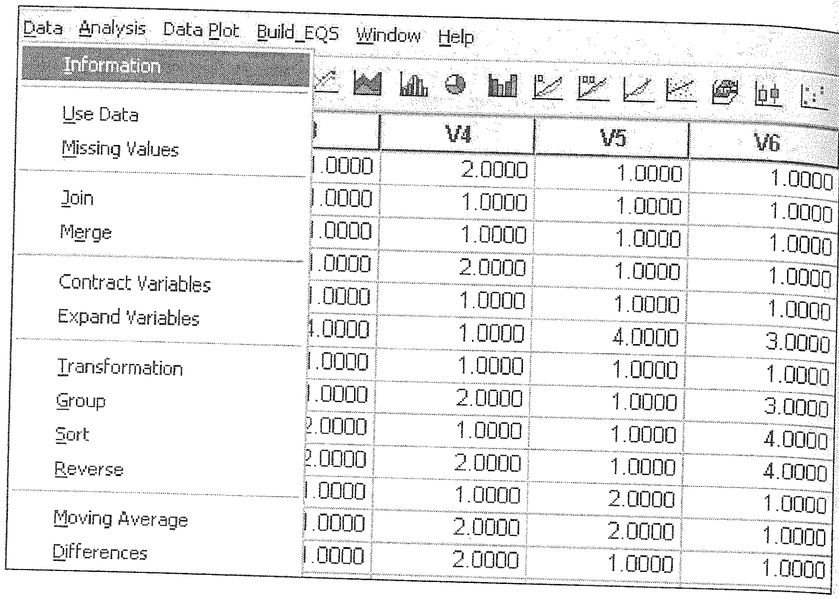

FIG. 5.3. Open .ess file with Data drop-down menu showing Information option.

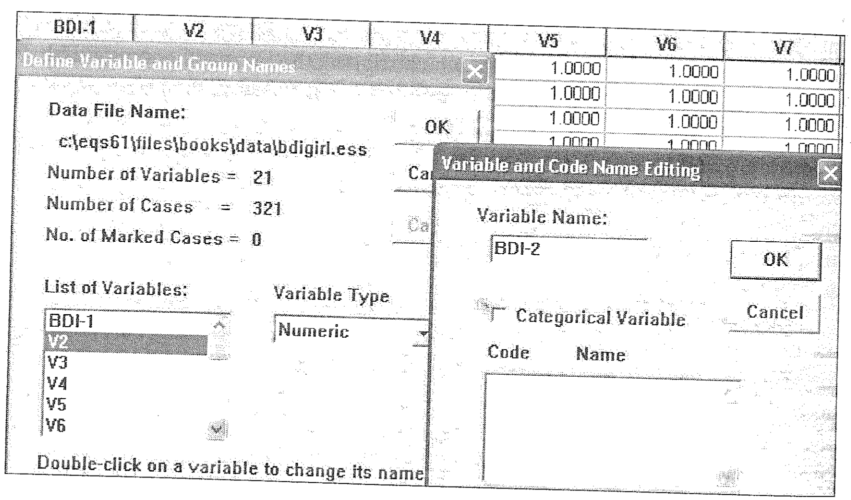

FIG. 5.4. Define Variables and Group Names dialog box with Variable and Code Name Editing dialog box.

name. For example, review of Fig. 5.4 shows that the variable V1 label has already been changed to BDI-1. The variable undergoing change in Fig. 5.4 is V2, and the label has already been edited to read as BDI-2. This process continues until all variables in the complete data set have been relabeled. The ESS. file is saved using Save As with a meaningful file name.

Analysis of Categorical Data. Thus far in this book, analyses have been based on maximum likelihood (ML) estimation (see chap. 3) and Robust ML estimation (see chap. 4). An important assumption underlying both estimation procedures is that the scale of the observed variables is continuous. In both chapters, however, the observed variables were Likert-scaled items that realistically represent categorical data of an ordinal scale, albeit they were treated as if they were continuous. Indeed, such practice has been the norm for many years and applies to traditional statistical techniques (e.g., ANOVA and MANOVA) as well as SEM analyses. Paralleling this widespread practice of treating ordinal data as if they were continuous, however, has been ongoing debate concerning the pros and cons of doing so. Given (a) the prevalence of this practice in the SEM field, (b) the importance of acquiring an understanding of the issues involved, and (c) the intent, in this chapter, to illustrate analysis of data based on categorically coded variables, it is important to address these issues before examining the input file related to the hypothesized model of BDI structure (see Fig. 5.1).

Categorical Variables Analyzed as Continuous Variables

Review of SEM applications during the past 15 years (in psychological research, at least) reveals most to be based on Likert-type scaled data with estimation of parameters using ML procedures (see, e.g., Breckler, 1990). Given the known limitations associated with available alternative estimation strategies (described later), however, this common finding is not surprising. The primary issues associated with this customary practice are briefly reviewed in the next subsection.

The Issues. From a review of Monte Carlo studies that addressed this issue (see, e.g., Babakus, Ferguson, & Jöreskog, 1987; Boomsma, 1982; and Muthén & Kaplan, 1985), West and colleagues (1995) reported several important findings. First, Pearson correlation coefficients appear to be higher when computed between two continuous variables than when computed between the same two variables restructured with an ordered categorical scale. However, the greatest attenuation occurs with variables having fewer than five categories and those exhibiting a high degree of skewness—the latter condition being made worse by variables skewed in opposite directions (i.e., one variable positively skewed, the other negatively skewed; see Bollen & Barb, 1981). Second, when categorical variables approximate a normal distribution, (a) the number of categories has little effect on the χ^2 likelihood ratio test of model fit. Nonetheless, increasing skewness—particularly differential skewness (i.e., variables skewed in opposite directions)—leads to increasingly inflated χ^2 values: (b) factor loadings and factor correlations are only modestly underestimated. However, underestimation becomes more critical when there are fewer than three categories, skewness is greater than 1.0, and differential skewness occurs across variables; (c) error variance estimates, more so than other parameters, appear to be most sensitive to the categorical and skewness issues noted in (b); and (d) standard error estimates for all parameters tend to be too low, with this result being more so when the distributions are highly and differentially skewed (see Finch, West, & MacKinnon, 1997).

In summary, the literature to date appears to support the notion that when the number of categories is large and the data approximate a normal distribution, failure to address the ordinality of the data is likely to be negligible (Atkinson, 1988; Babakus et al., 1987; and Muthén & Kaplan, 1985). Indeed, Bentler and Chou (1987, p. 88) argued that given normally distributed categorical variables, "continuous methods can be used with little worry when a variable has four or more categories." More recent findings support these earlier contentions and have further shown that the χ^2 statistic is influenced most by the two-category response format and becomes less so as the number of categories increases (Green, Akey, Fleming, Hershberger, & Marquis, 1997).

Categorical Variables Analyzed as Categorical Variables

The Theory. In addressing the categorical nature of observed variables, the researcher automatically assumes that each has an underlying continuous scale. As such, the categories can be regarded as only crude measurements of an unobserved variable that, in truth, has a continuous scale (Jöreskog & Sörbom, 1993) with each pair of thresholds (or initial scale points) representing a portion of the continuous scale. The crudeness of these measurements arises from the splitting of the continuous scale of the construct into a fixed number of ordered categories (DiStefano, 2002). Indeed, this categorization process led O'Brien (1985) to argue that the analysis of Likert-scaled data actually contributes to two types of error: (a) categorization error resulting from the splitting of the continuous scale into categorical scale, and (b) transformation error resulting from categories of unequal widths.

For purposes of illustration, let's consider the measuring instrument under study in this chapter in which each item is structured on a four-point scale. The work of Jöreskog and Sörbom (1993) is drawn upon to describe the decomposition of these categorical variables. Let z represent the ordinal variable (the item) and z^* the

unobserved continuous variable. The threshold values can then be conceptualized as follows:

If z^* < or = τ_1, z is scored 1.
If $\tau_1 < z^*$ <or = τ_2, z is scored 2.
If $\tau_2 < z^*$ <or = τ_3, z is scored 3.
If $\tau_3 < z^*$, z is scored 4.

Where $\tau_1 < \tau_2 < \tau_3$ represent threshold values for z^*.

In conducting SEM with categorical data, analyses must be based on the correct correlation matrix. Where the correlated variables are both of an ordinal scale, the resulting matrix comprises, *polychoric correlations*; where one variable is of an ordinal scale and the other is of a continuous scale, the resulting matrix comprises *polyserial correlations*. If two variables are dichotomous, this special case of a polychoric correlation is called a *tetrachoric correlation*. If a polyserial correlation involves a dichotomous rather than a more general ordinal variable, the polyserial correlation is also called a *biserial correlation*.

The Assumptions. Applications involving the use of categorical data are based on three critically important assumptions: (a) underlying each categorical observed variable is an unobserved latent counterpart, the scale of which is both continuous and normally distributed; (b) sample size is sufficiently large to enable reliable estimation of the related correlation matrix; and (c) the number of observed variables is kept to a minimum. As Bentler (2005) cogently notes, however, it is this very set of assumptions that essentially epitomizes the primary weakness in this methodology. Let's now take a brief look at why this should be so.

That each categorical variable has an underlying continuous and normally distributed scale is undoubtedly a difficult criterion to meet and, in fact, may be totally unrealistic. For example, in this chapter, scores tapping aspects of depression for nonclinical adolescents are examined. Clearly, we would expect such item scores for normal adolescents to be low, thereby reflecting no incidence of depressive symptoms. As a consequence, we can expect to find evidence of kurtosis and possibly skewness related to these variables, with this pattern being reflected in their presumed underlying continuous distribution. Consequently, in the event that the model under test is deemed to be less than adequate, it may well be that the normality assumption is unreasonable in this instance.

The rationale underlying the latter two assumptions stems from the fact that in working with categorical variables, analyses must proceed from a frequency table comprising number of thresholds x number of observed variables to an estimation of the correlation matrix. The problem lies with the occurrence of cells having zero or near-zero cases, which can subsequently lead to estimation difficulties (Bentler, 2005). This problem can arise because (a) sample size is small relative to the number of response categories (i.e., specific category scores across all categorical variables); (b) the number of variables is excessively large; and/or (c) the number of thresholds is large. Taken in combination, the larger the number of observed variables and/or number of thresholds for these variables and the smaller the sample size, the greater the chance of having cells comprising zero to near-zero cases.

General Analytic Strategies. Until recently, two primary approaches to the analysis of categorical data (Jöreskog, 1990, 1994; and Muthén, 1984) have dominated this area of research. Both methodologies use standard estimates of polychoric and polyserial correlations followed by a type of asymptotic distribution-free (ADF) methodology for the structured model. Unfortunately, the positive aspects of these categorical variable methodologies have been offset by the ultra restrictive assumptions noted previously and which, for most practical researchers, are both impractical and difficult to meet. In particular, conducting ADF estimation has the same problem of requiring huge sample sizes as in Browne's (1984a) ADF method for continuous variables. Attempts to resolve these difficulties in recent years have resulted in the development of several different approaches to modeling categorical data (see, e.g., Bentler, 2005; Coenders, Satorra, & Saris, 1997; Moustaki, 2001; and Muthén & Muthén, 2004). One of these newer strategies is incorporated in the EQS 6.1 program described in the following subsection.

The EQS Strategy. Given both the stringency and dubious appropriateness of assumptions underpinning the analysis of categorical data, Bentler (2005) argued that it may make more sense to correct the test statistic while using a mode of estimation that works well with not-too-large samples. Using a normal theory-based method such as ML followed by Satorra-Bentler corrections (Satorra & Bentler, 1988) yields a reliable procedure (see, e.g., DiStefano, 2002). The use of an improved estimator of polychoric and polyserial correlations (Lee, Poon, & Bentler, 1995), together with ROBUST methodologies, distinguishes the EQS approach to the analysis of categorical data from that of other SEM programs.

Consistent with the traditions of Muthén (1984), Jöreskog (1994), and Lee, Poon, and Bentler (1990, 1992), EQS follows a three-step sequential approach to estimation. Univariate statistics such as thresholds are estimated first, followed by estimation of bivariate statistics such as correlations. Estimation of the SEM model is completed using a method like ML followed by ROBUST computations based on an appropriate weight matrix. (For technical details related to this three-stage approach, see Bentler, 2005, and the original articles.) It is important to note that although the correlation estimates and weight matrices in EQS are similar to those of Muthén (1984) and Jöreskog (1994), they are not identical.

From the perspective of sample size, at least, the EQS approach to analysis of categorical data is more practical than the one based on full estimation. Whereas sample size requirements for both the Muthén (1984) and Jöreskog (1994) methodological strategies have been reported as substantial (see, e.g., Dolan, 1994; and

Lee, Poon, & Bentler, 1995), those associated with the ML ROBUST approach in EQS are much less so. Indeed, Bentler (2005) contends that the ROBUST methodology allows for the attainment of correct statistics, which are quite stable even in relatively small samples. Although the ML estimator (or another simpler estimator—e.g., GLS) is not asymptotically optimal when used with categorical variables, the inefficiency is small and certainly offset by improved performance in smaller samples. The Satorra–Bentler scaled χ^2 and ROBUST standard errors provide trustworthy statistics. Of course, if sample size is huge, ME=AGLS can always be used, which, in EQS, gives the asymptotically optimal solution.

With an understanding of the issues involved in the analysis of categorical variables, we move to an application based on the BDI data described at the beginning of this chapter.

ANALYSES BASED ON DATA REGARDED AS CATEGORICAL

The EQS Input File

By now, you will be fairly familiar with the EQS input file setup so details related to all aspects of the file shown in Table 5.1 are not reiterated; my explanation is to therefore limited model specifications not previously addressed. Two features of the current application are of particular interest: (a) that the ordinality of the data is being taken into account and (b) that the model under study is a higher order CFA model.

We turn first to /SPECIFICATIONS and, in particular, the first line of this paragraph. Here we see that the score data are based on 321 cases, an adequate sample to use with the ML estimator but certainly not large enough to use with AGLS, the distribution-free estimator (see Bentler, 2005). Thus, the next specification of note is the method to be used in analyzing the data; here we see ME=ML, ROBUST. This specification conveys two important pieces of information: (a) that ML estimation is to be used in analyzing the correlation matrix, and (b) that the χ^2 and standard errors are to be corrected (i.e., made robust) through use of a large optimal weight matrix appropriate for analysis of categorical data. Given that ML estimation assumes the variables under study are continuous, it is important to acknowledge this obvious misspecification. Bentler (2005) notes that although the estimates will be good, it is essential to follow up with the ROBUST option to obtain the correct S-Bχ^2 and Yuan–Bentler tests and standard errors. As a final point, analyses are based on a raw matrix (MA=RAW)—another necessary requirement in the analysis of categorical data.

Line 2 contains commands that must be specified to perform analyses that include categorical variables. The CATEGORY specification identifies which variables are of a categorical nature. In this case, all 21 variables have an ordinal

TABLE 5.1
EQS Input for Initially Hypothesized Model

```
/TITLE
 CFA OF 2nd-order BDI Structure for Adolescent Females "BDIGIRL1"
 Treated as Categorical Variables
/SPECIFICATIONS
 CASE=321; VAR=21; ME=ML,ROBUST; MA=RAW; FO='(21F1.0)';
 CATEGORY=V1 to V21; ANALYSIS=CORRELATION;
 DATA='C:\EQS61\Files\Books\Data\bdigirl.ess';
/LABELS
 V1=I1SAD;  V2=I2PESS;  V3=I3FAIL;  V4=I4DISSAT;  V5=I5GUILT;
 V6=I6PUNISH; V7=I7SDISL; V8=I8SACCUS; V9=I9SUI;  V10=I10CRY;
 V11=I11IRRIT; V12=I12WDRL; V13=I13INDEC; V14=I14SIMAGE; V15=I15WINHIB;
 V16=I16INSOM; V17=I17FATIG; V18=I18ALOSS; V19=I19WLOSS; V20=I20HYPOC;
 V21=I21LLOSS;

 F1=NEGATT; F2=PERFDIFF; F3=SOMELEM; F4=DEPRESS;
/EQUATIONS
 V1 =  F1 + E1 ;
 V2 = *F1 + E2 ;
 V3 = *F1 + E3 ;
 V5 = *F1 + E5 ;
 V6 = *F1 + E6 ;
 V7 = *F1 + E7 ;
 V8 = *F1 + E8 ;
 V9 = *F1 + E9 ;
 V10 = *F1 + E10 ;
 V14 = *F1 + E14 ;
        V4 =  F2 + E4;
        V11 = *F2 + E11;
        V12 = *F2 + E12 ;
        V13 = *F2 + E13 ;
        V15 = *F2 + E15 ;
        V17 = *F2 + E17 ;
        V20 = *F2 + E20 ;
               V16 = F3 + E16 ;
               V18 = *F3 + E18 ;
               V19 = *F3 + E19 ;
               V21 = *F3 + E21 ;
 F1= *F4 + D1;
 F2= *F4 + D2;
 F3= *F4 + D3;
/VARIANCES
   F4= 1.0;
   D1= *;
   D2= *;
   D3= *;
   E1 to E21 = *;
/CONSTRAINTS
 (D2,D2) = (D3,D3);
/PRINT
 FIT = ALL;
/LMTEST
 SET=PEE,GVF;
/END
```


scale; hence, the specification of V1 to V21. However, it may well be that in some other data set, the number of categorical variables may only be a subset of otherwise continuous variables. In such a case, only these categorical variables need be identified. In EQS, there is no need to specify the number of scale points associated with categorical variables because the program automatically determines this information as you will see later (demonstrated when the output is reviewed). The second specification on this line advises the program that analyses are to be based on a correlation rather than the default covariance structure. Finally, Line 3 of the /SPECIFICATION paragraph specifies the filename and location of the data, which is the bdigirl.ess file created from raw data at the beginning of this chapter.

In the /VARIANCES paragraph, the variance associated with each of the measurement errors (E1 to E21) as well as with the disturbance terms (D1 to D3) is to be estimated. However, variance related to each of the first-order factors is not estimated. These factors represent dependent variables in the model and, as discussed in chapter 1, dependent variables and their covariances (in the Bentler–Weeks sense) cannot be estimated; they remain to be explained by the model. Finally, you may wonder why the variance for Factor 4 (F4; Depression) is fixed to a value of 1.0. This specification derives from an important corollary in SEM, which states that either a regression path or a variance can be estimated but not both. Before relating this corollary to Factor 4 (i.e., the second-order factor that explains correlations among the first-order factors F1–F3), allow me to first illustrate its application using a simple example. Let's turn to Fig. 5.1 and review the error terms. In each case, the variance is estimated, whereas the related regression path is fixed to 1.0. In this instance, a choice had to be made: either estimate the variance or the regression path. The error variance, of course, is of greater interest and, therefore, the regression path must be fixed to 1.0. However, if we want to estimate the regression path rather than the variance (which does not make much sense but is possible nonetheless), we need to fix the variance to 1.0. Returning to the input file in Table 5.1, note that each of the higher order factor loadings (i.e., F1 = *F4 + D1; F2 = *F4 + D2; F3 = *F4 + D3) is estimated; as a result, the variance of Factor 4 must be fixed to 1.0. Had we elected to fix one of these second-order paths to 1.0, the variance of Factor 4 could be freely estimated. However, typically with higher order models, the loadings rather than the variance of the higher order factor are of interest.

The final specification of note lies within the /CONSTRAINTS paragraph. The information being conveyed is that the variance of the disturbance term associated with Factor 2 (D2,D2) is to be constrained equal to that for Factor 3 (D3,D3). What is the rationale for such specification? Recall that in Chapter 2, I emphasized the importance of computing the degrees of freedom associated with hypothesized models to ascertain their status with respect to statistical identification. With hierarchical models, it is additionally critical to check the identification status of the higher order portion of the model. In the current case, given the specification of only three first-order factors, the higher order structure is just-identified unless a constraint is placed on at least one parameter in this upper level of the model (see, e.g., Bentler, 2005; and Rindskopf & Rose, 1988). More specifically, with three first-order factors, there are six (i.e., [4 × 3]/2) pieces of information; the number of estimable parameters is also six (i.e., three factor loadings and three residual variances), thereby resulting in a just-identified model. This result is acceptable; but if we wish also to resolve this condition of just-identification, equality constraints can be placed on particular parameters known to yield estimates that are approximately equal. An initial test of the hypothesized model shown in Fig. 5.1 revealed the estimated values for D2 and D3 to be very close. For this reason, the variance of D3 was equated with that of D2, thereby providing 1 degree of freedom at the higher order level of the model.

The EQS Output File

Table 5.2 presents the first citation from the output related to the hypothesized model. Here we see that the program has identified 21 variables, with all but one (V12) consisting of four categories. Although Item 12 actually had four categories, no subject responded to the fourth category; as a result, EQS assumed that this item had only three categories. Appearing next in the output are the average thresholds for each categorical variable, followed by the polychoric correlation matrix, shown in Table 5.3. Note that Variables with four categories have three thresholds, whereas V12 (Item 12) has two thresholds for its three categories (i.e., there were no response scores in Category 4). Only a portion of this matrix is presented here to give you a flavor of the type of information that EQS provides when the variables under study are categorical.

TABLE 5.2
Selected EQS Output for Initially Hypothesized Model: Categorical Variable Summary

```
YOUR MODEL HAS SPECIFIED CATEGORICAL VARIABLES
    TOTAL NUMBER OF VARIABLES ARE          21
    NUMBER OF CONTINUOUS VARIABLES ARE      0
    NUMBER OF DISCRETE   VARIABLES ARE     21
    INFORMATION ON DISCRETE VARIABLES
       V1  WITH   4 CATEGORIES
       V2  WITH   4 CATEGORIES
       V3  WITH   4 CATEGORIES
       V4  WITH   4 CATEGORIES
       V5  WITH   4 CATEGORIES
       V6  WITH   4 CATEGORIES
       V7  WITH   4 CATEGORIES
       V8  WITH   4 CATEGORIES
       V9  WITH   4 CATEGORIES
       V10 WITH   4 CATEGORIES
       V11 WITH   4 CATEGORIES
       V12 WITH   3 CATEGORIES
       V13 WITH   4 CATEGORIES
       V14 WITH   4 CATEGORIES
       V15 WITH   4 CATEGORIES
       V16 WITH   4 CATEGORIES
       V17 WITH   4 CATEGORIES
       V18 WITH   4 CATEGORIES
       V19 WITH   4 CATEGORIES
       V20 WITH   4 CATEGORIES
       V21 WITH   4 CATEGORIES
```


TABLE 5.3
Selected EQS Output for Initially Hypothesized Model: Polychoric Thresholds and Matrix

RESULTS OF POLYCHORIC PARTITION

AVERAGE THRESHOLDS

V 1	.2354	1.2766	1.7013
V 2	.3924	1.1114	1.9264
V 3	.5438	1.1877	1.9875
V 4	-.0559	.9789	1.3744
V 5	.4835	1.6311	2.0618
V 6	.3134	.8468	1.1581
V 7	.0634	1.3318	1.6990
V 8	-.1990	1.0297	1.5416
V 9	.1531	1.6638	2.1366
V10	.1095	.7752	.9779
V11	-.4173	.8731	1.1118
V12	.6826	1.7347	
V13	.0044	.5114	1.8171
V14	.1520	.5708	1.1428
V15	-.0631	.9901	2.2324
V16	.0565	1.0979	1.5381
V17	-.3536	1.2066	1.6979
V18	.2054	.9647	1.4175
V19	1.0154	1.5975	1.8670
V20	.3853	1.2065	1.9227
V21	1.0692	1.5396	1.9816

POLYCHORIC CORRELATION MATRIX BETWEEN DISCRETE VARIABLES

	V 1	V 2	V 3	V 4	V 5
V 1	1.000				
V 2	.357	1.000			
V 3	.444	.486	1.000		
V 4	.381	.284	.322	1.000	
V 5	.336	.345	.409	.282	1.000
V 6	.428	.383	.436	.312	.468
V 7	.475	.499	.631	.420	.431
V 8	.321	.332	.385	.316	.339
V 9	.546	.411	.381	.369	.226
V 10	.477	.244	.467	.284	.289

TABLE 5.4

Selected EQS Output for Initially Hypothesized Model: Warning Messages

SAMPLE STATISTICS BASED ON COMPLETE CASES

***** NOTE *** CATEGORICAL VARIABLES LISTED ABOVE ARE INDICATORS OF LATENT CONTINUOUS VARIABLES. THEIR UNIVARIATE AND JOINT STATISTICS MAY NOT BE MEANINGFUL.**

UNIVARIATE STATISTICS

VARIABLE	BDI1SAD	BDI2PESS	BDI3FAIL	BDI4DISSAT	BDI5GUILT
MEAN	1.5296	1.4829	1.4081	1.7508	1.3645
SKEWNESS (G1)	1.5320	1.4757	1.7337	1.1455	1.8754
KURTOSIS (G2)	2.0716	1.3265	2.1816	.6015	3.9313
STANDARD DEV.	.7623	.7627	.7279	.8910	.6184

***** WARNING *** NORMAL THEORY STATISTICS MAY NOT BE MEANINGFUL DUE TO ANALYZING CORRELATION MATRIX**

	BDI1SAD V 1	BDI2PESS V 2	BDI3FAIL V 3	BDI4DISSAT V 4	BDI5GUILT V 5
BDI1SAD V 1	1.000				
BDI2PESS V 2	.357	1.000			
BDI3FAIL V 3	.444	.486	1.000		
BDI4DISSAT V 4	.381	.284	.322	1.000	
BDI5GUILT V 5	.336	.345	.409	.282	1.000
BDI6PUNISH V 6	.428	.383	.436	.312	.468
BDI7SDISL V 7	.475	.499	.631	.420	.431
BDI8SACCUS V 8	.321	.332	.385	.316	.339
BDI9SUI V 9	.546	.411	.381	.369	.226
BDI10CRY V 10	.477	.244	.467	.284	.289

Consistent with output related to continuous variables, EQS presents the sample univariate statistics, which represent statistics for the data file. Because the scores 1, 2, 3, and 4 in the data file are not of interest, the program presents the warning messages shown in Table 5.4 advising that the univariate statistics may not be meaningful—and they are not; therefore, this output should be ignored. Thereafter, the program presents the polychoric correlation matrix to be analyzed, but it prints a message reminding the user that normal theory statistics such as ML (which follow) should be scrutinized for relevance. The ML $\chi 2$ test and standard errors should be ignored in favor of their ROBUST counterparts; this reminder is shown in the top line of Table 5.5. The table presents information related to the standardized residuals: the discrepancy between the sample polychoric correlations and those estimated from the factor model. Appearing first is an excerpt from the standardized residual matrix followed by values for the average residual estimate, ignoring their signs (.0528; over both diagonal and off-diagonal elements) and average off-diagonal residual estimate (.0581; over cross-diagonal elements only). In the largest of these standardized residuals, we see that the largest misspecification

TABLE 5.5

Selected EQS Output for Initially Hypothesized Model: Standardized Residuals

MAXIMUM LIKELIHOOD SOLUTION (NORMAL DISTRIBUTION THEORY) WITH ROBUST STATISTICS (LEE, POON, AND BENTLER OPTIMAL WEIGHT MATRIX)

STANDARDIZED RESIDUAL MATRIX:

	BDI1SAD V 1	BDI2PESS V 2	BDI3FAIL V 3	BDI4DISSAT V 4	BDI5GUILT V 5
BDI1SAD V 1	.000				
BDI2PESS V 2	-.045	.000			
BDI3FAIL V 3	-.042	.045	.000		
BDI4DISSAT V 4	.014	-.048	-.081	.002	
BDI5GUILT V 5	-.028	.014	.008	-.020	.000
BDI6PUNISH V 6	.022	.014	-.011	-.024	.133
BDI7SDISL V 7	-.045	.028	.060	-.011	.002
BDI8SACCUS V 8	-.037	.007	-.009	.019	.043
BDI9SUI V 9	.103	.009	-.106	.002	-.140
BDI10CRY V 10	.096	-.101	.049	-.031	-.025

AVERAGE ABSOLUTE STANDARDIZED RESIDUALS = .0528
AVERAGE OFF-DIAGONAL ABSOLUTE STANDARDIZED RESIDUALS = .0581

LARGEST STANDARDIZED RESIDUALS:

NO.	PARAMETER	ESTIMATE	NO.	PARAMETER	ESTIMATE
1	V21, V20	.278	11	V19, V7	-.155
2	V11, V10	.209	12	V9, V5	-.140
3	V19, V14	-.193	13	V12, V11	-.137
4	V19, V8	.192	14	V6, V5	.133
5	V21, V19	.189	15	V15, V6	-.132
6	V19, V3	-.183	16	V19, V18	.130
7	V11, V2	-.178	17	V18, V10	.129
8	V19, V2	-.175	18	V20, V4	-.128
9	V20, V6	.162	19	V18, V9	.128
10	V13, V8	.161	20	V17, V2	-.124

DISTRIBUTION OF STANDARDIZED RESIDUALS

```
    ----------------------------------------
    !                                      !
100-                 *                     -
    !                *  *                  !
    !                *  *                  !
    !                *  *                  !
    !                *  *                  !
 75-                 *  *                  -
    !                *  *                  !
    !                *  *                  !
    !                *  *                  !
    !                *  *                  !
 50-                 *  *                  -
    !                *  *                  !
    !                *  *                  !
    !                *  *                  !
    !                *  *                  !
 25-                 *  *                  -
    !             *  *  *                  !
    !             *  *  *  *               !
    !             *  *  *  *               !
    !             *  *  *  *               !
    ----------------------------------------
     1  2  3  4  5  6  7  8  9  A  B  C
```

	RANGE			FREQ	PERCENT
1	-0.5	-	--	0	.00%
2	-0.4	-	-0.5	0	.00%
3	-0.3	-	-0.4	0	.00%
4	-0.2	-	-0.3	0	.00%
5	**-0.1**	**-**	**-0.2**	**18**	**7.79%**
6	**0.0**	**-**	**-0.1**	**100**	**43.29%**
7	**0.1**	**-**	**0.0**	**97**	**41.99%**
8	**0.2**	**-**	**0.1**	**14**	**6.06%**
9	**0.3**	**-**	**0.2**	**2**	**.87%**
A	0.4	-	0.3	0	.00%
B	0.5	-	0.4	0	.00%
C	++	-	0.5	0	.00%
	TOTAL			231	100.00%

EACH "*" REPRESENTS 5 RESIDUALS

in the model appears to involve Items 21 and 20 (V21,V20). Finally, a distribution table summarizes the spread of these residuals. Ideally, this distribution should be symmetric with residual values clustered around the zero point. Although the distribution shown in Table 5.5 shows the bulk of these residuals falling into this category, with values ranging from −.1 to 1.0 (85.28%), there is nonetheless some indication of misfit, with 7.79% of residual values ranging from −.1 to −.2 and 6.06% ranging from .1 to .3. The LM Test statistics will shed more light on this possible model misspecification.

Turning to the goodness-of-fit statistics presented in Table 5.6, we observe a vast difference in values derived from ML normal theory estimation versus those based

TABLE 5.6
Selected EQS Output for Initially Hypothesized Model: Goodness-of-Fit Statistics

```
          GOODNESS OF FIT SUMMARY FOR METHOD = ML

CHI-SQUARE =      766.221 BASED ON      187 DEGREES OF FREEDOM
PROBABILITY VALUE FOR THE CHI-SQUARE STATISTIC IS       .00000

THE NORMAL THEORY RLS CHI-SQUARE FOR THIS ML SOLUTION IS       698.784.

FIT INDICES
-----------
BENTLER-BONETT      NORMED FIT INDEX =       .709
BENTLER-BONETT NON-NORMED FIT INDEX =       .732
COMPARATIVE FIT INDEX (CFI)         =       .761
ROOT MEAN-SQUARE RESIDUAL (RMR)     =       .071
STANDARDIZED RMR                    =       .071
ROOT MEAN-SQUARE ERROR OF APPROXIMATION (RMSEA)    =      .098
90% CONFIDENCE INTERVAL OF RMSEA (          .091,        .105)

RELIABILITY COEFFICIENTS
------------------------
CRONBACH'S ALPHA                    =       .889
RELIABILITY COEFFICIENT RHO         =       .898

          GOODNESS OF FIT SUMMARY FOR METHOD = ROBUST

SATORRA-BENTLER SCALED CHI-SQUARE =    264.5675 ON    187 DEGREES OF FREEDOM
PROBABILITY VALUE FOR THE CHI-SQUARE STATISTIC IS      .00016

RESIDUAL-BASED TEST STATISTIC                     =   784.402
PROBABILITY VALUE FOR THE CHI-SQUARE STATISTIC IS      .00000

YUAN-BENTLER RESIDUAL-BASED TEST STATISTIC        =   227.784
PROBABILITY VALUE FOR THE CHI-SQUARE STATISTIC IS      .02240

YUAN-BENTLER RESIDUAL-BASED F-STATISTIC      =     1.757
DEGREES OF FREEDOM =                          187,   134
PROBABILITY VALUE FOR THE F-STATISTIC IS          .00030

FIT INDICES
-----------
BENTLER-BONETT      NORMED FIT INDEX =       .798
BENTLER-BONETT NON-NORMED FIT INDEX =       .921
COMPARATIVE FIT INDEX (CFI)         =       .930
ROOT MEAN-SQUARE ERROR OF APPROXIMATION (RMSEA)    =      .036
90% CONFIDENCE INTERVAL OF RMSEA (          .025,        .046)
```


on the robust statistics; these appear to be particularly discrepant with respect to the Fit Indexes. For example, whereas the CFI is .76 with uncorrected ML estimation, it is .93 with corrected robust estimation. However, it is important to emphasize again, that when EQS analyses are based on categorical data, interpretation of model fit must be based on the ROBUST statistical output.

In the ROBUST goodness-of-fit statistics, we see that, in addition to the S-Bχ^2 value (264.57 with 187 df) there are three statistics that have not been addressed. These distribution-free statistics are based on the distribution of residuals, and each is included in the output when ROBUST statistics are requested. These are new statistics (Bentler, 2005). The first, the RESIDUAL-BASED STATISTIC, is of a type developed by Browne (1982, 1984a). The use of this statistic, however, is curtailed by the fact that its interpretation is meaningful only when sample size is very large. The YUAN-BENTLER RESIDUAL-BASED STATISTIC (based on the work of Yuan & Bentler, 1998; and Bentler & Yuan, 1999) represents an extension of Browne's residual-based test such that it can be used with smaller samples. In this regard, Bentler (2005) notes that in addition to performing better in smaller samples than the original RESIDUAL-BASED STATISTIC, it does so without any loss of its large-sample properties. Finally, the YUAN-BENTLER RESIDUAL-BASED F-STATISTIC (Yuan & Bentler, 1998), designed to take sample size into account more adequately, represents a more extensive modification of Browne's (1984a) statistic and is considered by Bentler (2005) to be the best available residual-based test at this time. (For technical details related to these residual-based tests, see Bentler, 2005). In this input, all test statistics imply some degree of misfit in the model.

We now turn to an evaluation of the hypothesized BDI structure shown in Fig. 5.1 using fit indexes. Focusing on the ROBUST fit indexes, we find a CFI value of .93 and a RMSEA value of .036, with a 90% C.I. ranging from .025 to .046. On the basis of these indexes, this model exemplifies a relatively good fit to the data, although, admittedly, it does not reach the CFI value of .95 recommended by Hu and Bentler (1999). However, recall that the standardized residuals indicated some degree of misfit with respect to Items 20 and 21. To further assess this situation, we turn now to the results of the LM Test presented in Table 5.7.

As expected, review of the LM Test univariate incremental values reveals an error covariance between Items 21 and 20 to contribute most to any misfit in the model. Item 21 is concerned with loss of interest in sex, whereas Item 20 targets health concerns. It is interesting that in the original study (Byrne et al., 1993), which focused on a comparison of the BDI structure across gender, this error covariance did not exist for boys. In light of the degree of social attention accorded sexually transmitted diseases in general and AIDS in particular, we argued that it is not surprising that female adolescents develop health concerns related to sexual activity. Given that the content of Items 20 and 21 appears to elicit responses reflective of the same mind set, we argued that specification of an error covariance

TABLE 5.7
Selected EQS Output for Initially Hypothesized Model: Modification Indexes

MULTIVARIATE LAGRANGE MULTIPLIER TEST BY SIMULTANEOUS PROCESS IN STAGE 1

PARAMETER SETS (SUBMATRICES) ACTIVE AT THIS STAGE ARE: PEE GVF

		CUMULATIVE MULTIVARIATE STATISTICS			UNIVARIATE INCREMENT		HANCOCK'S SEQUENTIAL	
STEP	PARAMETER	CHI-SQUARE	D.F.	PROB.	CHI-SQUARE	PROB.	D.F.	PROB.
1	E21,E20	41.006	1	.000	41.006	.000	187	1.000
2	V19,F4	77.172	2	.000	36.166	.000	186	1.000
3	E19,E8	108.537	3	.000	31.365	.000	185	1.000
4	V20,F4	129.980	4	.000	21.443	.000	184	1.000
5	E11,E10	150.814	5	.000	20.834	.000	183	1.000
6	E9,E5	169.776	6	.000	18.962	.000	182	1.000
7	E9,E3	192.556	7	.000	22.780	.000	181	1.000
8	E13,E8	209.477	8	.000	16.921	.000	180	1.000
9	E11,E2	226.103	9	.000	16.626	.000	179	1.000
10	E11,E7	242.605	10	.000	16.502	.000	178	1.000
11	E12,E11	257.768	11	.000	15.163	.000	177	1.000
12	E20,E6	271.329	12	.000	13.561	.000	176	1.000
13	E13,E12	284.842	13	.000	13.514	.000	175	1.000
14	E17,E13	299.161	14	.000	14.319	.000	174	1.000
15	V10,F4	312.412	15	.000	13.251	.000	173	1.000

between these two items was substantively reasonable. In contrast, it is difficult to substantiate estimation of the two subsequent parameters (i.e., V19,F4 and E19,E8), the only two worthy of consideration. Although the loading of Item 19 (i.e., measuring weight loss) on the higher order factor of Depression might seem reasonable substantively, it is not realistic psychometrically. With respect to the third parameter, specification of an error covariance between Item 19 (weight loss) and Item 8 (self-accusation) is substantively unjustified. Keeping a watchful eye on parsimony, then, I consider only the error covariance between Items 20 and 21 to be a reasonable addition to the model, for two reasons: (a) the specification is substantively reasonable, and (b) the model already represents a fairly adequate fit to the data. We now move into exploratory mode and peruse EQS output related to Model 2.

POST HOC ANALYSES: MODEL 2

The EQS Output File

Goodness-of-fit statistics related to Model 2 are presented in Table 5.8. With the inclusion of the one error covariance between Items 20 and 21 and a CFI of .944

TABLE 5.8
Selected EQS Output for Model 2: Goodness-of-Fit Statistics

```
GOODNESS OF FIT SUMMARY FOR METHOD = ML

CHI-SQUARE =       723.505 BASED ON      186 DEGREES OF FREEDOM
PROBABILITY VALUE FOR THE CHI-SQUARE STATISTIC IS        .00000

FIT INDICES
-----------
BENTLER-BONETT      NORMED FIT INDEX =       .725
BENTLER-BONETT NON-NORMED FIT INDEX =       .750
COMPARATIVE FIT INDEX (CFI)         =       .778
ROOT MEAN-SQUARE RESIDUAL (RMR)     =       .068
STANDARDIZED RMR                    =       .068
ROOT MEAN-SQUARE ERROR OF APPROXIMATION (RMSEA)    =      .095
90% CONFIDENCE INTERVAL OF RMSEA (          .088,         .102)

GOODNESS OF FIT SUMMARY FOR METHOD = ROBUST

SATORRA-BENTLER SCALED CHI-SQUARE =     247.1578 ON      186 DEGREES OF FREEDOM
PROBABILITY VALUE FOR THE CHI-SQUARE STATISTIC IS        .00180

YUAN-BENTLER RESIDUAL-BASED TEST STATISTIC          =  225.840
PROBABILITY VALUE FOR THE CHI-SQUARE STATISTIC IS        .02452

YUAN-BENTLER RESIDUAL-BASED F-STATISTIC      =      1.728
DEGREES OF FREEDOM   =                        186,   135
PROBABILITY VALUE FOR THE F-STATISTIC IS           .00042

FIT INDICES
-----------
BENTLER-BONETT      NORMED FIT INDEX =       .811
BENTLER-BONETT NON-NORMED FIT INDEX =       .937
COMPARATIVE FIT INDEX (CFI)         =       .944
ROOT MEAN-SQUARE ERROR OF APPROXIMATION (RMSEA)    =      .032
90% CONFIDENCE INTERVAL OF RMSEA (          .020,         .042)
```

and RMSEA of .032, the BDI structure as specified in Model 2 represents a very adequate fit to the data.

In Table 5.9, only a few parameter estimates are again included to provide an overview of the printout when analyses are based on categorical data. Note first the reminder that results based on the normal theory standard errors are not to be used; only the categorical variable ROBUST statistics (in parentheses) should be interpreted. As seen in the last set of estimates, the error covariance between Items 20 and 21 was statistically significant ($Z = 3.553$). The standardized estimates are presented in Table 5.10, which shows the error correlation between these two items to be quite high, considering that this correlation represents similarity in responses to items with different content.

Before we close this chapter, I thought it would be interesting to test the original model again but, rather than honoring the categorical nature of the variables, we treat them as if they were continuous. Let's see how much difference this change in approach really makes.

TABLE 5.9
Selected EQS Output for Model 2: Parameter Estimates

```
*** WARNING *** WITH CATEGORICAL DATA, NORMAL THEORY RESULTS WITHOUT
                CORRECTION SHOULD NOT BE TRUSTED.

MEASUREMENT EQUATIONS WITH STANDARD ERRORS AND TEST STATISTICS
STATISTICS SIGNIFICANT AT THE 5% LEVEL ARE MARKED WITH @.
(CATEGORICAL-VARIABLE ROBUST STATISTICS IN PARENTHESES)

I1SAD   =V1  =   1.000 F1   + 1.000 E1

I2PESS  =V2  =    .907*F1   + 1.000 E2
                  .093
                 9.709@
              (   .109)
              (  8.291@

I3FAIL  =V3  =   1.095*F1   + 1.000 E3
                  .096
                11.450@
              (   .104)
              ( 10.487@

CONSTRUCT EQUATIONS WITH STANDARD ERRORS AND TEST STATISTICS

NEGATT  =F1  =    .588*F4   + 1.000 D1
                  .052
                11.407@
              (   .055)
              ( 10.625@

PERFDIFF=F2  =    .633*F4   + 1.000 D2
                  .054
                11.608@
              (   .050)
              ( 12.691@

SOMELEM =F3  =    .504*F4   + 1.000 D3
                  .056
                 8.951@
              (   .064)
              (  7.905@

COVARIANCES AMONG INDEPENDENT VARIABLES
---------------------------------------

                   E
                  ---
E21 -I21LLOSS              .291*
E20 -I20HYPOC              .050
                          5.838@
                         ( .082)
                         (3.553@
```


TABLE 5.10
Selected EQS Output for Model 2: Standardized Solution

```
STANDARDIZED SOLUTION:                                     R-SQUARED

I1SAD    =V1  =   .666 F1   + .746 E1                        .444
I2PESS   =V2  =   .604*F1   + .797 E2                        .365
I3FAIL   =V3  =   .730*F1   + .684 E3                        .532
I4DISSAT=V4   =   .645 F2   + .764 E4                        .416
I5GUILT  =V5  =   .547*F1   + .837 E5                        .299
I6PUNISH=V6   =   .610*F1   + .793 E6                        .372
I7SDISL  =V7  =   .782*F1   + .623 E7                        .612
I8SACCUS=V8   =   .540*F1   + .842 E8                        .292
I9SUI    =V9  =   .669*F1   + .744 E9                        .447
I10CRY   =V10 =   .571*F1   + .821 E10                       .326
I11IRRIT=V11  =   .402*F2   + .916 E11                       .161
I12WDRL  =V12 =   .555*F2   + .832 E12                       .308
I13INDEC=V13  =   .684*F2   + .729 E13                       .468
I14SIMAG=V14  =   .511*F1   + .859 E14                       .261
I15WINHI=V15  =   .556*F2   + .831 E15                       .309
I16INSOM=V16  =   .519 F3   + .854 E16                       .270
I17FATIG=V17  =   .622*F2   + .783 E17                       .387
I18ALOSS=V18  =   .533*F3   + .846 E18                       .284
I19WLOSS=V19  = -.155*F3    + .988 E19                       .024
I20HYPOC=V20  =   .503*F2   + .864 E20                       .253
I21LLOSS=V21  =   .386*F3   + .922 E21                       .149
NEGATT   =F1  =   .882*F4   + .471 D1                        .778
PERFDIFF=F2   =   .981*F4   + .195 D2                        .962
SOMELEM  =F3  =   .970*F4   + .242 D3                        .941

CORRELATIONS AMONG INDEPENDENT VARIABLES
---------------------------------------

                   E
                  ---
E21 -I21LLOSS              .367*
E20 -I20HYPOC
```

ANALYSES BASED ON DATA REGARDED AS CONTINUOUS

The EQS Output File

Table 5.11 presents a summary of the standardized residuals related to the hypothesized model. You will quickly recognize that the format of this table is consistent with Table 5.5, in which the values were based on categorical data. Comparing the results in these two tables reveals at least two interesting points: (1) in general, standardized residuals derived from the categorical methodology were larger than those derived from the continuous methodology; and (2) although the distributional pattern remained the same, the extent to which the standardized residuals spread

TABLE 5.11

Selected EQS Output for Initially Hypothesized Model: Standardized Residuals

```
MAXIMUM LIKELIHOOD SOLUTION (NORMAL DISTRIBUTION THEORY)

STANDARDIZED RESIDUAL MATRIX:

                    BDI1SAD   BDI2PESS  BDI3FAIL  BDI4DISSAT  BDI5GUILT
                     V  1      V  2      V  3       V  4        V  5

BDI1SAD    V  1      .000
BDI2PESS   V  2     -.031      .000
BDI3FAIL   V  3      .000      .027      .000
BDI4DISSAT V  4      .005     -.029     -.072      -.002
BDI5GUILT  V  5     -.044      .018      .037      -.020        .000
BDI6PUNISH V  6      .019      .032     -.019      -.004        .073
BDI7SDISL  V  7     -.036      .038      .047      -.019       -.010
BDI8SACCUS V  8     -.013     -.007     -.024       .039        .035
BDI9SUI    V  9      .048     -.004     -.090       .017       -.089
BDI10CRY   V 10      .075     -.090      .041      -.053       -.013

           AVERAGE ABSOLUTE STANDARDIZED RESIDUALS        =      .0420
   AVERAGE OFF-DIAGONAL ABSOLUTE STANDARDIZED RESIDUALS   =      .0462

LARGEST STANDARDIZED RESIDUALS:

 NO.    PARAMETER    ESTIMATE        NO.   PARAMETER    ESTIMATE
 ---    ---------    --------        ---   ---------    --------
  1     V21, V20       .246          11    V15, V6        -.101
  2     V11, V10       .163          12    V14, V2         .099
  3     V13, V8        .152          13    V19, V14       -.098
  4     V20, V6        .151          14    V17, V2        -.096
  5     V11, V2       -.135          15    V15, V8         .095
  6     V20, V4       -.126          16    V18, V4        -.094
  7     V18, V9        .112          17    V20, V3         .094
  8     V12, V11      -.108          18    V19, V16        .092
  9     V17, V1        .106          19    V19, V8         .092
 10     V20, V10       .102          20    V19, V2        -.090

DISTRIBUTION OF STANDARDIZED RESIDUALS
  ----------------------------------------
  !                                      !
140-                                     -
  !                                      !
  !               *                      !
  !               *                      !             RANGE      FREQ   PERCENT
  !               *                      !
105-              *                      -
  !               *   *                  !    1   -0.5  -   --       0      .00%
  !               *   *                  !    2   -0.4  -  -0.5      0      .00%
  !               *   *                  !    3   -0.3  -  -0.4      0      .00%
  !               *   *                  !    4   -0.2  -  -0.3      0      .00%
 70-              *   *                  -    5   -0.1  -  -0.2      4     1.73%
  !               *   *                  !    6    0.0  -  -0.1    123    53.25%
  !               *   *                  !    7    0.1  -   0.0     97    41.99%
  !               *   *                  !    8    0.2  -   0.1      6     2.60%
  !               *   *                  !    9    0.3  -   0.2      1      .43%
 35-              *   *                  -    A    0.4  -   0.3      0      .00%
  !               *   *                  !    B    0.5  -   0.4      0      .00%
  !               *   *                  !    C     ++  -   0.5      0      .00%
  !               *   *                  !   -------------------------------------
  !           *   *   *   *              !            TOTAL          231   100.00%
  ----------------------------------------
    1   2   3   4   5   6   7   8   9   A   B   C    EACH "*" REPRESENTS 7 RESIDUALS
```


TABLE 5.12

Selected EQS Output for Initially Hypothesized Model: Goodness-of-Fit Statistics

```
           GOODNESS OF FIT SUMMARY FOR METHOD = ML

CHI-SQUARE =        340.157 BASED ON      187 DEGREES OF FREEDOM
PROBABILITY VALUE FOR THE CHI-SQUARE STATISTIC IS         .00000

THE NORMAL THEORY RLS CHI-SQUARE FOR THIS ML SOLUTION IS          341.950.

FIT INDICES
-----------
BENTLER-BONETT       NORMED FIT INDEX =       .778
BENTLER-BONETT NON-NORMED FIT INDEX =         .870
COMPARATIVE FIT INDEX (CFI)            =      .884
ROOT MEAN-SQUARE RESIDUAL (RMR)        =      .036
STANDARDIZED RMR                       =      .055
ROOT MEAN-SQUARE ERROR OF APPROXIMATION (RMSEA)      =       .051
90% CONFIDENCE INTERVAL OF RMSEA  (           .042,          .059)

RELIABILITY COEFFICIENTS
------------------------
CRONBACH'S ALPHA                       =      .844
RELIABILITY COEFFICIENT RHO            =      .855

           GOODNESS OF FIT SUMMARY FOR METHOD = ROBUST

SATORRA-BENTLER SCALED CHI-SQUARE =     266.6617 ON      187 DEGREES OF FREEDOM
PROBABILITY VALUE FOR THE CHI-SQUARE STATISTIC IS         .00012

RESIDUAL-BASED TEST STATISTIC                      =    695.619
PROBABILITY VALUE FOR THE CHI-SQUARE STATISTIC IS         .00000

YUAN-BENTLER RESIDUAL-BASED TEST STATISTIC         =    219.643
PROBABILITY VALUE FOR THE CHI-SQUARE STATISTIC IS         .05127

YUAN-BENTLER RESIDUAL-BASED F-STATISTIC      =          1.558
DEGREES OF FREEDOM  =                              187,  134
PROBABILITY VALUE FOR THE F-STATISTIC IS             .00334

FIT INDICES
-----------
BENTLER-BONETT       NORMED FIT INDEX =       .765
BENTLER-BONETT NON-NORMED FIT INDEX =         .903
COMPARATIVE FIT INDEX (CFI)            =      .914
ROOT MEAN-SQUARE ERROR OF APPROXIMATION (RMSEA)      =       .036
90% CONFIDENCE INTERVAL OF RMSEA  (           .026,          .046)
```

across the zero point for the categorical variables was much greater than when the variables were treated as continuous. For example, whereas 85.28% of the residuals ranged between −0.1 and 0.1 for variables treated as categorical, this range occurred for 95.24% of the residuals associated with variables treated as continuous. Although these results suggest that the degree of misfit was less when the ordinal variables were treated as if they were continuous, this conclusion does not bear out with review of the goodness-of-fit statistics in Table 5.12. Clearly, the information provided in this table reveals that the model is extremely poor-fitting under normal theory estimation and is only slightly better when estimates are derived from the robust methodology. It is evident from comparing this table with Table 5.6 that the model was best fitted to the data when the categorical nature of the variables was taken into account.

TABLE 5.13

Selected EQS Output for Initially Hypothesized Model: Modification Indexes

MULTIVARIATE LAGRANGE MULTIPLIER TEST BY SIMULTANEOUS PROCESS IN STAGE 1

PARAMETER SETS (SUBMATRICES) ACTIVE AT THIS STAGE ARE: PEE GVF

		CUMULATIVE MULTIVARIATE STATISTICS			UNIVARIATE INCREMENT		HANCOCK'S SEQUENTIAL	
STEP	PARAMETER	CHI-SQUARE	D.F.	PROB.	CHI-SQUARE	PROB.	D.F.	PROB.
1	E21,E20	22.594	1	.000	22.594	.000	187	1.000
2	V20,F4	38.406	2	.000	15.813	.000	186	1.000
3	E13,E8	50.682	3	.000	12.275	.000	185	1.000
4	E11,E10	61.896	4	.000	11.214	.001	184	1.000
5	E17,E1	72.375	5	.000	10.479	.001	183	1.000
6	V19,F4	82.404	6	.000	10.029	.002	182	1.000
7	E18,E9	91.763	7	.000	9.360	.002	181	1.000
8	E11,E2	100.179	8	.000	8.416	.004	180	1.000
9	E9,E3	107.903	9	.000	7.723	.005	179	1.000
10	E20,E6	114.735	10	.000	6.832	.009	178	1.000
11	E19,E8	121.538	11	.000	6.803	.009	177	1.000
12	E9,E5	128.296	12	.000	6.759	.009	176	1.000
13	E15,E8	134.915	13	.000	6.619	.010	175	1.000
14	E12,E11	141.293	14	.000	6.378	.012	174	1.000
15	E11,E7	148.032	15	.000	6.738	.009	173	1.000

In comparing the LM Test statistics in Table 5.13 with those in Table 5.7, it is evident that, overall, the ordering of the parameters tagged for inclusion in the model differed across the two analytic approaches. However, the identification of the error covariance between Items 20 and 21 was consistent, albeit the size of the univariate chi-square value was substantially different.

Model 2

The EQS Output File

Let's turn first to the goodness-of-fit statistics in Table 5.14 where we see that model fit is higher within the framework of the ROBUST statistics (CFI = .930) than within the framework of ML estimation (e.g., CFI = .901). Now, if we compare the statistics in this table with those in Table 5.8, we see that the same pattern holds with respect to ML fit indexes being lower (e.g., CFI = .778) than the ROBUST fit indexes (e.g., CFI = .944). Conversely, if we compare values across Tables 5.8 and 5.14, we see that whereas the ML fit indexes for the categorical data (e.g., CFI = .778) are less than those for continuous data (e.g., CFI = .901), the ROBUST fit indexes for the categorical data are higher (e.g., CFI = .944) than those for the continuous data (e.g., CFI = .930). Overall, it appears that model fit is optimal when the four-category variables are treated as categorical data.

TABLE 5.14

Selected EQS Output for Model 2: Goodness-of-Fit Statistics

```
GOODNESS OF FIT SUMMARY FOR METHOD = ML

CHI-SQUARE =       316.797 BASED ON      186 DEGREES OF FREEDOM
PROBABILITY VALUE FOR THE CHI-SQUARE STATISTIC IS          .00000

FIT INDICES
-----------
BENTLER-BONETT      NORMED FIT INDEX =        .793
BENTLER-BONETT NON-NORMED FIT INDEX =         .888
COMPARATIVE FIT INDEX (CFI)          =        .901
ROOT MEAN-SQUARE RESIDUAL (RMR)      =        .036
STANDARDIZED RMR                     =        .053
ROOT MEAN-SQUARE ERROR OF APPROXIMATION (RMSEA)      =      .047
90% CONFIDENCE INTERVAL OF RMSEA  (           .038,         .055)

RELIABILITY COEFFICIENTS
------------------------
CRONBACH'S ALPHA                     =        .844
RELIABILITY COEFFICIENT RHO          =        .851

GOODNESS OF FIT SUMMARY FOR METHOD = ROBUST

ROBUST INDEPENDENCE MODEL CHI-SQUARE =    1136.751 ON     210 DEGREES OF FREEDOM

SATORRA-BENTLER SCALED CHI-SQUARE =    251.1182 ON      186 DEGREES OF FREEDOM
PROBABILITY VALUE FOR THE CHI-SQUARE STATISTIC IS          .00103

RESIDUAL-BASED TEST STATISTIC                          =   697.296
PROBABILITY VALUE FOR THE CHI-SQUARE STATISTIC IS          .00000

YUAN-BENTLER RESIDUAL-BASED TEST STATISTIC             =   219.810
PROBABILITY VALUE FOR THE CHI-SQUARE STATISTIC IS          .04543

YUAN-BENTLER RESIDUAL-BASED F-STATISTIC      =        1.582
DEGREES OF FREEDOM =                           186,    135
PROBABILITY VALUE FOR THE F-STATISTIC IS              .00249

FIT INDICES
-----------
BENTLER-BONETT      NORMED FIT INDEX =        .779
BENTLER-BONETT NON-NORMED FIT INDEX =         .921
COMPARATIVE FIT INDEX (CFI)          =        .930
ROOT MEAN-SQUARE ERROR OF APPROXIMATION (RMSEA)      =      .033
90% CONFIDENCE INTERVAL OF RMSEA  (           .022,         .043)
```

Table 5.15 presents partial parameter estimates and standard errors related to variables treated as continuous data. Robust standard errors are somewhat larger than those for ML. Consistent with the pattern found for the standardized residuals, the parameter estimates are somewhat lower than those produced when the variables are treated as categorical data (see Table 5.9). However, a direct comparison is not possible without going to the standardized solution. In general, the factor loadings are smaller in Table 5.16 than the corresponding ones in Table 5.10. These findings support those of West and colleagues (1995) (discussed previously) that with fewer than five categories and data that exhibit evidence of non-normality, parameter estimates tend to be attenuated. Nonetheless, the bottom-line results regarding statistical significance remain across the two sets of analyses.

TABLE 5.15
Selected EQS Output for Model 2: Parameter Estimates

```
 MEASUREMENT EQUATIONS WITH STANDARD ERRORS AND TEST STATISTICS
 STATISTICS SIGNIFICANT AT THE 5% LEVEL ARE MARKED WITH @.
 (ROBUST STATISTICS IN PARENTHESES)

I1SAD    =V1  =  1.000 F1   + 1.000 E1

I2PESS   =V2  =   .888*F1   + 1.000 E2
                  .112
                 7.898@
              (   .150)
              (  5.898@

I3FAIL   =V3  =  1.003*F1   + 1.000 E3
                  .112
                 8.984@
              (   .132)
              (  7.622@

CONSTRUCT EQUATIONS WITH STANDARD ERRORS AND TEST STATISTICS
NEGATT   =F1  =   .424*F4   + 1.000 D1
                  .044
                 9.737@
              (   .054)
              (  7.781@

PERFDIFF=F2   =   .479*F4   + 1.000 D2
                  .052
                 9.172@
              (   .053)
              (  8.952@

SOMELEM  =F3  =   .346*F4   + 1.000 D3
                  .049
                 7.059@
              (   .055)
              (  6.291@

 COVARIANCES AMONG INDEPENDENT VARIABLES
 ---------------------------------------

                  E
                 ---
E21 -I21LLOSS         .104*
E20 -I20HYPOC         .023
                     4.583@
                    (  .038)
                    ( 2.773@
```


TABLE 5.16
Selected EQS Output for Model 2: Standardized Solution

```
 STANDARDIZED SOLUTION:                                          R-SQUARED
I1SAD    =V1  =   .602 F1    + .799 E1                            .362
I2PESS   =V2  =   .534*F1    + .845 E2                            .285
I3FAIL   =V3  =   .632*F1    + .775 E3                            .400
I4DISSAT=V4   =   .586 F2    + .810 E4                            .344
I5GUILT  =V5  =   .469*F1    + .883 E5                            .220
I6PUNISH=V6   =   .535*F1    + .845 E6                            .286
I7SDISL  =V7  =   .695*F1    + .719 E7                            .483
I8SACCUS=V8   =   .482*F1    + .876 E8                            .232
I9SUI    =V9  =   .571*F1    + .821 E9                            .326
I10CRY   =V10 =   .495*F1    + .869 E10                           .246
I11IRRIT=V11  =   .293*F2    + .956 E11                           .086
I12WDRL  =V12 =   .442*F2    + .897 E12                           .196
I13INDEC=V13  =   .618*F2    + .786 E13                           .382
I14SIMAG=V14  =   .443*F1    + .897 E14                           .196
I15WINHI=V15  =   .494*F2    + .869 E15                           .244
I16INSOM=V16  =   .490 F3    + .872 E16                           .240
I17FATIG=V17  =   .541*F2    + .841 E17                           .293
I18ALOSS=V18  =   .548*F3    + .837 E18                           .300
I19WLOSS=V19  =  -.046*F3    + .999 E19                           .002
I20HYPOC=V20  =   .414*F2    + .910 E20                           .172
I21LLOSS=V21  =   .235*F3    + .972 E21                           .055
NEGATT   =F1  =   .923*F4    + .384 D1                            .852
PERFDIFF=F2   =   .915*F4    + .404 D2                            .837
SOMELEM  =F3  =   .853*F4    + .522 D3                            .728
 CORRELATIONS AMONG INDEPENDENT VARIABLES
 ---------------------------------------

                  E
                 ---
E21 -I21LLOSS             .275*
E20 -I20HYPOC
```

Overall, in the case of the current data, it appears that analyses for which the ordinality of the data was considered yielded the best fit to the data and was ultimately the most appropriate approach to follow. Nonetheless, Hutchinson and Olmos (1998) admonish that when assessment of model fit is based on data that are both categorical and non-normally distributed, researchers must realize that external artifacts such as model complexity, sample size, type of estimator, and degree of non-normality are all important to this goodness-of-fit criterion.

In conclusion, I leave you with one further caveat regarding this topic of categorical data. Because there is no way as yet to evaluate whether the assumption underlying polychoric and polyserial correlations is reasonable, we may be unaware that we are misusing this methodology. What would we do if we really doubted normality of the latent traits? Bentler (2005, p. 150) suggests that "in practice, we should do the technically wrong thing and treat the ordinal variables as continuous."