STABILITY AND CHANGE IN MIDDLE SCHOOL STUDENTS' SCHOOL VALUE: AN APPLICATION OF LATENT GROWTH CURVE MODELING

Markku Niemivirta
University of Helsinki, Finland

Abstract: Much of the educational and psychological research deals with abstract constructs that rarely are directly measurable. However, it is assumed that such latent constructs do influence observable indicators (e.g., test scores or responses to certain questions), which then can be specified and, subsequently, measured. Structural equation modeling (SEM) is a general statistical modeling technique that can be used not only to model latent constructs but also to examine relations between different latent constructs. Moreover, SEM is usually applied in a confirmatory fashion, meaning that researchers are more likely to use SEM to determine whether a certain model is valid, rather than using SEM to 'find' a suitable model. The flexibility of SEM makes it a powerful modeling tool; Complex issues such as construct equivalence or stability and change over time can be easily approached within the SEM framework. The purpose of this paper is to illustrate the utility of SEM in such contexts. Accordingly, the use of longitudinal means and covariance structures analysis and latent growth curve modeling on substantive research problems will be demonstrated in a non-technical manner.

Key words: Latent growth curve modeling, Measurement invariance, Stability and change.

Address: Markku Niemivirta, Helsinki Collegium for Advanced Studies, P.O. Box 4, FIN-00014 University of Helsinki, Finland. Email: markku.niemivirta@helsinki.fi

Introduction

Many psychological and educational phenomena are dynamic and evolving by nature thus creating patterns of intraindividual change over time (Heckhausen, 2000; Magnusson, 1997; Pulkkinen & Caspi, 2002). Repeated measurements from individuals over multiple time points allow the assessment of the intraindividual change process as it unfolds over time (Bergman, Magnusson, & El-Khouri, 2003; Lerner, Lerner, De Stefanis, & Apfel, 2001). Of the different methodological approaches developed for the study of change, current advancements in *latent growth curve modeling* (LGCM) seem especially promising (Duncan, Duncan, Strycker, Li, & Alpert, 1999; Muthen & Khoo, 1998). As a non-technical introduction to the subject, the present paper illustrates the use of LGCM for assessing stability and change in middle school students' school value.

The contentual focus of our example study is on middle school students' (7^{th} to 9^{th} graders) school value. Following Eccles and her colleagues' work on task value (Eccles & Wigfield, 1995; Wigfield & Eccles, 1992), we define school value as the perceived meaningfulness of schooling in general. In operationalizational terms, the concept of meaningfulness reflects the extent to which students consider school going and studying to be useful, important, and interesting.

Eccles and her colleagues have shown that while ability self-concepts and performance expectancies predict graded performance, task values are more likely to predict course plans and enrollment decisions – even after controlling for prior performance levels. Both expectancies and values have been found to predict career choices. With respect to developmental changes, the research shows quite systematic decrease in task values over the elementary school years. The findings concerning middle school years are similar, although the degree of decline seems to somewhat vary across different school subjects (for reviews, see Wigfield & Eccles, 2000; Wigfield & Eccles, 2002; Wigfield, Eccles, & Rodriguez, 1998).

Based on these findings, we can now formulate a number of research questions. The most relevant question naturally is whether the level of students' school value changes over time. Although this particular question could be addressed with other, more traditional, methods, the utility of LGCM be-comes explicit when we consider the additional questions that can be further dealt with within the LGCM framework. For example: Is there variation in how students' school value changes over time? Does students' prior school performance predict the rate of change in school value? And, does the rate of change in school value predict students' later school performance?

To illustrate the use of LGCM for answering these questions, data from a longitudinal study on student motivation will be used. The participants were 606 students who completed motivation questionnaires once a year during their middle school grades (i.e., 7th, 8th, and 9th grades). The scale on school value comprised of six items that assessed the perceived utility, importance, and interestingness of school going and studying (see Appendix). The internal consistency coefficient (Cronbach's alpha) for the measurement at 7th, 8th, and 9th grade was .83, .83, and .87, respectively.

The assessment of change over time proceeds in two sequential phases (cf. Chan, 1998).[1] First, before we can claim anything about the construct's mean level changes (Phase 2), we must ascertain that we are *assessing the same thing* at each measurement point (Phase 1). In other words, we must establish sufficient measurement invariance over time (Byrne, Shavelson, & Muthen, 1989; Horn & McArdle, 1992; Vandenberg & Lance, 2000). This exceedingly important – yet often overlooked – phase focuses on the structural stability of the given construct. As with many constructs that differentiate or otherwise structurally evolve over time (e.g., self-concept), it would be entirely possible that the *empirical structure* of school value at Time 3 was different from that of, say, Time 1. If that was the case, the change in the mean level would lose its meaning – the scores would simply not reflect identical constructs anymore.

The change in mean level has been referred to as *alpha change*, whereas the fluctuation in structural stability has been referred to as *gamma change* (Golembiewski, Billingsley, & Yeager, 1975). Another type of change that we are interested in here concerns the *normative stability* of the construct (cf. Mortimer, Finch, & Kumka, 1982). This basically refers to the stability of individual ranks on the given attribute; high correlations across time reflect high stability in relative individual differences. Accordingly, although Phase 1 in our analysis focuses on gamma change, it provides some information

[1] This procedure could also be carried out in one single phase by means of a second-order growth model (see Sayer & Cumsille, 2001). However, for the purpose of illustration, the two key phases – invariance testing and growth modeling – are addressed separately here.

about alpha change and normative stability as well, which, in turn, serves as a source of input for Phase 2. Let us now begin with the first phase.

Assessing measurement invariance over time using longitudinal mean and covariance structures analysis

The analytical approach adopted here grounds on longitudinal mean and covariance structures (MACS) analysis. MACS analysis extends the standard structural equation modeling (SEM) techniques by utilizing information on observed mean structures in addition to the usual variance-covariance information (Little, 1997). The strength of MACS analysis comes from the possibility to simultaneously fit factor models with mean structures in different groups or over time and thereby assess differences on disattenuated latent means and covariances.

Figure 1 illustrates the hypothesized model for our example study. In the longitudinal MACS analysis framework, six types of parameters are estimated (Chan, 1998): the factor loadings of the indicators (λ's), the residual (error) variances of the indicators (ε's), the intercepts of the indicators (τ's), the factor means (μ's), the factor variances (σ^2's), and the factor covariances (σ's). All theses parameters can be constrained to be equivalent with the corresponding parameters across the different measurement points. When testing for measurement invariance, the tenability of those constraints is then tested.

The assessment of measurement invariance proceeds in hierarchical steps (see Table 1). A series of models are estimated, and invariance is tested by comparing the goodness of fit statistics of a particular model with a model having additional constraints. For example, testing metric invariance involves comparing the fit of an unconstrained model (Model 1 in Table 1), with a constrained model in which all factor loadings associated with a particular construct are constrained to be equal across measurement points (Model 2). If the imposition of additional constraints results in a significantly poorer fit, then the more restricted model is less correct.

For the purpose of invariance testing, a model similar to the one illustrated in Figure 1 was specified. Equality restrictions were added according to the scheme outlined in Table 1. Following the recommendations by Cheung and Rensvold (2002), the comparative model fit was assessed be means of changes in $\chi^2(\Delta\chi^2)$ and changes in CFI, Comparative Fit Index (ΔCFI). Significant $\Delta\chi^2$ and values > .01 for ΔCFI suggest improvement in the model fit. Indices used for evaluating overall fit were CFI, Root Mean Square Error of

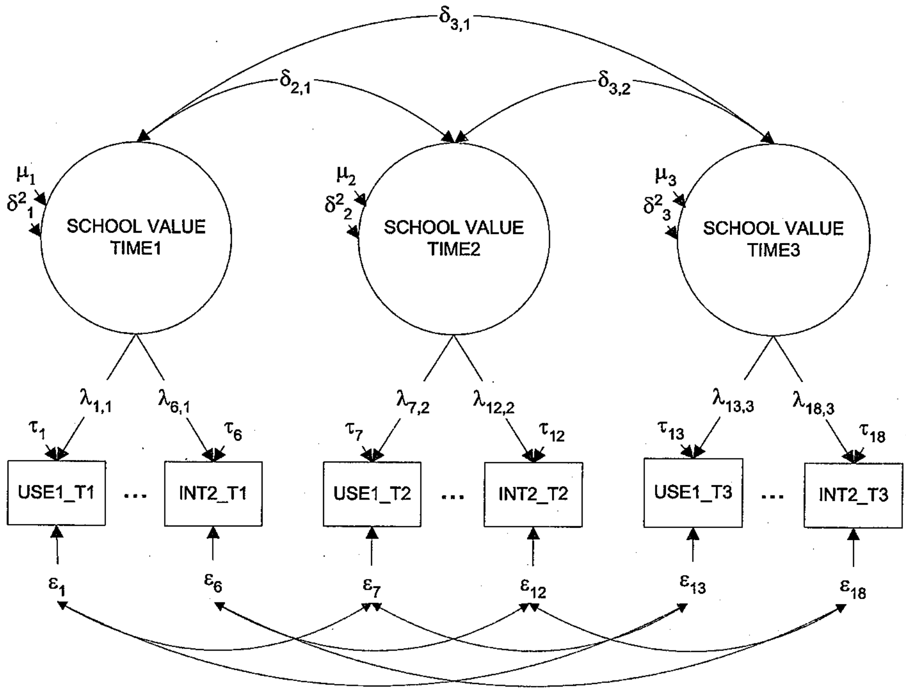

Figure 1. Representation of the Longitudinal Means and Covariance Structures Model.

Table 1. Hierarchical steps in invariance testing

Model	Hypothesis	Comparative Test	Meaning
1	Configural invariance	Overall fit	Equivalent factorial structure over time
2	Metric invariance	2 – 1	Equivalent factor loadings over time
3	Equivalence of residual variance	3 – 2	Equivalent internal consistency (same quality of measures) over time
4	Scalar (item intercept) invariance	4 – 2	Equivalent measurement scales over time
5	Equivalence of construct variance	5 – 2	Equivalent range of responses over time
6	Equivalence of construct covariance	6 – 2	Equivalent relationships among constructs over time
7	Equivalence of latent means	7 – 4	Equivalent mean level over time

Table 2 Goodness of fit statistics for alternative models

Model	Hypothesis	χ^2	*df*	*p*	CFI	RMSEA	SRMR	Hypothesis test	$\Delta\chi^2$	*df*	*p*	ΔCF
M1	Configural invariance	239.24	111	.000	.97	.043	.049	Overall fit				
M2	Metric invariance	252.58	121	.000	.97	.042	.055	M2-M1	13.34	10	.205	.00
M3	Equivalence of residual variance	260.75	131	.000	.97	.040	.059	M3-M2	8.17	10	.612	.00
M4	Scalar (item intercept) invariance	293.88	141	.000	.96	.042	.063	M4-M2	41.30	20	.003	-.01
M4B	M4 + one intercept free	280.99	139	.000	.97	.041	.062	M4B-M2	28.41	2	.056	.00
M5	Equivalence of factor variance	289.01	141	.000	.96	.041	.074	M5-M2	36.43	20	.014	-.01
M6	Equivalence of factor means	305.37	143	.000	.96	.044	.068	M6-M4B	24.38	4	.000	-.01

Approximation (RMSEA) and Standardized Root Mean Square Residual (SRMR). Values ≥ .95 for CFI, ≤ .06 for RMSEA, and ≤ .09 for SRMR are suggested as criteria for good model fit (Hu & Bentler, 1999).

Table 2 summarizes the results of invariance testing. Metric invariance was clearly achieved; the model with equal factor pattern and loadings at different measurement point fit the data better than the base model did. With respect to item-level constraints, the model with equivalent residual variances (M3) obtained slightly better fit than the model with additional constraints on item intercepts (M4). The freeing of one intercept that, according to the modification index, was unjustifiably constrained significantly improved the model fit (cf. model M4B). Adding further equality constraints on factor variances and factor means resulted in relatively poorer fit thus suggesting some degree of non-invariance.

In sum, our tests demonstrated *partial invariance* over time (Byrne et al., 1989). In other words, sufficient construct equivalence was clearly achieved despite the slight time-related non-invariance on one intercept. The results concerning the non-equivalence of factor variances and factor means imply that the range of responses varied slightly at different measurement points, and that the factor means were not identical over time. As pointed out earlier, these findings provide some important preliminary information about the nature of stability and change in the given construct. Most importantly, the latent factor means, 5.19, 4.98, and 4.87 for measurement points 1, 2, and 3, respectively, suggest a steady overall decrease in school value over time. Changes in factor variance (1.19, 1.39, and 1.57 for time 1, 2, and 3, respectively) imply increased heterogeneity in students' responses, yet the disattenuated correlations between latent factors at different measurement points

(65, .71, and .49 between times 1 and 2, times 2 and 3, and times 1 and 3, respectively) demonstrate quite extensive normative stability.

Since the necessary condition for valid LGCM is hereby fulfilled, we are able to proceed to the second phase of the study.

Assessing growth over time using latent growth curve modeling

Within the LGCM framework we are not particularly interested in the observed repeated measures of the given construct over time as such. Instead, we are interested in the unobserved latent factors that are hypothesized to underlie those repeated measures (Curran & Hussong, 2002; Duncan et al., 1999). In other words, we are interested in estimating growth trajectories that presumably give rise to the repeated observed measures.

The strength of LGCM comes from its ability to produce a broad scope of information relevant for describing individual differences in growth. A latent growth curve model regards development as a continuous underlying process and fits a regression curve to a series of repeated measures taken on the same individual. With LGCM, it is possible to describe individual differences in terms of initial levels and their developmental trajectories from those levels. Further, LGCM provides means for estimating variability across individuals in the initial levels and trajectories as well as for testing the contribution of other variables or constructs in explaining those initial levels and growth trajectories. In doing so, LGCM simultaneously focuses on correlations over time, changes in variance, and shifts in mean values, thus using more information available in the measured variables than do traditional methods (Curran & Hussong, 2002).

The Phase 2 of our study included three steps. First, an *unconditional univariate* LGC model was specified in order to assess the general developmental trend in school value. Second, a *conditional model* with prior GPA (Grade Point Averages) as a predictor was specified. This served to evaluate the extent to which the developmental parameters in school value were dependent on prior school achievement. Third, a *full growth model* with both a predictor and sequelae of change was specified. Here the goal was to evaluate whether changes and individual differences in school value predicted later school achievement when the effects of prior achievement were controlled for. An illustration of these models is given in Figure 2.

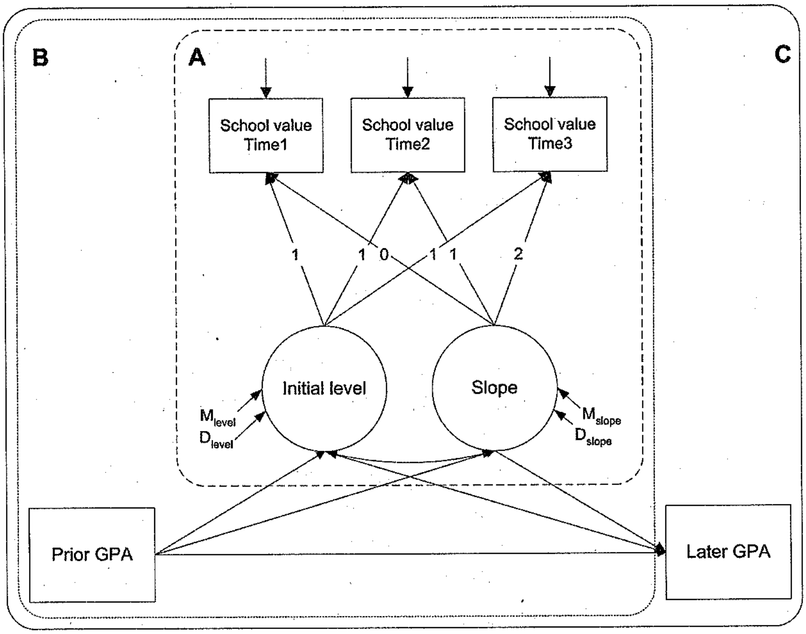

Figure 2. Representation of the Different Latent Growth Curve Models within the Structural Equation Modeling Framework.

Developmental trends in school value

First, an unconditional growth model of school value was specified. The composite scores representing repeated measures at each measurement point were included as observed variables. Two latent factors were defined to represent the intercept (initial level) and slope (rate of change) of the growth trajectory. The factor loadings relating the three observed measures to the intercept factor were fixed to 1 in order to define the starting point of the growth trajectory, and the factor loadings relating the observed measures to the slope factor were fixed to 0, 1, and 2, respectively, to capture a linear growth over the three measurement points (see Model A in Figure 2). Residual variances were constrained to be equal across the measures. The means of the two latent factors were freely estimated while the intercepts of the observed measures were fixed to 0. Therefore, the mean structure among the repeated measures was reproduced through the latent factor means. The mean estimate of the intercept factor (M_{level}) thus represents the mean initial level of the growth trajectory, and the estimate of the intercept variance (D_{level}) represents the degree of individual variability in the initial levels. Similarly, the mean estimate of the slope factor (M_{slope}) represents the mean slope of growth trajectory (i.e., rate of change), and the slope variance (D_{slope}) represents individual variability in the rates of change over time.

The estimated model fit the data well, $\chi^2(3) = 4.464, p = .215$, CFI = .99, RMSEA = .028, SRMR = .067. Parameter estimates revealed both significant decrease in school value over time (M_{slope} = -.151, z = -5.573) and significant variation in the slope of the growth trajectory (D_{slope} = .110, z = 3.893). The model's estimated means for measurement points 1, 2, and 3 were 5.12, 4.97, and 4.82, respectively. The variance of the initial level was also significant (D_{level} = .658, z = 9.324), suggesting that the onset of the growth trajectory varied considerably among the students. Finally, given that the correlation between the intercept and slope factor was not significant (r = -.08, z = -.614), the slope of growth trajectory was not dependent on the starting point.

Prior school performance as a predictor of change in school value

Given the presence of variability in the growth trajectories of school value, we were now able to proceed to the next step and try to model this variance using additional explanatory variables. This allowed us to examine the predictors of change in school value. In the present context, we sought to test whether prior school performance influences the growth trajectories of school value. To do this, we extended the prior growth model by regressing the two growth factors (i.e., intercept and slope factors) on our exogenous variable, prior GPA (see Model B in Figure 2).

This conditional model fit the data well, $\chi^2(4) = 4.592, p = .331$, CFI = 1.00, RMSEA = . 016, SRMR = .055. An examination of the regression parameters linking growth factors with the predictor revealed that prior school performance was a significant predictor of the initial level of school value (β = .39, z = 5.359), but not of the rate of change (β = -.01, z = -.093). In other words, higher grades at 6^{th} grade were associated with higher level of school value at 7^{th} grade. Note, however, that the variance in both the intercept and slope factors remained significant even after the inclusion of prior GPA as a predictor, which means that additional variables would be needed to fully capture individual differences in change over time.

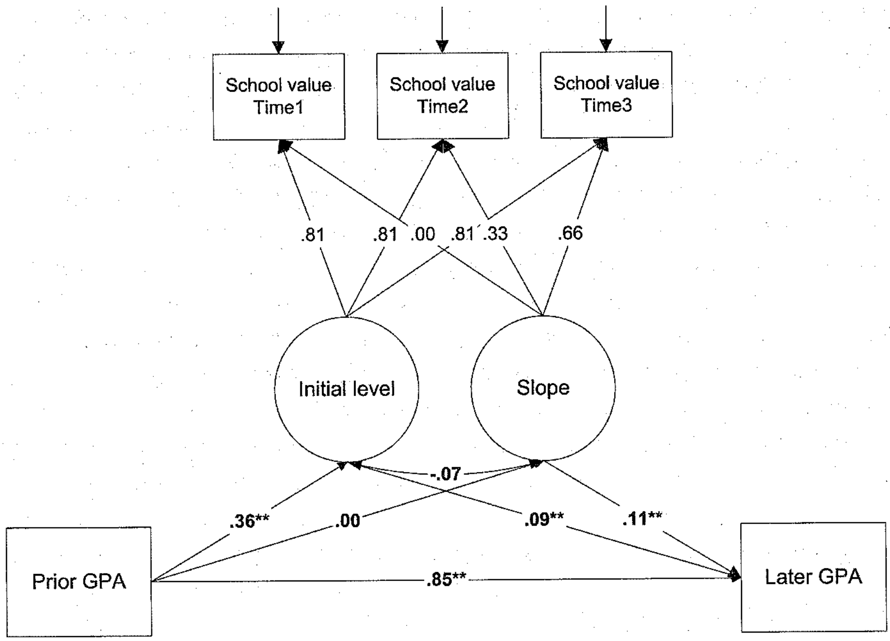

Figure 3. Final full growth model with a predictor and sequelae of change.

Change in school value as a predictor of later school performance

The above analysis revealed that prior school performance influences the level of middle school students' school valuing, but not the rate of change in it. Another interesting question is whether either the level or change in school value influences later school performance when the level of prior school performance in taken into account. This can be accomplished by further extending the conditional model to include an additional dependent variable, later GPA, and regress it on prior GPA and the two growth factors (see Model C in Figure 2).

The fit of this full growth model was excellent, $\chi^2(5) = 4.902, p = .428$, CFI = 1.00, RMSEA = .000, SRMR = .048. The results (see Figure 3) showed that later school performance was predicted not only by prior school performance ($\beta = .851, z = 30.866$), but also by the initial level of school value ($\beta = .09, z = 3.353$) as well as the rate of change in it ($\beta = .11, z = 2.633$). In other words, after controlling for the effects of prior school performance, better later school performance was linked with higher initial level of school value and less steep decrease in school value.

CONCLUSIONS

The aim of this paper was to provide the reader with a non-technical introduction to latent growth curve modeling. Data from a longitudinal study on middle school students' school value were used to illustrate the different phases of assessing stability and change over time. The first phase focused on the assessment of measurement invariance (i.e., the evaluation of construct equivalence over time), while the second dealt with the assessment of change as such as well as the predictors and consequences of that change. Both phases were undertaken within the structural equation modeling framework.

The assessment of measurement invariance showed that the measurements of school value were virtually identical at different time points. In other words, equivalent constructs were assessed each year. The results also suggested quite substantial normative stability in school valuing, as was indicated by high disattenuated correlations between the latent constructs at different measurement points. However, latent factor means revealed slight decrease in school value over time, whereas larger latent factor variance at different time points alluded to increased heterogeneity in students' responses.

The results from the LGC models confirmed these initial impressions. Indeed, significant linear decrease was found in middle school students' school valuing over time. Significant variance in the slope factor was also found, which implies considerable individual differences in the rate of change. Further analyses showed that the level of school value at 7th grade was influenced by 6th grade school performance so that higher prior grades were associated with higher level of later school valuing. The same did not hold for the developmental change. That is, prior achievement did not predict the rate of change in later school value. However, both the initial level of school value and the rate of change in it influenced later school achievement, even after controlling for the effects of prior achievement. Higher grades at the end of 9th grade were associated with higher ratings of school value at grade 7 as well as with a less steep decrease in school value during the middle school years. These findings imply that despite the age-typical decrease in school value over middle school years in general, a more positive 'base line' and a less negative developmental change in school value have a potential of promoting higher achievement in the long run.

The present paper has, hopefully, illustrated the applicability and utility of LGCM for assessing change over time. The main strengths of this approach lie in its flexibility and comprehensiveness. In contrast to some alternative methods, LGCM focuses on various sources of information simultaneously, and, in addition to the assessment of the nature of change itself, allows for the concurrent assessment of the effects of predictors and the consequences of different parameters of change. Although the present example study utilized a simple linear growth model, similar procedure could also be applied to fitting different types of growth trajectories (e.g., quadratic trends, cubic trends, etc.). This would be useful, for example, if one needed to conduct a more precise assessment of the type of change taking place over an extended period of time or when a non-linear developmental trend was more likely than a linear one (for an example, see Curran, Muthen, & Harford, 1998).

Another extension not considered in this presentation, but worth mentioning, concerns the way variation in growth trajectories is examined. The conventional growth model applied here allows heterogeneity corresponding to different growth trajectories across individuals and captures that heterogeneity by variation in the continuous growth factors. However, it cannot capture heterogeneity that corresponds to *qualitatively different development* (Muthen, 2001a). This is important to note, since a single-population model may not always account for all types of individual differences *within a sample*. For example, it would be entirely possible that the apparent heterogeneity in growth was masked by the fact that the sample under study consisted of two or more homogeneous subgroups of individuals with qualitatively different forms of developmental trajectories. Capturing such heterogeneity in development is possible by means of *growth mixture modeling*, which is a method that integrates growth curve modeling with categorical latent variable modeling (Muthen, 2001b; for a simple example, see Niemivirta, 2002).

Finally, it must be noted that, although comprehensiveness and modifiability can be considered as the strengths of the LGCM, they can also be considered as its weaknesses. The fact that the SEM framework enables both the specification of very complex models and a very detailed model modification can result in either so unique models that they are extremely difficult to replicate or so complex models that the findings are extremely difficult to interpret unambiguously (MacCallum & Austin, 2000; MacCallum, Roznowski, & Necowitz, 1992). Careful design and model parsimony are thus the two keys that help to avoid the pitfalls of excess complexity.

APPENDIX

Items of the School Value Scale

Domain	Item
Usefulness	In my opinion, things to be learned in school are useful.
Usefulness	I believe that most of the subjects we study in school will be of use.
Importance	In my opinion, the things we study in school are important.
Importance	I think it is important to manage the issues we study in school.
Interestingness	In my opinion, the things to be learned in school are interesting.
Interestingness	I like most of the subjects we study in school.

REFERENCES

Bergman, L. R., Magnusson, D., & El-Khouri, B. M. (2003). *Studying individual development in an interindividual context: A person-oriented approach*. Mahwah, NJ: Erlbaum.

Byrne, B. M., Shavelson, R. J., & Muthen, B. (1989). Testing for the equivalence of factor covariance and mean structures: The issue of partial measurement invariance. *Psychological Bulletin, 105*, 456-466.

Chan, D. (1998). The conceptualization and analysis of change over time: An integrative approach incorporating longitudinal mean and covariance structures analysis (lmacs) and multiple indicator latent growth modeling (mlgm). *Organizational Research Methods, 1*(4), 421-483.

Cheung, G. W., & Rensvold, R. B. (2002). Evaluating goodness-of-fit indexes for testing measurement invariance. *Structural Equation Modeling, 9*(2), 233-255.

Curran, P. J., & Hussong, A. M. (2002). Structural equation modeling of repeated measures data: Latent curve analysis. In D. S. Moskowitz & S. L. Hershberger (Eds.), *Modeling intraindividual variability with repeated measures data: Methods and applications* (pp. 59-85). Mahwah, NJ: Erlbaum.

Curran, P. J., Muthen, B., & Harford, T. C. (1998). The influence of changes in marital status on developmental trajectories of alcohol use in young adults. *Journal of Studies on Alcohol, 59*(6), 647-658.

Duncan, T. E., Duncan, S. C., Strycker, L. A., Li, F., & Alpert, A. (1999). *An introduction to latent variable growth curve modeling: Concepts, issues, and applications*. Mahwah, NJ: Erlbaum.

Eccles, J. S., & Wigfield, A. (1995). In the mind of the actor - The structure of adolescents' achievement task values and expectancy-related beliefs. *Personality and Social Psychology Bulletin, 21*(3), 215-225.

Golembiewski, R. T., Billingsley, K., & Yeager, S. (1975). Measuring change and persistence in human affairs: Types of change generated by OD designs. *Journal of Applied Behavioral Science, 12*(2), 133-157.

Heckhausen, J. (2000). *Motivational psychology of human development: Developing motivation and motivating development*. New York: Elsevier.

Horn, J. L., & McArdle, J. J. (1992). A practical and theoretical guide to measurement invariance in aging research. *Experimental Aging Research, 18*(3-4), 117-144.

Hu, L.-T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling, 6*(1), 1-55.

Lerner, R. M., Lerner, J. V., De Stefanis, I., & Apfel, A. (2001). Understanding developmental systems in adolescence: Implications for methodological strategies, data analytic approaches, and training. *Journal of Adolescence Research, 16*, 9-27.

Little, T. D. (1997). Mean and covariance structures (macs) analyses of cross-cultural data: Practical and theoretical issues. *Multivariate Behavioral Research, 32*, 53-76.

MacCallum, R. C., & Austin, J. T. (2000). Applications of structural equation modeling in psychological research. *Annual Review of Psychology, 51*, 201-226.

MacCallum, R. C., Roznowski, M., & Necowitz, L. B. (1992). Model modifications in covariance structure-analysis - The problem of capitalization on chance. *Psychological Bulletin, 111*(3), 490-504.

Magnusson, D. (Ed.). (1997). *The lifespan development of individuals: Behavioral, neurobiological, and psychosocial perspectives: A synthesis*. New York: Cambridge University Press.

Mortimer, J. T., Finch, M. D., & Kumka, D. (1982). Persistence and change in development: The multidimensional self-concept. In P. Baltes & O. Brim (Eds.), *Life-span development and behavior* (Vol. 4, pp. 263-313). New York: Academic.

Muthen, B. (2001a). Latent variable mixture modeling. In G. A. Marcoulides & R. E. Schumacker (Eds.), *Advanced structural equation modeling: New developments and techniques* (pp. 1-33). Mahwah, NJ: Erlbaum.

Muthen, B. (2001b). Second-generation structural equation modeling with a combination of categorical and continuous latent variables: New opportunities for latent class-latent growth modeling. In L. M. Collins & A. G. Sayer (Eds.), *New methods for the analysis of change. Decade of behavior* (pp. 291-322). Washington, DC: American Psychological Association.

Muthen, B., & Khoo, S.-T. (1998). Longitudinal studies of achievement growth using latent variable modeling. *Learning & Individual Differences. Special Issue: Latent growth curve analysis, 10*(2), 73-101.

Niemivirta, M. (2002). Individual differences and developmental trends in motivation: Integrating person-centered and variable-centered methods. In P. R. Pintrich & M. L. Maehr (Eds.), *Advances in motivation and achievement* (Vol. 12, pp. 241-275): Amsterdam: JAI Press.

Pulkkinen, L., & Caspi, A. (2002). *Paths to successful development: Personality in the life course*. New York: Cambridge University Press.

Sayer, A. G., & Cumsille, P. E. (2001). Second-order latent growth models. In L. M. Collins & A. G. Sayer (Eds.), *New methods for the analysis of change* (pp. 179-200). Washington, DC: APA.

Vandenberg, R. J., & Lance, C. E. (2000). A review and synthesis of the measurement invariance literature: Suggestions, practices, and recommendations for organizational research. *Organizational Research Methods, 3*(1), 4-69.

Wigfield, A., & Eccles, J. S. (1992). The development of achievement task values - A theoretical analysis. *Developmental Review, 12*(3), 265-310.

Wigfield, A., & Eccles, J. S. (2000). Expectancy-value theory of achievement motivation. *Contemporary Educational Psychology, 25*(1), 68-81.

Wigfield, A., & Eccles, J. S. (2002). The development of competence beliefs, expectancies for success, and achievement values from childhood through adolescence. In A. Wigfield & J. S. Eccles (Eds.), *Development of achievement motivation* (pp. 91-120). San Diego, CA: Academic.

Wigfield, A., Eccles, J. S., & Rodriguez, D. (1998). The development of children's motivation in school contexts. *Review of Research in Education, 23*, 73-118.