CHAPTER 2

Emphasizing Intraindividual Variability in the Study of Development Over the Life Span

Concepts and Issues

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Animate objects, including behavioral scientists, respond to variation. There is an old adage to the effect that “we don’t know who discovered water, but we’re pretty sure it was not a fish.” This piscine allusion harbors the fundamental notion of variation, or actually, in this case, the lack of variation. The fish that only experiences water as its surrounding milieu must remain “unaware” of it because constancy does not register on its senses. If variation is not present, the organism may actively produce it. For instance, the microsaccades of the human eye create variation on the retina of an image that would otherwise be still. We remain vertical by continuously beginning to fall, and subtly and exquisitely correcting for it. The successful sculptor may be the one who is able to introduce “movement” into an otherwise immobile representation of nature. The basic sentiment is captured in such utterances as “variety is the spice of life.” In this chapter, we focus directly on variation, especially a particular kind—that manifested by an individual over time, conditions, and situations—intraindividual variation.

Study of intraindividual variation began early in the history of psychological research (Wundt, 1897). Classical discussions of intraindividual variation include those by Cattell (1966a), Fiske and Rice (1955), Flugel (1928),

Age cannot wither her, nor custom stale her infinite variety.
— William Shakespeare, Antony and Cleopatra

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Horn (1972), Thouless (1936), and Woodrow (1932). More recent, quite illuminating portrayals of the nature of intraindividual variability include those by Hultsch and MacDonald (2003), Hultsch, Strauss, Hunter, and MacDonald (2008), Moskowitz and Hershberger (2002), and Overton (2006). Diverse applications of intraindividual variability concepts are found in personality (e.g., Cattell, 1973; Mischel, Shoda, & Mendoza-Denton, 2002), cognition (e.g., Hertzog, Dixon, & Hultsch, 1992; Hultsch et al., 2008; Salthouse, Nesselroade, & Berish, 2006; Sliwinski, Smyth, Hofer, & Stawski, 2006), health-related behaviors (e.g., Ghisletta, Nesselroade, Featherman, & Rowe, 2002), religious beliefs (Kim, Nesselroade, & McCullough, 2009), and many other areas.

Taken seriously, we believe that a sincere appreciation for variation within the individual over time or situation, or both, has powerful, far-reaching implications for how one studies most behavioral phenomena, including developmental ones (e.g., see Baltes, Reese, & Nesselroade, 1977; Lerner, Schwartz, & Phelps, 2009; Magnusson, 2000; Molenaar, 2004; Nesselroade, 1988, 1991; Overton, 2006; Wohlwill, 1973). We have some sense that these implications have not been understood and allowed to play out to the extent warranted by their significance, and as a result, the study of developmental phenomena has not prospered as much as it might otherwise have. In addition to the exceedingly broad influences of overarching models and worldviews (e.g., Overton & Reese, 1973; Reese & Overton, 1970), sincere concern of developmentalists with intraindividual variability also influences fundamentally how the study of development proceeds. Attention to intraindividual variability leads to favoring some kinds of research designs over others, how and what one measures, and the data analyses one performs. Even more fundamentally, intraindividual variability concerns help to delimit the very way one formulates his or her research questions and the manner in which one conceptualizes and deals with fundamental scientific matters such as prediction and generalizability. These latter concerns, in turn, rightfully have strong “trickle-down” effects on the design, measurement, and modeling efforts of students of development.

It is our belief that over the past several decades discrepancies between professed substantive concerns and preferred methods have had unintended negative consequences for the study of behavioral change processes, including developmental ones. This chapter aims to take a close look at the matter with the goal of being constructive regarding several methodological issues that bear directly on the study of human development over the life span. Although it may not always seem so as we lay out our views, some of which will appear to be in conflict with contemporary developmental research efforts, we are intent on trying to strengthen the developmental research enterprise, especially as we view it from a life-span perspective, a perspective that, as delineated by Baltes (1987) and his colleagues (Baltes, Lindenberger, & Staudinger, 1997; see also Baltes et al., 1977), leans heavily on methodological variety and innovation.

**CHARACTER OF VARIATION**

Differences are the most elemental character of variation, and they are defined on three fundamental kinds of comparisons (e.g., Nesselroade, 2002): (1) comparisons among kinds of entities (e.g., qualitative differences); (2) comparisons among entities of the same kind (interindividual differences); and (3) comparisons of an entity with itself over different occasions (intraindividual differences). This characterization is not so dissimilar from the definition of variation used by Molenaar (2004): “The degree to which something differs, for example, from a former state or value, from others of the same type, or from a standard” (pp. 204–205). Variation that represents differing from a standard is at base akin to variation attributed to interindividual differences. If the standard remains constant, the ways individuals differ from the standard are the ways they differ from each other. In any case, taken together, these definitions cover well the phenomena of our concern in writing this chapter.

Clearly, the operation of “differencing,” in one form or another, is at the heart of the variation concept. Even the psychologist’s arguably most common index of variation, the standard deviation, can be calculated by first taking every possible difference of each pairing of scores in a distribution, although far more efficient ways are typically invoked, such as taking the square root of the average squared deviation about the mean.

Whichever working definition one uses, the study of behavior has a long history of emphasizing differences among individuals (variation), whether they are differences created by Mother Nature or by experimental manipulation (e.g., see Cattell, 1966a; Cronbach, 1957, 1975). Study of the former, differential psychology, involves primarily comparisons among entities of the same kind (interindividual differences) and, to some extent, comparisons among kinds of entities (e.g., qualitative differences). In contrast, the production and study of the latter, experimental
psychology, rests on treatment manipulations and comparisons among entities of the same kind that have been treated differently or on comparisons of the same entities before and after treatments.

Somewhat ironically, given the rightful emphasis on variability, a basic, if generally stated goal of science is to ascertain what attributes of entities remain invariant under which transformations (Keyser, 1956)—a question of generality. Put simply, out of the variability that we study, we strive to find invariant relations. The goal is to establish invariance, but the road to that goal is paved with variability. Like the watery milieu of the aforementioned fish, without variability, not much surrounding us is of interest to either the layperson or the developmental scientist. As we were writing this chapter, a brief piece by Barlow and Nock (2009) was published in which they quote Sidman (1960) to the effect that generality and variability are antithetical concepts. At one level, we agree. However, Sidman was referring to unaccounted for variability—the kind that weakens relations. Here, we focus on the very process of accounting for variability through the articulation of general relations.

Students of behavior and development should understand that the underlying theme of this chapter is that the most meaningful and informative differences to examine are those at the level of the individual, as the individual behaves over time. This perspective leads to the conclusion that one’s primary focus should be on intraindividual variation. More specifically, we argue that a primary scientific research focus should be on similarities in patterns of intraindividual variation defined over multiple variables simultaneously. Furthermore, we suggest that the sought-after similarities may not be found to reside at the manifest variable level, but rather at the more abstract, latent variable level (see later for further discussion). Given these considerations, we train our major emphasis in the remainder of this chapter on the third kind of difference mentioned earlier—comparisons within the same entity over different occasions, conditions, or situations—as the basis on which to build more general lawful relations concerning development over the life span.

**INTRAINDIVIDUAL VARIATION AND THE STUDY OF CHANGE PROCESSES**

A major objective of developmental research is to study processes of change. Development includes many processes occurring simultaneously. Whether that time frame is limited to some early portion of life or encompasses the entire human life span has been a key distinction between more traditional views of development (e.g., infancy, child development, adolescence) and the life-span development perspective (e.g., Goulet & Baltes, 1970), which, in large measure, is oriented toward long-term processes that span decades (e.g., Baltes, 1987; Baltes et al., 1997).

The history of behavioral science is rich with discussion and debate concerning the measurement of change (e.g., see Cronbach & Furby, 1970; Harris, 1963), and the measurement of change would seem to be a *sine qua non* for the rigorous study of development. Despite the best efforts of large numbers of sophisticated methodologists, many of the basic questions about change measurement remain unresolved (see also McArdle, Chapter 3 of this volume). A general reaction of methodologists to this dilemma, if such it be, over the past three decades or so has been to move beyond two occasions of measurement and change scores to many occasions of measurement (e.g., see Rogosa, 1988; Wohllwill, 1973) and some version of growth curve modeling (see McArdle, Grimm, Hamagami, & Bowles, 2009; and McArdle & Nesselroade, 2003, for reviews). In general, we believe this change of emphasis from two occasion differences to multi-occasion change functions has been constructive and can be seen as the opening of a renewed effort to focus on process. Indeed, we subscribe enthusiastically to the value of going beyond basic notions of change to focus on more highly structured temporal organizations, which is what we believe researchers are trying to convey with the use of the term *process* and the application of a variety of approaches, including “person-centered” ones and various systems theoretic ideas and models such as the damped linear oscillator (Boker & Nesselroade, 2002) that has been used to model bereavement and adjustment to widowhood (e.g., Bisconti & Bergeman, 2007). A difference score based on two occasions of measurement cannot begin to convey the same richness of content as does a more or less invariant sequence of events that constitutes a process. For example, studying the inexorable losses of physical and cognitive resources, and the continuing adaptations one makes to them described in the Selection, Optimization, Compensation (SOC) model (Baltes & Baltes, 1990; see also Carstensen, 1993) contrasts sharply with merely taking the difference in one’s cognitive performance scores over a similar period. However, as we proceed, we advocate for even more intensive measurement schemes than the typical growth curve and some other longitudinal modeling efforts to emphasize time-series designs. Such designs enable researchers...
to obtain the kinds of data that allow them to capitalize
on the power of methods and procedures that we believe
offer increased promise for better understanding of de-
velopment. If the reader’s “inner ear” is beginning to detect
rumblings that can be construed as leading to an emphasis
on the general themes of relational developmental systems
theory (e.g., Ford, 1987; Ford & Lerner, 1992; Lerner &
Overton, 2008, Overton, 2006), we do not discourage that
line of speculation.

The study of processes is rightly a basic activity of the
developmentalist, but as has been suggested elsewhere
(Browne & Nesselroade, 2005; Nesselroade & Molenaar,
2003), from a methodological perspective, development-
alists can hardly be satisfied with the way processes are
being conceptualized and modeled. Capturing the nature of
process in a quantitatively rigorous way is not easy, and yet
doing so is necessary for building a scientifically valuable
knowledge base concerning developmental phenomena—
their description and their explanation. Subsequently, we
focus on this topic in some detail.

Here, however, we first want to examine more closely
the role of intraindividual variability in this most impor-
tant arena to the developmentalist—the study of process.
To get started, we again use a working definition of the
concept of process (Nesselroade & Molenaar, 2003) pro-
vided by the Oxford English Dictionary (1989): “A con-
tinuous and regular action or succession of actions, taking
place or carried on in a definite manner, and leading to
the accomplishment of some result.” What this definition
lacks in quantitative rigor is compensated for with its stark
implication for the need to measure changes over time—a
clear signal to study intraindividual variation. We attempt
to flesh out the definition more extensively and precisely
in the following text.

In the context of developmental research and the anal-
ysis of variability, a dichotomy that has surfaced in the
late 20th century under a variety of labels pits persons
against variables. For example, the terms person-centered
versus variable-centered are preferred by some life-span
developmentalists (Bergman, Magnusson, & El-Kouri,
2003; Magnusson, 1997, 2003) who have contributed
extensively to both the methodology and the substance
of developmental research. Although good reasons exist
for wanting to clarify differences in orientation and pro-
cedures via the use of dichotomies, it is also the case
that students of human behavior do not study persons
without using variables, and they do not study variables
without using persons. One need only hark back to what
Cattell called the “data box” or basic data relations matrix
(Cattell, 1966a) to be reminded that empirical data inevi-
tably involve at least one person, at least one variable, and
at least one occasion of measurement. Figure 2.1 depicts
a version of the data box emphasizing that any datum is
simultaneously defined as an intersection of person, vari-
able, and occasion coordinates. Usually, several elements
of at least one of this triad are involved in defining a set
of data.

The data box in Figure 2.1 is more than an anchoring
heuristic for contemplating the nature of data acquired in
empirical research, especially with regard to the study of
process and change. The various covariation techniques
can be derived from it (Cattell, 1952), out of which one
can begin to fashion a systematic approach to the study of
processes. The version of the data box shown in Figure 2.1
emphasizes what we believe to be a fundamentally im-
portant locus of intraindividual variability—multiple vari-
ables measured over multiple occasions of measurement
on one individual—and a covariation procedure called
P-technique, which will play a highly visible role in our
discussion because of the features of the empirical data on
which it rests. The (factor) analysis of P-technique data is
described in more detail at appropriate places in the text.

It suffices here to emphasize that P-technique analysis
involves exploiting data arising from the intensive mea-
urement of the single case, both over many successive
occasions of measurement and with the use of many mea-
surement variables. This data configuration sets the stage
for modeling intraindividual variability at both the mani-
ifest and latent variable levels, with the individual as the
primary unit on which the analysis is focused. As explained
in the next section, coupled with the appropriate measure-
ment methods, design conditions, and analysis techniques,
some of which are rather novel and innovative, we believe

![Figure 2.1](image-url)
such data are the key ingredients for a powerful approach to the study of developmental processes.

**THREE KEY EMPHASES IN STUDYING DEVELOPMENTAL PROCESSES THROUGH INTRAINDIVIDUAL VARIABILITY**

Efforts to further the study of processes via capitalizing on the riches of intraindividual variation by means of relatively recent methodological developments have led us both jointly (Nesselroade & Molenaar, 2003) and separately (e.g., Browne & Nesselroade, 2005; Molenaar, 2004; Nesselroade, 2005) to examine more critically the way behavioral research in general is conducted, but always with due concern for the particularly demanding challenges of studying developmental change. As our thinking has evolved on these matters, we have come to believe that the study of behavior should rely on a strong focus on intraindividual variability, and that three key emphases can be identified for capitalizing on intraindividual variability that are critical to further strengthening the study of development as a life-span phenomenon. We see these emphases, each of which has a long history in our science, to be instrumental in defining an approach that amounts to something distinctly different from the experimental and differential traditions that Cronbach (1957, 1975) discussed. Moreover, for the study of developmental phenomena, these emphases are especially critical because they provide a direct approach to the modeling of process. The three emphases are as follows:

1. **Recognize the individual as the appropriate unit of analysis in behavioral research, including the study of development.** Obviously, a focus on the individual requires adopting some kind of repeated measurements regimen to obtain variance to study, which necessarily involves some version of a time-series design (e.g., univariate or multivariate time series, panel studies). But time-series designs do seem, after all, to produce the kind of data appropriate for students of development and other kinds of changes—a lot of information regarding the individual over substantial time spans. Clearly, these notions are, in many respects, compatible with the general approach of relational developmental systems theory.

2. **Define patterns of intraindividual variation on multiple variables, thus allowing one to rely on the methods and techniques of multivariate analysis, including powerful multivariate measurement models that emphasize and target for closer scrutiny unmeasured, latent variables (e.g., see Cattell, 1966b). Baltes and Nesselroade (1973) and Nesselroade and Ford (1987) laid out a rationale for the use of multivariate measurement in developmental research (see later). Such a multivariate perspective is compatible with a more holistic view of the organism promoted by other developmental scientists (e.g., see Baltes et al., 1997; Bergman et al., 2003; Magnusson, 2000; Overton, 2006) and offers considerable flexibility in building promising, technically sound measurement schemes. We believe that the capacity to model relations at the latent variable level is a virtue of multivariate measurement, the value of which is difficult to overestimate because it affords the use of some of the most powerful measurement innovations that behavioral/social scientists have developed to date.

3. **Identify similarities and differences among persons in patterns of intraindividual variation.** Somewhat in contrast with the prevalent emphasis on interindividual differences one sees in most correlational research, it is our contention that with an emphasis on establishing lawful relations, one is actually more intent on identifying and studying the similarities than the differences among persons. Therefore, individuals are neither conceived of as interchangeable elements nor as randomly equivalent entities, but rather as distinct entities among whom one seeks to replicate lawful relations. Considerably more will be said about this later because the locus of such similarities may be found only at more abstract latent levels rather than in the interrelations of the manifest variables.

In addition to serving as an important corollary of emphasizing the individual as the unit of analysis, emphasizing interindividual similarities rather than interindividual differences dictates a quite different approach to data aggregation than most behavioral scientists practice (e.g., see Molenaar, 2004; Nesselroade & Molenaar, 1999; Ram, Carstensen, & Nesselroade, 2009; Zevon & Tellegen, 1982). Rather than blindly aggregating information across multiple individuals as the initial step in data analysis, as is done in computing the usual "descriptive statistics" (e.g., means, variances, and covariances) of traditional individual differences research, one takes an informed approach to aggregation that features using as much knowledge about the individual as possible.
Our emphasis on identifying similarities in multivariate patterning of variables also leads us to argue for some alternate conceptions of measurement (Nesselroade, Gerstorf, Hardy, & Ram, 2007; Nesselroade, Ram, Gerstorf, & Hardy, 2009), as is discussed more fully later in this chapter.

These three key features—individuals as the units of analysis, modeling with latent variables, and emphasizing similarities rather than differences across persons—help define an approach to scientific psychology that we believe has important implications for the conduct of behavioral research in general and developmental science in particular. Moreover, each of the three features is rooted deeply in the history of our discipline (Nesselroade, in press), and in concert, they define an approach that appears to be distinct from the two disciplines of scientific psychology that Cronbach (1957, 1975) discussed. In those highly influential articles, Cronbach (1957, 1975) identified two disciplines of scientific psychology: experimental psychology and differential (correlational) psychology. The latter is often referred to as the study of individual differences. There is no doubt that, in many respects, this distinction has served psychology well. We believe signs exist that a third discipline incorporating features from both the experimental and differential disciplines but with different emphases and methods can be identified. It was characterized by Molenaar (2004) as idiographic science.

As noted earlier, idiographic science emphasizes the individual as the primary unit of analysis, but individuals are not viewed as randomly equivalent replicates of one another; nor is the emphasis on synthesizing the behaving individual from the differences among the ways individuals behave. Rather, the individual is the focus of analysis, and identifying similarities of behavior patterns across individuals is a key goal of applying empirical inquiry to the study of lawful relations. This third discipline of scientific psychology is driven by substantive interests and methodological developments that extend primarily the analytical tools of differential psychology, including latent variable modeling.

We recognize that much empirical research in the operant conditioning/learning paradigm was conducted on very small samples and involved careful attention to intraindividual variability in performance. In some ways, the recognition of the importance of the topography of a response versus its specific features agrees with the notion of idiosyncratic aspects of observable behavior that we discuss in detail later in considering measurement issues. Where we diverge remarkably from an operant perspective is on the use of multivariate measurement schemes to model interesting phenomena at the latent variable level.

THE INDIVIDUAL AS THE UNIT OF ANALYSIS

Emphasizing the individual as the unit of analysis is by no means new to behavioral research, and the arguments supporting it have appeared in quite diverse contexts. Indeed, over the years, many writers have promoted the individual as the proper unit of analysis for studying behavior. Allport (1937) argued elegantly for it. Carlson (1971) asked: Where is the person in personality research? Gottlieb (2003) called for more emphasis on the individual in behavior genetics studies. Lamiell (1981, 1988) proposed an idiographic approach to blend the strengths of individual-level and group-based analyses. In developmental research, Magnusson (2000, 2003) pleaded for more emphasis on the individual. Molenaar (2004) argued rigorously for such an emphasis generally in behavioral science. Zevon and Tellegen (1982) illustrated how one could use the intensive study of the individual in the service of reaching conclusions of greater generality by focusing first on the structuring of the individual’s behavior (through intraindividual variability) and then looking for common patterns across these individual structures at a more abstract level (e.g., see Friedman & Santucci, 2003). Clearly, a critical feature of empirical research in any discipline concerns not only how the basic unit of analysis is defined but how it is used.

As indicated later in this chapter, emphasizing the individual as the unit of analysis is not the same as arguing for single-case studies, although they tend to be somewhat related in the perspective of many researchers. Two of the key corollary matters in this regard are replication and generalizability, which will receive explicit attention toward the end of this chapter.

Molenaar (2004) described how a sample of scientists nominated the revolutionary idea of Brownian motion as the single most important scientific breakthrough of the 20th century. Molenaar went on to point out that a central feature of Brownian motion—that it applies to the random, time-dependent behavior of a single particle—has been substantially ignored by behavioral scientists even though the latter rely heavily, for example, on various statistics resting on probability models. Parenthetically, it seems that probability models are sometimes convenient and sometimes not. In any case, behavioral scientists tend not to focus on
the time-dependent behavior of a single individual—our counterpart to a single particle. Obviously, there are exceptions (e.g., operant learning paradigms, psychotherapeutic process analysis), but by and large, our research designs do not capitalize on the individual qua individual, but rather on the individual as either one of many interchangeable parts or one of many randomly equivalent parts.

In spite of the fact that psychologists generally tend not to embrace an N = 1 time-series perspective and its emphasis on variation within individuals, it is our belief that the appropriate unit of analysis for the study of behavior is the individual (and his or her intraindividual variability), and that the principal domain for building generalizations regarding behavior is across individuals. Following Molenaar (2004) and in line with the Brownian motion concept, we conceive of each person as a system of interacting dynamic processes, the unfolding of which produces an individual life trajectory in a high-dimensional psychological space (Figure 2.2).

Focusing in this way on N = 1 research designs emphasizes the time-dependent variation within a single individual and invites the dedicated, intensive study of intraindividual variation, before a second, equally important step—aggregating information across individuals. This is discussed in further detail later because there are other important aspects of generalization to which we should attend, including variables and occasions of measurement, as implied by Figure 2.1.

As noted earlier, identifying the individual as the primary unit of analysis carries with it the necessary corollary of performing a sufficiency of repeated measurements if one is to have variation to analyze. This, of course, tends to “fly in the face” of the traditional individual differences orientation that has carried many of us through the bulk of our careers—obtaining the variation needed for further analysis over people instead of over occasions of measurement. As alluded to earlier, within the study of behavior, however, intensive examination of the individual traces back to various sources, including the old distinction between idiographic and nomothetic approaches to the study of behavior; this distinction has helped shape behavioral research over the past century in important ways. Idiographic concerns emphasize the uniqueness of the individual, whereas nomothetic concerns emphasize generality in behavioral lawfulness (e.g., Allport, 1937; Barlow & Nock, 2009; Friedman & Santucci, 2003; Lamiell, 1981, 1988; Molenaar, 2004; Rosenzweig, 1958, 1986; van Kampen, 2000; Zevon & Tellegen, 1982).

Of the many writers who have called for greater emphasis on the individual as the unit of analysis for studying behavior, Cattell (1963b; see also Cattell, Cattell, & Rhymer, 1947) not only described and promoted P-technique factor analysis (applying the factor model to multivariate time series) as a way of identifying individual traits, but in the process exemplified the use of multivariate measurement models to represent underlying constructs at the individual level; we attend closely to this application in the next section.

Molenaar (2004) greatly strengthened the case for elevating the individual to prime status as the unit of analysis for behavioral science through the use of the ergodicity theorems of classical mechanics. In the context of Molenaar’s discussion, ergodicity is a characteristic of multidimensional systems evolving through time such that an individual trajectory over time yields the same information as a cross section of trajectories at one point in time and vice versa. The pertinence of this concept has to do with the extent to which one can synthesize one individual’s longitudinal trajectory from an instantaneous snapshot of many individuals’ trajectories. Molenaar’s arguments, which are summarized here, conclude that by their very nature, developmental phenomena, although intraindividual, are nonergodic behavioral systems, in large measure because they are not stationary processes, but rather manifest time-related trends. This conclusion carries the striking implication that the traditional study of individual differences—one of two disciplines of scientific psychology mentioned earlier—is certainly not optimal and most likely unable to provide a sound basis for synthesizing intraindividual processes. Molenaar states, “Only under very strict conditions—which are hardly obtained in real psychological processes—can a generalization be made
from a structure of interindividual variation to the analogous structure of intraindividual variation” (p. 201).

Thus, Molenaar rested his arguments on the contrast of what we have been calling *intraindividual and interindividual variation*, and focused his attention primarily on covariation matrices of the observations—a common concern for those who quantitatively model behavior and behavior change. These covariation matrices of concern include the usual information regarding the extent to which measured variables rise and fall together over occasions of measurement, but also the extent to which the measured variables rise and fall together when the variables are lagged on each other (and themselves) by different amounts. For example, if \( x \) and \( y \) are out of phase, they may not covary at all if one does not correct for the phase differences. But if \( x \) at time 1 is paired with \( y \) at time 3, \( x \) at time 2 paired with \( y \) at time 4, \( x \) at time 3 paired with \( y \) at time 5, and so on, \( x \) and \( y \) might be found to covary substantially. Under these circumstances, lagging \( y \) on \( x \) by two occasions of measurement reveals a relation between \( x \) and \( y \) that has a strong temporal component. For example, ingesting food and feeling satiated for having done so are not contemporaneous events. A relation clearly exists between the two, but feelings of satiation lag food ingestion by perhaps 30 minutes. Developmental researchers have long understood the basic ideas concerning how early events may be predictors, if not causes, of later events (e.g., see Kagan, 1994, 2007). For example, differences in heart-rate variability in infants predict much later personality characteristics (e.g., Fox & Porges, 1985).

In a similar way, when a variable is lagged on itself (autocorrelation), the magnitude of the relation tends to vary with the amount of lag. The dependence of autocorrelation on lag is valuable information in time-related modeling of individual-level data (Newell & Molenaar, in press).

Molenaar defined the *phase space* as the multivariate domain whose dimensions were the measured variables of interest. Addition of another dimension—time—to the phase space yielded the behavior space. The values of a person’s variables at a given time, \( t \), define a point in the phase space. The values of all the variables for that same person at successive repeated measurements define a trajectory (life history) in the behavior space, and the complete set of such trajectories represents the life spans of a population of persons (see Figure 2.2). To define a *random process*, Molenaar considered the trajectory of a specific person in the behavior space up to some arbitrary time point, \( t \), through which time point all the relevant information for that person is available. Predicting the value of the trajectory at \( t + 1 \) will, in general, not be exact; thus, the trajectory is considered to be the result of a random process—a process characterized by some amount of uncertainty. If the amount of uncertainty approaches zero, which happens seldom, if ever, with human behavior, the process becomes deterministic. Illustrating the act of predicting in this way, within the individual over time (e.g., from \( t \) to \( t + 1 \)), foreshadows a discussion presented later in this chapter concerning the roles of prediction and selection within the general intraindividual variability approach considered here.

Molenaar concluded his line of argument by indicating that the projection of a random trajectory along the time axis of the multidimensional behavior space yields a multivariate time series. He then used the time series literature to argue that such a process is ergodic (affords generalization from a structure of interindividual variation to the analogous structure of intraindividual variation) only if its first-order moment function (mean vector) and second-order moment function (lagged covariance matrices) are invariant in time. Such conditions scarcely seem to characterize developmental processes. Indeed, developmentalists are generally indifferent to phenomena that do not show growth or decline as the individual ages.

Finally, Molenaar (2004) demonstrated that longitudinal factor models based on interindividual differences, even though the participants may have been measured multiple times, do not meet the stringent assumptions necessary to conclude that the processes described by interindividual variation accurately characterize those described by intraindividual variation. The rather striking conclusion, as noted earlier, is that with regard to development, one cannot synthesize intraindividual processes from interindividual differences. Harking back to Figure 2.2, one can get a sense of the ergodicity argument by imagining comparing a cross section of all the trajectories at one point in time with one of the individual trajectories over all the time points. Would these be likely to yield the same picture? Most likely they would not in the case of developmental phenomena (e.g., cognitive development) because a developmental process that involves incremental gains (or losses) over long periods is not a stationary phenomenon. Somewhat in contrast, variation in emotion/affect seems a more likely candidate to behave according to ergodic principles in the sense that emotions do wax and wane repeatedly over time. It is not completely out of the question that the individual, over his or her lifetime, might experience the gamut of emotions that one might find in a cross
section of the population at one point in time. Thus, over the course of an individual’s lifetime, the array of affective behavior might well approximate the array of affective behavior of many individuals at a given point in time and vice versa. In any case, the contrast between the more or less unidirectional changes in cognitive measurements and more or less reversible changes in emotion measurements, while representing two very different kinds of intraindividual variability, helps to convey the nature of the ergodicity argument.

In summary, behavior is what individuals do. Therefore, the articulation of lawful relations regarding behavior should involve the individual as the main unit of analysis. Classical experimental psychology involves the manipulation of variables at the individual level but does not allow for systematic differences among individuals unless they receive different manipulations. Classical differential psychology capitalizes on differences among individuals but does not necessarily reconstitute a meaningful individual from those differences. We are arguing for maintaining the individual as the unit of analysis but for seeking similarities in patterns of individuals’ behavior, thereby describing a functioning individual of some generality rather than trying to synthesize an individual from the ways people differ from one another.

In terms of variation, we are primarily seeking similarities in intraindividual variability. Baltes, Reese, and Nesselroade (1977) defined developmental research as seeking interindividual differences (and similarities) in patterns of intraindividual change. This view rather closely parallels traditional differential psychology but with an initial emphasis on individual-level measurement to identify intraindividual change patterns. In their discussion of rationales for conducting longitudinal research, Baltes and Nesselroade (1979) saw interindividual differences and similarities in patterns of intraindividual variability and change as a key means by which to identify developmental influences.

Of course, it is understood that if one does not find similarities in intraindividual variability patterns, then one still has to deal with interindividual differences in those patterns. However, given interindividual differences, we do not believe the appropriate next step is to blindly aggregate those differences by, for example, averaging them, as was done often before the seminal work of Tucker (1958, 1966; see also Rao, 1958) in analyzing data from learning studies. Tucker’s proposal is now recognized as one of the key lead-ins to what is currently known as growth curve modeling (e.g., see Meredith & Tisak, 1990; and McArdle, Chapter 3 of this volume). Tucker (1966) proposed the decomposition of learning performance (repeated measurements over many trials on a learning task) in such a way that distinctly different trajectories could be identified. Up to that time, most learning data were simply averaged over participants to provide a relatively smooth curve that was used to describe the learning process. Tucker’s proposal, which applies more widely than merely to learning data, recognized the possibility that individual trajectories were not necessarily well described by an average curve. Rather, he proposed methods for identifying different sub-group trajectories, as well as multiple functions underlying the observed performance. Cronbach (1975) hailed Tucker’s influential proposal as an example of rapprochement between the classical experimental and differential approaches to the study of behavior because it yielded both general curves applicable to multiple participants and individualized weights by which those general curves could be combined to produce a close approximation to the unique performance of each of the individual participants.

Rather than ignoring among persons differences by, for example, summarizing with an average curve, it may be possible to fashion patterns that do manifest similarities across persons, if the comparisons involve other levels of abstraction. For example, the more abstract process of exhibiting a stress reaction may accurately describe what happens to many individuals placed in a public speaking context even though the actual symptoms displayed (e.g., sweaty palms, shallow respiration, accelerated heart rate) during that stress reaction may well differ substantially from one individual to the next. Two very different child-rearing styles, one featuring physical coercion and the other abusive verbal attempts at control, both reflect dominating behavior on the part of the parent over the child. Similarly, one child may manifest resistance to such coercion by “acting out,” whereas another displays passive-aggressive behavior. Obviously, admission of such a variety of manifestations under common labels is required if theories are to have generality, but it places a strong burden on our ability to measure behavioral constructs at the individual level very well, a topic to which we now turn.

MULTIVARIATE MEASUREMENT SCHEMES

Lobbying as energetically as we have for recognizing the individual as the unit of analysis in developmental research carries with it the responsibility to examine the
implications for measurement. It is rather clear that the general orientation we are propounding impinges heavily on the area of measurement. Measurement is always a thorny issue in behavioral research and it is no less so when studying development, especially if one takes seriously the individual as the unit of analysis with its corollary repeated measurements. There are two broad concerns we want to examine here. The first concern has to do with general psychometric practice; the second has to do with recognizing idiosyncrasy, and whether and how a multivariate perspective on measurement can accommodate it. This, in turn, has implications for how one models processes; we elaborate on this topic in the next section.

Many of the current debate topics in measurement theory hinge on such matters as how true scores are defined, the nature of measurement error, and the quantification of item difficulty level. We propose to enter the discussion of measurement a level or so above these concerns that, for example, pit definitions from item response theory against those of classical test theory. These are interesting, important matters ultimately in need of resolution, but their resolution is not critical for our discussion and further scrutiny at that level would distract us from our principal concerns for this chapter. Valuable examinations of these issues can be found, for example, in works by Embretson (1996) and Schmidt and Embretson (2003).

Bearing more directly on this discussion—from the joint perspective of emphasizing the individual as the unit of analysis and viewing the study of development as not fitting well with the individual differences orientation because of the ergodicity principles—Molenaar (2004) raised fundamental concerns regarding traditional approaches to psychological measurement when he argued “that test theory, yielding the formal and technical underpinning of psychological test construction (Lord & Novick, 1968), gives rise to serious questions regarding its applicability to individual assessment” (p. 203). For example, true scores and errors of measurement in classical test theory are individual-level concepts linked to intraindividual variability, but in practice, they are typically estimated from data that involves many people measured once rather than one person measured many times. Such substitution of interindividual variation for intraindividual variability is not uncommon in the quantitative modeling lore of psychology. For example, descriptions of various scaling methods (e.g., Torgerson, 1958) illustrate how the judgments of many participants are substituted for the behavior of one participant rendering many judgments.

One of our guiding premises here is that focusing on the individual as the appropriate unit of analysis and looking for similarities in intraindividual change patterns is inadequate if undertaken solely at the level of manifest variables. Although we do not go so far as to “declare a pox” on standardized measurement, we depart from the traditional measurement orientation to recognize that the sought-after similarities among individuals simply may not be found at the manifest variable level, but rather should be sought at the latent variable level. This means, for example, that somewhat different emphases must be applied to issues of measurement and matters of analysis. For this, we turn to a more general discussion of multivariate measurement schemes.

Because of their prominent role in modeling with latent variables, multivariate measurement schemes have held an important place in the psychometric literature for several decades. From early work in the human abilities area by such pioneers as Burt, Spearman, Thomson, and Thurstone through large programs of research on personality traits by investigators such as Cattell, Eysenck, and Guilford, multivariate, factor analytic approaches to studying interrelations among arrays of variables have made important contributions to the study of behavior. Since the 1970s, multivariate measurement schemes have reached a fairly dominant position in psychometrics through the evolving sophistication of measurement models within a structural equations modeling framework. Research on the so-called big 5 personality factors well illustrate the progression (e.g., see Costa, 1992; Goldberg, 1990; McCrae & Costa, 1999), as does work on human abilities and cognition (see McArdle, Chapter 3 of this volume; Tucker-Drob, 2009).

As mentioned earlier, Baltes and Nesselroade (1973) articulated three primary aspects of a rationale for why measurement schemes should be multivariate in nature in studying developmental processes. Subsequently, Nesselroade and Ford (1987) elaborated the rationale to emphasize its pertinence to dynamical systems representations. The elements of the combined rationale are: (1) any dependent variable (or consequent) is potentially a function of multiple determinants; (2) any determinant or antecedent has potentially multiple consequents; (3) any determinant or antecedent may also be considered a consequent of other determinants or antecedents, and any consequent may also be considered a determinant or antecedent of some other consequents; and (4) the study of multiple antecedent-consequent relations provides a useful model for the organization of complex systems.
With the encouragement and contributions of a large cadre of methodologically sophisticated behavioral scientists, the variety and power of multivariate modeling procedures increased enormously during the latter half of the 20th century (e.g., see Cudeck & MacCallum, 2007; Little, Bouvard, & Card, 2007). Probably one of the most influential aspects has been the improvements in the ways to measure latent variables coupled with the ability to evaluate how well this is being done, much of it tracing back to the seminal work of Jöreskog (1969). Confirmatory factor analysis and structural equation modeling have come of age during this period and, both because of its intuitive appeal and its technical advantages such as the innate correction for attenuation of relations because of measurement error, the measurement model has virtually become a “fixture” for representing latent variables or constructs in a wide variety of modeling efforts.

P-technique factor analysis and its newer derivatives such as dynamic factor analysis (Browne & Nesselroade, 2005; Molenaar, 1985; Nesselroade, McArdle, Aggen, & Meyers, 2002), state-space modeling (e.g., Molenaar, Sinclair, Rovine, Ram, & Corneal, 2009), and other time-series analysis approaches (see, e.g., Chow, Ferrer, & Hsieh, 2010; Hamaker, Dolan, & Molenaar, 2005; Newell & Molenaar, in press), which also feature multivariate measurement but are much more oriented toward the study of process at the individual level, have an important role to play in this context (Boker, 2002; Nesselroade, 2007). Early on, Cattell and Williams (1953) anticipated a multivariate, person-oriented approach by acknowledging a trend toward measuring many variables simultaneously on one animal instead of a few variables measured on many animals, whereas decrying the fact that this “holistic” functional understanding had not availed itself of P-technique as a statistical device for discovering the functional units. Cattell and Williams went on to warn that being able to give the constructs empirical representation either directly as depression, life satisfaction, morale, wisdom, and experience in ways that are appropriately different for different individuals or age groups while holding constant the meaning of those abstract qualities being assessed. The rationale for Nesselroade et al.'s (2007) proposal is that at its heart, good theory rests on constructs and their interrelations. But without appropriate measurement operations to give the constructs empirical representation either directly through observable indicators of the construct or through other constructs, empirical deductions cannot be tested and hypotheses are not falsifiable. Nesselroade et al. (2007) sought alternative measurement operations that permitted the maintenance of rigorous mathematical concepts of invariance whereas accommodating idiosyncratic features of individuals and of subgroups that differ by variables such as age. A way to meet these conditions with mathematical rigor was discussed, and the procedures were illustrated with extant data. Subsequently, Nesselroade and Estabrook (2009) extended the general line of argument to the case of subgroups and presented an examination of how the factorial nature of the items of the Center for Epidemiologic Studies-Depression Depression Scale (CES-D; Radloff, 1977) varied with age.

How was this alternative measurement goal accomplished? From a multivariate measurement perspective, in psychology, the measurement model of structural equation modeling and a conception of measurement invariance relying heavily on the common factor model have become mainstays in the effort to build and empirically test models involving latent variables. The various elements of the common factor model—loading patterns, factor covariance matrices, unique parts covariance matrices, and
factor loadings, although sometimes difficult to achieve in the relations described by the factor loadings). Invariance of factor loadings, although sometimes difficult to achieve in practice, has in many ways been the gold standard for the traditional evaluation of measurement models.

When one focuses on intraindividual variability and the individual as the primary unit of analysis, of necessity the specter of idiosyncrasy looms into the picture. Indeed, idiosyncrasy is a natural, substantial phenomenon when the unit of analysis is the person, but under standard measurement invariance notions, there is virtually no place for it in the manifest and latent variables or in their relations. Ignoring it does not make it go away; rather, it continues to hover and attenuate relations among variables. Trying to corner it into a “catchall” error term is not satisfying if one truly believes in the appropriateness of individual-level analysis. In the conventional notions of measurement invariance, there is virtually no useful place for idiosyncrasy in the manifest and latent variables or in their relations when the unit of analysis is the person.

How pervasive is the notion of idiosyncrasy? Many concepts for which we attempt to provide empirical representation imply some idiosyncrasy (e.g., expertise, intelligence, and creativity). Expertise, for instance, can be equally great in some sense in two individuals, but it may be manifested in entirely different domains. Can expertise be measured in a standardized format? Must it be measured in a standardized format? The medical concept of a syndrome, which presumes a common core of meaning across individuals, whereas allowing for different but overlapping subsets of indicators of that core from one individual to another, allows for idiosyncrasy in the pattern of manifest variables that pertain, but our traditional notions of rigorous, standardized measurement do not. Individual specificity of psychophysiological response patterns (Friedman & Santucci, 2003; Stemmler, 1992) represents another arena in which idiosyncrasy is present in the observable manifestations of behavior patterns and must somehow be accommodated in the measurement operations if lawful relations between context and behavior are to have generality.

Thus, the objective of Nesselroade et al. (2007) was to allow measurement operations to accommodate idiosyncrasy and still provide representation for the same construct across individuals. An individually oriented modeling procedure (P-technique factor analysis) was used to provide a measurement approach that accommodated idiosyncrasy but continued to impose rigorous mathematical concepts of invariance. The standard measurement invariance approach was replaced with one in which invariance was imposed at a higher level of abstraction—in the relations (correlations) among the factors. Nesselroade et al. (2007) retained the traditional concept of factorial invariance but in a somewhat different way, by allowing the P-technique factor loading patterns, which are the relations between manifest variables and unmeasured or latent variables, to reflect some idiosyncrasy for the different individuals who were being studied. At the same time, out of respect for the traditional scientific values on eventually building nomothetic relations and the role that factorial invariance has played in trying to establish them, a necessary condition of invariance was imposed. In this case, however, the invariance constraints were imposed on the factor intercorrelation matrices across the multiple individuals under consideration. This condition, in turn, yields second-order factors (factors based on the intercorrelations of the first-order factors) that manifested the traditional factor loading pattern invariance.

This higher order invariance approach is somewhat analogous to the syndrome concept in medicine that was mentioned earlier. Many observable indicators are associated with a given syndrome, but not all individuals so afflicted will manifest all of the symptoms. For instance, suppose there are nine symptoms known to be part of syndrome A. Each of three persons could manifest six of the nine symptoms, but any pair of individuals might have only three of the symptoms in common. Still, all three individuals would be characterized as manifesting syndrome A. This thinking is not unrelated to that underlying the measurement of developmental risk as a predictor of later adjustment by counting the number of risk factors for each person, regardless of their precise nature, and using the count as the measurement (e.g., see Sameroff, Peck, & Eccles, 2004).

Nesselroade et al. (2007) allowed the factor loadings to differ somewhat from person to person even though the driving argument involved measuring the same underlying constructs. But the interrelations among the latent variables (the factor intercorrelations) characterized by the individually tailored loading patterns were rigidly constrained to be the same from individual to individual. This was the “idiographic filter” aspect of the approach. The idea was that the constructs were the “same” constructs for different individuals and would share some common structural features, albeit each construct could manifest
The essential idiographic filter ideas are portrayed in Figures 2.3 and 2.4. Figure 2.3 illustrates the general idea of the idiographic filter—to separate the idiographic space from the nomothetic relations space by means of the idiographic filter. The idiographic filter consists of the first-order factors and their loadings on the manifest variables. These loadings are allowed to reflect idiosyncrasy in the relations between the latent and manifest variables without necessarily indicating why these idiosyncratic relations obtain.

In Figure 2.4, three spaces are identified. A measurement space is identified for each of two individuals, but it could just as well include many individuals. The measurement space contains a set of manifest variables (a through f) that are made distinct for each individual because they may not be the “same” variables for each person, even though they have the “same” name. Spanning the measurement space for multiple individuals is the idiographic filter space, which includes the first-order factors (latent variables) and the factor loadings, which describe the manifest variables in the measurement space as linear combinations of the primary factors. This is the site of traditional factorial invariance of factor loading patterns, which if it holds across individuals, affords an interpretation that the manifest variables are “measuring the same thing” in different individuals. In Figure 2.4, the loading patterns for individuals i and j are different to indicate that the manifest variables are not the same measures from individual to individual; hence the need for the idiographic filter. The third space is labeled nomothetic relations because, as the figure portrays, the higher order factors (F_i and F_j), which derive from the interrelations among the first-order factors, are the same for different individuals. This is the case because the relations (e.g., factor intercorrelations) of the primary factors (in the idiographic filter space) are identical for different individuals, thus defining identical higher order factors.

More concretely, we have elsewhere (Nesselroade et al., 2007) illustrated the basic idea with the concepts of Area and Volume in geometric objects playing the role of higher order constructs. Both cylinders and boxes, for example, have volumes equal to their cross-sectional area times their length. But the cross-sectional area of a cylinder (a circle) is \( \pi \) times the square of the radius, and the cross-sectional area of a box (a rectangle) is length times width. A rectangle does not have a radius and a circle does not have a length, so the measures (manifest variables) defining the area are different in the two cases, but no one doubts that the concept Area is the same. Similarly, Volume in both cases is cross-sectional Area times the length of the three-dimensional object (cylinder or box). Thus, the relation between Area and Volume is the same for the cylinder and the box, but the two concepts rest on different measures (radius and length vs. width, height, and length). The basic idea, we would argue, is not unfamiliar to developmental psychologists. Designers of longitudinal research, for example, have long had to deal with devising age-appropriate measurement instruments to study continuity and change over longer spans of time.

Procedurally, fitting this idiographic filter model involves conducting multiple P-technique analyses simultaneously, constraining the factor intercorrelations to be equal across individuals but allowing, within the conditions of identifiability, the factor loading patterns to reflect some idiosyncrasy, and then testing the fit of this model to the multiple P-technique data. If the model fits the data, one can interpret the outcome as having identified an invariant second-order factor solution while “filtering” out the idiosyncratic aspects of measurement at the first-order factor level.

**Figure 2.3** Schematic portrayal of the measurement space, the idiographic filter space, and the nomothetic relations space. Circles represent latent variables (factor); boxes represent manifest variables; straight arrows represent factor loading; curved double arrows represent factor intercorrelation.
Higher order measurement invariance is highly pertinent to the study of development because each of us has a unique history of experience, learning, conditioning, language usage, and so forth that, in part, contributes idiosyncrasy to our behavior patterns ranging over the gamut from self-reporting in a testing room to neurological activity in a magnetic resonance imaging (MRI) chamber. Nesselroade et al. (2007) argued that it is desirable to separate idiosyncratic aspects of the linkages between latent and manifest variables from the core meaning of constructs. But the question is how to filter out the irrelevant aspects of behavior. The example given earlier with ANXIOUS as a self-report stimulus item illustrates how differences in the use of what purports to be a common language can introduce interindividual variation that is not just irrelevant, but actually damaging, into one’s data. One promising answer was to use some form of P-technique to capture intraindividual variability. However, it was also clear that it would need to be linked to the simultaneous use of multiple P-technique cases to capitalize on the strengths of the approach. Obviously, this filtering effort represents an attempt to eliminate some interindividual differences en route to emphasizing similarities among individuals.

Something akin to what we are calling idiographic filtering is found in a wide variety of contexts ranging from other approaches to measurement (e.g., Sameroff, Peck, & Eccles, 2004), to developmental concepts such as vicariance (e.g., Lautrey & de Ribaupierre, 2004), to the modeling of electroencephalograph/magnetoencephalography and functional MRI time series. In the latter, for example, multivariate time series are collected for a sample of N subjects. In the first phase, each subject is analyzed individually. In neural source modeling of electroencephalograph/magnetoencephalography time series, for instance, often an individual (idiographic) head model for each subject is determined by means of an MRI scan and then used in the source model fits. In functional MRI studies, the scans of individual subjects can be compared only after “warping” them unto a common atlas; this is a rather drastic idiographic filtering step based on diffeomorphic transformations of the scans.

We acknowledge that the idiographic filter proposal represents a daring (some would say foolhardy) assault on the principles and traditional notions of standardized measurement. For a diversity of viewpoints on this proposal, refer to the critical commentaries appearing with Nesselroade et al.’s (2007, 2009) articles. The commentaries on the higher order invariance article are both substantive and technical in nature. More important for this chapter are the technical commentaries. In brief, there are two primary arguments against the idiographic filter proposal. The first has to do with the matter of identification, which is explained later. The second argument, which is related to the first, has to do with relying on the
interrelations of first-order factors as a sufficient basis for construct identification.

The essential issue is that because the higher order invariance measurement approach relaxes the strict invariance of factor loading patterns, there is the possibility that unless sufficient constraints are placed on the loadings, one can always find a solution that will appear to yield higher order invariance regardless of the fit (in the abstract sense) to the data. In other words, one is not entitled to take a completely laissez-faire approach to representing the relations between constructs and manifest variables. Currently, we are in the process of working out the specific identification conditions to be imposed to be able to provide a rigorous test of the hypothesis that one has a reasonable fit to one’s data using the higher order invariance approach (Molenaar & Nesselroade, 2010; Zhang, Browne, & Nesselroade, 2009). Being able to reject or falsify the hypothesis of higher order invariance is key if the idiographic filter is to be a valuable measurement tool.

Some commentators who were critical of the idiographic filter conception were opposed to the notion that invariant factor intercorrelations could be relied on to identify constructs as the same from one individual to another. Working out the conditions for identification of the measurement models will, in large measure, help take care of this second concern regarding higher order invariance. Our aim is not to ignore completely any information regarding the nature of the constructs that is provided by the manifest variables, but rather to augment the condition of invariant construct interrelations with what useful information the manifest variables can supply. It is important to recognize, however, that we do not rely solely on the manifest variables to define the constructs as is the case with the traditional measurement invariance approach. Instead, the idiographic filter allows for the manifest variables to exhibit some idiosyncratic features and set these aside rather than allow them to dilute or obscure important relations.

Relying more on the interrelations among constructs, as we do with the higher order invariance approach, stands in marked contrast to the traditional measurement invariance notions. It is our belief, however, that this alternative is timely, especially when one is emphasizing the individual as the primary unit of analysis. From a traditional perspective, when one’s emphasis is on modeling interindividual variation, it is easy to avoid asking the difficult question, namely, Do the differences among people represent common phenomena, that is, variation that can be analyzed meaningfully between individuals? Our contention is that some of the ways individuals differ from each other, for instance, when they are responding to stimulus material in a measurement context, are idiosyncratic rather than common, and aggregating across them interferes with the relations one is trying to establish.

A version of our concern with idiosyncrasy seems to be reflected in currently popular modeling procedures that aim to deal with so-called heterogeneity. However, they tend to emphasize “fixes” at the level of modeling, rather than at the level of measurement. For example, many solutions to the problem of “heterogeneity,” including mixture modeling, spline regression, latent class analysis, and so forth, tacitly reinforce the idea that all people do not fit the same mold and segregate them into subgroups of like individuals. We question the value of this line of approach in the sense that we all abhor the idea of a science of individuals, so we have to ask just how much better is a science that explicitly involves many different subgroups?

Although the possible gains in the measurement of constructs are considerable, the higher order invariance model obviously must involve strong constraints, and the appropriateness of imposing them can (and should) be evaluated as a hypothesis. As noted earlier, minimum conditions for identification are currently being worked out for such statistical tests to be practical (Molenaar, 2009; Molenaar & Nesselroade, 2010; Zhang, Browne, & Nesselroade, 2009). However, to the extent that this hypothesis is supported by the data, it means that the structure of the factors at the second-order level (factors derived from the factor intercorrelations) is invariant across individuals in the traditional sense. Thus, one can indeed have an invariant measurement framework at a more general level by filtering out idiosyncratic aspects at another level. This speaks directly to our aim of looking for similarities among individuals, but at the measurement level. This is discussed more generally in the following text.

An important distinction must be made here and, to broaden the scope of our discussion, it can be illustrated with subgroup, rather than individual comparisons. What is considered to be irrelevant for one investigator’s research question may be the focus of another’s. More concretely, suppose one is studying age differences in depression in younger and older adults, and measures depression with a self-report instrument such as the CES-D (Radloff, 1977). Younger and older adults represent different cohorts, different educational systems, perhaps different socioeconomic levels, and so on—differences that may result in the content of some of the items being interpreted differently by participants. This, in turn, may cause the responses not to be comparable, jeopardizing any age comparisons. Such
behavior is to create a basis for the identification of similarities in more explanatory relations among constructs. The operations "steer" the researcher's interpretation of data processes, for we believe that imposing such measurement schemes and the idiographic filter primarily dismiss it as an inappropriate procedure (see also Cattell & Scheier, 1961), which subsequently led to the development of various measurement instruments such as the Spielberger State Trait Anxiety Inventory (STAI; Spielberger, Gorsuch, & Lushene, 1969). An important piece of both the historical lore and current practice regarding individual level analysis and modeling is P-technique factor analysis, to which we have alluded several times. Applications of P-technique exemplify both the individual as the unit of analysis and the use of multivariate measurement schemes because it involves repeated measurements of one individual with a battery of measures over many successive occasions as was depicted in Figure 2.1.

P-technique factor analysis has played a pivotal role in the quantitative study of intraindividual variability (for reviews of the substantive literature, see Jones & Nesselroade, 1990; Luborsky & Mintz, 1972). Cattell et al. (1947; see also Cattell, 1963a) promoted P-technique as an integral way to get at individual-level traits of personality. For example, P-technique was instrumental in the articulation of the state (as opposed to trait) anxiety concept (Cattell & Scheier, 1961), which subsequently led to the development of various measurement instruments such as the Spielberger State Trait Anxiety Inventory (STAI; Spielberger, Gorsuch, & Lushene, 1969).

The developmental trajectory for P-technique was by no means a smooth one, despite the great interest in factor analytic procedures in general in the mid-20th century. Fifteen years after the first P-technique article was published (Cattell et al., 1947), Anderson (1963) essentially dismissed it as an inappropriate procedure (see also Holtzman, 1963). At the same time, however, Bereiter (1963, p. 15) was calling P-technique "the logical technique for studying the interdependencies of measures." Despite the controversies, P-technique has continued to be instrumental in a variety of substantive research contexts including the analysis of psychophysiological recordings (e.g., Friedman & Santucci, 2003), studying short-term affective variability at the individual level (Lebo & Nesselroade, 1978; Nesselroade & Ford, 1985; Zevon & Tellegen, 1982). In this chapter, we are interested in more general patterns of intraindividual variability organized over time—process—and the general tack we are taking is to use the basic idiographic filter idea as described earlier in a measurement context as a key component of a basis for identifying similarities (and differences) among individual patterns of intraindividual variability. This section explores how this can be accomplished.

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1982), and introducing alternative conceptions of construct measurement (Nesselroade et al., 2007). Subsequent important elaborations of the basic P-technique idea (Browne & Nesselroade, 2005; Molenaar, 1985) led to the dynamic factor model and various state-space modeling approaches (e.g., Browne & Zhang, 2007; Chow et al., 2010; Molenaar et al., 2009) that promise to enhance substantially our ability to study developmental processes because they offer mathematically rigorous ways to model relational systems at the individual level (Newell & Molenaar, in press). Thus, although epitaphs for P-technique have been written a few times, to paraphrase Mark Twain, “the reports of its death have been greatly exaggerated.” The basic P-technique model still retains merit in both its own right and as a relatively efficient way to establish the basic dimensionality of a multivariate time series (Molenaar & Nesselroade, 2009)—something one may want to determine before undertaking more complex analyses.

Measurement and modeling procedures in psychology are rather firmly built on the premise that much of what is common—the stuff of lawful relations—resides at the observable or manifest level rather than at the abstract level. This view, which reflects the epistemologic stance taken by early and mid-20th-century neopositivists and behaviorists that concepts must be reducible to observables, is exemplified by the concept of factorial invariance and the strong role it has played in measurement and modeling, as most discussions will attest. However, the use of the idiographic filter represents a deliberate attempt to “alter the playing field” somewhat in the sense of emphasizing the latent variables as the level of abstraction for which invariance was sought.

Given our concern with merging the individual level of analysis and modeling with a focus on ascertaining similarities, it seems timely to explore approaches other than the traditional group-based, interindividual differences designs that emphasize invariant relations between latent and manifest variables. Instead, we focus on invariant relations found at a more abstract level, for example, among latent variables. Consider an example that comes from the structural literature of physics of separating a system’s idiosyncratic features from its general features. Eddington (1956) described the behavior of an atom that had one electron that, at a given time, circled the nucleus in one of nine orbits. The electron could perform nine possible behaviors. It could jump to any of the other eight orbits or it could remain in the orbit in which it was currently. Eddington went on to illustrate how the jumping operations exemplified the closure property of a mathematical group because the result of combining any two operations in succession was equal to executing one of the other operations. For example, jumping two orbits and then three orbits had the same effect as jumping five orbits. Eddington then erased the atom from the equations to dramatize the idea that the structure of interest was in the interrelations of the jumping operations rather than in the behavior of the electron itself. Eddington went on to argue that this was not trivial because, as he put it, another well-known “jumper,” the knight on a chessboard, also had a repertoire of nine possible moves. It could jump to any of eight squares or it could remain in its current location. However, a knight on a chessboard can get to a square in two successive jumps that it could not reach in one jump, thereby negating the closure property characterizing the atom’s jumping operations. This example illustrates looking for similarities (and differences) in systems at the abstract rather than the manifest variable level because the two systems are so disparate in virtually every aspect except the jumping operations.

But consider still another “jumper”: the baseball. During a baseball game, at any given inning there are nine gloved players on the field. The baseball “jumps” from one glove to another, much like the electron in the Eddington example. The baseball can “jump” to any of the other eight gloves or it can remain in the one in which it is currently. Moreover, like the electron, the baseball could get in one “jump” where it can get in two successive “jumps.” For example, in the service of putting out a runner who is about to score, the ball may “jump” from the left fielder’s glove to the third baseman’s glove to the catcher’s glove, or it may “jump” directly from the left fielder’s glove to the catcher’s glove. Perhaps this stretches the metaphor a bit, but it is for the sake of making a key point: Two very different systems—the atom in Eddington’s case and the baseball in ours—that have virtually no resemblance in their physical forms (manifest variables) or in their behavioral repertoires (manifest variables) do share a common abstract structure in their behavior.

The example involving the atom, the knight, and the baseball illustrates a key feature for the study of development over the life span. Indeed, the example reflects a general disavowal of neopositivism by emphasizing the “reality” of the abstract interrelations rather than the manifest ones. Overton (2006) discusses in more detail the nature of this philosophical position and its pertinence to the study of development.

The “idiographic filter” within a measurement context strongly reflects these sentiments. In the context of
studying development as a life-span phenomenon, we believe that the ideas are reflected in one of our major goals stated earlier—the search for generality in patterns of behavior across time/age. Clearly, this search does not have to be constrained to the relations among manifest variables; nor, we argue, should the search be so constrained. Had the atom, the knight, and the baseball been thrown together, some measurements taken, and then a mean and standard deviation calculated, the two statistics would have been utter nonsense—descriptions of a jumping nonentity. But by focusing on properties residing at a more abstract level, similarities could be identified between the baseball and the atom that were, however, not shared by the knight. Indeed, the aggregation of information, which is at the heart of such important issues as generalizability, should be so informed by these abstract relations rather than blindly conducted at the level of manifest variables (e.g., see Molenaar, 2004).

Referring back to the analyses of imaging time series involving “warping” images to a common reference scheme, in the second phase of such studies, selected aspects of the models or warped scans obtained in P-technique, like analyses of the time series data for each individual subject are entered in analysis of variance analyses. The results of these analyses can be generalized to the population from which the sample was drawn. This exemplifies one traditional, yet effective way to address the matter of generalizability in analyses of intraindividual variation.

It is the case that we do not yet have a great variety of innovative tools on which to base the search for similarities in intraindividual variability patterns, but as noted earlier, important steps have been taken with the extensions of P-technique factor analysis such as dynamic factor analysis and state-space models. As we have argued elsewhere (Molenaar & Nesselroade, 2010; Nesselroade & Molenaar, 2003), these methods offer a promising, rigorous approach to the concept of process. Processes involve sequential organizations of events that are related within a larger scheme. However, all events occurring simultaneously are not necessarily part of the same process, and multiple processes can simultaneously influence the same variables, thus complicating the task of the developmentalist trying to detail the nature of developmental change. Nesselroade and Molenaar illustrated the ideas with the example of children simultaneously growing physically, learning to read and write, and so forth, at the same time they were being “socialized” through influences at home, school, and other environments. The child’s sense of self, for instance, is simultaneously impacted by all these processes (physical growth, cognitive development, socialization), some of which are individual and some institutional. To go beyond a mere static description of what is going on by plotting the child’s sense of self-trajectory over age, you can remarkably enrich the picture by incorporating dynamics into it. How this can be done is easily illustrated. Suppose that the rate of change (velocity) in the developing child’s sense of self is inversely proportional to the child’s current sense of self, implying that the child with a strong sense of self is changing less rapidly than a child with a weak sense of self—both are approaching some equilibrium value by the same general rule, but the rate of change differs for the two.

How to model the kind of system just described? As we have been arguing, a focus on modeling process at this stage of life-span developmental psychology’s evolution needs to rest on both a multivariate orientation to measurement and analysis, and an idiographic emphasis in pursuing nomothetic relations. Models that look promising for this purpose represent significant elaborations of the basic P-technique approach, such as dynamic factor models, as well as state-space models and dynamical systems models, among others. Furthermore, we believe that the dynamical models can be made even more valuable for the study of process by implementing two innovations. The first is to create versions of the modeling procedures that can cope with non-stationary time-series data (e.g., see Molenaar et al., 2009). The second is to extend the idiographic filter notion to the modeling of process. Molenaar and Nesselroade (2010) discuss how this can be accomplished in a rigorous way.

Somewhat analogous to the way other constructs are conceptualized, processes are latent entities that are “realized” in the empirical world via a set of manifest or indicator variables. In the spirit of the “multivariate orientation” (Baltes & Nesselroade, 1973; Cattell, 1966b; Nesselroade & Ford, 1987) and discussed earlier in a measurement context, we believe that dynamic factor models, state-space models, and so forth can play for processes a role similar to that played by P-technique for latent variables as in the idiographic filter described earlier. In this vein, the dynamic factor models, for example, represent a kind of invariant “wire frame” for the “same” process that can be realized differently at the manifest variable level for different individuals. For example, socialization is generally conceptualized as a process, but the specific socializing behaviors of parents and socialized outcomes displayed by their offspring are not necessarily the same from one family unit to another. Therefore, developing a general understanding of how the process of socialization unfolds cannot be tied to a...
particular set of manifest variables. Rather, in analogy to the “jumping operations” of the atom and the baseball, a set of abstract principles must be determined if a claim to “understanding the process of socialization” is to be validly made. This is the general direction in which we believe the study of developmental processes can profitably head. It features a dynamic orientation and assumes that there are common, underlying processes, whereas allowing the actual physical manifestations (indicators or manifest variables) to differ from individual to individual. This is the underlying idea of the idiographic filter applied to the notion of process. For further discussion of the issues and procedures see the article by Molenaar and Nesselroade (2010).

SOME FINAL METHODOLOGICAL ISSUES

The somewhat unique perspective that we have been discussing may have seemingly foreclosed on a couple of general concerns that have been of major interest to behavioral scientists for decades. One of these is the matter of prediction, which we may seem to have placed in some jeopardy by our indifference to the traditional differential psychology orientation. The other is the matter of generalizability, the traditional notion of which we may seem to have threatened with our strong focus on the individual case. We want to consider each of these in more detail because we think their roles are different in the intraindividual variability approach we have been discussing. We hasten to add, however, that far from being diminished in our intraindividual variability scheme, we believe that their importance may actually be enhanced.

Prediction and Selection

Prediction and the traditional differential psychology approach go together nicely because prediction typically rests on differential inputs pointing to differential outcomes. One measures differences among the attributes of individuals and, to the extent that these differences remain stable, they can be used at a later point to predict other differences such as those in performance. However, from an intraindividual variability perspective, prediction takes a somewhat different form. As we have been pointing out in this chapter, we are intent on focusing more on the similarities among individuals than on their differences. But the similarities among individuals do not lend themselves to differential predictions regarding future behavior.

Have we backed ourselves into a difficult corner? We don’t think so. From a perspective emphasizing intraindividual variability, concern is on predicting what an individual will do in the future based on his or her past behavior rather than on what one individual will do relative to another. This is a further illustration of how a focus on intraindividual variability leads us into a somewhat different kind of issue than those on which the traditional nomothetic perspective rests. Predicting whether a given individual, X, can accomplish feat Y can be based on X’s past performance. Given that X is predicted to succeed at Y, whether X should actually be the person selected out of a larger pool of those capable to do Y is not an individual question. Rather, it is a different kind of question; perhaps one requiring knowledge of how X differs from others. This forced discrimination between prediction and selection obviously calls for richer information on the individual than might otherwise be the case, but obtaining such information is quite in line with the fundamental thrust of our arguments.

Generalizability

Generalizability is another key concern of behavioral researchers, and emphasizing the individual case usually invites a vigorous critique centered on the lack of it. Campbell and Stanley (1963) defined generalizability or external validity in terms of the range of other variables, groups, treatments, and so on, for which a given finding held. One of the obstacles to be overcome from an intraindividual variability perspective is that research designs involving a time-series orientation often involve small numbers of cases, even single cases sometimes, and thus are probably among the most heavily criticized for their lack of generalizability. Yet, a dominant recommendation that we have been discussing is basing the search for similarities across individuals on patterns of intraindividual variability generated by such designs. It seems to us that the search for similarities in patterns of intraindividual variability over individuals is very much in the spirit of generalizability from our idiographic perspective. Moreover, as Molenaar (2004) has argued, technology for the kinds of designs we are describing will surely make them feasible for much larger numbers of cases in the near future. As the numbers of cases on which such research can be conducted increases, concerns regarding generalizability of findings will decrease accordingly.

Aggregation of information is closely bound to the matter of generalizability, which in traditional interindividual
Differences designs is often considered accomplished if one simply uses large, representative samples of participants. We cannot underscore strongly enough, however, that simply gathering information on large samples of participants and averaging over them as the way to develop general conclusions is a false hope for developmental science. The most likely outcome of basing averages on larger and larger samples is weaker and weaker relations among important variables. We should remember, and take seriously, the old adage regarding learning less and less about more and more until one knows nothing about everything.

As Molenaar (2004) indicated, there is much more to be concerned about in large aggregations than sheer numbers of participants. Heterogeneity of within-person structures in large numbers of participants may be obscured, and standard kinds of analyses such as factor analysis of cross sections of the participants can fail to detect that is the case. Plausible modeling outcomes can be obtained under such conditions, and no indications arise to warn the data analyst that the apparently meaningful results are, in fact, meaningless. A thorough examination of intra-individual variability is necessary to detect such circumstances. That is a primary reason why our approach to aggregation (and generalizability) is more one of accretion based on informed judgments regarding the appropriateness of combining cases rather than blithely aggregating and finding some kind of average.

DEVELOPMENTAL RESEARCH ISSUES AND QUESTIONS

Closing a methodological chapter with a discussion of research issues and questions may seem a little like putting the horse after the cart. But in this case, we believe that it is first imperative to state a number of points regarding methodology if the comments we wanted to make regarding research issues and questions are to be construed the way we intend. This final section examines the matter of research issues and questions in light of our emphases on individuals and intra-individual variability, latent variable modeling via multivariate measurement models, and looking at similarities rather than differences.

Browne and Nesselroade (2005) distinguished between studying changes from a stasis/equilibrium versus studying change from a process/change perspective. The stasis/equilibrium perspective dominated psychology, even developmental psychology (e.g., see Overton, 2006), the biological sciences (Levins & Lewontin, 1985), and the physical sciences (Holling, 1973), well into the 20th century. One need only attend to the psychometric literature on the measurement of change up through the 1960s and beyond (e.g., see Cronbach & Furby, 1970) to understand the profound grip an ontological commitment to a world that is ultimately static and fixed has had on the nature of the research enterprise. A strong parallel exists here with the distinctions raised by Baltes (1973) in discussing the significance of bringing a “developmental perspective” to bear on research problems, and not just developmental research problems—any research problems. This distinction implies that not only are the measurement, design, and modeling efforts at stake but also the very phrasing of the research questions. In the presentation of some individual-level modeling techniques, Browne and Nesselroade (2005) illustrated the point simply with the contrast between asking, “Which of these intelligence tests shows the highest test-retest correlation?” versus “How much more does Anxiety fluctuate than Guilt?” Underlying the first question is the belief that intelligence is a highly stable attribute, and departures of the test-retest correlation from 1.00 are mainly indicative of unreliability of measurement. Underlying the second question is the belief that emotions naturally fluctuate. Given that, it is of interest to see how they fluctuate. In one view, stability and equilibrium are tacitly assumed; in the other view, change is a given.

It bears repeating (see Browne & Nesselroade, 2005) that one can measure and analyze intraindividual variation from a purely static perspective, if that is one’s goal. For example, in a sample of older adults, Eizenman, Nesselroade, Featherman, and Rowe (1997) found that those who showed greater week-to-week fluctuation in their reported control (internality) beliefs were at greater risk for mortality than those who showed small amounts of week-to-week fluctuation, regardless of mean level around which the fluctuations occurred. Here the predictor was the magnitude of within-person fluctuations (intraindividual variability). In this case, however, the analytical thrust was the traditional one of predicting between-person differences from between-person differences. Although the between-person differences had to do with within-person variability, the emphasis was on stable features (amount of intraindividual variability) of the within-person changes.

Psychological research has not had the rich history with the study of intraindividual variability via time series modeling that it has enjoyed with other kinds of variability that is typically modeled via various forms of regression analysis. It is not easy to collect sufficient numbers of
repeated measurements on N = 1 to provide reliable parameter estimates. Multiplying the number of such intensively measured cases further increases the difficulties of collecting such data. Moreover, outspoken concerns regarding generalizability have been overemphasized. We believe the concerns over generalizability have been overstated, because of a narrow interpretation of the important features of generalizability. With a few exceptions (e.g., psychophysiology; see also Glass, Willson, & Gottman, 1972; Gottman, McFall, & Barnett, 1969; Larsen, 1987), psychologists have tended to frame their research questions, and collect and analyze their data from other perspectives. If the study of development is to embrace what we believe is a much needed, more process-oriented, intraindividual variability perspective, this will have to change.

Finally, we believe that a commitment to the intraindividual variability emphasis promoted in this chapter is highly consistent with, and perhaps even foundational to, a life-span perspective in the study of development. We close with three points for why we believe this to be the case. The three ideas underlying these points are by now familiar to the reader. First, focusing on the individual as the proper unit of analysis sets the stage for an examination of developmental processes, first and foremost, as an individual phenomenon. Of course, individuals develop in contexts, typically contexts that include other people who are also undergoing changes. But as Baltes, Reese, and Nesselroade (1977) stated several decades ago, the fundamental task of life-span developmental researchers involves identifying intraindividual change patterns first, and then interindividual differences and similarities in those intraindividual change patterns. Specifying intraindividual change patterns precisely requires making a sufficiency of repeated measurements of the individual—one of the central ideas running throughout this chapter.

Second, to be of value to the elaboration of a knowledge base, theories of development need to have the level of generality that can be achieved only when key elements include latent variables and their interrelations. We would argue that our most useful current level of sophistication in “tying down” latent variables both in terms of their manifest representations and their interrelations resides in the so-called measurement models of structural equation modeling. The measurement model approach, in turn, is highly dependent on multivariate measurement schemes of one kind or another. As discussed several times in this chapter, multivariate measurement models provide the kinds of data that we think are appropriate and necessary for exploiting intraindividual variability conceptions and data. By carefully evaluating the proper role of concepts such as invariance, proposals such as the idiographic filter are meant to help us further capitalize on the inherent strengths of a multivariate measurement orientation.

Third, we have vigorously promoted the identification of similarities and differences among persons in patterns of intraindividual variation as a key aspect of the capitalization on intraindividual variability phenomena to understand behavior. Tools such as the idiographic filter used at the measurement level can help to eliminate irrelevant differences whereas emphasizing similarities. Clearly, this fits well with the life-span objective of identifying interindividual differences and similarities in intraindividual change patterns. Obviously, some interindividual differences can be central to our understanding of developmental mechanisms, but others ought to be minimized or even ignored. Being able to make the difficult call regarding which is which is a task with which the idiographic filter should be able to help.

Do other general approaches to building a scientific knowledge base also mesh with the objectives of elaborating the life-span approach to the study of development? Of course they do. The two disciplines of scientific psychology that Cronbach (1957, 1975) described so well involve methods that have served the study of development substantially for a century or more. However, from the perspective of extracting the most from a growing body of life-span development research and the further elaboration of a knowledge base, the surface has barely been scratched. We want more and we believe that a clearer focus on the individual and the exploitation of intraindividual variability approaches through more sophisticated measurement and modeling techniques opens some promising avenues to new advances.

REFERENCES


Emphasizing Intraindividual Variability in the Study of Development Over the Life Span


Molenar, P. C. M. (2004). A manifesto on psychology as idiographic science: Bringing the person back into scientific psychology —
References 53


