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HANDBOOK OF LIFE-SPAN DEVELOPMENT

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Dedication

TK
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The science of human development seeks to understand how individuals change on physical, cognitive, and social dimensions of functioning across the life span. Although many informative developmental studies have relied on cross-sectional comparisons among individuals of different ages, optimal designs for addressing developmental questions must involve the study of intraindividual change across time. Often, the time frame in developmental studies spans years and may be indexed with reference to particular events, such as one’s birth, entrance to a particular grade in school, and the onset of puberty, menopause, or retirement. There is also growing interest in the study of short-term change and variability observed across moments or days as means of gaining insight into developmental phenomena (Fleeson & Jolley, 2006; Li et al., 2004). However, it is relatively uncommon for researchers to simultaneously examine both short-term variability and long-term change in the same study. This is unfortunate, because processes that unfold rapidly (e.g., strategy selection, emotion regulation) can be both a cause and consequence of long-term developmental changes in trait-manifesting behavior and health outcomes.

In this chapter, I will discuss the conceptual underpinnings and methodological approaches for linking change processes that operate across different time scales. First, I will discuss important distinctions (i.e., variability vs. change, intraindividual vs. interindividual differences in change) in developmental methodology and how they map onto commonly used analytic approaches. Second, I will explore the utility of different research designs for studying both the intraindividual and interindividual facets of developmental change across different time scales (i.e., over the short-term and long-term). Emphasis will be given to a relatively novel hybrid research design, the measurement burst (Nesselroade, 1991; Sliwinski, 2008). Most longitudinal designs consist of measuring behavior once every several months or years to detect long-term developmental trends. In contrast, measurement-burst designs consist of “bursts” of intensive (e.g., daily) measurements that are repeated over longer intervals (e.g., every several months). Thus, the measurement burst combines elements of intensive short-term measurement designs (e.g., microgenetic, daily diary, experience sampling) with more conventional longitudinal designs that focus on longer-term follow-up. For example, a researcher interested in developmental changes in emotion regulation might examine affective reactivity to daily stress and how characteristics such as personality and chronic stress exposure influence these changes. A measurement-burst approach to this problem could involve repeating a week-long daily diary study every few months to examine longer-term intraindividual changes...
Handbook of Life-Span Development

in patterns of variability and covariation between affect and stress. This type of design affords researchers with the opportunity to pose and address a rich array of questions regarding processes of intraindividual variability and change that operate across very different time intervals.

CROSS-SECTIONAL AND LONGITUDINAL METHODS IN LIFE-SPAN DEVELOPMENT

Developmental research focuses on maturational changes that are part of the normal developmental course of individuals over their life span. This fact emphasizes a design choice that developmental researchers must make—cross-sectional versus longitudinal designs. Cross-sectional designs involve studying groups of individuals of different ages at a single point in time. By comparing the differences among individuals of different ages, cross-sectional designs make indirect inferences regarding how these persons may have or may be expected to change. For example, a cross-sectional approach to studying developmental changes in arithmetic ability might involve comparing a sample of 8-year-old children to a sample of 10 year olds. Longitudinal studies involve studying one group of individuals over a particular time period (e.g., studying how math ability changes over a 2-year period in one sample of 8 year olds). By comparing the same individuals across different points in time, longitudinal studies permit the direct measurement of intraindividual change. Both designs have strengths and weaknesses that influence the validity of inferences researchers can draw from them. In the following section, I describe a few of the more important issues for interpreting results from cross-sectional and longitudinal designs.

One important limitation of cross-sectional designs is their inability to distinguish age-graded developmental changes from cohort effects. Cohort effects refer to differences on developmentally relevant variables that arise from (non-age-related) factors to which each birth cohort is exposed. For example, recent generations have more experience with technology than earlier generations, and this differential exposure could affect computer-based cognitive assessments over and above any developmental (i.e., age) differences in cognitive ability. Generational differences in exposure to environmental hazards (e.g., lead), access to health care, and educational practices are a few other examples that produce cohort effects that may masquerade as maturational effects in cross-sectional designs.

Longitudinal designs must contend with other types of confounds, such as those arising from time-of-measurement effects, reactivity effects, and attrition effects. Time-of-measurement effects threaten the validity of longitudinal studies intended to elucidate maturational effects by confounding common historical exposures with maturational processes. For example, in a recent study, my colleagues and I demonstrated longitudinal increases in negative emotional states and in emotional responses to daily stressors across the adult life span (Sliwinski, Almeida, Smyth, & Stawski, 2009). However, this study spanned certain historical events (e.g., the September 11 World Trade Center attack, initiation of two wars, etc.) that could have resulted in a downturn of emotional well-being in individuals, independent of maturational processes. Reactivity effects result when measurements change as a mere
function of previous exposure to the assessment protocol. Retest effects (Ferrer, Salthouse, Stewart, & Schwartz, 2004; Salthouse, 2009) on measures of cognitive performance are a good example of this type of threat to the internal validity of longitudinal development studies. Finally, attrition effects result when the observed effect (e.g., a decrease in well-being) reflects the process by which individuals select out of longitudinal follow-up. For example, if unhealthy individuals are more likely to drop out of a longitudinal study than are their healthier age peers, the study population may look like it is getting healthier across time when in fact this change reflects nonrandom (selective) attrition. These are just a few examples of threats to the internal validity of cross-sectional and longitudinal studies. There are many excellent scholarly papers (e.g., Schaie & Hofer, 2001) that discuss these and other threats in detail. The remainder of this chapter focuses on longitudinal design issues that have not received as much attention in the literature.

INTRAINDIVIDUAL VARIABILITY AND CHANGE

Nesselroade (1991) distinguished between intraindividual change, which he characterized as “more or less enduring,” and intraindividual variability, which he characterized as “changes that are . . . more or less reversible” (p. 215). This characterization distinguishes between variability and change primarily along one dimension—durability. It is often, but not always, the case that durable developmental change manifests over longer time periods and intraindividual variability manifests across a much narrower time interval. In fact, relatively durable developmental changes may occur quite quickly and be observable within a single experimental session (e.g., Siegler & Svetina, 2002), whereas intraindividual variability may transpire over longer intervals (e.g., Sliwinski et al., 2009). For example, adolescents exhibit developmental changes in their ability to engage in formal, abstract reasoning but may, at any given time, revert to less complex forms of reasoning. Advancing age in adulthood has been associated with a trend toward less frequent negative emotional states, but individuals across the adult life span exhibit substantial daily and even momentary fluctuations in their negative mood. These examples distinguish between more or less enduring intraindividual (developmental) changes and transient fluctuations.

Both types of intraindividual dynamics—variability and change—are important for developmental theory. Studying very short-term variability in behavior can provide insight into the current developmental state of a person—this has been shown in the context of skill acquisition in children (e.g., Siegler, 2007), motor development (e.g., Newell, Liu, & Mayer-Kress, 2001), and cognitive aging (e.g., Lovden, Li, Shing, & Lindenberger, 2007). The premise that developmentally relevant change and variability can occur across very different time scales carries two implications. The first is that developmental theories should incorporate temporal as well as functional and structural components. That is, developmental hypotheses must specify not only what types of changes occur but also the time scale over which these changes should occur (e.g., across moments, days, months, or years). The second is that research designs and analytic methods need to provide information regarding variability and change across more than one time scale.
In their seminal chapter on developmental methodology, Baltes and Nesselroade (1979) enumerated five rationales for longitudinal designs:

1. Direct identification of intraindividual change
2. Direct identification of interindividual differences in intraindividual change
3. Analysis of interrelationships in behavioral change
4. Analysis of causes of intraindividual change
5. Analysis of causes of interindividual differences in intraindividual change

The first two rationales pertain to the description of intraindividual developmental change (e.g., the form and timing) and how individuals differ in their patterns and rates of change. In addition to being necessary for describing change, longitudinal studies allow researchers to examine how changes in one variable (e.g., emotion regulation) relate to changes in other variables (e.g., well-being). However, the most important reason for conducting longitudinal studies is to test developmentally relevant hypotheses about the causes of change. In particular, Baltes and Nesselroade drew a distinction between causes of “intraindividual change” and causes of “interindividual differences in intraindividual change” (i.e., “interindividual change”). The vast majority of longitudinal studies of developmental phenomena have focused exclusively on the fifth rationale—examining causes of interindividual change—such that the study of developmental change has become nearly synonymous with the study of how and why people differ in rates of change. Very few attempts have reflected the fourth rationale for conducting longitudinal developmental research—to identify causes of intraindividual change—and it is not entirely clear that the developmental literature acknowledges the distinction between a cause of intraindividual change (i.e., why people change) and a cause of interindividual differences in change (i.e., why people change differently).

To understand the critical distinction between modeling intraindividual and interindividual change, it is necessary to frame these concepts in a formal analytic approach. Most approaches to modeling longitudinal data have relied on multilevel or growth curve models that represent intraindividual change as a function of a time metric such as time in study, time since birth (i.e., age), time to an event (e.g., dementia diagnosis), or time to death. The descriptive part of this approach usually consists of estimating average rates of change and person-specific deviations from that average. The explanatory part consists of introducing between-person variables to account for those person-specific deviations, that is, to explain the rank order differences among persons in their rates of change. For example, the descriptive part of longitudinal modeling might describe the rate at which infants acquire and use new words, and the explanatory part would include examining how some relatively stable variables (e.g., the mother’s vocabulary size) could explain why some infants vocabulary grows at a faster rate than other infants.

To illustrate the approach formally, consider the representation of a simple multilevel model (MLM) for change (Table 1.1). As an example, consider how this approach would be used to model longitudinal changes in levels of self-reported negative affect. This approach consists of a level-1 equation, which represents intraindividual change in affect as a function of changes in chronological age, and
a set of level-2 equations, which describe interindividual differences in intraindividual change.

The level-1 coefficients, $b_{0k}$ and $b_{1k}$, represent the intercept and slope (rate of change), and $e_{ik}$ represents the residual for a given person, $k$, at a particular time, denoted by the index $i$. This level-1 equation is estimated simultaneously for everyone in the analysis, so that each person has their own person-specific intercept ($b_{0k}$) and age-slope ($b_{1k}$). The intercept and slope parameters $b_{1k}$ then function as outcome variables for the level-2 equation. The important difference between the level-1 and the level-2 equations is that the former refers to intraindividual (within-person) processes and the latter refers to interindividual (between-person) processes.

Explanatory modeling typically occurs in the level-2 equations, which are also regression equations. So, for example, a researcher might hypothesize that individuals who are under more stress tend to have higher levels of negative affect and tend to increase more in negative affect over time than their less-stressed age peers. The variable $Stress_k$, which refers to a variable that describes a person’s level of stress, functions as a predictor variable in the level-2 equations. Predictor variables added at level 2 can be any variable that provides information about the rank ordering of individuals (i.e., a between-person variable). This can include status variables such as gender or “change” variables such as a slope estimate of change on another variable. The main point is that typical modeling of developmental processes treats change as an outcome and emphasizes explanatory modeling of interindividual or rank order differences among persons in that outcome (Rationale 5).

Identifying predictors of change ($Stress_k$ in this example) in developmental research has become synonymous with explaining between-person differences in rates or amounts of change. By listing them as separate rationales, Baltes and Nesselroade (1979) viewed modeling predictors of intraindividual change and predictors of interindividual differences in change as distinct activities. So, how would this analytic framework differentiate between modeling these two types of predictors? One important limitation of most approaches to modeling developmental change is that our analytic models imply that the change in any individual is solely a function of the passage of time. This is because most level-1 models of intraindividual change only include some index of time, and the inclusion of “explanatory” variables is confined to level 2, the between-person level. My colleagues and I have previously addressed this issue by discussing the utility of “process-based” models which represent intraindividual change as a function not only of the passage of time but also of cognitive, physiological, and psychosocial processes hypothesized to drive intraindividual change (Sliwinski & Buschke, 2004; Sliwinski & Mogle, 2008). Equation 2 (Table 1.2) depicts how one would represent predictors of intraindividual change by including a time-varying variable in the level-1 equation for intraindividual change.

The variable $Stress_{ik}$ represents a predictor of intraindividual change, which must, by definition, be a time-varying variable—it must take on different values for
person $k$ across time points ($i$). Thus, the model in equation 2 is asking whether, for a given person ($k$), changes in stress predict concurrent changes in affect. In contrast, predictors of interindividual differences in change are intended to account for the differences among individuals in the magnitude or rate of change and that is why some individuals are changing more or less rapidly than others over time. Contrasting Figures 1.1a and 1.1b clarifies what it means to “explain” intraindividual change (Figure 1.1a) and interindividual differences in intraindividual change (Figure 1.1b). The former focuses on understanding why changes experienced by an individual during one time period differ from changes experienced by the same individual during a different time period. So, in Figure 1.1a an explanation of intraindividual change would entail understanding why the variable $y$ decreases from $t_1$ to $t_2$ and then increases from $t_2$ to $t_3$ by linking those changes to concurrent or previous changes in a predictor variable ($\text{Stress}_{ik}$ in equation 2). In contrast, explanations of interindividual differences in intraindividual change focus on between-person differences in variables ($\text{Stress}_k$ in equation 2) that can predict why one person changes more (or less) rapidly than another. Thus, the model for intraindividual change (level 1) postulates that a person’s affect goes up (or down) as a function of concurrent changes in stress, whereas the model for interindividual change (level 2) postulates that the affect of individuals with higher levels of stress will change more (or less) rapidly than their less-stressed age peers. Thus, intraindividual modeling is concerned with when or under what conditions any given individual experiences change and interindividual modeling is concerned with who experiences more (or less) change.

A major motivation to conduct longitudinal studies of development is to identify the causes of developmentally relevant change. I have discussed two directions from which to approach this task. The first (and most common) direction involves attempts to understand why individuals change at different rates (Rationale 5) and is, at its core, an essentially between-person (interindividual) approach. The second direction involves taking a within-person (intraindividual) approach by asking how variables are coupled, or travel together over time, within individuals (Rationale 4). Although there is little research on the topic, examination of between-person correlates of interindividual differences in change does not necessarily yield information about the correlates of intraindividual change (Sliwinski, Hofer, & Hall, 2003; Sliwinski & Mogle, 2008).

Theorists and methodologists have argued that developmental theories and their predictions must be evaluated at the intraindividual level of analysis (Ford & Lerner, 1992; Wohlwill, 1973). Some have forcefully argued that the analyses of between-person relationships provide no information about how variables are associated within individuals (Borsboom, Mellenbergh, & van Heerden, 2003), except under a highly restrictive set of assumptions that developmental processes, by their
very nature, are unlikely to satisfy (Molenaar, Sinclair, Rovine, Ram, & Corneal, 2009). Most examinations of how variables are coupled within individuals have come from studies involving intensive repeated measurements conducted over a relatively short time period, such as daily diary and experience sampling studies (e.g., Carstensen, Pasupathi, Mayr, & Nesselroade, 2000; Gruhn, Rebucal, Diehl, Lumley, & Labouvie-Vief, 2008; Mroczek & Almeida, 2004; Rocke, Li, & Smith, 2009). These types of studies tend to focus on intraindividual modeling by expressing short-term fluctuations in one variable (e.g., negative affect) as a function of concurrent changes in a predictor variable (e.g., day-to-day minor stressors). With few exceptions (MacDonald, Hultsch, & Dixon, 2003; MacDonald, Hultsch, Strauss, & Dixon, 2003; Sliwinski & Buschke, 1999, 2004), studies of longer-term change have focused almost exclusively on between-person analyses of interindividual differences in intraindividual change and have not attempted to identify predictors of intraindividual changes.

Although many developmental phenomena are most clearly observable over longer time periods (months, years, or even decades), many developmentally relevant processes operate over very short time scales. These include emotion regulation, impulse control, how we allocate attention, and how we select strategies for problem solving. The developmentally relevant processes and behavior transpire and change across multiple time scales entails important conceptual and methodological challenges. Conceptually, developmental theories must provide mechanisms that bridge processes operating on different time scales. Methodologically, researchers must endeavor to link measurements of behaviors, cognitions, and emotional states that fluctuate day-to-day or even moment-to-moment to changes that occur over the long term. Measurement-burst designs offer one approach to meeting this challenge because they explicitly incorporate the notion that dynamic processes important for development occur with different cadences. In the next two sections, I will present some examples of how measurement-burst designs can represent and link dynamic processes across different time scales.
DIFFERENT TEMPORAL SCALES OF INTRAINDIVIDUAL VARIABILITY AND CHANGE

Nesselroade (1991) introduced the notion of measurement bursts as a useful design tool to capture the “warp and the woof” of developmental dynamics. This analogy implies that the structure underlying human development consists of interwoven threads that signify longer-term trends (warp) and shorter-term variability (woof) on which those trends are built. Figure 1.2 is a simple elaboration of a figure from Nesselroade’s chapter (p. 215) that illustrates the importance of explicitly incorporating time scale in developmental theories, using negative affect as an example. Negative affect is an important outcome variable in research on developmental changes in emotional regulation that exhibits variability and change across different time scales—moment-to-moment variability (e.g., Carstensen et al., 2000; Schneider et al., 2007; van Eck, Nicolson, & Berkhof, 1998), day-to-day variability (e.g., Eid & Diener, 1999; Kleban, Lawton, Nesselroade, & Parmelee, 1992), and variability across months (Sliwinski et al., 2009). In addition, important developmental theories (e.g., Carstensen, Isaacowitz, & Charles, 1999; Labouvie-Vief, 2003) make predictions about gradual changes in affect that occur across adulthood over the course of years and decades. Bear in mind that negative affect is used only as an example and that many or, perhaps, most other cognitive, psychosocial, and health-related variables also exhibit dynamics across multiple time scales (e.g., cognitive function, physical activity, stress, blood pressure, job satisfaction).

Because most developmental research is traditionally concerned with long-term changes in behavior and individual characteristics that manifest over years or decades, analyses usually focus on smoothed, long-term trends. The dashed line in Figure 1.2 represents such a smoothed trend of a hypothetical individual’s long-term changes—moment-to-moment variability (e.g., Interpersonal tension, sleep quality, fatigue, day of week) and day-to-day variability (e.g., chronic strain, life event, health status) and variability across months (e.g., cumulative health constraints, motivational shifts).
changes in negative affect. However, in reality we would never expect developmental changes in the negative affect of any individual to be so orderly. If we could measure this person’s “real” negative affect continuously, we could also see that over the course of adulthood there are numerous peaks and valleys in their negative affect across months and years, as indicated by the wavy solid line. We could further drill down to examine more local changes that characterize even narrower temporal epochs that span weeks, days, or even moments within a day, as indicated by the boxed wavy line segment in the figure. Thus, an individual’s developmental pathway consists of global trends (increasing in this figure) and local changes restricted to particular segments of the overall developmental path.

Most longitudinal studies tend to focus on variability or change across a single time scale and thereby relegate the dynamics of other time scales to irrelevance or measurement error. These studies focus on the “average” or typical change trajectory and in understanding what predicts differences in trajectories among individuals and are characterized by widely spaced single measurements, usually spanning years if not decades. For example, studies of how personality and health might influence the rate of developmental changes in self-reports of emotion measure individuals every year or several years (Charles, Reynolds, & Gatz, 2001; Griffin, Mroczek, & Spiro, 2006). Studies of cognitive aging often have retest intervals that span several years or even several decades (e.g., Salthouse, Schroeder, & Ferrer, 2004), with annual assessments considered relatively intensive (e.g., Wilson et al., 2002). While such designs can provide valuable information about rates of change that transpire over long retest intervals, they provide less information about what occurs in the space between the changes during which developmentally relevant events and causal influences may operate.

Accurate description of an individual’s developmental path would, ideally, consist of continuous measurements obtained over relatively long time periods. Although the possibility of semicontinuous measurement over extended time periods is possible (Pavel et al., 2008), it can be resource-intensive and in many circumstances, unfeasible. The measurement-burst design offers a practical approach to obtaining measurements across widely different time scales (Nesselroade, 1991). The structure of a measurement-burst design consists of intensive measurements obtained within a sequence of discrete temporal epochs. Figure 1.3 depicts such a design that captures variability and change operating over three different time periods—short-term (or state) variability, midterm (or state-of-state) variability, and long-term (global) trends. The descriptors “short term,” “midterm,” and “long term” are meant to imply relative rather than absolute time scales. In some contexts “short term” might refer to variability across milliseconds (MacDonald, Nyberg, Sandblom, Fischer, & Backman, 2008; Schmiedek, Lovden, & Lindenberger, 2009), and “long term” might refer to trends observed over months (e.g., Sliwinski et al., 2009) or decades (e.g., Schaie, 1989). Another way to conceptualize multiple time scales in developmental research is by identifying “fast” and “slow” change processes (e.g., Newell et al., 2001; Sosnoff & Newell, 2006). What constitutes appropriate short-term (fast) and long-term (slow) time scales will depend on the cadence of both the phenomenon of interest and its causal influences.

Characterizing change across different time scales is critical not only for describing developmental phenomena but also for testing predictions about the antecedents of change. Different types of influences may drive similar changes in a variable
across different time scales (see Figure 1.3). Continuing with the example of negative affect, an uptick from one day to the next may result from a recent interpersonal conflict (e.g., Mroczek & Almeida, 2004), whereas an increase of similar magnitude across months may result from the chronic strain of a financial hardship (e.g., Conger et al., 1993). Longer-term global trends might reflect the cumulative effects of health constraints (e.g., Griffin et al., 2006; Lockenhoff & Carstensen, 2004) or gradual shifts in motivational goals (e.g., Carstensen et al., 1999). Thus, an individual’s current level of negative affect reflects the joint influence of these change and variability processes that operate across different time scales.

My colleagues and I have conducted measurement-burst studies that provide an example of decomposing variability and change in negative affect across different time scales (Sliwinski et al., 2009). One of the burst studies consisted of six daily assessments repeated every 6 months for a 2-year period in a sample of 116 older adults. During each assessment, individuals reported on their positive and negative mood, stress, and health constraints they experienced on that day. Multilevel modeling (Snijders & Bosker, 1999) provides a useful and straightforward approach to analyzing data from multiple time scales. Typically, when MLMs are applied to longitudinal data, they consist of two levels—the within-person (level 1) and the between-person (level 2) levels. However, a measurement-burst design produces a somewhat more complex data structure in which closely repeated measurements are “clustered” into repeated bursts, which are separated by longer time intervals. This data structure can entail three levels—two within-person levels (within-burst, across-burst) and one between-person level. By representing burst data as a three-level MLM one can examine random variation across a fast time scale (within-burst), across a slower time scale (between bursts), as well as across individuals. This approach also permits modeling both local (within-burst) and global (across-burst) trends, as well as allowing for different sets of predictors at different time scales.
TABLE 1.3 Equation 3

<table>
<thead>
<tr>
<th>Equation</th>
<th>Level</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \text{affect}<em>{ijk} = b</em>{0jk} + e_{ijk} )</td>
<td>(level 1: Daily time scale)</td>
</tr>
<tr>
<td>( b_{0jk} = \beta_{00k} + v_{0jk} )</td>
<td>(level 2: biannual 'burst' time scale)</td>
</tr>
<tr>
<td>( \beta_{00k} = \gamma_{000} + u_{00k} )</td>
<td>(level 3: between-person variability)</td>
</tr>
</tbody>
</table>

The MLM for measurement-burst data is a simple extension of the MLM described in equations 1 and 2 earlier in this chapter. Instead of a two-level model, with levels 1 and 2 describing intraindividual and interindividual change, respectively, the measurement burst implies a three-level MLM in which the intrindividual part is broken into two components. The level-1 part of this model refers to "fast" intraindividual change and the level-2 part refers to "slow" intraindividual change. Level 3 is now the interindvidual or between-person part of the model.

The “empty” MLM in Table 1.3 provides a framework for decomposing variability across different time scales (i.e., days and biannual bursts), where \( \text{affect}_{ijk} \) is the score for day \( i \), burst \( j \), and person \( k \). The parameters in this model estimate the mean level of negative affect for a given person on a given burst averaged across days within that burst \( (\beta_{0jk}) \), for a given person averaged across all days and bursts \( (\beta_{00k}) \), and the grand mean averaged across all days, bursts, and persons \( (\gamma_{000}) \). As noted earlier, most applications of MLMs to repeated measures data consist of two levels: one level (level 1) refers to within-person variability and another level (level 2) refers to between-person variability. In contrast, equation 3 has two levels of within-person variability: level 1, which refers to (fast) within-person variability on the daily time scale, and level 2, which refers to (slow) within-person variability on the biannual time scale. Level 3 of this model refers to between-person or stable variability. Fitting a model with no predictors to these data allowed decomposition of the total variance in negative affect into these three components. When we applied this model to our longitudinal data, we found that approximately 53% \( (\text{var}[e_{ijk}] = 3.03) \), 17% \( (\text{var}[v_{0jk}] = 0.96) \), and 30% \( (\text{var}[e_{ijk}] = 1.72) \), corresponded to the daily (fast), biannual (slow), and between-person (stable), respectively (Sliwinski et al., 2009). A conventional single-shot longitudinal design could not have distinguished between the two sources of within-person variability across the slow \( (\text{var}[v_{0jk}]) \) and fast \( (\text{var}[e_{ijk}]) \) time scales.

In contrast, the measurement-burst approach permits analysis of predictors that operate across different time scales. For example, one could examine how stress predicted concurrent changes in negative affect across both daily and biannual time scales, as well as between persons using the MLM in Table 1.4:

TABLE 1.4 Equation 4

<table>
<thead>
<tr>
<th>Equation</th>
<th>Level</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \text{affect}<em>{ijk} = b</em>{0jk} + b_{1jk} (\text{Stress}<em>{ijk}) + e</em>{ijk} )</td>
<td>(level 1: within bursts)</td>
</tr>
<tr>
<td>( b_{0jk} = \beta_{00k} + \beta_{01k} (\text{Stress}<em>{ijk}) + v</em>{0jk} )</td>
<td>(level 2: across bursts)</td>
</tr>
<tr>
<td>( b_{1jk} = \beta_{10k} + v_{1jk} )</td>
<td></td>
</tr>
<tr>
<td>( \beta_{00k} = \gamma_{000} + \gamma_{001} (\text{Stress}<em>{k}) + u</em>{00k} )</td>
<td>(level 3: between person)</td>
</tr>
<tr>
<td>( \beta_{10k} = \gamma_{100} + u_{10k} )</td>
<td></td>
</tr>
<tr>
<td>( \beta_{10k} = \gamma_{100} + u_{10k} )</td>
<td></td>
</tr>
</tbody>
</table>
The variable \( \text{Stress}_{jk} \) refers to the amount of stress reported by a given person \((k)\) on a given day \((i)\) during a given burst \((k)\). The burst-level stress variable \( \text{Stress}_{jk} \) reflects the amount of stress reported by a given person \((k)\) during a given burst \((j)\), averaged across all days within that burst, and \( \text{Stress}_k \) is the amount of stress for a given person, averaged across all bursts \((j)\) and all days \((i)\). There are two basic approaches to representing a predictor variable at different levels in an MLM. One approach involves within-burst \( \text{Stress}_{ijk} - \text{Stress}_{jk} \) and within-person \( \text{Stress}_{jk} - \text{Stress}_k \) centering of the level-1 and level-2 stress variables, respectively. However, this approach would imply that it is the level of stress relative to a person’s average stress (or to the person’s average stress for a given burst) that predicts negative affect, rather than the absolute level of stress. For example, within-person centering implies that a daily stress score of 0 (i.e., no stress on a particular day) has a different meaning for persons (and bursts) with different average levels of stress.

A second option (which we chose) is to use the raw (or grand-mean centered) values to maintain a consistent meaning of the daily-stress values across individuals and bursts. This approach results in the following interpretation of the stress regression coefficients: \( \gamma_{100} \) is the average within-person day-level stress slope, \( \gamma_{010} \) is the difference between the within-person day-level and within-person burst-level slopes, and \( \gamma_{001} \) is the difference between the within-person burst-level and the (between-person) person-level slopes (Snijders & Bosker, 1999). The “correct” manner in which to define predictor variables in order to separate influences across different time scales will depend on whether the researcher believes the predictor variable is best scaled in relative or absolute terms.

The parameters \( b_{ijk} \) and \( \beta_{0ijk} \) reflect the within-person relationships between stress and negative affect across daily and biannual time scales, respectively. At the fast (daily) time scale, a positive association between stress and negative affect would imply that on days when stress is high, negative affect is also high. On the slow (biannual) time scale, a positive association between stress and negative affect would mean that a person’s average daily negative affect is higher during bursts when their average daily stress is also high, compared to bursts during which their average daily stress is lower. We fit a model similar to equation 4 to measurement-burst data described in Sliwinski et al. (2009) and demonstrated that within-person variability in stress was positively and significantly associated with negative affect on both time scales. However, variables do not always or even generally operate in the same way across different time scales. For example, Miller, Chen, and Zhou (2007) have shown in a meta-analysis that the relationship between stress and hypothalamic–pituitary–adrenal (HPA) activity depends critically on the timing of the stress—recent upticks in stress are associated with increased HPA activity (fast time scale), but over the long term (slow time scale) chronic stress may result in depressed HPA activity.

Characterizing change across multiple time scales can also help to distinguish effects resulting from short-term reactivity to the assessment procedure from longer-term developmental change. In response to repeated assessments, research participants may become increasingly annoyed, shift response criteria, or become more skilled on performance measures. If change is examined only across one time scale, distinguishing these measurement-induced effects from developmental changes becomes difficult or even impossible. Two examples come from a measurement-burst study conducted in my laboratory. The first example involves determining whether intraindividual...
changes in negative affect were attributable to long-term aging-related influences or could be attributed to reactivity to the repeated assessment protocol (e.g., becoming annoyed with the intensive assessment demands). To address this issue, we compared local trends in negative affect within each burst to longer-term across burst trends (Sliwinski et al., 2009). Across bursts, on average, individuals exhibited an increase in negative affect, but within bursts this trend was not present (in fact, there was a slight positive trend). This allowed us to rule out reactivity to repeated assessment as an explanation for across-burst increases in negative affect, because reactivity, if present, should also, and perhaps more strongly, manifest across shorter time scales.

A second example involves retest effects in longitudinal studies of cognitive aging—the improvement in performance on cognitive tests because of repeated test-taking. Although these practice effects dissipate over long durations, positive retest effects may endure for years, which can bias estimates of age-related decline (e.g., Ronnlund, Nyberg, Backman, & Nilsson, 2005; Salthouse, 2009). The measurement burst presents a possible avenue for approaching this problem if one reasonably assumes that across short time scales retest improvement would be most prominent and aging-related decline minimal, and aging-related changes would be easier to observe across longer time scales (Salthouse, 2009). My colleagues and I used data from a measurement-burst design to simultaneously model short-term (within-burst) retest speed up in perceptual speed and long-term (across-burst) aging-related slowing (Sliwinski, Hoffman, & Hofer, 2010). We found that across short time scales (within-bursts), response time is decreasing with each repeated assessment, but across the longer time scales (across-bursts) the asymptotic (i.e., fastest) response time is shifting upward. By modeling change across two time scales, we were able to distinguish short-term practice improvement from long-term aging-related decrements in asymptotic processing speed.

The measurement-burst design can support improved description of developmental phenomena by jointly modeling variability across different time scales. Recognizing that many variables exhibit dynamic properties across different time scales is a necessary first step toward accurately describing development processes. This recognition implies that an individual’s current status on any developmentally relevant measure (e.g., behavior, personality, physiology) reflects the confluence of dynamics that operate across very different time scales (e.g., Martin & Hofer, 2004). The inability to tease apart these processes that operate across different cadences is a significant limitation of conventional longitudinal studies consisting of widely spaced single-shot measurements. An important advantage of measurement-burst designs is that they provide an opportunity to distinguish among relatively stable (e.g., trait neuroticism), slow-changing (e.g., diminishing cognitive resources), and more fast-changing dynamic processes (e.g., mood), respectively. In the next section, I will discuss how the measurement burst also permits researchers to test hypotheses that link processes transpiring across different scales.

**LINKING INTRAINDIVIDUAL VARIABILITY AND CHANGE ACROSS DIFFERENT TIME SCALES**

In the previous section, I described how analysis of data from a measurement-burst design can distinguish variability and change across different time scales. In this
section, I describe three ways in which short-term processes may be linked to long-term developmentally relevant change. First, changes observed over a short time scale may *directly* reflect developmental phenomena. A clear example comes from the use of microgenetic designs to study cognitive development in children (Siegler, 2006; Siegler & Crowley, 1991). This approach involves high-frequency observations across relatively short time periods (e.g., days, weeks, or months) that allow a moment-by-moment analysis of change processes, usually associated with learning and cognitive development. The microgenetic approach has mostly been applied to circumstances when the occurrence of change is highly predictable or can be brought under experimental control. For example, Siegler (1995) examined the development of number conversation in children as a function of different feedback conditions. The intensive microgenetic measurement and analysis allowed Siegler to identify and model the source, path, and rate of cognitive change.

Siegler (1997) identified three principles for the study of change that underlie the microgenetic approach: (1) measurements should span as much of the period from the beginning of change to the time when behavior has stabilized, (2) the density of measurements should be high relative to the rate of the change, and (3) measurements should be subjected to intensive analysis across the shortest time scale (e.g., momentary, trial-by-trial) to support inferences regarding processes that caused the change. The rationale behind this approach is that only by studying change as it occurs can researchers identify underlying mechanisms. However, there are practical challenges to applying this approach to the study of a broad range of developmental phenomena, especially those occurring in adulthood. It may be extremely difficult, inefficient, or even impossible to measure relevant variables at the moment when change is occurring if it is not strongly age-graded or linked to identifiable events and transitional periods (e.g., retirement, menopause, becoming a parent) or if it occurs with a relatively low frequency. That said, designs that better satisfy these principles (e.g., high measurement density) should provide greater insight into developmental processes compared to more conventional designs that consist of few repeated measurements.

In the case of this first example, the measurement processes play a precipitating role in producing developmental gains—children repeatedly exposed to a specific type of math problem will, as a result of this exposure, have an opportunity to learn new strategies and exhibit relatively durable cognitive gains. Other types of developmentally relevant phenomena are less amenable to experimental control and cannot be predicted with a high degree of accuracy. Prominent developmental theories, for example, postulate that certain emotion regulation skills improve with age (e.g., Carstensen et al., 1999), but examining behavior at the “moment” at which this change occurs would be extremely challenging to say the least. Although specific momentary upticks or downturns in negative or positive affect are not themselves developmental changes, their magnitude, patterning, and temporal characteristics are of relevance for developmental theories (Carstensen et al., 2000; Rocke et al., 2009).

The second way in which short-term variability may be linked to long-term change is as an antecedent or early indicator. In general, we cannot expect changes in behaviors, cognitions, or physiology over very short time scales (e.g., moments, days) to represent in either magnitude or form the long-term changes of typical interest to developmental researchers. But measuring the magnitude of short-term
variability may provide insight into the long-term processes of interest to developmental researchers (Hultsch & MacDonald, 2004; Nesselroade & Ram, 2004). Increases in intraindividual variability may signify an imminent developmental gain, for example, children’s strategies exhibit increased variability associated with exploratory behavior prior to adopting a novel problem strategy (Siegler, 1995). In contrast, increasing behavioral variability may also signify concurrent or imminent neurocognitive impairment (Lovden et al., 2007; MacDonald, Nyberg, & Backman, 2006), decrements in sensorimotor integrity (Newell, Mayer-Kress, & Liu, 2009), and even mortality (Deary & Der, 2005; Eizenman, Nesselroade, Featherman, & Rowe, 1997). Lovden and colleagues (2007) provided compelling demonstration of this point by examining the hypothesis that greater moment-to-moment performance fluctuations at a given time point would predict subsequent declines in mean levels of functioning. Using a bivariate dual change score model (McArdle & Hamagami, 2001), Lovden and colleagues (2007) demonstrated that individuals who exhibited greater increases in momentary reaction time variability also exhibited greater decline on ideational fluency and processing speed during the following 2 years, but that the reverse was not the case. These results replicate and extend earlier findings (MacDonald et al., 2003) that very short-term performance variability covaries with 6-year changes in level of cognitive function. These findings are consistent with predictions from computational models that postulated age-related reductions in the efficiency of dopaminergic neuromodulation (Li, Brehmer, Shing, Werkle-Bergner, & Lindenberger, 2006). As theoretical models become increasingly precise in their mechanistic accounts of developmental change, researchers will find increasingly valuable methodological approaches which allow them to link short time scale processes (mechanisms) to long time scale changes (outcomes).

The earlier examples illustrate how the magnitude of intraindividual variability across a short time scale can predict global trends across longer time scales. A third way of linking processes across different time scales involves examining how intraindividual covariability changes over time. Most studies of development that focus on intraindividual changes rely on sequences of widely spaced, repeated, single measurements which allow researchers to examine changes in the level of functioning. However, this approach does not provide the opportunity to examine how within-person relationships (i.e., the coupling of variables) across short time scales change across longer time scales. This is an important limitation because it precludes evaluating developmental hypotheses about how within-person processes (e.g., affective responses to stress, the influence of health on well-being) might evolve over time. For example, some evidence suggests that aging adults are better able to regulate their emotions in response to negative events. This prediction has been tested longitudinally, but mostly by examining changes in level of negative affect assessed once every several years (e.g., Charles et al., 2001; Griffin et al., 2006). An alternative and potentially more powerful test of this prediction would involve directly assessing daily events and mood states, and then examining whether advancing age is associated with increased or decreased emotional responses to daily stressors. Although a number of studies have examined age differences in emotional reactivity to minor stressors using experiencing sampling (Uchino, Berg, Smith, Pearce, & Skinner, 2006) and daily diary methods (Mróczek & Almeida, 2004; Rocke et al., 2009; Stawski, Sliwinski, Almeida, & Smyth, 2008), there is little information on intraindividual change in coupling between daily affect and stress. The only way in which
change in within-person relationships can be studied is by overlaying intensive measurement protocols on more conventional longitudinal designs. For example, in the study described earlier, my colleagues and I analyzed data from two measurement-burst studies to examine intraindividual variability and change in how the daily coupling between stress and negative affect changed (Sliwinski et al., 2009). Equation 4 described the part of this analysis that separated the within-person relationships between affect and stress into two time scales—daily and biannual. We demonstrated that the average magnitude of the daily stress–affect relationship ($b_{1k}$ in equation 4) increased within individuals across periods ranging from 2 to 10 years, implying that the average negative emotional responses to daily stressors increases in aging individuals.

In addition to exhibiting long-term trends, the magnitude of coupling between variables may also fluctuate across periods or “epochs,” reflecting midterm or “state-of-states” variability. That is, there is a space between the very fast time scales (e.g., moments, days) and slow time scales (e.g., years, decades) in which developmentally relevant variables may operate. There are many types of variables, such as those indexing a person’s health status and psychosocial contexts (e.g., available social support, external demands) that are relatively constant during a given brief temporal epoch (e.g., a given week), but may vary considerably across somewhat longer intervals (e.g., weeks and months). Coupling parameters (e.g., the magnitude of negative emotional responses to daily stress) may vary within-persons in accordance with influences that exhibit short-term stability but midterm lability. Figure 1.4 illustrates this point in the context of a measurement-burst design. Data collected in each burst can be thought of as a “mini” daily diary or experience sampling study during

![Figure 1.4](image.png)

**FIGURE 1.4** This figure provides an example of how a measurement-burst approach can distinguish between variability across persons (rows) as well as across time (columns) in short-term relationships as indexed by the coupling between variables.
which the coupling (within-person, across time covariability) between two variables X and Y is examined. Linear models are frequently used to quantify the magnitude of coupling—a common example comes from studies of daily stress and affect, in which the slope relating daily stress (X) to self-reports of negative affect (Y) operationalizes “reactivity” (Bolger & Schilling, 1991). Individuals with steep slopes are more reactive than individuals with shallower slopes because steep slopes imply a greater increase in negative affect for a unit increase in subjective stress.

Assume that the first column in Figure 1.4 represents data from three individuals whose level of stress and mood were assessed each day for 1 week. Person 1 would be the most reactive, with Person 2 being less reactive, and Person 3 hardly showing any reactivity. Multilevel modeling most often emphasizes examination of between-person predictors of individual differences in intraindividual relationships. For example, researchers have attempted to explain individual differences in emotional responses to daily stress by examining between-person variables such as gender or stable personality dispositions (e.g., Mroczek & Almeida, 2004). However, it is possible that the variability observed in the left-most column in Figure 1.4 does not only (or even mostly) reflect stable individual differences in reactivity. Rather, the reasons why Person 1 is more reactive than Person 3 during this week of daily assessments may have more to do with differences in life circumstances than with stable differences in personal characteristics. That is, it may not be the case that Person 1 is generally more reactive than the others, but was more reactive during this week of assessments because of the specific nature of the stressors experienced during the week or other demands or events that have occurred recently but prior to the assessment week. Along these lines, Sliwinski and colleagues (2009) demonstrated that within-person fluctuations across 6-month intervals in the coupling of daily stress and negative affect were predictable by the level of psychological distress experienced by individuals during the month prior to each measurement burst. This finding provides an example of how data from a measurement-burst design can reveal slower time scale processes that create a temporal context for processes that operate across faster time scales.

ANALYTIC AND DESIGN ISSUES

The discussion so far has focused on the merits of measurement-burst designs for modeling change as an intraindividual process, and for distinguishing and linking dynamic processes operating across different time scales. In doing so, I have ignored some of the more thorny issues that confront researchers attempting to design measurement-burst studies. I have discussed some of the practical and feasibility issues related to the implementation of measurement bursts elsewhere (Sliwinski, 2008). In the current discussion, I will focus on the conceptual basis for making principled decisions about the frequency with which repeated measurements should be taken. It is worth noting that this is just as relevant for the design of more conventional longitudinal studies that consist of single-shot measurements, although they become less ignorable in the context of intensive measurement designs.

There is no single answer to the question of “how often do I need to measure Y?” and decisions regarding the optimal frequency and duration of repeated measurements are often based on practical rather than principled basis. For example,
longitudinal studies are resource intensive and almost always require funding from grant agencies. The duration of grant awards is usually limited to 5 years or less, which places constraints on the amount of follow-up, although sometimes repeated awards can allow studies to continue for longer durations. However, for the most part, researchers are constrained to frame and test scientifically interesting developmental predictions regarding intraindividual changes that occur within a 5-year period. The critical question then becomes one of how to study developmental processes within a limited time period.

Individuals may decide to maximize the number of subjects in their study to improve the chances of detecting statistically significant average change and individual differences in the amount or rate of change. Also, given that some developmental change especially in adulthood is thought to be subtle or gradual, researchers may also adopt the common sense position that a longer time period between observations will provide a better opportunity for change to occur. As it turns out, it is never a good idea from a design perspective to increase the duration between assessments if that entails obtaining fewer measurements, which would usually be the case. Simulation work by Hertzog and colleagues (Hertzog, Lindenberger, Ghisletta, & von Oertzen, 2006; Hertzog, von Oertzen, Ghisletta, & Lindenberger, 2008) provide convincing demonstrations that power for detecting individual differences in rates of change drops dramatically as the number of measurement occasions decreases. In addition, their power tables indicate that if the cost of adding either another participant or obtaining an additional measurement occasion is equivalent, adding additional occasions is always the better choice (Figure 1, Hertzog et al., 2008).

The work by Hertzog et al. clearly illustrates that improving what they term “growth curve reliability” (GCR) provides a substantial effect on power. The GCR is related to the intraclass correlation and is defined as the variance in \( y \) determined by a growth curve model at each time \( t \), divided by the total variance, where \( \sigma^2_{yt} \) is the variance in \( y \) at time \( t \) and \( \sigma^2_{\varepsilon y} \) is the residual variance, constrained to be equal across time (Table 1.5). Because growth curves that allow variability in rates of change imply that \( \sigma^2_{yt} \) will vary over time, the GCR is scaled to baseline or \( t(0) \). Even modest improvements in GCR can yield dramatic increases in power for detecting variance and covariances of and among rates of change. Conventional single-shot multiwave longitudinal designs require that a single measurement occasion can adequately capture the location of an individual on the variable of interest at a given point in time \( t \). This requirement assumes that there is relatively little intraindividual variability on the variables being measured compared to the expected amount of intraindividual change between measurements. This assumption might be reasonable for research on long-term change in variables that exhibit little variability across short time relative to long time scales. However, it would be highly problematic to rely on

### TABLE 1.5 Equation 5

\[
\text{GCR} = \frac{\sigma^2_{yt} - \sigma^2_{\varepsilon y}}{\sigma^2_{\varepsilon y}}
\]
a single measurement if interest is on long-term change on any variable that exhibits short-term variability. If a behavior or attribute is highly variable from one day to the next (or from one moment to the next within a given day), then relying on a single measurement point change may provide a relatively poor approximation of a person’s level at a given time point.

The measurement-burst designs provide one approach to boosting GCR by averaging across short-term scale variability, which would effectively reduce the magnitude of the error variance. This approach requires a reconceptualization of how to measure an individual’s level on any time-varying variables. Rather than thinking of defining an individual’s level at a given time by measuring them once, we could define their level for a given temporal epoch by taking a local average of repeated assessments distributed across a short time scale. For example, consider a measurement-burst study consisting of seven daily assessments with bursts repeated every year for 2 years. In this design, we would define a person’s level at any burst not by a single measurement but by taking the average of seven measurements within a given burst. Long-term change would not be based on a sequence of individual measurements but on a series of aggregated measurements that signify each person’s level during a given narrow temporal epoch or burst. This has the direct result of reducing the error variance, $\sigma^2_\varepsilon$, by a factor proportional to the number of within-burst repeated measurements ($n$), resulting in an error variance equal to $\sigma^2_\varepsilon/n$. The equation in Table 1.6 illustrates the effect of analyzing long-term change in burst level averages on GCR, where GCR is the reliability as defined in equation 5 and GCR* is the GCR obtained from analyzing intraindividual changes in the average of $n$ observations. Following our example with seven measurements per burst, if GCR is equal to 0.5, the effective GCR* from the measurement burst would be 0.88.

Although increasing the number and frequency of measurements can aid in the identification of correlates of the between-person aspects of change (Rationale 5), the timing of repeated measurements must depend on the cadence of the variable of interest. In general terms, the frequency of repeated measurements must match the dynamic of the changes in the phenomenon under study. Matching the frequency of measurements to the cadence of change is essential for a process-based approach modeling of intraindividual change and to satisfy Baltes and Nesselroade’s fourth rationale. The good news is that there is a well-established principle from the signal processing literature that provides guidance for determining measurement frequency. This principle states that measurements should occur with at least twice the frequency as the maximum frequency ($f_{\text{max}}$) of the signal you want to detect, or at a rate of $2f_{\text{max}}$. This means that if one hypothesizes that the process of interest varies from day to day, one must measure that process at least twice a day. Or if one is interested in modeling annual intraindividual

### Table 1.6 Equation 6

$\text{GCR}^* = \frac{(n \times \text{GCR})}{1 + [n - 1] \times \text{GCR}}$
change, they must obtain measurements at least every 6 months. This principle runs slightly counter to the intuition that if the interest is in annual change, then obtaining annual measurements would be sufficient. Failure to measure dynamic processes with sufficient frequency can result in aliasing errors, an example of which is provided by Figure 1.5. Aliasing errors occur when measurements of a dynamic process too infrequently to accurately characterize the form of the underlying function. The solid wavy line illustrates a continuous time series representing intraindividual variability for a given individual, with the dotted line connecting low frequency measurements (open circles) of that time series and the solid line connecting high frequency measurements (open and closed circles). The less frequent measurements (indicated by the open circles) provide a distorted picture of the process because they miss critical information about the temporal dynamics of the underlying process, making it impossible to accurately describe or model the causes of the intraindividual change. This leads us to the conclusion that developmental researchers must design studies with far more intensive measurements than is the norm in order to measure the dynamics of developmental processes with adequate frequency to satisfy Baltes and Nesselroade’s first and fourth rationales—the modeling of intraindividual change and identification of its causes.

**FUTURE DIRECTIONS IN THE METHODOLOGIES TO STUDY LIFE-SPAN DEVELOPMENT**

Because most of our longitudinal data comes from studies in which individuals are measured relatively infrequently, there has been little opportunity to understand the timing of developmental changes across any but the longest time scales. Perhaps, our conceptions of the temporal characteristics of developmental changes reflect more the constraints of our research designs than the characteristics of the underlying phenomena. If a researcher is interested in very slow change, obtaining measurements every year or several years may suffice for descriptive purposes. However, we
must be careful to measure the mechanisms driving change that operate within the long intervals separating widely spaced repeated measurements.

This chapter presented the rationale for incorporating more intensive measurements into longitudinal developmental designs. However, there are nontrivial barriers to implementing intensive measurement designs that future research needs to address. First, intensive repeated measurement studies are both burdensome to research participants and costly. Development of remote and intensive data-capture technologies, such as the use of smartphones and unobtrusive sensors for collecting behavioral and physiological data, promises to be an exciting and active area of research. Mobile communication technology has become an integral part of daily life. Developmental researchers will have the opportunity to leverage this familiarity and implement intensive data collection protocols in relatively unobtrusive and inexpensive ways. Collecting momentary reports on a person’s emotional states and social interactions, and then connecting these behavioral measurements to physiological activity (e.g., heart rate variability) in real time and in ecological valid settings, promise to advance as well as challenge our understanding of human development. However, there is still much work to be done to advance efforts to adapt this technology to provide rigorous tests of developmental hypotheses.

One such challenge is the need to develop measurement instruments that are suitable for repeated and intensive administration. Most measurement scales used in developmental research have been validated for between-person analysis at cross-section; the psychometric properties for within-person (intraindividual) analyses for many widely used scales are unknown. It is also likely that some of the properties we view as psychometrically desirable (e.g., retest stability) for between-person analysis would be less desirable for the study of short-term variability and intraindividual change (Nesselroade, 1991). Measurement scales that are useful for one purpose (e.g., analysis of individual differences) may be far less useful for other purposes (e.g., analysis of intraindividual variability). For example, questionnaires used to assess personality traits, such as neuroticism, may not be suitable to administer on a daily basis. Instead, researchers would need to specify how neuroticism manifests in daily life (e.g., negative affect, increased emotional reactivity, or lability) and develop new measurement tools that can capture the dynamic aspects of what may be a relatively stable trait. Thus, as intensive measurement designs become more common, theorists will be challenged to take a more process-oriented perspective in studying developmental influences on what have been commonly viewed as relatively stable personality and behavioral traits. Additional research is needed to develop and apply approaches for assessing the utility of psychometric scales for intensive measurement designs (e.g., Cranford et al., 2006).

Intensive measurement designs also present numerous challenges as well as opportunities for the analysis of developmental data. Most analytic approaches, even those described in this chapter, impose the same formal model of change and variability on each individual. This approach involves aggregation of individuals into an “average” person and then describing each individual as a deviation from that average. Such aggregation may be necessary for conventional longitudinal studies in which each person has been measured only a few times, but it requires several untenable assumptions (Molenaar, 2004). Intensive measurement designs, such as the measurement burst, can provide dozens or even hundreds of observations for each person, which opens the door for truly individual-level analysis (Boker, Molenaar, &
Nesselroade, 2009; Molenaar et al., 2009). The shifting emphasis to individual-level analysis is long overdue in the study of human development. This shift, which is already taking place, entails a rather drastic change in how researchers frame hypotheses, design studies, measure constructs, and conduct analyses. This chapter has focused on the importance of measuring developmentally relevant processes that operate very different dynamics. It is highly likely that the more we look for them, the more we will discover that processes transpiring at the daily and even momentary time scales both shape and are shaped by more long-term developmental trends. Our rapidly advancing methodologies challenge theorists to explicitly incorporate the element of time into their mechanistic accounts of developmental processes. Only by specifying the temporal as well as structural and functional elements of human development, can our theories offer a principled basis for making critical design decisions about not only what to measure but also when to measure it.

1 A detailed discussion of centering in multilevel models is beyond the scope of this chapter. The interested reader should refer or consult one of the many excellent textbooks on multilevel modeling, such as Hox (2002), Raudenbush and Bryk (2002), or Snijders and Bosker (1999).

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REFERENCES


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