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Modeling True Intraindividual Change: True Change as a Latent Variable

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Abstract

It is shown how to specify a structural equation model in such a way that the *true intraindividual change scores* between two occasions of measurement are the values of an endogenous latent variable in the model. This makes possible to explain (and/or study the correlates of) interindividual differences in intraindividual change. An empirical example with data on the mood state of well-being, a well-being trait scale, and a daily hassles and uplift scale, each assessed on four occasions of measurement, illustrates the approach.

Keywords: Intraindividual change, true scores, structural equation modeling, growth curve analysis, measurement of change

The correlation between pretest and posttest usually is not perfect. Oftentimes this correlation is even considerably smaller than expected solely from the existence of measurement errors. In these cases, we often have good reasons to assume that the correlations of the corresponding true score variables are smaller than one and to assume that a retest correlation estimates *stability* instead of *reliability* (see, e.g., Nesselroade, Pruchno & Jacobs, 1986). However, 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. Explaining interindividual differences in intraindividual change is one of the key interests of Developmental Psychology, as well as in other areas such as Evaluation Research and Differential Psychology. In fact, interindividual differences with respect to true change might be an interesting issue for trait theories, e.g., a theory of learning ability. Which are the correlates and the predictors of intraindividual change?

Considerable progress has been made in the last decade in the development and application of structural equation modeling techniques (see, e.g., Marcoulides & Schumacker, 1996). A structural equation model (SEM) explicitly states the relationship between observables and latent variables as well as the relationships among different latent variables. Therefore, SEMs also model the relationship between the covariances (and correlations) of the observables and the covariances (and correlations) of the latent variables. In special cases, the latent variables may be interpreted as true score variables. Hence, SEMs are an appropriate tool to model the relationships between observables and true score variables as well as between the correlations between the two kinds of variables.

A considerable part of the progress in applying SEMs is in analyzing *latent growth curves*. A careful exposition of this topic which builds on the contributions of Rao (1958), Tucker (1958), Rogosa and Willet (1985), McArdle and Anderson

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(1990), McArdle and Epstein (1987), Meredith and Tisak (1990), Tisak and Meredith (1990), as well as Muthén (1991) has been presented by Willet and Sayer (1994), who also provide a review of the relevant literature (see also Willet & Sayer, 1996).

Building on this line of research, Raykov (1996) introduced a model in which the true scores of the observables are explained by a linear function of the true score on occasion one of measurement and of the difference between true score on occasion one and the true score on the last occasion of measurement (see his Model 3). (See Raykov, 1992, for a version of this model for two occasions of measurement.) Although this model again enriches our tool box for modeling intraindividual change, it encorporates the assumption that the true score variable of an observable on occasion of measurement k is a *deterministic* function of the true score variable pertaining to the initial occasion and the true score variable pertaining to the last occasion of measurement. For more than two occasions of measurement this assumption will only hold under very specific circumstances.

The present paper presents a simpler and less restrictive approach to the analysis of interindividual differences in intraindividual change. The basic idea is to specify a structural equation model in such a way that the *true change scores* between each pair of two subsequent occasions of measurement are the values of the endogenous latent variables in the model. This makes possible to explain and/or study the correlates of interindividual differences in intraindividual change. Hence, in contrast to Raykov's Model 3, true intraindividual change between two subsequent occasions of measurement may not be a deterministic linear function of true change between first and last occasion but may vary unsystematically, instead. In the next section, the basic idea will be described in more detail and then illustrated by an empirical example with data on a mood state questionnaire of well-being, a trait questionnaire of well-being, and a daily hassles and uplifts scale.

1 True intraindividual change as a latent variable

Consider the following tautological equation:

$$Y_1 = \tau_1 + \epsilon_1, \text{ where } \epsilon_1 := Y_1 - \tau_1, \tag{1}$$

which is well known from Classical Test Theory (CTT). Such a tautological equation is always true. Since, in science, too, truth is rare, we should try to find more such tautological equations. Here is another one:

$$Y_2 = \tau_2 + \epsilon_2 = 1 \cdot \tau_1 + 1 \cdot (\tau_2 - \tau_1) + \epsilon_2, \text{ where } \epsilon_2 := Y_2 - \tau_2. \tag{2}$$

Readers familiar with structural equation modeling will immediately recognize what we have gained when representing these two tautological equations in a path diagram (see Fig. 1) and read the indices as occasions of measurement. If τ_1 and τ_2 represent the true score variables pertaining to times 1 and 2, the scores of the second latent variable represent *true intraindividual change* which developmental psychologists and others seek to explain by other variables.

Before continuing this line of thought, we should first realize and then get rid of the identification problem in the model characterized by Equations 1 and 2. There are too many unknown parameters pertaining to the latent variables compared to the number of variances and covariances of the observed variables Y_1 and Y_2. Even assuming $Cov(\epsilon_1, \epsilon_2) = 0$, there are five unknown parameters and only two variances and one covariance of the observables Y_1 and Y_2. Considering at least two observables on at least each of two occasions will solve this identifiability problem. Assuming

$$Y_{i1} = \tau_1 + \epsilon_{i1}, \text{ where } \epsilon_{i1} := Y_{i1} - \tau_1, \tag{3}$$

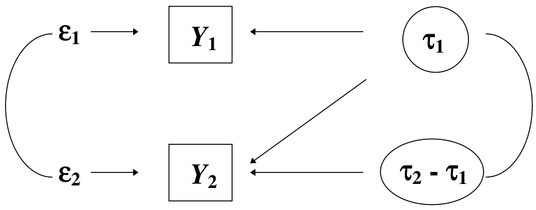

Figure 1: A (nonidentified) model in which the scores of the second latent variable represent the person's true changes between times 1 and 2 with respect to the observables considered.

$$Y_{i2} = \tau_2 + \epsilon_{i2} = 1 \cdot \tau_1 + 1 \cdot (\tau_2 - \tau_1) + \epsilon_{i2}, \text{ where } \epsilon_{i2} := Y_{i2} - \tau_2, \tag{4}$$

$i = 1, \ldots, m,\ m \geq 2$, and uncorrelated measurement errors,

$$Cov(\epsilon_{ik}, \epsilon_{jl}) = 0,\ i \neq j,\ k, l = 1, \ldots, n, \tag{5}$$

(n being the number of occasions of measurement; here $n = 2$) yields an overidentified, testable model. As the two equations in 4 show, this is the model of τ-equivalent variables of CTT for each occasion of measurement. However, using the tautological second equation in 4 shows how to express the relationship between the observables and the true score variables equivalently as a relationship between the observables, the true score variable pertaining to occasion 1, and the difference between the true score variables pertaining to occasions 1 and 2. Note that the second equation in 4 is only a trick to make the true change variable $\tau_2 - \tau_1$ a latent variable in a SEM. Substantively, this second equation means exactly the same as the first one: the decomposition of an observable Y_{i2} into a true score variable τ_2 that is common for all observables at time 2 and a measurement error variable ϵ_{i2}.

Replacing Equation 4 by

$$Y_{ik} = \tau_k + \epsilon_{ik} = 1 \cdot \tau_1 + 1 \cdot (\tau_k - \tau_1) + \epsilon_{ik}, \text{ where } \epsilon_{ik} := Y_{ik} - \tau_k, \tag{6}$$

$k = 1, \ldots, n$, shows how to generalize this model for more than two occasions of measurement. In the sequel, this model (i.e., Equations 3, 5, and 6) will be called the *type 1 true intraindividual change model* (TIC_1 model; see Fig. 2a). Using Equation 6, we consider the true changes between each occasion k of measurement and the first one. If the τ_k are the true score variables pertaining to the occasion k of measurement, it is the true score at the first occasion of measurement against which the true scores at the other occasions of measurement are contrasted.

Of course, differences between other true score variables might be considered as well. For instance, one might want to focus the true change between each pair of two subsequent occasions of measurement. In this case one may *supplement* Equations 3 and 4 by

$$Y_{ik} = \tau_k + \epsilon_{ik} = 1 \cdot (\tau_k - \tau_{k-1}) + 1 \cdot (\tau_{k-1} - \tau_{k-2}) + \ldots + 1 \cdot \tau_1 + \epsilon_{ik}, \tag{7}$$

$$\text{where } \epsilon_{ik} := Y_{ik} - \tau_k,$$

and $k = 3, \ldots, n$. Figures 2a and 2b represent the path diagrams of the resulting models for $n = 3$ occasions of measurement. In the sequel, this model (i.e., Equations 3, 4, 5, and 7) will be called the *type 2 true intraindividual change model* (TIC_2 model; see Fig. 2b). Note that the equations above do neither explicitly

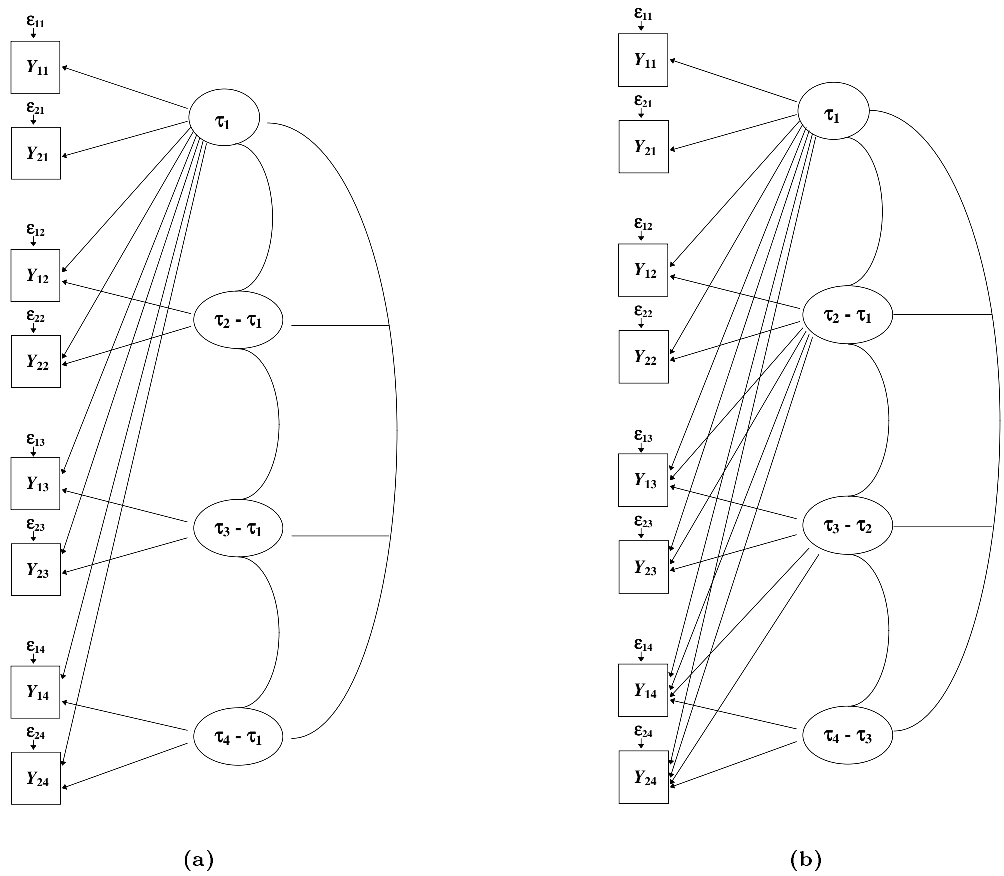

Figure 2: Two single construct true intraindividual change models for two measures on each of three occasions of measurement. All paths are fixed to one. a: TIC_1-model; b: TIC_2-model.

mention the expectations of the observables nor the expectations of the true score variables. Nevertheless, we do *not* have to assume that these expectations are zero. However, the equations above imply: $E(Y_{ik}) = E(\tau_k)$. Therefore, within this model of τ-equivalent variables (see, e.g., Lord & Novick, 1968; Steyer & Eid, 1993), the analysis of the expectations of the true change variables $\tau_k - \tau_{k-1}$ is equivalent to the analysis of the expectations of the observed change $Y_{ik} - Y_{ik-1}$. In Figure 2b, the paths from the each latent variable to the simultaneous observables and all later ones might be confusing at first sight. Note, however, that these paths are a simple translation of the tautological Equation 7 into a path diagram. The only purpose of writing the almost trivial model $Y_{ik} = \tau_k + \epsilon_{ik}$ in this equivalent but more complicated way is to interpret the latent variables in Figure 2b as the true change variables occuring in Equation 7. The substantive theory remains that the observables Y_{ik} at occasion k are determined by the common true score variable τ_k and the specific measurement error variable ϵ_{ik}. Equation 7 (and the implied covariance structure) show that this simple theory already contains the information about the associated true change variables and their covariance structure. Hence, the TIC models only make this information explicit in a very convenient way, allowing to consider the true change variables both as endogenous and as exogenous variables in SEMs.

It should be noted that the models in Figures 2a and 2b are very restrictive in their measurement parts. Especially, the assumptions of uncorrelated errors across different occasions of measurement may not hold in many applications. The well known extensions with correlated errors across time (see, e.g., Marsh, 1993) may be applied to solve this problem. (See also the next section.) Note that the models are *not restrictive at all* in their structural parts, because there, they are saturated. The two models do in no way restrict the correlations between the true score variables τ_k. They are equivalent to a model assuming essential τ-equivalence with each occasion of measurement, uncorrelated errors of measurement, and allowing for arbitrary correlations between the true score variables τ_k. (These models are called *multistate models* by Steyer, Ferring, & Schmitt, 1992).

Allowing for an arbitrary correlation structure between the true score variables may be criticized or welcomed depending on the application considered. The example below shows one out of many possibilities how to restrict the correlations of the latent variables to a certain structure warranted in the specific application. Wherever such restrictions can safely be assumed to hold, they should be implemented in order to increase the precision of estimation.

Extending the models represented in Figures 2a and 2b to include variables on which the true intraindividual change variables $\tau_k - \tau_1$ or $\tau_k - \tau_{k-1}$ may be regressed or with which they may be correlated does not pose any problem: these true intraindividual change variables may be treated as any other latent endogenous variable in structural equation modeling. Nevertheless, an example may help to illustrate this approach.

2 An Example

Sample. A sample of 291 females and 212 males between 17 and 77 years of age (mean age: 31.2 years) filled in a couple of questionnaires on four occasions of measurement, each of them three weeks apart. The subjects were paid DM 50 for completing the tests on all four occasions of measurement. About half of the subjects were assessed in group sessions in a lecture room at the University of Trier. The other half of the subjects were recruited via a snowball system and filled in their questionnaires at home. (For a more detailed description of the sample and design, see Steyer, Schwenkmezger, Eid, & Notz, 1991.) The sample analyzed consists of those 503 among the 548 original subjects who delivered their questionnaires on all four occasions. Among some others, a mood state questionnaire, a mood trait questionnaire, and a daily hassles and uplifts scale were administered.

Variables. The mood state questionnaire MDBF (Steyer, Schwenkmezger, Notz & Eid, 1994, 1997) consists of three mood state scales, only one of which, the *well-being state scale*, is analyzed in this example. The well-being state scale (WS) consists of four positively ("In this moment I feel ... well") and four negatively ("... not well") formulated items each of which has to be rated on a five point Likert scale. Two negatively formulated items were recoded and aggregated together with two positively formulated items to a first score (WS_{1k}) and the same procedure was applied to the other four items yielding a second (parallel) score (WS_{2k}), both indicating the well-being state on occasion k of measurement.

The *well-being trait scale* (WT) has been adopted from the German version of the "Mood Survey" (Bohner, Schwarz, & Hormuth, 1989) originally developed by Underwood and Froming. It consists of nine positively ("most of the time I feel happy") or negatively ("I often feel blue") formulated items each of which has to be rated on a five point Likert scale, too. Negatively formulated items were recoded and aggregated together with the positively formulated items to one scale value for each of the four occasions of measurement. Finally, these four scale values were aggregated into two parallel forms by aggregating the scores of occasions one and three (WT_1) as well as the scores of occasions two and four (WT_2).

The daily hassles and uplifts scale (HU) consists of 60 dichotomous items asking whether or not a daily hassle ("I missed a bus or a train") or a daily uplift ("I had a good conversation") occured. Two parallel scales (HU_{1k} and HU_{2k}), each consisting of an equal number of uplifts and hassles, were constructed for each of the four occasions k of measurement such that a high score indicates few hassles and/or many uplifts. The 60 items of this scale were extracted from the German translation of the Lazarus and Cohen (1977) scales published by Filipp, Ahammer, Angleitner, and Olbrich (1980). (For a complete documentation of all questionnaires mentioned see Steyer et al., 1991). Table 1 displays the correlations, standard deviations, and means of these variables for all four occasions of measurement.

Model 1. Figure 3 displays a TIC_2 model with across time correlations among the error variables pertaining to the same "parallel" form. All loadings are fixed to one. The measurement error variances are .14 for the errors pertaining to WS_{11} and WS_{21} and .09 for the other six measurement error variables. (There are equality constraints.) The variances and correlations of the latent variables are shown in Table 2. WS_1 denotes the true well-being state variable at occasion 1, whereas WS_{2-1} is an abbreviation for the difference $\mathrm{WS}_2-\mathrm{WS}_1$ between the true well-being state variables WS_2 and WS_1. The other latent variables such as WS_{3-2} and WS_{4-3} are defined correspondingly. Allowing for correlated measurement errors considerably increases the fit of the model. The χ^2-difference is $107.22 - 23.93 = 83.29$ with $27 - 25 = 2$ degrees of freedom. According to Figure 3 (and Table 2), there are only nonzero correlations between neighboured latent variables, whereas there are no correlations between the latent variables WS_1 and WS_{3-2}, WS_1 and WS_{4-3}, and between WS_{2-1} and WS_{4-3}. In fact, the corresponding correlations were fixed to zero without significant loss of fit. (The χ^2-difference is $23.93-23.39 = 0.54$ with $25 - 22 = 3$ degrees of freedom.) Note that $\mathrm{WS}_{2-1} = \mathrm{WS}_2-\mathrm{WS}_1$, for instance, correlates with $\mathrm{WS}_{3-2} = \mathrm{WS}_3-\mathrm{WS}_2$ because of the common component WS_2. The same argument holds for the correlation of the difference variables WS_{3-2} and WS_{4-3} because of their common component WS_3.

A caveat concerns the interpretation of the latent variables. As soon as there are correlated measurement errors, it is doubtful if the variables WS_k should still be interpreted as true score variables. However, if in fact the residuals of the observables *are* interpreted as measurement error variables, then the latent variables such as WS_{2-1} must be interpreted as the difference between the true score variables WS_2 and WS_1. Note that this conclusion does not rely on any plausibility argument. It is also not based on the correlation structure of the latent variables. Instead this conclusion is a logical derivation from the equations defining the TIC_2 model.

Model 2. Which are important correlates of the true intraindividual change variables? Model 2 gives an answer. This model consists of:

(a) a measurement model of the type discussed above for the well-being state variables WS_{ik},

(b) another measurement model of the same type for the daily hassles and uplifts scales HU_{ik},

(c) a third measurement model for the two well-being trait scales WT_1 and WT_2.

Again, for all three measurement models the loadings are all fixed to one and the same correlation structure of the measurement error variables as in Model 1 is assumed. The first measurement model for the variables WS_{ik} is exactly the same as Model 1. Even the estimates of the variances of the measurement errors are the same: .14 for the first occasion of measurement and .09 for the other occasions.

Table 1: Means, standard deviations, and correlations of the observables.

	WS_{11}	WS_{21}	WS_{12}	WS_{22}	WS_{13}	WS_{23}	WS_{14}	WS_{24}	WT_1	WT_2	HU_{11}	HU_{21}	HU_{12}	HU_{22}	HU_{13}	HU_{23}	HU_{14}	HU_{24}
Mean	3.751	3.649	3.773	3.715	3.753	3.669	3.871	3.773	3.436	3.416	3.496	3.532	3.487	3.479	3.501	3.418	3.483	3.515
Std	0.878	0.918	0.911	0.939	0.922	0.915	0.866	0.880	0.750	0.752	0.411	0.530	0.456	0.516	0.465	0.521	0.461	0.527
WS_{11}	1.0000																	
WS_{21}	.8191	1.0000																
WS_{12}	.2197	.2272	1.0000															
WS_{22}	.2235	.2864	.8907	1.0000														
WS_{13}	.2303	.2209	.2777	.2893	1.0000													
WS_{23}	.2484	.2865	.3007	.3468	.8895	1.0000												
WS_{14}	.2579	.2182	.3393	.3293	.3338	.3571	1.0000											
WS_{24}	.2304	.2438	.3233	.3501	.3664	.4279	.8772	1.0000										
WT_1	.3851	.4648	.3342	.3728	.3602	.4302	.3350	.4189	1.0000									
WT_2	.3480	.4209	.3830	.4313	.3628	.4290	.3979	.4749	.9285	1.0000								
HU_{11}	.2845	.3302	.1393	.1574	.1374	.1533	.1774	.1867	.2889	.2598	1.0000							
HU_{21}	.4021	.3790	.1393	.1397	.2094	.2396	.2042	.1729	.2969	.2802	.4724	1.0000						
HU_{12}	.1371	.1432	.3694	.3820	.1388	.1691	.2104	.1761	.2631	.2929	.3625	.3613	1.0000					
HU_{22}	.1565	.1543	.4310	.4163	.1774	.1942	.2014	.1643	.2533	.2866	.3099	.4011	.5358	1.0000				
HU_{13}	.1380	.1369	.1834	.1842	.3471	.3611	.2491	.2426	.2808	.2884	.3354	.3058	.3648	.2514	1.0000			
HU_{23}	.1482	.1298	.1929	.1877	.4623	.4392	.2936	.2790	.3093	.3192	.2348	.3943	.2899	.4072	.5009	1.0000		
HU_{14}	.0991	.1242	.1579	.1704	.1452	.2045	.3896	.4025	.3013	.3129	.3111	.2621	.3459	.2809	.4006	.3391	1.0000	
HU_{24}	.1315	.1281	.1939	.1731	.1793	.2244	.4360	.4306	.2601	.2905	.2220	.3123	.2642	.3443	.3253	.3755	.5797	1.0000

Note. The labels of the variables are explained in the text.

Table 2: Variances and correlations of the latent variables for Model 1

	WS_1	WS_{2-1}	WS_{3-2}	WS_{4-3}
Var	0.661	1.055	0.999	0.831
WS_1	1.000			
WS_{2-1}	-.573	1.000		
WS_{3-2}	.000	-.494	1.000	
WS_{4-3}	.000	.000	-.495	1.000

Note. The covariances of the error variables are estimated .00 for the errors pertaining to WS_{1k} and WS_{1l} and .04 for the errors pertaining to WS_{2k} and WS_{2l}. All zeroes in the table denoted .000 are also fixed to zero.

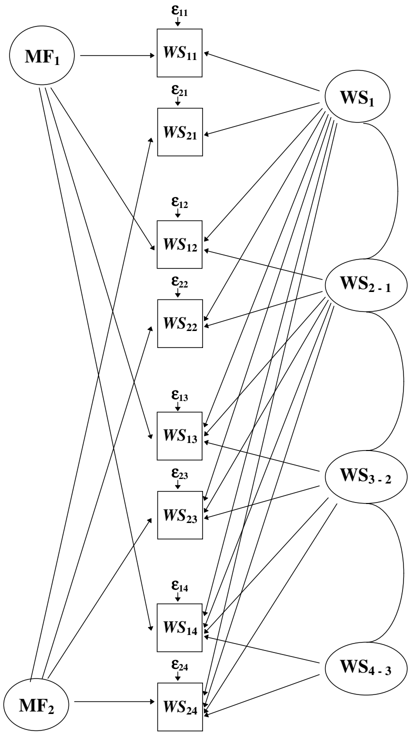

Figure 3: A single construct true intraindividual change model for two measures on each of four occasions of measurement. The measurement errors are allowed to correlate across time. However, their correlation structure is restricted by $Cov(\epsilon_{1k}, \epsilon_{1l}) = \theta_1$ and $Cov(\epsilon_{2k}, \epsilon_{2l}) = \theta_2$ for all $k, l = 1, \ldots, 4, k \neq l$. All paths are fixed to one. Goodness of fit statistics: χ^2 with 25 degrees of freedom: = 23.93 ($p = 0.52$), RMSEA = 0.0, adjusted goodness of fit index AGFI = 0.98.

The second measurement model for the daily hassles and uplifts scales HU_{ik} is the same as the previous one, with the exception that the equality constraints now hold for those variances of the measurement errors that pertain to the same scale. Their estimates are .09 and .14, respectively. The third measurement model is a model of parallel tests, i.e., equal loadings (fixed to one) and equality constraints for the two measurement error variances. Their estimates are .04.

Figure 4 describes the correlation structure between the true score change variables and the effect of the well-being trait (WT) on the true well-being state at

Table 3: Variances and correlations of the latent variables of Model 2

	WS_1	WS_{2-1}	WS_{3-2}	WS_{4-3}	HU_1	HU_{2-1}	HU_{3-2}	HU_{4-3}	WT
Var	0.656	1.055	0.997	0.835	0.103	0.092	0.111	0.103	0.524
WS_1	1.000								
WS_{2-1}	-.568	1.000							
WS_{3-2}	.000	-.497	1.000						
WS_{4-3}	.000	.000	-.499	1.000					
HU_1	.553	-.216	.000	.000	1.000				
HU_{2-1}	-.358	.630	-.357	.000	-.398	1.000			
HU_{3-2}	.000	-.286	.588	-.214	.000	-.524	1.000		
HU_{4-3}	.000	.000	-.285	.538	.000	.000	-.402	1.000	
WT	.454	.000	.000	.000	.438	.000	.000	.000	1.000

occasion 1 (WS_1) and on the true daily hassle state at occasion 1 (HU_1). The estimated correlations are given in Table 3. Whereas there is a considerable effect of the well-being trait on the well-being state and on the daily hassle state on occasion 1, there is neither an effect of the well-being trait on the true change variables, nor are there correlations between nonneighboured true change variables. In fact, the corresponding effects and correlations could be fixed to be zero. (The χ^2-difference between the restricted and the nonrestricted model is $225.00 - 214.07 = 10.93$ with $135 - 117 = 18$ degrees of freedom.)

The correlations between the true change variables within each occasion of measurement range from .538 to .630. This shows that the true change in daily hassles is in fact an important correlate of the true change in the state of well-being. Whereas a causal interpretation of the state-trait regression seems reasonable, there is no safe ground for explaining the true well-being change by the true change of the daily hassles, although such an interpretation might seem natural at first sight. The reason for being cautious with respect to such a causal interpretation is that the daily hassles are *self-reported*. Hence, it may very well be that the number of daily hassles *reported* is determined to some degree by the actual mood state.

One might also raise the question whether or not it is meaningful to introduce a true score variable for a daily hassles and uplifts scale. How to interpret such a variable? Although a careful discussion of the pros and cons of this procedure is not the focus of this paper, note that the number of daily hassles and uplifts reported in each of the two "parallel" forms is certainly error prone to a certain extent. Hence it seems better to filter out the measurement error by introducing a true score variable. However, there might be better ways to model the daily hassles and uplifts scales.

3 Discussion

In TIC models, each individual may have a different latent growth curve, the growth (or decline) between two subsequent occasions of measurement being the scores of the latent variables $\tau_k - \tau_{k-1}$, for instance. Although it may simplify the clarity of results, there is no logical necessity for the time intervals between subsequent observations to be the same for each individual. In fact, different time intervals between two subsequent occasions of measurement k and $k-1$ may serve as a predictor for interindividual differences in intraindividual change. Of course, a measure of interindividually varying time intervals would need to be included in the design in order to disentangle time effects from other effects on true change. Otherwise, the actual time distance between two subsequent occasions of measurement is not taken

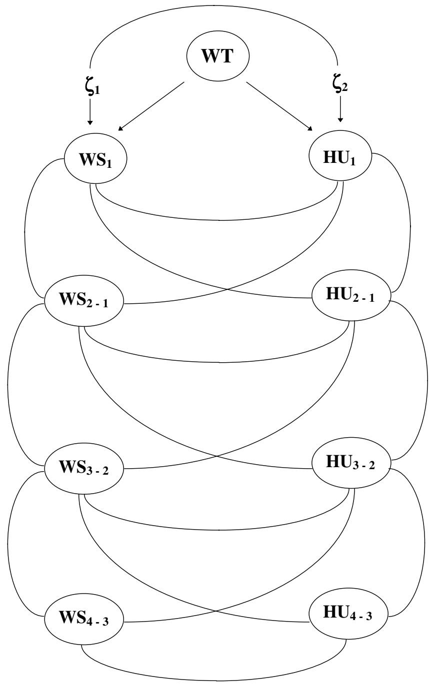

Figure 4: The structural model for Model 2. Goodness of fit statistics: χ^2 with 135 degrees of freedom: 225.00 ($p \leq 0.01$), RMSEA = 0.036, adjusted goodness of fit index (AGFI) = 0.94.

into account in TIC models. In this perspective, different time intervals for different individuals is considered one out of many possible reasons for interindividual differences in intraindividual change. It should also be realized that, in contrast to the latent growth curve models, our approach may not be used to model growth curves for *continuous* time.

Whereas in latent growth curve models, certain *components* (such as the linear component) *of intraindividual change* may be correlated or explained by linear regressions, in TIC models the *true intraindividual change* itself, not a particular component of it, may be correlated with, or, alternatively, explained in linear regressions by other variables. One approach may be prefered over the other depending on the substantive questions investigated.

It should be noted that, if the occasions of measurement are replaced by different constructs, we may now model interindividual differences in true intraindividual differences with respect to the similarity of their scores on two true score variables. Why do some people have a larger gap between their true IQ and their achievement in school than others? What are the determinants and consequences of larger or smaller discrepancies in action control beliefs and actual school performance (cf., e.g., Little, Oettingen, Stetsenko, & Baltes, 1995)? In questions like these we use true score differences as an endogenous or as an exogenous variable.

Note that we have been able to answer questions of this type all the time. The equivalence of the TIC models with the corresponding latent state models (see, e.g., Steyer et al., 1992) shows that the TIC models do not give any new information that is not already implicitly contained in the well-known latent state models. The TIC models only make this information explicit in a very convenient way.

What are the limitations? Clearly, we did not show how to analyze changes in means and group differences, although this might be important for many applications. Furthermore, we did not address the question how to generalize the TIC models for congeneric (in lieu of parallel) variables. Another issue would be a more systematic treatment of correlated measurement errors in true intraindividual change models. Last but not least, factor score estimates of the true score difference variables might be of interest for the assessment of individual consistency. A comparison with Asendorpf's (1990) approach might be fruitful. All these points seem promising issues for future research.

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Appendix

LISREL 8 input files for Model 1 and Model 2

Model 1

TI: Simple true change model for a single construct which is assessed with 2 indicators on each of 4 occasions. Correlations across time between measurement errors are allowed.

```
DA NI = 18 NO = 503 MA=CM
LA FI = change.lab
KM FI = change.cor
SD FI = change.std
SE
1 2  3 4  5 6  7 8  /
MO NY=8 NE=4 TE=SY,FI PS=SY,FI
LE
WS1 WS2-1 WS3-2 WS4-3
VA 1.0 LY(1,1) LY(2,1) LY(3,1) LY(4,1) LY(5,1) LY(6,1) LY(7,1) LY(8,1)
VA 1.0 LY(3,2) LY(4,2) LY(5,2) LY(6,2) LY(7,2) LY(8,2)
VA 1.0 LY(5,3) LY(6,3) LY(7,3) LY(8,3)
VA 1.0 LY(7,4) LY(8,4)
FR PS(1,1) PS(2,2) PS(3,3) PS(4,4)
```



```
FR PS(2,1) PS(3,2) PS(4,3)
FR TE(1,1) TE(2,2) TE(3,3) TE(4,4) TE(5,5) TE(6,6) TE(7,7) TE(8,8)
EQ TE(1,1) TE(2,2)
EQ TE(3,3) TE(4,4) TE(5,5) TE(6,6) TE(7,7) TE(8,8)
FR TE(3,1) TE(5,1) TE(7,1) TE(5,3) TE(7,3) TE(7,5)
FR TE(4,2) TE(6,2) TE(8,2) TE(6,4) TE(8,4) TE(8,6)
EQ TE(3,1) TE(5,1) TE(7,1) TE(5,3) TE(7,3) TE(7,5)
EQ TE(4,2) TE(6,2) TE(8,2) TE(6,4) TE(8,4) TE(8,6)
OU ND=3 WP SI=LISOUT.MAT AD=OFF MI SE SC
```

Model 2

TI: Simultaneous true change model for 2 constructs, each of which is assessed with 2 indicators on each of 4 occasions. One additional trait is assessed with two indicators. Correlations across time between measurement errors are allowed.

```
DA NI = 18 NO = 503 MA=CM
LA FI = change.lab
KM FI = change.cor
SD FI = change.std
SE
1 2  3 4  5 6  7 8    11 12  13 14  15 16  17 18   9 10 /
MO NY=18 NE=9 BE=FU,FI TE=SY,FI PS=SY,FI
LE
WS1 WS2-1 WS3-2 WS4-3
HU1 HU2-1 HU3-2 HU4-3  WT
VA 1.0 LY(1,1) LY(2,1) LY(3,1) LY(4,1) LY(5,1) LY(6,1) LY(7,1) LY(8,1)
VA 1.0 LY(3,2) LY(4,2) LY(5,2) LY(6,2) LY(7,2) LY(8,2)
VA 1.0 LY(5,3) LY(6,3) LY(7,3) LY(8,3)
VA 1.0 LY(7,4) LY(8,4)
VA 1.0 LY(9,5) LY(10,5) LY(11,5) LY(12,5) LY(13,5) LY(14,5) LY(15,5) LY(16,5)
VA 1.0 LY(11,6) LY(12,6) LY(13,6) LY(14,6) LY(15,6) LY(16,6)
VA 1.0 LY(13,7) LY(14,7) LY(15,7) LY(16,7)
VA 1.0 LY(15,8) LY(16,8)
VA 1.0 LY(17,9) LY(18,9)
FR BE(1,9) BE(5,9)
FR PS(1,1) PS(2,2) PS(3,3) PS(4,4) PS(5,5) PS(6,6) PS(7,7) PS(8,8) PS(9,9)
FR PS(2,1) PS(5,1) PS(6,1) PS(3,2) PS(5,2) PS(6,2) PS(7,2)
FR PS(4,3) PS(6,3) PS(7,3) PS(8,3) PS(7,4) PS(8,4) PS(6,5) PS(7,6) PS(8,7)
FR TE(1,1) TE(2,2) TE(3,3) TE(4,4) TE(5,5) TE(6,6) TE(7,7) TE(8,8) TE(9,9) TE(10,10)
FR TE(11,11) TE(12,12) TE(13,13) TE(14,14) TE(15,15) TE(16,16) TE(17,17) TE(18,18)
FR TE(3,1) TE(5,1) TE(7,1) TE(5,3) TE(7,3) TE(7,5)
FR TE(4,2) TE(6,2) TE(8,2) TE(6,4) TE(8,4) TE(8,6)
FR TE(11,9) TE(13,9) TE(15,9) TE(13,11) TE(15,11) TE(15,13)
FR TE(12,10) TE(14,10) TE(16,10) TE(14,12) TE(16,12) TE(16,14)
EQ TE(3,1) TE(5,1) TE(7,1) TE(5,3) TE(7,3) TE(7,5)
EQ TE(4,2) TE(6,2) TE(8,2) TE(6,4) TE(8,4) TE(8,6)
EQ TE(11,9) TE(13,9) TE(15,9) TE(13,11) TE(15,11) TE(15,13)
EQ TE(12,10) TE(14,10) TE(16,10) TE(14,12) TE(16,12) TE(16,14)
EQ TE(1,1) TE(2,2)
EQ TE(3,3) TE(4,4) TE(5,5) TE(6,6) TE(7,7) TE(8,8)
EQ TE(9,9) TE(11,11) TE(13,13) TE(15,15)
EQ TE(10,10) TE(12,12) TE(14,14) TE(16,16)
EQ TE(17,17) TE(18,18)
OU ND=3 WP SI=LISOUT.MAT AD=OFF MI SE SC
```

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