figure. We found consistent evidence for nonlinear relationships between measures of negative cognitive styles and depressive symptoms. Specifically, the relation was relatively weak among participants who scored in the middle of the cognitive style distributions, somewhat stronger in the lower tail of the distributions, and strongest among participants scoring in the upper tail of the cognitive style distributions.

Discussion

Results from this study provide consistent support for the dimensional nature of cognitive vulnerability to depression. It appears, therefore, that the heterogeneity of negative cognitive styles is best conceptualized as reflecting quantitative rather than qualitative differences among individuals. An implication of the taxometric findings is that researchers should exercise caution in dichotomizing or forming subgroups of individuals based on their negative cognitive styles because (a) any cutpoint would be arbitrary given the dimensional nature of negative cognitive styles, and (b) dichotomization would result in a significant loss of statistical

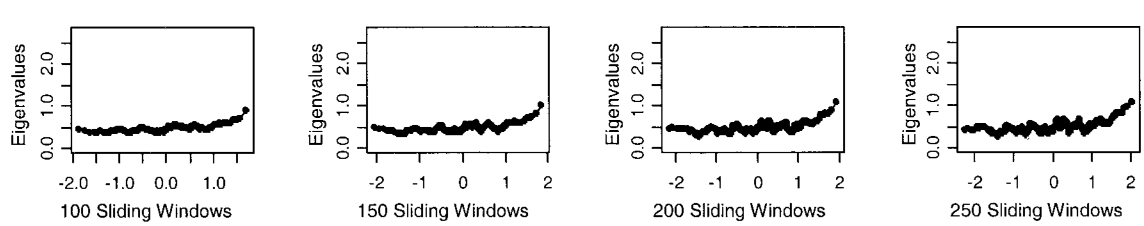

Figure 3. Results of the inchworm consistency test for one of the negative cognitive style indicators with 100, 150, 200, and 250 sliding windows, respectively.

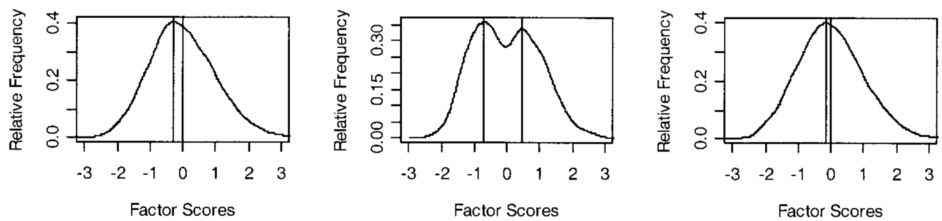

Figure 4. Results of L-MODE analyses for the research (left), simulated taxonic (middle), and simulated dimensional (right) analyses. L-MODE = latent mode.

power (see MacCallum, Zhang, Preacher, & Rucker, 2002; cf. A. M. Ruscio & Ruscio, 2002, for similar conclusions with regard to depressive symptoms). We do recognize, however, that sometimes the formation of subgroups is desirable for a variety of reasons. For example, high and low cognitive risk groups were formed in the CVD Project representing individuals scoring in the most negative and the most positive quartiles, respectively, on both the CSQ and DAS. This was done primarily because when the CVD Project was conceptualized, there was limited evidence for the hypothesis that negative cognitive styles prospectively predict the onset of clinically significant episodes of depression. Therefore, extreme scores were chosen to provide the strongest possible test of the vulnerability hypothesis (see Alloy & Abramson, 1999). Second, including the full range of participants was not feasible because of the time and expense that would have been required. By forming cognitive subgroups in the CVD Project, however, it is recognized that individuals in each group represent extreme scores along a continuum, and no argument is made for the existence of distinct subgroups in the population.

Although cognitive vulnerability to depression appears to be dimensional rather than taxonic, there does appear to be a point along the continuum at which the strength of the relationship between negative cognitive styles and depression is significantly stronger. Specifically, we found evidence for nonlinear trends in the relationships between the cognitive style measures and participants' depressive symptom levels. Although our confidence in this result is strengthened by the fact that it was replicated across five different measures of negative cognitive style, we remain tentative in our conclusions, pending replications with independent samples and alternate measures of negative cognitive styles. For example, it is possible that the nonlinear relations observed may be a function of the manifest indicators included and may not generalize to relations among latent variables.[5] Future studies should evaluate this possibility. If replicated, however, these findings would suggest that studies including a relatively high percentage of individuals with low to moderate scores on measures of negative cognitive styles (e.g., studies of nonclinical samples) may underestimate their relation with depression.

Table 4
Results of Trend Analyses Predicting Depressive Symptoms

Predictor and trend	*df*	*F*	ΔR^2
CSQ–Generality			
Linear	1, 5000	373.12**	.069
Quadratic	1, 4999	214.44**	.010
Cubic	1, 4998	156.09**	.007
CSQ–Consequences			
Linear	1, 5000	476.50**	.087
Quadratic	1, 4999	278.00**	.013
Cubic	1, 4998	195.30**	.005
CSQ–Self-Characteristics			
Linear	1, 5000	610.50**	.109
Quadratic	1, 4999	340.61**	.011
Cubic	1, 4998	229.10**	.001
DAS–PE			
Linear	1, 5000	1,128.51**	.184
Quadratic	1, 4999	610.18**	.012
Cubic	1, 4998	411.00**	.002
DAS–AO			
Linear	1, 5000	445.12**	.082
Quadratic	1, 4999	276.20**	.018
Cubic	1, 4998	186.46**	.001

Note. CSQ = Cognitive Style Questionnaire; DAS–PE = Dysfunctional Attitudes Scale—Performance Evaluation subscale; DAS–AO = Dysfunctional Attitudes Scale—Approval by Others subscale.
** $p < .01$.

The current study exhibited a number of strengths, such as the inclusion of a large sample, the use of multiple taxometric procedures to evaluate the replicability of the results, and the comparison of results from the study sample to those obtained with simulated taxonic and dimensional samples. A potential limitation of this study and all taxometric studies, however, is that the search for taxonicity is limited by the indicators chosen to represent each construct (Widiger, 2001). Therefore, it is possible that the dimensional results were due in part to the cognitive style indicators chosen. Two lines of evidence, however, argue against this possibility. First, the indicators chosen were based on well-established cognitive vulnerability–stress theories of depression (the hopelessness theory [Abramson et al., 1989] and Beck's theory [Beck, 1967, 1987]). Second, the MAMBAC analyses, in which individual indicator pairs were examined, also provided consistent support for the dimensional nature of cognitive vulnerability to depression, even when we focused specifically on pairs of indicators taken from the same theory (i.e., analyses of CSQ or DAS indicator pairs). Therefore, it appears unlikely that the current dimensional results were due simply to a poor choice of construct indicators. This said, however, the results apply to cognitive vulnerability to depression, broadly conceived, rather than to any of the specific cognitive style indicators examined (e.g., sociotropy) or to forms of cognitive vulnerability not included in this study

[5] We thank John Ruscio for suggesting this possibility.

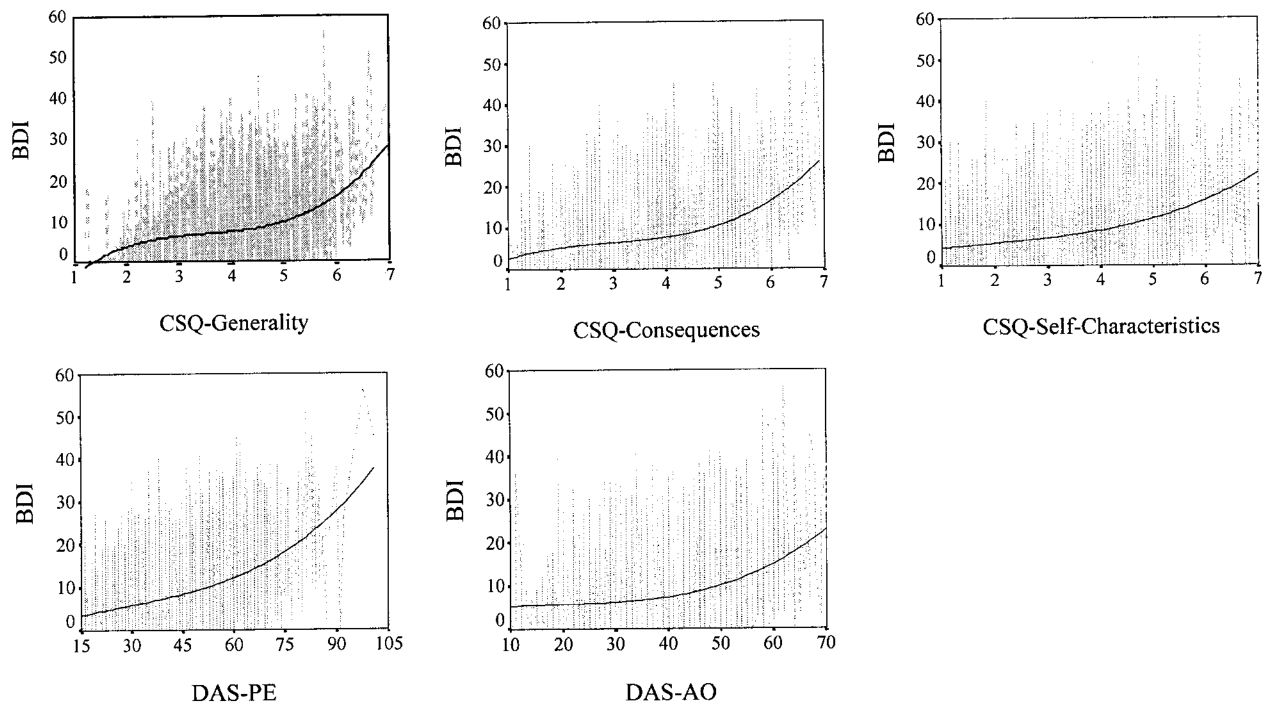

Figure 5. Graph of cubic trends for the relationships between the cognitive style measures and participants' BDI scores. BDI = Beck Depression Inventory; CSQ = Cognitive Style Questionnaire; DAS–PE = Dysfunctional Attitudes Scale—Performance Evaluation subscale; DAS–AO = Dysfunctional Attitudes Scale—Approval by Others Subscale. The dashed gray line in each graph represents the observed data. The solid black line in each graph represents the cubic trend.

(e.g., rumination or information-processing biases). Future studies should evaluate whether any of these more specific forms of cognitive vulnerability to depression exhibit taxonicity.

A second limitation was the reliance on participants' self-reports in assessing cognitive vulnerability to depression. Future studies, therefore, would benefit from the inclusion of multi-method assessments of negative cognitive styles. For example, studies could include questionnaire assessments as well as assessments of information-processing biases (e.g., attentional biases).

Another potential limitation of this study was the use of an undergraduate sample, which may limit the generalizability of the results. For example, one could argue that the dimensional findings were due to the use of relatively nondepressed participants, whose negative cognitive styles were not primed. However, analyses conducted among the subset of participants with elevated depressive symptom levels also supported the dimensional findings. Therefore, it appears unlikely that the current results were due to the relatively low overall levels of depression in this sample.

In conclusion, therefore, it appears that the heterogeneity of cognitive vulnerability to depression is best considered as representing quantitative rather than qualitative differences among individuals. That is, a cognitive vulnerability to depression appears to be present to a greater or lesser degree in all individuals. Future studies should take this into account before dichotomizing their samples and recognize that any cutpoints used represent arbitrary distinctions rather than preexisting subgroups. In addition, researchers should continue to explore the possibility of nonlinear effects of negative cognitive styles on depression rather than limiting their search to linear effects.

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