TABLE 6.1 Descriptive Statistics and Intercorrelations (n = 202)

	Mean	SD	1	2	3	4
 Participation Willingness to 	2.62	1.71	1.00			
work for the union	10.32	3.88	0.47	1.00		
3. Union loyalty	20.00	5.55	0.39	0.71	1.00	
4. Instrumentality beliefs	19.87	5.60	0.29	0.48	0.61	1.00
5. Subjective norms	18.09	9.99	0.29	0.53	0.51	0.39

a better fit to the data than did the original model, $\chi^2_{\text{difference}}(1) = 30.44$, p < .01; $\chi^2(4) = 2.80$, ns; GFI = .99; AGFI = .98; RMSEA = .00; NFI = .99; CFI = 1.00; PNFI = .40.

Standardized parameter estimates for the revised model are presented in Figure 6.4. As shown, participation in union activities was predicted by willingness to work for the union ($\beta = .47$, p < .01), which in turn was predicted by both union loyalty ($\beta = .60$, p < .01) and subjective norms ($\beta = .22$, p < .01). Union loyalty was predicted by both perceptions of instrumentality ($\beta = .49$, p < .01) and subjective norms ($\beta = .32$, p < .01). The model explained 22% of the variance in participation, 54% of the variance in willingness to work for the union, and 46% of the variance in union loyalty.

Note

 Rank and order conditions refer to the identification of nonrecursive structural models and will not be dealt with further.

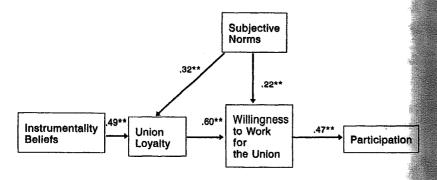


Figure 6.4.

CHAPTER 7 Latent Variable Path Analysis

The true power of structural equation modeling is the ability to estimate a complete model incorporating both measurement and structural considerations. In this chapter, we consider such a latent variable path analysis. Latent variable path analysis uses the full LISREL model (all eight matrices) to combine measurement and structural considerations. Thus, in conducting the analysis we will be equally concerned with assessing the proposed measurement relations (i.e., through confirmatory factor analysis) and the proposed structural relations (i.e., through path analysis).

Model Specification

To illustrate the use of latent variable path analysis, we will consider a reduced form of the model of perceived risk and participation in occupational health and safety programs presented by Cree and Kelloway (in press). There are two components to the model. First, the structural model specifies the predictive relationships among the latent variables. Second, the measurement model defines how the latent variables are measured (i.e., represented by indicators).

The structural model we were interested in was based on the hypotheses that two factors, perceived health and safety climate and accident history, predicted perceived risk in the workplace, which in turn predicted willingness to participate in health and safety programs (see Figure 7.1).

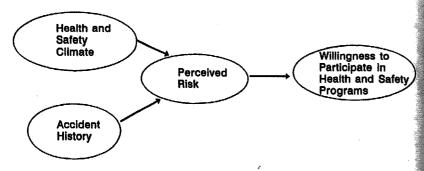


Figure 7.1.

In addition to the structural relations, we also were interested in using latent variables; that is, each construct in the model would be represented by multiple indicators. Bentler (1980, p. 425) notes that

choosing the right number of indicators for each LV [latent variable] is something of an art; in principle, the more the better; in practice, too many indicators make it difficult if not impossible to fit a model to data.

Moreover, as noted in Chapter 5, Bollen (1989) has suggested that a confirmatory factor analysis model (which uses indicators to represent latent variables or factors) should incorporate at least two indicators per latent variable. For each construct (latent variable) in the model, therefore, we attempted to identify at least two observed indicators (actual items).

Specifically, perceived health and safety climate was assessed with three scales that asked respondents to rate their perceptions of their manager's, supervisor's, and coworkers' commitment to health and safety in the workplace. Accident history was assessed by two questionnaires: one asking about the respondent's own history with accidents in the workplace and the other asking whether respondents had heard about or witnessed accidents in the workplace.

The endogenous variables also were measured with multiple indicators. Perceived risk in the workplace was measured by two questionnaires asking respondents how risky they thought the workplace was (a) for them personally and (b) for their coworkers. Finally, willingness to participate in health and safety programs was measured by a 12-item questionnaire assessing respondents' willingness to participate in a

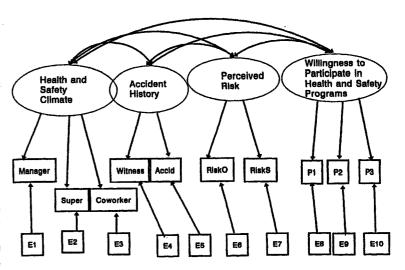


Figure 7.2.

variety of health and safety programs. Because we wanted to generate multiple indicators for this construct, we randomly assigned items to one of three indicator variables (i.e., three subscales with four items per scale). The measurement model described above is given in Figure 7.2. Integrating the structural and measurement models results in the full latent variable path analysis model given in Figure 7.3.

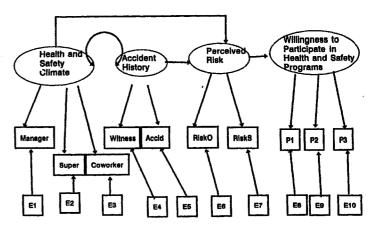


Figure 7.3.

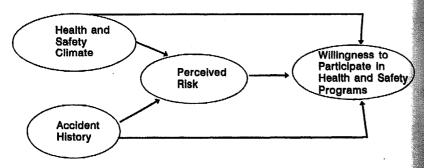


Figure 7.4.

Alternative Model Specifications

The central hypothesis of our model is that risk perceptions mediate the relationships between health and safety climate and accident history, as the predictors, and willingness to participate in health and safety programs in the workplace, as the outcome. Consistent with the discussion of mediated relationships in the previous chapter, two plausible rival model specifications are the partially mediated (which adds paths from the two predictors to willingness to participate, see Figure 7.4) and nonmediated (which deletes the path from risk perception to willingness to participate, see Figure 7.5) models.

Model Testing Strategy

There is a major complication in testing latent variable models. If the model does not fit, the lack of fit can be attributable to (a) an ill-fitting

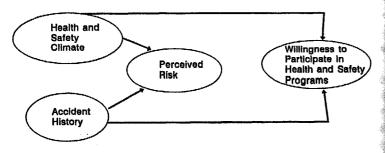


Figure 7.5.

measurement model, (b) an ill-fitting structural model, or (c) both (Anderson & Gerbing, 1988). Accordingly, Anderson and Gerbing recommend a strategy of two-stage modeling in which one first assesses the fit of the measurement model and then moves to a consideration of the structural model.

The strategy is based on the observation that the latent variable structural model incorporates the measurement model. In fact, at least with respect to the relationships among the latent variables, one can think of the measurement model as a saturated or just-identified model. That is, the measurement model allows a relationship (i.e., a correlation, see Figure 7.2) between each pair of latent variables.

This being the case, the fit of the measurement model provides a baseline for the fit of the full latent variable model. The full model, incorporating both structural and measurement relationships, cannot provide a better fit to the data than does the measurement model.

Incorporating Anderson and Gerbing's (1988) suggestions with our three hypothesized structural models suggests a sequence of model tests in which we first establish the fit of the measurement model and then move to a consideration of the structural parameters of interest. The remainder of this chapter, therefore, provides the assessment of the measurement model, followed by assessment of the full model.

From Pictures to LISREL

The translation of the path diagrams proceeds just as in previous examples. First, we will translate the measurement model. For purposes of illustration, we will assess the measurement model on the endogenous (Y) side of the LISREL model. (Note that it should not matter whether one operationalizes the factor analysis on the endogenous or exogenous side of the model.)

Operationalizing a confirmatory factor analysis on the endogenous side of the LISREL model still requires that you specify a scale of measurement for the latent variables. Recall that in Chapter 5 we specified the scale of measurement by declaring PH = ST, which assigned the latent variables to be standardized. This option is not available on the endogenous side of the model (you cannot declare PS = ST). The scale of measurement therefore is assigned by fixing one of the latent variable-indicator paths to equal 1.0 for each latent variable. In effect, this specification tells LISREL that the latent variable is on the same scale of measurement as the indicator. It should not make a great deal of difference which indicator is chosen to represent the scale of measure-

TABLE 7.1 Lambda Y (Factor Loadings for Y)

******		Health and Safety Climate	Accident History	Perceived Risk	Willingness to Participate
1.	Manager commitment	1.00	FIxed	Fixed	FIxed
2.	Supervisor commitment	FRee	Fixed	FIxed	FIxed
3.	Coworker commitment	FRee	Fixed	Flxed	FIxed
4.	Own accident history	Fixed	1.00	FIxed	Fixed
5.	Witnessed accidents	Fixed	FRee	Fixed	FIxed
6.	Risk for self	Fixed	FIxed	1.00	Fixed
7.	Risk for others	Fixed	Fixed	FRee	FIxed
8.	Participate 1	Fixed	FIxed	FIxed	1.00
9.	Participate 2	Flxed	Fixed	Fixed	FRee
10.	Participate 3	Fixed	FIxed	FIxed	FRee

ment for the latent variable (assuming that the indicators are all measured along a similar scale).

The forms of the three matrices (LY, PS, and TE) are presented below. Because there are four latent variables with ten indicators, LY will have four columns and ten rows. PS will be a 4 × 4 symmetric matrix. Note that PS has all elements freed; that is, we are going to estimate both the variances for the latent variables and the covariances among the latent variables. Because we will again assume that there are no correlated errors of measurement among the indicator variables, TE is declared to be diagonal and free; that is, TE is a vector with ten elements (one for each observed variable).

Identification and Estimation

The model meets Bollen's (1989) criteria for identification. That is, each latent variable has at least two indicators, and the latent variables are

TABLE 7.2 PSI (Covariances for E)

	Health and afety Climate	Accident History	Perceived Risk	Willingness to Participate
1. Health and safety climat	e FRee			
2. Accident history	FRee	FRee		
3. Perceived risk	FRee	FRee	FRee	
4. Willingness to participat	e FRee	FRee	FRee	FRee

 TABLE 7.3 TE (Unique Factors for the Endogenous Variables)

Manager commitment	FRee	
2. Supervisor commitment	FRee	
3. Coworker commitment	FRee	
4. Own accident history	FRee	
. Witnessed accidents	FRee	
6. Risk for self	FRee	
7. Risk for others	FRee	
3. Participate 1	FRee	
9. Participate 2	FRee	
). Participate 3	FRee	

allowed to correlate freely with one another. Moreover, like all confirmatory factor analysis models, the model is recursive. (The causal flow is always from the latent variables to the observed indicators.)

The source code used to estimate the model is given below.

```
TI MEASUREMENT MODEL

DA NI = 13 NO = 115 MA = CM
```

Note: There are 10 indicators and 115 observations, and I want to analyze the covariance matrix.

E 10.7 8.9 10.9 18.6 3.8 5.5 5.7 5.5 1.7 0.9

Note: These are the item means.

SD 2.7 3.1 2.9 7.3 1.5 1.4 1.2 1.2 1.7 0.8

Note: These are the item standard deviations.

```
KM SY

1.00
.76 1.00
.78 .68 1.00
-.05 .01 -.05 1.00
.10 .09 .08 .52 1.00
.01 .08 .14 -.28 -.22 1.00
```

Latent Variable Path Analysis

.20 .18 .29 -.44 -.29 .54 1.00 .22 .25 .29 -.42 -.31 .57 .65 1.00 .00 .00 -.05 .42 .22 -.13 -.26 -.20 1.0 .12 .03 .11 .26 .30 -.12 -.20 -.17 .4

Note: This is the lower half of the correlation matrix.

LA

1.00

p1 p2 p3 risks riskc mgr super cow own witness

Note: These are variable labels for the indicator variables.

MO NY = 10 NE = 4 PS = SY.FR

Note: The model declares 10 indicators and 4 latent variables. By declaring NY and NE, LISREL selects a confirmatory factor analysis on the endogenous side of the model involving matrices LY, PS, and TE.

LE

part risk climate accid

Note: These are labels for the latent variables.

VA 1.0 LY(1,1) LY(4,2) LY(6,3) LY(9,4)

Note: This statement inserts the value 1.0 in the designated locations, thereby declaring a scale for the latent variables. Recall that matrix LY has all elements Fixed by default, so no further specification is necessary.

FR LY(2,1) LY(3,1) LY(5,2) LY(7,3) LY(8,3) LY(10,4)

Note: Frees the remaining parameters specified in the measurement model.

OU ML SC TV MI

Note: Asks for maximum likelihood estimation. I want to see the completely standardized solution, the t values, and the modification indices.

Edited Output

NUMBER OF INPUT VARIABLES 10
NUMBER OF Y - VARIABLES 10
NUMBER OF X - VARIABLES 0
NUMBER OF ETA - VARIABLES 4
NUMBER OF KSI - VARIABLES 0
NUMBER OF OBSERVATIONS 115

COVARIANCE MATRIX TO BE ANALYZED

	p1	p2	р3	risks	riskc	plant
						
p1	7.30					
p2	6.27	9.27				
р3	6.05	5.93	8.21			
risks	-1.03	0.20	-1.11	53.60		
riskc	0.40	0.43	0.34	5.68	2.23	
plant	0.04	0.35	0.59	-2.99	-0.47	2.08
super	0.67	0.67	1.03	-3.97	-0.54	0.96
COM	0.70	0.90	0.98	-3.61	-0.54	0.96
dir	-0.02	-0.01	-0.24	5.21	0.55	-0.31
vic	0.26	0.08	0.25	1.53	0.36	-0.14

COVARIANCE MATRIX TO BE ANALYZED

	super	COW	dir	vic
				
super	1.55			
COW	0.95	1.39		
dir	-0.55	-0.39	2.82	
vic	-0.20	-0.17	0.64	0.66

PARAMETER SPECIFICATIONS

LAMBDA-Y

	part	risk	climate	accid
				
p1	0	0	0	0
p2	1	0	0	0
p3	2	0.	0	0
risks	0	0	0	0
riskc	0	3	0	0
plant	0	0	0	0
super	0	0	4	0

COW	0	0	5	0
dir	0	0	0	0
vic	0	0	0	6
PSI				
	part	risk	climat	te accid
part	7			
risk	8	9		
climate	10	11	12	
accid	13	14	15	16
THETA-EPS				
p:	l p2	p3	risks	riskc plant
1	7 18	19	20	21 22
THETA-EPS				
	super	COM	dir	vic
	23	24	25	26
Number of	Iterations	= 9		
LISREL EST LAMBDA-Y	IMATES (MAX	IMUM LIKEL	(dooh)	
	part ———	risk	climate	e accid
p1	1.00			
, p2	1.00			
·	(0.00)			
	(0.09)			
	11.18			
, p3	11.18 0.97	. -		
, p3	11.18 0.97 (0.08)	. .		
	11.18 0.97			
risks	11.18 0.97 (0.08)	1.00 0.15		
risks	11.18 0.97 (0.08)	0.15		
risks	11.18 0.97 (0.08)			
risks riskc plant	11.18 0.97 (0.08)	0.15 (0.03)	 1.00	
risks riskc plant	11.18 0.97 (0.08)	0.15 (0.03)	1.05	
risks riskc plant	11.18 0.97 (0.08)	0.15 (0.03)	1.05 (0.16)	
p3 risks riskc plant super	11.18 0.97 (0.08)	0.15 (0.03)	1.05	

(0.15) 6.75

dir vic			- -		1.00 0.37 (0.10) 3.62
COVARIAN	_	RIX OF part	ETA risk	climate	accid
	•				
part		6.22			
risk		-0.14	38.39	0.00	
climate		0.68	-3.51	0.90	
accid		0.10	4.84	-0.43	1.73
PSI					
131		part	risk	climate	accid
part		6.22 (1.01) 6.14			
risk		-0.14 (1.74)	38.39 (9.44))	
climate		-0.08 0.68 (0.27) 2.46	4.07 -3.51 (0.88) -4.00	0.90 (0.25) 3.63	
accid		0.10 (0.39) 0.26	4.84 (1.22) 3.97	-0.43	1.73 (0.56) 3.09
TUETA ED	c				
THETA-EP	o p2	р3	risks	riskc	plant
	<u></u>	- РЭ			
1.07	3.04	2.34	4 15.20	1.39	1.19
(0.36)	(0.53)	(0.44	4) (6.84)	(0.23)	(0.19)
2.95	5.78	5.27	7 2.22	5.95	6.41
THETA-EP	S				
super	COV	4	dir	vic	
0.55	0.4	- 14	1.09	0.43	
(0.12)	(0.1	1)	(0.46)	(0.08)	
4.63	4.1	•	2.33	5.13	

SQUARED p1	MULTIPLE p2	CORRELAT			Y - VA riskc	RIABLES plant	
0.85	0.67	0.72	0.72		0.38	0.43	
SQUARED super	MULTIPLE COW	CORRELA'		FOR vic		RIABLES	
0.64	0.68	0.61		0.36	5		
GOODNES: CHI- ESTIMAT 90 PE POPULATIO 90 P ROOT MEAN SQUA 90 PERC P-VALUE FOR EXPEC 90 PER	S OF FIT, SQUARE WIT SQUARE WIT SENT CONFIDENT	STATISTIC H 29 DEGI ITRALITY I FIDENCE II IMUM FIT INCY FUNC IFIDENCE INTI CLOSE FIT VALIDATIC CVI FOR S FOR INDI DEPENDENCE DEGI	CS REES OPARAME NTERVA FUNCT TION V INTERV IMATIO ERVAL (RMSE ON IND TERVAL SATURA EPENDE E MODE REES ON NDEPEN	F FR TER L FO ION ALUE AL FI N (R FOR A < (FOR TED L WI F FR DENC MODE	EEDOM = (NCP) = R NCP = VALUE = (FO) = OR FO = MSEA) = RMSEA = 0.05) = ECVI = ECVI = MODEL =	1.89 (0.0; 0.27 0.017 (0.0; 0.024 (0.0; 0.73 0.73 (0.71; 0.96 4.41 482.66 502.66 82.89	19.50)).17)).077)
		IN			CAIC =		
			-		CAIC =		
	ROOT MEA	N SQUARE					
•	000				RMR =		
AD BI	GOOL STED GOODN	NESS OF T					
	MONY GOODI						
171101	10111 00001	NORMED					
	NON-	NORMED F					
	PARSIMONY			-	-		
		PARATIVE					
	INCF	REMENTAL	FIT IN	DEX	(IFI) =	1.00	

RELATIVE	FIT	INDEX	(RFI)	=	0.90
	CRIT	TICAL N	(CN)	=	184.00

			• •		
MODIFICATIO		AND EXPECT	ED CHANGE M	ODIFICATIO)
INDICES FOR					
	part	risk	climate	accid	
p1		0.02	2.74	0.28	
p2		0.39	0.00	0.00	
p3		0.54	3.56	0.38	
risks	2.51		0.12	0.22	
riskc	2.51		0.12	0.22	
plant	3.42	0.64		0.60	
super	0.15	0.79		1.47	
COM	1.01	0.05		0.36	
dir	1.75	1.84	0.01		
vic	1.75	1.84	0.01		
EXPECTED CH			.12	• •	
	part ——	risk	climate ——	accid	
p1		0.00	-0.30	0.07	
p2		0.02	0.00	0.00	
p3		-0.02	0.38	-0.09	
risks	-0.55		-0.63	0.63	
riskc	0.08		0.09	-0.09	
plant	-0.09	0.02		0.09	
super	0.02	-0.02		-0.11	
COW	0.04	0.01		0.05	
dir	-0.11	0.72	0.02		
vic	0.04	-0.27	-0.01		
STANDARDIZE					
	part	risk	climate	accid	
p1		0.02	-0.28	0.09	
p2		0.13	0.00	0.00	
p3		-0.14	0.36	-0.12	
risks	-1.38	V.17	-0.59	0.83	
riskc	0.20		0.09	-0.12	
plant	-0.23	0.14	0.03	0.11	
Piune	-0.23	0.17		0.11	

super	0.04	-0.14		-0.15
Super	0.07			-0.13
COM	0.10	0.03		0.07
dir	-0.27	4.46	0.02	
vic	0.10	-1.66	-0.01	

COMPLETELY STANDARDIZED EXPECTED CHANGE FOR LAMBDA-Y risk part climate accid 0.03 pl -0.10 0.01 p2 0.04 0.00 0.00 рЗ -0.04 -0.05 0.13 - --0.08 0.11 risks -0.19- -0.14 -0.08 riskc 0.06 - -0.08 plant -0.16 0.10 -0.12 0.03 -0.11 super

0.03

2.66

-2.03

0.01

-0.01

0.06

- -

vic

NO NON-ZERO MODIFICATION INDICES FOR PSI MODIFICATION INDICES FOR THETA-EPS

0.08

-0.16

0.12

COW

dir

vic

MODILICA	LION TUDIC	ES FUN II	HEIM-EF3			
	p1	p2	p3	risks	riskc	plant
p1						
•						
p2	4.07					
р3	0.24	4.67				
risks	3.32	1.24	0.13			
riskc	0.28	0.00	0.25			
plant	5.22	0.17	0.87	0.99	0.02	
super	0.01	0.97	1.42	0.28	0.05	0.28
COM	0.18	1.38	0.00	0.00	0.25	1.54
dir	0.01	0.20	1.08	5.47	4.24	0.45
vic	0.88	1.81	1.24	4.94	3.74	0.02

MODIFICATION INDICES FOR THETA-EPS super cow dir

super				
COW	4.18			
dir	0.59	0.57	-	
vic	0.06	0.10		

	p1	p 2	р3	risks	riskc	plant
						
p1						
p2	2.80					
p3	0.71	-2.54				
risks	-1.46	1.13	0.33			
riskc	0.09	0.00	0.10			
plant	-0.37	0.09	0.18	0.63	-0.02	
super	0.01	-0.16	0.17	-0.27	0.02	0.08
COM	-0.05	0.17	0.01	0.02	-0.05	0.17
dir	-0.02	0.11	-0.24	2.66	-0.39	0.10
vic	0.09	-0.17	0.13	-1.10	0.17	-0.01

EXPECTED CHANGE FOR THETA-EPS

	super	COW	uir	VIC
super				
COW	-0.35			
dir	-0.09	0.09		
vic	-0.01	-0.02		

COMPLETELY STANDARDIZED EXPECTED CHANGE FOR THETA-EPS

	p1	p2	р3	risks	riskc	plant
						
p1						
p2	0.34					
р3	0.09	-0.29				
risks	-0.07	0.05	0.02			
riskc	0.02	0.00	0.02			
plant	-0.09	0.02	0.04	0.06	-0.01	
super	0.00	-0.04	0.05	-0.03	0.01	0.04
COW	-0.02	0.05	0.00	0.00	-0.03	0.10
dir	0.00	0.02	-0.05	0.22	-0.16	0.04
vic	0.04	-0.07	0.06	-0.18	0.14	-0.01

COMPLETELY STANDARDIZED EXPECTED CHANGE FOR THETA-EPS

	super	COW	dir	vic	

super					
COW	-0.24				
dir	-0.04	0.04			
vic	-0.01	-0.02			

risks

MAXIMUM MO THETA-EPS	DIFICATION	INDEX IS	5.47 FOR ELE	MENT (9, 4)	0F
	ED SOLUTION				
LAMBDA-Y	ED SOCUTION				
	part	risk	climate	accid	
p1	2.49				
p2	2.50				
p3	2.42				
risks		6.20			
riskc		0.92			
plant			0.95		
super			1.00		
COM			0.98		
dir				1.32	
vic		·		0.49	
CORRELATIO	ON MATRIX OF	FTA			
	part	risk	climate	accid	
	·				
part	1.00				
risk	-0.01	1.00			
climate	0.29	-0.60	1.00		
accid	0.03	0.59	-0.35	1.00	
PSI					
	part	risk	climate	accid	
part	1.00				
risk	-0.01	1.00			
climate	0.29	-0.60	1.00		
accid	0.03	0.59	-0.35	1.00	
COMPLETELY LAMBDA-Y	STANDARDIZE	D SOLUTIO	N		
LANDUA-1	part	risk	climate	accid	
	·	1134		acc10	
p1	0.92				, with
p2	0.82		** **		market of the
р3	0.85				

0.85

0.36	0.32	0.3).64	
THETA-EI super	PS COW	d i	r	vic	
0.15	0.33	0.28	0.28	0.6	0.57
THETA-E	p2 	p3	risks	riskc	plant
TUCTA F	ne				
accid		0.03	0.59	-0.35	1.00
climate		0.29	-0.60	1.00	
risk		0.01	1.00		
part		1.00			***************************************
PSI		part	risk	climate	e accid
accid		0.03	0.59	-0.35	1.00
climate		0.29	-0.60	1.00	
risk	-	0.01	1.00		
part		1.00			
		part ———	risk	climate	accid
CORRELA	TION MAT	RIX OF	ETA		
vic					0.60
dir					0.78
COM				0.83	
super				0.66 0.80	
plant				0 66	

Assessment and Modification

As specified, the measurement model provides an acceptable fit to the data $[\chi^2(29) = 30.89, \text{ ns}; \text{ GFI} = .95; \text{ AGFI} = .90; \text{ RMSEA} = .02; \text{ NFI} = .94; \text{ CFI} = 1.00; \text{ PNFI} = .60; \text{ PGFI} = .50], \text{ and all estimated parameters are significant. We can proceed, therefore, with the assessment of the structural model.}$

From Pictures to LISREL

Although the measurement model was estimated entirely on the endogenous side of the LISREL model, the full latent variable model requires the use of both the exogenous and endogenous sides of the model. We begin by setting up the measurement of the exogenous and endogenous variables (thereby using both methods of setting a scale of measurement for the latent variables) and then proceed to set up the structural model. The setups are shown in Tables 7.4–7.11.

Note that the correlation between risk and willingness to participate is fixed in the PS matrix (PS 2, 1). Recall that PS appears in both the measurement model for the endogenous variables and the structural model. Because we are estimating a path between risk and willingness to participate [BE (2, 1], we cannot simultaneously estimate the correlation between the two factors. Thus, PS takes the form appropriate for the structural model.

TABLE 7.4 LX (Factor Loading for Exogenous Variables)

	Health and Safety Climate	Accident History
1. Manager's commitment	FRee	FIxed
2. Supervisor's commitment	FRec	Fixed
3. Coworker's commitment	FRee	Fixed
4. Own accident history	Fixed	FRee
5. Witnessed accidents	Fixed	FRee

Table 7.5 PH (Factor Covariances for Exogenous Variables)

	Health and Safety Climate	Accident History	
Health and safety climate Accident history	1.00 FRee	1.00	

TABLE 7.6 TD (Unique Factors for Exogenous Variables)

1. Manager's commitment	FRee	
2. Supervisor's commitment	FRee	
3. Coworker's commitment	FRee	
4. Own accident history	FRee	
5. Witnessed accidents	FRee	

TABLE 7.7 LY (Factor Loadings for Endogenous Variables)

	Risk	Willingness to Participate
1. Risk for self	1.00	FIxed
2. Risk for Coworkers	FRee	Flxed
3. Participation 1	FIxed	1.00
4. Participation 2	Fixed	FRee
5. Participation 3	FIxed	FRee

TABLE 7.8 TE (Unique Factors for Endogenous Variables)

1. Risk for self	FRee	
2. Risk for coworkers	FRee	
3. Participation 1	FRee	
4. Participation 2	FRee	
5. Participation 3	FRee	

TABLE 7.9 GA (Relates Exogenous to Endogenous Variables)

	Health and Safety Climate	Accident History
1. Risk	FRee	FRee
2. Willingness to participate	FIxed	Fixed

TABLE 7.10 BE (Relates Endogenous to Endogenous Variables)

	Risk	Willingness to Participate
1. Risk	Flxed	FIxed
2. Willingness to participate	FRee	FIxed

TABLE 7.11 PS (Factor Covariances for Endogenous Variables)

	Risk	Willingness to Participate
l. Risk	FRee	
2. Willingness to participate	Fixed	FRee

Identification and Estimation II

The measurement relationships incorporated in the model have not changed from the previous analysis; therefore, the measurement component of the model is identified. Because the structural model involves only recursive relationships, the structural component also is identified (Bollen, 1989).

The source code used to estimate the model is given below.

```
DA NI = 10 NO = 115 MA = CM
    10.7 8.9 10.9 18.6 3.8 5.5 5.7 5.5 1.7 0.9
SD
    2.7 3.1 2.9 7.3 1.5 1.4 1.2 1.2 1.7 0.8
KM SY
 1.00
  .76 1.00
  .78
        .68
              1.00
 -.05
         .01
              -.05 1.00
  .10
         .09
               .08
                     .52 1.00
  .01
               .14 -.28
                          -.22 1.00
  .20
        .18
               .29 -.44 -.29
                                   .54 1.00
  .22
        .25
               .29 -.42 -.31
                                   .57
                                         .65 1.00
  .00
                     .42
                            .22
                                 -.13 -.26 -.20
                                                    1.00
  .12
               .11
                     .26
                            .30 -.12 -.20 -.17
                                                      .47 1.00
LA
pl p2 p3 risks riskc plant super cow dir vic
MO NY = 5 NE = 2 NK = 2 NX = 5 PS = DI, FR PH = ST GA = FU, FI BE = FU, FI
LE
  part risk
LK
  climate accid
FR GA(2,1) GA(2,2) BE(1,2)
VA 1.0 LY(1,1) LY(4,2)
FR LY(2,1) LY(3,1) LY(5,2)
FR LX(1,1) LX(2,1) LX(3,1) LX(4,2) LX(5,2)
OU ML SC TV MI
```

Edited Output

NUMBER OF INPUT VARIABLES 10
NUMBER OF Y - VARIABLES 5
NUMBER OF X - VARIABLES 5
NUMBER OF ETA - VARIABLES 2
NUMBER OF KSI - VARIABLES 2
NUMBER OF OBSERVATIONS 115

PARAMETER SPECIFICATIONS

LAMBDA-Y

	part	risk
p1	0	0
p2	1	0
p3	2	0
risks	0	0
riskc	0	3

LAMBDA-X

	climate	accid
plant	4	
super	5	0
COW	. 5 6	0
dir	0	7
vic	0	, 8
V.C	U	0

BETA

	part	risk
part	0	9
risk	0	0

GAMMA

	climate	acci
part	0	0
risk	10	11

Pŀ	I

LUI		
	climate	accid
climate	0 .	
accid	12	0
PSI		
	part	risk
	13	14

THETA-EPS p1 p2 p3 risks riskc 15 16 17 18 19 THETA-DELTA plant super dir vic

22

23

24

LISREL ESTIMATES (MAXIMUM LIKELIHOOD)

21

LAMBDA-Y

20

	part	risk
p1	1.00	
p2	0.98	
	(0.09)	
	11.06	
р3	0.95	
	(0.08)	
	11.48	
risks		1.00
riskc		0.14
		(0.03)
		4.67
LAMBDA~X		
	climate	accid
plant	0.97	
	(0.13)	
	7.43	
super	0.99	
•	(0.11)	
	9.19	

COW	0.97 (0.10) 9.45			
dir		1.37 (0.22) 6.15		
vic		0.47 (0.09) 5.00		
BETA	part	risk ——		
part		-0.02 (0.04) -0.51		
risk				
GAMMA			•	
	climate	accid		
nant		_ =		
part risk	-2.86	2.69		
LIZK	(0.72) -3.99	(0.78) 3.44		
	(0.72) -3.99	(0.78) 3.44	Ī	
	(0.72)	(0.78) 3.44	I climate	accid
	(0.72) -3.99 MATRIX OF E	(0.78) 3.44 TA AND KS		accid
COVARIANCE	(0.72) -3.99 MATRIX OF E part	(0.78) 3.44 TA AND KS		accid
COVARIANCE part	(0.72) -3.99 MATRIX OF E part 	(0.78) 3.44 TA AND KS risk	climate	accid
COVARIANCE part risk	(0.72) -3.99 MATRIX OF E part 6.39 -0.89	(0.78) 3.44 TA AND KS risk ————————————————————————————————————	climate ——	accid
COVARIANCE part risk climate	(0.72) -3.99 MATRIX OF E part 	(0.78) 3.44 TA AND KS risk 41.09 -3.77	climate	
part risk climate accid	(0.72) -3.99 MATRIX OF E part 	(0.78) 3.44 TA AND KS risk 41.09 -3.77	climate	
part risk climate accid	(0.72) -3.99 MATRIX OF E part 	(0.78) 3.44 TA AND KS risk 	climate	
part risk climate accid PHI	(0.72) -3.99 MATRIX OF E part 6.39 -0.89 0.08 -0.08 climate	(0.78) 3.44 TA AND KS risk 	climate	
part risk climate accid PHI climate	(0.72) -3.99 MATRIX OF E part 6.39 -0.89 0.08 -0.08 climate 1.00 -0.34 (0.12)	(0.78) 3.44 TA AND KS risk 41.09 -3.77 3.65	climate	
part risk climate accid PHI climate accid	(0.72) -3.99 MATRIX OF E part 6.39 -0.89 0.08 -0.08 climate 1.00 -0.34 (0.12)	(0.78) 3.44 TA AND KS risk 41.09 -3.77 3.65	climate	

(1.02)(8.04)6.25 2.55

SQUARED MULTIPLE CORRELATIONS FOR STRUCTURAL EQUATIONS

part risk 0.00 0.50

THETA-EPS

p1	p2	р3	risks	riskc
0.90	3.13	2.48	12.51	1.45
(0.38)	(0.54)	(0.46)	(7.52)	(0.24)
2.41	5.83	5.41	1.66	6.11

SQUARED MULTIPLE CORRELATIONS FOR Y - VARIABLES

p1	p2	р3	risks	riskç
				-
0.88	0.66	0.70	0.77	0.35

THETA-DELTA

plant	super	COM	dir	vic
1.15	0.56	0.46	0.93	0.45
(0.18)	(0.12)	(0.11)	(0.52)	(0.08)
6.25	4.51	4.14	1.80	5.37

SOUARED MULTIPLE CORRELATIONS FOR X - VARIABLES

płant	super	COW	dir	vic
0.45	0.64	0.67	0.67	0.33

GOODNESS OF FIT STATISTICS

CHI-SQUARE WITH 31 DEGREES OF FREEDOM = 39.60 (P = 0.14)

ESTIMATED NON-CENTRALITY PARAMETER (NCP) = 8.60

90 PERCENT CONFIDENCE INTERVAL FOR NCP = (0.0 : 28.92)

MINIMUM FIT FUNCTION VALUE = 0.35

POPULATION DISCREPANCY FUNCTION VALUE (FO) = 0.075

90 PERCENT CONFIDENCE INTERVAL FOR FO = (0.0; 0.25)

ROOT MEAN SQUARE ERROR OF APPROXIMATION (RMSEA) = 0.049

90 PERCENT CONFIDENCE INTERVAL FOR RMSEA = (0.0; 0.090)

P-VALUE FOR TEST OF CLOSE FIT (RMSEA < 0.05) = 0.48

EXPECTED CROSS-VALIDATION INDEX (ECVI) = 0.77

90 PERCENT CONFIDENCE INTERVAL FOR ECVI = (0.69; 0.95)

ECVI FOR SATURATED MODEL = 0.96

ECVI FOR INDEPENDENCE MODEL = 4.41

CHI-SOUARE FOR INDEPENDENCE MODEL WITH 45

DEGREES OF FREEDOM = 482.66

INDEPENDENCE AIC = 502.66

MODEL AIC = 87.60

SATURATED AIC = 110.00

INDEPENDENCE CAIC = 540.11

MODEL CAIC = 177.48

SATURATED CAIC = 315.97

ROOT MEAN SQUARE RESIDUAL (RMR) = 0.35

STANDARDIZED RMR = 0.087

GOODNESS OF FIT INDEX (GFI) = 0.94

ADJUSTED GOODNESS OF FIT INDEX (AGFI) = 0.89

PARSIMONY GOODNESS OF FIT INDEX (PGFI) = 0.53

NORMED FIT INDEX (NFI) = 0.92

NON-NORMED FIT INDEX (NNFI) = 0.97

PARSIMONY NORMED FIT INDEX (PNFI) = 0.63

COMPARATIVE FIT INDEX (CFI) = 0.98

INCREMENTAL FIT INDEX (IFI) = 0.98

RELATIVE FIT INDEX (RFI) = 0.88

CRITICAL N (CN) = 151.25

MODIFICATION INDICES AND EXPECTED CHANGE MODIFICATION INDICES FOR LAMBDA-Y

	part	risk
p1		0.00
p2		0.45
р3		0.42
risks	0.01	
riskc	3.50	

MODIFICATION INDICES FOR LAMBDA-X

	climate	accid
plant		0.95
super		1.62
COW		0.23
dir	0.23	
vic	0.23	

p1

0.94

Latent	Variable	Path	Anal	ysis
--------	----------	------	------	------

MODIFICATION	INDICEC	FOR RETA			
MODIFICATION	part	ruk BETA risk			
part					
risk	3,28				
					•
MODIFICATION					
	climate	accid			
part	7.84	0.30			
risk					
NO NONZERO M	ODIFICATI	ON INDICES	FOR PHI		
MODIFICATION	INDICES	FOR PSI			
	part	risk			
part risk	7.00	•			
FISK	3.28				
MODIFICATION	INDICES	FOR THETA-E	:PS		
•	p1	p2	р3	risks	risko
m.1			*********		
p1 p2	0.42				
p3	0.45	0.00			
risks	2.05	1.70	0.39		
riskc	0.44	0.00	0.21	3.28	
MODIFICATION	INDIATO I				
MODIFICATION	p1	-UK IHEIA-D p2	ELTA-EPS p3	må mlen	
	—— hr		<u>рэ</u>	risks ——	riskc
plant	3.92	0.39	1.13	0.72	0.03
super	0.17	0.68	1.49	0.21	0.09
COW	0.00	1.73	0.06	0.00	0.14
dir	0.02	0.22	0.88	3.66	3.66
vic	0.92	1.69	1.07	3.87	4.58
MAXIMUM MODIF	ICATION IN	DEX IS 7.84	FOR ELEMEN	T (1, 1) 0	f gamma
COMPLETELY S	TANDARDIZE	D SOLUTION			
LAMBDA-Y		, .			
	part	risk			

p2	0.81				
р3	0.84				
risks		0.88			
riskc		0.59			
I AMPDA V					
LAMBDA-X	climate	accid			
plant	0.67				
•	0.80				
super	0.82				
COW		0.00			
dir		0.82			
vic		0.57			
BETA					
	part	risk			
part		-0.06			
risk					
GAMMA			•		
Granik	climate	accid			
	·				
part					
risk	-0.45	0.42			
CORRELATION	MATDIY OF	ETA AND K	21		
CORRELATION	part	risk	climate	accid	
					
part	1.00				
risk	-0.06	1.00			
climate	0.03	-0./59	1.00		
accid	-0.03	0.57	-0.34	1.00	
-0.					
PSI	part	risk			
	part -	1.124			
	1.00	0.50			

Latent	Variable	Path	Analysis
--------	----------	------	----------

THETA-E	PS			
p1	p2	р3	risks	riskc
0.12	0.34	0.30	0.23	0.65
THETA-D	ELTA			
plant	super	COW	dir	vic
A 55	0.06			
0.55	0.36	0.33	0.33	0.67

REGRESSION MATRIX ETA ON KSI (STANDARDIZED)

climate	accid
0.02	-0.02
-0.45	0.42
	0.02

Assessment and Modification II

This is an interesting case in that although the model provides an acceptable fit to the data $[\chi^2(31) = 39.60, \text{ ns}; \text{ GFI} = .94; \text{ AGFI} = .89; \text{ RMSEA} = .05; \text{ NFI} = .92; \text{ CFI} = .98; \text{ PNFI} = .63; \text{ PGFI} = .53], \text{ not all the paths in the model are significant. Risk perceptions do not significantly predict willingness to participate (<math>\beta = -.06, \text{ ns}$).

The partially mediated model (resulting from adding paths from both exogenous variables to willingness to participate) provided a significantly better fit to the data $[\chi^2_{\text{difference}}(2) = 8.72, p < .02; \chi^2(29) = 30.89$, ns; GFI = .95; AGFI = .90; RMSEA = .02; NFI = .94; CFI = 1.00; PNFI = .60; PGFI = .50]. The nonmediated model (which deletes the path from risk perceptions to willingness) also provided a good fit to the data $[\chi^2(30) = 32.07, \text{ ns; GFI} = .95; \text{AGFI} = .90; \text{RMSEA} = .03; \text{NFI} = .93; \text{CFI} = 1.00; \text{PNFI} = .62; \text{PGFI} = .52] but did not differ from the partially mediated model, <math>\chi^2_{\text{difference}}(1) = 1.17$, ns. Given that the partially mediated model and nonmediated model provide equivalent fits to the data, the nonmediated model is accepted based on the consideration of parsimony.

Post hoc inspection of the model parameters suggested that the nonsignificant path from accident history to willingness to participate could be deleted from the model. Doing so did not change the fit of the model $[\chi^2_{\text{difference}}(1) = 1.70, \text{ ns}; \chi^2(31) = 33.77, \text{ ns}; \text{GFI} = .95; \text{AGFI} = .90; \text{RMSEA} = .03; \text{NFI} = .93; \text{CFI} = .99; \text{PNFI} = .64; \text{PGFI} = .531$

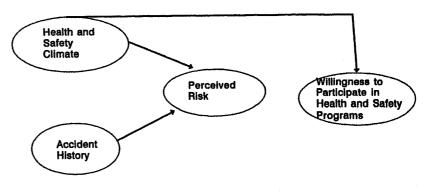


Figure 7.6.

but it did result in a more parsimonious model. The revised nonmediated model is presented in Figure 7.6.

Sample Results Section

A sample results section reflecting these findings is presented below.

Results

Descriptive statistics and intercorrelations for all study variables are presented in Table 7.12. All model tests were based on the covariance matrix and used maximum likelihood estimation as implemented in LISREL VIII (Jöreskog & Sörbom, 1992).

The measurement model provided an acceptable fit to the data $[\chi^2(29) = 30.89, \text{ ns}; \text{ GFI} = .95; \text{ AGFI} = .90; \text{ RMSEA} = .02; \text{ NFI} = .94; \text{ CFI} = 1.00; \text{ PNFI} = .60; \text{ PGFI} = .50]. Standardized parameter estimates for the measurement model are presented in Table 7.13.$

Table 7.14 presents the fit indices for the three structural models of interest. As shown, the partially mediated model provided a better fit to the data than did the fully mediated model $[\chi^2_{\text{difference}}(2) = 8.72, p < .02]$. The nonmediated model and partially mediated model did not differ $[\chi^2_{\text{difference}}(1) = 1.17, \text{ns}]$. Based on the consideration of parsimonious fit, the nonmediated model was retained for further analysis.

Variable	1	?	n	4	'n	9	7	0 0	6	10
1. Participation 1										
2. Participation 2	26									
3. Participation 3	78	89								
4. Risk to self	-05	5	-05							
5. Risk to others	10	69	80	52						
6. Manager's										
commitment	01	80	14	-28	-22					
7. Supervisor's										
commitment	70	18	29	- 44	-29	54				
8. Coworkers'										
commitment	77	25	53	- 42	-31	57	65			
9. Accident history	00	8	- 05	42	22	-13	-26	-20		
10. Witnessed								}		
accidents	12	8	11	76	30	-12	-20	-17	47	
Mean	10.7	8.9	10.9	18.6	3.8	5.5	5.7	5.5	1.7	6.0
SD	2.7	3.1	2.9	7.3	1.5	1.4	1.2	1.2	17	0.8

TABLE 7.13 Standardized Parameter Estimates for the Measurement Model

	Willingness to Participate	Risk	Health and Safety Climate		R²
1. Participation 1	0.92				0.85
2. Participation 2	0.82				0.67
3. Participation 3	0.85				0.72
4. Risk to self		0.85			0.72
5. Risk to others		0.61			0.38
6. Manager's commitment			0.66		0.43
7. Supervisor's commitment			0.80		0.64
8. Coworkers' commitment			0.83		0.68
9. Accident history				0.78	0.61
0. Witnessed accident	ts			0.60	0.36

TABLE 7.14 Fit Indices for the Three Models

	χ²	df	GFI	AGFI	RMSEA	NFI	CFI	PNFI	PGFI
1. Partially mediated	30.9	29	.95	.90	.02	.94	1.00	.60	.50
2. Fully mediated	39.6	31	.94	.89	.05	.92	.98	.63	.53
3. Nonmediated	32.1	30	.95	.90	.03	.93	1.0	.62	.52

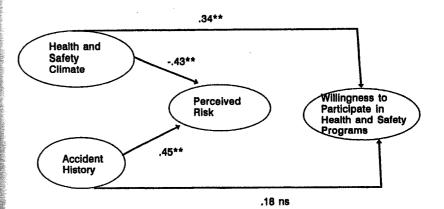


Figure 7.7.

Standardized parameter estimates for the structural model are presented in Figure 7.7. As shown, both risk perceptions ($\beta = -.43$, p < .01) and willingness to participate in health and safety programs ($\beta = .34$, p < .01) were predicted by perceived health and safety climate. Risk perceptions ($\beta = .45$; p < .01) but not willingness to participate ($\beta = .18$, ns) were predicted by respondents' accident history.

Deleting the nonsignificant path from the model did not result in a significant change to model fit, $[\chi^2_{\text{difference}}(1) = 1.70, \text{ ns}]$.

CHAPTER 8 Concluding Comments

In previous chapters, we considered the logic and mechanics of structural equation modeling with specific reference to the three most common versions of structural equation models: confirmatory factor analysis, observed variable path analysis, and latent variable path analysis. In this final chapter, I introduce two useful extensions to the procedures discussed thus far.

Single Indicator Latent Variables

As a general rule, one should strive for at least two or three indicators (observed variables) for every latent variable. Following this guideline generally will steer you clear of the shoals of underidentified models. In some cases, this rule must be violated because of either lack of available data or lack of forethought.

Unfortunately, we are sometimes stuck with only one indicator for a construct. Two solutions to this dilemma are possible. First, one can divide the scale items to form multiple indicators, as was done in the previous chapter. The second solution is to declare a latent variable with only one indicator. This is bound to leave us with an identification problem (trying to estimate both a unique and a common factor loading as well as the variance for one construct using only one indicator). The solution is to FIx the common (LY) and unique (TE) factor loadings at predetermined values and to estimate only the variance of the latent variable.