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Studying Intraindividual Variability: What We Have Learned That Will Help Us Understand Lives in Context

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We examine some features of intraindividual variability and the research outcomes from its study. Selected current modeling techniques focused on individual-level analyses are briefly discussed, including some promising applications stemming from dynamical systems theory work. We turn these ideas into issues prominent in the study of behavioral development and examine how the general intraindividual variability orientation can strengthen the further study of lives in context.

> The future is not some place we are going to, but one we are creating. The paths are not to be found, but made, and the activity of making them, changes both the maker and the destination.
>
> —*John Schaar, futurist*

New beginnings are opportunities and the launching of a new journal is no exception. In the mid-1960s, one of us (John R. Nesselroade) was a graduate student in Raymond B. Cattell's laboratory at the University of Illinois when Cattell wrote the initial editorial to *Multivariate Behavioral Research* (Cattell, 1966). Cattell seized the opportunity not so much to say where people had been as to tell them where he thought they should go. We would like to engage in a bit of such "goal directing" behavior in this article albeit in a somewhat kinder, gentler manner than was often characteristic of Cattell.

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The focal points around which we have constructed this discussion are some of the concepts and methodological tools by which the study of intraindividual variability, primarily at the individual rather than group level, is being conducted, some findings, and the latter's implications for studying lives in context. We believe that some of the innovations that have helped shape the study of intraindividual variability offer considerable promise for tackling some key issues in examining lives in context. We will begin by briefly reviewing where the study of intraindividual variability currently stands and identifying, very selectively because of space limitations, some of the concepts and methods that have secured this information. Then, we will address some promising extensions of the work toward the study of lives in context.

INTRAINDIVIDUAL VARIABILITY

Basic precepts of the study of intraindividual variability are that an individual, at any given moment, is a complex configuration of characteristics and that some of these characteristics are changing from moment to moment, day to day, week to week, whereas others are relatively stable. Thus, instead of being well characterized as a static set of relatively fixed values, individuals exist as complex dynamic systems, many of the characteristics of which are constantly changing. The study of intraindividual variability is focused on how, when, and why the individual changes over time (see, e.g., Baltes, Reese, & Nesselroade, 1977; Nesselroade, 2002).

A number of investigators have proposed taxonomies of intraindividual variability (e.g., Cattell, 1957; Fiske & Rice, 1955; Hultsch & MacDonald, in press; Nesselroade & Featherman, 1997). We have found it useful to differentiate among three types of within-person changes: (a) those that may or may not be reversible and that may or may not be synchronous across individuals, for example, development and learning; (b) those that are more or less reversible and that may or may not be synchronous across individuals, for example, states and mood; and (c) patterns of organization such as the salience and frequency of multiple attributes within the individual.

The study of intraindividual variability can be located within a more general empirical framework by means of Cattell's (1952) data-box heuristic (persons × variables × occasions) as illustrated in Figure 1. Of the three 2-way data samples definable within the data-box, the study of intraindividual variability is defined on the O/P (variables × occasions) and S/T (persons × occasions) slices (see, e.g., Nesselroade & Molenaar, 2003). Both of these data samples are characterized by multiple occasions of measurement (i.e., time series), in the former case on multiple variables-one individual and in the latter case on multiple individuals-one variable. If one focuses on the interrelations among variables defined across occasion (rather than over per-

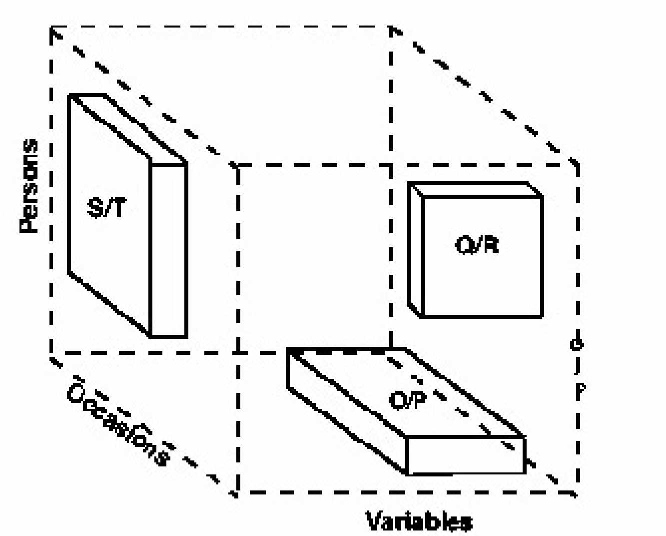

FIGURE 1 Cattell's (1955) three-dimensional data-box (persons × variables × occasions of measurement).

sons, as is traditional in differential psychology), one can use a variety of methods to model the between-variable and between-occasion variance in the individual's data. It is this variance with which we concern ourselves here. In the strict interpretation of intraindividual variability there is no between-person variance or interindividual differences to model, because one is examining only one individual's data. However, issues of generalizability and aggregation must be considered, and multiperson extensions of concepts and methods must generally be kept in mind. Our present goal, however, is to examine how understanding the patterns of variability within an individual contributes to an understanding of human behavior.

HOW THE STUDY OF INTRAINDIVIDUAL CHANGE HAS CONTRIBUTED TO UNDERSTANDING BEHAVIOR

In the last 40 years, investigators have studied intraindividual variability in a wide variety of domains, including affect, emotion, and mood (Larsen, 1987; Lebo & Nesselroade, 1978; Wessman & Ricks, 1966; Zevon & Tellegen, 1982), personality (Hooker, 1991; Hooker, Nesselroade, Nesselroade, & Lerner, 1987; Roberts & Nesselroade, 1986; Shoda, Mischel, & Wright, 1994); human abilities (Hampson, 1990; Horn, 1972); cognitive performance (Hultsch & MacDonald, in press; May, Hasher, & Stoltzfus, 1993; Nesselroade & Salthouse, 2003; Siegler, 1994); work values (Schulenberg, 1988); and teacher performance (Hundleby & Gluppe, 1974). The findings from these studies indicate that there are coherent, systematic patterns of intraindividual variability for many different kinds of psychological attributes, characteristics, and behaviors, some of which are traditionally considered to be highly stable within the individual. We now highlight how a few of these lines of research have helped further our understanding.

First, research on intraindividual variability has substantially enriched conceptions and theories of personality. For example, focusing on intraindividual variability was instrumental in the development of the state-trait distinction (Cattell & Scheier, 1961; Spielberger, Gorsuch, & Lushene, 1969). By studying individuals over time with some sensitivity toward change patterns rather than dramatizing only patterns of stability, it has been possible to distinguish rigorously and productively among *stable* and *labile* dimensions of personality (Nesselroade, 1988). Shoda et al. (1994), for example, reformulated the concept of personality consistency to include intraindividual variability patterns defined across contexts. In this sense, an individual's variations in behavior across situations constitute a coherent and predictable "behavioral signature." This line of research reinforces the idea that the structure of intraindividual variation, rather than just profiles of single scores, is fundamental to defining and understanding personality.

Similarly, studies in the human abilities domain, wherein individuals were measured repeatedly over a relatively short timeframe, demonstrated that patterns of intraindividual variability in abilities are an important class of individual characteristics in their own right. For instance, Horn (1972) identified patterns of week-to-week intraindividual variability that reflected the fluid-crystallized intelligence distinction. Hampson (1990) demonstrated the existence of short-term patterns in ability measure fluctuations that appear to be hormonally driven. These lines of research emphasize that meaningful and informative "state-like" patterns of intraindividual variability coexist with the more traditional "trait-like," inter-individual-differences ability patterns.

Second, constructs of intraindividual variability can be used as sources of individual differences. As such, they can be used to predict other interindividual characteristics. For instance, in developmental psychology, investigators have examined how differences in the intraindividual variability in infants' heart rates predict later differences in temperament (Fox & Porges, 1985; Kagan, 1994). Others have found that increases in intraindividual variability in performance are a leading indicator of cognitive developmental transition (see, e.g., Siegler, 1994). In the personality-social arena, investigators have found self-esteem lability to be predictive of depression proneness (Butler, Hokanson, & Flynn, 1994) and, for older adults, week-to-week variability in internality beliefs to be a risk factor for mortality some five years later (Eizenman, Nesselroade, Featherman, & Rowe, 1997). These lines of research point to the utility of using intraindividual variability as an inter-individual-difference variable.

Third, intraindividual variability studies have also furthered the integration of idiographic and nomothetic approaches. For instance, Zevon and Tellegen (1982) found between-subject congruence for a two-factor structure of emotion by identifying similarities and differences in within-person structures. This study demonstrated that systematic and rigorous idiographic analyses could provide valuable and relevant information to the nomothetic description of mood. New advances in the methodology for integrating within- and between-person analyses have furthered this integration and can greatly strengthen the general validity of findings (Nesselroade & Ford, 1985; Nesselroade & Molenaar, 1999). We discuss some of these methods in more detail later.

Finally, the study of intraindividual variability and its ability further to dissect and explain sources of variance provides a key to greater understanding of age-related developmental processes (Nesselroade & Jones, 1991). Assessing within-person changes provides a way to "capture" and organize important sources of variance that might otherwise be misunderstood. For example, May et al. (1993) illustrated how within-day intraindividual variability in intellectual ability could confound age comparisons. More generally, group differences, such as increased between-person variability in older compared with younger groups, may in part be explained by age related increases in within-person variability. The apparently greater between-person variance noted in older (compared to younger) groups may be attributable, in some portion, to greater intraindividual variation that exists asynchronously and manifests as between-persons variance at any one occasion of measurement.

Although studying intraindividual variability can be very useful in one's attempts better to understand interindividual differences, researchers must not stop there. Such variability deserves to be studied in its own right. Researchers need to determine how it is structured both within and between domains, how it evolves, what causes it to change, and, ultimately, why it forms and changes in the way it does. Toward this end, in the following sections we outline a selection of concepts and methodologies that are proving to be useful in the study of intraindividual variability.

STUDYING INTRAINDIVIDUAL VARIABILITY

As the research that we just briefly summarized points out, there is much to be gained from the measurement and analysis of within-person changes and patterns. It is also clear that, if further progress is to be made in capitalizing on this kind of information, the researcher's toolkit needs to be augmented over and above the standard one built up over psychology's first 100 years. For example, measures need be sensitive enough to detect (sometimes subtle) changes from one time to another. By definition, research designs must be longitudinal, but they also have to be more sophisticated with respect to the matters of number and spacing of measurement occasions than has often been the case in the past (for further design considerations see Nesselroade, 1991a, 1991b; Nesselroade & Boker, 1994; Nesselroade & Ghisletta, 2003). Finally, the way data are modeled requires different emphases than have been learned in the usual courses in analysis of variance and regression for graduate students. It is the last matter with which we are most directly concerned here. Our main emphasis will be on modeling repeated measurements at the individual level, although these methods are adaptable to group analysis format in many instances (see, e.g., Nesselroade & Molenaar, 1999).

In addition to classical tools, such as multivariate time series analysis, that are designed for analyzing frequently repeated measurements, adaptations of the common-factor and latent-variable structural modeling tools now commonly used in psychology are also being used to study intraindividual variability (e.g., Browne & Nesselroade, in press; Hamaker, Dolan, & Molenaar, 2003). If we take a quasi-chronological perspective on the development of methods for studying intraindividual variability within behavioral science, a good place to begin the presentation of such methods is with P-technique factor analysis. The P-technique factor model (Cattell, 1963; Cattell, Cattell, & Rhymer, 1947), portrayed in Figure 2, has been used in a large number of intraindividual variability studies for over half a century (for reviews of this literature, see Luborsky & Mintz, 1972; Jones & Nesselroade, 1990).

P-technique factor analysis involves the application of the common-factor model to P-data (variables occasions for one person; see Figure 1). Thus, the common-factor model, rather than being used to identify patterns in the relations between variables that are defined across persons (R-technique), is used to identify patterns in the relations between variables that are defined across occasions—for one individual. In other words, the P-technique model represents the factorial structure that prevails for a given person across occasions of measurement. Note, however, that this model implies that unobserved or latent factors, represented as circles in Figure 2, exert their influence on the observed variables, represented by squares, only concurrently: There is no allowance for lagged effects such as the value of the factor *yesterday* affecting the value of the observed variable *today.* Thus, by applying the P-technique model, one accounts only concurrently for aspects of intraindividual change and variability—no memory that might be present in the repeated measurements is given expression in this model.

This limitation of no "memory" in the system was recognized early (see e.g., Cattell, 1963); nevertheless, at a descriptive level, much has been learned from the application of P-technique factor analysis. As mentioned previously, for example, the first P-technique studies (Cattell & Sheier, 1961; Cattell et al., 1947) were instrumental in the development of the trait-state distinction and subsequent measurement devices. More recently, applications of P-technique have enhanced our understanding of psychoanalytic counseling (Patton, Kivlighan, & Multon, 1997), child therapy sessions (Russell, Bryant, & Estrada, 1996), adult psychotherapy (Czogalik & Russell, 1994, 1995), and mood changes associated with depression

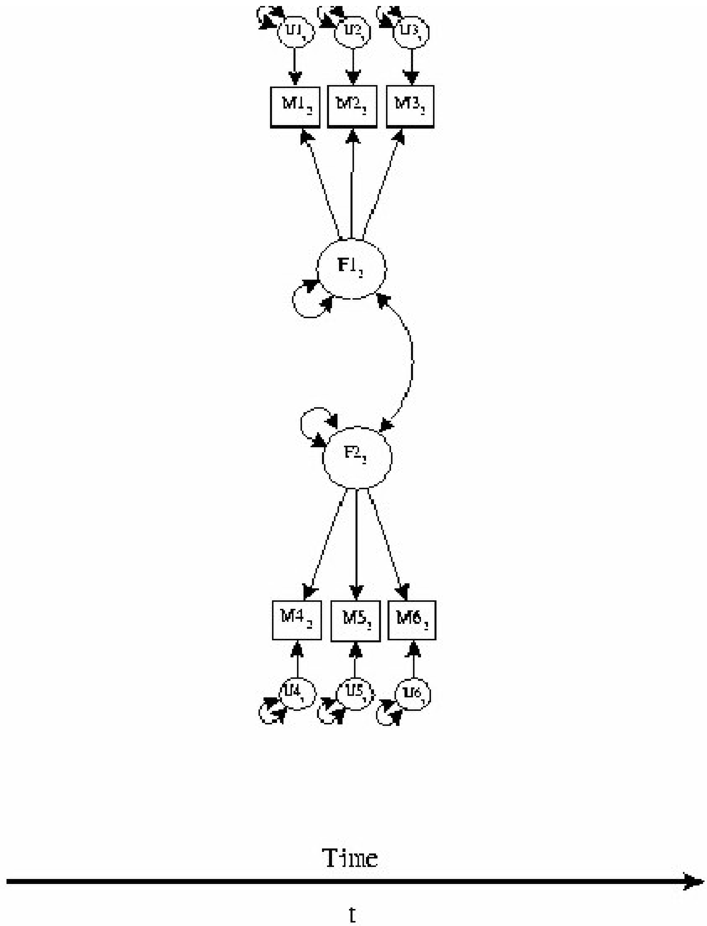

FIGURE 2 P-technique factor model (Nesselroade, McArdle, Aggen, & Meyers, 2002). The factor loadings are invariant across time. From “Alternative Dynamic Factors Models for Multivariate Time-Series Analyses” by J. R. Nesselroade, J. J. McArdle, S. H. Aggen, & J. M. Meyers. In D. M. Moskowitz & S. L. Hershberger (Eds.), *Modeling Intraindividual Variability With Repeated Measures Data: Advances and Techniques* (pp. 235-265). Copyright © 2002. Used by permission of Lawrence Erlbaum Associates, Inc.

(Garfein & Smyer, 1991) and Parkinson’s disease (Shifrin, Hooker, Wood, & Nesselroade, 1997).

A second limitation of the P-technique model is that the factor loadings are implicitly constrained to be invariant over time. The model represents only the variability patterns that are repeatable across all occasion of measurement. In other words, the factor loadings are rendered identical across all occasions, in the same manner that loadings are implicitly constrained to be invariant across persons in R-technique factor analysis (see, e.g., Molenaar, Huizinga, & Nesselroade, 2003, for a critical discussion of this point). This may be a reasonable condition to impose on data in some cases, but probably not in others. The way variables are organized is, in many instances, evolving across time, thus rendering the P-technique modeling approach inadequate in such circumstances.

In the past 30 years or so, the P-technique model has been extended in a number of ways to incorporate the influence of past history on the current state of the organism. For example, dynamic factor analysis, and its incorporation of time series modeling into the common-factor model, represents a more compelling way to model intraindividual variability and change as it evolves over time (Browne & Nesselroade, in press; Molenaar, 1985; Nesselroade, McArdle, Aggen, & Meyers, 2002). One of two principal specifications—what has elsewhere been referred to as the direct autoregressive factor score specification (McArdle, 1982)—is shown in Figure 3. Although the values of the manifest variables (squares) are "driven" by concurrent values of the factors (common and specific, represented by circles), those concurrent common-factor values are, in turn, driven by the prior common factor scores as represented by the arrows from earlier to later representations of the factors. For clarity, we have omitted cross-factor regressions, but these are estimable in many cases. Thus, manifest variables are determined, in part, by the common factors, which are determined, in part, by the values of those same common factors at earlier occasions. Memory in the system, or a "sense of history"—and therefore some sense of continuity—is represented at the latent variables level - by auto- and possibly cross-correlated common factors and the autocorrelated uniquenesses. Positive and negative affect (as latent variables) driving responses to particular adjective rating scales (as manifest variables) illustrate the kind of data that might be modeled in this way. To the extent that positive and negative affect are autocorrelated, their earlier levels predict their later levels and thus are reflected in the actual responses made by the participant.

In a somewhat different vein, Molenaar (1985) specified a dynamic factor model in which the factor scores were uncorrelated over time, as portrayed in Figure 4. Nesselroade et al. (2002) dubbed it the *white noise* factor score model. In the white noise factor score model, current values of the manifest variables (squares) are driven to some extent not only by concurrent values of the common and specific factors (circles) but also by prior values of the common factors. In essence, the configuration of loadings, concurrent and lagged, define the nature of process underlying the observed data. Thus, a sense of history spans the latent variable–manifest variable barrier by residing in the lagged factor loadings as well as the autocorrelated uniquenesses. As depicted in Figure 4, this model is a "shock" model (Browne & Nesselroade, in press), with day-to-day uncorrelated events driving the system, but the system still manages some amount of continuity, depending on the strength of the factor loadings.

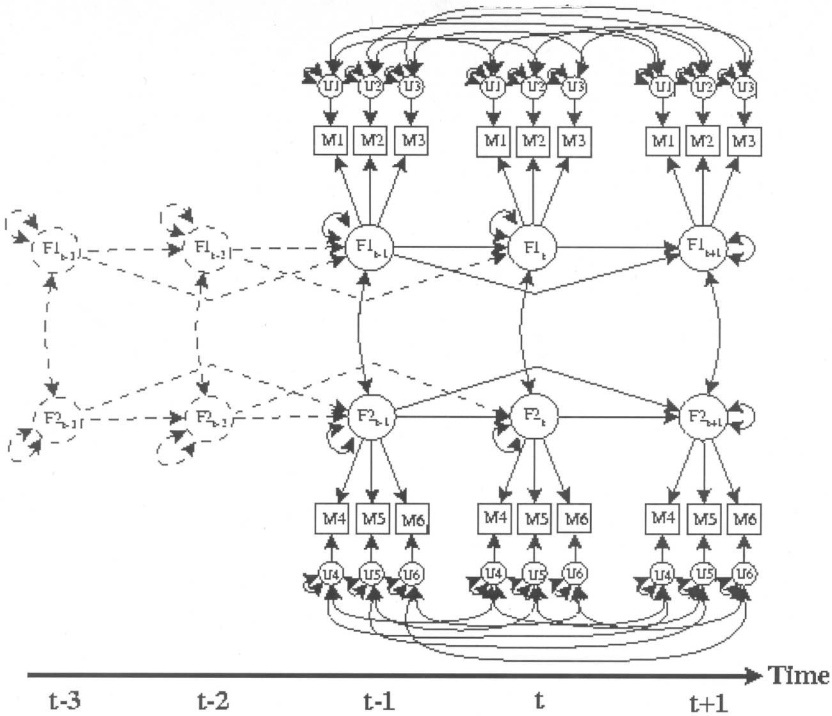

FIGURE 3 Direct auto-regressive factor score model (Nesselroade, McArdle, Aggen, & Meyers, 2002). The model allows for time-lagged relationships such that factor scores at previous time points influence factor scores at later time points. From "Alternative Dynamic Factors Models for Multivariate Time-Series Analyses" by J. R. Nesselroade, J. J. McArdle, S. H. Aggen, & J. M. Meyers. In D. M. Moskowitz & S. L. Hershberger (Eds.), *Modeling Intraindividual Variability With Repeated Measures Data: Advances and Techniques* (pp. 235-265). Copyright © 2002. Used by permission of Lawrence Erlbaum Associates, Inc.

Dynamic factor analysis has been used to model time-lagged relationships in psychophysiology (Kettunen & Ravaja, 2000; Molenaar, 1987b), mood (Nesselroade et al., 2002; Shifrin et al., 1997), and psychotherapy (Molenaar, 1987a). All in all, P-technique and its dynamic derivatives provide useful, still-promising tools for modeling intraindividual variability and change over time. We see great promise for furthering our understanding of psychological processes through future applications of these models, especially if their strengths can be capitalized on by appropriate design and data collection.

Some other key developments for representing intraindividual variability extend early work of Arminger (1986), Coleman (1968), Tuma and Hannan (1984), and oth-

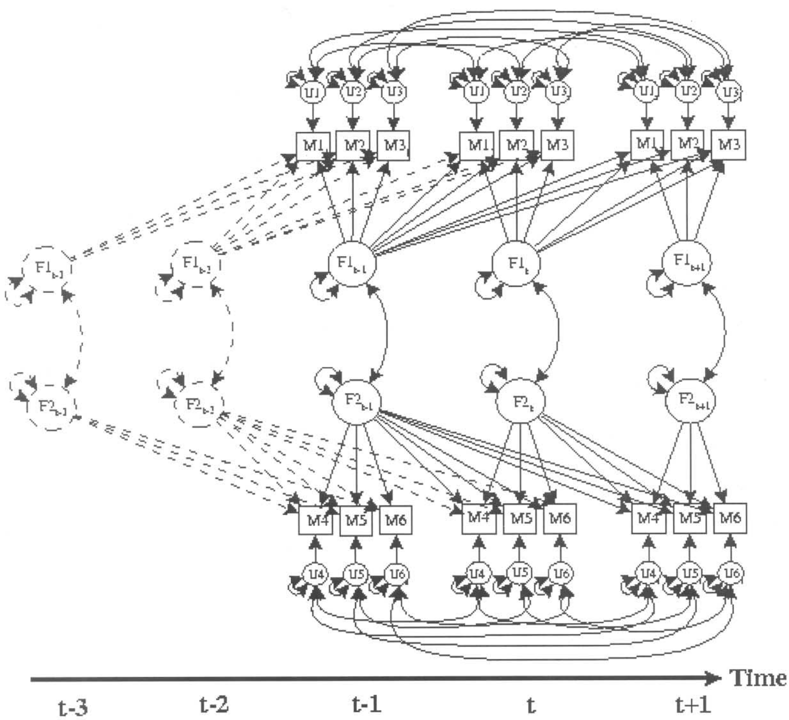

FIGURE 4 White-noise factor score (WNFS) model (from Nesselroade, McArdle, Aggen, & Meyers, 2002). The model presented by Molenaar (1985) allows for time-lagged relationships such that factor scores at previous time points can directly influence manifest variable scores at later time points. From "Althernative Dynamic Factors Models for Multivariate Time-Series Analyses" by J. R. Nesselroade, J. J. McArdle, S. H. Aggen, & J. M. Meyers. In D. M. Moskowitz & S. L. Hershberger (Eds.), *Modeling Intraindividual Variability With Repeated Measures Data: Advances and Techniques* (pp. 235–265). Copyright © 2002. Used by permission of Lawrence Erlbaum Associates, Inc.

ers by specifying dynamical systems models such as the damped linear oscillator model[1] in differential equation form (Boker & Graham, 1998; Boker & Nesselroade, 2002; Boker, Postolache, Naim, & Lebenluft, 1998; Nesselroade & Boker, 1994) and by latent difference score models (e.g., McArdle & Hamagami, 2001).

Whereas the dynamic factor models just described are used to represent rates of change, this class of models goes a step further to include how rates of change may

[1]The damped linear oscillator is a much more general model than its name implies. It has been put to good use in modeling intraindividual variability in a number of substantive domains.

be changing. Specifically, in the dampened linear oscillator model depicted in Figure 5, changes in acceleration (second derivative, d^2x) are driven by changes in the location (from equilibrium) of the system, x, and the velocity, dx, (first derivative) of the variable of interest. Sense of history is represented by the highly formal structure of the differential equation that describes the way the system behaves, including the values of its parameters η (a function of the frequency of oscillation) and ξ (the damping parameter).

Another key concept of this modeling approach is the *coupling* of systems and/or subsystems, a representation of which is depicted in Figure 6, which shows two coupled, damped linear oscillators. Subsystems that influence one another are said to be coupled. Such interrelations can be modeled explicitly and are described by *coupling* parameters (e.g.,γ_1 and γ_1, in Figure 6). These parameters explicitly model how the dynamics or changes in one system influence the dynamics in another system.

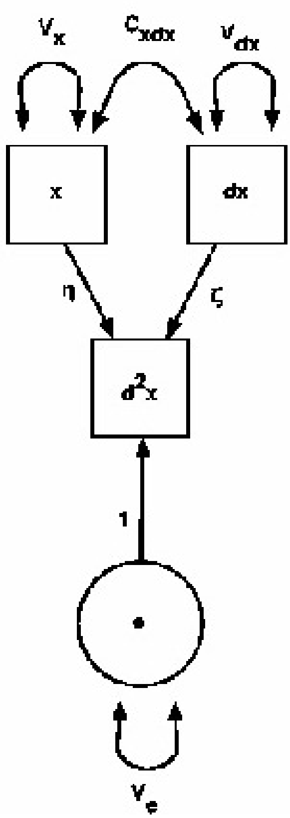

FIGURE 5 Damped linear oscillator model (after Boker & Nesselroade, 2002).

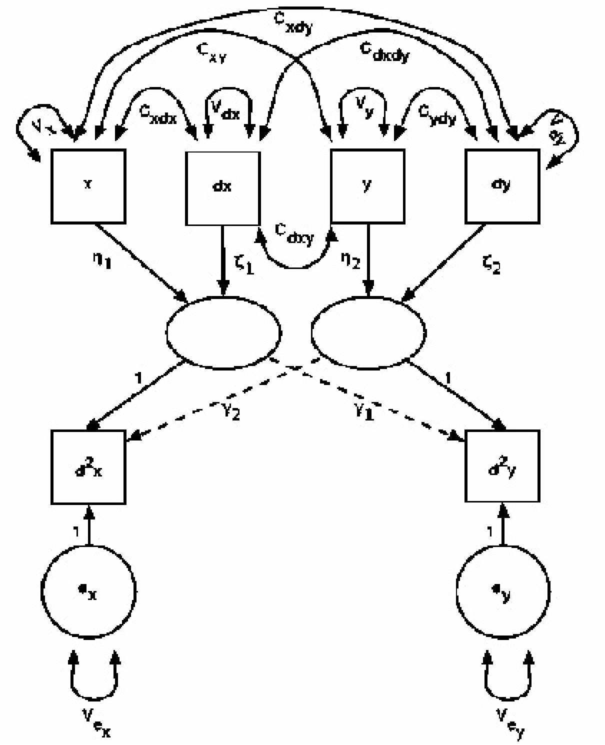

FIGURE 6 Two coupled, damped linear oscillators model (after Boker & Nesselroade, 2002).

For example, coupling parameters can be used to examine dynamic interrelations between cognitive and emotive systems. One can model how cognitive performances might drive emotional change and how such emotions might drive subsequent changes in cognitive performance. McArdle and Hamagami (2001) discussed the modeling of discrete time versions of similarly coupled models, focusing on first and second differences rather than first and second derivatives.

INCLUDING CONTEXT IN INTRAINDIVIDUAL VARIABILITY MODELING

So far, we have taken an implicit, essentially methodological approach to recognizing context. Here we will try to be somewhat more explicit and directive in considering it. Empirical and theoretical work on intraindividual variability reminds us over and over that the use of single scores implying stable, trait-like attributes (e.g., true scores of classical test theory) that are invariant across contexts do not adequately characterize many features of the individual. Contextualists have been saying (or implying) this for years. Features of contexts tend to vary constantly; is it any wonder that behavior is so rich and interesting—and difficult to predict? As we consider how the study of intraindividual variability might help us better understand lives in context we can use the data-box (see Figure 1) to explore some of the ways context information can be incorporated into the design of intraindividual-variability research.

Capitalizing on the three dimensions that define the various data-box samples discussed earlier, we can regard context as where an individual exists within time (occasions), space (variables), and among people (persons). The study of intraindividual variability assures us that measuring an individual on multiple occasions yields a richer picture of his or her existence within the temporal context of his or her life. Similarly, with regard to the conditions or environment in which the individual exists, augmenting the variable space to include situational-contextual measures provides a more complete picture of one's surrounding circumstances. Finally, by measuring multiple people, especially those with whom the target interacts, we can better understand how the individual influences and is influenced by others.

Thus, in regard to the three dimensions of the data-box, we regard context involving the location of the individual within time and space and among persons. Although a parsimonious scheme, these three dimensions do an adequate job of capturing key theoretical notions of context, including cultural settings and historical epochs (Baltes, 1987); biological, social, and historical changes (Lerner, 1984); 2nd persons, objects, symbols, environment, and social continuities and changes (Bronfenbrenner, 1979). More to the point, they provide a way to characterize context within the methodological framework of studying intraindividual variability.

The models just outlined provide promising ways of examining intraindividual variability; however, they all invoke particular constructions of the dimensions of the data-box and the structure of their relations. In other words, each model rests on a particular notion of the context in which the individual exists. In the following section, we briefly examine what some of these constructions are and how they may extend or limit the interpretation of study results. Overall, we see that these models, although still limited in some respects, can be used to provide more flexible and perhaps more meaningful representations of individuals within their life contexts.

CONSTRUCTIONS OF TIME, SPACE, AND PERSON CONTEXTS

Time: Occasions

The models presented here vary somewhat in how the time dimension is construed. In practice, when fitting the P-technique factor model, the occasions of measurement are treated as though they are independent of one another and the factor structure (i.e., relations between factors and variables) as identical across all those occasions. Thus, as noted earlier, this model is sensitive only to the variability arising from events that are repeatable across all occasion of measurement, whereas variability due to occasional, rare, and isolated events is consigned to the uniqueness. Similarly, in dynamic factor analysis, the context of each window of observation is taken to be identical. In other words, it is only in the ways in which every "today" is related to its "yesterday" in the same manner on which the model capitalizes. Likewise, in the dynamical systems models, velocity and acceleration are considered to be related in consistent ways across occasion, although their values are constantly changing. The relation between-variables for all points in time is taken to be adequately represented by one equation. In sum, all of these models tacitly rest on the assumption that the between-variable structure is identical on each occasion or on each window of occasions. The models thus capitalize on the consistent effects that exist in the temporal context and disregard the rest, providing a clearer understanding of the consistent ways in which individuals exist within the temporal context of their lives.

Space: Variables

As with all models, the relations among variables are determined only in the context of the variables included in the model. Representation of the context is, in a sense, limited to the variable space (*viz.*, those variables that have been explicitly included in the model). Boker et al. (1998) illustrated this idea with a study in which they measured a series of daily weather variables as context for changes in the affective status of participants with bipolar affective disorder. Obviously, other variables and processes that were not measured or included in the variable space also affect the individual. Thus, one's understanding of the individual and the space in which he or she exists is limited by the selection of variables included in the model. In this sense, if one hypothesizes that a person's mood is affected by his or her personality, then one must include measures of both. Similarly, if an individual's mood is, in part, affected by the moods of his or her significant other, measures of both individuals should be included in the variable space to obtain a fruitful representation. In all of the preceding models, background variables such as personality, family and school characteristics, and so on, can be easily incorporated so that one can understand how the patterns of intraindividual variability are affected by, or affect, the space in which the individual exists.

Extending the notions of intraindividual variability to spatial context, the environment in which an individual exists is itself constantly changing (e.g., Ford & Lerner, 1992). This intracontextual variability can also be modeled with the methods discussed here. Furthermore, the inclusion of coupling parameters in the models allows for the identification of patterns in how the dynamics, or changes, in the contextual variables influence changes in the individual variables. Although modeling the interacting dynamics of multiple variables in the space can become rather complicated, it promises a closer understanding of how people interact with other parts of themselves and their environments.

People: Persons

Thus far, we have discussed the models as though we were indeed studying an individual entity. However, often the intended unit of analysis consists of multiple persons, such as dyads (Ferrer & Nesselroade, in press; Mitteness & Nesselroade, 1987) or families (Jones, Nesselroade, & Birkel, 1991). Separate from the question of the definition of a proper unit of analysis, it is not always clear when it is reasonable and appropriate to include multiple units of analysis (however they are defined) within the same analytical exercise. This question is one aspect of the idiographic–nomothetic debate (Lamiell, 1998; van Kampen, 2000). There is growing discussion about when information from different people can meaningfully be pooled in the same analysis (Daly, Bath, & Nesselroade, 1974; Molenaar et al., 2003; Nesselroade & Molenaar, 1999). In the multiperson extension of the P-technique model, termed *chain P-technique* (Cattell & Scheier, 1961), the assumptions about occasion equivalence are extended to persons. The structure, or context, of each occasion of measurement is considered to be identical across both persons and occasions. In other words, just as in R-technique factor analyses, persons are considered to be replicates of one another as far as structure is concerned. Similarly, in the multiperson extensions of the various dynamic models the temporal relations are assumed to be the same for each person. For example, the relation between each person's "yesterday" and "today" is assumed to be the same. This is quite a strong assumption, and the careful researcher may question making it. It is likely not true that one individual exists within time and space in the same way as another.

Before pooling the data of different persons in the same analysis of the kind we are discussing here, we advocate prior testing for similarity in intraindividual patterns of variability (e.g., Nesselroade & Molenaar, 1999). Pooling data over individuals without testing for similarity in the patterns of variability can lead to the aggregation of qualitatively different structures and a distortion of the aggregate into entities that do not actually exist within the group (Daly et al., 1974; Lamiell, 1988; Molenaar et al., 2003). We encourage the use of formal processes to assess the "poolability" of individuals' data (e.g., Nesselroade & Molenaar, 1999). In brief, the patterns of variability are first determined at the individual level. Second, these structures of intraindividual variability are examined for similarity. Finally, if the lagged covariance structures are not different, individuals' data may be aggregated into a single analysis. However, if the individual structures are different, these differences can be taken as an indication that the processes of interest may be qualitatively different, and individual-level information should be examined separately.

Testing the poolability of intraindividual variability data structures provides one way of examining how an individual exists among people. For instance, one might conclude that a poolable set of individuals exist within time and space in much the same way. Likewise, different individual structures might indicate that these individuals exists within different time and space contexts. In the same way that one would not automatically assume that males and females could be pooled in the same analysis, we must also not automatically assume that the temporal and spatial contexts are identical for everyone.

Another possibility for understanding how an individual (or entity) exists among others is the use of coupling, described earlier. It is possible, using the methods described earlier, to model the interactions between persons or processes. For example, Mitteness and Nesselroade (1987) used the P-technique approach to study the affective interdependence between older mothers and their middle-age daughters. More recently, Ferrer and Nesselroade (in press) used dynamic factor analysis to investigate the interrelations in mood between a husband and wife. By modeling mood ratings over time, they found that, within the dyad defined by the married couple, the husband's current mood affected the wife's future mood, but not vice versa: The wife's current mood did not affect the husband's future mood. The model captures each partner's mood process within the context of their relationship. In sum, we see two main avenues of understanding within the person dimension of context. First, poolability analyses of lagged covariance structures can help researchers identify the qualitative differences and similarities among persons. Second, intraindividual variability modeling techniques can be used to directly represent the social interactions between persons. Both sources of information provide a clearer notion of how the individual behaves within the context of other people. More generally, such analyses demonstrate the viability of using intraindividual-variability methods to understand how processes manifest within temporal, spatial, and personal contexts.

CONCLUSION

In general, through the application of formal mathematical and statistical models, researchers attempt to describe the patterns existent in behavioral data. Often, in exploratory analyses from the fitted models, they try to make inferences about what the nature and causes of those patterns might be. However, the methods briefly described here have also been used to study contextual influences more directly for nearly the length of the methods' existence. Cattell and Scheier (1961), for example, presented what they termed *stimulus-controlled* P-technique, which involved including measurements of the context (e.g., daily) in analyses of measurements of the behaviors of interest. The purpose was to estimate the direction and strength of the relations between variations in contextual features and variations in behavior. Cattell and Scheier made the point that, in addition to naturalistic study, contextual variation could be introduced systematically as a treatment, thus the term *stimulus controlled*. As we mentioned earlier, Mitteness and Nessleroade (1987) used the P-technique model to study interdependencies in affect variation in mother–daughter dyads, and Ferrer and Nesselroade (in press) applied the dynamic-factor model simultaneously to husband and wife scores to examine affective coupling patterns. In the latter two cases, each member of a dyad was construed as a highly salient component of the social context for the other member. These examples represent more or less natural extensions of traditional design in which additional explanatory variables are included so as to provide empirical evidence bearing on putative cause–effect relationships. More of this can and should be done as models for studying intraindividual variability are applied to answering new questions.

In concluding, as we have examined what seems to be a strong affinity between the study of intraindividual variability in behavior and an enriched notion of research design and measurement aimed at capturing more detailed contextual information, it seems appropriate to emphasize the building and testing of dynamical systems models that represent occasion-to-occasion variability in the context as well. This view, although not exactly spurning traditional notions of important contextual variables such as socioeconomic status, level of parental education, and so on, encourages more concern for identifying dynamical mechanisms of contextual influences appropriate to a systems view of development and change (e.g., Ford & Lerner, 1992). Intraindividual variability, whether in behavior or contextual measures, signals activity and activity, in turn, is a manifestation of mechanisms—something more than the static concepts that have dominated much of researchers' thinking, even in developmental research (e.g., Gergen, 1977). As we have illustrated here, such mechanisms can be modeled and studied using some of the methods we have described.

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