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The integrated trait–state model ☆

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Abstract

It has been acknowledged that both trait and state contribute to psychological measurements. However, existing structural equation models for disentangling these sources of variability are based on assumptions that are not tenable in the light of empirical results. A new model is presented, termed the integrated trait–state (ITS) model, which both decomposes state and trait variance and allows one to test the assumptions that underly existing approaches. This is illustrated with an empirical example. The relationship between the ITS model and other analytic approaches as well as conceptual models of traits and states are discussed.

Keywords: Trait; State; Intraindividual; Idiographic; P-technique; Dynamic factor analysis

1. Introduction

Traditionally, traits have been an important object of psychological research, especially in the realm of personality and ability. The trait concept and its utility have also received sharp and lingering criticism at various times even from those committed to the study of personality (e.g., Mischel, 1968; Pervin, 1994). One of the major concerns has arisen in longitudinal research where it was shown that traits are not as stable as they were once thought to be both across occasions and over situations. Also, the prediction of future

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behaviors based on current traits turned out to be less than impressive. Consequently, social psychologists, for instance, argued that not person (i.e., trait-like) characteristics but situational characteristics should be a key focus of psychological research. Still other writers claimed that both person and situation characteristics and their interactions are fundamental to understanding cross-situational stability and variability in a person's behavior (Buss, 1989; Epstein, 1984; Smith, 1988). This interactional view is closely related to the trait–state distinction, in which a trait is considered to be a person characteristic that remains stable across time and situations, and a state is considered to reflect a person's adaptation to a particular situation. From this it follows that when individuals are measured at a given occasion it is likely that variation in both trait and state contribute to the variation in observed behavior.

By acknowledging that traits and states may be confounded in psychological measurements, how to disentangle them becomes a salient issue. Several structural equation modeling (SEM) approaches to this problem have been suggested. For instance, Kenny and Zautra (2001) have introduced the stable trait, autoregressive trait and state (STARTS) model. While this model can be used to model the relatedness of observations over time, it cannot be used to investigate similarities and differences across people's state structures, or across the trait and the state level since it is an univariate technique. A multivariate longitudinal SEM approach is the latent state–trait (LST) model developed by Steyer and his colleagues (Schmitt & Steyer, 1993; Steyer, Schwenkmezger, & Auer, 1990; for extensions see Cole, Martin, & Steiger, 2005; Schermelleh-Engel, Keith, Moosbrugger, & Hodapp, 2004; Tisak & Tisak, 2000), which allows for the simultaneous modeling of trait-like and state-like variability in a factor model. However, it is based on the assumption that the factor structure underlying these two kinds of variability are identical. This implies that the factor structure of states must be identical across individuals. Although there exists some evidence for this assumption (e.g., Borkenau & Ostendorf, 1998; Garfein & Smyer, 1991), there are many studies that led to the conclusion that individuals' state structures are characterized by important idiosyncracies (Hamaker, Dolan, & Molenaar, 2005; Hooker, Nesselroade, Nesselroade, & Lerner, 1987; Hurlburt & Melancom, 1987; Quinn & Martin, 1999; Shifren, Wood, Hooker, & Nesselroade, 1997; Zevon & Tellegen, 1982).

In the current paper, a new SEM-based technique is presented to overcome the limitations of these previous techniques through combining several existing ideas from the trait–state literature. We illustrate the use of this new approach with an empirical example. At the end of this paper we discuss ways in which this new approach can be extended, and how it is connected to other conceptualizations of traits in the personality literature. For clarity we begin by indicating how the terms *trait* and *state* are used throughout this paper.

1.1. Defining traits and states

The distinction between traits and states dates back at least to the beginning of the Christian era (Eysenck, 1983). It has been cast in terms of stability versus change (Hertzog & Nesselroade, 1987), consistency versus change (Cervone, 2004), consistency versus discriminativeness (Funder, 1994), invariance versus variability (Mischel, 2004), disposition versus dynamics (Mischel, 1973), and person versus situation (Meijer, 1994; Steyer, Schmitt, & Eid, 1999). Although few (if any) will hold the extreme viewpoint that trait level never changes across the individual's life-span, most will probably agree that stability in some form (see e.g., Mortimer, Finch, & Kumka, 1982) is the most distinctive feature of a trait. Traits have been defined as relatively stable, interindividual differences in proneness (Eysenck, 1983; Spielberger & Sydeman, 1994), tendency (Spielberger & Sydeman, 1994), style (Mischel, 1968), or disposition (Block, 1993; Forgays, Forgays, & Spielberger, 1997) to behave (Block, 1993; Mischel, 1968), feel (Spielberger & Sydeman, 1994), or think in certain ways (Goldberg, 1994; Pervin, 1994; Spielberger & Sydeman, 1994). A straight forward application of this idea is to consider an individual's mean over time (which is cleared from situational influences) as his/her trait score (Buss, 1989; Epstein, 1980). While this is the way in which trait is conceptualized in the following sections, we discuss a more general conceptualization in the final section of this paper.

Defining traits as invariant across time and situations implies that traits are *time-invariant* interindividual or between-person differences. In addition, we can distinguish between two kinds of *time-varying* interindividual differences, both of which are depicted in Fig. 1. The first is *intraindividual* or within-person *change*, also referred to as *trait change* (Cattell, 1978), which has been defined as relatively slow changes that are (more or less) irreversible, reflecting processes such as maturation, learning, and progressive organic damage (Nesselroade, 1991). The second is *intraindividual variability*, also referred to as *state variation* (Nesselroade, 1991; Nesselroade, 2001), and it is defined as relatively rapid and reversible variability that takes place around the intraindividual's mean or trend. This implies that the intraindividual mean represents a person's trait-level, while a changing mean represents trait change. The discrepancy between the mean or trend and the actual observation is the state.[1] These states may be associated with the exogenous environment, such as the social and physical situation, or the endogenous environment, such as physiological, emotional, and cognitive processes taking place within the individual. Hence, what is often referred to as measurement error and discarded, we refer to as state and consider potentially meaningful.

Clearly, the concepts of intraindividual stability, variability, and change are closely related. In this paper, we focus on intraindividual stability (i.e., trait) and variability (i.e., state) because we hold the opinion that understanding the trait–state issue is a prerequisite for studying the dynamics of trait change.

1.2. Interindividual and intraindividual relationships between variables

Factor analysis and principal component analysis are two techniques that are widely used in trait and state research to determine a reduced number of dimensions underlying the observed set of variables. Both techniques are based on analyzing the covariance structure of the observed variables. Thus, to explain how it is possible that dimensions found at the interindividual level are not necessarily replicable at the intraindividual level, we need to look at the covariance between variables at these different levels. To simplify matters, we look at a bivariate example.

[1] This definition differs from definitions used by Steyer and his colleagues (e.g., Steyer et al., 1990; Fleeson, 2001; Kenny and Zautra, 2001). Their definitions stem in part from the models they use and particular aspects of these models (such as factor structures and autoregressive relationships). Here, we strive for definitions that can be used regardless of the model that is employed.

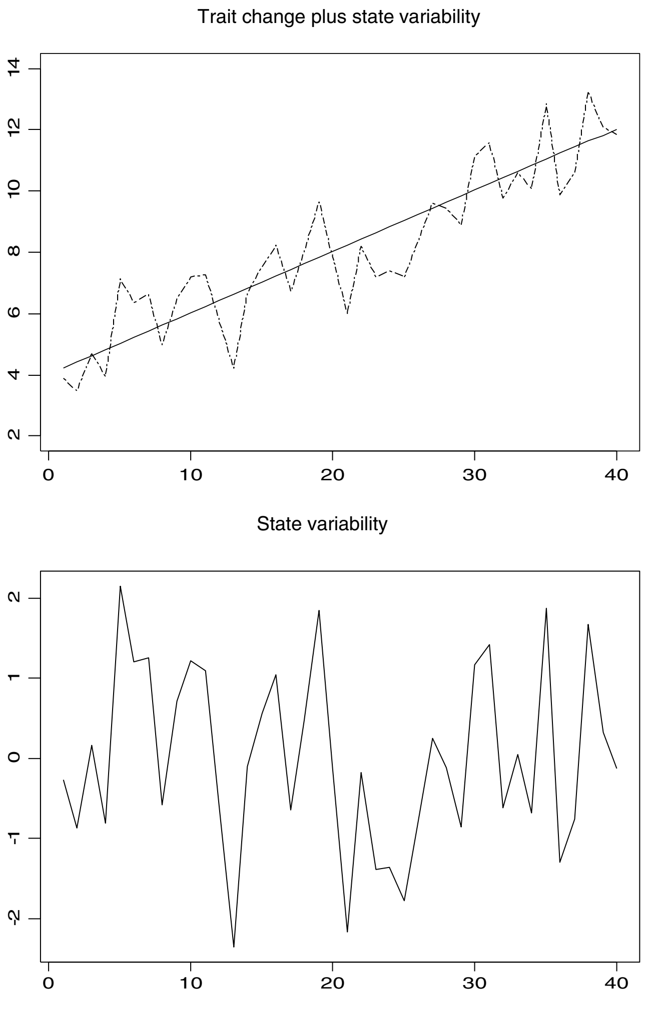


Fig. 1. The upper graph consists of 40 repeated measurements containing trait change (represented by the solid line) and state variability. The lower graph is the detrended data consisting of state variability only.

Suppose we take shyness and sociability: Shyness refers to inhibition and feelings of insecurity when with others, while sociability is a preference for being with others (Buss, 1989). Shyness and sociability are negatively correlated in the population implying that scoring high on shyness is associated with scoring low on sociability and vice versa, as illustrated in Fig. 2a. However, this is a relationship at the population level, which does not have to hold for each individual case: An individual may deviate from this population pattern by scoring low on both shyness and sociability (see Fig. 2a).

But there is another way in which the individual may differ from the pattern found in the population: The negative relationship between shyness and sociability may prove nonexistent or even reversed at the intraindividual level. To determine the intraindividual relationship between shyness and sociability we have to measure these same two

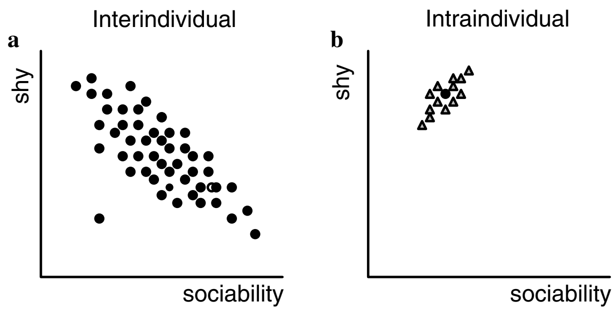


Fig. 2. Interindividual correlation on the left with one individual deviating from the population pattern, and intraindividual correlation on the right between sociability and shyness. This illustrates that these correlations are not necessarily identical or indicative of one another.

variables repeatedly in the same individual. Based on these measurements we can determine the intraindividual correlation, which provides insight into the way different states covary within a particular person. In Fig. 2b we illustrated the relationship between shyness and sociability for a particular individual who is quite high on shyness while low on sociability compared to others. Within this individual a positive relationship between shyness and sociability emerges. A possible explanation for this is that when this person feels an increased desire to participate in social interaction, this also raises his/her social anxiety levels. Other individuals may be characterized by other intraindividual relationships, for instance, no relationship or a relationship which is more in agreement with the relationship found at the interindividual level.

We want to stress here that we do not expect that for many psychological phenomena the intraindividual relationship between two variables is opposite to the relationship at the interindividual level: The above is simply meant to exemplify that *relationships between variables may differ at different levels*. This fact has been recognized by many (e.g., Baldwin, 1946; Borsboom, Mellenbergh, & Van Heerden, 2003; Epstein, 1994; Grice, 2004; Hamaker et al., 2005; Lamiell, 1990; Nesselroade & Molenaar, 1999; Schmitz & Skinner, 1993; Von Eye & Bergman, 2003). When the relationships between variables are identical at both levels, this has been referred to as local homogeneity, while a difference between the structures at different levels has been coined local heterogeneity (Borsboom et al., 2003). This notion is crucial for the model developed in this paper, which allows individuals to differ from one another with respect to their structure of intraindividual variation: As a result, this model offers the opportunity to test the assumptions underlying other approaches, i.e., whether there is a universal state structure that applies to all, and whether or not it coincides with the trait structure. As such it allows us to investigate whether constructs are locally homogeneous or heterogeneous (Borsboom et al., 2003).

2. The integrated trait–state model

We begin with a fairly simple assumption, based on common sense and supported by empirical results, namely that both traits and states contribute to our observations, so that

$$\text{observation} = \text{trait score} + \text{state score}. \tag{1}$$

While the trait score is an unchanging entity, the state score is a temporary departure from this trait score. Hence, the trait score is equal to the intraindividual mean (across time and situations), while the state score is the difference between this average and the observed score at a particular occasion.

If we consider multiple observed variables we can investigate the relationship between these variables by use of factor analysis. Conform terminology in literature on factor analysis we use the term *common factor* to refer to a latent variable that accounts for variance shared by multiple observed variables, while the term *unique factor* refers to a latent variable that accounts for variance of one of the observed variables not shared with any other (observed) variable. We suggest that the trait score associated with an observed variable consists in part of a common trait that is measured by other variables as well, and in part of an unique trait that is not measured by any of the other variables. The latter may also be thought of as specificity (Lord & Novick, 1968) or the specific factor (Gorsuch, 1983; Harman, 1968), as it is measured by only one of the indicators and it does not vary over time. This trait model is then

$$\text{trait score} = \text{(weighted) common trait} + \text{unique trait}. \tag{2}$$

From this it follows that we can determine the trait structure if we factor analyze the intraindividual means (i.e, trait scores) of multiple subjects.

Similarly, the state score associated with an observed variable consists in part of a common state that is measured by multiple variables, with the rest being unique state. The latter may be referred to as random error or measurement error, as it is measured by only one variable and it varies over time. The state model is thus

$$\text{state score} = \text{(weighted) common state} + \text{unique state}. \tag{3}$$

Eq. (3) may be recognized as Cattell's P-technique analysis, which consists of factor analyzing the repeated measures from a single individual (Baldwin, 1946; Cattell, Cattell, & Rhymer, 1947; Cattell, 1966). The state structure of a particular individual is determined by both the number and nature of state factors (the latter refers to the signs and relative sizes of the factor loadings). This structure is independent of both the state structures of other individuals, *and* the trait structure found across individuals.

Because each individual can have his/her own factor structure this implies that each individual may be characterized by his/her own idiosyncracies in intraindividual variation. This is illustrated in Fig. 3. Such differences are indicative of different processes underlying the patterns of our observations and imply local heterogeneity (Borsboom et al., 2003). The state model in Eq. (3) also allows us to investigate whether there are individuals that have the same factor structure, which is illustrated in the following section. In case all individuals prove to have the same factor structure (that is, if we can set all factor loadings of the state factors equal across individuals), this means that all individuals vary on the same dimensions. Note however that this does not necessarily imply local homogeneity, since the enduring, time-invariant differences between individuals may be described on different dimensions: The latter differences are due to the trait model in Eq. (2), which exists independently from the state model in Eq. (3).

The P-technique as described in Eq. (3) has been extended to include sequential or lagged relationships which allow one to model the time order of the data (Molenaar, 1985; Nesselroade, McArdle, Aggen, & Meyers, 2002; Nesselroade & Molenaar, 2003). The simplest extension is a model in which the current common state is regressed on

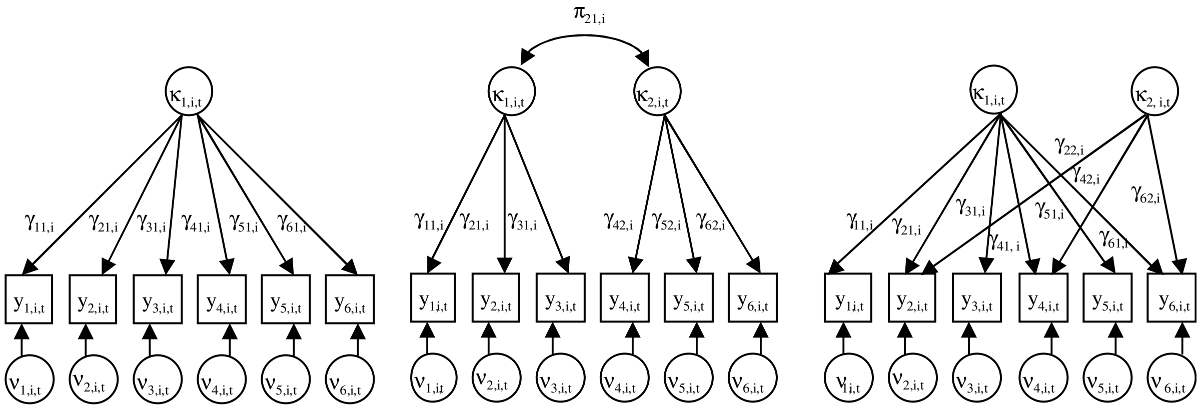
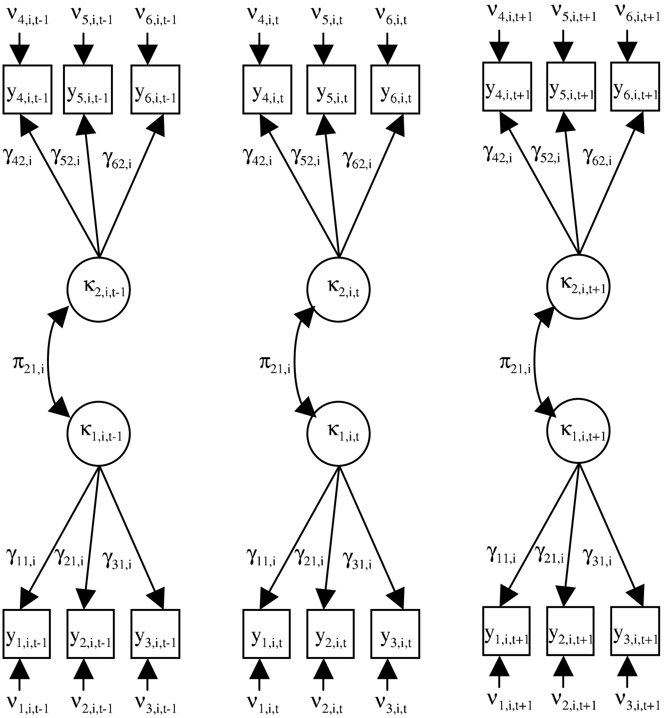


Fig. 3. Path diagrams of three different intraindividual factor structures. Suppose the first three observed variables are ‘shy’, ‘reserved’, and ‘silent’, which are indicators of Introversion (the opposite of Extraversion), and the latter three are the variables ‘irritable’, ‘vulnerable’, and ‘bad-tempered’, which are indicators of Neuroticism. The first individual is characterized by a single factor which (assuming that all factor loadings are positive) may represent general negative affect. The other two individuals are characterized by a two-factor structure, but the nature of their factors differs. The second person has an introversion factor and a neuroticism factor conform the interindividual structure. The third person has a general negative affect factor and a second factor indicated by ‘reserved’, irritable’ and ‘bad-tempered’, and may be called a hostility factor.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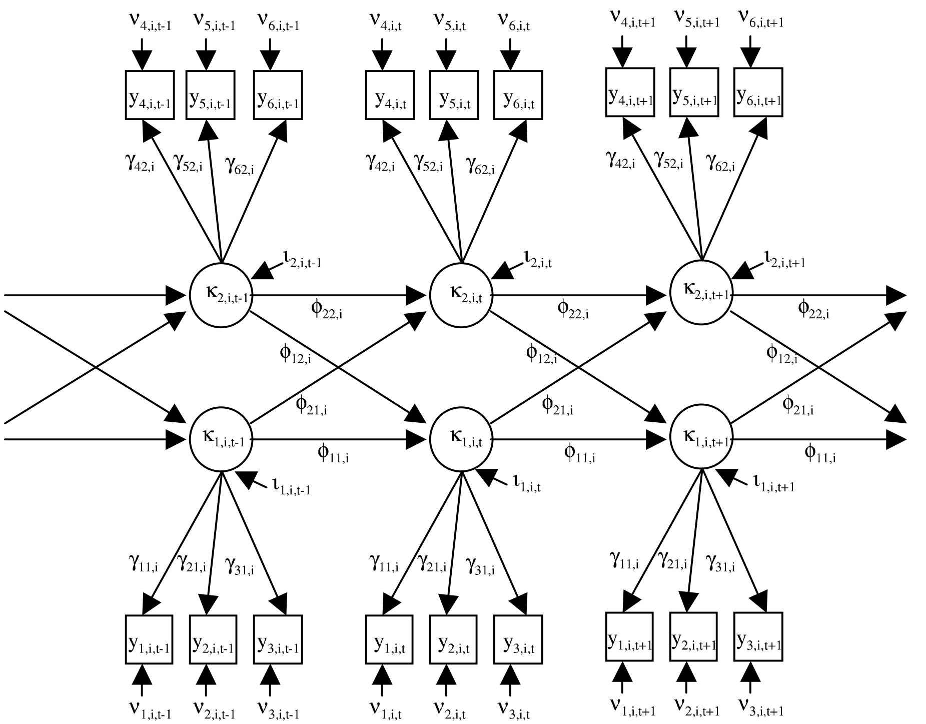
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Table 1

State model at the intraindividual level
$\mathbf{y}_{it} = \boldsymbol{\mu}_i + \boldsymbol{\Gamma}_i \boldsymbol{\kappa}_{it} + \nu_{it}$, with:
$\mathbf{y}_{it}$, an $ny \times 1$ vector with observations of subject i at occasion t
$\boldsymbol{\mu}_i$, an $ny \times 1$ vector with means of individual i
$\boldsymbol{\Gamma}_i$, an $ny \times nk_i$ matrix with factor loadings of individual i
$\boldsymbol{\kappa}_{it}$, an $nk_i \times 1$ vector with common state scores of individual i at occasion t, with $\mathrm{E}[\kappa_{it} \mid i] = 0$ and $\mathrm{E}[\kappa_{it}\kappa'_{it} \mid i] = \boldsymbol{\Pi}_i$
$\boldsymbol{\nu}_{it}$, an $ny \times 1$ vector with unique state scores of individual i at occasion t with $\mathrm{E}[\nu_{it} \mid i] = 0$ and $\mathrm{E}[\nu_{it}\nu'_{it} \mid i] = \boldsymbol{\Xi}_i$ with:
$\boldsymbol{\kappa}_{it} = \boldsymbol{\Phi}_i \boldsymbol{\kappa}_{i,t-1} + \boldsymbol{\iota}_{it}$
$\boldsymbol{\Phi}_i$ an $nk_i \times nk_i$ matrix with auto- and cross-regression parameters of individual i
$\boldsymbol{\iota}_i$ an $nk_i \times 1$ matrix with residuals of individual i at occasion t, with $\mathrm{E}[\boldsymbol{\iota}_{it} \mid i] = 0$ and $\mathrm{E}[\boldsymbol{\iota}_{it}\boldsymbol{\iota}'_{it} \mid i] = \mathbf{U}_i$
Trait model at the interindividual level
$\boldsymbol{\mu}_i = \boldsymbol{\mu} + \boldsymbol{\Delta}\boldsymbol{\beta}_i + \zeta_i$, with:
$\boldsymbol{\mu}$, an $ny \times 1$ vector with grand means
$\boldsymbol{\Delta}$, an $nb \times nb$ matrix with factor loadings
$\boldsymbol{\beta}_i$, an $nb \times 1$ vector with common trait scores of individual i, with $\mathrm{E}[\boldsymbol{\beta}_i] = 0$ and $\mathrm{E}[\boldsymbol{\beta}_i\boldsymbol{\beta}'_i] = \boldsymbol{\Omega}$
ζ_i, an $ny \times 1$ vector with unique trait scores of individual i, with $\mathrm{E}[\zeta_i] = 0$ and $\mathrm{E}[\zeta_i\zeta'_i] = \boldsymbol{\Upsilon}$

the common state at the preceding occasion, which is called autoregression. When more than one common state factor exists, there may also be cross-regressions on different common state factors at earlier occasions, meaning that a current common state is a weighted sum of previous common states (including the same common state, and other common states). If we consider daily measurements, this could be represented as

$$\text{common state}_{\text{today}} = \text{(weighted) common states}_{\text{yesterday}} + \text{residual}. \tag{4}$$

Again, because this model is formulated at the intraindividual level, it may differ across individuals. Hence, while some individuals are characterized by such sequential or lagged relationships, others may not which implies that the common state equals the residual in Eq. (4). These two possibilities are illustrated in Fig. 4.

The Eqs. (1)–(4) together make up the integrated trait–state (ITS) model. The corresponding algebraic expressions are provided in Table 1. In the ITS model both trait and states contribute independently to our observations. The trait part of the model (Eq. 2) allows us to make quantitative comparisons between individuals regardless of their intraindividual state model: It can be used to determine who is more extraverted or depressed *in general* by determining who scores higher on the dimensions describing enduring interindividual differences. In addition, the state part of the model (Eqs. 3 and 4) allows us to investigate five other ways in which individuals may differ from each other: (a) the *number of common state factors* may differ, where individuals characterized by more state factors can be said to have a more complex or differentiated state structure; (b) the *nature of common states* may differ, so that even individuals with the same number of common states may be characterized by different dimensions; (c) the *correlation between*

◀

Fig. 4. Path diagrams of two different intraindividual sequential structures of the common states. The top represents an individual whose state is not influences by previous states, that is, every day is experienced as a new day. The bottom represents an individual who is influenced by his/her state at the preceding occasion. For this person his/her state today depends to some extent on how (s)he was feeling, thinking and acting yesterday.

the common states may differ, so that even when individuals have identical common states they may differ in how strongly variation on one of these dimensions is related to variation on another dimension; (d) the *lagged relationships* may differ, indicating that the dynamics are different for different individuals (see Fig. 4); and (e) the *amount of variation* may differ, where some individuals are more "traited" (Baumeister & Tice, 1988), i.e., less susceptible to situational inlfuences.

3. Illustration

3.1. Data

In order to illustrate the model discussed above a data set is needed that includes a large number of repeated multivariate measurements taken from a large number of individuals. The Borkenau–Ostendorf data set is one of the few data sets that meet these requirements (Borkenau & Ostendorf, 1998): These data arose from 22 subjects filling out a 30 item questionnaire daily for 90 consecutive days. Although the items represented the Five Factor Model (FFM) of personality, the participants were asked how true this description was of their behavior that day in order to obtain state measurements. Borkenau and Ostendorf (1998) analyzed these data using Cattell's P-technique to determine whether the FFM was also useful in describing state variation within individuals. Their approach consisted of rotating the first five principle components that were obtained for each individual separately towards a reference factor structure based on R-technique analysis (i.e., standard factor analysis on a cross-sectional data set; see Cattell, 1966). They used congruence correlations to evaluate the correspondence between the individual solutions and the R-technique solution and concluded that, although these congruences were quite low, this was due to the unreliability of P-technique solutions.

In our illustration we only use the items of the Extraversion and Neuroticism factors for practical reasons: If the number of variables is larger than the number of individuals, the interindividual covariance matrix that is needed to determine the trait structure would be singular, making factor analysis by some methods impossible. Focussing on the Extraversion and Neuroticism items reduces the number of items to 12. The Extraversion items are: Dynamic, sociable, lively, shy, silent, and reserved. The Neuroticism items are: Irritable, bad-tempered, vulnerable, emotionally stable, resistant, and calm.

3.2. Method

Given the current data set, we can choose from several approaches based on the ITS model. One possibility is to take an exploratory approach in which the number and nature of factors is determined for each individual separately, quite similar to (multisubject) exploratory P-technique studies and exploratory dynamic factor analysis (cf. Baldwin, 1946; Borkenau & Ostendorf, 1998; Hamaker et al., 2005; Hershberger, Corneal, & Molenaar, 1995; Hooker et al., 1987; Jones & Nesselroade, 1990; Nesselroade & Molenaar, 1999; Quinn & Martin, 1999; Shifren et al., 1997; Timmerman & Kiers, 2003; Zevon & Tellegen, 1982). In contrast, a more confirmatory approach to the data is taken here to illustrate several important possibilities the ITS model offers to researchers.

In particular, we want to illustrate how this model can be used to investigate whether individuals are characterized by identical state structures, and whether this state structure

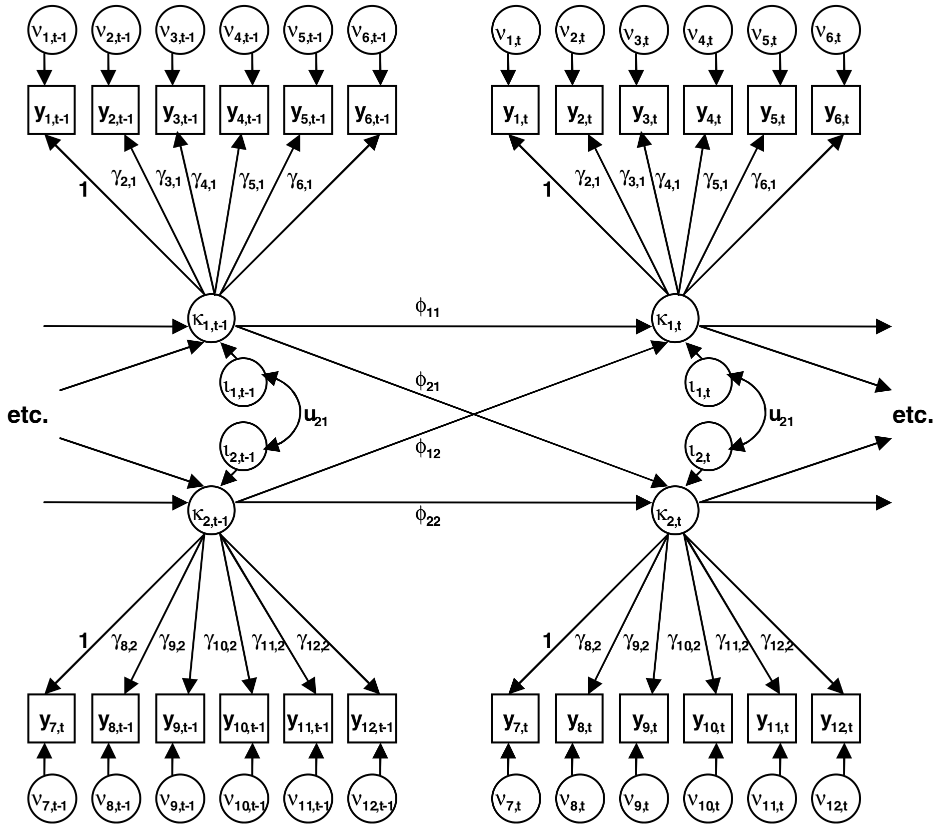

Fig. 5. State model that was fitted to the data of each individual separately. For ease of presentation the subject index i was omitted. Two occasions are represented: The current occasion t and the previous occasion $t-1$. At each occasion there are twelve observed variables y's (respectively: Dynamic, sociable, lively, shy, silent, reserved, irritable, bad-tempered, vulnerable, emotionally stable, resistant, and calm), which are related to two latent variables: Extraversion (κ_1) and Neuroticism (κ_2). The latent variables are regressed upon themselves and each other at the previous occasion by the lagged regressions ϕ's. The unpredictable parts of the latent variables (ι's) are allowed to correlate (u_{21}).

is identical to the trait structure. To this end we impose the same pattern of factor loadings (i.e., loadings that are fixed to zero and loadings that are estimated freely) on each individual's data (see Fig. 5), and on the interindividual covariance structure. By constraining the factor loadings across individuals to be identical we can test whether there is factorial congruence (Dolan, 2000).[2] In doing so we can determine whether or not individuals have identical dimensions underlying their state variation, and thus whether the constructs are locally homogenous or heterogenous (Borsboom et al., 2003). If there is local homogeneity, we can investigate whether the intraindividual dimensions and the interindividual dimensions are identical, that is, whether there is factorial congruence across levels.

[2] Factorial congruence implies identical factor loadings across groups, and is a weaker constraint than factorial invariance which requires both the factor loadings and intercepts to be identical across groups (Lubke, Dolan, Kelderman, & Mellenbergh, 2003; Meredith, 1993).

Testing for factorial congruence should be preferred over the use of congruence coefficients (as used by Borkenau & Ostendorf, 1998), because the latter is not based on a statistical test, while the sampling distribution of the congruence coefficients is not known.

Before presenting the results, we need to elaborate on two features of our approach. The first concerns the estimation of the model's parameters. As indicated above, the trait model and the state model are independent of each other. Although in theory it is possible to estimate the complete ITS model simultaneously, the program we used[3] could not handle the vast number of free parameters associated with the total model. Hence, we analyzed the state variability of each individual separately first (this is possible since there are no equality constraints across individuals in the first step of the analyses). This approach requires us to estimate the intraindividual means which are then factor analyzed in the trait model. However, in estimating these intraindividual means we need to correct for differences in intraindividual reliabilities: The estimated mean of an individual with a large amount of intraindividual variability is less reliable than the mean of an individual exhibiting little intraindividual variability. Failing to correct for this leads to a biased estimation of interindividual (co)variances (cf. Nezlek, 2001). Therefore prior to factor analyzing the intraindividual means, the estimates of the intraindividual means were corrected for differences in reliability in analogy to Stijnen (2000). In Fig. 6 the separate contributions of trait-like and state-like sources of variance are indicated for each of the 12 variables.

A second matter of interest concerns model evaluation. In structural equation modeling the fit of a model is evaluated by how well the model describes the data compared to either a saturated model or an independence model (Hu & Bentler, 1999). To this end, the discrepancies between the observed covariance matrix and the covariance matrices associated with these alternative models are determined. In time series analysis one has at his disposal only one case and it is therefore not possible to determine an observed covariance matrix that can be used in the assessment of the fit of models.[4] Hence, there are no fit statistics that inform us how well the data are described by the model. However, the appropriateness of a model can be determined to some extent by looking at the significance of the parameter estimates. In addition, the comparison between nested models (where one model is a more restricted version of the other) can be carried out using the log-likelihood difference test (Bollen, 1989). Both of these methods are used below.

3.3. Results

The results are presented in Tables 2 and 3, where all non-significant parameter estimates are underlined. These results were obtained by analyzing the intraindividual state variation (using Eqs. 3 and 4), and by factor analyzing the individual trait scores (Eq. 2).

[3] A Fortran program called MKFM6: See http://users.fmg.uva.nl/cdolan/.

[4] If one uses the block-Toeplitz method to analyze time series analysis, one can use the lagged covariance matrix to determine the fit (Molenaar, 1985; Wood & Brown, 1994). In this case, the fit of the model is based on how well the model describes the covariance structure of the data up to the maximum lag that is included in the block-Toeplitz matrix. However, it is not entirely clear whether the fit indices thus obtained are correct (see Hamaker, Dolan, & Molenaar, 2002). An alternative is to determine the fit for each lag separately (up to a certain lag), as proposed by Browne (see the documentation regarding the DyFA package, http://quantrm2.psy.ohio-state.edu/browne/).

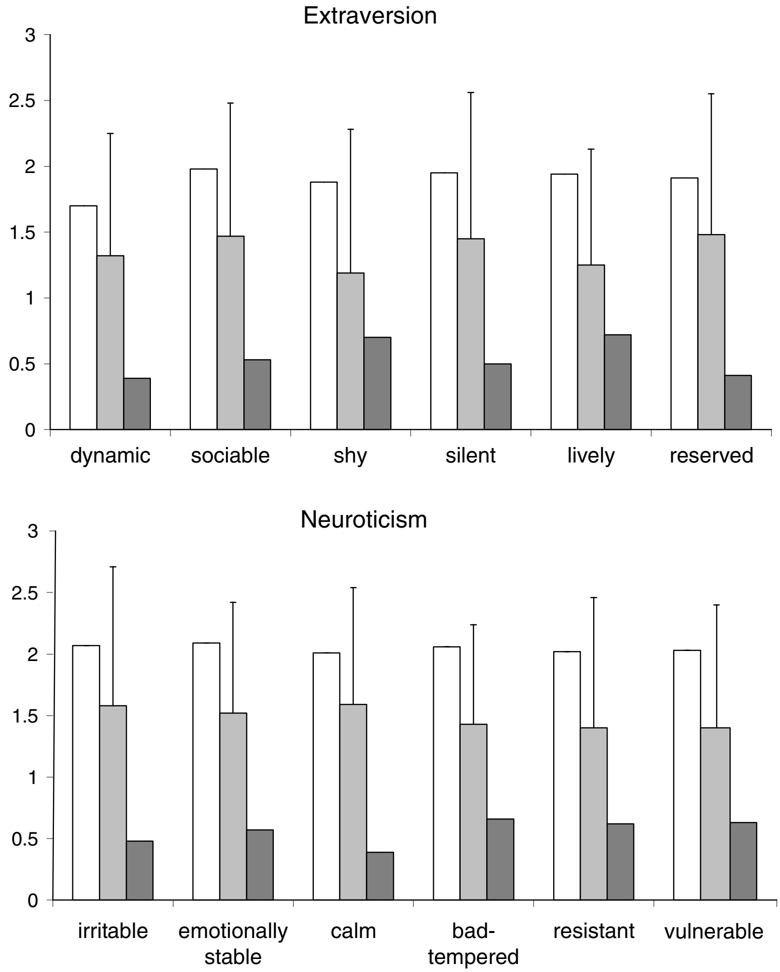

Fig. 6. Variance per variable. White bars represent the total variance, i.e., across occasions and persons. Light grey bars represent state variance, that is, the average (across individuals) of intraindividual variance across time. The bar indicates the standard deviation across individuals. The dark bars represent trait-like variance, that is, the variance of the intraindividual means. As can be seen the average state variance and the trait variance add up to the total variance.

The factor loadings for all 22 individuals are printed in Table 2. Note that since the first factor loading of each factor was used for scaling (i.e., set at the value 1.00), these are not estimated. It can be seen that there are 10 individuals for whom one or more of the factor loadings is not significantly different from zero. In particular for individuals 3, 18, and 21 the assumed two factor structure does not seem very appropriate. Their state structure could be further studied using a more exploratory approach, which we don't do here. Based on a visual inspection of the results in Table 2 we selected individuals with sufficient correspondence across their factor loadings to warrant a statistical check of factor congruence. For those cases, we analyzed the data of multiple individuals simultaneously with the factor loadings constrained across individuals while leaving all other parameters

Table 2

Subjects	Parameters									
	$\lambda_{2,1}$	$\lambda_{3,1}$	$\lambda_{4,1}$	$\lambda_{5,1}$	$\lambda_{6,1}$	$\lambda_{8,2}$	$\lambda_{9,2}$	$\lambda_{10,2}$	$\lambda_{11,2}$	$\lambda_{12,2}$
1	2.78	2.64	−2.74	−2.38	−2.76	.51	.87	−1.08	−.92	−1.01
2	1.10	1.07	−.85	−1.23	−.83	.99	1.43	−1.19	−.78	−.74
3	.83	.79	−.75	$\underline{-.33}$	$\underline{-.73}$	$\underline{.02}$	.72	$\underline{-.05}$	$\underline{.42}$	$\underline{-.28}$
4	1.34	.83	−.96	−1.41	−1.04	.81	.80	−1.43	$\underline{.20}$	−1.04
5	1.35	1.02	−1.32	−1.49	−1.71	$\underline{.17}$	1.01	−.94	−.94	−.86
6	2.23	2.96	−1.69	3.93	−3.57	.48	.77	−.84	−1.07	−.57
7	1.10	1.07	−.61	−.99	−1.15	.83	.69	−.76	−.95	−.58
8	2.3	1.06	−.66	−1.47	$\underline{-.77}$	.97	1.27	−1.14	−.88	−.84
9	.87	1.04	−.74	−.71	−1.13	$\underline{.13}$	.91	−.86	−.76	−.67
10	2.59	1.70	−2.43	−2.41	−2.00	1.02	.87	−1.01	−1.06	−.95
11	1.19	1.29	−.53	−.94	−1.03	.51	.75	−.75	−.59	−.69
12	1.01	1.14	−.83	−1.13	−1.06	.84	.74	−.97	−.97	−.58
13	.08	1.19	−.87	−1.12	−.98	.71	.91	−.75	−.98	−.46
14	1.15	1.07	−1.21	−1.24	−1.18	.51	.72	−.71	−.79	−.32
15	1.07	.90	−.72	−.74	−.66	.57	1.04	−1.08	−.79	−1.01
16	1.38	.85	−.99	−1.52	$\underline{-.43}$	.51	.67	−.89	−.90	−.76
17	1.77	1.15	−1.68	−1.85	−2.27	.67	.93	−.69	−.77	−.27
18	.63	.46	−.86	$\underline{.21}$	−.67	1.23	.62	.19	$\underline{-.27}$	$\underline{.37}$
19	1.20	.99	−.71	−.91	−.85	.81	1.06	−1.04	$\underline{-.12}$	−.95
20	1.06	1.47	−1.17	−1.69	−1.18	.28	.84	−.37	−.54	−.39
21	$\underline{.95}$	$\underline{.63}$	$\underline{-1.35}$	$\underline{-.61}$	$\underline{-0.66}$	.83	.79	−.72	−.43	−.85
22	1.02	.94	−.88	−1.13	−.96	1.49	1.16	−.86	−1.15	−1.11
Inter	1.96	2.36	−2.09	−2.26	−1.86	.52	1.02	−.74	−1.08	$\underline{.06}$

Note: Factor loadings for the state model (22 subjects) and the trait model (inter). Non-significant parameters are underlined. The first five factor loadings are for: Sociable, lively, shy, silent, and reserved; $\lambda_{1,1}$ (dynamic) was set to 1.00 for scaling. The last five factor loadings are for: Bad-tempered, vulnerable, emotionally stable, resistent, and calm; $\lambda_{7,2}$ (irritable) was set to 1.00 for scaling.

in the model unconstrained. Using the log-likelihood difference test to determine whether these constrains were tenable, we found one group consisting of 3 individuals (7, 12, and 13) and four groups of 2 individuals (1 and 12, 2 and 8, 14 and 17, and 15 and 22).[5] Although these individuals proved to have the same dimensions underlying their state variability, no universal state structure was found. As a consequence, the trait structure (last row in Table 2) can not be identical to the state structure of each individual. When comparing the interindividual factor loadings to the results obtained for separate individuals, there does not seem to be much congruence across levels. However, since the interindividual analyses are based on only 22 cases these results are subject to sample fluctuations making definite conclusions difficult.

In Table 3 the standardized results pertaining to the latent level are presented. The second and third columns contain the proportion of variance of the Extraversion factor and Neuroticism factor that could not be explained by the states at the previous occasion. Since these are quite high we can conclude that the sequential influences are minor.

[5] In these multi-subject analyses the previously non-significant variances u_1^2 and u_2^2 reported in Table 3 were all significant.

Table 3

Subjects	Parameters							
	u_1^2	u_2^2	u_{21}	π_{21}	ϕ_{11}	ϕ_{12}	ϕ_{21}	ϕ_{22}
1	1.00	.99	−.64	−.64	−.04	.00	.09	−.03
2	.97	1.00	−.15	−.14	.12	−.11	.04	.00
3	.67	.84	1.29	1.45	.56	.01	−.19	.71
4	.93	.93	−.64	−.65	.16	−.14	.07	.29
5	.89	.86	−.64	−.68	−.06	−.36	.21	.48
6	.92	.85	−.43	−.49	.05	−.26	−.07	.35
7	.95	.65	−.32	−.38	−.07	−.23	.35	.63
8	.64	.81	−.89	−.90	.00	−.60	.00	.44
9	.69	.79	.03	−.11	.36	−.38	.15	.45
10	.98	.76	−.12	−.03	.11	.12	.18	.46
11	.97	.98	−.33	−.32	.09	−.12	.14	.13
12	.98	.96	−.15	−.15	.07	−.11	.14	.18
13	1.00	.98	−.13	−.13	.04	−.04	.15	.04
14	1.00	.96	−.95	−.94	−.03	.02	.51	.39
15	.92	.99	−.63	−.62	.12	−.20	.02	.09
16	.96	.95	−.14	−.18	−.17	−.16	.18	.16
17	1.00	.75	−.75	−.68	−.07	−.09	.48	.68
18	.80	.74	−.74	−.76	.59	.21	−.35	.19
19	.89	.89	−.64	−.66	.32	−.01	−.09	.27
20	.91	.97	−.45	−.38	.30	.00	.19	.12
21	1.00	.91	−.13	−.11	−.05	.03	−.23	.16
22	.98	.92	.01	.04	−.12	.08	−.18	.21
Inter	.10	.46	−.15	−.15	—	—	—	—

Note: Standardized results at the latent level for the state model of the 22 subjects and the trait model (inter). Non-significant parameters are underlined. First two columns (u_1^2 and u_2^2) are the proportions of the state Extraversion and Neuroticism respectively that could not be predicted based on the scores at the previous day. The third column is the correlation between these unpredictable parts, and the fourth column is the correlation between the common state factors themselves. Finally, ϕ_{11} and ϕ_{22} are the autoregressive parameters of Extraversion and Neuroticism, ϕ_{12} is the cross lagged regression parameter from Neuroticism to Extraversion, and ϕ_{21} is the cross lagged regression parameter from Extraversion to Neuroticism.

The correlation π_{12} between the Extraversion factor and Neuroticism factor (π_{21}) runs from −.03 to −.94.

3.4. Conclusion

Based on the ITS model five sources of differences between individuals with respect to their intraindividual state model were identified: (a) number of factors; (b) the nature of factors; (c) the correlation between the factors; (d) the sequential relationships of the factor; and (e) the amount of variability. With respect to these five features we can summarize the results from our empirical study as follows. First, we did not considering different *numbers* of factors, but rather we imposed the same two factor structure on every one. For most individuals the theoretical distinction between Extraversion and Neuroticism items seemed appropriate to summarize their daily behavioral fluctuations. Second, although there was considerable variability across individuals with respect to the actual *nature* of the Extraversion and Neuroticism factors, we found subgroups of individuals who are characterized by qualitatively identical factors underlying their daily variations. Third, for some individuals the factors were unrelated (individuals 2, 6, 10, 12, 13, 16, and 22), but for all other individuals the correlation between Extraversion and Neuroticism was negative implying that an elevated state of extraversion is accompanied by a dampened state of neuroticism. Fourth, about half of the individuals were characterized by at least one significant sequential relationships (individuals 5, 6, 7, 8, 9, 10, 17, 19, and 20). All these autoregressive relations were positive, indicating that elevated scores on a particular factor are likely to persist for several days, as do dampened states. All of the significant lagged relations from Neuroticism to Extraversion were negative, indicating that an elevated state of Neuroticism is likely to be followed by a decrease in Extraversion. In contrast, all of the significant relations from Extraversion to Neuroticism were positive, indicating that an elevated state of Extraversion is likely to be followed by an increase in Neuroticism the next day. Fifth, with respect to the *amount of intraindividual variability* suffice it to say that there is considerable variation across individuals in amount of observed intraindividual variability (see Fig. 6), as well as in the proportion of observed variance explained by the latent variables.

Since there was no universal state model, we can conclude that local homogeneity (that is, identical intraindividual and interindividual factor structures, see Borsboom et al., 2003) is absent in this case. However, our example also illustrates how one can still look for similarities across individuals when factorial congruence proves absent.

4. Discussion

The ITS model presented in this paper offers a method by which traits and states can be linked, both analytically and theoretically. This model allows us to test whether there is a universal state structure and whether that state structure coincides with the trait structure. If this proves to be the case it implies that variability within a person takes place on the exact same dimensions that describe the enduring differences between individuals. Even when factorial congruence across individuals and across levels proves absent, the ITS model can still be valuable. First, as we have shown in our illustration we can look for subgroups displaying factorial congruence. Second, we can look for regularities across individuals at a more abstract level such as the relationships between factors over time (Nesselroade, 2004): Even though the actual dimensions differed across individuals, we provided some evidence for a general principle underlying the dynamics of the Extraversion and Neuroticism factors. Third, we can always compare individuals with respect to their positions on the interindividual trait-dimensions that describe the enduring differences between them. For this comparison it does not matter whether there is local homogeneity or heterogeneity (or irrelevance for that matter, see Borsboom et al., 2003): If necessary the ITS model allows us to consider individuals partly as unique entities (because of qualitative differences between them with respect to their state structures), while it simultaneously allows us to make meaningful quantitative comparisons between them to the extent that they are entities of the same kind and can be ordered on a trait dimension.

It is clear that the ITS model is closely related to standard factor analysis and dynamic factor analysis: The ITS model integrates these techniques in a multilevel framework, where the first level is formed by the individual, and the second level is formed by the interindividual differences (see Timmerman, in press, for a slightly different approach to such data). The ITS model can also be linked to several approaches in personality psychology, such as the act frequency approach (AFA; Buss & Craik, 1983) and the cognitive affective personality system (CAPS; Mischel & Shoda, 1995), both of which are discussed briefly below.

The AFA implies that people who are characterized by a particular disposition will engage more frequently in particular acts that are associated with this disposition. Buss and Craik (1985) indicate that the trait ratings that are typically used in factor analysis to determine the underlying dispositions could be considered as surrogates for act-trend indices. Our intraindividual means can be considered to be better estimate of these act-trend indices: If someone often acts in a particular fashion, his/her intraindividual means will be higher than those of other people. As a result, this person will have a higher score on the interindividual trait factor.

Until now we have considered the term trait as referring to the intraindividual mean. However, Fleeson (2001) proposed to use the term trait to refer to all sorts of intraindividual distributional parameters, such as means and variances of the constructs, providing these proved stable over time. We take Fleeson's suggestion one step further and consider *stable intraindividual patterns of covariation* as a trait-like property: This structure is represented by the number of factors, the factor loadings, the correlations between the factors and the sequential relationships between the factors. Such trait-like properties that differ across individuals may be useful when comparing individuals. For instance, an individual with very few intraindividual factors might be less stable than a person with a larger number of factors, as for the first variability is likely to effect the system as a whole, while for the second variability may remain more local. Also, individuals who are characterized by an absence of sequential relationships begin every day with a clean sheet, while individuals who display significant sequential relationships are effected by their state the previous day. This extension of the trait concept may help to better understand differences between individuals.

Now it is only a small step to include situational features into the model in order to obtain a truly interactional model. Mischel and Shoda (1995) developed the CAPS to account for both the stability of the personality system and the variability in behavior of an individual across different situations. The stability of the CAPS is expressed in the profile of an individual across situations: Certain situational cues will increase a particular behavior, while other cues will diminish it, and such patterns can be highly idiographic. These patterns are referred to as stable "If..., then..." situation-behavior relations which are important features of personality: Although two individuals may have the same average score across time and situations, they may be characterized by quite distinct "If..., then..." profiles. In the ITS model situational cues can be incorporated as (observed) characteristics that influence the individuals common state at that particular occasion, as is depicted in Fig. 7.

For instance, consider the five situations Mischel and Shoda (1995) describe for children at a residential summer camp: (1) being teased by a peer; (2) being approached by a peer; (3) being warned by an adult; (4) being punished by an adult; and (5) being praised by an adult. These can be represented by four dummy variables, represented as x-variables in Fig. 7 (i.e., the presence of a particular situation is indicated by score 1, the absence by score 0 on the corresponding dummy variable; the fifth situation is represented by zero-scores on all four dummy variables). These dummy variables are used to predict the aggression of the kid, which is also partly influenced by the amount of aggression exhibited

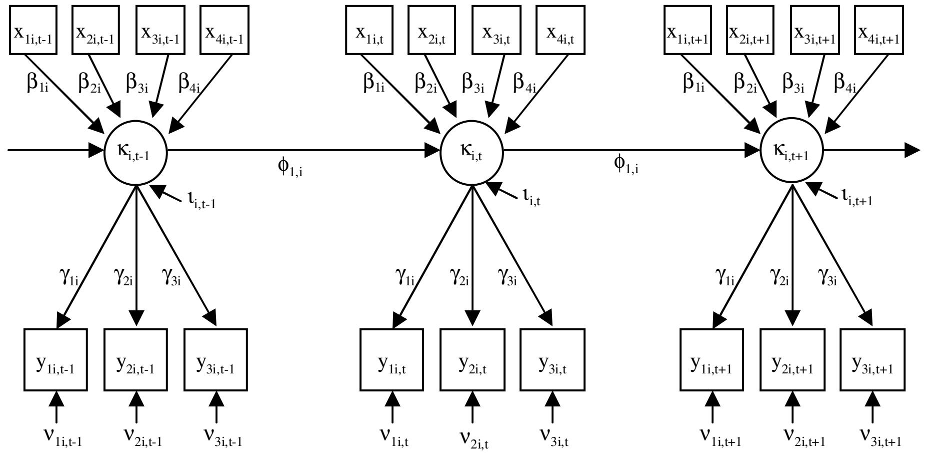

Fig. 7. ITS model including situational cues.

at the previous occasion (depicted by the autoregressive relationship $\phi_{1,i}$). Aggression is measured by three indicators in this case, for instance, verbal aggression, posture, and physical aggression. By estimating the β's, one can determine which situations increase the child's aggression, and which situations lessen his/her aggressive state. Clearly, knowing these relationships for a particular indivitrun dual will be helpful in predicting his/her behavior in a particular situation. Even for some one who is characterized by a large amount of intraindividual variability and who might be considered quite unpredictable based on his/her mean(s) (cf. Bem & Allen, 1974), knowing the specific relationships between his/her behavior and situational cues can make this person's behavior predictable.

To summarize, the ITS model allows the researcher to incorporate idiosyncracies into the model, while retaining intact the possibility of making meaningful quantitative comparisons between individuals. If desired, idiosyncracies can be minimized by constraining to equality an increasing number of parameters across individuals and testing whether these constraints are tenable. Hence, one can statistically test the assumptions underlying existing trait–state SEM approaches discussed in the beginning of this paper. We have also indicated how this model can be related to important trait–state approaches in personality psychology. The continued application of such modeling procedures will help us better understand the complexities of interindividual differences and similarities in intraindividual variability and stability.

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