CHAPTER 5 Confirmatory Factor Analysis

In this chapter, we consider the operationalization of a measuremen model through confirmatory factor analysis. As will become apparent applications of confirmatory factor analysis are particularly appropriat when there is a debate about the dimensionality or factor structure of scale or measure. In this chapter, we consider the dimensionality of measure of union commitment.

Since the original publication of the Gordon, Philpot, Burt, Thompson and Spiller (1980) 30-item union commitment scale, there have bee numerous factor analytic studies of the scale (e.g., Friedman & Harvey 1986; Fullagar, 1986; Kelloway, Catano, & Southwell, 1992; Klander mans, 1990). Kelloway and colleagues (1992) proposed a shorter 13 item version of the scale designed to represent three factors: Unio Loyalty; Willingness to Work for the Union; and Responsibility to th Union.

In this chapter, we will conduct a confirmatory factor analysis of th shortened scale based on data drawn from 217 union stewards. I developing and conducting the analysis, we will follow Bollen an Long's (1993) description of structural equation modeling as comprisin five steps:

1. model specification,
2. identification,
3. estimation,
4. testing fit, and
5. respecification.

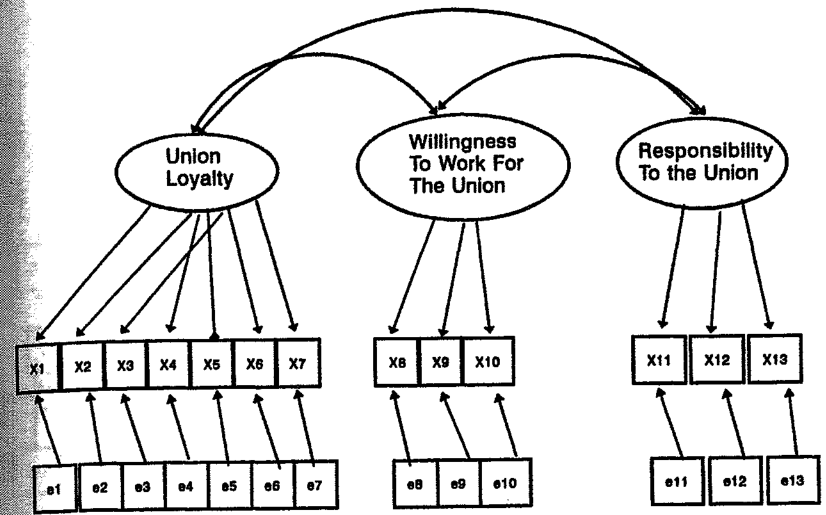

Figure 5.1.

Model Specification

The first step in operationalizing the model was to clarify exactly what relationships the model proposed. Figure 5.1 presents the proposed model. Note that the first factor (Union Loyalty) is measured by seven items, the second (Willingness to Work for the Union) by three items, and the third (Responsibility to the Union) by three items. Note also that each observed variable is also caused by a second latent variable representing the residual (or unique factors for factor analysts). Finally, each of the three factors is allowed to correlate with the other latent variables (i.e., the factors are oblique).

Given our focus on comparing models, it is appropriate to develop rival models to contrast with the proposed three-factor solutions. As noted earlier, ideally these rival models will stand in nested sequence with the model of interest to allow for the use of direct comparisons with the $\chi^2_{difference}$ test. The best source of such rival specification is the literature. In the case of the union commitment scale, for example, Friedman and Harvey (1986) reanalyzed the data from Gordon and colleagues (1980) and suggested a two-factor solution, with one factor representing attitudes and the other representing behavioral intentions.

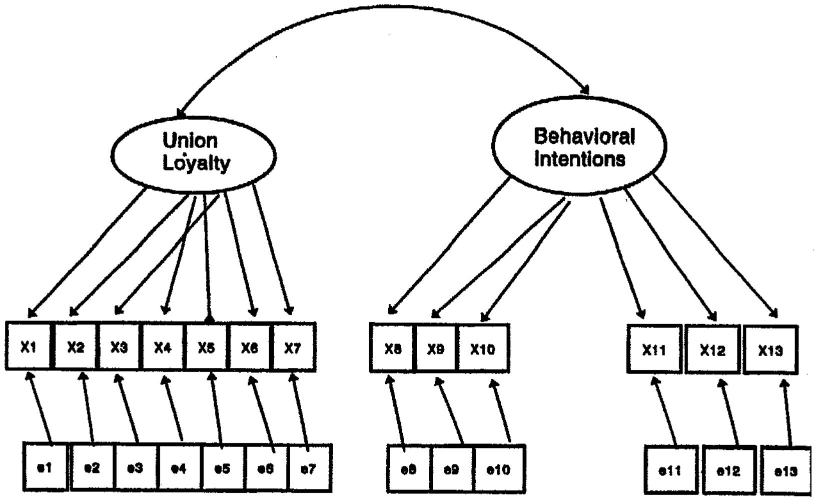

Figure 5.2.

For the current example, the two-factor model is depicted in Figure 5.2. Essentially, one obtains the two-factor model by combining the Willingness to Work for the Union and Responsibility to the Union factors. Although it is not intuitively obvious, the two-factor model is nested within the three-factor model. That is, by fixing the correlation between Willingness and Responsibility to equal 1.0, you obtain the two-factor model from the original three-factor model. The $\chi^2_{difference}$ test therefore will have 2 degrees of freedom (because there will be two fewer intercorrelations estimated).

If the literature does not provide a reasonable alternative to the factor structure you hypothesize, alternative structures may be obtained by constraining one or more parameters in the original model. In general, for any model that contains a number of correlated factors, nested models may be obtained by estimating (a) a model containing orthogonal factors (i.e., constraining all interfactor correlations to equal zero, see Figure 5.3) and/or (b) a unidimensional model (i.e., constraining all interfactor correlations to equal 1.0, see Figure 5.4).

From Pictures to LISREL

The model thought to explain the observed correlations between the union commitment items implies a set of structural equations. In the

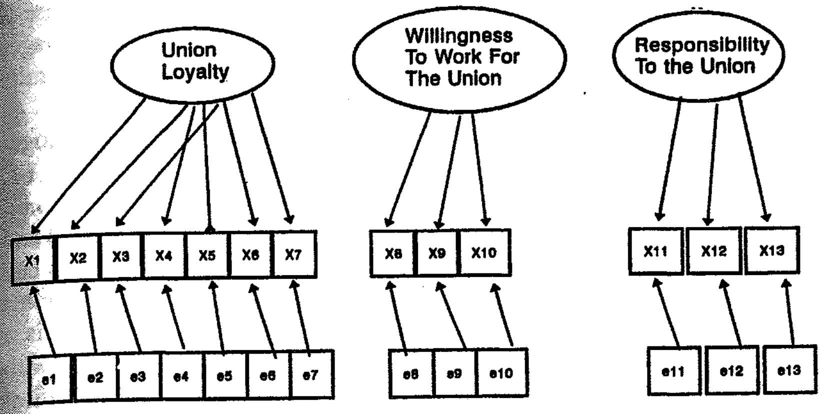

Figure 5.3.

LISREL environment, you do not have to worry about the exact form of the equations, but you do have to be concerned with the form of the relevant matrices. The process of translating the models into LISREL analyses is similar for all models, so we will focus on the three-factor model as an example.

Before beginning the process of translating the figures into LISREL commands, it is important to note that LISREL allows you to conduct confirmatory factor analyses on both the exogenous (i.e., using matrices **LX**, **PH**, and **TD**) and endogenous (i.e., using matrices **LY**, **PS**, and **TE**)

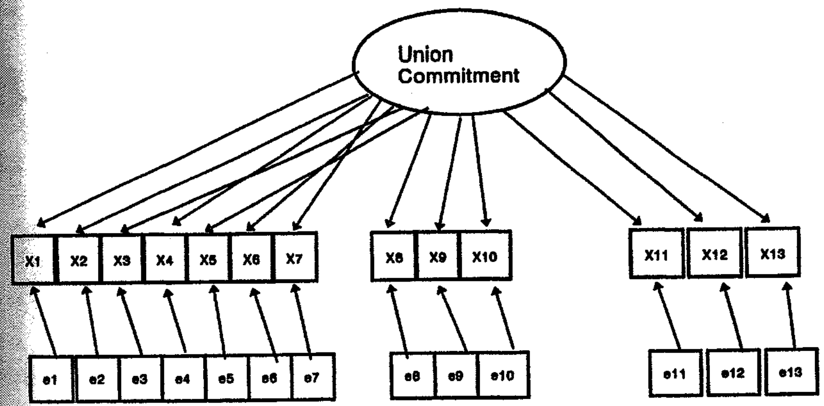

Figure 5.4.

sides of the full model. The choice of which side of the model to use largely left to the user. As will become apparent, there are some advantag to using the exogenous (X) side of the model, but the numerical resu should be exactly the same whichever side is used.

Because this is a factor analysis (for convenience only, of the exog nous variables), there are three matrices to be concerned with: L (factor loadings), PH (interfactor correlations), and TD (unique factor The LX matrix will have three columns (one for each latent variable) a 14 rows (one for each item). The PH matrix will have three columns a three rows and will be symmetrical (i.e., the elements above the diagon will be the same as the elements below the diagonal because it is correlation matrix). Finally, the TD matrix will be a vector (one row) wi 14 columns (representing the 14 unique factors). The complete specific tion for the three matrices (indicating which elements are FRee or FIxe is given below.

There are 29 parameters to be estimated (13 factor loadings + 1 unique factors + 3 interfactor correlations). With 13 variables, th implies a number of degrees of freedom for the model equal to

$$13 \times (13 + 1)/2 - 29 = 62.$$

Following the matrix presentations, I have enclosed the annotated co used to test the model. Note the correspondence between the code a the matrix forms presented.

LX MATRIX

	K1	K2	K3
X1	FR	FI	FI
X2	FR	FI	FI
X3	FR	FI	FI
X4	FR	FI	FI
X5	FR	FI	FI
X6	FR	FI	FI
X7	FR	FI	FI
X8	FI	FR	FI
X9	FI	FR	FI
X10	FI	FR	FI
X11	FI	FI	FR
X12	FI	FI	FR
X13	FI	FI	FR

PHI MATRIX

	K1	K2	K3
K1	1.00		
K2	FR	1.00	
K3	FR	FR	1.00

TD MATRIX

X1	X2	X3	X4	X5	X6	X7	X8	X9	X10
FR	FR	FR	FR	FR	FR	FR	FR	FR	FR

X11	X12	X13
FR	FR	FR

ANNOTATED CODE

```
TI Confirmatory Factor Analysis of the Union Commitment
   Scale
```

Note: The title is optional but recommended.

```
DA NI = 13 NO = 217 MA = CM
```

Note: There are 13 input variables (items), with 217 respondents, and I want to analyze the covariance matrix (CM).

```
ME
3.922 4.336 3.940 3.811 4.198 4.479 4.101
4.083 4.221 4.060 4.171 3.899 3.820
```

Note: This is the vector of means for each item.

```
SD
.937  .856  .991  .921  .851  .714  .917
.878  .837  .987  .846  .976 1.050
```

Note: This is the vector of standard deviations for each item.

```
KM FU
 1.000  .443  .643  .621  .635  .423  .564
  .531  .370  .331  .542  .497  .550
  .443 1.000  .531  .421  .480  .432  .504
  .351  .283  .288  .476  .323  .371
```

```
 .643  .531 1.000  .510  .634  .414  .485
 .405  .368  .359  .448  .343  .426
 .621  .421  .510 1.000  .698  .392  .615
 .529  .367  .339  .511  .452  .616
 .635  .480  .634  .698 1.000  .468  .603
 .529  .361  .388  .551  .426  .553
 .423  .432  .414  .392  .468 1.000  .427
 .549  .604  .577  .477  .369  .406
 .564  .504  .485  .615  .603  .427 1.000
 .455  .314  .372  .532  .441  .634
 .531  .351  .405  .529  .529  .549  .455
1.000  .561  .571  .392  .302  .413
 .370  .283  .368  .367  .361  .604  .314
 .561 1.000  .629  .391  .288  .377
 .331  .288  .359  .339  .388  .577  .372
 .571  .629 1.000  .370  .309  .382
 .542  .476  .448  .511  .551  .477  .532
 .392  .391  .370 1.000  .727  .712
 .497  .323  .343  .452  .426  .369  .441
 .302  .288  .309  .727 1.000  .710
 .550  .371  .426  .616  .553  .406  .634
 .413  .377  .382  .712  .710 1.000
```

Note: This is the full correlation matrix.

```
MO NX = 13 NK = 3 PH = ST
```

Note: The first line of the model command defines 13 *X* variables and three *K* variables, thereby specifying a factor analysis model using matrices TD, LX, and PH. "PH = ST" indicates that the interfactor covariance matrix is the lower part of a symmetric matrix and has 1s in the diagonal; hence, it is a correlation matrix—the off-diagonal elements contain the disattenuated (corrected for unreliability) correlations between the three latent variables (factors). The ST form is a convenience provided by the LISREL authors for confirmatory factor analysis. It applies only to analyses using the exogenous side of the LISREL model.

```
FR LX(1,1) LX(2,1) LX(3,1) LX(4,1) LX(5,1) LX(6,1)
```



```
FR LX(7,1)
```

Note: Here I define the first factor by telling LISREL to freely estimate the loadings of the first seven variables (seven Union Loyalty items) on the first factor.

```
FR LX(8,2) LX(9,2) LX(10,2)
```

Note: These lines define the second factor by telling LISREL to freely estimate the loadings for the next three variables (three Willingness to Work for the Union items) on the second factor (Willingness).

```
FR LX(11,3) LX(12,3) LX(13,3)
```

Note: Left as an exercise for the reader. It may help you to know that the Responsibility to the Union scale has three items.

```
OU ML SC TV
```

Note: The output command tells LISREL that I want a maximum likelihood solution (ML). I also want LISREL to provide the completely standardized solution for the estimated parameters (SC) and the *t* values (significance tests) for the parameters.

Additional Comments

You will note that I did not have to specify the FIxed elements in the LX matrix. This is because the default form of the matrix is full (*NX* rows × *NK* columns), and all elements are fixed. To specify the loadings I want, therefore, I only have to free the elements I want estimated.

By declaring the PH matrix to be ST, I have declared the matrix to be symmetrical, with 1s in the diagonal and free elements in the off-diagonals. No further specification is necessary to produce the correlation matrix I want. The ST specification is a convenience provided by the authors of LISREL for doing confirmatory factor analysis. It applies only to the PH matrix and can be used only for a factor analysis of the exogenous variables.

Because this command sets 1s in the diagonals of the factor covariance matrix, and because the diagonals of PH represent the variances of the latent variables, using the PH = ST specification tells LISREL that latent variables are in standard score form. In effect, the specification assigns a metric (i.e., a scale of measurement) to the latent variables. Recall that latent variables are, by definition, not directly measured. Unless the user indicates a scale of measurement for the latent variables, LISREL will not be able to estimate a solution.

Although the PH = ST specification is a convenience provided for confirmatory factor analyses, there is another way to set the scale of measurement for latent variables. That is, you can tell LISREL that the latent variable uses the same scale of measurement as one of the observed variables. Although this is the method typically used when conducting confirmatory factor analysis on the endogenous (Y) side of the model, it works equally well on the exogenous (X) side.

For example, you can set the scale of measurement for an endogenous latent variable by FIxing an element of the LY matrix to equal 1. For example:

```
VA 1.0 LY(1,1)
 FI LY(1,1)
```

These lines tell LISREL that the first factor is on the same scale as the first variable.

TD by default is diagonal (a vector of one row by *NX* columns) with all free elements. Because this is what I want, no further specification is necessary. Conceptually, the form of the TD matrix represents the assumption that error variances (unique factors) are uncorrelated. Although this assumption is universal in the psychological literature on factor analysis, it is not required by LISREL.

Identification

For confirmatory factor analyses, issues of model identification typically are dealt with by default. That is, in most applications of confirmatory factor analysis, the latent variables or factors are hypothesized to "cause" the observed variables. In such applications, the model is recursive in that the causal flow is expected to be from the latent variables to the observed variables.

Although this formulation of the measurement model is the most common, it is important to note that Bollen and Lennox (1991) have recently pointed out that it is not a necessary formulation. Specifically, Bollen and Lennox (1991) distinguish between the use of "effect" indicators (those that are caused by latent variables) and "causal" indicators (those that cause latent variables). Although recognition of this distinction may have substantial implications for how organizational researchers test hypotheses about measurement relations, the implementation of "causal" indicator measurement models is not straightforward (MacCallum & Browne, 1993) and the Bollen and Lennox (1991) formulation has not yet seen widespread application in the research literature. In any event, reliance on the common factor model as the basis for confirmatory factor analyses implicitly assumes a one-way causal flow. The second overidentifying condition is the imposition of the constraint that at least some factor loadings are 0.

Bollen (1989) summarizes the issue of model identification in confirmatory factor analyses by citing three rules for model identification. As previously discussed, the "t rule" suggests that the number of estimated parameters be less than the number of nonredundant elements in the covariance matrix. Bollen (1989) also indicates that confirmatory factor analyses models are identified if (a) there are at least three indicators (observed variables) for each latent variable (factor) or (b) there are at least two indicators for each latent variable and the factors are allowed to correlate (i.e., an oblique solution). Both the two-indicator and three-indicator rules assume that the unique factor loadings (i.e., error terms) are uncorrelated.

Although the three-indicator rule is perhaps the most commonly cited, the empirical evidence supports the use of two indicators for each latent variable when the sample size is large. Specifically, in their Monte Carlo study, Anderson and Gerbing (1984) found that with small samples (e.g., $n < 100$), the use of only two indicators for each latent variable led to both convergence failures and improper solutions for confirmatory factor analyses. Using three indicators for each latent variable and sample sizes above 200 almost eliminated both convergence failures and the occurrence of improper solutions.

Estimation

The following is a sample of the type of output you obtain from LISREL. The output is divided into a number of sections. First, LISREL echoes the model specifications you entered and displays each matrix involved in the model in its specified form. Freely estimated parameters are numbered consecutively.

The next section of output is the maximum likelihood estimates provided by LISREL. These are the unstandardized estimates (comparable to unstandardized regression weights) and should be interpreted in the light of the scales on which the variables are measured. LISREL then presents the fit indices for the model. The R^2 values for each variable are indications of how well the latent variables explain the variance in the observed variables. The fit indices are then presented, followed by the optional output you have requested. Following is the annotated output for the three-factor union commitment model previously presented.

```
Ti Confirmatory Factor Analysis of the Union Commitment Scale
NUMBER OF INPUT VARIABLES 13
NUMBER OF Y - VARIABLES    0
NUMBER OF X - VARIABLES   13
NUMBER OF ETA - VARIABLES  0
NUMBER OF KSI - VARIABLES  3
NUMBER OF OBSERVATIONS   217
```

Note: This is a useful check to make sure LISREL is reading the model the way you intended. The commands specify 13 *X* variables and 3 *k* variables (factors). There are 217 observations.

Ti Confirmatory Factor Analysis of the Union Commitment Scale

COVARIANCE MATRIX TO BE ANALYZED

	VAR 1	VAR 2	VAR 3	VAR 4	VAR 5	VAR 6
VAR 1	0.88					
VAR 2	0.36	0.73				
VAR 3	0.60	0.45	0.98			
VAR 4	0.54	0.33	0.47	0.85		
VAR 5	0.51	0.35	0.53	0.55	0.72	
VAR 6	0.28	0.26	0.29	0.26	0.28	0.51
VAR 7	0.48	0.40	0.44	0.52	0.47	0.28
VAR 8	0.44	0.26	0.35	0.43	0.40	0.34
VAR 9	0.29	0.20	0.31	0.28	0.26	0.36
VAR 10	0.31	0.24	0.35	0.31	0.33	0.41
VAR 11	0.43	0.34	0.38	0.40	0.40	0.29
VAR 12	0.45	0.27	0.33	0.41	0.35	0.26
VAR 13	0.54	0.33	0.44	0.60	0.49	0.30

COVARIANCE MATRIX TO BE ANALYZED

	VAR 7	VAR 8	VAR 9	VAR 10	VAR 11	VAR 12
VAR 7	0.84					
VAR 8	0.37	0.77				
VAR 9	0.24	0.41	0.70			
VAR 10	0.34	0.49	0.52	0.97		
VAR 11	0.41	0.29	0.28	0.31	0.72	
VAR 12	0.39	0.26	0.24	0.30	0.60	0.95
VAR 13	0.61	0.38	0.33	0.40	0.63	0.73

COVARIANCE MATRIX TO BE ANALYZED

	VAR 13
VAR 13	1.10

Ti Confirmatory Factor Analysis of the Union Commitment Scale

PARAMETER SPECIFICATIONS

LAMBDA-X

	KSI 1	KSI 2	KSI 3
VAR 1	1	0	0
VAR 2	2	0	0
VAR 3	3	0	0
VAR 4	4	0	0
VAR 5	5	0	0
VAR 6	6	0	0
VAR 7	7	0	0
VAR 8	0	8	0
VAR 9	0	9	0
VAR 10	0	10	0
VAR 11	0	0	11
VAR 12	0	0	12
VAR 13	0	0	13

PHI

	KSI 1	KSI 2	KSI 3
KSI 1	0		
KSI 2	14	0	
KSI 3	15	16	0

THETA-DELTA

VAR 1	VAR 2	VAR 3	VAR 4	VAR 5	VAR 6
17	18	19	20	21	22

THETA-DELTA

VAR 7	VAR 8	VAR 9	VAR 10	VAR 11	VAR 12
23	24	25	26	27	28

THETA-DELTA

VAR 13
29

Note: LISREL tells you what parameters are freely estimated and numbers them consecutively. This is a useful to check that you have specified the model correctly.

```
Ti Confirmatory Factor Analysis of the Union Commitment
Scale
OUTPUT =   Number of Iterations = 8
LISREL ESTIMATES (MAXIMUM LIKELIHOOD)
```

LAMBDA-X

	KSI 1	KSI 2	KSI 3
VAR 1	0.73	- -	- -
	(0.05)		
	13.37		
VAR 2	0.52	- -	- -
	(0.05)		
	9.54		
VAR 3	0.71	- -	- -
	(0.06)		
	11.87		
VAR 4	0.72	- -	- -
	(0.05)		
	13.37		
VAR 5	0.70	- -	- -
	(0.05)		
	14.43		
VAR 6	0.43	- -	- -
	(0.05)		
	9.48		

	KSI 1	KSI 2	KSI 3
VAR 7	0.68	- -	- -
	(0.05)		
	12.45		
VAR 8	- -	0.69	- -
		(0.05)	
		12.68	
VAR 9	- -	0.63	- -
		(0.05)	
		11.84	
VAR 10	- -	0.75	- -
		(0.06)	
		11.97	
VAR 11	- -	- -	0.73
			(0.05)
			15.23
VAR 12	- -	- -	0.80
			(0.06)
			14.04
VAR 13	- -	- -	0.90
			(0.06)
			15.16

PHI

	KSI 1	KSI 2	KSI 3
KSI 1	1.00		
KSI 2	0.72	1.00	
	(0.05)		
	15.96		
KSI 3	0.78	0.56	1.00
	(0.04)	(0.06)	
	21.78	9.42	

THETA-DELTA

VAR 1	VAR 2	VAR 3	VAR 4	VAR 5	VAR 6
0.34	0.46	0.47	0.33	0.23	0.32
(0.04)	(0.05)	(0.05)	(0.04)	(0.03)	(0.03)
8.83	9.82	9.34	8.83	8.30	9.83

THETA-DELTA

VAR 7	VAR 8	VAR 9	VAR 10	VAR 11	VAR 12
0.37	0.29	0.31	0.42	0.19	0.32
(0.04)	(0.04)	(0.04)	(0.06)	(0.03)	(0.04)
9.17	6.89	7.69	7.57	6.81	7.94

```
THETA-DELTA
VAR 13
 ----
 0.29
(0.04)
 6.89
```

Note: For each estimated parameter, LISREL provides the unstandardized maximum likelihood estimate, the standard error of the estimate (in brackets), and the *t* value associated with the estimate (i.e., the estimate divided by its standard error).

SQUARED MULTIPLE CORRELATIONS FOR X - VARIABLES

VAR 1	VAR 2	VAR 3	VAR 4	VAR 5	VAR 6
0.61	0.37	0.52	0.61	0.68	0.37

SQUARED MULTIPLE CORRELATIONS FOR X - VARIABLES

VAR 7	VAR 8	VAR 9	VAR 10	VAR 11	VAR 12
0.56	0.62	0.56	0.57	0.74	0.66

SQUARED MULTIPLE CORRELATIONS FOR X - VARIABLES

VAR 13
(0.74)

Note: The squared multiple correlations for each variable represent the amount of variance explained by the model in each observed variable.

```
GOODNESS OF FIT STATISTICS
                     CHI-SQUARE WITH 62 DEGREES OF FREEDOM  =  211.92 (P = 0.0)
           ESTIMATED NON-CENTRALITY PARAMETER (NCP)  =  149.92
                         MINIMUM FIT FUNCTION VALUE  =    0.98
             POPULATION DISCREPANCY FUNCTION VALUE (F0)  =    0.69
    ROOT MEAN SQUARE ERROR OF APPROXIMATION (RMSEA)  =    0.11
          P-VALUE FOR TEST OF CLOSE FIT (RMSEA < 0.05)  =    0.00000040
            EXPECTED CROSS-VALIDATION INDEX (ECVI)  =    1.25
                           ECVI FOR SATURATED MODEL  =    0.84
                        ECVI FOR INDEPENDENCE MODEL  =    8.06
```



```
CHI-SQUARE FOR INDEPENDENCE MODEL WITH 78 DEGREES OF
                                        FREEDOM  =  1715.53
                               INDEPENDENCE AIC  =  1741.53
                                      MODEL AIC  =   269.92
                                  SATURATED AIC  =   182.00
                              INDEPENDENCE CAIC  =  1798.47
                                     MODEL CAIC  =    96.93
                                 SATURATED CAIC  =   580.57
                ROOT MEAN SQUARE RESIDUAL (RMR)  =     0.050
                               STANDARDIZED RMR  =     0.065
                    GOODNESS OF FIT INDEX (GFI)  =     0.87
          ADJUSTED GOODNESS OF FIT INDEX (AGFI)  =     0.81
         PARSIMONY GOODNESS OF FIT INDEX (PGFI)  =     0.59
                         NORMED FIT INDEX (NFI)  =     0.88
                     NON-NORMED FIT INDEX (NNFI)  =     0.88
              PARSIMONY NORMED FIT INDEX (PNFI)  =     0.70
                     COMPARATIVE FIT INDEX (CFI)  =     0.91
                     INCREMENTAL FIT INDEX (IFI)  =     0.91
                        RELATIVE FIT INDEX (RFI)  =     0.84
                               CRITICAL N (CN)  =    93.55
```

Note: These are the fit indices described in Chapter 2.

```
CONFIDENCE LIMITS COULD NOT BE COMPUTED DUE TO TOO SMALL
P-VALUE FOR CHI-SQUARE
Ti Confirmatory Factor Analysis of the Union Commitment Scale
SUMMARY STATISTICS FOR FITTED RESIDUALS
SMALLEST FITTED RESIDUAL =  -0.11
MEDIAN FITTED RESIDUAL   =   0.00
LARGEST FITTED RESIDUAL  =   0.17
STEMLEAF PLOT

 - 1|1
 - 0|988766555555
 - 0|444444433333332222222222111110000000000000000000
   0|11111222222333344444
   0|5577789
   1|33
   1|67
SUMMARY STATISTICS FOR STANDARDIZED RESIDUALS
SMALLEST STANDARDIZED RESIDUAL  =  -3.71
MEDIAN STANDARDIZED RESIDUAL    =   0.00
LARGEST STANDARDIZED RESIDUAL   =   6.10
```

```
STEMLEAF PLOT

 - 3|732
 - 2|8765321
 - 1|9998776665544211000
 - 0|999988766555421000000000000000
   0|11134456889
   1|0003668899
   2|45679
   3|129
   4|27
   5|5
   6|1
```

LARGEST NEGATIVE STANDARDIZED RESIDUALS

RESIDUAL FOR	VAR 6 AND	VAR 4	-2.76
RESIDUAL FOR	VAR 10 AND	VAR 1	-2.72
RESIDUAL FOR	VAR 12 AND	VAR 3	-3.19
RESIDUAL FOR	VAR 12 AND	VAR 5	-3.28
RESIDUAL FOR	VAR 13 AND	VAR 11	-3.71

LARGEST POSITIVE STANDARDIZED RESIDUALS

RESIDUAL FOR	VAR 3 AND	VAR 1	3.19
RESIDUAL FOR	VAR 3 AND	VAR 2	2.72
RESIDUAL FOR	VAR 5 AND	VAR 4	2.88
RESIDUAL FOR	VAR 8 AND	VAR 6	4.68
RESIDUAL FOR	VAR 9 AND	VAR 6	6.10
RESIDUAL FOR	VAR 10 AND	VAR 6	5.47
RESIDUAL FOR	VAR 10 AND	VAR 9	3.90
RESIDUAL FOR	VAR 13 AND	VAR 4	3.10
RESIDUAL FOR	VAR 13 AND	VAR 7	4.24

Note: The foregoing is diagnostic information provided by LISREL. The two residual plots should look approximately normal. The listing of standardized residuals may provide clues to sources of ill-fitting models. In general, large standardized residuals indicate a lack of fit. LISREL prints any residual > 2.00.

Ti Confirmatory Factor Analysis of the Union Commitment Scale

MODIFICATION INDICES AND EXPECTED CHANGE

MODIFICATION INDICES FOR LAMBDA-X

	KSI 1	KSI 2	KSI 3
VAR 1	- -	0.47	0.49
VAR 2	- -	0.72	0.04
VAR 3	- -	0.54	6.49
VAR 4	- -	0.42	0.52

	KSI 1	KSI 2	KSI 3
VAR 5	- -	1.38	2.01
VAR 6	- -	54.27	0.52
VAR 7	- -	1.17	4.72
VAR 8	14.95	- -	0.28
VAR 9	3.27	- -	0.04
VAR 10	4.40	- -	0.13
VAR 11	1.06	0.75	- -
VAR 12	13.77	6.52	- -
VAR 13	6.51	2.26	- -

EXPECTED CHANGE FOR LAMBDA-X

	KSI 1	KSI 2	KSI 3
VAR 1	- -	-0.06	0.06
VAR 2	- -	-0.08	-0.02
VAR 3	- -	-0.07	-0.25
VAR 4	- -	-0.05	0.06
VAR 5	- -	-0.08	-0.11
VAR 6	- -	0.54	0.06
VAR 7	- -	-0.09	0.19
VAR 8	0.38	- -	0.04
VAR 9	-0.16	- -	-0.01
VAR 10	-0.23	- -	-0.03
VAR 11	0.09	0.05	- -
VAR 12	-0.35	-0.17	- -
VAR 13	0.26	0.10	- -

STANDARDIZED EXPECTED CHANGE FOR LAMBDA-X

	KSI 1	KSI 2	KSI 3
VAR 1	- -	-0.06	0.06
VAR 2	- -	-0.08	-0.02
VAR 3	- -	-0.07	-0.25
VAR 4	- -	-0.05	0.06
VAR 5	- -	-0.08	-0.11
VAR 6	- -	0.54	0.06
VAR 7	- -	-0.09	0.19
VAR 8	0.38	- -	0.04
VAR 9	-0.16	- -	-0.01
VAR 10	-0.23	- -	-0.03
VAR 11	0.09	0.05	- -
VAR 12	-0.35	-0.17	- -
VAR 13	0.26	0.10	- -

COMPLETELY STANDARDIZED EXPECTED CHANGE FOR LAMBDA-X

	KSI 1	KSI 2	KSI 3
VAR 1	- -	-0.06	0.07
VAR 2	- -	-0.09	-0.02
VAR 3	- -	-0.07	-0.26
VAR 4	- -	-0.06	0.07
VAR 5	- -	-0.10	-0.13
VAR 6	- -	0.76	0.08
VAR 7	- -	-0.10	0.21
VAR 8	0.44	- -	0.04
VAR 9	-0.20	- -	-0.02
VAR 10	-0.23	- -	-0.03
VAR 11	0.10	0.06	- -
VAR 12	-0.36	-0.17	- -
VAR 13	0.25	0.10	- -

MODIFICATION INDICES FOR THETA-DELTA

	VAR 1	VAR 2	VAR 3	VAR 4	VAR 5	VAR 6
VAR 1	- -					
VAR 2	1.30	- -				
VAR 3	10.21	7.37	- -			
VAR 4	0.14	3.54	4.64	- -		
VAR 5	0.30	0.69	3.58	8.30	- -	
VAR 6	2.95	2.47	0.40	7.60	1.39	- -
VAR 7	0.68	2.41	3.52	1.81	0.28	0.55
VAR 8	5.47	0.27	2.28	4.90	2.01	0.01
VAR 9	0.57	0.07	0.33	0.83	4.24	20.34
VAR 10	6.27	0.01	0.05	4.73	0.58	13.32
VAR 11	0.09	8.10	0.06	4.69	0.28	4.27
VAR 12	2.94	0.77	1.24	0.27	2.77	0.03
VAR 13	0.38	5.11	2.38	10.73	0.08	2.31

MODIFICATION INDICES FOR THETA-DELTA

	VAR 7	VAR 8	VAR 9	VAR 10	VAR 11	VAR 12
VAR 7	- -					
VAR 8	0.03	- -				
VAR 9	3.40	4.46	- -			

VAR 10	0.21	3.33	15.20	- -		
VAR 11	0.86	0.59	1.61	0.00	- -	
VAR 12	1.38	1.48	0.11	0.53	6.51	- -
VAR 13	15.34	0.00	0.00	0.08	13.74	1.05

MODIFICATION INDICES FOR THETA-DELTA

VAR 13
- -

EXPECTED CHANGE FOR THETA-DELTA

	VAR 1	VAR 2	VAR 3	VAR 4	VAR 5	VAR 6
VAR 1	- -					
VAR 2	-0.03	- -				
VAR 3	0.10	0.09	- -			
VAR 4	0.01	-0.06	-0.07	- -		
VAR 5	-0.01	-0.02	0.05	0.07	- -	
VAR 6	-0.04	0.04	-0.02	-0.07	-0.03	- -
VAR 7	-0.02	0.05	-0.06	0.04	-0.01	-0.02
VAR 8	0.06	-0.02	-0.05	0.06	0.03	0.00
VAR 9	-0.02	-0.01	0.02	-0.02	-0.05	0.11
VAR 10	-0.08	0.00	0.01	-0.07	-0.02	0.11
VAR 11	-0.01	0.07	0.01	-0.05	0.01	0.04
VAR 12	0.05	-0.03	-0.03	-0.01	-0.04	0.00
VAR 13	-0.02	-0.07	-0.05	0.09	-0.01	-0.04

EXPECTED CHANGE FOR THETA-DELTA

	VAR 7	VAR 8	VAR 9	VAR 10	VAR 11	VAR 12
VAR 7	- -					
VAR 8	0.01	- -				
VAR 9	-0.05	-0.09	- -			
VAR 10	0.01	-0.09	0.17	- -		
VAR 11	-0.02	-0.02	0.03	0.00	- -	
VAR 12	-0.03	-0.03	-0.01	0.02	0.09	- -
VAR 13	0.11	0.00	0.00	0.01	-0.15	0.04

EXPECTED CHANGE FOR THETA-DELTA

	VAR 13
VAR 13	- -

COMPLETELY STANDARDIZED EXPECTED CHANGE FOR THETA-DELTA

	VAR 1	VAR 2	VAR 3	VAR 4	VAR 5	VAR 6
VAR 1	- -					
VAR 2	-0.04	- -				
VAR 3	0.11	0.11	- -			
VAR 4	0.01	-0.07	-0.07	- -		
VAR 5	-0.02	-0.03	0.06	0.09	- -	
VAR 6	-0.07	0.07	-0.03	-0.11	-0.04	- -
VAR 7	-0.03	0.06	-0.07	0.05	-0.02	-0.03
VAR 8	0.08	-0.02	-0.05	0.07	0.04	0.00
VAR 9	-0.03	-0.01	0.02	-0.03	-0.07	0.19
VAR 10	-0.09	0.00	0.01	-0.07	-0.02	0.15
VAR 11	-0.01	0.10	0.01	-0.06	0.01	0.07
VAR 12	0.05	-0.03	-0.04	-0.02	-0.05	0.01
VAR 13	-0.02	-0.08	-0.05	0.09	-0.01	-0.05

COMPLETELY STANDARDIZED EXPECTED CHANGE FOR THETA-DELTA

	VAR 7	VAR 8	VAR 9	VAR 10	VAR 11	VAR 12
VAR 7	- -					
VAR 8	0.01	- -				
VAR 9	-0.07	-0.12	- -			
VAR 10	0.02	-0.10	0.21	- -		
VAR 11	-0.03	-0.02	0.04	0.00	- -	
VAR 12	-0.04	-0.04	-0.01	0.02	0.10	- -
VAR 13	0.12	0.00	0.00	0.01	-0.16	0.04

COMPLETELY STANDARDIZED EXPECTED CHANGE FOR THETA-DELTA

	VAR 13
VAR 13	- -

MAXIMUM MODIFICATION INDEX IS 54.27 FOR ELEMENT (6, 2) OF LAMBDA-X

Note: For each fixed parameter, LISREL reports the modification index and the expected amount of change. The modification index is the amount by which the model χ^2 will decrease if the parameter is freed.

The expected change for the parameter is the expected value of the parameter if it were freed. The standardized and completed standardized expected changes are the expected values in the standardized and completely standardized solution if the parameter were freed.

Ti Confirmatory Factor Analysis of the Union Commitment Scale

STANDARDIZED SOLUTION

LAMBDA-X

	KSI 1	KSI 2	KSI 3
VAR 1	0.73	- -	- -
VAR 2	0.52	- -	- -
VAR 3	0.71	- -	- -
VAR 4	0.72	- -	- -
VAR 5	0.70	- -	- -
VAR 6	0.43	- -	- -
VAR 7	0.68	- -	- -
VAR 8	- -	0.69	- -
VAR 9	- -	0.63	- -
VAR 10	- -	0.75	- -
VAR 11	- -	- -	0.73
VAR 12	- -	- -	0.80
VAR 13	- -	- -	0.90

PHI

	KSI 1	KSI 2	KSI 3
KSI 1	1.00		
KSI 2	0.72	1.00	
KSI 3	0.78	0.56	1.00

Note: The standardized solution is based on standardized latent variables but unstandardized observed variables. As a result, the parameters are not constrained to have an absolute value less than 1.

Ti Confirmatory Factor Analysis of the Union Commitment Scale

COMPLETELY STANDARDIZED SOLUTION

LAMBDA-X

	KSI 1	KSI 2	KSI 3
VAR 1	0.78	- -	- -
VAR 2	0.61	- -	- -
VAR 3	0.72	- -	- -
VAR 4	0.78	- -	- -
VAR 5	0.82	- -	- -
VAR 6	0.61	- -	- -
VAR 7	0.75	- -	- -
VAR 8	- -	0.79	- -
VAR 9	- -	0.75	- -
VAR 10	- -	0.75	- -
VAR 11	- -	- -	0.86
VAR 12	- -	- -	0.82
VAR 13	- -	- -	0.86

PHI

	KSI 1	KSI 2	KSI 3
KSI 1	1.00		
KSI 2	0.72	1.00	
KSI 3	0.78	0.56	1.00

THETA-DELTA

VAR 1	VAR 2	VAR 3	VAR 4	VAR 5	VAR 6
0.39	0.63	0.48	0.39	0.32	0.63

THETA-DELTA

VAR 7	VAR 8	VAR 9	VAR 10	VAR 11	VAR12
0.44	0.38	0.44	0.43	0.26	0.34

THETA-DELTA

VAR 13
0.26

Note: The completely standardized solution is based on standardized latent and observed variables. These are the values that typically are reported in a results section.

TABLE 5.1 Fit Indices for the Models

Model	χ^2	df	*GFI*	*AGFI*	*RMSEA*	*NFI*	*CFI*	*PNFI*	*PGFI*
1. 3-factor oblique	211.92	62	.87	.81	.11	.88	.91	.70	.59
2. 3-factor orthogonal	449.50	65	.78	.70	.17	.74	.77	.61	.56
3. 2-factor oblique	359.39	64	.77	.67	.15	.79	.82	.65	.54
4. 1-factor	414.10	65	.74	.64	.16	.76	.79	.63	.64

Assessment of Fit

Given the models described earlier, assessing the fit of the three-factor model is based on (a) whether the model fits better than rival specifications and (b) whether the model provides a good absolute fit to the data. The fit indices for all the models described earlier are presented in Table 5.1.

As shown, the fit indices all converge in suggesting the superiority of the model hypothesizing three oblique factors. Comparison with the other models shows that the three-factor (oblique) model provides a better fit to the data than does a model hypothesizing three orthogonal factors [$\chi^2_{\text{difference}}(3) = 237.58, p < .01$], two oblique factors [$\chi^2_{\text{difference}}(2) = 147.47, p < .01$], or one factor [$\chi^2_{\text{difference}}(3) = 202.18, p < .01$]. Moreover, inspection of the indices of parsimonious fit (i.e., the PNFI and PGFI) suggest that the three-factor model provides the most parsimonious fit to the data.

As is typical in confirmatory factor analysis (Kelloway, 1995, 1996), although the three-factor model provides a better fit to the data than do rival specifications, the model itself does not provide a very good fit to the data. Although inspection of the preceding printout suggests that all the estimated parameters in the hypothesized three-factor model are significant, the χ^2 associated with the model is also significant. With the exception of the CFI (CFI = .91), all the fit indices are outside the bounds that indicate a good fit to the data (e.g., GFI, AGFI, NFI < .90; RMSEA >.10). Thus, the most that can be concluded from these results is that the hypothesized three-factor model provides a better fit than do plausible rival specifications.

Model Modification

Faced with results like these, researchers may well be tempted to engage in a post hoc specification search to improve the fit of the model. Given that all the estimated parameters are significant, theory trimming (i.e., deleting nonsignificant paths) does not seem to be a viable option. Theory building (i.e., adding parameters based on the empirical results) remains an option.

Inspection of the LISREL-produced modification indices suggests several likely additional parameters (i.e., modification indices greater than 5.0). Most strikingly, the largest modification index (54.27) suggests freeing the path from the second factor to the sixth item. Although the modification index suggests that a substantial improvement in fit could be obtained from making this modification, the reader is reminded of the dangers associated with post hoc model modifications. In this case, I would not typically make the change because (a) of the dangers of empirically generated modifications, (b) there is no theoretical justification for the change, and (c) the item is clearly not designed to assess Willingness to Work for the Union.

Sample Results Section

We conclude this example of confirmatory factor analysis with the presentation of a sample results section. A useful guide to reporting the results of structural equation modeling was provided by Raykov, Tomer, and Nesselroade (1991). As a minimum set of reporting standards, they suggest that all reports of structural equation modeling analyses include

1. a graphic presentation of the structural equation model following conventional symbols (see, for example, Bentler, 1990; Jöreskog & Sörbom, 1992);
2. parameters for the structural equation run, including the type of matrix analyzed, the treatment of missing values and outliers, the number of groups to be analyzed (if appropriate), and the method of parameter estimation;
3. an assessment of model fit, such as Condition 10 tests (James et al., 1982). As previously noted, researchers are well advised to report multiple fit indices and should report indices that reflect different conceptions of model fit;

4. an examination of the obtained solution including the Condition 9 tests (James et al., 1982) referred to earlier, the coefficient of determination, the R^2 values associated with each equation in the model, and examination of direct/indirect effects (when appropriate);
5. nested model comparisons; and
6. model modifications and alternate models—When the model is modified on the basis of empirical results, a minimum standard of reporting would include the change in overall fit associated with modification as well as the change in specific parameters as a result of model modification. As noted earlier, such modifications should be treated as exploratory until cross-validated on an independent sample.

Results

All model tests were based on the covariance matrix and used maximum likelihood estimation as implemented in LISREL VIII (Jöreskog & Sörbom, 1992).

Fit indices for the four models are presented in Table 5.1. As shown, the indices converge in suggesting the superiority of the model hypothesizing three oblique factors. In particular, the three-factor (oblique) model provides a better fit to the data than does a model hypothesizing three orthogonal factors [$\chi^2_{difference}(3) = 237.58, p < .01$], two oblique

TABLE 5.2 Standardized Parameter Estimates for the Three-Factor Model

Item	*Union Loyalty*	*Willingness to Work*	*Responsibility to the Union*	R^2
1	0.78			0.61
2	0.61			0.37
3	0.72			0.52
4	0.78			0.61
5	0.82			0.68
6	0.61			0.37
7	0.75			0.56
8		0.79		0.62
9		0.75		0.56
10		0.75		0.57
11			0.86	0.74
12			0.82	0.66
13			0.86	0.74

TABLE 5.3 Interfactor Correlations

	1	*2*	*3*
1. Union Loyalty	1.00		
2. Willingness to Work for the Union	0.72	1.00	
3. Responsibility to the Union	0.78	0.56	1.00

NOTE: All parameters $p < .01$.

factors [$\chi^2_{difference}(2) = 147.47, p < .01$], or one factor [$\chi^2_{difference}(3) = 202.18, p < .01$]. Moreover, inspection of the indices of parsimonious fit (i.e., the PNFI and PGFI) suggests that the three-factor model provides the most parsimonious fit to the data.

Standardized parameter estimates for the model are presented in Table 5.2. As shown, model parameters were all significant ($p < .01$) and explained substantial amounts of item variance (R^2 ranged from 0.37 to 0.74). As shown in Table 5.3, the three factors were significantly correlated ($r = .56, .72$, and $.78$).

CHAPTER 6 *Observed Variable Path Analysis*

Path analysis with observed variables is the "oldest" variety of structural equation modeling. In contrast to the assessment of a measurement model as presented in the previous chapter, the goal of path analysis is to test a "structural" model, that is, a model comprising theoretically based statements of relationships among constructs.

For an example of path analysis, I will use a scaled-down version of the model presented by Kelloway and Barling (1993). The intent of the research was to predict union members' involvement in union activities (attending meetings, serving as officers, reading union literature, voting in elections). The theoretical development of the model relied heavily on Fishbein and Ajzen's (1975) theory of reasoned action. In brief, the theory of reasoned action suggests that the best predictor of actual behavior is an individual's intent to engage in the behavior. In turn, behavioral intentions are predicted by one's attitudes toward the activity and subjective norms. One's beliefs about the activity predict attitudes toward the behavior.

Model Specification

In our study, we had measures of participation in union activities (the behavior), willingness to participate in the union (which we treated as a behavioral intention), union loyalty (attitudes toward the union), and subjective norms (perceptions of family, friends, and important people