Modeling Longitudinal and Multilevel Data

Practical Issues, Applied Approaches and Specific Examples

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Modeling True Intraindividual Change in Structural Equation Models: The Case of Poverty and Children's Psychosocial Adjustment

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Across the behavioral sciences it is often observed that some people change more than others. For example, some individuals learn faster than others in their youth; some lose their cognitive capacities more quickly than others in old age. Why do individuals differ in their patterns of change? What variables predict differences in growth and decline? Questions such as these require models of change. Yet observed change may be due to fluctuations of measurement error, which necessitates models of growth that depict the true change experienced by individuals across occasions of measurement.

How can we conclude that there is true differential intraindividual change? A simple rule of thumb is to compare the retest correlations of the observed variables to their reliability estimates. If there were no true differential intraindividual change, the retest correlations and the reliability estimates should be about the same. If, however, the retest correlations are considerably smaller than the reliability estimates, the underlying true score variables are correlated less than one, and a correlation less than one between true score variables pertaining to a test and retest means that some individuals change more than others with respect to the attribute considered; otherwise, this correlation would be equal to one. Hence, in such a situation the question: "Why do some individuals change more than others?" is meaningful.

Structural equation models (SEMs) (see e.g., Arbuckle, 1997; Bentler, 1995; Bollen, 1989; Bollen & Long, 1993; Hayduk, 1987; Hoyle, 1995; Jöreskog & Sörbom, 1993; Marcoulides & Schumacker, 1996) have been developed to decompose observed values into true components and measurement error components and to directly interrelate the true components to each other. Within SEMs, *latent growth curve* models have proven useful in the study of development (see e.g., McArdle & Anderson, 1990; McArdle & Epstein, 1987; Meredith & Tisak, 1990; Muthén, 1991; Raykov, 1992, 1996; Tisak & Meredith, 1990; Willet & Sayer, 1994, 1996). The basic idea of a standard latent growth curve model is to decompose individual growth curves into latent variables that represent an intercept (a level) and a linear (the slope) or higher order component of change. These latent variables are then interrelated to other variables that might explain the interindividual differences in levels and slopes.

Steyer, Eid, and Schwenkmezger (1997) presented a more direct approach to modeling interindividual differences in intraindividual change: the *true intraindividual change* models. According to this approach, the true intraindividual change scores (i.e., the difference between two true score variables) between two occasions of measurement are the values of the latent variables. However, Steyer et al. (1997) consider neither (a) models with different factor loadings for each observed variable (i.e., models with congeneric variables) nor (b) models with non-zero expectations of the latent variables. In the present chapter, we generalize the approach of Steyer et al. (1997) with respect to these two points and illustrate this more general model with an application involving children's psychosocial adjustment and poverty.

The chapter is organized as follows: We first specify the *multistate model (for multiple occasions of measurement) with invariant parameters* (MSIP). We then rewrite this model so that the true intraindividual change scores between two occasions of measurement are the values of the latent variables. Because the models with true intraindividual change scores are just reparameterizations of the MSIP model, we call them the *change versions of the MSIP* model, as opposed to its *state version*. Next, we study issues of identification. Finally, we illustrate the model in its two versions by examining poverty and change in children's psychosocial adjustment.

MULTISTATE MODEL WITH INVARIANT PARAMETERS

The model on which the rest of this chapter is based assumes that there are at least two observed variables measuring the same latent variable within each of at least two occasions of measurement. Additionally, it is assumed that the measurement model (i.e., the coefficients of the regressions of the observed values on the latent variables) is invariant across occasions. Hence, we call this model the *multistate model* (for multiple occasions of measurement) *with invariant parameters* (MSIP).

Figure 6.1 illustrates this assumption: Each Y_{ik} measures the same η_k, although the effects of η_k on the observable Y_{ik} may be different for each measurement instrument, i. However, it is important to notice that the coefficients of the regressions of the observed values on the latent variables are invariant across occasions. Hence, in Figure 6.1, there are only three different loadings for nine observables because three measurement instruments are repeatedly applied at three time points. In the next two subsections, we first treat the state version and then the two change versions of this model.

The State Version

Suppose that within each of n occasions of measurement there are m observables Y_{ik} measuring the same latent variable η_k such that

$$Y_{ik} = \lambda_{i0} + \lambda_{i1}\,\eta_k + \varepsilon_{ik}, \quad \lambda_{i0}\,\lambda_{i1} \in \mathrm{IR}, \quad \lambda_{i1} > 0, \tag{1}$$

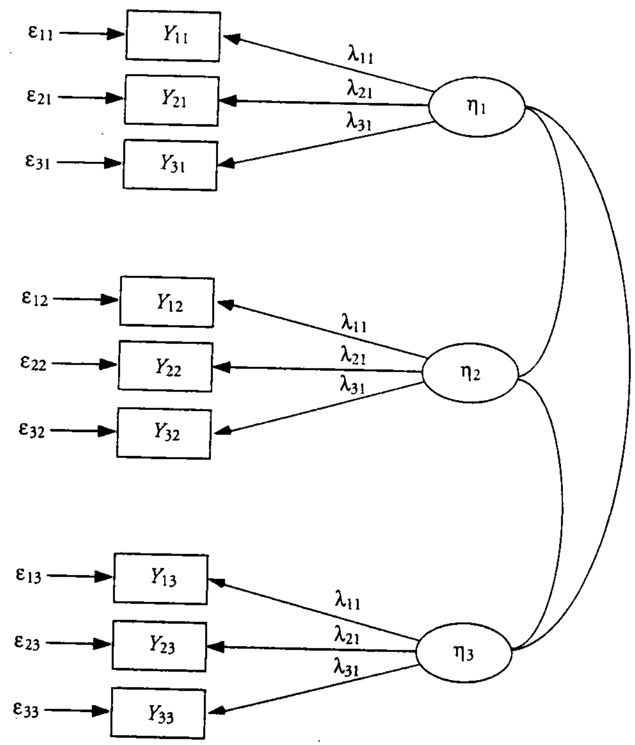
and

$$Cov(\eta_k, \varepsilon_{ik}) = E(\varepsilon_{ik}) = 0 \tag{2}$$

hold for each $i = 1, \ldots, m$ and each occasion $k = 1, \ldots, n$. This will be called the *multistate model* (for multiple occasions of measurement) *with invariant parameters* (MSIP). Furthermore, we assume that the measurement errors, ε_{ik}, are uncorrelated, that is,

$$Cov(\varepsilon_{ik}, \varepsilon_{jl}) = 0, \quad \text{for } (i, k) \neq (j, l). \tag{3}$$

FIGURE 6.1
The State Version of the Multistate Model for Multiple Occasions With Invariant Parameters



Note that variations of these assumptions may be formulated allowing some measurement error variables ε_{ik} to be correlated (see e.g., Marsh, Byrne, & Craven, 1992). Alternatively, it is possible to introduce method factors in order to account for a certain covariance structure of the variables, ε_{ik}. In fact, in the application section, we present an example with method factors. The only limitations to the MSIP are the invariant regression coefficients λ_{i0} and λ_{i1} in Equation 1 and the general limitations of identifiability. This state version of the MSIP is illustrated by Figure 6.1 for three occasions of measurement for each of which there are three observables.

The Change Versions

For simplicity, let us consider three occasions of measurement. Then Equation 1 may more explicitly be rewritten and reparameterized as follows:

$$Y_{i1} = \lambda_{i0} + \lambda_{i1}\eta_1 + \varepsilon_{i1} \quad (4)$$

$$Y_{i2} = \lambda_{i0} + \lambda_{i1}\eta_2 + \varepsilon_{i2} = \lambda_{i0} + \lambda_{i1}\eta_1 + \lambda_{i1}(\eta_2 - \eta_1) + \varepsilon_{i2} \quad (5)$$

$$Y_{i3} = \lambda_{i0} + \lambda_{i1}\eta_3 + \varepsilon_{i3} = \lambda_{i0} + \lambda_{i1}\eta_1 + \lambda_{i1}(\eta_3 - \eta_1) + \varepsilon_{i3} \quad (6)$$

$i = 1, \ldots, m$. These three equations capture the basic idea of the class of models presented in this chapter. Hence, note that the right-hand sides of Equations 4 to 6 are equivalent to Equation 1. However, some of the latent variables, namely $\eta_2 - \eta_1$ and $\eta_3 - \eta_1$, are now latent difference variables. The values of these variables are the true intraindividual change scores between occasions 2 versus 1 and 3 versus 1. This set of equations is called the *baseline version* of the MSIP (see Figure 6.2): Occasion 1 serves as a baseline against which change at subsequent occasions is to be analyzed.

Equation 1 can also be rewritten so that true intraindividual change always refers to the neighbored occasions of measurement:

$$Y_{i1} = \lambda_{i0} + \lambda_{i1}\eta_1 + \varepsilon_{i1} \quad (7)$$

$$Y_{i2} = \lambda_{i0} + \lambda_{i1}\eta_2 + \varepsilon_{i2} = \lambda_{i0} + \lambda_{i1}\eta_1 + \lambda_{i1}(\eta_2 - \eta_1) + \varepsilon_{i2} \quad (8)$$

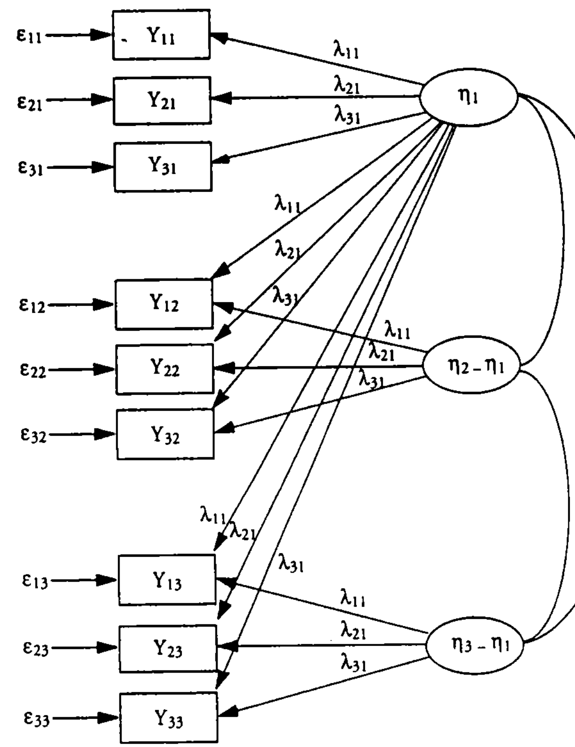
$$Y_{i3} = \lambda_{i0} + \lambda_{i1}\eta_3 + \varepsilon_{i3} = \lambda_{i0} + \lambda_{i1}\eta_1 + \lambda_{i1}(\eta_2 - \eta_1) + \lambda_{i1}(\eta_3 - \eta_2) + \varepsilon_{i3} \quad (9)$$

(see Figure 6.3). Hence, we call such a set of equations the *neighbor version* of the MSIP model.

Extensions to more than three measurement occasions are straightforward. The basic principle is to preserve the equalities between the equation $Y_{ik} = \lambda_{i0} + \lambda_{i1}\eta_k + \varepsilon_{ik}$ and its reformulation involving latent difference variables. Hence, for a fourth occasion, we would add

$$Y_{i4} = \lambda_{i0} + \lambda_{i1}\eta_4 + \varepsilon_{i4} = \lambda_{i0} + \lambda_{i1}\eta_1 + \lambda_{i1}(\eta_4 - \eta_1) + \varepsilon_{i4} \quad (10)$$

FIGURE 6.2
The Baseline Version of the Multistate Model for Multiple Occasions With Invariant Parameters



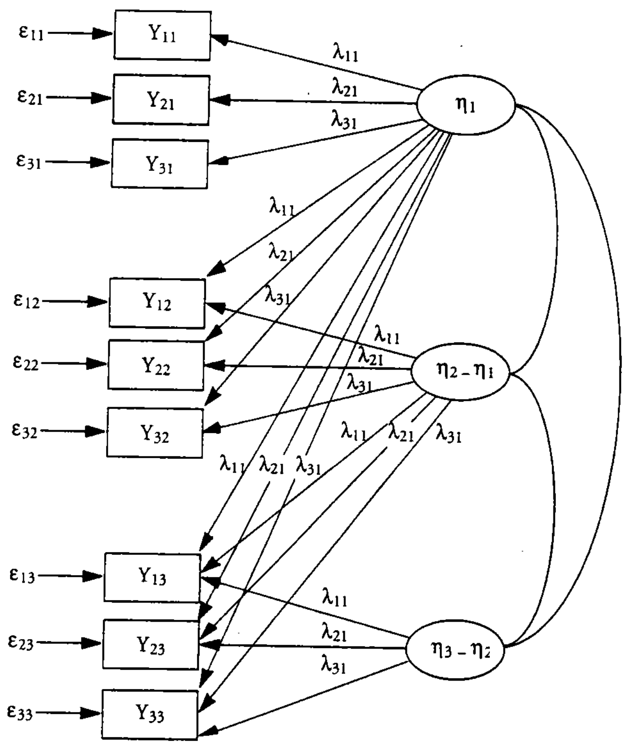
in the baseline model and, in the neighbor model:

$$\begin{aligned} Y_{i4} &= \lambda_{i0} + \lambda_{i1}\eta_4 + \varepsilon_{i4} \\ &= \lambda_{i0} + \lambda_{i1}\eta_1 + \lambda_{i1}(\eta_2 - \eta_1) + \lambda_{i1}(\eta_3 - \eta_2) + \lambda_{i1}(\eta_4 - \eta_3) + \varepsilon_{i4} \end{aligned} \quad (11)$$

To summarize: Every multistate model with invariant parameters (MSIP model; Equations 1–3) may be transformed into a baseline version and/or a neighbor version. In these versions of the MSIP model, latent variables occur, the values of which are the true intraindividual change scores. In the baseline version, these latent variables represent the true change between occasions 1 and k, whereas in the neighbor version they represent the true change between occasions k and $k + 1$.

After a model involving latent difference variables is formulated, it is easy to treat the latent difference variables as ordinary latent variables in structural equation models. Equations 4 to 11 may be translated into path diagrams using the usual conven-

FIGURE 6.3
The Neighbor Version of the Multistate Model for Multiple Occasions With Invariant Parameters



tions, and the latent difference variables can serve as endogenous variables to be explained by other latent variables or as exogenous variables explaining other variables. Both ways of using latent difference variables open up interesting possibilities. Using them as endogenous variables is tantamount to explaining interindividual differences in intraindividual change, one of the key interests of developmental science. However, using latent difference variables as exogenous variables may also be of interest in many applications, because it is often change, and not necessarily the actual state, that is the important causal agent (e.g., Wu, 1996).

IDENTIFICATION

If there is one latent variable η_k for each occasion k of measurement such that Equations 1 to 3 hold, then there is an infinite number of such variables fulfilling these equations. This can be seen from

$$\begin{aligned} Y_{ik} &= \lambda_{i0} + \lambda_{i1}\eta_k + \varepsilon_{ik} \\ &= (\lambda_{i0} - \alpha\lambda_{i1}/\beta) + (\lambda_{i1}/\beta)(\alpha + \beta\eta_k) + \varepsilon_{ik} = \lambda_{i0}{}^* + \lambda_{i1}{}^*\eta_k{}^* + \varepsilon_{ik}, \end{aligned} \tag{12}$$

where $\lambda^*_{i0} = \lambda_{i0} - \alpha\,\lambda_{i1}/\beta$, $\lambda^*_{i1} = \lambda_{i1}/\beta$, $\eta^*_k = \alpha + \beta\,\eta_k$, and $\alpha, \beta \in \mathbb{R}$, $\beta > 0$.

A uniquely defined latent variable η_k is obtained only if its expectation and variance are fixed in one way or another. There are two ways to fix the expectations and variances—and in this sense, the scales—of the latent variables η_k: a direct and an indirect way.

Fixing the Expectation and the Variance

A direct way is to set

$$E(\eta_1) = 0 \quad \text{and} \quad Var(\eta_1) = 1, \tag{13}$$

for instance. That is, fix the expectation and the variance of the latent variable for the first measurement occasion. This has two consequences. First, this identifies (i.e., uniquely determines) the regression constants λ_{i0} and the regression slopes (loadings) λ_{i1}. Second, it identifies the expectations and variances of the latent variables η_k at other occasions of measurement. Table 6.1 summarizes the identification formulas that can be derived from the MSIP model (i.e., from Equations 1–3) and scale fixing via Equation 13.

According to Equation 14 in Table 6.1, the regression constants λ_{i0} are equal to the expectations, $E(Y_{i1})$, of the observables, Y_{i1}, assessed on occasion 1, provided that the scales of the latent variables are fixed via Equation 13. According to Equation 15 in Table 6.1, two observables at each of two occasions of measurement are sufficient to compute the loadings λ_{i1} from the covariances of the observables. Note that, in Equation 13, we only fix the expectation and variance of η_1. The expectations and variances of the latent variables η_k at other occasions $k > 1$ can be determined from the expectations, variances, and covariances of the observables (see Equations 16 and 17 in Table 6.1). Thus, it is meaningful to test hypotheses about expectations and variances of the latent variables η_k, $k > 1$.[1] Furthermore, the covariances of the latent variables η_k are identified (see Equation 18 in Table 6.1), as well as the variances of the measurement error variables (see Equation 19 in Table 6.1).

[1] Note that the possibility to test hypotheses about expectations and variances of latent variables η_k is a consequence of presuming a measurement model that is invariant across time.

TABLE 6.1
Identification Formulas for Setting $E(\eta_1) = 0$ and $Var(\eta_1) = 1$

$$\lambda_{i0} = E(Y_{i1}) \tag{14}$$

$$\lambda_{i1} = \sqrt{\frac{Cov(Y_{i1}, Y_{j1})}{\sqrt{\frac{Cov(Y_{jk}, Y_{jk})}{Cov(Y_{ik}, Y_{il})}}}}, \quad i \neq j, \quad k \neq l \tag{15}$$

$$E(\eta_k) = \frac{E(Y_{ik}) - E(Y_{i1})}{\lambda_{i1}}, \quad k > 1 \tag{16}$$

$$Var(\eta_k) = \frac{Cov(Y_{ik}, Y_{jl})}{\lambda_{i1}\lambda_{j1}}, \quad k > 1 \tag{17}$$

$$Cov(\eta_k, \eta_l) = Cov(Y_{ik}, Y_{jl}) \,/\, (\lambda_{i1}\, \lambda_{j1}) \tag{18}$$

$$Var(\varepsilon_{ik}) = Var(Y_{ik}) - [\,\lambda^2_{i1}\; Var(\eta_k)] \tag{19}$$

Fixing the Intercept and the Slope

An indirect way to fix the expectations and variances of the latent variables η_k is setting

$$\lambda_{10} = 0 \quad \text{and} \quad \lambda_{11} = 1, \tag{20}$$

for instance. With these equations, fix the intercept and the slope of the regression of the first observable Y_{1k} on the latent variable η_k on each occasion k of measurement. Again, this has two consequences. First, this identifies (uniquely determines) the expectations and variances of the latent variables η_k and second, it identifies the other regression constants λ_{i0} and the other regression slopes (loadings) λ_{i1}, $i > 1$. Table 6.2 shows the identification formulas for the theoretical parameters in the case of fixing the intercept and slope for the first observable.

Compare the formulas displayed in Table 6.2 to those displayed in Table 6.1. Note that the different way of fixing the scales of the latent variables affects all identification formulas. Even in those cases in which the formulas look alike, the numerical values might be different, because the parameters that go into the right-hand sides of the equations change their numerical values. This is the case, for instance, for the covariances $Cov(\eta_k, \eta_l)$ of the latent variable, whereas the error variances $Var(\varepsilon_{ik})$ are not affected at all by the different ways of fixing the scales of the latent variables.

TABLE 6.2
Identification Formulas for Setting $\lambda_{10} = 0$ and $\lambda_{11} = 1$

$$\lambda_{i0} = E(Y_{ik}) - \lambda_{ik}E(Y_{1k}), \quad i > 1 \tag{21}$$

$$\lambda_{i1} = \frac{Cov(Y_{ik}, Y_{1k})}{Var(\eta_k)}, \quad i > 1 \tag{22}$$

$$E(\eta_k) = E(Y_{1k}) \tag{23}$$

$$Var(\eta_k) = \frac{Cov(Y_{1k}, Y_{ik})}{\sqrt{\frac{Cov(Y_{ik}, Y_{il})}{Cov(Y_{1k}, Y_{1l})}}}, \quad i > 1, \quad k \neq 1 \tag{24}$$

$$Cov(\eta_k, \eta_l) = Cov(Y_{ik}, Y_{jl}) \,/\, (\lambda_{i1}\, \lambda_{j1}) \tag{25}$$

$$Var(\varepsilon_{ik}) = Var(Y_{ik}) - [\lambda^2_{i1} Var(\eta_k)] \tag{26}$$

Thus far, we have examined identification for the state version of the model. However, if the state version is identified, the change versions are also identified because the expectations, variances, and covariances of difference variables can be computed from the expectations, variances, and covariances of the components of the difference:

$$E(\eta_k - \eta_l) = E(\eta_k) - E(\eta_l), \tag{27}$$

$$Var(\eta_k - \eta_l) = Var(\eta_k) + Var(\eta_l) - 2\; Cov(\eta_k, \eta_l), \tag{28}$$

and

$$Cov(\eta_k - \eta_l, \eta_{k'} - \eta_l) = Cov(\eta_k, \eta_k) - Cov(\eta_k, \eta_l) - Cov(\eta_l, \eta_k) + Cov(\eta_l, \eta_l). \tag{29}$$

Because the terms on the right-hand sides of Equations 27, 28, and 29 are identified, the terms on the left-hand sides are likewise identified.

To summarize, we have shown that in the MSIP model it is sufficient to fix the expectation and the variance of the latent variable at a single occasion of measurement. If there are at least two observables measuring a common latent variable on each of at least two occasions of measurement, then the expectations, variances, and covariances of the latent variables and the measurement error variances are identified for the other occasions of measurement. This is true not only for the state version but also for the change versions of the MSIP model. Hence, we may estimate the expectations, variances, and covariances of the latent change variables.

The identification status will be slightly different if method factors are introduced. In this case, identification of all parameters involved might be possible only if some loadings are fixed or if there are at least three observables for each occasion.

APPLICATION: POVERTY AND CHILDREN'S PSYCHOSOCIAL ADJUSTMENT

Our approach can be illustrated by examining the true change in children's psychosocial adjustment as well as how poverty experiences predict interindividual differences in these patterns of change. Many studies provide evidence that poverty is related to the well-being of children (Hill & Sandfort, 1995). Previous research suggests links between economic deprivation and behavior problems (Erickson, Sroufe, & Egeland, 1985; Verhulst, Akkerhuis, & Althaus, 1985; Werner, 1985), depression (Gibbs, 1986), and troubled relationships with peers (Parker & Asher, 1987). However, virtually all previous research is based on cross-sectional comparisons between impoverished and nonimpoverished children (Goldstein, 1990; Walker, 1994). Thus, our current understanding of children in poverty largely fails to acknowledge the developmental patterns of children's well-being.

A few studies using latent growth curve models (McArdle, 1986) indicate that poverty experiences predict both the level and shape of children's growth curves. Drawing on repeated assessments of children between 1986 and 1990 in the National Longitudinal Survey of Youth (NLSY), McLeod and Shanahan (1996) showed that the number of years children are in poverty correlates significantly and positively with the latent slope of their antisocial behavior (see also Bolger, Patterson, Thompson, & Kupersmidt, 1995; Shanahan, Brooks, & Davey, 1997). That is, poverty experiences are related to the way in which children develop, not merely to their score at one measurement occasion. These results underscore the value of examining children's well-being in terms of both change and stability through the early life course. Yet, these models say little about true intraindividual change between two measurement occasions, because they depict change across all of the waves of data. In contrast, the neighbor version of the proposed true intraindividual change models, for instance, offers an approach to growth that decomposes change into a series of true change difference scores between consecutive sets of two measurement occasions. This allows for a more finely grained analysis of development.

Data and Measures

The data come from three waves of the National Longitudinal Survey of Youth and cover a cohort of young women who had been interviewed annually since 1979, at which time they were between 14 and 21 years of age (Center for Human Resources Research, 1988). In 1986, when the women were between the ages of 21 and 28, the first of a series of assessments of their children was conducted to track their develop-

TABLE 6.3
Items Constituting the Two Psychosocial Adjustment Scales

Scale 1	Internalizing	• Feels or complains that nobody loves him/her • Feels worthless or inferior • Cries too much • Is too dependent on others
	Externalizing	• Cheats, tells lies • Does not seem to feel sorry after he/she misbehaves • Argues too much • Is stubborn, sullen, or irritable
Scale 2	Internalizing	• Has sudden changes in mood or feeling • Is too fearful or anxious • Is unhappy, sad, or depressed • Demands a lot of attention
	Externalizing	• Bullies or is cruel to others • Is rather high-strung, tense, and nervous • Is disobedient at home • Has a very strong temper and loses it easily

mental progress. Child assessments were repeated in 1988, 1990, and 1992 (for further information, see McLeod & Shanahan, 1993).

We use data from the 1986, 1988, and 1990 waves, namely, a selection of items completed by the mothers and covering four types of behavior exhibited by their children ages 4 or older: depression, dependency, antisocial behavior, and headstrong behavior. The rating scale is a modification of the Achenbach Behavior Problems Checklist (Achenbach & Edelbrock, 1981) created by Zill and Peterson (Baker, Keck, Mott, & Quinlan, 1993). All indicators share the rating categories *often true, sometimes true, not true,* coded as 3, 2, and 1, respectively.

Out of a larger pool of items, we constructed two new "parallel" scales of psychosocial adjustment, Y_1 and Y_2, taking care that each represented internalizing problems (depression, dependency), and externalizing problems (antisocial or headstrong behavior) in a balanced way. When selecting the items for each scale, we were guided mainly by substantive considerations, but also tried to avoid items with overly skewed distributions. The items used for the two scales are shown in Table 6.3.

The values of the two scales were calculated as simple averages across the scores for the corresponding eight items, subject to the condition that there were nonmissing data for at least four items per scale. In spite of this procedure, the percentage of missing data of the scales is considerable. Computing the covariance matrix of the six measures showed that some covariances were computed from 93%, others from only 60% of the cases (median 75%, interquartile range 71% through 81%). Hence, an alternative way of treating the missing data problem was chosen: the Amos full information maximum likelihood approach (Wothke, chap. 12, this volume). This method seemed optimal in face of the large amount of missing data.

The reliabilities of the resulting six measures (the two scales at three measurement occasions), as estimated by Cronbach's α, were between .66 and .77, with a median of .72. These values seem acceptable for scales that are short and heterogeneous in nature. We used a measure of poverty, expressed as the proportion of time the family lived in poverty during the survey, as a predictor of level and change in psychosocial adjustment (for details, see McLeod & Shanahan, 1996).

Models and Results

We present all three versions of the MSIP model: the state version, the baseline version, and the neighbor version. In all versions we used the indirect way of fixing the scales of the latent variables, and all versions include intercepts of the structural regressions and the expectations of the latent variables involved. Note, however, that, according to Equation 1, the intercepts and loadings of the measurement models are fixed across time. To achieve good fit, we included one method factor that is uncorrelated with the latent state/change variables and loads on one of the two scales for each occasion of measurement. Including a method factor was necessary because the two scales are not perfectly parallel in the sense of classical test theory (see Lord & Novick, 1968; or Steyer & Eid, 1993). (Eid, 1998, provides the theoretical background for this kind of modeling method factors with one method factor less than the number of methods.) We also allowed the residuals of the latent state variables to correlate because we cannot expect the poverty variable to explain all the correlation between the latent psychosocial adjustment state variables. In fact, most of that covariance can be explained by a latent psychosocial adjustment trait variable (see Steyer, Ferring, & Schmitt, 1992, for an introduction to latent state-trait theory). Figures 6.4 to 6.6 show the models fitted. For simplicity, the intercepts and means are not displayed in the figures. However, they are reported in Tables 6.5 to 6.7.

TABLE 6.4
Means, Standard Deviations, and Correlations of Poverty Duration and the Psychosocial Adjustment Scales (Implied Moments Under Saturated Model, Amos Estimates)

	Y_{11}	Y_{21}	Y_{12}	Y_{22}	Y_{13}	Y_{23}	*Poverty*
Means	1.448	1.501	1.457	1.505	1.438	1.495	0.310
SD	0.311	0.330	0.330	0.355	0.336	0.371	0.358
Y_{11}	1.000						
Y_{21}	0.724	1.000					
Y_{12}	0.431	0.456	1.000				
Y_{22}	0.408	0.502	0.758	1.000			
Y_{13}	0.416	0.435	0.532	0.472	1.000		
Y_{23}	0.379	0.457	0.491	0.552	0.779	1.000	
Poverty	0.127	0.115	0.147	0.131	0.128	0.111	1.000

Table 6.4 shows the means, standard deviations, and correlations of the poverty measure and the two psychosocial adjustment scales at each of three occasions of measurement. These quantities have been estimated by Amos and are actually the moments implied by the saturated model. However, they are not sufficient statistics and fitting our model with them only approximately reproduces our results.

The saturated model had a log-likelihood function of −13753.33 with 35 estimated parameters, and our model had a log-likelihood of −13741.89 with 24 estimated parameters. The difference in the two log-likelihood functions is a chi-squared statistic of 11.44, which, at 11 degrees of freedom, indicates a very good fit (p = .406; RMSEA = 0.005).

The State Version

The unstandardized solution of the state version of the MSIP model is depicted in Figure 6.4. Additional information on the model is given in Table 6.5. Figure 6.4 reveals that the loadings of the two psychosocial adjustment scales are almost equal. However, they are not fixed to be equal, in order to demonstrate that, in true intraindividual change models, one may have different loadings for the observables.

According to Table 6.5, the means of the latent state psychosocial adjustment variables are stable over time. Their estimates range between 1.440 and 1.454.[2] This indicates that there is no general trend in the sample toward an increase or a decrease in psychosocial adjustment.

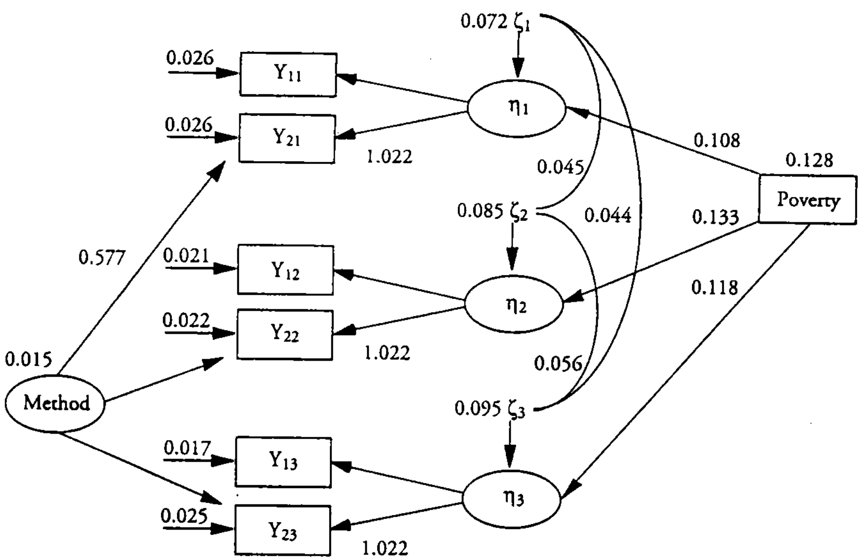
Nevertheless, there is differential intraindividual change over time with respect to psychosocial adjustment because the retest correlations are between .54 and .63, whereas the reliability estimates (the squared multiple correlations for the observables

TABLE 6.5
Means, Variances, Correlations, and Regressions for the State Model
(Full Information ML Estimates)

	η_1	η_2	η_3
Means	1.448	1.454	1.440
Variances	0.073	0.087	0.096
η_1	1.000		
η_2	0.583	1.000	
η_3	0.541	0.630	1.000
Correlations with poverty	0.143	0.162	0.137
Regression on poverty: slopes	0.108	0.133	0.118
Intercepts	1.415	1.413	1.403

[2] A model comparison between the two models with and without equality restrictions on these three means yields a χ^2-difference of 3.00 with two degrees of freedom. This comparison was made excluding the poverty variable from the model with the effect that we have direct access to the means of the three latent psychosocial adjustment variables.

FIGURE 6.4
The Final Model in Its State Version, With Amos Estimates of the Free Parameters
(χ^2 = 11.444, df = 11, p > 0.406, RMSEA = 0.005)



in Figure 6.4) range between .74 and .85. If there were no differential intraindividual change, the retest correlations and the reliability estimates should be about the same. Hence, the question: "Why do some children change more than others?" is meaningful in this context, although there is no change in the mean of the psychosocial adjustment variables.

According to Table 6.5, there are small but significant positive correlations between poverty duration and the latent state psychosocial adjustment variables ranging between .14 and .16. Hence, poverty duration could predict psychosocial adjustment. Figure 6.4 shows the corresponding unstandardized path coefficients for the regressions of the three psychosocial adjustment statevariables on poverty.

The Baseline Model

How is true intraindividual change in psychosocial adjustment related to poverty duration? Looking at the correlations between the two latent change variables $\eta_2 - \eta_1$ or $\eta_3 - \eta_1$ and poverty duration (see Table 6.6 and Figure 6.5) reveals that true intraindividual change in psychosocial adjustment is not related to poverty duration in this study. The estimates of the two correlations are 0.034 and 0.013, which are not significantly different from zero. (The corresponding test yields a nonsignificant χ^2-

difference of 0.87 with two degrees of freedom.) Note that the negative correlation between η_1 and $\eta_2 - \eta_1$ is because η_1 is a component of the difference $\eta_2 - \eta_1$, because $Cov(\eta_1, \eta_2 - \eta_1) = Cov(\eta_1, \eta_2) - Var(\eta_1)$. Hence, if the variances of two latent variables are equal and their correlation is smaller than one, the covariance (and therefore the correlation) between η_1 and $\eta_2 - \eta_1$ will be negative. A similar argument holds

FIGURE 6.5
The Final Model in Its Baseline Version, With Amos Estimates of the Free Parameters
(χ^2 = 11.444, df = 11, p > 0.406, RMSEA = 0.005)

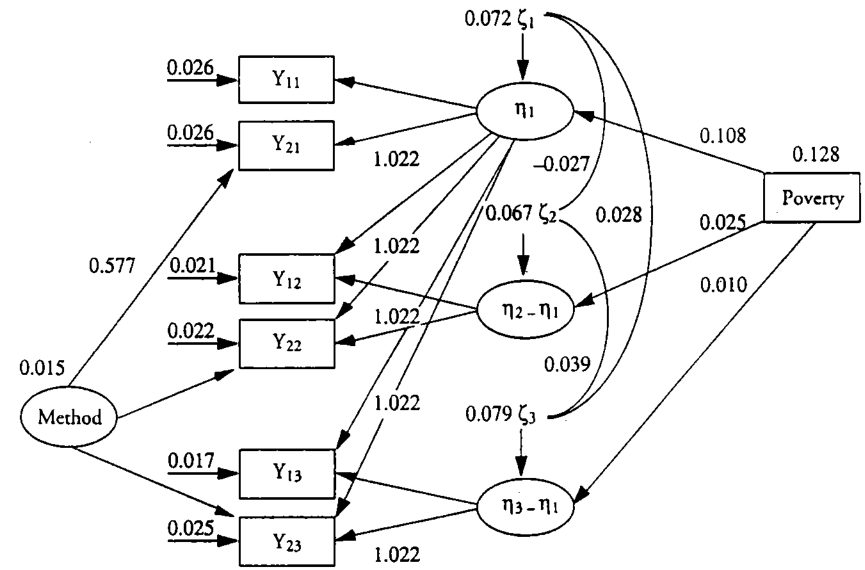


TABLE 6.6
Means, Variances, and Correlations for the Baseline Model (Full Information ML Estimates)

	η_1	$\eta_2 - \eta_1$	$\eta_3 - \eta_1$
Means	1.448	0.006	–0.009
Variances	0.073	0.067	0.079
η_1	1.000		
$\eta_2 - \eta_1$	–0.380	1.000	
$\eta_3 - \eta_1$	–0.364	0.536	1.000
Correlations with poverty	0.143	0.034	0.013
Regression on poverty: slopes	0.108	0.025	0.010
Intercepts	1.415	–0.002	–0.012

for the negative correlation between the two latent change variables $\eta_2 - \eta_1$ and $\eta_3 - \eta_1$. In this version of the MSIP model, the means of the latent change variables are close to zero, reflecting the finding that the means of the latent psychosocial adjustment variables do not change over time.

The Neighbor Model

A similar story is told by the neighbor model. Figure 6.6 displays the neighbor version of the MSIP model. Looking at the correlations between the two latent change variables $\eta_2 - \eta_1$ or $\eta_3 - \eta_2$ and poverty duration (see Table 6.7) again reveals that true intraindividual change in psychosocial adjustment between the neighbored occasions (two vs. one and three vs. two) is not related to poverty duration. The empirical estimates of the correlations are .034 and −.020 (see Table 6.7) and a test of significance yields again a nonsignificant χ^2-difference of 0.87 with two degrees of freedom. In this version of the model, too, the negative correlations between η_1, $\eta_2 - \eta_1$ and $\eta_3 - \eta_2$ are due to the fact that η_1 is a component of both latent difference variables.

The means of the latent change variables are close to zero, which again reflects the finding from the state version of the MSIP model that the means of the latent psychosocial adjustment variables are invariant over time.

FIGURE 6.6
The Final Model in Its Neighbor Version, With Amos Estimates of the Free Parameters (χ^2 = 11.444, df = 11, p > 0.406, RMSEA = 0.005)

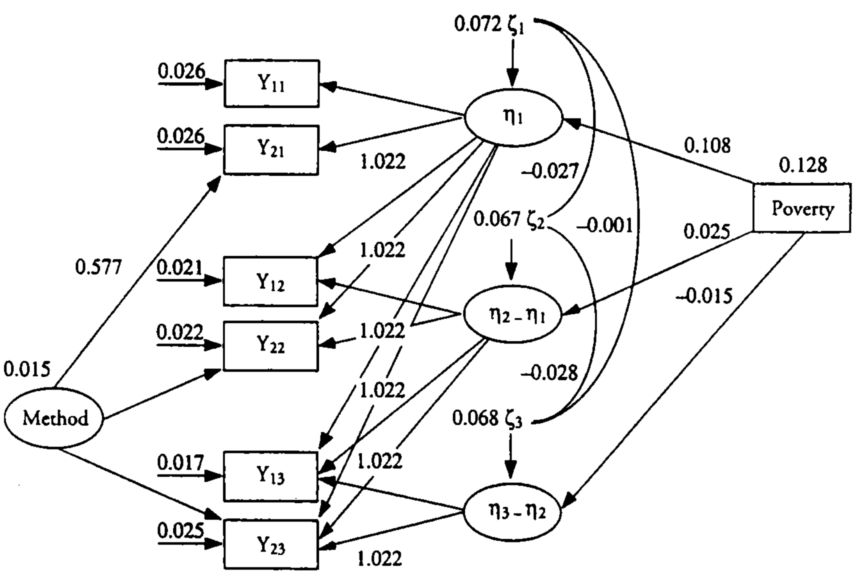


TABLE 6.7
Means, Variances, and Correlations for the Neighbor Model (Full Information ML Estimates)

	η_1	$\eta_2-\eta_1$	$\eta_3-\eta_1$
Means	1.448	0.006	−0.015
Variances	0.073	0.067	0.068
η_1	1.000		
$\eta_2 - \eta_1$	−0.380	1.000	
$\eta_3 - \eta_2$	−0.014	−0.418	1.000
Correlations with poverty	0.143	0.034	−0.020
Regression on poverty: slopes	0.108	0.025	−0.015
Intercepts	1.415	−0.002	−0.010

Discussion

We have shown how to specify a structural equation model such that the true intraindividual change scores between two occasions of measurement are the values of the endogenous latent variables in the model. Whereas the presentation of Steyer et al. (1997) was restricted to the model of essential τ-equivalent variables, we generalized the true intraindividual change approach to the case with different factor loadings for each observed variable (i.e., models with congeneric variables). This was possible only under the assumption of invariant loadings over time. If this restriction holds, one can specify the loading matrix in such a way that certain latent variables can be interpreted as true intraindividual change variables and can examine the predictors of interindividual differences in true intraindividual change. The models presented include mean structures and intercepts of the regressions of the latent psychosocial adjustment (state and change) variables on poverty duration. Within these models it is possible to test hypotheses about the expectations of the latent state (and change) variables and about the effects of explanatory variables on the true intraindividual state (and change) variables.

What are the differences between the true intraindividual change approach and the latent growth curve approach to modeling change? As already noted by Steyer et al. (1997), in latent growth curve models, certain components (such as the linear component) of intraindividual change may be correlated or explained by linear regressions. In contrast, in true intraindividual change models, the true intraindividual change itself, not a particular component of it, may be correlated with other variables, or, alternatively explained through linear regressions on other variables.

In the baseline model, one may study how the true intraindividual changes (in psychosocial adjustment) between the first and the second as well as between the first and the third time points are related to one or more explanatory variables (such as poverty). In the neighbor model, one may study true intraindividual changes between the first and the second as well as between the second and third time points. In contrast, in traditional growth curve models, one may study the linear and/or the quadratic trend in true change across all three time points. Hence, in our mind, true intraindividual change models offer a more direct approach to modeling true change.

In both classes of models, that is, true intraindividual change models and growth curve models, individual growth curves could be estimated via factor score estimation. However, this would be meaningful only for diagnoses of individual change.

According to our example, poverty duration was significantly correlated with the latent psychosocial adjustment state variables but not with the latent intraindividual change variables. Analyzing the data with a growth curve model, we found no significant effect of the poverty variable on the latent slope component or on the latent quadratic component. This finding is not surprising. If poverty is neither related to change between occasions one and two nor to change between occasions two and three, then it will not be related to either the linear or the quadratic trend of change across all three occasions of measurement.

Our empirical findings should not be generalized to say that poverty duration does not have a destructive effect on children's psychosocial adjustment. There are many studies that show a strong, negative effect of poverty on children's development (Duncan & Brooks-Gunn, 1997). In the present case, it may be that the effects of poverty can only be detected when subscales of the Behavioral Problems Index (BPI) are used. Our example uses the entire BPI, although other studies show both that this scale is comprised of multiple factors and that subscales of the BPI (such as antisocial behavior and anxiety/depression) are indeed related to developmental patterns of children's well-being (e.g., Shanahan et al., 1997). The example illustrates our approach to change, but also alerts the analyst that these models require the careful measurement and selection of the change variable, with special attention devoted to securing multiple, relatively parallel indicators.

The neighbor model is especially well-suited to the study of developmental phenomena characterized by discontinuous and rapid change. In such instances, the analyst can test whether exogenous variables differentially predict the $\eta_3 - \eta_2$ change score versus the $\eta_2 - \eta_1$ change score. Thus, one can examine how and why phenomena change before, during, and after transitions. Such an approach has a wide range of applications, including the ability to study in detail the effects of an experimental manipulation or an intervention. In a quasi-experimental framework, data can be organized around naturally occurring transitions. What is the typical pattern of depression before and after retirement and why do some adults get more depressed? What causes some children to be more anxious with the transition to school or some adolescents to suffer losses in self-efficacy with the transition to a new school setting? What predicts changes in marital relationships both before and after the birth of a child? With its focus on true change between measurement occasions, the neighbor model represents a potentially powerful and flexible tool to address questions such as these.

The true intraindividual change versions make explicit in a very convenient way the relationships of the true latent change variables with other variables included in the model. This specification can serve as a useful tool for detailed examinations of intraindividual patterns of developmental change and their interindividual predictors.