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On the Relation between Person-Oriented and Subject-Specific Approaches

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Abstract: The necessity of using subject-specific data analysis of non-ergodic psychological processes is explained, emphasizing the difference between inter-individual and intra-individual variation. It is argued that subject-specific data analysis not only matches the principles underlying Developmental Systems Theory, but also enables testing of all principles of person-oriented theory. A new generalized perspective on measurement equivalence in subject-specific data analysis is introduced. The importance of computational optimal control of psychological processes within the context of subject-specific data analysis is emphasized. In closing, some broader aims of subject-specific data analysis are considered.

Keywords: Ergodicity, Developmental Systems Theory, Intra- and Inter-Individual Variation, Principles of Person-Oriented Theory, Measurement Equivalence, Optimal Control

The origin of subject-specific data analysis as considered in this paper is mathematical-statistical theory. A concise presentation of the relevant part of this theory is given. In contrast, the origin of person-oriented theory and methods is theoretical psychology. Despite these different origins there exists an interesting communality among the two approaches. Subject-specific data analysis has a natural affinity with Developmental Systems Theory (to be described in a later section) and in this respect is in harmony with person-oriented theoretical perspectives. Moreover, subject-specific data analysis constitutes one important method to test person-oriented principles.

In what follows it is first explained what is inter-individual variation and what is intra-individual variation. The difference between these two types of variation is essential to understand the rationale of subject-specific data analysis. Then the relation between results obtained with data analysis of inter-individual variation versus intra-individual variation is discussed. It will become apparent that in general no such relation exists, even if the same variables are measured using the same instruments. It is explained that this lack of relation has fundamental consequences for psychological data analysis, necessitating the use of subject-specific data analysis. Next it is argued that subject-specific data analysis conforms to the basic tenets of Developmental Systems Theory (DST). It is also argued that the basic tenets of DST are compatible with person-oriented theory. The remainder of this paper then discusses how subject-specific data analysis provides empirical tests of the theoretical principles underlying person-oriented theory, as formulated by Sterba & Bauer (2010a). For extensive background material on subject-specific methods the reader is referred to Molenaar & Newell (2010), Molenaar, Lerner & Newell (2014) and Valsiner et al. (2009).

Definition of Inter- and Intra-Individual Variation

To make the concepts of inter- and intra-individual variation more concrete, a design heuristic is introduced that has proven to be very useful for several decades of psychological research—the data box (Cattell, 1952). The essential data box is a cube defined by an axis for persons, one for variables, and one for occasions of measurement. Each element in the data box is a datum representing an intersection of axes and is thus a single score for a given person on a given variable at a given occasion of measurement. In Figure 1 a data box is depicted organized by person, variable, and occasion of measurement. Two orthogonal slices taken from this data box correspond, respectively, to inter- and intra-individual data. In its purest form the inter-individual data slice involves the data of a sample of persons assessed at a single occasion on a given set of variables. In its purest form the intra-individual data slice involves the data of a single person assessed at a sample of consecutive occasions on the same given set of variables.

Given that inter-individual and intra-individual data slices taken from the same data box are orthogonal to each other, the question arises how the structures of these obviously different kinds of variation are related. For instance, using the same set of variables, does factor analysis of inter-individual variation yield the same results as factor analysis of intra-individual variation? This question is of fundamental importance to scientific psychology in so far as its results are assumed to pertain to individual persons. If there is no relation between results obtained in statistical analyses of inter-individual and intra-individual variation, then results obtained by analyzing inter-individual variation cannot be validly applied at the level of individual assessment. That is, those results would not pertain to individual persons and therefore might be relevant in non-psychological settings (e.g., epidemiology, sociology) but would not be of direct importance to psychology as the science of individual human functioning.

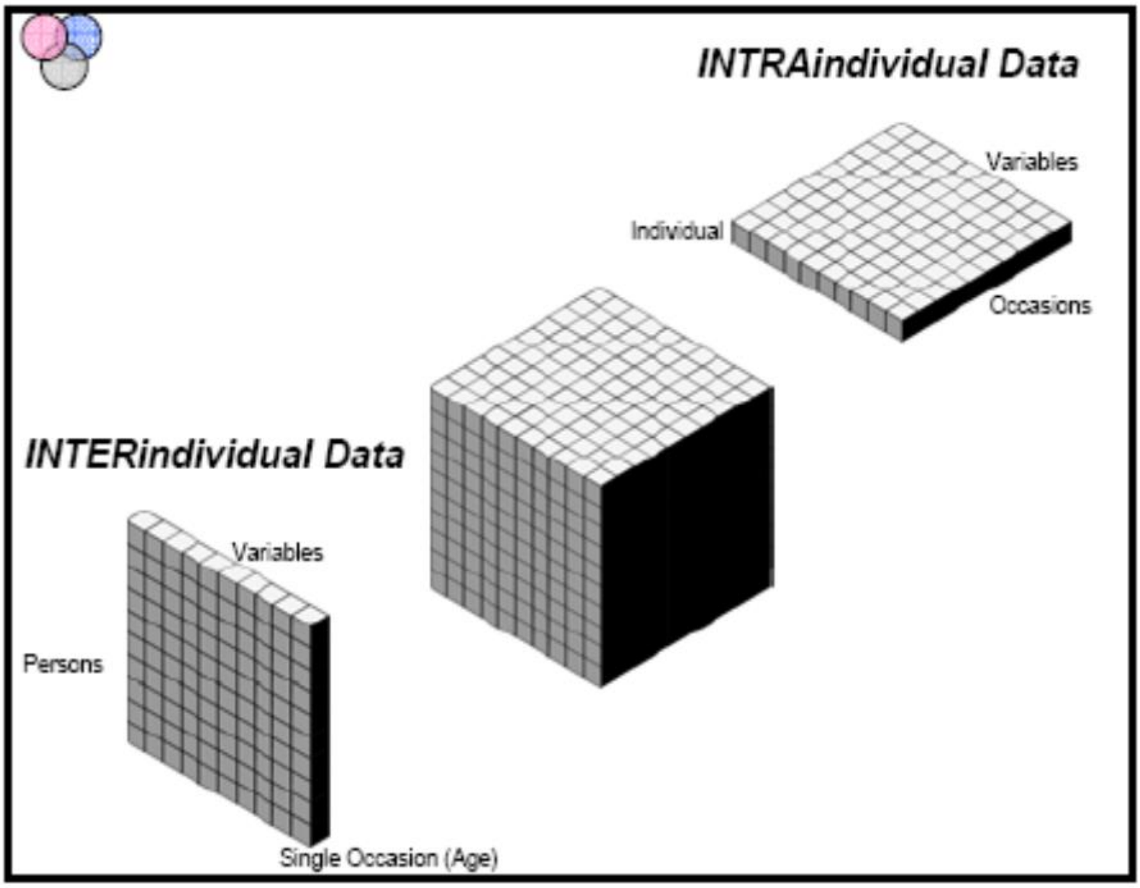

Figure 1. Cattell's (1952) data box (middle) with two orthogonal slices corresponding to inter-individual variation (lower left) and intra-individual variation (upper right).

Relation between Inter- and Intra-Individual Variation

What follows in this and the next section is a summary of parts of Molenaar & Nesselroade (in press) to which the reader is referred for a complete statement. The standard approach to statistical analysis in psychology is to draw a random sample of subjects from a presumably homogeneous population of subjects, analyze the structure of inter-individual variation in this sample, and then generalize the results thus obtained to the population. Such analyses of inter-individual variation underlie all standard statistical techniques in psychology, including analysis of variance, regression analysis, factor analysis, multilevel (latent growth curve) modeling, cluster analysis, mixture modeling, etc. Consequently the standard approach to psychological data analysis aims to describe the state of affairs at the population level, not at the level of individual subjects. Accordingly, the individuality of each of the persons in the sample and population is deemed immaterial: the subjects are considered to be mere replications (i.e., exchangeable random draws from the same probability space having the same measure). This is expressed by the assumption that subjects are homogeneous in all respects relevant to the analysis. This essential homogeneity assumption allows for the averaging (pooling) of the scores of the sampled subjects in the estimation of statistics (means, variances, correlations, etc.) to be generalized to the population. Pooling across subjects is the hall-mark of analyses of inter-individual variation.

The natural mathematical-statistical model for intra-individual variation is a dynamic systems model of the time-dependent changes of an individual's behavior. Given that the standard statistical approach to the analysis of psychological processes unfolding in time is based on inter-individual variation, not intra-individual variation, the fundamental question arises whether such a psychometric approach is valid. This question has been addressed before, for instance in Wohlwill's (1973) monograph on developmental processes. Here a definitive negative answer is presented.

The standard statistical approach to dynamic systems modeling of developmental processes based on analysis of inter-individual variation can be shown to yield results that cannot be validly applied at the individual level if these processes do not obey stringent conditions (Molenaar, 2004). The proof is based on classical ergodic theory; a set of theorems of extreme generality which apply to all measurable processes irrespective of their content (cf. Choe, 2005, for a modern proof of the first, so-called individual ergodic theorem of Birkhoff, 1931). To appreciate the implications of these theorems, it is helpful to first characterize the elementary methodological situation in psychological measurement. Instead of postulating an abstract population of subjects, consider an ensemble of actually existing human subjects whose measurable psychological processes are functions of time (and space, which will be neglected in what follows). The ensuing basic scientific representation of each human subject in psychology therefore is in terms of a high-dimensional dynamic system generating a set of time-dependent processes. The system includes important functional subsystems such as the perceptual, emotional, cognitive and physiological systems, as well as their dynamic interrelations. The complete set of measurable time-dependent variables characterizing the system's behavior can be represented as the coordinates of a high-dimensional space which will be referred to as the behavior space. The behavior space contains all the scientifically relevant information about a person (cf. De Groot, 1954).

A useful dictionary definition of variation is: "The degree to which something differs, for example, from a former state or value, from others of the same type, or from a standard" (Molenaar, 2004). To simplify the following discussion, variation will be understood to be quantified in terms of covariance matrices, although the gist of what follows also applies to more general operationalizations of the dictionary definition. Within the behavior space, inter-individual variation is defined as follows:

(i) select a fixed subset of variables;
(ii) select one or a few fixed time points as measurement occasions;
(iii) determine the variation of the scores on the selected variables at the selected time points by pooling across subjects.

Analysis of inter-individual variation thus defined is called R-technique by Cattell (1952). In contrast, intra-individual variation is defined as follows:

(i) select a fixed subset of variables;
(ii) select one or more fixed subject(s);
(iii) determine the variation of the scores of each single subject on the selected variables by pooling across a sampled time interval.

Analysis of intra-individual variation thus defined is called (replicated) P-technique by Cattell (1952).

With these preliminary specifications in place, the following heuristic description of the content of Birkhoff's (1931) individual ergodic theorem can be given. This theorem details the conditions that must be met in order to generalize results from analyses of inter-individual variation to results from analyses of intra-individual variation, and vice versa. A process is non-ergodic if the results of analyses of inter-individual variation do not generalize to the level of intra-individual change over time, and vice versa. In what follows we only consider Gaussian (normally distributed) processes. The criteria that Gaussian processes must meet in order to be ergodic are twofold (cf. Hannan, 1970).

(1) The process has to be *homogeneous in time*, having constant mean levels, no cycles and sequential dependencies which only depend upon relative time differences (lags). Such a process is called "weakly stationary."

(2) The process has to be *homogeneous across different subjects* in the population. That is, each subject in the population (ensemble) has to obey exactly the same dynamic model.

In the context of longitudinal factor analysis, for instance, the first criterion implies that all model parameters (factor loadings, etc.) have to be constant in time while the latter criterion implies that each subject has to obey the same factor model in which the number of factor, the factor loadings, the measurement error variances, and the factor score inter-correlations are invariant across subjects.

In case a Gaussian process is either non-stationary (violating the homogeneity in time criterion), or heterogeneous across subjects (violating the homogeneity across subjects criterion), or both, then this process is non-ergodic. This means that there is no lawful relation between the process structure of inter-individual variation at the population level and the structures of intra-individual variation at the level of individual subjects belonging to the population. Put another way, if the conditions of ergodicity are violated, no lawful relations exist between results obtained in an analysis of inter-individual variation (R-technique) and results obtained in an analogous analysis of intra-individual variation (P-technique).

The consequences of the classical ergodic theorems affect all psychological statistical methodology (Borsboom, 2005; Molenaar, Huizenga, & Nesselroade, 2003). Because a wide range of central psychological processes like learning, information processing, habituation, development and adaptation generally imply that some kind of growth or decline occurs, these processes are almost always non-stationary (violating the homogeneity in time criterion for ergodicity) and are, therefore, non-ergodic. This implies that their analysis has to be based on intra-individual variation in order to obtain valid information at the level of individual persons. It will be indicated below that starting with analyses of intra-individual variation does not preclude valid generalization across subjects. But such generalization cannot validly proceed in the standard way of pooling across subjects in standard analysis of inter-individual variation techniques.

Developmental Systems Theory

Subject-specific data analysis can be shown to be the method that matches well with important principles of DST. The principles concerned are the following. DST conceptualizes development as the result of multiple co-acting influences which are context sensitive and contingent. This implies that development is inherently subject-specific and stochastic (probabilistic or random) because the contexts within which a subject develops have contingent subject-specific effects that continuously build up within the developing system due to ongoing interactions (cf. Gottlieb, 2001). A second important feature of DST is that development is understood to be a constructive process in which nonlinear epigenetic influences play central roles (cf. Lickliter & Honeycutt, 2009). The most successful class of mathematical-biological models explaining such epigenetic influences are the so-called nonlinear reaction-diffusion models. These are nonlinear dynamic models generating emergent qualitative developmental changes that are not caused by genetic or environmental influences but instead are the result of dynamic self-organization (cf. Meinhardt, 1982). Such nonlinear epigenetic influences create substantial subject-specific variation (Molenaar, 2007) which reinforces the subject-specific effects due to contingent contextual influences. A third important feature of DST is its focus on the potential for change evolving at multiple time scales and at multiple levels (e.g., Smith & Thelen, 2003). This implies that dynamic systems models inspired by DST will include time-varying parameters located at different levels and changing with different rates.

In sum, DST emphasizes heterogeneity in time (violation of the first criterion for ergodicity) and heterogeneity across subjects (violation of the second criterion for ergodicity). Only subject-specific data analysis can validly accommodate these sources of heterogeneity.

The Priciples of Person-Oriented Theory

For an excellent general exposition of the holistic-interactionistic perspective of person-oriented theory the reader is referred to Bergman, Magnusson & El-Khouri (2003). In what follows the focus is on the six principles or tenets underlying person-oriented theory as presented in Sterba & Bauer (2010a). These are summarized in their Table 1 (Sterba & Bauer, 2010a, p.240) as follows: (1) *Individual Specificity* (psychological processes are at least in part unique to the individual). (2) *Complex Interactions* (psychological processes involve interactions at multiple levels). (3) *Inter-Individual Differences in Intra-Individual Change*. (4) *Pattern Summary* (psychological processes show lawful patterns of the involved factors). (5) *Holism* (factors derive their meanings from their mutual interactions). (6) *Pattern Parsimony* (at a sufficiently macro level psychological processes show a finite number of patterns).

Sterba & Bauer (2010a) then consider four types of methods to test these six principles. These four types are called (a) *Less Restrictive Variable Oriented* (latent growth curve modeling), (b) *Classification* (latent class growth analysis and latent Markov modeling), (c) *Hybrid Classification* (growth mixture modeling and mixed latent Markov modeling), and (d) *Single Subject* (dynamic factor analysis). In their Table 2 (Sterba & Bauer, 2010a, p. 245) these four types of method are cross-classified with the six principles of person-oriented theory in terms of how well they enable testing these principles. In what follows the focus is on the Single Subject type of method.

Sterba & Bauer (2010a) conclude that the Single Subject type of method enables testing of principles 1 (Individual Specificity), 4 (Pattern Summary), 5 (Holism) and 6 (Pattern Parsimony). In contrast, they consider principle 2 (Complex Interactions) untestable with Single Subject methods, while principle 3 (Inter-Individual Differences in Intra-Individual Change) is considered to have limited testability.

The commentary of Molenaar (2010a) points out that dynamic factor analysis in its current form is much more general than assumed by Sterba & Bauer (2010a). In particular the following generalizations are important for the present discussion: (1) The assumption of weak stationarity (criterion 1 for ergodicity), on which versions of the dynamic factor model have been based since the introduction of this model into psychometrics (Molenaar, 1985), can be dropped (Molenaar et al., 2009). This yields dynamic factor models in which arbitrary subsets of parameters (factor loadings, auto- and cross-lagged regression parameters, mean vectors) can be time-varying. (2) The dynamic factor model can be extended to include time-varying covariates (called measured input in engineering). For an interesting application of this extension involving an application to subject-specific optimal control of diabetes type 1 patents in real time, see Wang et al. (2014). (3) The dynamic factor model can be applied to multivariate time series obtained in replicated time series designs. In fact, this can be done in various ways, one of which will be considered below. Given this, the label Single Subject for this type of data analysis is unfortunate because it incorrectly suggest that application to multiple subjects is not possible.

Using the current generalized form of the dynamic factor model, Molenaar (2010a) argues that it enables testing of all six principles characterizing person-oriented theory. In their reply Sterba & Bauer (2010b) qualifiedly agree. The reader is referred to their well-argued reply for further details. Here I want to single out, and comment on, one particular observation made by Sterba & Bauer (2010b) in which they address the issue of measurement invariance in the context of dynamic factor models with time-varying factor loadings. According to Sterba & Bauer (2010b) time-varying factor loadings violate the criteria for measurement invariance and therefore the meanings of the latent dynamic factors would become time-dependent.

Genealized Measurement Invariance in Dynamic Factor Models

The operationalization of measurement invariance in terms of invariant factor loadings is well-established and almost universally accepted by psychometricians (cf. Millsap, 2011). Using this operationalization it indeed is immediately evident that the occurrence of time-varying factor loadings implies a continuous violation of measurement invariance and, again given this operationalization, leads to the conclusion that the meanings of the latent factor series concerned also change continuously. But recently it has been suggested that the standard operationalization of measurement invariance in terms of invariant factor loadings is too limited for the purpose of analysis of intra-individual variation (Molenaar, 2014). If a factor loading in a dynamic factor model is changing continuously then this may not always be due to a change in the meaning of the latent factor series. One spectacular (though not psychological) example concerns the detection of the direction-of-arrival of N airplanes (Nesselroade & Molenaar, 2015). Given an array of radar stations, a complex-valued N-factor model in the frequency domain is used to solve this in which each airplane constitutes a factor and its reflected radar signal on each station constitute the factor loadings. This factor model has time-varying factor loadings because the solid angle of each moving plane with each radar station is changing continuously and hence continuously violates the criterion of invariant factor loadings for measurement invariance. But it would be nonsensical to conclude that the meanings of the N factors, that is, the identity of the N airplanes, change in time-dependent ways (see Nesselroade & Molenaar, 2015, for further details and mathematical specifications).

Other examples could be given (Molenaar, 2014), but instead I will focus here on a theoretical argument. For a given dynamic q-factor model the q-variate latent factor series is identified up to rotation, similar to the situation in standard factor analysis of inter-individual variation. That implies that two different linear factor models are equivalent if the matrix of factor loadings of the one can be rotated towards the other (Procrustes rotation). If that is indeed possible then the two models are measurement invariant and the meaning of the respective q-variate factor series is the same. Hence the set of measurement invariant linear (dynamic) factor models constitutes a group with (q,q)-dimensional rotation as group action.

The theoretical question can now be raised how to generalize this algebraic perspective on measurement invariance in terms of sets of measurement invariant models in a way that accommodates time-varying factor loadings. Which alternative group with different appropriate group action could be considered? A key observation in this context is the following. Suppose attention is restricted to linear state space models with time-varying factor loadings, auto-regressive and/or cross-lagged regression coefficients. To fit such a state space model with q-variate latent state process to the data it is transformed by adding all M free model parameters to the latent state process (latent factor series; Molenaar et al., 2009). This extension to a (q+M)-dimensional state process transforms the initial linear state space model into a nonlinear equivalent one. This transformation of linear state space models with time-varying parameters to nonlinear equivalent models suggests that the question stated above can be answered by considering equivalence transformations in nonlinear state space models. Hence what is the analog for nonlinear state space models of factor rotation in linear state space models?

The following theorem in Isidori (1985) provides the answer. Let $\mathbf{z} = \boldsymbol{\Gamma}(\mathbf{x})$ be an invertible smooth state transformation (global diffeomorphism). Let

(♦) $\mathbf{y}(t) = \mathbf{h}[\mathbf{x}(t),t] + \mathbf{v}(t)$

$\mathbf{x}(t+1) = \mathbf{f}[\mathbf{x}(t),t] + \mathbf{w}(t+1)$

be a nonlinear state space model where **y**(t) is a p-variate observed series, **x**(t) is the q-variate latent state process, **h**[.] and **f**[.] are, respectively, p- and q-variate smooth nonlinear functions, and **v**(t) and **w**(t) are, respectively p-variate measurement error and q-variate process noise. Then applying the global diffeomorphism $\mathbf{z} = \Gamma(\mathbf{x})$ it follows that (♦) is equivalent to (Isidori, 1985):

(♦♦) $y(t) = \mathbf{h}^*[z(t),t] + v(t)$
$\mathbf{z}(t+1) = \mathbf{f}^*[\mathbf{z}(t),t] + \mathbf{g}^*[\mathbf{z}(t),t]\mathbf{w}(t+1)$

where $h^*[\mathbf{z},t] = \mathbf{h}[\mathbf{x},t]$ at the point $\mathbf{x} = \Gamma^{-1}(\mathbf{z})$, while $f^*[z,t] = [\frac{\partial\Gamma}{\partial\mathbf{x}}f[x,t]$, and $g^*[z,t] = [\frac{\partial\Gamma}{\partial\mathbf{x}}]$, taking the **x**-value in the derivatives at the right hand sides of these equations again at the point $\mathbf{x} = \Gamma^{-1}(\mathbf{z})$. Especially noteworthy is that if $\Gamma(x)$ is linear, $\mathbf{z} = \Gamma\mathbf{x}$ with Γ a (q,q)-dimensional nonsingular matrix, then this diffeomorphic transformation reduces to standard rotation in the linear SSM.

My conjecture is that this diffeomorphic equivalence transformation for smooth nonlinear state space models opens up the possibility to substantially generalize the operationalization and testing of measurement invariance. In particular it allows for a principled generalization of measurement equivalence in linear state space models with time-varying parameters. Further implementation and testing of this generalized measurement equivalence is a work in progress – it was presented for the first time before a psychometric audience only recently (Molenaar, 2014).

Optimal Guidance and Control of Psychological Processes

A final topic, also mentioned in Molenaar's (2010[a]) commentary, concerns the possibility of optimal guidance/control of psychological processes. If a dynamic factor model yields a satisfactory fit to an observed p-variate time series **y**(t), and this model involves a dynamic regression of the q-variate latent factor series $\eta(t)$ on a measured s-variate time-varying covariate process **u**(t), then optimal control of $\eta(t)$ is possible by judicious choice of **u**(t). The measured covariate process **u**(t) is called the input. What is required is only that at least some of the s univariate input processes making up **u**(t) can be at least partially manipulated by the controller.

To apply optimal guidance/control nothing else is required but a dynamic factor model as described above. Computational control theory is introduced in Molenaar (2010[b]). Suppose that the required dynamic factor model is available at time t. Then at this time t the expected value of $\eta(t+1)$ is determined and the (partly) manipulable components of **u**(t) are computed such that a so-called cost function is minimized. This cost function usually consists of the squared deviation of $\eta(t)$ from its desired value $\eta^*(t)$ in combination with the cost of exercising control. The latter cost usually is quantified by the squared deviation of **u**(t) from its desired value **u***(t). Notice that this computational scheme can be applied recursively in real time at t, t+1, t+2, etc., as the observed series **y**(t) become available sequentially.

The choice of the desired values of the state $\eta^*(t)$ and manipulated input **u***(t) are up to the controller. For instance if $\eta(t)$ quantifies disease symptoms then an obvious choice for $\eta^*(t)$ is zero, although more sophisticated choices are possible in which the development of particular patterns of values for $\eta(t)$ (syndromes) is especially penalized. Together the choice of the details of the cost function and the mathematical techniques used to determine optimal input are called the design parameters. The presentation in Molenaar (2010[b]) uses as design parameters an additive quadratic cost function and assumes that the dynamic factor model is linear and has Gaussian measurement error and process noise. Then the so-called Linear Quadratic Gaussian (LQG; cf. Whittle, 1981) optimal control scheme can be obtained which has proven to be a robust and powerful technique even in sub-optimal circumstances.

Actual application of mathematical optimal guidance/control to psychological processes is still rare, although consideration of feedback and homeostasis at the theoretical level appears to be quite popular. Molenaar (1987) presents a successful application to the optimization of an individual psychotherapeutic process. A recent application to the optimal control of individual diabetes type 1 patients in real time under normal living conditions is presented in Wang et al. (2014). By recursively fitting a dynamic factor model with time-varying parameters to each individual patient it is possible to predict each patient's blood glucose level 30 minutes later with more than 90% fidelity. This time interval of 30 minutes is sufficient for fast-acting insulin to have noticeable effects. Fitting the model to each patient individually is necessary because the time-dependent changes in blood glucose and insulin effects are varying substantially in subject-specific ways both within and between patients.

Broader Tenets of Subject-Specific Data Analysis

The implications of the classical ergodic theorems are straightforward: To obtain results about nonergodic psychological processes that validly apply at the level of individual persons it is required to base the analysis on intra-individual variation, not inter-individual variation. Because most psychological processes violate the two necessary criteria for ergodicity, subject-specific analysis of intra-individual variation as described above should become the new norm in psychometrics. This, however, may raise the specter of a completely fragmentized psychological science – in the words of one anonymous reviewer: a different psychological theory for each individual subject. On closer scrutiny this is not the case.

Consider the application to optimal control of diabetes type 1 patients discussed above. This application has to be starkly subject-specific in order to obtain high-fidelity predictions and control. Yet the same mathematical-statistical dynamic model is applied to each individual patient. That is, at the level of modeling the same state space model with time-varying parameters is applied. Only the estimated model parameters are subject-specific. This allows not only for a posteriori comparison of parameter estimates, but also opens up possibilities to carry out standard analyses of inter-individual variation of these parameter estimates (MANOVA, cluster analysis, etc.). This is a commonly followed data analysis plan in cognitive neuroscience: in the first phase obtain parameter estimates based on single-subject analyses of intra-individual variation (EEG, MEG, fMRI) and then in a second phase carry out analysis of inter-individual variation of these estimated parameter values to arrive at conclusions that can be generalized to the population level. In this way nomothetic knowledge about idiographic processes can be obtained.

If the number N of replications in a time series design is large and if heterogeneity also affects model structure (that is, different subjects obeying different dynamic models) then a new approach to arrive at nomothetic knowledge even in this more fundamentally heterogenic situation has been developed (Gates & Molenaar, 2012). While this so-called GIMME modeling approach has been mainly applied in the context of fMRI data analysis, it can also be applied much more generally to the analysis of any psychological process assessed in a replicated time series design (see Beltz et al. 2013, for an application to social interaction processes). GIMME consists of a data-driven automatic two-step approach using standard likelihood criteria. In the first step a common (group) dynamic model structure is determined for all N replications. While this common structure is shared by all N replications, the beta weights associated with each directed link are allowed to vary across replications. In the second step subject-specific directed links are added to the common structure until the goodness-of-fit no longer can be significantly improved. GIMME has been validated with truly large-scale simulated data (cf. Gates & Molenaar, 2012) and shown to be extremely precise. GIMME can be freely accessed at http://www.nitrc.org/projects/gimme/. An extension to a finite set of multiple common models is described in Gates et al. (2014).

Clearly, the common (group) models detected by means of GIMME with possibly heterogeneous replicated time series data again constitute nomothetic knowledge about idiographic processes. It therefore is concluded that the broader tenets of subject-specific data analysis are commensurable with those characterizing standard analysis of inter-individual variation. That is, the broader tenets still are to arrive at nomothetic knowledge that can be generalized to the population level. But instead of assuming *ad hoc* in the latter type of analysis that psychological processes are ergodic, in subject-specific analysis it is recognized that ergodicity is a rare feature of such processes and that therefore appropriate data analysis plans have to recognize this.

Conclusion

The relation between subject-specific and person-oriented approaches is in the first instance quite indirect. The necessity to use subject-specific approaches has its origin in mathematical-statistical theory while person-oriented approaches originate from holistic interactionistic perspectives within psychological theory. It was argued that subject-specific data analysis has a contingent, but natural affinity with Developmental Systems Theory (DST). The important paper by Sterba & Bauer (2010a) shows that subject-specific data analysis also enables testing of most principles underlying person-oriented theory. Molenaar (2010a) argued that subject-specific data analysis enables testing of all six principles of person-oriented theory. In the present paper Molenaar's (2010a) argument has been extended in a number of ways, thus further corroborating the importance of subject-specific data analysis for the testing of person-oriented theory. In view of the spectacular increase in intensive repeated measurement designs in psychology in general, it is expected that subject-specific data analysis also will become the new norm for applications of person-oriented theory.

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