Byrne, B. M., 2006: Structural Equation Modeling with EQS. Basic Concepts, Applications and Programming (2nd edition). Mahwah: Erlbaum, S. 186-224.

6

Application 4: Testing for the Validity of a Causal Structure

In this chapter, we take our first look at a full structural equation model (SEM). The hypothesis to be tested relates to the pattern of causal structure linking several stressor variables that bear on the construct of burnout. The original study from which this application is taken (Byrne, 1994c) tested and cross-validated the impact of organizational and personality variables on three dimensions of burnout for elementary, intermediate, and secondary school teachers. For purposes of illustration here, however, the application is limited to the calibration sample of secondary school teachers only.

As was the case with the factor analytic applications illustrated in chapters 3 through 5, those structured as full SEMs are presumed to be of a confirmatory nature. That is, postulated causal relations among all variables in the hypothesized model must be grounded in theory and/or empirical research. Typically, the hypothesis to be tested argues for the validity of specified causal linkages among the variables of interest. Let's turn now to an in-depth examination of the hypothesized model under study in this chapter.

THE HYPOTHESIZED MODEL

Formulation of the hypothesized model shown in Fig. 6.1 derived from the consensus of findings from a review of the burnout literature as it relates to the teaching

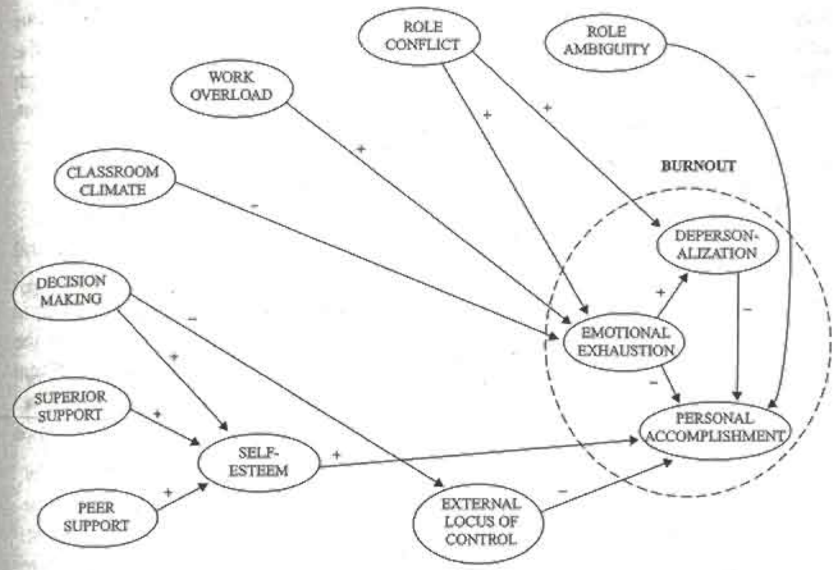

FIG. 6.1. Hypothesized model of causal structure depicting determinants of teacher burnout. Reprinted from Byrne (1994). Burnout: testing for the validity, replication, and invariance of causal structure across elementary, intermediate, and secondary teachers. *American Educational Research Journal, 31*, pp. 645–73 (Fig. 1, p. 656). Copyright (1994) by the American Educational Research Association. Reprinted by permission of the publisher.

profession. (For a more detailed summary of this research, see Byrne, 1994c, 1999.) Review of this model shows that burnout is represented as a multidimensional construct with Emotional Exhaustion (EE), Depersonalization (DP), and Personal Accomplishment (PA) operating as conceptually distinct factors. This part of the model is based on the work of Leiter (1991) in conceptualizing burnout as a cognitive-emotional reaction to chronic stress. The paradigm argues that EE holds the central position because it is considered the most responsive of the three facets to various stressors in a teacher's work environment. DP and reduced PA, on the other hand, represent the cognitive aspects of burnout in that they indicate the extent to which teachers' perceptions of their students, their colleagues, and themselves become diminished. As indicated by the signs associated with each path in the model, EE is hypothesized to impact positively on DP but negatively on PA; DP is hypothesized to impact negatively on PA.

The paths (and their associated signs) leading from the organizational (i.e., role ambiguity, role conflict, work overload, classroom climate, decisionmaking, superior support, peer support) and personality (i.e., self-esteem, external locus of control) variables to the three dimensions of burnout reflect findings in the literature.[1] For example, high levels of role conflict are expected to cause high levels of emotional exhaustion; in contrast, high (i.e., good) levels of classroom climate are expected to generate low levels of emotional exhaustion.

Preliminary Analyses

The model in Fig. 6.1 represents only the structural portion of the full structural equation model. Thus, before testing this model, it is necessary to know how each construct in this model is to be measured. In other words, the measurement portion of the structural equation model (see chap. 1) must be established. In contrast to the CFA models studied previously, the task involved in developing the measurement model of a full structural equation model is twofold: (a) to determine the number of indicators to use in measuring each construct, and (b) to identify which items to use in formulating each indicator.

Formulation of Indicator Variables

In the applications examined in chapters 3 through 5, the formulation of measurement indicators was relatively straightforward; all examples involved CFA models and, therefore consisted of only measurement models. In the measurement of multidimensional facets of self-concept (see chap. 3), each indicator represented a subscale score (i.e., the sum of all items designed to measure a particular self-concept facet). In chapters 4 and 5, the factorial validity of a measuring instrument was the focus of interest. As such, we were concerned with the extent to which items loaded onto their targeted factor. Adequate assessment of this phenomenon demanded that each item be included in the model. Thus, the indicator variables in these cases each represented one item in the measuring instrument under study.

In contrast to these previous examples, formulation of the indicator variables in the present application is somewhat more complex. Specifically, multiple indicators of each construct were formulated through the judicious combination of particular items to comprise item parcels. Items were carefully grouped according to content to equalize the measurement weighting across the set of indicators measuring the same construct (Hagtvet & Nasser, 2004). For example, the Classroom Environment Scale (Bacharach, Bauer, & Conley, 1986) used to measure Classroom Climate consists of items that tap classroom size, ability/interest of students, and various types of abuse by students. Indicators of this construct were formed so that each item in the composite measured a different aspect of classroom climate.

[1] To facilitate interpretation, particular items were reflected such that high scores on role ambiguity, role conflict, work overload, EE, DP, and external locus of control represented negative perceptions; high scores on the remaining constructs represented positive perceptions.

In the measurement of classroom climate, self-esteem, and external locus of control, indicator variables consisted of items from a single unidimensional scale; all other indicators comprised items from subscales of multidimensional scales. (For an extensive description of all measuring instruments used in construction of this model, see Byrne, 1994c.) In total, 32 item-parcel indicator variables were used to measure the hypothesized structural model; Fig. 6.2 is a schematic presentation of this model.

Since the current study was conducted (1994), there has been growing interest in the question of item-parceling. Research has focused on such issues as method of parceling (Bandalos & Finney, 2001; Hagtvet & Nasser, 2004; Kim & Hagtvet, 2003; Kishton & Widaman, 1994; Little, Cunningham, Shahar, & Widaman, 2002; and Rogers & Schmitt, 2004), number of items to include in a parcel (Marsh, Hau, Balla, & Grayson, 1998), extent to which item parcels affect model fit (Bandalos, 2002), and, more generally, whether researchers should even engage in item-parceling at all (Little et al., 2002). The latter article is an excellent summary of the pros and cons of using item-parceling, and the Bandalos and Finney (2001) chapter, a thorough review of the related issues. (For details related to each of these aspects of item parceling, readers are advised to consult these references directly.)

Confirmatory Factor Analyses

Because (a) the structural portion of a full structural equation model involves relations among only latent variables, and (b) the primary concern in working with a full model is to assess the extent to which these relations are valid, it is critical that the measurement of each latent variable be psychometrically sound. Thus, an important preliminary step in the analysis of full latent variable models is to first test for the validity of the measurement model before attempting to evaluate the structural model. Accordingly, CFA procedures are used in testing the validity of the indicator variables. Once it is known that the measurement model is operating adequately, researchers can have more confidence in findings related to assessment of the hypothesized structural model.

In this case, CFAs were conducted for indicator variables derived from each of the two multidimensional scales: the Teacher Stress Scale (TSS; Pettegrew & Wolf, 1982) and the MBI (Maslach & Jackson, 1986). The TSS comprises six subscales, with items designed to measure Role Ambiguity, Role Conflict, Work Overload, Decision-making, Superior Support, and Peer Support. The MBI (see chap. 4) comprises three subscales, with items designed to measure three facets of burnout: Emotional Exhaustion, Depersonalization, and Personal Accomplishment.

As with all analyses conducted in this chapter, CFA testing of these two measurement models was based on Robust ML estimation. Although both the TSS (*CFI = .96; *RMSEA = .069) and the MBI (*CFI = .97; *RMSEA = .075) were found to be reasonably well fitting, the LM Test univariate incremental

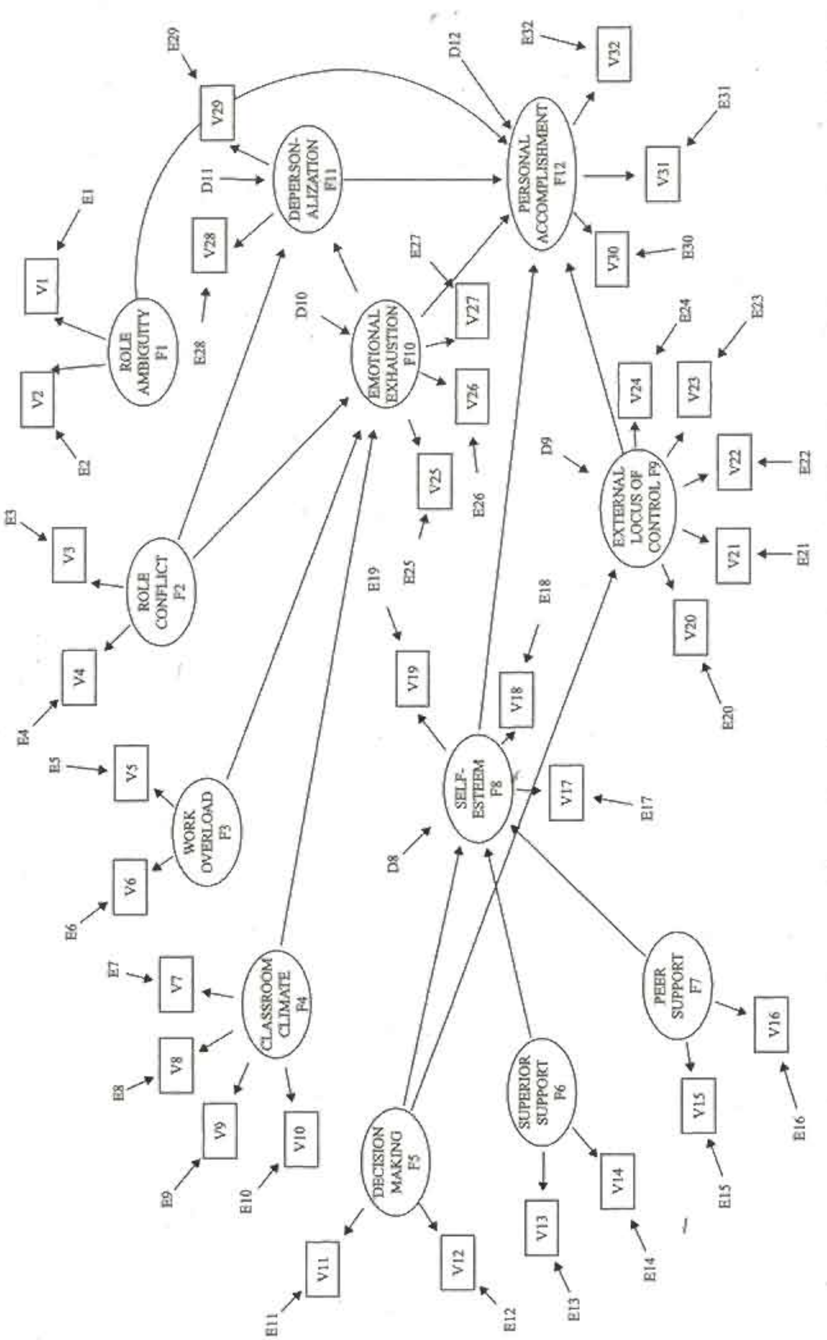

FIG. 6.2. Hypothesized model of teacher burnout: Initially specified measurement and structural components.

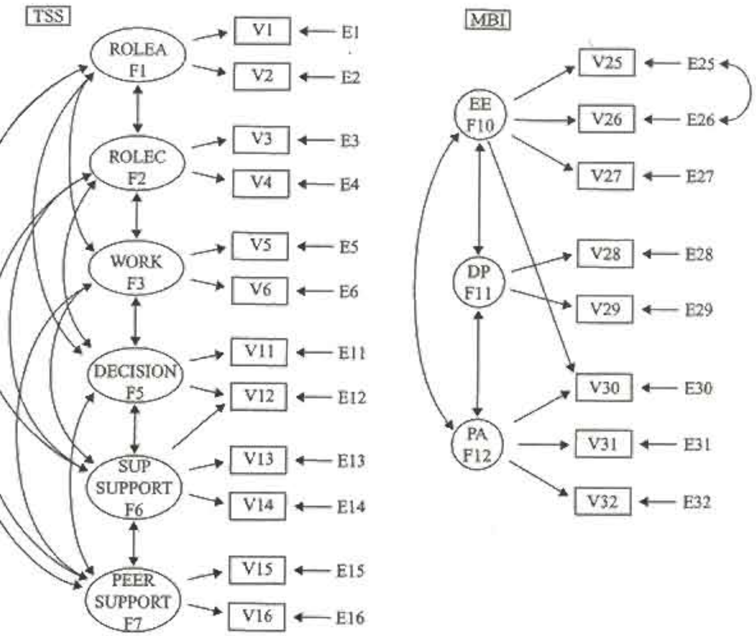

FIG. 6.3. Final CFA models of indicator variables representing the TSS and the MBI.

χ^2 statistic revealed sharp evidence of misspecification with respect to three parameters overall. These suggested misspecifications included one cross-loading for the TSS (V12 on F6) and one cross-loading (V30 on F1) and one error covariance (E26,E25) for the MBI. Both models were respecified to include these parameters, as schematically portrayed in Fig. 6.3. The final measurement model retained this revised specification throughout all analyses of the full causal model, the modification of which is shown in Fig. 6.4.

THE EQS INPUT FILE

With the measurement model fully established, certain aspects of the input file for the initially hypothesized model are highlighted, as shown in Table 6.1. Turning first to the /SPECIFICATIONS paragraph, we see that this calibration sample of secondary school teachers comprises 716 cases and the model includes 32 indicator variables. In the /EQUATIONS paragraph, it will appear that there are two sections. The first set of equations, easily identified by their augmenting indentation, defines the measurement model; as such, each equation is specified in terms of the indicator

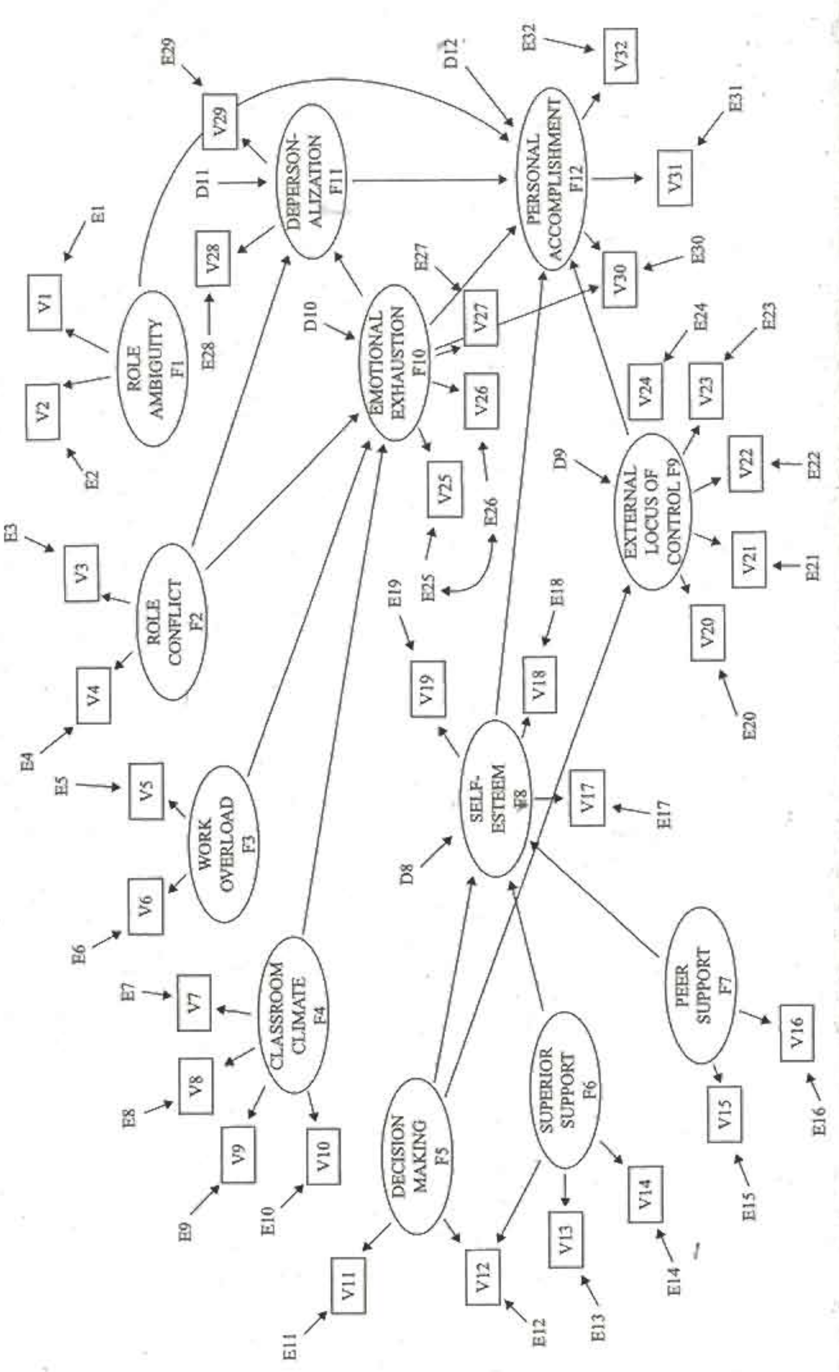

FIG. 6.4 Hypothesized model of teacher burnout: Revised measurement model

TABLE 6.1
EQS Input for Hypothesized Model of Burnout

```
/TITLE
FULL BURNOUT MODEL FOR SECONDARY TCHRS (GRP1); "BURNHS1LEQS"
INITIAL MODEL
CROSS-LOADINGS: F6 TO V12 (SSUP TO DEC2); F10 TO V30 (EE TO PA1)
ERROR COV: E26,E25 (EE)
/SPECIFICATION
CASE=716; VAR=32; ME=ML,ROBUST; MA=RAW; FO='(19F4.2/13F4.2)';
DATA='C:\EQS61\Files\Books\Data\secind1.ess';
/LABELS
V1=ROLEA1; V2=ROLEA2; V3=ROLEC1; V4=ROLEC2; V5=WORK1;
V6=WORK2; V7=CLIMATE1; V8=CLIMATE2; V9=CLIMATE3; V10=CLIMATE4;
V11=DEC1; V12=DEC2; V13=SSUP1; V14=SSUP2; V15=PSUP1;
V16=PSUP2; V17=SELF1; V18=SELF2; V19=SELF3; V20=XLOC1;
V21=XLOC2; V22=XLOC3; V23=XLOC4; V24=XLOC5; V25=EE1;
V26=EE2; V27=EE3; V28=DP1; V29=DP2; V30=PA1;
V31=PA2; V32=PA3;
F1=ROLEA; F2=ROLEC; F3=WORK; F4=CLIMATE; F5=DEC; F6=SSUP; F7=PSUP;
F8=SELF; F9=XLOC; F10=EE; F11=DP; F12=PA;
/EQUATIONS
V1= F1+E1;
V2= *F1+E2;
    V3= F2+E3;
    V4= *F2+E4;
        V5= F3+E5;
        V6= *F3+E6;
            V7= F4+E7;
            V8= *F4+E8;
            V9= *F4+E9;
            V10= *F4+E10;
                V11= F5+E11;
                V12= *F5+*F6+E12;
                    V13= F6+E13;
                    V14= *F6+E14;
                        V15= F7+E15;
                        V16= *F7+E16;
                            V17= F8+E17;
                            V18= *F8+E18;
                            V19= *F8+E19;
                                V20= F9+E20;
                                V21= *F9+E21;
                                V22= *F9+E22;
                                V23= *F9+E23;
                                V24= *F9+E24;
                                    V25= F10+E25;
                                    V26= *F10+E26;
                                    V27= *F10+E27;
                                        V28= F11+E28;
                                        V29= *F11+E29;
                                            V30= F12+*F10+E30;
                                            V31= *F12+E31;
                                            V32= *F12+E32;
```

(Continued)

TABLE 6.1
(Continued)

```
F8= *F5+ *F6+*F7+D8;
F9= *F5+D9;
F10= *F2+ *F3+ *F4+D10;
F11= *F2+ *F10+D11;
F12= *F1+ *F8+ *F9+ *F10+ *F11+D12;
/VARIANCES
 F1 TO F7 = *;
 E1 to E32 = *;
 D8 TO D12=*;
/COVARIANCES
 F1 to F7 =*;
 E26,E25 = *;
/PRINT
 FIT=ALL;
/LMTEST
 SET=GFF, BFF, PDD;
/END
```

variables (i.e., the V's). In particular, note the cross-loadings associated with V12 and V30. The second set of equations defines the model in terms of the latent variables; as such, it describes the structural model or causal network encompassing these variables, as depicted in Fig. 6.1.

The /VARIANCES paragraph specifies the estimation of variances for the independent factors (F1 to F7), error terms associated with each indicator variable (E1 through E32), and disturbance terms associated with each dependent factor (D8 through D12). Estimated covariances in the/COVARIANCES paragraph are specified for all factor pairs involving the independent Factors 1 through 7.[2] Also included is the error covariance (E26,E25) specified for the MBI component of the measurement model.

Finally, the /LMTEST paragraph incorporates, the SET command to limit LM Test statistics to (a) misspecified structural paths (i.e., paths that are not specified but should be)—these paths can flow from either independent to dependent factors (GFF) or one dependent factor to another (BFF); and (b) misspecified covariances among the disturbance terms (PDD).

The input file just reviewed was created manually; however, it is likely that you may prefer to build it interactively using the Build EQS option. Thus, before proceeding to the output file, let's walk through the process of building this same file using Build EQS. As outlined in chapter 2, the first step is to open the data file upon which the analyses will be based; in this case, the data file is labeled

[2]Recall that variances and covariances can be estimated only for independent variables (observed or latent) in a model.

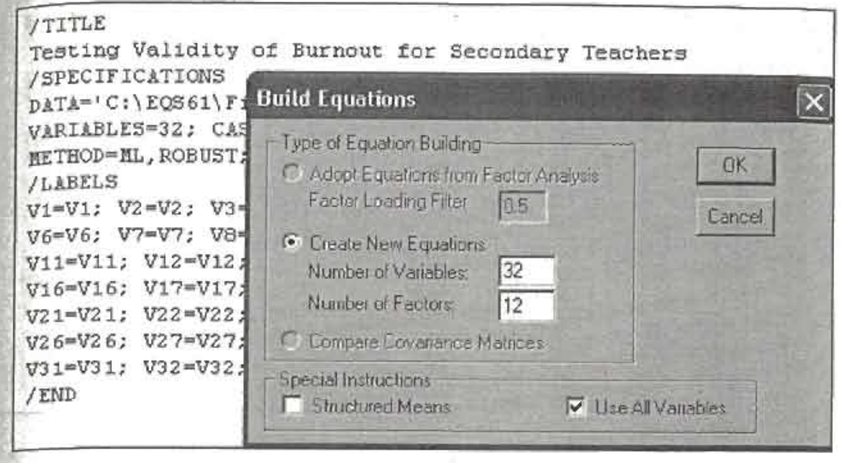

FIG. 6.5. Build Equations dialog box to create an EQS input file using BUILD EQS.

"secind1.ess".[3] After dropping down the Build EQS menu, the first step is to click the Title/Specification tab and complete the required information. This portion of the completed file is shown in the background of Fig. 6.5. Superimposed on this part of the input file is the Build Equations dialog box, which was obtained by clicking the Build Equations tab of the menu. In this box, we note that the model comprises 32 variables and 12 factors; additionally, it is noted that all variables are to be used in the analyses. Clicking OK yields the first of two dialog boxes in which the user specifies the model. The first dialog box relates to the measurement model, the second relates to the structural model. Fig. 6.6 shows the portion of the measurement model involving complete specification for Factors 9 through 12 (note the cross-loading of V30 onto Factor 10 highlighted within the rectangle). Specifications pertinent to the structural model are shown in Fig. 6.7. The location of the asterisks, however, requires explanation. To interpret these specifications, the user reads down from the factor listed at the top of the column and then across to the factor in the far left column. For example, the asterisk appearing in column 1 indicates that F1 causes F12; those in column 2 indicate, first, that F2 causes F10 and, second, that F2 causes F11.

The final step in building the full structural equation model file concerns specifications related to the variances and covariances. Fig. 6.8 shows partial specification for the factors with respect to their variances, albeit full specification regarding

[3]The data file used for all analyses in this chapter is based on raw data and thus carries the .dat extension (i.e., secind1.dat). However, to build the file using Build EQS, the data file must be in the .ess format. The procedure used in converting files in this manner is described in chapter 5.

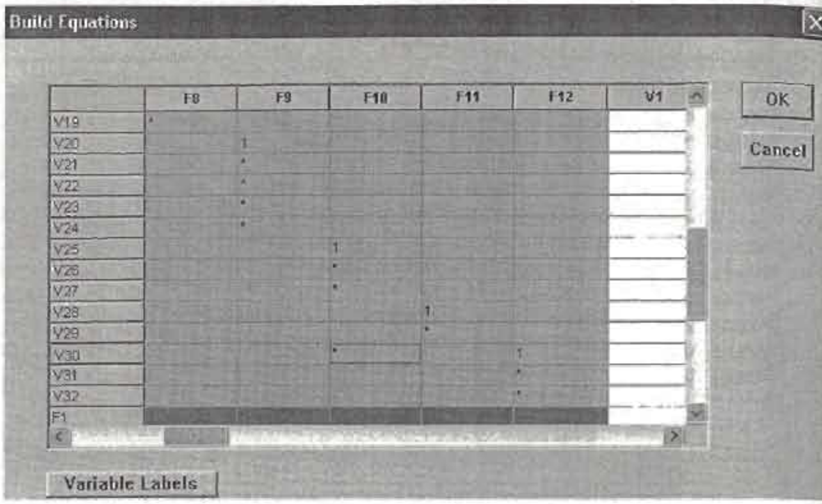

FIG. 6.6. Build Equations dialog box showing partial measurement model specification.

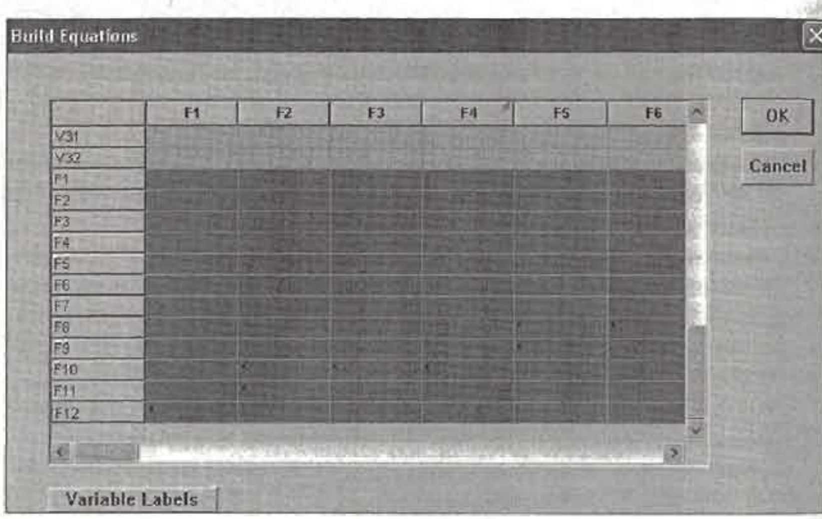

FIG. 6.7. Build Equations dialog box showing structural/model specification.

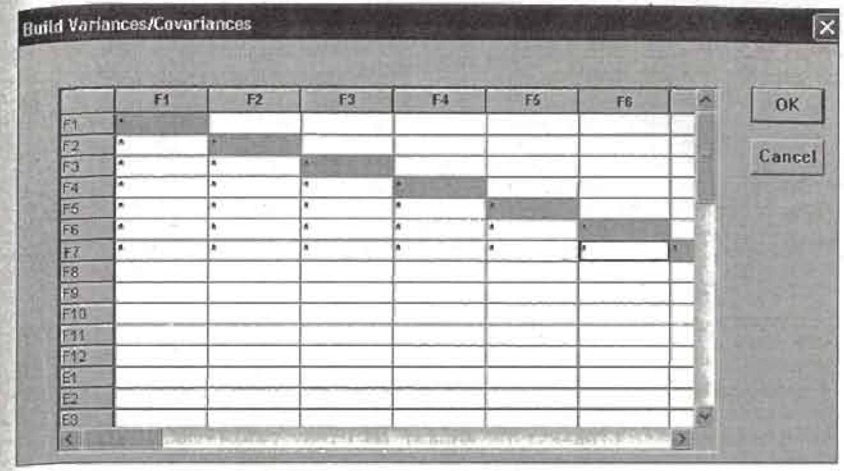

FIG. 6.8. Build Variances and Covariances dialog box showing partial specification of factor variances, albeit full specification of their covariances.

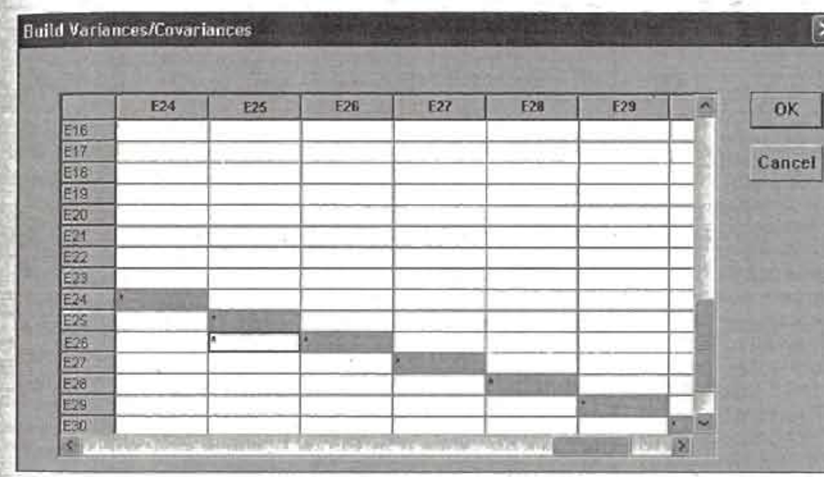

FIG. 6.9. Build Variances and Covariances dialog box showing partial specification of error variances as well as error covariance between E26,E25.

their covariances. As seen in this dialog box, covariances are specified only for the independent factors in the model (F1–F7) and all factors are specified as being intercorrelated. Fig. 6.9 shows the specification of variances for error terms associated with Variables 24 through 29 (E24–E29) as well as the error covariance (boxed) between E25 and E26.

TABLE 6.2
Hypothetical EQS Output: Failure to Address Model Identification

```
IN ITERATION # 1, MATRIX W-CFUNCT MAY NOT BE POSITIVE DEFINITE.
  YOU HAVE BAD START VALUES TO BEGIN WITH.
  IF ABOVE MESSAGE APPEARS ON EVERY ITERATION, PLEASE PROVIDE
BETTER START VALUES AND RE-RUN THE JOB.
IN ITERATION #  2, MATRIX W-CFUNCT MAY NOT BE POSITIVE DEFINITE.
IN ITERATION #  3, MATRIX W-CFUNCT MAY NOT BE POSITIVE DEFINITE.
IN ITERATION #  4, MATRIX W-CFUNCT MAY NOT BE POSITIVE DEFINITE.
IN ITERATION #  5, MATRIX W-CFUNCT MAY NOT BE POSITIVE DEFINITE.
IN ITERATION #  6, MATRIX W-CFUNCT MAY NOT BE POSITIVE DEFINITE.
*** NOTE *** RESIDUAL-BASED STATISTICS CANNOT BE
           CALCULATED BECAUSE OF PIVOTING PROBLEMS.
```

PARAMETER	CONDITION CODE
F2,F1	LINEARLY DEPENDENT ON OTHER PARAMETERS
F3,F2	LINEARLY DEPENDENT ON OTHER PARAMETERS
F4,F1	LINEARLY DEPENDENT ON OTHER PARAMETERS
F7,F3	LINEARLY DEPENDENT ON OTHER PARAMETERS
F7,F4	LINEARLY DEPENDENT ON OTHER PARAMETERS
D10,D10	CONSTRAINED AT LOWER BOUND
D12,D12	LINEARLY DEPENDENT ON OTHER PARAMETERS
V12,F5	LINEARLY DEPENDENT ON OTHER PARAMETERS
V13,F6	LINEARLY DEPENDENT ON OTHER PARAMETERS
F10,F3	LINEARLY DEPENDENT ON OTHER PARAMETERS
V17,F8	LINEARLY DEPENDENT ON OTHER PARAMETERS
V21,F9	LINEARLY DEPENDENT ON OTHER PARAMETERS
V29,F11	LINEARLY DEPENDENT ON OTHER PARAMETERS

Before leaving this Build EQS walk-through, there is an important caveat regarding specification of the measurement model that reminds users to be sure to fix one factor-loading parameter within each set of indicator variables per factor. This model identification condition is reiterated here because in working with the Build EQS option, it is especially easy to forget to change the asterisk to a fixed value. If this step is omitted, the output file will include the error messages shown in Table 6.2.

Let's now revisit the input file, shown in Fig. 6.1, where you will note no evidence of start values. Unless a model is very complex or the actual parameter estimates are far from the initial EQS start values used in the iterative process, typically it is not necessary to be concerned about inserting these values. If the program is having difficulty with the minimization process, all action stops after 30 iterations and users are presented with a message about bad start values. However, this situation is easily rectified within the EQS program by using the extremely valuable RETEST option.

Admittedly, the input file shown in Fig. 6.1 runs quite satisfactorily without the addition of start values. However, because the RETEST feature of EQS is a

remarkable option that can save hours of frustration if start values must be provided, its implementation is demonstrated with the present causal model. To begin, the command RETEST = 'filename.out' is included within the /PRINT paragraph. In the present file, for example, this paragraph would appear as follows:

```
/PRINT
 FIT = ALL;
 RETEST = 'HSSTART.OUT';
```

With invocation of the RETEST command, EQS executes the input file and simultaneously creates a separate output file (as labeled) in which the start values are included for all estimated parameters. The user simply cuts and pastes this section into the input file. A reduced version of this section of the output is shown in Table 6.3.[4]

THE EQS OUTPUT FILE

Reviewing the output file related to the hypothesized causal model, we look first at the univariate statistics shown in Table 6.4, where relatively high kurtosis values for four indicator variables are circled. (Of the remaining 22 indicator variables, kurtosis values were all less than 1.00 except for ROLEA2, which had a value of 1.29.) Overall, Mardia's normalized estimate was 40.7136, thereby indicating some degree of non-normality for the data. Hence, estimation based on the Robust statistics was considered appropriate.

At the bottom of Table 6.4 is a listing of case numbers that EQS identified as making the largest contribution to normalized multivariate kurtosis. In determining possible multivariate outliers in the data, we compare the size of these estimates relative to one another; the absolute values of these estimates are meaningless. What a user looks for in the determination of outliers is the extent to which the estimate for one case is strikingly different from all the rest. In Table 6.4, I would consider the value estimate for Case #440 to be substantially different from those for all other cases.

In addressing this data problem, the same input file was estimated again but with Case #440 deleted from the analyses. This analysis again revealed one multivariate outlier (#77). No additional outliers were identified in the subsequent run in which both Cases #440 and #77 were deleted from the analyses; thus, all subsequent tests of the model specified deletion of these two cases. This input specification is shown in Table 6.5 and the resulting output is shown in Table 6.6.

[4]Due to space limitations, only a few values were included in the /VARIANCES and /COVARIANCES paragraphs.

TABLE 6.3

EQS Output for Restart Option: Start Values

```
!
! FOLLOWING LISTS ARE GENERATED FROM RETEST
!
/EQUATIONS
  V1  =   1.000 F1   +  1.000 E1    ;
  V2  =   1.308*F1   +  1.000 E2    ;
  V3  =   1.000 F2   +  1.000 E3    ;
  V4  =   1.253*F2   +  1.000 E4    ;
  V5  =   1.000 F3   +  1.000 E5    ;
  V6  =    .708*F3   +  1.000 E6    ;
  V7  =   1.000 F4   +  1.000 E7    ;
  V8  =   1.664*F4   +  1.000 E8    ;
  V9  =    .987*F4   +  1.000 E9    ;
  V10 =   1.385*F4   +  1.000 E10   ;
  V11 =   1.000 F5   +  1.000 E11   ;
  V12 =    .242*F5   +   .898*F6  +  1.000 E12  ;
  V13 =   1.000 F6   +  1.000 E13   ;
  V14 =   1.101*F6   +  1.000 E14   ;
  V15 =   1.000 F7   +  1.000 E15   ;
  V16 =   1.060*F7   +  1.000 E16   ;
  V17 =   1.000 F8   +  1.000 E17   ;
  V18 =   1.263*F8   +  1.000 E18   ;
  V19 =   1.417*F8   +  1.000 E19   ;
  V20 =   1.000 F9   +  1.000 E20   ;
  V21 =    .911*F9   +  1.000 E21   ;
  V22 =   1.060*F9   +  1.000 E22   ;
  V23 =    .957*F9   +  1.000 E23   ;
  V24 =   1.246*F9   +  1.000 E24   ;
  V25 =   1.000 F10  +  1.000 E25   ;
  V26 =   1.052*F10  +  1.000 E26   ;
  V27 =   1.219*F10  +  1.000 E27   ;
  V28 =   1.000 F11  +  1.000 E28   ;
  V29 =    .920*F11  +  1.000 E29   ;
  V30 =   -.171*F10  +  1.000 F12 +  1.000 E30  ;
  V31 =   1.234*F12  +  1.000 E31   ;
  V32 =   1.179*F12  +  1.000 E32   ;
  F8  =    .363*F5      -.114*F6     -.044*F7  + 1.000 D8   ;
  F9  =   -.262*F5   +  1.000 D9    ;
  F10 =   -.128*F2   +   .745*F3     -.898*F4  + 1.000 D10  ;
  F11 =    .549*F10  +   .147*F2   + 1.000 D11 ;
  F12 =    .512*F8      -.188*F9   +  .019*F10   -.195*F11    -.041*F1
      +   1.000 D12  ;
/VARIANCES
       F1=   .388* ;
        .
        .
       F7=   .622* ;
       E1=   .446* ;
        .
        .
       E32=   .382* ;
       D8=   .077* ;
        .
        .
       D12=   .270*  ;
```

(Continued)

TABLE 6.3

(Continued)

```
/COVARIANCES
    F2,F1 =     .389* ;
        .
        .
    F7,F6 =     .391* ;
    E26,E25 =    .259* ;
/END
```

TABLE 6.4

Selected EQS Output for Initially Hypothesized Model:
Descriptive Statistics and Outliers

UNIVARIATE STATISTICS

VARIABLE	PSUP2	SELF1	SELF2	SELF3	XLOC1
MEAN	4.6056	3.6286	3.6367	3.4988	2.9263
SKEWNESS (G1)	-.7470	-1.7292	-1.8829	-1.3731	-.0946
KURTOSIS (G2)	.8260	5.1611	4.3166	2.3505	-.0574
STANDARD DEV.	.9392	.4439	.5076	.5522	.6143

VARIABLE	EE2	EE3	DP1	DP2	PA1
MEAN	3.5354	3.1362	2.3842	2.1684	5.7729
SKEWNESS (G1)	.3811	.6495	1.1237	1.4611	-.8599
KURTOSIS (G2)	-.3170	-.1712	1.2063	2.0608	.6924
STANDARD DEV.	1.2536	1.3205	1.1369	1.2427	.8983

MULTIVARIATE KURTOSIS

MARDIA'S COEFFICIENT (G2,P) = 141.9525
NORMALIZED ESTIMATE = 40.7136

CASE NUMBERS WITH LARGEST CONTRIBUTION TO NORMALIZED MULTIVARIATE KURTOSIS:

CASE NUMBER	77	297	306	316	440
ESTIMATE	1945.8853	1838.9729	1769.1764	1733.7342	3037.6603

TABLE 6.5

Selected EQS Input for Hypothesized Model of Burnout: Deleted Cases

```
/TITLE
FULL BURNOUT MODEL FOR SECONDARY TCHRS (GRP1); "BURNHS1ID.EQS"
INITIAL MODEL
Two Cases Deleted
CROSS-LOADINGS: F6 TO V12 (SSUP TO DEC2); F10 TO V30 (EE TO PA1)
ERROR COV: E26,E25 (EE)
/SPECIFICATIONS
CASE=716; VAR=32; ME=ML, ROBUST; MA=RAW; FO='(19F4.2/13F4.2)'; DEL=440,77;
DATA='C:\EQS61\Files\Books\Data\secind1.dat';
/EQUATIONS
```

TABLE 6.6
Selected EQS Output for Initially Hypothesized Model: Possible Outlying Cases

MULTIVARIATE KURTOSIS

MARDIA'S COEFFICIENT (G2,P) = 132.2515
NORMALIZED ESTIMATE = 37.8783

CASE NUMBERS WITH LARGEST CONTRIBUTION TO NORMALIZED MULTIVARIATE KURTOSIS:

CASE NUMBER	297	298	306	316	570
ESTIMATE	1829.5197	1645.9204	1934.5730	1732.5257	1692.0514

TABLE 6.7
Selected EQS Output for Initially Hypothesized Model: Bentler–Weeks Representation

BENTLER-WEEKS STRUCTURAL REPRESENTATION:

NUMBER OF DEPENDENT VARIABLES = 37

DEPENDENT V'S :	1	2	3	4	5	6	7	8	9	10
DEPENDENT V'S :	11	12	13	14	15	16	17	18	19	20
DEPENDENT V'S :	21	22	23	24	25	26	27	28	29	30
DEPENDENT V'S :	31	32								
DEPENDENT F'S :	8	9	10	11	12					

NUMBER OF INDEPENDENT VARIABLES = 44

INDEPENDENT F'S :	1	2	3	4	5	6	7			
INDEPENDENT E'S :	1	2	3	4	5	6	7	8	9	10
INDEPENDENT E'S :	11	12	13	14	15	16	17	18	19	20
INDEPENDENT E'S :	21	22	23	24	25	26	27	28	29	30
INDEPENDENT E'S :	31	32								
INDEPENDENT D'S :	8	9	10	11	12					

NUMBER OF FREE PARAMETERS = 102
NUMBER OF FIXED NONZERO PARAMETERS = 49

PARAMETER	CONDITION CODE
D10,D10	CONSTRAINED AT LOWER BOUND

The Bentler–Weeks representation summary of the hypothesized model is shown in Table 6.7. To assure full comprehension of the status of each variable in the model, it is helpful to check this decomposition of parameters for the model against its schematic presentation in Fig. 6.4. Review of Table 6.7 reveals the following:

- 37 dependent variables
  - ➢ 32 observed indicators (V1–V32)
  - ➢ 5 factors (F8–F12)
- 44 independent variables
  - ➢ 7 factors (F1–F7)
  - ➢ 32 error terms (E1–E32)
  - ➢ 5 disturbance terms (D8–D12)
- 102 estimated parameters
  - ➢ 22 factor loadings (20 original, 2 additional)
  - ➢ 44 variances (7 F's, 32 E's, 5 D's)
  - ➢ 22 covariances (21 factor, 1 error)
  - ➢ 14 structural regression paths
- 49 fixed parameters
  - ➢ 32 error regression paths
  - ➢ 5 disturbance regression paths
  - ➢ 12 factor-loading regression paths

Of import also, is the Condition Code for parameter D10,D10, the disturbance variance for Factor 10 (Emotional Exhaustion). The program notes that this parameter has been constrained to lower bound, which means that it has been constrained to 0.0. Bentler (2005, p. 113) notes that "the constraint of a parameter at an upper or lower bound may be a cause for celebration or a reason for distress. If the bound is desired, the solution may be totally acceptable. If the bound is not desired, it implies a possible problem." In the present case, the disturbance variance for F10 is probably close to zero and, as a boundary parameter, can just as easily be a negative as a positive value. If the estimate is negative, EQS automatically constrains the value to zero because its variability cannot be computed accurately. Interpreted literally in the present case, this condition code implies that the combination of Role Conflict (F2), Work Overload (F3), and Classroom Climate (F4) was perfect in its prediction of Emotional Exhaustion (F10), thereby resulting in no residual variance. As shown in Table 6.8, whenever a condition code is identified, the program cautions about the appropriateness of the resulting parameter estimate. However, in the testing of full structural equation models, post hoc model-fitting often results in a solution in which the condition code disappears—which is the case in the present example.

Turning to the goodness-of-fit statistics in Table 6.8, notice first the substantial drop in χ^2 value between the ML uncorrected and the Satorra–Bentler scaled statistics, thereby providing evidence of some degree of non-normality in the data, as noted previously. Both the corrected CFI (i.e., *CFI) value of .944 and the *RMSEA value of .042 indicate that the hypothesized model sustained a very reasonable fit to the sample data. However, given that this model of burnout determinants was mapped solely from a review of the empirical literature, it is highly possible that other paths should be more appropriately added, whereas other paths already specified in the model may not be worthy of inclusion. Thus, the next step is to examine the LM Test statistics to determine what degree of modification, if any, might be considered. These statistics are presented in Table 6.9.

As noted earlier in this book EQS provides first, a set of ordered univariate LM Test statistics, together with both unstandardized and standardized expected parameter change statistics. Each univariate LM Test statistic is associated with an estimated value the parameter might assume if this fixed parameter is freely estimated rather than constrained. These values are followed by a set of multivariate

TABLE 6.8

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

```
*** WARNING *** TEST RESULTS MAY NOT BE APPROPRIATE DUE TO CONDITION CODE

            GOODNESS OF FIT SUMMARY FOR METHOD = ML

CHI-SQUARE =     1077.784 BASED ON     426 DEGREES OF FREEDOM
PROBABILITY VALUE FOR THE CHI-SQUARE STATISTIC IS          .00000

FIT INDICES
-----------
BENTLER-BONETT       NORMED FIT INDEX =        .911
BENTLER-BONETT NON-NORMED FIT INDEX =          .935
COMPARATIVE FIT INDEX (CFI)          =         .944
ROOT MEAN-SQUARE RESIDUAL (RMR)      =         .044
STANDARDIZED RMR                     =         .054
ROOT MEAN-SQUARE ERROR OF APPROXIMATION (RMSEA)    =        .046
90% CONFIDENCE INTERVAL OF RMSEA  (            .043,        .050)

            GOODNESS OF FIT SUMMARY FOR METHOD = ROBUST

SATORRA-BENTLER SCALED CHI-SQUARE =    963.3964 ON    426 DEGREES OF FREEDOM
PROBABILITY VALUE FOR THE CHI-SQUARE STATISTIC IS          .00000

FIT INDICES
-----------
BENTLER-BONETT       NORMED FIT INDEX =        .905
BENTLER-BONETT NON-NORMED FIT INDEX =          .935
COMPARATIVE FIT INDEX (CFI)          =         .944
ROOT MEAN-SQUARE ERROR OF APPROXIMATION (RMSEA)    =        .042
90% CONFIDENCE INTERVAL OF RMSEA  (            .039,        .046)
```

statistics. Decisions regarding which parameters to consider for addition to the model are based on the multivariate statistics because correlation among all variables has been taken into account. Examination of the column labeled Parameter shows that the variables suggested for addition to the model represent both structural paths (e.g., F11,F3) and correlated disturbance terms (D10,D8). The easiest way to identify the path being targeted as a misspecified parameter is to conceptualize the causal flow as going from the second factor in a pair of latent factors to the first factor in the pair. For example, the first parameter specified in the output is F11,F3; this parameter is interpreted as the structural path flowing from F3 (Work Overload) to F11 (Depersonalization). These results suggest that if this path were to be specified in the model, Work Overload would have a substantial impact on Depersonalization.

Given the substantive reasonableness of this new path, the sharp drop in the univariate increment from $\chi^2_{(1)} = 63.440$ to $\chi^2_{(2)} = 31.712$, and the substantial size of the expected parameter change statistic, this parameter certainly qualifies for inclusion in the model. Likewise, several other parameters representative of structural paths can be considered as logical candidates for inclusion and could all be included at this time. However, my preference, at this time, is to limit modification to the inclusion of only the first parameter. As with the CFA analyses conducted

TABLE 6.9

Selected EQS Output for Initially Hypothesized Model: Modification Indexes

LAGRANGE MULTIPLIER TEST (FOR ADDING PARAMETERS)

ORDERED UNIVARIATE TEST STATISTICS:

*** WARNING *** TEST RESULTS MAY NOT BE APPROPRIATE DUE TO CONDITION CODE

NO	CODE		PARAMETER	CHI-SQUARE	PROB.	HANCOCK 426 DF PROB.	PARAMETER CHANGE	STANDARDIZED CHANGE
1	2	16	F11,F3	63.440	.000	1.000	-3.277	-3.574
2	2	16	F11,F4	63.440	.000	1.000	-1.110	-3.525
3	2	10	D10,D8	31.688	.000	1.000	-.082	.000
4	2	22	F10,F8	31.414	.000	1.000	-1.141	-3.494
5	2	22	F8,F10	27.911	.000	1.000	-.167	-.510
6	2	22	F10,F11	24.033	.000	1.000	-.539	-.529
7	2	10	D11,D10	24.033	.000	1.000	-.337	.000
8	2	22	F9,F8	23.708	.000	1.000	-.309	-2.334
9	2	16	F8,F1	20.932	.000	1.000	.292	1.438
10	2	16	F9,F2	18.820	.000	1.000	.163	.493

		CUMULATIVE MULTIVARIATE STATISTICS			UNIVARIATE INCREMENT		HANCOCK'S SEQUENTIAL	
STEP	PARAMETER	CHI-SQUARE	D.F.	PROB.	CHI-SQUARE	PROB.	D.F.	PROB.
1	F11,F3	63.440	1	.000	63.440	.000	426	1.000
2	D10,D8	95.152	2	.000	31.712	.000	425	1.000
3	F9,F8	120.344	3	.000	25.193	.000	424	1.000
4	F12,F5	136.719	4	.000	16.374	.000	423	1.000
5	F11,F12	147.255	5	.000	10.536	.001	422	1.000
6	F10,F6	156.239	6	.000	8.984	.003	421	1.000
7	F9,F2	165.073	7	.000	8.834	.003	420	1.000
8	F10,F11	170.974	8	.000	5.901	.015	419	1.000
9	F11,F6	176.041	9	.000	5.067	.024	418	1.000

previously, we now move into exploratory mode as we respecify and analyze models that vary from the one originally hypothesized and tested. This first respecified model is Model 2.

POST HOC ANALYSES: MODEL 2

The EQS Input File

Model respecification with the new parameter (F11,F3) included is shown in boldface in Table 6.10. Note that no start value is included because it is unnecessary.

The EQS Output File

Let's see now what difference the addition of this new path made to the model. In Table 6.11, note first that the condition code for the variance of D10 is still

TABLE 6.10
Selected EQS Input: Model 2

```
/TITLE
 FULL BURNOUT MODEL FOR SECONDARY TCHRS (GRP1); "BURNHS2.EQS"
 MODEL 2
 ADDED: F3 to F11 (Work -> DP)
    .
    .
/EQUATIONS
    .
    .
 F8  =  .363*F5 - .114*F6 -.044*F7 + 1.000 D8;
 F9  = -.262*F5 + 1.000 D9;
 F10 = -.128*F2 + .745*F3 -.898*F4 + 1.000 D10;
 F11 =  .549*F10 + .147*F2 + *F3 + 1.000 D11;
 F12 =  .512*F8 -.188*F9 + .019*F10 -.195*F11 -.041*F1 + 1.000 D12;
    .
    .
/LMTEST
 SET=GFF, BFF, PDD;
/END
```

TABLE 6.11
Selected EQS Output for Model 2: Goodness-of-Fit Statistics

```
PARAMETER    CONDITION CODE
 D10,D10     CONSTRAINED AT LOWER BOUND

          GOODNESS OF FIT SUMMARY FOR METHOD = ML

CHI-SQUARE =     1012.059 BASED ON    425 DEGREES OF FREEDOM
PROBABILITY VALUE FOR THE CHI-SQUARE STATISTIC IS         .00000

FIT INDICES
-----------
BENTLER-BONETT      NORMED FIT INDEX =       .917
BENTLER-BONETT NON-NORMED FIT INDEX =        .941
COMPARATIVE FIT INDEX (CFI)          =       .950
ROOT MEAN-SQUARE RESIDUAL (RMR)      =       .039
STANDARDIZED RMR                     =       .049
ROOT MEAN-SQUARE ERROR OF APPROXIMATION (RMSEA)   =       .044
90% CONFIDENCE INTERVAL OF RMSEA  (          .040,        .047)

          GOODNESS OF FIT SUMMARY FOR METHOD = ROBUST

SATORRA-BENTLER SCALED CHI-SQUARE = 903.1202 ON 425 DEGREES OF FREEDOM
PROBABILITY VALUE FOR THE CHI-SQUARE STATISTIC IS         .00000

FIT INDICES
-----------
BENTLER-BONETT      NORMED FIT INDEX =       .911
BENTLER-BONETT NON-NORMED FIT INDEX =        .942
COMPARATIVE FIT INDEX (CFI)          =       .951
ROOT MEAN-SQUARE ERROR OF APPROXIMATION (RMSEA)   =       .040
90% CONFIDENCE INTERVAL OF RMSEA  (          .036,        .043)
```


TABLE 6.12
Selected EQS Output for Model 2: Modification Indexes

MULTIVARIATE LAGRANGE MULTIPLIER TEST BY SIMULTANEOUS PROCESS IN STAGE 1
PARAMETER SETS (SUBMATRICES) ACTIVE AT THIS STAGE ARE:
PDD GFF BFF

	CUMULATIVE MULTIVARIATE STATISTICS				UNIVARIATE INCREMENT			
							HANCOCK'S SEQUENTIAL	
STEP	PARAMETER	CHI-SQUARE	D.F.	PROB.	CHI-SQUARE	PROB.	D.F.	PROB.
1	D10,D8	38.225	1	.000	38.225	.000	425	1.000
2	F9,F8	63.285	2	.000	25.059	.000	424	1.000
3	D12,D9	80.017	3	.000	16.732	.000	423	1.000
4	F10,F6	89.151	4	.000	9.134	.003	422	1.000
5	F9,F2	98.219	5	.000	9.068	.003	421	1.000
6	F12,F3	105.312	6	.000	7.093	.008	420	1.000
7	F11,F6	109.563	7	.000	4.251	.039	419	1.000

there. Otherwise, the goodness-of-fit information reveals substantial improvement in overall fit as indicated by a *CFI value of .951 (from .944) and a *RMSEA value of .040 (from .042). In Table 6.12, there is a somewhat bewildering situation in which there are now two correlated disturbance terms noted, with the first one (D10,D8) showing the greatest potential improvement in model fit if this parameter is estimated. However, once again, I prefer to limit modification to only the structural path exhibiting the highest univariate incremental χ^2 value (F9,F8), a path leading from Self-esteem to External Locus of Control.

MODEL 3

The EQS Input File

Specification of this new structural path is shown in boldface in Table 6.13 and no start value has been included. To make it easier for you in keeping track of the changes made to this model, I have also included the /TITLE paragraph in which I have noted the most recent addition (F8 to F9) has been included.

The EQS Output File

Table 6.14 shows (a) evidence that the condition code is still maintained, and (b) that the inclusion of a path from Self-esteem to External Locus of Control resulted in a slight improvement to model fit (i.e., *CFI = .953; *RMSEA = .039). Review of the modification indexes in Table 6.15 shows the parameter D10,D8 still exhibiting the highest univariate incremental LM Test χ^2 value. Also shown, however, are five structural paths that represent reasonable additions to

TABLE 6.13
Selected EQS Input: Model 3

```
/TITLE
 FULL BURNOUT MODEL FOR SECONDARY TCHRS (GRP1); "BURNHS3.EQS"
 MODEL 3
 ADDED: F3 to F11 (Work -> DP)
 ADDED: F8 to F9 (SE -> XLOCUS)
        .
        .
/EQUATIONS
        .
        .
 F8 =  .363*F5 -.114*F6 -.044*F7 + 1.000 D8;
 F9 = -.262*F5 + *F8 + 1.000 D9;
 F10 = -.128*F2 + .745*F3  -.898*F4 + 1.000 D10;
 F11 = .549*F10 + .147*F2 + *F3 + 1.000 D11;
 F12 = .512*F8 -.188*F9 + .019*F10 -.195*F11 -.041*F1 + 1.000 D12;
        .
        .
/LMTEST
 SET=GFF, BFF, PDD;
/END
```

TABLE 6.14
Selected EQS Output for Model 3: Goodness-of-Fit Statistics

```
PARAMETER    CONDITION CODE
 D10,D10     CONSTRAINED AT LOWER BOUND

GOODNESS OF FIT SUMMARY FOR METHOD = ML

CHI-SQUARE =        988.239 BASED ON       424 DEGREES OF FREEDOM
PROBABILITY VALUE FOR THE CHI-SQUARE STATISTIC IS          .00000

FIT INDICES
-----------
BENTLER-BONETT       NORMED FIT INDEX  =         .919
BENTLER-BONETT NON-NORMED FIT INDEX  =         .943
COMPARATIVE FIT INDEX (CFI)             =         .952
ROOT MEAN-SQUARE RESIDUAL (RMR)         =         .038
STANDARDIZED RMR                        =         .046
ROOT MEAN-SQUARE ERROR OF APPROXIMATION (RMSEA)    =      .043
90% CONFIDENCE INTERVAL OF RMSEA    (          .040,      .047)

GOODNESS OF FIT SUMMARY FOR METHOD = ROBUST

SATORRA-BENTLER SCALED CHI-SQUARE =     882.3626 ON      424 DEGREES OF FREEDOM
PROBABILITY VALUE FOR THE CHI-SQUARE STATISTIC IS          .00000

FIT INDICES
-----------
BENTLER-BONETT       NORMED FIT INDEX  =         .913
BENTLER-BONETT NON-NORMED FIT INDEX  =         .944
COMPARATIVE FIT INDEX (CFI)             =         .953
ROOT MEAN-SQUARE ERROR OF APPROXIMATION (RMSEA)    =      .039
90% CONFIDENCE INTERVAL OF RMSEA    (          .035,      .043)
```


TABLE 6.15
Selected EQS Output for Model 3: Modification Indexes

```
MULTIVARIATE LAGRANGE MULTIPLIER TEST BY SIMULTANEOUS PROCESS IN STAGE  1
 PARAMETER SETS (SUBMATRICES) ACTIVE AT THIS STAGE ARE:
   PDD GFF BFF
```

	CUMULATIVE MULTIVARIATE STATISTICS				UNIVARIATE INCREMENT			
							HANCOCK'S SEQUENTIAL	
STEP	PARAMETER	CHI-SQUARE	D.F.	PROB.	CHI-SQUARE	PROB.	D.F.	PROB.
1	D10,D8	37.582	1	.000	37.582	.000	424	1.000
2	F12,F5	53.760	2	.000	16.178	.000	423	1.000
3	F9,F2	66.701	3	.000	12.941	.000	422	1.000
4	F10,F6	75.660	4	.000	8.959	.003	421	1.000
5	F12,F3	82.639	5	.000	6.978	.008	420	1.000
6	F11,F6	86.942	6	.000	4.303	.038	419	1.000

the model. Although cognizant of obtaining the most parsimonious model that concomitantly best represents the data and ever wary of overfitting a model, I nonetheless believe that each of these paths should be included because they all have substantive meaning. Indeed, research has shown that in an exploratory context, it is wise to overfit a model (i.e., add more parameters than may be needed) before considering which parameters to drop from the model (see, e.g., Bentler, 2005; and Green, Thompson, & Poirier, 1999).

MODEL 4

The EQS Input File

Table 6.16 shows the five additional paths specified for the model, again presented in boldface and without start values. The/TITLE paragraph was revised to include these new paths.

The EQS Output File

Reviewing the goodness-of-fit statistics in Table 6.17, note first that the D10 condition code is gone; this message was replaced by "no special problems were encountered during the minimization process." In the Robust statistics, the inclusion of these five parameters produced only a small increment in overall model fit (i.e., *CFI = .956; *RMSEA = .038).

In Table 6.18, the correlated disturbance term, D10,D8, still displays prominently as a parameter to be addressed. In many models, the covariance between two independent factors and the direct paths between them are identical and cannot be statistically differentiated (Bentler, pers. comm., November 2, 2004). For example,

TABLE 6.16
Selected EQS Input: Model 4

```
/TITLE
 FULL BURNOUT MODEL FOR SECONDARY TCHRS (GRP1); "BURNHS4.EQS"
 MODEL 4
 ADDED: F3 to F11 (Work -> DP)
 ADDED: F8 to F9 (SE -> XLOCUS)
 ADDED: F5 to F12 (SSUP->PA; F2 to F9 (ROLEC->XLOCUS); F6 to F10 (PSUP->EE);
        F3 to F12 (WORK->PA); F6 to F11 (PSUP->DP)
      .
      .
/EQUATIONS
      .
      .
 F8 =  .363*F5 -.114*F6 -.044*F7 + 1.000 D8;
 F9 = -.262*F5 + *F8 + *F2 + 1.000 D9;
 F10 = -.128*F2 + .745*F3 -.898*F4 + *F6 + 1.000 D10;
 F11 = .549*F10 + .147*F2 + *F3 + *F6 + 1.000 D11;
 F12 = .512*F8 -.188*F9 + .019*F10 -.195*F11 -.041*F1+ *F5 + *F3 + 1.000 D12;
      .
      .
/LMTEST
 SET=GFF, BFF, PDD;
/END
```

Fl and F2: If these two factors are correlated, then an equivalent representation is Fl->F2 (or F2->F1). However, if these two factors are dependent variables in a model, the same situation may or may not hold true. Conversely, Bentler further suggests that if their χ^2 values are identical, it is likely that equivalence of their covariance and direct path does hold true.

This information is important to the results presented in Table 6.18. Given the strength of the univariate incremental χ^2 statistic for D10,D8, it is evident that this parameter should be specified in the model. Although it appears to make little sense to include the correlation of D10,D8 in the model, it does make sense to include a structural path from F8 (self-esteem) to F10 (emotional exhaustion). Further support for this specification comes with a review of the expected parameter change statistic associated with each parameter. Indeed, the path F10,F8 is shown to have a particularly strong standardized change value (−3.685). Given that both of these factors are dependent variables in the model, I considered it important to check first on the equivalence of the fit indexes between two models according to Bentler's caveat: (a) Model A, in which D10,D8 was specified as the free parameter; and (b) Model B, in which, alternatively, a path from F8 to F10 was specified as the free parameter. In each case, the *CFI and *RMSEA were identical (.96 and .036, respectively) and the S-Bχ^2 statistic almost identical (808.13 versus 805.61). Based on these results, the model was respecified (i.e., Model 5) with an estimated path flowing from F8 to F10.

TABLE 6.17
Selected EQS Output for Model 4: Goodness-of-Fit Statistics

```
PARAMETER ESTIMATES APPEAR IN ORDER,
NO SPECIAL PROBLEMS WERE ENCOUNTERED DURING OPTIMIZATION.

      GOODNESS OF FIT SUMMARY FOR METHOD = ML

CHI-SQUARE =      935.518 BASED ON    419 DEGREES OF FREEDOM
PROBABILITY VALUE FOR THE CHI-SQUARE STATISTIC IS      .00000
FIT INDICES
-----------
BENTLER-BONETT     NORMED FIT INDEX =        .923
BENTLER-BONETT NON-NORMED FIT INDEX =        .948
COMPARATIVE FIT INDEX (CFI)         =        .956
ROOT MEAN-SQUARE RESIDUAL (RMR)     =        .033
STANDARDIZED RMR                    =        .041
ROOT MEAN-SQUARE ERROR OF APPROXIMATION (RMSEA)    =      .042
90% CONFIDENCE INTERVAL OF RMSEA   (         .038,        .045)

      GOODNESS OF FIT SUMMARY FOR METHOD = ROBUST

SATORRA-BENTLER SCALED CHI-SQUARE =     844.0545 ON    419 DEGREES OF FREEDOM
PROBABILITY VALUE FOR THE CHI-SQUARE STATISTIC IS      .00000
FIT INDICES
-----------
BENTLER-BONETT     NORMED FIT INDEX =        .917
BENTLER-BONETT NON-NORMED FIT INDEX =        .948
COMPARATIVE FIT INDEX (CFI)         =        .956
ROOT MEAN-SQUARE ERROR OF APPROXIMATION (RMSEA)    =      .038
90% CONFIDENCE INTERVAL OF RMSEA   (         .034,        .041)
```

TABLE 6.18
Selected EQS Output for Model 4: Modification Indexes

LAGRANGE MULTIPLIER TEST (FOR ADDING PARAMETERS)

ORDERED UNIVARIATE TEST STATISTICS:

NO	CODE		PARAMETER	CHI-SQUARE	PROB.	HANCOCK 419 DF PROB.	PARAMETER CHANGE	STANDARDIZED CHANGE
1	2	10	D10,D8	43.930	.000	1.000	-.095	-1.422
2	2	22	F10,F8	41.626	.000	1.000	-1.210	-3.685
3	2	22	F8,F11	25.169	.000	1.000	-.106	-.321
4	2	22	F8,F10	23.007	.000	1.000	-.200	-.610
5	2	10	D11,D8	17.885	.000	1.000	-.055	-.279

	CUMULATIVE MULTIVARIATE STATISTICS				UNIVARIATE INCREMENT		HANCOCK'S SEQUENTIAL	
STEP	PARAMETER	CHI-SQUARE	D.F.	PROB.	CHI-SQUARE	PROB.	D.F.	PROB.
1	D10,D8	43.930	1	.000	43.930	.000	419	1.000
2	F9,F1	47.993	2	.000	4.063	.044	418	1.000

MODEL 5

The EQS Input File

Table 6.19 shows the partial input file for Model 5; in particular, the specification of a path leading from F8 to F10.

The EQS Output File

Goodness-of-fit statistics related to the estimation of Model 5 are shown in Table 6.20. As noted previously, this analysis resulted in excellent model fit that improved over that of Model 4 (*CFI = .960 versus .956; *RMSEA = .036 versus .038). Shown in Table 6.21 are the LM Test results for this model. Here we find yet another parameter to be considered for inclusion in the model, a path from Role Ambiguity to Depersonalization (F11,F1). Given that nonsignificant paths are identified and deleted before a final model is established, I considered it appropriate to test one more model in which this parameter was estimated.

TABLE 6.19
Selected EQS Input: Model 5

```
/TITLE
 FULL BURNOUT MODEL FOR SECONDARY TCHRS (GRP1); "BURNHS5.EQS"
 MODEL 5
 ADDED: F3 to F11 (Work -> DP)
 ADDED: F8 to F9 (SE -> XLOCUS)
 ADDED: F5 to F12 (SSUP->PA; F2 to F9 (ROLEC->XLOCUS); F6 to F10 (PSUP->EE);
        F3 to F12 (WORK->PA); F6 to DP (PSUP->DP)
 ADDED: F8 to F10 (SE -> EE)
     .
     .
/EQUATIONS
     .
     .
   F8 =  .363*F5 -.114*F6 -.044*F7 + 1.000 D8;
   F9 = -.262*F5 + *F8 + *F2 + 1.000 D9;
   F10 = -.128*F2 + .745*F3 - .898*F4 + *F6 + *F8 + 1.000 D10;
   F11 = .549*F10 + .147*F2 + *F3 + *F6 + 1.000 D11;
   F12 = .512*F8 - .188*F9 + .019*F10 - .195*F11 - .041*F1 + *F5 + *F3 + 1.000 + D12;
     .
     .
/LMTEST
 SET=GFF, BFF, PDD;
/END
```


TABLE 6.20
Selected EQS Output for Model 5: Goodness-of-Fit Statistics

```
               GOODNESS OF FIT SUMMARY FOR METHOD = ML

CHI-SQUARE =        895.790 BASED ON      418 DEGREES OF FREEDOM
PROBABILITY VALUE FOR THE CHI-SQUARE STATISTIC IS          .00000
FIT INDICES
-----------
BENTLER-BONETT      NORMED FIT INDEX =        .926
BENTLER-BONETT NON-NORMED FIT INDEX =         .951
COMPARATIVE FIT INDEX (CFI)          =        .959
ROOT MEAN-SQUARE RESIDUAL (RMR)      =        .032
STANDARDIZED RMR                     =        .040
ROOT MEAN-SQUARE ERROR OF APPROXIMATION (RMSEA)    =      .040
90% CONFIDENCE INTERVAL OF RMSEA  (          .036,        .044)

              GOODNESS OF FIT SUMMARY FOR METHOD = ROBUST

SATORRA-BENTLER SCALED CHI-SQUARE =      808.1292 ON     418 DEGREES OF FREEDOM
PROBABILITY VALUE FOR THE CHI-SQUARE STATISTIC IS          .00000
FIT INDICES
-----------
BENTLER-BONETT      NORMED FIT INDEX =        .920
BENTLER-BONETT NON-NORMED FIT INDEX =         .952
COMPARATIVE FIT INDEX (CFI)          =        .960
ROOT MEAN-SQUARE ERROR OF APPROXIMATION (RMSEA)    =      .036
90% CONFIDENCE INTERVAL OF RMSEA  (          .032,        .040)
```

TABLE 6.21
Selected EQS Output for Model 5: Modification Indexes

```
MULTIVARIATE LAGRANGE MULTIPLIER TEST BY SIMULTANEOUS PROCESS IN STAGE 1
   PARAMETER SETS (SUBMATRICES) ACTIVE AT THIS STAGE ARE:
      PDD GFF BFF
```

	CUMULATIVE MULTIVARIATE STATISTICS				UNIVARIATE INCREMENT			
							HANCOCK'S SEQUENTIAL	
STEP	PARAMETER	CHI-SQUARE	D.F.	PROB.	CHI-SQUARE	PROB.	D.F.	PROB.
1	F11,F1	6.041	1	.014	6.041	.014	418	1.000

MODEL 6

The EQS Input File

Table 6.22 is the related EQS input file showing the specification of F1 leading to F11. The model changes are summarized in the /TITLE paragraph.

The EQS Output File

As shown in the goodness-of-fit summary in Table 6.23, incorporation of the path F11,F1 resulted in virtually no change in overall model fit from the previous model (i.e., Model 5). Thus, although the LM Test Statistics shown in Table 6.24 suggested another structural path to be incorporated into the model, this addition was not considered.

Thus far in this chapter, discussion related to model fit has considered only the addition of parameters to the model. However, another side to the question of fit—particularly as it pertains to a full causal model—is the extent to which certain initially hypothesized paths and possibly post hoc additional paths may be redundant to the model. One way to determine such redundancy is to examine the statistical significance of all structural parameter estimates. This information, as derived from the estimation of Model 6, is presented in Table 6.25.

Examining z-statistics associated with these structural estimates, we can determine five that are nonsignificant; these parameters are circled in Table 6.25 and represent structural paths flowing from F7 to F8, F1 to F11, F6 to F11, F10 to F12, and F1 to F12. The limiting factor in using these statistics as a basis for pinpointing redundant parameters, however, is that they represent univariate tests of significance. When sets of parameters are to be evaluated, a more appropriate approach is to implement a multivariate test of statistical significance. Indeed, the EQS program is unique in its provision of the Wald Test (WTest; Wald, 1943) for

TABLE 6.22
Selected EQS Input: Model 6

```
/TITLE
 FULL BURNOUT MODEL FOR SECONDARY TCHRS (GRP1); "BURNHS6.EQS"
 MODEL 6
 ADDED:  F3 to F11 (Work -> DP)
 ADDED:  F8 to F9 (SE -> XLOCUS)
 ADDED:  F5 to F12 (SSUP->PA; F2 to F9 (ROLEC->XLOCUS); F6 to F10 (PSUP->EE);
         F3 to F12 (WORK->PA); F6 to F11 (PSUP->DP)
 ADDED:  F8 to F10 (SE -> EE)
 ADDED:  F1 to F11 (ROLEA -> DP)
     .
     .
/EQUATIONS
     .
     .
 F8 =  .363*F5 -.114*F6 -.044*F7 + 1.000 D8;
 F9 = -.262*F5 + *F8 + *F2 + 1.000 D9;
 F10 = -.128*F2 + .745*F3 -.898*F4 + *F6 + *F8 + 1.000 D10;
 F11 = .549*F10 + .147*F2 + *F3 + *F6 + *F1 + 1.000 D11;
 F12 = .512*F8 -.188*F9 + .019*F10 -.195*F11 -.041*F1 + *F5 + *F3 + 1.000 D12;
     .
     .
/LMTEST
 SET=GFF, BFF, PDD;
/END
```


TABLE 6.23
Selected EQS Output for Model 6: Goodness-of-Fit Statistics

```
                GOODNESS OF FIT SUMMARY FOR METHOD = ML

CHI-SQUARE =      889.534 BASED ON     417 DEGREES OF FREEDOM
PROBABILITY VALUE FOR THE CHI-SQUARE STATISTIC IS          .00000

FIT INDICES
-----------
BENTLER-BONETT      NORMED FIT INDEX =        .927
BENTLER-BONETT NON-NORMED FIT INDEX =        .952
COMPARATIVE FIT INDEX (CFI)         =        .960
ROOT MEAN-SQUARE RESIDUAL (RMR)     =        .032
STANDARDIZED RMR                    =        .040
ROOT MEAN-SQUARE ERROR OF APPROXIMATION (RMSEA)     =      .040
90% CONFIDENCE INTERVAL OF RMSEA   (          .036,       .043)

              GOODNESS OF FIT SUMMARY FOR METHOD = ROBUST

SATORRA-BENTLER SCALED CHI-SQUARE =    802.7997 ON    417 DEGREES OF FREEDOM
PROBABILITY VALUE FOR THE CHI-SQUARE STATISTIC IS          .00000

FIT INDICES
-----------
BENTLER-BONETT      NORMED FIT INDEX =        .921
BENTLER-BONETT NON-NORMED FIT INDEX =        .952
COMPARATIVE FIT INDEX (CFI)         =        .960
ROOT MEAN-SQUARE ERROR OF APPROXIMATION (RMSEA)     =      .036
90% CONFIDENCE INTERVAL OF RMSEA   (          .032,       .040)
```

TABLE 6.24
Selected EQS Output for Model 6: Modification Indexes

```
MULTIVARIATE LAGRANGE MULTIPLIER TEST BY SIMULTANEOUS PROCESS IN STAGE 1
  PARAMETER SETS (SUBMATRICES) ACTIVE AT THIS STAGE ARE:
     PDD GFF BFF

     CUMULATIVE MULTIVARIATE STATISTICS          UNIVARIATE INCREMENT
     ----------------------------------          ----------------------------
                                                                   HANCOCK'S
                                                                   SEQUENTIAL
STEP PARAMETER  CHI-SQUARE  D.F.  PROB.        CHI-SQUARE  PROB.  D.F.  PROB.
---- ---------  ----------  ----  -----        ----------  -----  ----  -----
  1     F9,F3        3.870     1   .049             3.870   .049   417  1.000
```

this very purpose. Essentially, the WTest ascertains whether sets of parameters, specified as free in the model, can in fact be simultaneously set to zero without substantial loss in model fit. It does so by taking the least significant parameter (i.e., the one with the smallest z-statistic) and adding other parameters in such a way that the overall multivariate test yields a set of free parameters that with high probability can simultaneously be dropped from the model in future EQS runs without significant degradation in model fit (Bentler, 2005). In other words, this

TABLE 6.25
Selected EQS Output for Model 6: Structural Path Estimates

```
CONSTRUCT EQUATIONS WITH STANDARD ERRORS AND TEST STATISTICS
STATISTICS SIGNIFICANT AT THE 5% LEVEL ARE MARKED WITH @.
(ROBUST STATISTICS IN PARENTHESES)
SELF  =F8  =      .360*F5    -    .120*F6      - .047*F7   +   1.000 D8
                  .060            .031            .034
                 5.984@         -3.827@         -1.374
            (     .068)     (     .035)          (.042)
            (    5.310@     (   -3.405@        (-1.120)

XLOC  =F9  =    -.269*F8    +    .131*F2    -     .081*F5   +   1.000 D9
                  .057            .037             .039
                -4.672@          3.553@          -2.076@
            (     .072)     (     .036)     (     .040)
            (   -3.738@     (    3.641@     (   -2.033@

EE    =F10 =    -.828*F8    -   2.118*F2    +    2.223*F3   -     .929*F4
                  .133            .650             .548           .178
                -6.247@         -3.259@           4.057@        -5.212@
            (     .168)     (     .687)     (     .569)    (      .187)
            (   -4.934@     (   -3.084@     (    3.907@    (    -4.957@

           -      .269*F6   +   1.000 D10
                  .108
                -2.487@
            (     .126)
            (   -2.132@

DP    =F11 =      .996*F10  -     .452*F1   +    4.213*F2   -    3.548*F3
                  .177            .233           1.493          1.244
                 5.623@         -1.942           2.822@        -2.852@
            (     .194)     (     .241)     (    1.598)    (     1.307)
            (    5.124@     (   -1.874)     (    2.637@    (    -2.715@

           +      .276*F6   +   1.000 D11
                  .210
                 1.313
            (     .236)
            (    1.170)

PA    =F12 =      .465*F8   -     .174*F9   -     .017*F10  -     .159*F11
                  .102            .075            .049            .035
                 4.541@         -2.317@          -.345          -4.523@
            (     .132)     (     .074)     (     .051)    (      .041)
            (    3.521@     (   -2.360@     (    -.334)    (    -3.893@

           +      .043*F1   +     .165*F3   +     .268*F5   +   1.000 D12
                  .103            .064            .072
                  .411           2.596@          3.708@
            (     .118)     (     .067)     (     .078)
            (     .362)     (    2.476@     (    3.419@
```


TABLE 6.26
Selected EQS Output for Model 6: Wald Test Results

```
WALD TEST (FOR DROPPING PARAMETERS)
ROBUST INFORMATION MATRIX USED IN THIS WALD TEST
MULTIVARIATE WALD TEST BY SIMULTANEOUS PROCESS
```

	CUMULATIVE MULTIVARIATE STATISTICS				UNIVARIATE INCREMENT	
STEP	PARAMETER	CHI-SQUARE	D.F.	PROBABILITY	CHI-SQUARE	PROBABILITY
1	F12,F10	.111	1	.739	.111	.739
2	F12,F1	.186	2	.911	.074	.785
3	F11,F6	1.511	3	.680	1.325	.250
4	F8,F7	2.895	4	.576	1.385	.239
5	F11,F1	6.048	5	.302	3.152	.076

multivariate WTest operates in a stepwise manner that is analogous to stepwise backward regression. In contrast, the stepping procedure for the LM Test is forward. The value of this stepwise implementation in EQS is that it may determine that only a few parameters actually carry all the weight in the multivariate test (Bentler, 2005). Implementation of the WTest is simple and involves only the typing of a separate line, as follows: /WTEST. Essentially, this specification replaces the /LMTEST specification.

To test multivariately for redundant structural paths in the model, the /WTEST paragraph was added to the EQS input for Model 6 and the model was reestimated; for this run also, there was no specification of LM Test statistics. Results from this invocation of the WTest are presented in Table 6.26.

Interestingly, the WTest identified the same five parameters noted in Table 6.25 as being redundant to the model. Of the five nonsignificant parameters, three represent structural paths present in the originally hypothesized model (F7 ->F8; F10 ->F12; F1 ->F12) and two represent paths added during the post hoc model-fitting stage (F1 ->F11; F6 ->F11).

Revision of the model in accordance with these results led to deletion of structural paths describing the impact of: Role Ambiguity on Personal Accomplishment, Role Ambiguity on Depersonalization, Superior Support on Depersonalization, Peer Support on Self-esteem, and Emotional Exhaustion on Personal Accomplishment. These deletions resulted in the Role Ambiguity and Peer Support constructs being totally eliminated from the causal model. To obtain fit statistics and estimates for this final model of burnout for secondary school teachers, Model 6 was respecified with these five parameters deleted and labeled Model 7, which was then estimated. Goodness-of-fit statistics related to this final model of burnout are presented in Table 6.27.

Of import in reviewing these statistics is the fact that both the *CFI and the *RMSEA values remained unchanged (.960 and .036, respectively) from those for Model 6 in which these five structural paths were estimated. Although there was a

TABLE 6.27
Selected EQS Output for Final Model: Goodness-of-Fit Statistics

```
        GOODNESS OF FIT SUMMARY FOR METHOD = ML

CHI-SQUARE =        901.634 BASED ON      422 DEGREES OF FREEDOM
PROBABILITY VALUE FOR THE CHI-SQUARE STATISTIC IS            .00000

FIT INDICES
-----------
BENTLER-BONETT      NORMED FIT INDEX =         .926
BENTLER-BONETT NON-NORMED FIT INDEX =          .952
COMPARATIVE FIT INDEX (CFI)          =         .959
ROOT MEAN-SQUARE RESIDUAL (RMR)      =         .032
STANDARDIZED RMR                     =         .040
ROOT MEAN-SQUARE ERROR OF APPROXIMATION (RMSEA)    =        .040
90% CONFIDENCE INTERVAL OF RMSEA  (            .036,       .043)

        GOODNESS OF FIT SUMMARY FOR METHOD = ROBUST

SATORRA-BENTLER SCALED CHI-SQUARE =        812.6905 ON      422 DEGREES OF FREEDOM
PROBABILITY VALUE FOR THE CHI-SQUARE STATISTIC IS            .00000

FIT INDICES
-----------
BENTLER-BONETT      NORMED FIT INDEX =         .920
BENTLER-BONETT NON-NORMED FIT INDEX =          .952
COMPARATIVE FIT INDEX (CFI)          =         .960
ROOT MEAN-SQUARE ERROR OF APPROXIMATION (RMSEA)    =        .036
90% CONFIDENCE INTERVAL OF RMSEA  (            .032,       .040)
```

slight increase in the overall χ^2 statistic value from Model 6 (S-B$\chi^2 = 802.80$) to the Final Model (S-B$\chi^2 = 812.69$), such degradation is expected with the removal of five parameters from the model. Of substantial importance, however, is whether this S-Bχ^2 difference value is statistically nonsignificant, which it should be.

When analyses are based on the usual ML estimation with no correction for non-normality, a comparison of nested models[5] is simply a matter of computing the difference between the χ^2 values and related degrees of freedom for the two models. This difference value ($\Delta\chi^2$) is distributed as χ^2, with degrees of freedom equal to the difference in degrees of freedom (Δdf). However, when analyses are based on Robust (i.e., corrected) ML estimation, it is not possible to perform this straightforward computation of the difference test because the ΔS-Bχ^2 value is not χ^2-distributed. However, Satorra and Bentler (2001) have shown how the ΔS-Bχ^2 value can be corrected and therefore used in the same way as the $\Delta\chi^2$ to judge for statistical significance. Readers are now walked through the computations involved in making this correction to the ΔS-Bχ^2 value.

The nested models of interest here are Models 6 and 7, the final model in which five structural paths were deleted. In this instance, Model 7 is considered the

[5]Nested models are hierarchically related to one another in the sense that their parameter sets are subsets of one another. That is, particular parameters are freely estimated in one model but fixed to zero in a second model (Bentler & Chou, 1987; and Bollen, 1989a).

more restrictive model because it has fewer parameters to be estimated than does Model 6. Based on statistical convention, Model 6 represents the more general model and is given the label M_1; Model 7 is the more restrictive model and is labeled M_0. Steps in the computation process are as follows:

1. (Model 7) $k_0 = T_0/\overline{T}_0$, where $T_0 = \text{ML}\chi^2$ and $\overline{T}_0 = \text{S-B}\chi^2$
$$= \frac{901.634}{812.6905} = 1.109$$
2. (Model 6) $k_1 = T_1/\overline{T}_1$, where $T_1 = \text{ML}\chi^2$ and $\overline{T}_1 = \text{S-B}\chi^2$
$$= \frac{889.534}{802.7997} = 1.108$$
3. Compute from model comparisons:
   (a) usual difference test ($\Delta\chi^2$; D) $= T_0 - T_1$
   $$= 901.634 - 889.534 = 12.10$$
   (b) S-B scaling coefficient, with $d = d_0 - d_1$, where d = degrees of freedom and k = $(d_0k_0 - d_1k_1)/d$
   $$d = 422 - 417 = 5$$
   $$k = \frac{(422)(1.109) - (417)(1.108)}{5} = \frac{5.962}{5} = 1.1924$$
4. Compute ΔS-Bχ^2 value
$$\overline{D} = D/k = \frac{12.10}{1.1924} = 10.148$$

As shown in these computations, the ΔS-Bχ^2 value between Model 6 and the final model of burnout (Model 7) was nonsignificant. These findings, therefore, argue for the redundancy of the five deleted structural paths. Table 6.28 presents both the unstandardized and standardized estimates for all remaining structural paths in the final model of burnout for secondary school teachers; Fig. 6.10 is a schematic representation, in which solid lines represent the originally hypothesized paths and dotted lines represented the paths subsequently added as a result of post hoc model-fitting.

In summary, of 14 causal paths specified in the hypothesized model (see Fig. 6.4), 11 were found to be statistically significant for secondary school teachers. These paths reflected the impact of (a) role conflict, classroom climate, and work overload on emotional exhaustion; (b) decision-making on both self-esteem and external locus of control; (c) self-esteem, depersonalization, and external locus of control on perceived personal accomplishment; (d) role conflict and emotional exhaustion on depersonalisation; and (e) superior support on self-esteem. Seven paths, not specified a priori (Work Overload → Depersonalization; Work Overload → Personal Accomplishment; Role Conflict → External Locus of Control; Decision-making → Personal Accomplishment; Superior Support → Emotional

TABLE 6.28
Selected EQS Output for Final Model: Structural Path Coefficients

Unstandardized Solution

```
CONSTRUCT EQUATIONS WITH STANDARD ERRORS AND TEST STATISTICS
STATISTICS SIGNIFICANT AT THE 5% LEVEL ARE MARKED WITH @.
(ROBUST STATISTICS IN PARENTHESES)
SELF  =F8   =      .305*F5    -    .105*F6     +   1.000 D8
                   .040            .027
                  7.705@         -3.875@
               (   .043)    (      .030)
               (  7.116@    (    -3.441@

XLOC  =F9   =     -.268*F8    +    .129*F2     -     .084*F5     +   1.000 D9
                   .057            .036              .039
                 -4.690@          3.529@           -2.150@
               (   .072)    (      .036)     (       .040)
               ( -3.753@    (     3.621@     (     -2.078@

EE    =F10  =     -.801*F8    -   1.918*F2     +    2.137*F3     -   1.146*F4
                   .123            .562              .500              .212
                 -6.517@         -3.414@            4.275@           -5.405@
               (   .154)    (      .569)     (       .503)     (      .233)
               ( -5.202@    (    -3.370@     (      4.248@     (    -4.917@

              -    .120*F6    +   1.000 D10
                   .043
                 -2.796@
               (   .048)
               ( -2.518@

DP    =F11  =      .898*F10   +   2.552*F2     -    2.442*F3     +   1.000 D11
                   .127            .651              .634
                  7.067@          3.919@           -3.850@
               (   .140)    (      .670)     (       .648)
               (  6.411@    (     3.808@     (     -3.771@

PA    =F12  =      .467*F8    -    .166**F9    -     .166**F11   +    .175*F3
                   .094            .075              .031              .047
                  4.960@         -2.224@           -5.385@            3.718@
               (   .120)    (      .073)     (       .036)     (      .051)
               (  3.891@    (    -2.267@     (     -4.591@     (     3.457@

              +    .261*F5    +   1.000 D12
                   .059
                  4.428@
               (   .063)
               (  4.109@
```

Standardized Solution

```
SELF = F8  =  .710*F5  -  .346*F6 +  .882 D8
XLOC = F9  = -.216*F8  +  .263*F2 -  .157*F5  + .852 D9
EE   = F10 = -.256*F8  - 1.564*F2 + 1.959*F3  - .352*F4  - .127*F6 + .544 D10
DP   = F11 =  .893*F10 + 2.067*F2 - 2.224*F3  + .594 D11
PA   = F12 =  .245*F8  -  .108*F9 -  .274*F11 + .263*F3  + .318*F5 + .817 D12
```


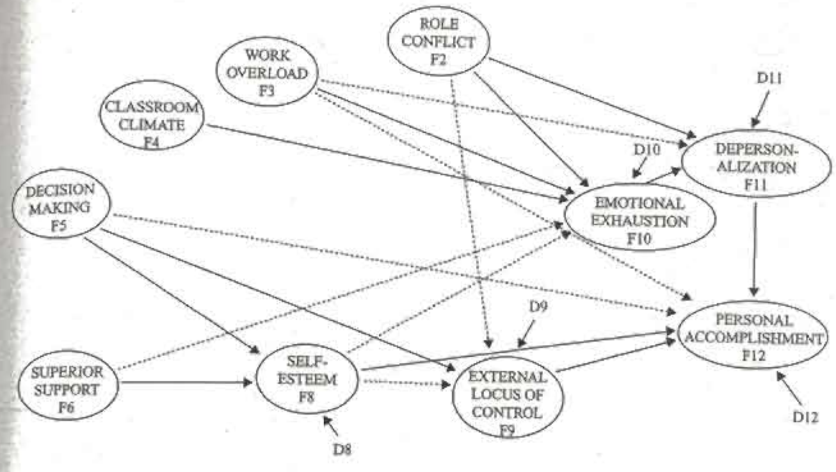

FIG. 6.10. Final model of teacher burnout. Solid lines represent originally hypothesized structural paths; broken lines represent structural paths added to the originally hypothesized model.
Note: For simplicity, the measurement model is not included.

Exhaustion; Self-esteem → Emotional Exhaustion; Self-esteem → External Locus of Control), proved to be essential components of the causal structure; therefore, they were added to the model. Finally, three originally hypothesized paths (Role Ambiguity → Personal Accomplishment; Peer Support → Self-esteem; Emotional Exhaustion → Personal Accomplishment) were found to be not statistically significant and were therefore deleted from the model.

Overall, the conclusion from this study is that role conflict, work overload, classroom climate, participation in the decision-making process, and support of superiors are potent organizational determinants of burnout for high school teachers. The process appears to be tempered, however, by a general sense of self-worth and locus of control.

III

Multiple-Group Analyses