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ASSESSING CONSTANCY AND CHANGE

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INTRODUCTION

He perfect, stable; but imperfect We, Subject to Change, and diff'rent in Degree. (John Dryden, *Palamon and Arcite: The Knight's Tale From Chaucer*).

A party of order or stability, and a party of progress or reform, are both necessary elements of a healthy state of political life. (John Stuart Mill, *On Liberty*).

Constancy and change are necessary complements of each other. Without a stable reference frame, the assessment of change is not possible. Conversely, without change events, there would be no need for a concept of constancy. Students of personality are obligated to account for both the constant and the changing properties of its order and organization. Although each kind of property has its peculiar features to be respected, constancy

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and change are advantageously considered together, rather than in isolation from, or in opposition to, each other (Nesselroade, 1990).

Students of personality have had an enduring interest in both constancy and change (Brim & Kagan, 1980). On the side of change, central concepts such as learning, development, growth, and emotion, all of which represent one or another kind of change or intraindividual variability, are inherent to the study of personality. Without such change-laden concepts, our field would be exceedingly dull and impoverished.

Constancy also has a high value placed on it for several reasons. At a popular level, people like to see constancy in the behavior of others, perhaps because it makes them more predictable. At the same time, however, most people do not want to be thought of by their fellows as being predictable. Probably one of the most important reasons stability is valued by psychologists is because of the long-standing emphasis on activities such as prediction, classification, and diagnosis. These activities are pointless unless there are some relatively constant features of behavior on which to base them. Putatively stable interindividual differences in a great variety of attributes have been assigned the largest role of providing the constancy demanded by prediction and classification activities. For example, human abilities, broadly defined, and general dispositional traits such as extraversion and anxiety have tended to be the work horses of psychometrics-based prediction schemes. But more or less stable aspects of change are also candidates for the role of predictor. For example, when someone is seen as volatile or emotional, the implication is that he or she is consistently distinct from others with respect to these inherently changeable dimensions.

Constancy and change also play important roles in the development of theory. The level of stability of interindividual differences, be it high, medium, or low, provides important information on which to base inferences about mechanisms, both endogenous and exogenous, hypothesized to be involved in development and change over the life span.

It is easy to oversimplify both concepts, or, perhaps more accurately, both sets of concepts, of constancy and change. Mortimer, Finch, and Kumka (1982), for example, pointed out that one of the problems inherent in clarifying issues of constancy and change with regard to the study of development is that there are at least four different conceptualizations of stability found in the literature. These include (a) structural invariance or the degree of continuity in the phenomenon under investigation, (b) normative stability or the persistence of relative amounts of an attribute across time, (c) level stability or maintenance of the absolute amounts of an attribute over time, and (d) ipsative stability or maintenance of an ordering of attributes (e.g., with respect to salience) within the individual over time. Similarly, change is by no means a single concept. Cattell (1966b), for example, in the area of personality research, distinguished between trait

change and state fluctuation. Fiske and Rice (1955) identified and discussed many different kinds of intraindividual variability.

Suffice it to say that psychologists studying personality need to become more adept at using concepts of constancy and change, to elaborate the definition, measurement, and use of concepts that are suited to the complexity of our subject matter. Moreover, it is necessary to do so with the precision and rigor of mathematical formulations. Until such rigorous representations are implemented, much of what psychologists aspire to know and understand about personality will continue to be elusive.

In the following section, we selectively review some issues pertinent to assessing constancy and change and highlight some aspects that we believe can be attended to more effectively. In the section following that, we examine the potential of some alternative ideas for helping to deal with some of those issues.

CURRENT APPROACHES

The need to assess both change and stability has had a broad influence on the shaping of current research and data analysis methodologies. Two very general developments that have helped to forge the array of tools with which both constancy and change are presently assessed are (a) longitudinal designs and (b) multivariate methods. The effects of these two major lines of development can be witnessed in the areas of measurement, research design, and data analysis and modeling.

Longitudinal Research Designs

The history of longitudinal research designs has been reviewed elsewhere (e.g., Baltes & Nesselroade, 1979; Goldstein, 1979; Kruse, Lindenberg, & Baltes, 1992). Longitudinal designs appear in many forms and enjoy a certain mystique, especially in the context of developmental research. Particularly during the past three decades, simple longitudinal designs, longitudinal sequences, panel studies, intensive measurement of individual cases, and so on, have all found substantial application in the conduct of behavioral research. Their use has led to both the sharpening of issues and a much fuller understanding of such phenomena as stability, developmental change, time of measurement effects, cohort differences, and short-term intraindividual variability.

In psychology, for example, the general developmental model of Schaie (1965; see also Baltes, 1968) raised serious questions about the usefulness of simple longitudinal designs involving a single birth cohort of individuals. Instead, Schaie, Baltes, and others argued for carefully struc-

tured, sequential designs if individual change was to be distinguished from other key manifestations such as sociocultural change. These ideas helped to regenerate and strengthen a nearly dormant focus on psychological development across the life span, a focus that, once renewed, has influenced personality research in important ways over the past three decades. These developments have paralleled important work on the life course deriving from a more sociological tradition (e.g., Elder & Caspi, 1990; Featherman, 1985).

Multivariate Methods

The systematic development and use of multivariate methods began around the turn of this century (see Baltes & Nesselroade, 1973; Cattell, 1966a, for discussions of the multivariate orientation). The development of multivariate analysis theory and methods and the articulation of several aspects of substantive theory have been closely intertwined. For example, in measurement, the development of concepts and theories of human abilities has closely paralleled the development of factor-analytic modeling procedures.

Multivariate methods have enhanced capabilities for defining and elaborating concepts in several ways. A key question in personality research is, How many variables are needed to identify, define, and measure a concept? For example, rather than selecting one exemplar from a substantive domain of many variables, a subset of variables can be used in concert to represent the domain. Anxiety, for example, represents a broad domain of content with putative indicators ranging from self-report and clinical ratings through respiration rate to handwriting pressure. When one is trying to use anxiety level as either an input variable or an outcome, it is risky to put all the "eggs in one basket" by choosing only one of the many possible indicators of anxiety. When definitions rest on a vector of several variables, the options for identifying concepts include focusing on what the multiple measures have in common as well as defining particular patterns of relationships across several variables. These multivariate capabilities, teamed with concepts such as factorial invariance (Meredith, 1964), have enabled researchers to provide rigorous definition and meaning to conceptually appealing notions such as *qualitative* versus *quantitative* changes as well as to elaborate concepts of stability, reliability, and so on, and to separate more effectively error from true variance in estimating the structural parameters of models.

Current concepts in and approaches to assessing constancy and change rely heavily on both multivariate approaches and longitudinal research designs. Together, they have provided a means for revamping change and stability concepts through the development and use of latent variable structural modeling (Bentler, 1980; McArdle, 1988). Descriptions of some of

the most current methods can be found in publications by Collins and Horn (1991), Molenaar (1985), and Millsap & Meredith (1988), among others. These methods deserve more extensive trial and further development as students of personality continue to wrestle with the difficult problems of assessing constancy and change. Along with improvements in assessment, necessary enhancements of working definitions of constancy and change are likely to develop.

Some Limitations

The gains accruing from longitudinal research designs and multivariate research methods have not been preceded, accompanied, or succeeded uniformly by improvements in the conceptualization of other pertinent issues. This has been especially true in the areas of measurement and research design. Some examples are presented in this chapter to illustrate the problems.

Measurement

Within the domain of human abilities, where attributes were thought to represent rock stable interindividual differences, it was rather natural that concerns with stability of interindividual differences tended to dominate the development of measuring instruments. Test-retest correlations, for example, are advocated for estimating reliability (e.g., Nunnally, 1967) and, therefore, the psychometric adequacy of measures. This seems appropriate when the attributes being measured reflect no, or only minimal, intraindividual change. But test-retest correlations can confound matters of method and substance (e.g., measurement unreliability and process-based changes) and, therefore, can fail as indicators of the goodness of a measure designed for assessing changeable phenomena such as states of anxiety and depression (Cattell & Scheier, 1961; Nesselroade, 1988; Spielberger, Gorsuch, & Lushene, 1969). Moreover, even measures of human abilities can show patterns of relatively short-term but coherent changes when studies are designed to look for them (Horn, 1972), a finding that suggests that personality researchers sometimes oversimplify matters of constancy and change.

Research Design

Poor measurement is not the only blot on the record of studies of constancy and change issues in personality. Innovations in research design have not always kept pace with other developments. The use of high speed, large capacity computational machinery has raised the possibility that the quality and power of methods may have begun to exceed the quality and comprehensiveness of much of the data collected in the typical investigator-initiated research study.

Some of the critical ways that data collection can be improved have been reviewed and discussed at length elsewhere (Nesselroade, 1983, 1991a). The general issue is the need to pay more direct attention to the fact that data are inherently multimodal (i.e., they reflect selection with respect to persons, variables, and occasions of measurement). The resources for any research project are limited, a constraint that dictates that there must be trade-offs in the breadth of representation that is given to the different data modalities. The exact nature of these trade-offs should be determined by the research questions and concerns regarding generalizability of the findings. The assessment of both constancy and change, for example, implies the need for multiple occasions of measurement. Sampling of persons, no matter how carefully and completely it is done, does not compensate for narrow and inadequate selection of occasions of measurement in those cases in which generalization is focused across occasions (e.g., on constancy or change). The most precisely constructed representative sampling of people does not yield information about degree of stability or amount of change in the attributes of concern if members of the sample are measured only once.

As a basis for sampling or selection in planning research, occasions unfortunately do not represent a highly homogeneous universe. Therefore, matters of duration and spacing of repeated measurements are critical aspects of longitudinal research design. However, simply including multiple occasions of measurement in the design does not adequately compensate for ill-defined selection of duration and spacing. Periodic phenomena in particular can generate extremely misleading results when analyzed with test-retest correlations and fixed-interval lags. In a fixed-interval lag design all of the intervals between assessments are equal, therefore they are perfectly correlated with each other. If the frequency of the periodic phenomenon under study is also correlated with the lag interval, the test-retest correlation will be artificially high, giving an overestimate of stability and an underestimate of intraindividual variability. Later in this chapter, we provide an example of this type of error, which is known as *aliasing error* in the fields of signal processing and computer graphics.

A second way to improve research design, and thereby data collection, involves attending as carefully to the selection of measurement instruments as to the selection of persons to study. Multivariate measurement batteries are indispensable for pinpointing concepts and patterns and for allowing the researcher to develop estimates of structural parameters that are not attenuated due to errors of measurement. However, not just any multivariate battery works as well as any other one. For example, using anxiety measures *x*, *y*, and *z* because they are more convenient, or shorter, or were developed by close colleagues, can yield remarkably different estimates of the relationship between anxiety as a latent variable and other latent variables than would have been the case if anxiety measures *a*, *b*, and *c* had been

used. Such choices must be informed by knowledge of the domain, the nature of focal concepts, and concerns about generalizability.

Consistency in Variability

There is another issue that becomes salient if one takes seriously the notion of looking at constancy and change as complementary. It is that constancy can be a relatively stable characteristic or attribute of changeable phenomena. For example, the broadcasts of an AM (amplitude modulation) radio station represent a high degree of variability (the amplitude of the carrier wave), but the frequency of the carrier wave must remain within a very tight tolerance or the station's license will be revoked. Thus, the station is locatable at a highly predictable spot on the AM dial, but superimposed on that highly stable frequency is a substantial amount of variability. Both are integral to the broadcasting process and the station might just as easily be denoted in terms of a stable feature of variability—"the one that plays all the good rock music"—as in terms of constancy—"the one at 1450 on the AM dial."

In a similar vein, the parameters of intraindividual variability distributions may carry important and stable interindividual differences information that can be used to bolster our predictive and explanatory schemes significantly (Nesselroade, 1991a). Indeed, concepts such as rhythmicity, volatility, and unpredictability are characterizations of intraindividual variability dimensions that are presumed to represent more or less stable differences among persons. There is also support for the importance of intraindividual variability as a component of behavior when it is examined in a multivariate, longitudinal framework such as by P-technique factor analysis (Cattell, 1963; Jones & Nesselroade, 1991; Luborsky & Mintz, 1972). Locus of control, work values, creativity, and self-concept are included among attributes that are typically regarded as stable and traitlike yet that manifest patterns of systematic, short-term, intraindividual variability (Nesselroade, 1991b).

Within a given occasion of measurement, intraindividual variability on some measure that is asynchronous across individuals cannot be disentangled from stability among interindividual differences. The two are hopelessly confounded in cross-sectional data. Hampson (1990) showed that women perform differentially better or worse on spatial and verbal ability tasks as a function of their estrogen levels at a given point in their monthly cycle. The pattern of changes was consistent with gender differences in performance on such tasks in that, in relation to their own levels, women performed better on verbal tasks when estrogen levels were highest and better on spatial tasks when estrogen levels were lowest. A one-shot, cross-sectional study involving women at different stages of their monthly cycles would not distinguish between the variation that is due to such cycle-related

sources and the variation that is due to relatively stable differences in spatial and verbal ability. If the variation among individuals at one occasion of measurement were computed for such data, it would be an overestimate of the magnitude of stable interindividual differences and, by implication, would lead to an underestimate of the relative magnitude of intraindividual variability. Further methods and techniques are needed by which constancy in patterns of intraindividual variability can be exploited in the pursuit of more accurate accounts of both the constancy and the change characteristics of behavior.

The Trait-State Distinction

The trait-state distinction in personality research (Allen & Potkay, 1981, 1983; Cattell & Scheier, 1961; Nesselroade, 1988; Spielberger et al., 1969; Zuckerman, 1983) is a useful vehicle for organizing some of the key issues and concepts related to the topics of constancy and change (e.g., Hertzog & Nesselroade, 1987). The distinction has a long history (Eysenck, 1983) but is not without controversy. One exchange (e.g., Allen & Potkay, 1981, 1983; Zuckerman, 1983) was focused on the arbitrariness of the distinction between trait and state. In this section, we do an "end run" around that controversy to some extent by recognizing a conceptual distinction between state and trait and the likelihood of different patterns of antecedents and correlates for them. In the next section, however, for purposes of illustration, we formalize the difference between trait and state in terms of period lengths.

In any event, we do not regard the dichotomy as comprehensive or exhaustive, but we have found the labels useful for conveying the essence of a distinction between relatively stable interindividual differences dimensions (traits) and dimensions of relatively short-term, intraindividual variability (states). The former also evince intraindividual change, but it is of much slower, less reversible character. Cattell (1966a), for example, referred to this kind of change as trait change. For the purposes of this chapter, we use the terms *trait* and *state* to label these two kinds of dimensions.

We assume the following generalized model to represent the score of individual *i* on observed variable *Y* at a given point in time *t*.

$$Y_{it} = T_{it} + S_{it} + E_{it} \quad (1)$$

where T_{it} = individual *i*'s trait component at time *t*, S_{it} = individual *i*'s state component at time *t*, and E_{it} = an error of measurement for individual *i* on observed variable *Y* at time *t*. Several points should be explicitly noted about this representation.

1. The observed score has both a trait and a state component at a given point in time. This means that the variance of a

distribution of scores for many persons, all measured at time *t*, potentially consists of both trait and state components.

2. Whereas the notion of trait conveys the idea that a given individual has a characteristic value at a given point in time, the notion of a state implies a hypothetical distribution of values for the individual at a given point in time, although, at a specific instance, the individual will have a particular value from that distribution.
3. Measuring individuals only once does not eliminate the state variance contribution from the observed scores; it merely ensures that it will be hopelessly confounded with the trait variance contribution.

The history of personality research reflects a strong emphasis on rather straightforward, linear, and additive representations of both constancy and change. In many respects, these have served the science well, but it seems fair to say that novel forms of representation should be sought even as researchers continue to explore the limits of current ones. It is our belief that there are potentially important alternatives to be explored, some of which seem well-suited to the extension of constancy and change concepts in new directions. We return to this point in the final sections of this chapter.

TWO SIMULATIONS AND THEIR OUTCOMES

To explore more systematically some of the issues pertinent to assessing constancy and change, we have constructed two simulations that rest on the trait-state distinction as represented in the model described above. We present the outcomes of the simulations in familiar terms: test-retest correlation estimates of stability. These two simulations are designed to illustrate the potential for erring in the overestimation or underestimation of stability when using test-retest correlations as stability indicators. The simulations rest on equations suggesting considerable regularity. This, admittedly, is an oversimplification, and it would not be difficult to program some shocks into the system. To do so, however, would unnecessarily complicate the presentation.

Prior to presenting the simulations, we develop the bases on which they rest. These include a generic equation to represent various functional relationships between personality attributes and time and an examination of the role of measurement spacing and duration in studying personality constancy and change.

A Generic Curve for Representing Traits and States

We start with the difference equation that is used to describe the motion of a linear spring as damped with a linear force (Hubbard &

West, 1991; Wylie, 1979), very much the same equation that describes the behavior of the springs on one's car as they are dampened by shock absorbers:

$$\frac{\Delta^2 y}{\Delta x^2} + \zeta \frac{\Delta y}{\Delta x} + \eta y = 0 \quad (2)$$

where Δx and Δy represent the finite change in the variables x and y , respectively, η represents a frequency parameter, and ζ represents a dampening parameter.

We hasten to assure the reader that Equation 2 is not as formidable as it may appear. A difference equation simply states that the future trajectory of a system can be predicted from its present and recent state and from its present and recent rates of change over some finite interval of time (Wylie, 1979). Thus, we explicitly quantify expectations regarding future behavior based on measurements of current behavior and measurements of behavior in the recent past.

We have chosen Equation 2 not because we believe that personality is appropriately represented as a spring, but because of the equation's precise and adaptive utility for the several points we wish to make. We note in passing that the notions of frequency and dampening do not seem incompatible with ideas of socialization and control on the one hand, and social support and buffering on the other that act to keep the organism functioning within some set of boundaries. Before introducing the simulations, we identify and discuss in some detail the model represented by Equation 2 and its parameters.

The Δx and Δy in Equation 2 represent differences in values across time or changes in the variables x and y . To give an intuitive feel for the two parameters, ζ and η , they have been assigned a series of values and the resulting equations plotted, as shown in Figure 1. By holding one parameter constant and varying the other parameter, one can see how changes in the parameters influence the precise shape of the curve.

The curves used to represent traits in these simulations are actually cyclic functions that decay within the first cycle. In Figure 1, parts 1a-1d illustrate various trait curves that are obtainable from Equation 2 by increasing the value of η while holding ζ constant: an *increasing cyclic frequency*. Notice that there is a secondary effect of a decrease in total amplitude of the first cycle of the trait curve as η is increased. This secondary effect is an important signature of the difference Equation 2.

In Figure 1, parts 2a-2d illustrate different state curves obtainable from the same general equation by decreasing the value of η while holding ζ constant: a *decreasing cyclic frequency*. Thus, η can be regarded as a term that controls the frequency of both the trait and state curves.

In Figure 1, parts 3a-3d show the effect of increasing ζ while holding η constant: a *greater dampening* of the trait curve. These trait curves are all

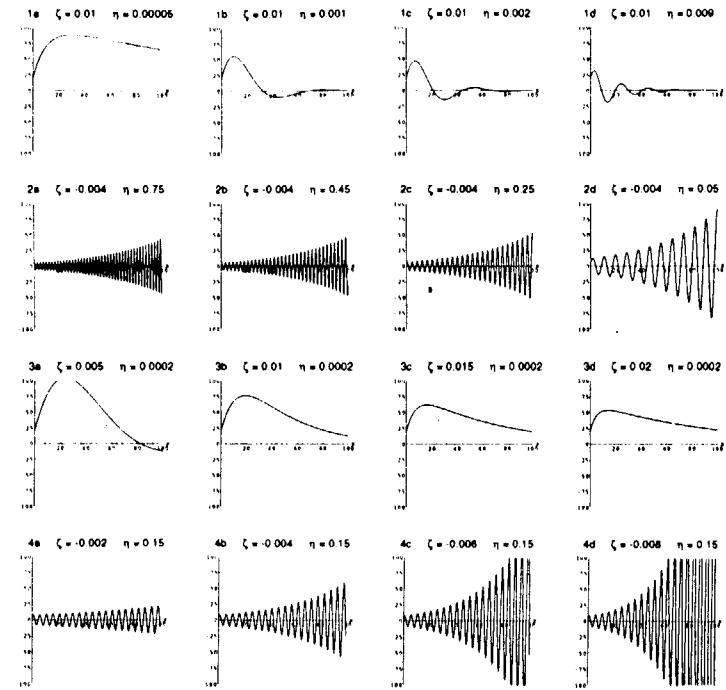


Figure 1: Varying the parameters of the state and trait curves. 1a-1d: Increasing η increases the frequency of the trait curve. 2a-2d: Decreasing η decreases the frequency of the state curve. 3a-3d: Increasing ζ increases the variance dampening of the trait curve. 4a-4d: Increasing negative ζ increases the variance growth of the state curve.

dampened within the first cycle, so it is difficult to recognize them as being from the same family of curves as the state curves. Using this equation, the degree of nonlinearity in the decay of the trait curve can be controlled by balancing a decreasing frequency against an increasing decay.

In Figure 1, parts 4a-4d show the effect of varying a negative value of ζ while holding η constant. When ζ is negative, its effect is one of negative variance decay, that is, an effect of variance growth. As ζ is made to be a larger negative number, the variance growth becomes more rapid. Thus, one can interpret ζ as a parameter that controls the dampening of the trait or state curves.

Thus, the curves shown in Figure 1 illustrate how very flexible Equation 2 is in that it can be used to describe prototypic trait and state curves

simply by varying the parameters ζ and η . An aspect that we want to emphasize here is that by means of Equation 2 trait and state concepts are both cases of a more general representation of constancy and change.

Example Trait Curve

In Figure 2, an example trait curve is presented that was produced by setting $\zeta = .01$ and $\eta = .0002$. Thus, the score on trait T for individual i at time t follows the expression

$$\frac{\Delta^2 T_{it}}{\Delta t^2} + .01 \frac{\Delta T_{it}}{\Delta t} + .0002 T_{it} = 0 \quad (3)$$

This curve has a period approximately equal to two human lifetimes and is 99% dampened within that period. If the x -axis in Figure 2 is taken to represent time in years and the y -axis to represent level of attribute (shown here on a scale of 0 to 100), the general shape of the curve bears more than a cursory resemblance to the way fluid intelligence is portrayed to change over the human life span (Cattell, 1957).

Example State Curve With Decreasing Variance

For the example state curve shown in Figure 3, parameter values of $\zeta = .005$ and $\eta = 3.85$ were given to Equation 2. These values produce

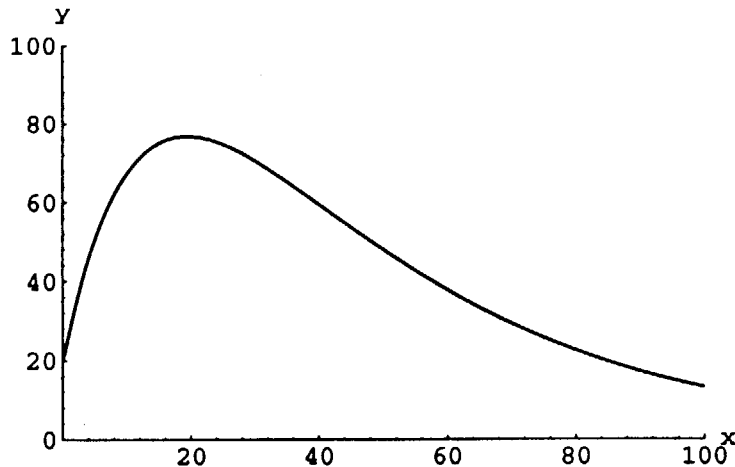


Figure 2: State curve with decreasing variance.

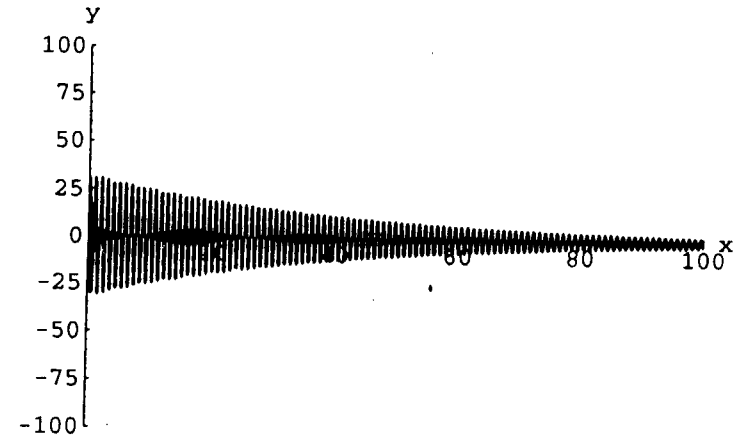


Figure 3: Example trait curve.

a curve with a period of 1 and a dampening force such that the fluctuation is 99% dampened within 200 periods. With the exception of the two parameter values, this example state curve and the preceding example trait curve are mathematically identical.

If the x -axis in Figure 3 represents time in years and the y -axis represents some personality attribute measured on a scale of 0 to 100, then the following is true for individual i :

$$\frac{\Delta^2 S_{it}}{\Delta t^2} + .005 \frac{\Delta S_{it}}{\Delta t} + 3.85 S_{it} = 0 \quad (4)$$

This state curve illustrates variability in some personality attributes that is correlated with the change in seasons, the magnitude of which variability diminishes with age. Something like seasonal affective disorder, for example, the amplitude of which wanes with increasing age or under a lengthy treatment regimen, exemplifies the basic idea.

A set of measurements of this state curve would show *aliasing artifacts* (Shannon, 1975) if measurements were performed at approximately the same day of the year for each wave of a panel study. In other words, if an individual's state score were correlated with the season of the year and measurements were always performed during that season, one would underestimate the intraindividual variability and overestimate the stability of the score. In an extreme case such as the idealized state curve that is perfectly correlated with the day of the year, if measurements were always performed on the same day of the year, one would estimate the state variance to be

zero and estimate perfect test-retest reliability when in actuality one would have entirely missed a large component of state variance. Illustrative of this kind of cyclicality but for a different time scale is the effect of estrogen level on various ability measures described by Hampson (1990) and mentioned earlier. Extrapolating from Hampson's data, repeated measurement built around equal measurement lags of one month on a sample of women would tend to produce high test-retest correlations in ability scores while missing a large component of state variability occurring within the intervening months.

The point is that if a variable is correlated with any time scale and a set of longitudinal measurements of that variable is also correlated with that same time scale, a spurious relationship is introduced between the scores and measurement occasions. It is common practice, for example, to make longitudinal measurements with equal lag times. This, in some cases, unfortunate practice ensures that the measurements are perfectly correlated with that time scale. Hence, any cyclic phenomenon whose period is also correlated with that time scale will be mismeasured in one way or another unless the spurious relationship due to the common time scale is taken into account.

Figure 4 shows a 10-year interval of the state curve from Figure 3 for one hypothetical individual. In this panel study, each individual is measured on the state function at three points (e.g., a_1 , a_2 , a_3) that are spaced

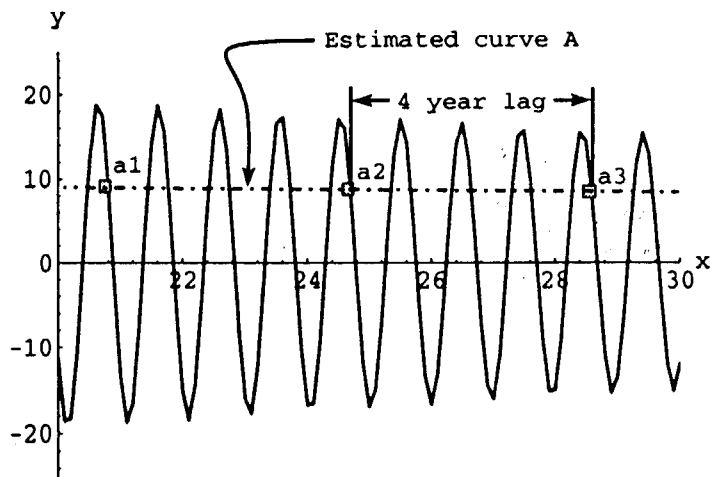


Figure 4: Measurement lag as a multiple of the cyclic period.

exactly four years apart. It can be assumed that individuals' curves, even though they are the same shape, are somewhat asynchronous across time. When some people are high, others are low, and vice versa. Because the measurement lag is an exact multiple of the period of the state, the curve A that would be estimated from these measurements for each individual would manifest no change in level. Thus, the average curve would also be flat, but a high test-retest measure of stability, computed over individuals, would be found.

Figure 5 shows the same 10-year interval of the state curve from Figure 3. Suppose a panel study were designed to measure the state at three points (e.g., b_1 , b_2 , b_3) that are spaced four years and three months apart. Again, it can be assumed that the state function of each individual is described by the same curve but that the individual curves are somewhat asynchronous. Because the measurement lag is a near multiple of the period of the state curve, a linear effect is seen for each individual's curve, but because of the asynchronicity of the curves, a low test-retest stability coefficient would be found, computed over individuals. If the individuals' curves were nearly in phase, then a linear effect and a high test-retest stability would prevail.

One way to avoid these aliasing artifacts is to use a random measurement lag. By choosing a uniform random distribution of lags, the selection of the measurement lag is guaranteed to be uncorrelated with the period of a cyclic phenomenon, no matter what period that cyclic phenomenon

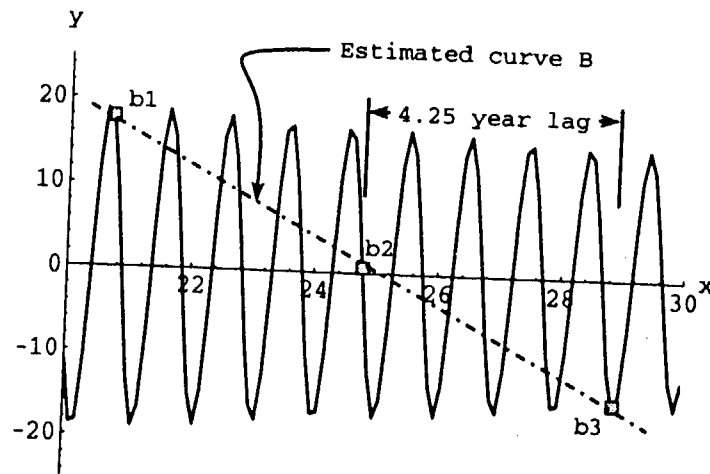


Figure 5: Measurement lag as a near multiple of the cyclic period.

may have. This technique turns the former problem into an advantage. Because the selection of lag is now uncorrelated with the period of a cyclic phenomenon, after removing the overall correlation between all of the scores, a partial correlation between the scores at lags that share common divisors can now be attributed to the period of a cyclic phenomenon. This technique gives much the same result as would a Fourier transform (Bracewell, 1978), but does not require sampling within the so-called Nyquist limit, that is, sampling with a lag less than half the period of the cyclic phenomenon.

Example State Curve With Increasing Variance

Figure 6 shows an example state curve with increasing variance. Here we have used Equation 2, with parameter values $\zeta = -.004$ and $\eta = 3.85$. These values produce a curve with a period of 1 and a negative dampening force such that the magnitude of intraindividual variability increases as x increases (e.g., increasing variability in health status with advancing age).

Specifically, if the x -axis in Figure 6 represents time in years and the y -axis represents some behavior or personality attribute measured on a scale of 0 to 100, for individual i

$$\frac{\Delta^2 S_n}{\Delta t^2} - .004 \frac{\Delta S_n}{\Delta t} + 3.85 S_n = 0 \quad (5)$$

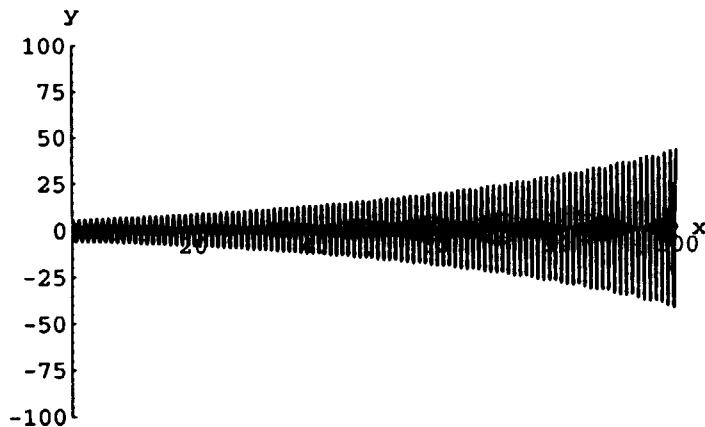


Figure 6: State curve with increasing variance.

Generally, the kind of intraindividual variability pattern portrayed in Figure 6 might be illustrated by the gradual blossoming of some full-blown cyclic dysfunction or the gradual erosion of emotional self-control, although a somewhat higher degree of regularity is implied by the curve than might be expected with psychological or behavioral attributes.

Example Compound Trait and State Curve

Figure 7 is the sum of the trait curve from Figure 2 and the state curve with increasing variance from Figure 6. The result is a linear combination of T_n from Equation 3 and S_n from Equation 5 such that Equation 1,

$$Y_n = T_n + S_n + E_n \quad (6)$$

holds where $E_n = 0$. Performance on a fluid intelligence measure, for example, influenced in part by increasing intraindividual variability in motivation to do well on the test with increased age would be expected to show such a compound curve.

Simulation 1: Random Trait Curves and Equal Lag Intervals

In this simulation, we emulated the sampling of 100 individuals on one variable in a three-wave panel study design of the kind mentioned

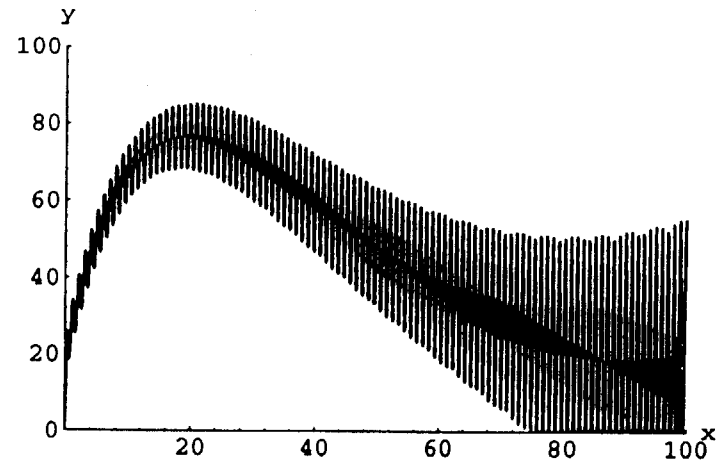


Figure 7: Compound trait and state curve with increasing state variance.

earlier. We constructed a population of 100 individuals who each have compound trait and state curves such that the trait curves vary randomly from individual to individual, but the state curves for each individual are identical to the state curve in Figure 6. The trait curves were individualized by adding a normally distributed random number to ζ and η from Equation 3. Thus, $\zeta = .01 + R_{\zeta}$ where $\bar{R}_{\zeta} = 0.0$ and $\sigma(R_{\zeta}) = .003$, and $\eta = .0002 + R_{\eta}$, where $\bar{R}_{\eta} = 0.0$ and $\sigma(R_{\eta}) = .00006$.

The difference equations were then iterated over $0 \leq t \leq 100$ with a step size $\Delta t = 0.1$ to produce a population of 100 compound trait and state curves. An age of measurement t_{i1} for the first wave of measurement was independently generated for each individual i as a normally distributed random number $t_{i1} = R_{m1}$, where $\bar{R}_{m1} = 40$ and $\sigma(R_{m1}) = .3$. The second and third ages of measurement for each individual were generated as $t_{i2} = t_{i1} + 5$ and $t_{i3} = t_{i2} + 5$.

Each individual's score Y_{in} at each measurement time t_{i1} , t_{i2} , t_{i3} was then sampled from the population of compound trait and state curves, and standard test-retest correlations were computed. The results are summarized in Table 1.

These stability coefficients reflect a rock solid attribute. Indeed, they are so high that the wary reader might suspect we intend to use them to make a point. In fact, this is the case, as we show shortly.

Simulation 2: Common Trait and State Curves

Random Lag Intervals

Next, we selected the compound trait and state curve of one of the individuals from the study population to simulate a panel study with random lags. We performed three waves of measurement on this individual curve 100 times using the same method as in Table 1 to find the age t_{n1} of each measurement n for the first wave. The second age for each measurement n was generated as $t_{n2} = t_{n1} + R_{m1}$, where $\bar{R}_{m1} = 5$ and $\sigma(R_{m1}) = .3$. Similarly, the third age for each measurement n was generated as $t_{n3} = t_{n2} + R_{m2}$, where $\bar{R}_{m2} = 5$ and $\sigma(R_{m2}) = .3$.

TABLE 1
Random Trait Curves Sampled at Equal Lag Intervals

Correlation Matrix			
	Wave 1	Wave 2	Wave 3
Wave 1	1.00000	0.98561	0.94050
Wave 2	0.98561	1.00000	0.98434
Wave 3	0.94050	0.98434	1.00000

TABLE 2
Single Trait Curve Sampled at Random Lag Intervals

Correlation Matrix			
	Wave 1	Wave 2	Wave 3
Wave 1	1.00000	-0.09183	0.02435
Wave 2	-0.09183	1.00000	0.23998
Wave 3	0.02435	0.23998	1.00000

In this way we attempted to capture the state variability of just one of the compound trait and state curves from the study population. The variability in Table 2 is almost entirely due to the state component, because the trait curve, which was the same for all individuals, is nearly linear in the target age range. When these correlations are compared with the correlations in Table 1, it becomes clear that the equal lag interval method used earlier to measure the random trait curves has missed an important source of variability and has therefore substantially overestimated the stability of the measure.

Equal Lag Intervals

To illustrate how the overestimation of test-retest stability occurs, we selected the compound trait and state curve of one of the individuals from the study population and performed a panel study with fixed-interval lags. To simulate 100 records for the panel study, we conducted three waves of measurement on this individual curve 100 times using the same method used earlier to find the age t_{n1} of each measurement n for the first wave. The second and third ages for each measurement n were generated as $t_{n2} = t_{n1} + 5$ and $t_{n3} = t_{n2} + 5$. Table 3 shows what happens to the intraindividual variability when we use the fixed lag method for our panel design study.

The individuals represented in Table 3 whose attributes seem truly set in stone are the same individuals who were portrayed in Table 2 with a

TABLE 3
Single Trait Curve Sampled at Fixed Equal Lag Intervals

Correlation Matrix			
	Wave 1	Wave 2	Wave 3
Wave 1	1.00000	0.99510	0.98080
Wave 2	0.99510	1.00000	0.99527
Wave 3	0.98080	0.99527	1.00000

large degree of variability. The measuring instrument is the same and we have assumed an ideal case with zero measurement error. The difference between these two correlation matrixes is due entirely to the randomization of lag intervals.

Seen in this light, the same population of random trait curves whose correlation matrix in Table 1 looked so stable just moments ago now seems to cast a lengthy shadow of doubt regarding the degree of stability. Indeed, one would be wise to consider the potential for periodic phenomena in one's data before announcing the discovery of stability in a set of population parameters.

DYNAMICAL SYSTEMS

In this, the penultimate section of the chapter, we examine some relatively new ideas and some of their implications for further work in the area of personality research. We focus on the field of dynamical systems theory, the vocabulary and mathematics of which are powerful tools that promise to better equip behavioral scientists to deal with some of the issues of constancy and change.

The preceding simulation examples were formulated in the terms of difference equations. To review, a difference equation states that the future trajectory of a system can be predicted from its present and recent state and from its present and recent rates of change over some finite interval of time (Wylie, 1979). We find this to be a convenient set of concepts for explicitly quantifying expectations regarding future behavior, based on measurements of current behavior and behavior in the recent past.

A conceptualization of deterministic change based on difference equations may not seem to be rich enough to account for the apparently unpredictable nature of much of human behavior. However, in recent years relatively simple systems of difference equations have been shown to be at once entirely deterministic and yet unpredictable in their trajectories after some small amount of time has elapsed (Parker & Chua, 1989; Ruelle & Takens, 1971; Thompson & Stewart, 1986). Systems that exhibit this type of deterministic unpredictability are said to be *chaotic*, a term that has seen much use and abuse in recent popular culture (Ruelle, 1990). A chaotic system exhibits a behavior that is called *sensitive dependence on initial conditions*. What this means is that an infinitesimal change in the current state or current rate of change will cause an unpredictably large change in the system after some finite amount of time has elapsed. Awareness of the potential for chaotic behavior is one consequence of adopting the dynamical systems perspective on constancy and change.

Cyclic or periodic behavior can be expressed simply and flexibly with difference and differential equations. Differential equations represent

change as an instantaneous quantity rather than over a finite time lag as do difference equations. Periodic behavior can be quite stable and its stability is well expressed in terms of the predictability of its difference equations. Tools such as *phase space embedding* are commonly used to reveal the nature of the stability of periodic and quasi-periodic phenomena that are studied as dynamical systems (Sevdel, 1988). At the risk of oversimplification, phase space embedding is a technique for representing a dynamical system in which a vector in a D dimensional phase space corresponds to the state of the dynamical system at D equal intervals of time. One finds that the dimension of the embedding space used to examine a dynamical system can be a critical factor in the apparent predictability of a set of sampled data. We used this fact to guide the creation of the simulation examples in the previous section. What may look like measurement error when viewed in an embedding space of one dimensionality may be perfectly correlated with something else when viewed in an embedding space of another dimensionality.

Another surprising finding resulting from dynamical systems theory is the existence of sets of deterministic difference equations that, although appearing quite stable, can exhibit sudden jumps or changes in the nature of their behavior (Glass & Mackey, 1988). These sudden changes in the nature of the behavior of a dynamical system are known as *bifurcations*. This characteristic of bifurcating systems of difference equations is an intriguing one for psychologists who are interested in representing and understanding mechanisms that produce sudden changes in patterns of human behavior.

In fact, observed intraindividual variability might not progress smoothly and continuously between states as indicated in our simulations; it might well proceed in apparently discontinuous jumps. There is some evidence that a cognitive time has an internal representation that is composed of discrete intervals rather than a continuum (Boker, 1993). Analysis of the degree of predictability of these bifurcations between relatively stable states represents a promising model for the process of change and constancy within an individual (Abarbanel, Brown, & Kadtke, 1990; Casdagli, 1989; Farmer & Sidorowich, 1987; Frank, Lookman, & Nerenberg, 1990; Packard, Crutchfield, Farmer, & Shaw, 1980; Sugihara & May, 1990).

If one's current personality is thought of as a set of mechanisms, built from one's genetic predispositions and past experiences, which translates current experience and current physiology into future behavior, then one is already working within a dynamical systems perspective (see, e.g., Cattell, 1980). Although applications of this methodology to the study of behavior are in their infancy, there is a clear promise that the use of the formal tools of differential equations and dynamical systems will result in a more precise communication of models of personality concomitant with increased awareness of the implications of such models.

DISCUSSION

Students of personality stability and change are entitled at this point to ask, "So what do we do to design future studies more optimally?" The material presented in this chapter has several notable implications for personality research. We focus primarily on two classes of implications; one having to do with general issues of research design, and the other with research on development and other kinds of changes.

In the course of the simulations presented here, we have made substantial use of the trait-state distinction, a conception that we believe to be a useful device for integrating ideas about constancy and change into one framework. Like most dichotomies, the label does not convey all the subtleties and gradations between constancy and the idealized change represented by a pure state. It does, however, force a consideration of more structured possibilities than just stable traits and noise or error. The distinction has enabled us to define and present some prototypic aspects of both constancy and change and to focus on what seem to be some key issues that students of personality should examine as they pursue their objectives.

1. Implications for the Design of Research Studies

The assessment of both constancy and change continues to be a desirable, but demanding, activity. Stability and change information is among the most carefully sought and interpreted information concerning personality. Although the practice of designing research studies to answer questions having to do with both stability and change has been improved in many ways during the past several decades, there is room for still further improvement.

For example, the use of both multivariate approaches to assessment and longitudinal measurement has strengthened research efforts in important ways. Measurement devices, however, are still often composed of little more than a few ad hoc items stuck together with a little dab of face validity. Slavish adherence to past practices has maintained a high premium on such criteria as internal consistency and high test-retest correlation when other concerns such as sensitivity to change and ability should also be duly weighted if an instrument is ultimately to be valid.

Moreover, using longitudinal design in itself is not sufficient to guarantee accurate information about process, change, and stability. There are many different kinds of longitudinal designs, and as the simulations presented here have shown, the most common approaches may not be the most valid or useful ones.

Research design concerns must be weighted carefully in relation to selection issues. Whereas psychologists generally have been trained to think

about selection issues with respect to people, this is less true when it comes to variables, and even less so in the case of occasions of measurement. Although this chapter has not focused directly on multivariate issues, it is clear that research design needs to take into account selection effects in all modes of data classification and selection, people, variables, occasions of measurement, and so on. The simulations presented here have pointed to the central importance of selection of occasions of measurement. For example, when it is defined too narrowly (e.g., measure every five years on the same data as nearly as possible), the apparent rigor and orderliness of the design may in fact jeopardize the conclusions regarding stability and change that can be drawn from the resulting data.

More generally, the examples presented here suggest that selection of occasions of measurement is a multifaceted issue. If one is to attend seriously to shorter term intraindividual variability, one needs a sufficient number of assessments in relatively quick succession to provide estimates of intraindividual variability parameters (e.g., amplitude, periodicity, and latency). In addition, if one seeks information about longer term stability and change (e.g., trait change), one needs to distribute assessments across an appropriate portion of the life span. As recommended elsewhere (Nesselroade, 1991a), optimal designs may require the implementation of bursts of measurements, the bursts being separated by appropriately long intervals in order to capture short-term intraindividual variability, longer term intraindividual change patterns, and interindividual differences in the patterns of intraindividual changes. Longer term intraindividual change patterns can include the parameters of intraindividual variability distributions as well as trait levels.

2. Implications for the Conceptualization of Developmental Phenomena

Plotting the course of developmental change is a valuable preliminary to the explication of changes including the identification of their underlying mechanisms. The simulations presented in this chapter suggest that distinguishing among kinds of intraindividual change dimensions (e.g., changes in traits versus state changes) can provide much more variety and texture to the descriptive phase of developmental work.

The integration of constancy and change will remain a general objective for researchers interested in developmental phenomena, whether from a more traditional or from a life span perspective. It may seem odd to encourage developmentalists to concern themselves explicitly with constancy, but, to the extent that constancy in some form is part of the target phenomena, it needs to be accounted for also. To act as though constancy is self-explanatory while seeking to account for change is a statement about one's biases. Moreover, the simulation outcomes suggest that it will be profitable for researchers to concern themselves explicitly with both con-

stancy and change if each is to be better understood and if the rich complexities of our subject matter are to be appropriately represented.

REFERENCES

- Abarbanel, H., Brown, R., & Kadtke, J. (1990). Prediction in chaotic, nonlinear systems: Methods for time series with broadband Fourier spectra. *Physical Review A*, 41(4), 1782-1807.
- Allen, B. P., & Potkay, C. R. (1981). On the arbitrary distinction between states and traits. *Journal of Personality and Social Psychology*, 41, 916-928.
- Allen, B. P., & Potkay, C. R. (1983). Just as arbitrary as ever: Comments on Zuckerman's rejoinder. *Journal of Personality and Social Psychology*, 44, 1087-1089.
- Baltes, P. B. (1968). Longitudinal and cross-sectional sequences in the study of age and generation effects. *Human Development*, 11, 145-171.
- Baltes, P. B., & Nesselroade, J. R. (1973). The development of analysis of individual differences on multiple measures. In J. R. Nesselroade & H. W. Reese (Eds.), *Life-span developmental psychology: Methodological issues* (pp. 219-251). San Diego, CA: Academic Press.
- Baltes, P. B., & Nesselroade, J. R. (1979). History and rationale of longitudinal research. In J. R. Nesselroade & P. B. Baltes (Eds.), *Longitudinal research in the study of behavior and development* (pp. 1-39). San Diego, CA: Academic Press.
- Bentler, P. M. (1980). Multivariate analysis with latent variables: Causal modeling. *Annual Review of Psychology*, 31, 419-456.
- Boker, S. M. (1993). *Foundations for a quantum theory of the perception and mnemonic representation of time and temporal structure*. Unpublished manuscript, University of Virginia, Psychology Department, Charlottesville.
- Bracewell, R. N. (1978). *The Fourier transform and its applications*. New York: McGraw-Hill.
- Brim, Jr., O. G., & Kagan, J. (Eds.). (1980). *Constancy and change in human development*. Cambridge, MA: Harvard University Press.
- Casdagli, M. (1989). Nonlinear prediction of chaotic time series. *Physica D*, 35, 335-356.
- Cattell, R. B. (1957). *Personality and motivation: Structure and measurement*. New York: World Book.
- Cattell, R. B. (1963). The structuring of change by P- and incremental-R techniques. In C. W. Harris (Ed.), *Problems in measuring change* (pp. 167-198). Madison: University of Wisconsin Press.
- Cattell, R. B. (1966a). Guest editorial: Multivariate behavioral research and the integrative challenge. *Multivariate Behavioral Research*, 1, 4-23.
- Cattell, R. B. (1966b). Patterns of change: Measurement in relation to state-dimension, trait change, lability, and process concepts. In R. B. Cattell (Ed.), *Handbook of multivariate experimental psychology* (pp. 355-402). Chicago: Rand McNally.
- Cattell, R. B. (1980). *Personality and learning theory* (Vol. 2). New York: Springer.
- Cattell, R. B., & Scheier, I. H. (1961). *The meaning and measurement of neuroticism and anxiety*. New York: Ronald Press.
- Collins, L., & Horn, J. L. (Eds.). (1991). *Best methods for the analysis of change: Recent advances, unanswered questions, future directions*. Washington, DC: American Psychological Association.
- Elder, G. H., & Caspi, A. (1990). Studying lives in a changing society: Sociological and personological explorations. In A. I. Rabin, R. A. Zucker, R. A. Emmons, & S. A. Frank (Eds.), *Studying persons and lives* (pp. 201-247). New York: Springer.
- Eysenck, H. J. (1983). Cicero and the state-trait theory of anxiety: Another case of delayed recognition. *American Psychologist*, 38, 114.
- Farmer, J., & Sidorowich, J. (1987). Predicting chaotic time series. *Physical Review Letters*, 59(8), 845-848.
- Featherman, D. L. (1985). Individual development and aging as a population process. In J. R. Nesselroade & A. von Eye (Eds.), *Individual development and social change: Explanatory analysis* (pp. 213-241). San Diego, CA: Academic Press.
- Fiske, D. W., & Rice, L. (1955). Intra-individual response variability. *Psychological Bulletin*, 52, 217-250.
- Frank, G., Lookman, T., & Nerenberg, M. (1990). Chaotic time series analyses of epileptic seizures. *Physica D*, 46(3), 427.
- Glass, L., & Mackey, M. (1988). *From clocks to chaos, the rhythms of life*. Princeton, NJ: Princeton University Press.
- Goldstein, H. (1979). *The design and analysis of longitudinal studies*. San Diego, CA: Academic Press.
- Hampson, E. (1990). Estrogen-related variations in human spatial and articulatory-motor skills. *Psychoneuroendocrinology*, 15, 97-111.
- Hertzog, C., & Nesselroade, J. R. (1987). Beyond autoregressive models: Some implications of the trait-state distinction for the structural modeling of developmental change. *Child Development*, 58, 93-109.
- Horn, J. L. (1972). State, trait, and change dimensions of intelligence. *British Journal of Educational Psychology*, 42, 159-185.
- Hubbard, J. H., & West, B. H. (1991). *Differential equations: A dynamical systems approach*. New York: Springer-Verlag.
- Jones, C. J., & Nesselroade, J. R. (1991). Multivariate, replicated, single-subject design and P-technique factor analysis: A selective review of intraindividual change studies. *Experimental Aging Research*, 16, 171-183.
- Kruse, A., Lindenberger, U., & Baltes, P. B. (in press). Longitudinal research on human aging: The power of combining real-time, microgenetic, and simulation approaches. In D. Magnusson (Ed.), *Methodological and research strategic issues in longitudinal research*. Cambridge, England: Cambridge University Press.

- Luborsky, L., & Mintz, J. (1972). The contribution of P-technique to personality, psychotherapy, and psychosomatic research. In R. M. Dreger (Ed.), *Multivariate personality research: Contributions to the understanding of personality in honor of Raymond B. Cattell* (pp. 387-410). Baton Rouge, LA: Claitor's Publishing Division.
- McArdle, J. J. (1988). Dynamic but structural equation modeling of repeated measures data. In J. R. Nesselrode & R. B. Cattell (Eds.), *Handbook of multivariate experimental psychology* (2nd ed., pp. 561-614). New York: Plenum Press.
- Meredith, W. (1964). Notes on factorial invariance. *Psychometrika*, 29, 177-185.
- Millsap, R. E., & Meredith, W. (1988). Component analysis in cross-sectional and longitudinal data. *Psychometrika*, 53, 123-134.
- Molenaar, P. C. M. (1985). A dynamic factor model for the analysis of multivariate time series. *Psychometrika*, 50, 181-202.
- Mortimer, J. T., Finch, M. D., & Kumka, D. (1982). Persistence and change in development: The multidimensional self-concept. *Life-Span Development and Behavior*, 4, 263-313.
- Nesselrode, J. R. (1983). Temporal selection and factor invariance in the study of development and change. In P. B. Baltes & O. G. Brim, Jr. (Eds.), *Life-span development and behavior* (Vol. 5, pp. 59-87). San Diego, CA: Academic Press.
- Nesselrode, J. R. (1988). Sampling and generalizability: Adult development and aging research issues examined within the general methodological framework of selection. In K. W. Schaie, R. T. Campbell, W. Meredith, & S. C. Rawlings (Eds.), *Methodological issues in aging research* (pp. 13-42). New York: Springer.
- Nesselrode, J. R. (1990). Adult personality development: Issues in assessing constancy and change. In A. I. Rabin, R. A. Zucker, R. A. Emmons, & S. Frank (Eds.), *Studying persons and lives* (pp. 41-85). New York: Springer.
- Nesselrode, J. R. (1991a). Interindividual differences in intraindividual changes. In J. L. Horn & L. Collins (Eds.), *Best methods for the analysis of change: Recent advances, unanswered questions, future directions* (pp. 92-105). Washington, DC: American Psychological Association.
- Nesselrode, J. R. (1991b). The warp and woof of the developmental fabric. In R. Downs, L. Liben, & D. S. Palermo (Eds.), *Visions of aesthetics, the environment, and development: The legacy of Joachim F. Wohlwill* (pp. 213-240). Hillsdale, NJ: Erlbaum.
- Nunnally, J. C. (1967). *Psychometric theory*. New York: McGraw-Hill.
- Packard, N. H., Crutchfield, J. P., Farmer, J. D., & Shaw, R. S. (1980). Geometry from a time series. *Physical Review Letters*, 45(9), 712-716.
- Parker, T. S., & Chua, L. O. (1989). *Practical numerical algorithms for chaotic systems*. New York: Springer.
- Ruelle, D. (1990). Deterministic chaos: The science and the fiction. *Proceedings of the Royal Society London A*, 427, 241-248.
- Ruelle, D., & Takens, F. (1971). On the nature of turbulence. *Communications on Mathematical Physics*, 20, 167-192.
- Schaie, K. W. (1965). A general model for the study of developmental problems. *Psychological Bulletin*, 64, 92-107.
- Seydel, R. (1988). *From equilibrium to chaos: Practical bifurcation and stability analysis*. New York: Elsevier Science.
- Shannon, C. E. (1975). *The mathematical theory of communication*. Urbana: University of Illinois Press.
- Spielberger, C. D., Gorsuch, R. L., & Lushene, R. (1969). *The State-Trait Anxiety Inventory (STAI) test manual, Form X*. Palo Alto, CA: Consulting Psychologists Press.
- Sugihara, G., & May, R. (1990). Nonlinear forecasting as a way of distinguishing chaos from measurement error in time series. *Nature*, 334, 734-741.
- Thompson, J. M. T., & Stewart, H. B. (1986). *Nonlinear dynamics and chaos*. New York: Wiley.
- Wylie, C. R. (1979). *Differential equations*. New York: McGraw-Hill.
- Zuckerman, M. (1983). The distinction between trait and state scales is not arbitrary: Comment on Allen and Potkay's "On the arbitrary distinction between traits and states." *Journal of Personality and Social Psychology*, 44, 1083-1086.