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The study of intraindividual variability is the study of fluctuations, oscillations, adaptations, and “noise” in behavioral outcomes that manifest on microtime scales. This article provides a descriptive frame for the combined study of intraindividual variability and aging/development. At the conceptual level, we show that the study of intraindividual variability provides access to dynamic characteristics—construct-level descriptions of individuals’ capacities for change (e.g., lability)—and to dynamic processes—the systematic changes that individuals exhibit in response to endogenous and exogenous influences (e.g., regulation). At the methodological level, we review how quantifications of net intraindividual variability and models of time-structured intraindividual variability are used to measure and describe dynamic characteristics and processes. At the research design level, we point to the benefits of measurement-burst study designs, wherein data are obtained across multiple time scales, for the study of development.

Keywords: intraindividual change, life span theory, developmental systems, idiographic, longitudinal

A key objective in developmental psychology is to describe or characterize the individual and to explain when and how the observed characteristics of the individual change over time (Baltes, Reese, & Nesselroade, 1977; Ford & Lerner, 1992; Molenaar & Campbell, 2009; see also Valsiner, 1986). From a life-span perspective, researchers seek to understand the dynamics of gain and loss, the interactions of persons and contexts, the limitations on and potential for adaptation, and the interplay and coordination of component parts and processes as they unfold over multiple time scales and contribute to development (Baltes, Lindenberger, & Staudinger, 2006; Lerner, 1984; Magnusson & Cairns, 1996; Thompson, 1959). The individual is the chosen unit of analysis—a unique, inviolable organism with parts that are to be understood as components of an integrated whole—a complex dynamic system, the many component characteristics and processes of which emerge from a variety of endogenous and exogenous influences.

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(Overton & Reese, 1973; Thelen & Smith, 1998). Emphasized are the variability, complexity, and dynamic (opposed to static) properties of the individual.

The emphasis on individual-level change brings to the forefront theoretical and methodological perspectives for examining how and when individuals change over time or age (Collins & Horn, 1991; Collins & Sayer, 2001; Hertzog & Nesselroade, 2003; Nesselroade, 1990; Nesselroade & Reese, 1973). In this article, we develop a descriptive frame for the combined study of intraindividual variability and aging/development. Drawing on the literature and ongoing discussions with colleagues near and far, we present a framework that links conceptual and methodological notions of intraindividual variability and indicate why and how the study of intraindividual variability is furthering the understanding of aging/development. Specifically, we (a) show that the study of intraindividual variability provides access to dynamic characteristics—construct-level descriptions of individuals’ capacities for change (e.g., lability)—and to dynamic processes—the transformations individuals undergo in response to endogenous and exogenous influences (e.g., adaptation), (b) review how quantifications of net intraindividual variability (e.g., intraindividual standard deviation, or iSD) and models of time-structured intraindividual variability (e.g., time series) are being used to measure and describe dynamic characteristics and processes, and (c) point to the benefits of measurement-burst study designs, wherein data are obtained across multiple time scales, for the study of development.

Intraindividual Variability

First, we clarify some concepts and terminology. As the life-span perspective was building momentum in the 1960s and 1970s, the interface between theoretical and methodological perspectives brought an increased focus on the need to study how individuals’
behavior changed over time (e.g., Harris, 1963; Nesselroade & Baltes, 1979; Thomae, 1959; Wohlwill, 1973). Behaviorists, biologists, contextuals, developmentalists, experimentalists, mathematicians, methodologists, philosophers, psychometricians, and scientists from other disciplines contributed to an ongoing exchange and innovation of concepts, designs, and analytical methods useful for the study of development (e.g., West Virginia University Conference on Life-Span Developmental Psychology series). In the midst of the ensuing dialectic, Nesselroade (1991) highlighted the distinction between intraindividual change—“more or less enduring changes that are construed as developmental”—and intraindividual variability—“relatively short-term changes that are construed as more or less reversible and that occur more rapidly than the former” (p. 215).

Depicted graphically in Figure 1 by the longer, dark gray lines, intraindividual change is conceptualized as directional changes resulting from long-term processes such as development, maturation, aging, or senescence that manifest on a macrotime scale (e.g., years, decades; also see Figure 8.1 in Nesselroade, 1991). For example, researchers have described distinctive lifetime trajectories for developmental change of individuals’ fluid and crystallized intellectual abilities, the former characterized by normative declines through the many decades of adulthood and the latter by relative stability across the same age span (e.g., Baltes, 1987; Cattell, 1971; Horn, 1982; Schaie, 2005). Typically, this is the way researchers think about and study aging—within-person changes that accrue with advancing age over the long term. We shall refer to such long-term changes as aging. We use the word aging as a venue-specific construct synonymous with development, keeping in mind that the concepts and methods discussed here apply widely and just as readily to biological, social, psychological, and other developmental phenomena that manifest at all ages.

In complement to long-term, intraindividual change, intraindividual variability, depicted in the shorter, black lines within the magnified circles in Figure 1, is conceptualized as fluctuations, inconsistency, instability, oscillations, or “noise” that manifests on microtime scales (e.g., minutes, hours, days, weeks) as the result of short-term processes. Its study is characterized by repeated measurement of individuals’ attributes over many relatively closely spaced occasions. For example, Eizenman, Nesselroade, Featherman, and Rowe (1997) obtained weekly reports of individuals’ perceived level of control over the course of half a year. Similar to the differences seen between the two sets of magnified circles in Figure 1, the level of control in some individuals was found to be more labile than in others. That is, some individuals’ control beliefs remained relatively stable from week to week (circles on left), while others’ fluctuated wildly from week to week (circles on right). We shall refer to such short-term changes as intraindividual variability and will, in distinguishing these changes from aging, associate them with other dynamic concepts such as plasticity, lability, adaptation, and homeostasis—attributes and processes that, theoretically, change with age.

Drawing on existing nomenclatures, especially those from Fiske and Rice (1955), and subsequent elaborations (e.g., Hultsch, MacDonald, & Dixon, 2002; Li, Huxold, & Schmiedek, 2004; Martin & Hofer, 2004; Nesselroade & Ghisletta, 2003; Nesselroade & Ram, 2004; Nesselroade & Schmidt McCollam, 2001; and also earlier discussions by Stern, 1911), we forward a conceptual, and corresponding methodological, distinction between two types of short-term within-person changes. In brief, net intraindividual variability is constituted of short-term within-person changes that are analyzed as being unstructured in relation to time (e.g., characterized by changes that are randomly ordered in time). In Figure 1, fluctuations of this type are shown in the A circles and are conceptualized as indicators of individuals’ dynamic characteristics (e.g., lability, plasticity, or robustness). In contrast, time-structured intraindividual variability is characterized by changes that are systematically ordered in time (e.g., lags or cycles). Visually intuitive depictions of one kind of time-structured fluctuations are shown in the B circles. More generally, time-structured fluctuations are conceptualized as indicators of the dynamic processes that underlie individuals’ behavior (e.g., adaptation or homeostasis). As can be obtained from comparisons of the two circles on the left side of Figure 1 (i.e., earlier in macrotime) with those on the right side (i.e., later in macrotime), both dynamic characteristics and processes can potentially change with advancing age (macrotime). The figure depicts both types of short-term change as increasing over the long term, but this may not always be the case. Depending on the construct, long-term changes in intraindividual variability may be best characterized by increases, decreases, stability, or other more complex, nonlinear forms of change (for discussion, see MacDonald, Li, & Bäckman, 2009; Rocke, Li, & Smith, 2009; Williams, Strauss, Hultsch, & Hunter, 2007).

Dynamic Characteristics and Processes

Theoretical accounts of individual development include descriptions of both individuals’ inherent capacity for change and the change processes in which individuals engage as they respond to endogenous and exogenous influences (e.g., Ford & Lerner, 1992; Magnusson, 2000; Overton & Reese, 1973; Thelen & Smith, 1998). In this section, we highlight how the study of intraindividual variability provides access to the constructs used to describe individuals’ capacity for change (i.e., dynamic characteristics) and systematic patterns of change that describe behavioral transformations (i.e., dynamic processes). To illustrate, we draw on examples from the psychological aging literature.

1 We use behavior as a catch-all term for the many aspects of human function, physiology, experience, thought, and action.
2 Note that these types of fluctuations may not necessarily be “random” but very well may reflect reactions to endogenous or exogenous factors. We use the term random to highlight that such fluctuations are treated as being unstructured in relation to time. Often, the amount of noise left in a model depends upon the analytic approach chosen.
3 Despite the possible redundancy of the adjective modifier, we use the term dynamic processes to highlight that the processes we are considering require manifest changes (variance > 0). In physics and chemistry, both quasi-static processes and steady-state processes are defined. The former are processes in which changes accrue infinitesimally slowly and the latter are processes in which “inputs” exactly equal “outputs.” They might be considered “pure” stability-maintenance processes. Methodologically, pure stability at the manifest level does not lend itself to statistical analysis (because there is no variance). Dynamic processes, though, allow for (perhaps require) deviation or perturbation from equilibrium and thus provide the variability needed for statistical analysis.
Dynamic Characteristics

Overview. Borrowing and expanding on terminology and concepts used in other disciplines (e.g., physics, chemistry, biology), psychologists use a number of constructs to describe individuals’ inherent capacity or potential for change (or stability). For example, plasticity refers to an entity’s (individual’s) capability of, or susceptibility to, being molded, shaped, modified, or otherwise changed (Baltes, 1987; Gottlieb, 1998; Lerner, 1984). Similarly, the constructs lability and rigidity describe either an individual’s proneness to or inability to change across contexts (Cattell, 1966; Leary, 1957). Robustness is the ability of an individual or system to maintain its functionality across a wide range of conditions (e.g., stresses or pressures; Hammerstein, Hagen, Herz, & Herzel, 2006).

On the one hand, these constructs describe traitlike capacities or abilities. At a given point in macrotime, they are considered fixed, inherent characteristics of the individual that may be quantified and examined. Individuals are described as labile or rigid or may be rank ordered with respect to their inherent plasticity in the same way that individuals are described as young or old or are rank ordered with respect to age or other interindividual differences. On the other hand,

4 Note that throughout the remainder of the article, we use change and variability to describe observable phenomena and terms such as lability, plasticity, and development to describe the substantive constructs researchers tether to those phenomena. Following these definitions, we use the terms short-term change and intraindividual variability synonymously.
these constructs are truly about within-person change or, more precisely, individuals’ potential for change (or stability). As such, attributes such as plasticity, lability, rigidity, and robustness require a conceptualization and description of the diversity of function and behavior that can be expressed by an individual.

How do we measure dynamic characteristics? We will use flexibility as an illustrative example. The main objective in describing individuals’ flexibility is to quantify the range of behaviors they exhibit (or might exhibit) across a variety of situations. Individuals who have a tendency to behave in the same way no matter the social situation would be considered inflexible, while individuals who do behave differently across social situations might be considered more flexible (for the moment, ignoring the appropriateness of the behavior). In analysis, the repeated measurements obtained from a single individual across a variety of situations are collected. Then, measures of central tendency and dispersion are used to describe that individual’s set of behaviors. Relevant to the current example, dispersion across categories of behavior can be quantified, through calculation of Shannon’s entropy (an index used in ecology to quantify the extent to which multiple species live in the same area—i.e., biodiversity; Morin, 1999). Using a stream of behavioral observations obtained in real time as individuals encounter a variety of social situations, researchers can use the entropy index as a measure of a person’s flexibility—a manifest indicator of a (latent) dynamic characteristic.

Applying the same principles to other aspects of human experience and behavior, we can ask questions such as, How much new information can an individual assimilate or accommodate (e.g., developmental reserve capacity; Kliegl, Smith, & Baltes, 1990), and to what extent can an individual maintain consistency of task performance despite abnormalities in neuronal or biological integrity (Li et al., 2004; Slifkin & Newell, 1998)? In each case, we might measure the range of behaviors exhibited across a variety of conditions. In aging research, for example, inconsistency, an indicator of neurobiological integrity, is often measured via variation in the latency of responses across multiple trials of a simple choice reaction-time task completed over a few minutes (Hultsch & MacDonald, 2004). In the motor domain, postural control has been examined via measurements of the extent to which individuals deviate from an upright stance over a few seconds (i.e., variation in center of pressure; Woollacott & Shumway-Cook, 2002). In research on emotions, individuals’ potential for experiencing mixed emotions, poignancy, has been measured through quantification of the covariation of emotions across hours or days (Carstensen, Pasupathi, Mayr, & Nesselroade, 2000). Even in the study of personality, behavioral signatures, individuals’ potential or likelihood of behaving in particular ways in particular situations, are indicated by the variation of behaviors expressed across a week or more of randomly encountered contexts (Mischel & Shoda, 1995). These and other manifestations of intraindividual variability have provided the raw material needed for describing specific dynamic properties of the individual.

**Dynamic characteristics and aging.** Once extracted from features of short-term change, the specific aspects of individual functioning indicated by these dynamic constructs can be examined with respect to aging. Questions to ask include the following: Are differences in level of robustness related to differences in age? Does an individual’s robustness decrease with age? Do some individuals lose their robustness faster than others? Are differences or changes in health related to differences or changes in robustness? For example, measuring neurobiological robustness as the total amount of intraindividual variability observed across multiple trials of a cognitive task, Lövdén, Li, Shing, and Lindenberger (2007) found that the level of robustness portended the extent of age-related change in intellectual ability. That is, lower levels of robustness were associated with greater subsequent declines in cognitive performance, providing some evidence for the hypothesized neurobiological underpinnings of long-term cognitive decline. As found by these and other researchers, careful examination and quantification of the diversity of behaviors over the short term can allow for a more precise accounting and tracking of long-term developmental changes in dynamic characteristics of individual functioning (Nesselroade, 1991; Siegler, 1994).

**Dynamic Processes**

**Overview.** At another level of inquiry, psychologists and developmentalists make good use of constructs that describe systematic changes in behavior, including regulation, homeostasis, adaptation, accommodation, differentiation, learning, and metamorphosis. Making liberal use of descriptions provided by developmental systems theorists (e.g., Ford, 1987; Ford & Lerner, 1992), we posit that processes underlying behavioral change can be considered as being of three types: stability maintenance processes, incremental change processes, and transformational change processes. There are of course many taxonomies of process. This one was chosen for use here because of its developmental roots and because it suits our current purposes. Other classifications can be applied to the study of variability in similar fashion.

Stability maintenance processes are those that maintain and restore the system’s organizational and functional unity. Examples include maintenance of physical, emotional, and cognitive function during or return to equilibrium after endogenous or exogenous perturbation or challenge (e.g., maintaining homeostasis or equilibration; e.g. Piaget, 1977). Incremental change processes are those in which an existing characteristic is refined, elaborated, or made larger or more complex. It is characterized by relatively smooth directional changes. A classic example that often manifests over the short term would be reinforcement learning. In contrast to incremental change processes, transformational change processes are marked by discontinuities that involve a relatively rapid reorganization of an existing state or pattern into a qualitatively different state or pattern. Examples include insights in learning, stage transitions, and “crucial shifts” in psychopathology.

Researchers can model and quantify the dynamics that govern these processes—how an individual moves from one state or moment in time to the next—by considering the serial patterning or across-time relations among successive observations (e.g., cycles, oscillations, or lagged effects; e.g. Nesselroade & Schmidt McCollam, 2000). Behaviormists and modern behavioral analysts, for instance, have long made use of time-series experiments and mathematical models in describing conditioning, reinforcement, extinction, and other change processes (Baum, 1994; Hull, 1943; Pavlov, 1927; Skinner, 1938). Tracking the pattern of successive changes in bar presses, pecks, or cognitive performances from trial to trial or session to session allows for precise description of many incremental change processes (see Lattal & Perone, 1998; Risley...
& Wolf, 1973). Similarly, tracking the progression of minute-to-
minute changes in cortisol after exposure to a stressful event is
necessary for the description of how the neuroendocrine system
contributes to the return to equilibrium levels or patterns of func-
tion—stability maintenance processes such as allostasis or ho-
meostasis (e.g., Granger & Kivlinghan, 2003; Kudielka & Kirsch-
baum, 2007; McEwen & Stellar, 1993; Seeman & Gruenewald,
2006; Sterling & Eyer, 1988).

On the one hand, processes and their outcomes can be consid-
ered traitlike descriptions of how an individual, at a given point in
macrot ime, functions. Individual patterns of adapti on might be
described as adaptive or maladaptive processes or may be rank
ordered with respect to the speed or quality of the processes as
interindividual difference characteristics. On the other hand, these
constructs are truly about within-person change. They describe a
series of transactions or activities that systematically connect prior
states to future states—dynamic processes (Martin & Hofer,
2004). As such, broad constructs such as adaptation or self-regulation
require a conceptualization and description of the systematic patterns
of change over time (Cole, Martin, & Dennis, 2004).

How do researchers measure dynamic processes? What they
require are parameters that describe systematic patterns of change.
Consider, for example, models used to describe warm-blooded
animals’ thermoregulation, a stability maintenance process. When
discrepancies arise between an individual’s current temperature and
his or her ideal equilibrium temperature, action is taken (e.g.,
shivering or sweating) that reduces these discrepancies until the
equilibrium state is attained. The systematic pattern of changes
observed during return to equilibrium are taken as the manifest
indicators of the thermoregulation process and are modeled ac-
cordingly (e.g., using mathematical models like a damped linear
oscillator, e.g. Boker, 2001; Chow, Ram, Boker, Fujita, & Clore,
2005; Nesselroade & Boker, 1994). The obtained model parameters
provide a mathematical description (qualitative or quantita-
tive) of when and how the process is likely to proceed.

If the same principles are applied to human behavior, dynamic
processes such as psychological adaptation or self-regulation can
be extracted from the regularity or order seen across repeated
observations over the short term (Martin & Hofer, 2004; Nessel-
roade & Boker, 1994). For example, in describing the process of
bereavement, Bisconti, Bergeman, and Boker (2004) obtained
information about processes of adaptation to loss by modeling the
time-ordered oscillations of emotional well-being present in the
daily reports that recently bereaved widows provided over 12
weeks of study. Specifically, a dynamical systems model (in this
case, a damped linear oscillator model) of a stability maintenance
process was invoked to describe the systematic patterns of change
wherein individuals’ day-to-day oscillations in emotion were reg-
ulated toward equilibrium. As this and other studies show, the
time-ordered repeated-mea sures nature of intraindividual variabili-
ty provides the opportunity for modeling and quantifying the
intrinsic dynamics that govern how an individual (or dyad) moves
from one state or moment in time to the next.

Dynamic processes and aging. Again, once obtained and mod-
eled, the specific aspects of the dynamic processes supporting
individual functioning that are indicated by model parameters can
be examined with respect to aging. Consistent with the typical
examination of age differences and age-related changes, we can
hypothesize about and track how the dynamic processes producing
individual behavior over the short term change over the long term.
Questions might take the following form: Does the speed of the
adaptation process change with age? Are age-related differences or
changes in health related to qualitative differences in the effec-
tiveness of a stability-maintenance process? For example, Brauer,
Woollacott, and Shumway-Cook (2002) found differential patterns
of moment-to-moment task performance among young and older
adults attempting to maintain postural control while completing
another attention-demanding cognitive task. Specifically, the
ordering of compensatory movements and responses differed, indi-
cating differential progression of stability maintenance processes
with age and impairment. Somewhat parallel notions emerge in
life-span theories of developmental regulation and coping, which
suggest that the dynamics of adaptation processes change qualita-
tively with age. In particular, while stability maintenance pro-
cesses may play a primary role in adaptation at young ages,
transformational change processes that involve a lowering of equi-
librium set-points become increasingly prominent at older ages
(e.g., accommodation, Brandstätter & Renner, 1990; compensa-
tory secondary control, Heckhausen & Schulz, 1995). As elabo-
rated by these and other researchers, careful modeling and exami-
nation of the systematic patterns of behavior exhibited over the
short term can allow for a more precise accounting and tracking of
long-term developmental changes in dynamic processes underly-
ing individual functioning (Molenaar, 2004; Nesselroade &
Schmidt McCollam, 2000; van Geert, & van Dijk, 2002). In the
final section of this article, we will discuss how measurement-burst
study designs may facilitate such multiple-time-scale inquiries.
Before doing so, though, we turn to the analytical methods.

Time-Structured and Net Intraindividual Variability

In the preceding section, we drew a conceptual distinction
between constructs used to describe individuals’ inherent capacity
for change—dynamic characteristics (e.g., lability, plasticity, ro-
 bustness)—and the systematic patterns of change that describe
behavioral transformations—dynamic processes (e.g. adaptation).
In this section, we tether this conceptual distinction to a corre-
sponding methodological distinction between measures of net in-
traindividual variability and models of time-structured intrain-di-
vidual variability. It must be acknowledged that there are infinitely
many ways to carve up the conceptual and methodological space
(for just a few, see Fiske & Rice, 1955; Ford & Lerner, 1992;
Hofer & Sliwinski, 2006; Li et al., 2004; Lindenberger & van
Oertzen, 2006; Martin & Hofer, 2004; Nesselroade & Ram, 2004;
Ram & Gerstorf, 2009). Here, we have prioritized the tethering of
intraindividual variability concepts and methods, with the objec-
tive of identifying a heuristic framework that may be useful to
researchers when selecting measures and models that are appro-
priately suited for the rendering of particular theoretical concepts,
and, vice versa, when interpreting analytical results and mapping
them onto substantive theory.

We follow most closely in the footsteps that Fiske and Rice
(1955) laid down in their classic review of intraindividual response
variability and attempt to push forward in a way that accommo-
dates and integrates their framework with many of the conceptual
and methodological innovations that have occurred in the decades
since publication of their article. Fiske and Rice defined pure
variability as variability across repeated assessments where (a) the
individual is exposed at each occasion to the same stimulus or to objectively indistinguishable stimuli and (b) the total situation in which the responses are made is the same on all occasions. Said differently, pure intraindividual variability is variability that manifests in a static, unchanging, stable context. As they admitted, “It is doubtful whether such an abstract case ever exists” (p. 217). From there, Fiske and Rice distinguished Type I (spontaneous) and Type II (reactive) intraindividual variability on the basis of how the data were structured with respect to time. Specifically, Type I intraindividual variability requires conformity to the additional assumptions that (c) the order of responses is immaterial, meaning that the data show no systematic trend over time (e.g., due to processes such as learning or fatigue), and (d) behavior at any occasion \( t \) is not affected by or related to either the response at \( t - 1 \) or any other previous (or future) occasion. Data that violate this latter assumption and that contain lagged effects or cycles (patterns other than a monotonic function of time) were considered to be manifestations of Type II (reactive) intraindividual variability.

Coming from a developmental perspective in which one of the fundamental principles is that both the individual and his or her environment are always changing (e.g., Baltes et al., 1977; Bronfenbrenner, 1979; Ford & Lerner, 1992), we are, in part, adapting Fiske and Rice’s (1955) notions of intraindividual variability for use outside the vacuum they described.\(^5\) Our framework takes for granted the idea that the individual and his or her context both change over time. A series of repeated observations of a person and the relevant context (endogenous or exogenous) can be collected into a multivariate time series of scores, \( y(t) \), with elements describing the person and elements describing the surrounding context. Methodologically, then, the task is to “decompose” this stream of information into interpretable components—some of which we can map onto dynamic characteristics and others we can map onto dynamic processes.

Building on Fiske and Rice’s (1955) distinction between intraindividual variability that is unstructured (Type I) or structured (Type II) with respect to time, we use a general scheme where the total intraindividual variability (intravar) contained in \( y(t) \) is partitioned into two parts by the investigator:

\[
\text{total intravar} = \text{time-structured intravar} + \text{net intravar}.
\]

Net intraindividual variability is constituted of short-term within-person changes that are treated as being \textit{unstructured} in relation to time (e.g., characterized by randomly ordered changes, as in the A circles in Figure 1) and will be tethered to dynamic characteristics. In contrast, time-structured intraindividual variability is constituted of short-term within-person changes that are analyzed as \textit{systematically structured} as a function of time or prior states (e.g., characterized by regular patterns like those shown in the B circles of Figure 1) and will be tethered to dynamic processes. Key to the distinction is that with net intraindividual variability, the ordering of the occasions is treated as immaterial, whereas with time-structured intraindividual variability, the serial ordering of the repeated measurements is of material interest. To be clear, the ordering of repeated assessments in a given study is inherently time structured (e.g., Occasion 1 occurs before Occasion 2). However, it is at the discretion of the researcher to select an analytic approach in which the data are treated as time structured or not. Such decisions about if and how to decompose total variability into time-structured and net portions and their relative size are typically based on a number of different considerations, including conceptual arguments and study design—a point we later will discuss in more detail. Also, our distinctions are designed for application to within-person variability. The structure of between-person differences is not addressed specifically, nor do we presume that the distinction has a straightforward between-person variability analogue. At most, we suggest that summary descriptions of individuals’ time-structured and net intraindividual variability (measured or modeled individual by individual) can be used in a secondary analysis of between-person differences. Our focus is on how the methodological landscape can be viewed in relation to the dynamic characteristics and processes that manifest at the level of the individual.

\textit{Time-Structured Intraindividual Variability}

Dynamic processes (e.g., stability maintenance, incremental, or transformational) are indicated by repeatedly observed systematic patterns of change (e.g. Ford & Lerner, 1992). The main objective in describing them is to identify, extract, and measure the systematic serial ordering within a stream of observed behavior (within person). Methodologically, the repeated measurements obtained from a single individual are examined for systematic time-related structures. The data are modeled in relation to time. The parameters obtained from the time-structured model are used to describe specific aspects of the dynamic process of interest. For example, the rate of linear change obtained from a regression model wherein repeated measures of cognitive performance are regressed on an index of time (e.g., trial number) would provide a quantification of the speed of an incremental change process (e.g., learning).

\textit{Structured with respect to time}. The important distinction between time-structured and net variability is how the data are structured or treated with respect to time. By definition, time-structured variability focuses on the temporal relations in the data. The objective is to use the repeated measures to describe and understand how a person’s state at one occasion, \( t \), is related to or leads to the person’s state at subsequent occasions, \( t + 1, t + 2, \ldots \) \( t + h \). The time-locked, serial ordering of the data is used to describe and understand dynamic processes. For example, Carstensen, Gottman, and Levenson (1995), in describing regulatory and control processes occurring while members of older married couples interacted with each another, modeled theoretically interesting sequences of global affect, some indicating stability maintenance processes (e.g., positive, neutral, and negative continuance) and others incremental change processes (negative startup, de-escalation). Each type of process was modeled by a specific pattern of how individuals’ affect changed from one moment to the next, from \( t \) to \( t + 1 \) to \( t + 2 \), and so on (see also Ferrer & Nesselroade, 2003; Sbarra & Ferrer, 2006).

Note that the time metric is open. Time can be indexed in a number of different ways, including calendar time, time from some universal event (e.g., the bombing of Hiroshima), or an individually defined event (e.g., birth or death). Further, the progression or

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\(^5\) Fiske and Rice (1955) also delineated Type III intraindividual variability, where the stimulus or situation differs across occasions. However, they did not treat this type of intraindividual variability in depth and were somewhat ambiguous as to whether the ordering of occasions was immaterial in Type III intraindividual variability.
serial ordering of time can also be conceptualized and tracked in
different ways. That is, the relevant ordering of observations may
be in relation to the progression of clock time, in relation to
progression of psychological or social time, or in relation to a
series of individually defined events (e.g., successive visits to the
laboratory or an interaction with Person A, then with Person B, and
so on; for aging-related discussions, see Baars & Visser, 2007;
Featherman & Petersen, 1986; Hertzog & Nesselroade, 2003; Li &
Schmiedek, 2002; Schroots & Birren, 1990; Settersten & Mayer
1997). The only basic requirement is that the observations have a
specific ordering, but the metric is of additional use (especially
with respect to causality) if it retains the special quality that time
always moves forward.

Measures and models. The methods used to measure and
model time-structured intraindividual variability all make heavy
use of the time-ordered nature of the data. The objective is to
construct a statistical model that adequately describes systematic
time-dependent structures in the data and that allows for the
prediction of future behaviors or outcomes. Estimates of specific
parameters from the selected model of time-structured intraindi-
vidual variability might then be used as an indicator of substanc-
tively important characteristics of specific within-person pro-
cesses. These models include autoregressive models, moving
average models, and spectral analysis—or more generally, time-
series analysis in the time domain (e.g., autoregressive; see Box &
Jenkins, 1976; Shumway & Stoffer, 2006) and frequency domain
(e.g., spectral; see Jenkins & Watts, 1968; Koopmans, 1995;
Warner, 1998). Additional models are drawn from the tools used to
describe linear and nonlinear dynamic systems (Gottman, Murray,
Swanson, Tyson, & Swanson, 2002; Tong, 1993; van der Maas &
Molenar, 1992).

Extensions to multivariate time-structured intraindividual vari-
ability are also available. They include dynamic factor analysis
(Molenar, 1985), vector autoregressive and moving average mod-
els (Browne & Nesselroade, 2005; Shumway & Stoffer, 2006),
hidden Markov models (Elliot, Aggoun, & Moore, 1995; Rabiner,
1989), multivariate spectral analysis (Jenkins & Watts, 1968), cou-
pled differential equation models (Boker, 2001), and state-space mod-
els (Ho, Shumway, & Ombao, 2006; Molenar & Ram, in press). Al-
though these multivariate models have not yet been applied widely
in the psychology of aging, there are some exemplars.

Chow, Nesselroade, Shifren, and McArdle (2004; see also Shi-
fren, Hooker, Wood, and Nesselroade, 1997) used dynamic factor
models to extract systematic patterns of change in the emotional
states experienced by a sample of patients with Parkinson’s disease
across 70 days. These researchers used the time-ordered nature of
the repeated-measures data to identify the extent to which individ-
uals’ mood states systematically persisted from day to day. In par-
cular, they obtained a description of the stability maintenance
processes engaged by a subset of individuals who maintained
positive mood in the face of a debilitating disease characterized by
symptoms that fluctuate unpredictably from day to day.

There is little doubt that the technological advances in intensive,
real-time data collection and highly speeded data manipulation
and calculation as well as the long base of theorizing about dynamic
processes in relation to aging will lead to much more applications
of such methods (Stone, Shiffman, Atienza, & Nebeling, 2007).
For example, vector autoregressive methods and multivariate spe-
cral analysis are being used in the modeling of functional connec-
tivity among brain regions (e.g., Kim, Zhu, Chang, Bentler, &
Ernst, 2007; Müller, Lohmann, Bosch, & von Cramon, 2001).
Combining such models with intensive longitudinal data collected
across many minutes, hours, days, or weeks allows for capture of
the dynamic processes occurring at other microtime scales. Such
examinations are now within reach (see Walls & Schafer, 2006).

Net Intraindividual Variability

Dynamic characteristics (e.g., flexibility and lability) are often
indicated by the range of behaviors that individuals exhibit (or
might exhibit) across a variety of situations or stimuli. For exam-
ple, a dancer’s flexibility is indicated by the diversity of positions
into which he or she can contort his or her body. The main objective
in describing an individual’s flexibility, or other dynamic charac-
teristic, is to identify, extract, and measure the diversity of behaviors
exhibited over time. Methodologically, the repeated measurements
obtained from a single individual are collected into a distribution or
ensemble of scores. Then, assuming exchangeability of observations,
standard measures of central tendency and dispersion are used to
describe that individual’s total ensemble of behaviors.

Of specific interest with respect to quantifying dynamic char-
acteristics describing an individual’s capacity for change are indi-
ces of dispersion that capture information about where the ends of
the distribution are. These are the measures that locate the ex-
tremes of behavior exhibited by that individual. For example, an
intraindividual standard deviation (iSD), calculated on the distri-
bution of scores obtained across repeated measurements of a single
individual, describes the extent to which his or her scores tend to
vary around the mean score. A large iSD would indicate that the
individual had a wide range of behaviors (e.g., high flexibility),
whereas a small iSD would indicate a narrow range of behaviors
(e.g., low flexibility). Calculated separately for the distributions
obtained from multiple individuals, the iSD (or other measures of
dispersion) can be treated as a measure of interindividual differ-
ces in capacity for change (e.g., lability, plasticity, or robustness) and
can be examined with respect to other interindividual differences,
including gender, age, and other abilities or capacities with standard corre-
lation, analysis of variance, regression, or other methods typically
applied to between-person analyses.

Unstructured with respect to time. As previously noted, the
key distinction between time-structured and net intraindividual
variability is how the data are structured or treated with respect to
time. Measures and models of net intraindividual variability as-
sume exchangeability of observations or, more precisely, locally
independent and identically distributed (iid) observations (i.e., the
usual iid assumption). That is, the observations are assumed to be
independent assessments, with time simply treated as a nominal
variable or identifier that holds the multivariate observations at a
given occasion intact (similar to the way in which a random
identification number usually is used to keep an individual’s data
organized within a data file).

Consider that the concept of flexibility does not have to do with
the process by which the dancer moves from one contorted posi-
tion to another. Rather, it is simply about the range of possible
positions (the level to which one leg can be raised while the dancer
is standing on the other, the extent to which the back bends, and so
on). In this sense, when measuring flexibility, the serial or time-
structured ordering of the contortions does not matter, only their
To be clear, a key assumption in the calculation of indices of net intraindividual variability (e.g., the iSD) is that the repeated observations forming the within-person distribution are independent and identically distributed. The benefit of these assumptions is that the repeated observations can then be straightforwardly “compressed” into a single distribution and quantified by a few summary statistics (e.g., iSD)—scores that represent substantively important dynamic characteristics of the individual (e.g., lability, flexibility, and robustness). For example, the mean, variance, skewness, and kurtosis of the distribution (1st, 2nd, 3rd, and 4th moments) provide a relatively comprehensive description of how that individual’s behaviors are dispersed across the range of possible scores.

The potential costs of the needed assumptions include incongruence between the dynamic characteristics of human behavior researchers seek to observe and examine and the statistical viability of measuring and modeling specific aspects of intraindividual variability. Given the conceptual priority developmentallists place on how individuals change with respect to time, it may be difficult to imagine that repeated observations of the same person are ever truly independent. Given organismic continuity, observations obtained at time \( t \) are likely to be related in some way to observations \( t + 1, t + 2, \ldots, t + h \). Although a few indices of dispersion make use of the time-ordered nature of repeated measurements (e.g., mean square of successive differences: see Lederman & Shapiro, 1962; von Neumann, Kent, Bellison, & Hart, 1941; probability of acute change: see Jahng, Wood, & Trull, 2008), most do not.

In principle, before calculating statistics that require the independence assumption, researchers should remove or covary all time-related patterns. Time dependencies in the data should be accounted for and set aside. For example, the data might be subjected to “detrending”, “filtering”, or “prewhitening” procedures that remove time-related trends and systematic oscillations (e.g., seasonal trends or cycles; see Shumway & Stoffer, 2006). The result is intraindividual variability that is residual, net of all time-structured variability—time-series data that conform to the iid assumptions and allow for statistically viable calculation of most dispersion indices—thus, our use of the term net intraindividual variability (similar usage as in net revenue or net profit).

**Measures and models.** Assuming independent and identically distributed observations, a plethora of summary statistics can be used to quantify how the repeated observations obtained from a single individual are dispersed or distributed across scores or categories. From these, one should choose the index that most appropriately coincides with the theoretical construct it is intended to measure.

Of the many indices and models available, the iSD is by far the most popular index of intraindividual variability in psychological aging research and has been used as a measure of a wide range of dynamic characteristics (e.g., lability, robustness, and flexibility). Although the iSD has proven particularly useful, there are also other quantifications of dispersion and models available. Other univariate measures for continuous variables include the variance, root mean square, absolute range (max–min), interquartile range, median absolute deviation, mean difference, average deviation, coefficient of variation (variance/mean), signal-to-noise ratio (mean/variance), quartile coefficient of dispersion, and relative mean difference. Correspondent indices for count data include the index of dispersion (IDV; also called coefficient of dispersion or variance to mean ratio) and, for categorical data, indices of qualitative variation (see Wilcox, 1973) and entropy (Shannon, 1950).

In some domains, skewness and kurtosis also provide useful indices for quantifying individuals’ dynamic characteristics (see Newell & Hancock, 1984). Net intraindividual variability measures can also be used to describe multivariate data. The amount or extent of association among multiple variables assessed in tandem repeatedly from a single individual or entity (multivariate time series) is often called intraindividual variation or coupled within-person variation (e.g., Fiske & Rice, 1955, for the former, and Hofer & Sliwinski, 2006, for the latter). In the bivariate case, the objective is the same as above—to quantify the amount of observed covariation between the two variables. Analogues to the univariate measures listed previously would include the various within-person correlation coefficients (e.g., polychoric, Pearson, and so on) and, for categorical data, within-person odds ratios. Again, the measures of intraindividual covariation (or more generally, association) are used as measures of individuals’ dynamic characteristics. For example, within-person correlations between positive and negative affect have been used as a measure of poignancy, individuals’ capacity to experience mixed emotions (e.g., Carstensen et al., 2000; Ernsler-Hershfield, Mikels, Sullivan, & Carstensen, 2008). Similarly, within-person associations between repeated measures of stress and negative affect have been used to measure individuals’ affective reactivity (e.g., Bolger, DeLongis, Kessler & Schilling, 1989). Multilevel modeling has provided a useful and increasingly popular framework for examining between-person differences in bivariate within-person associations (see Bolger, Davis, & Rafaeli, 2003). Note, however, that within the multilevel regression framework, precedence is implicitly given to one or the other of two variables. One variable is treated as an outcome, the other as a predictor. Care should be taken when interpreting results with respect to the intended univariate or bivariate nature of one’s theoretical construct.

Some recent additions to the lexicon of measures of explicitly bivariate net intraindividual variability include pulse and spin, wherein circular statistics are used to characterize the variability in a stream of behaviors sampled from a space defined by two orthogonal dimensions (or a circumplex; see Moskowitz & Zuroff, 2004, 2005). For example, Moskowitz and Zuroff (2004) used the bivariate (or circular) measures of dispersion to measure individuals’ behavioral flexibility with respect to behavioral extremity (pulse) and interpersonal style (spin). Similar applications to repeated measures of individuals’ core affect, as defined by dimensions of valence (pleasure–displeasure) and arousal (activation–deactivation), make use of pulse and spin to measure individuals’ emotional variability (Kuppens, Van Mechelen, Nezlek, Dossche, & Timmermans, 2007).

Moving beyond two variables, the main method for examining multivariate net intraindividual variability is P-technique analysis, wherein (detrended) multivariate time-series obtained from single individuals are quantified with correlational analyses (see Nesselroade & Ford, 1985). In short, P-technique methods model the intraindividual variation of and covariation among many measures using data reduction methods (e.g., common factor models; Cattell, Cattell, & Rhymen, 1947) or other quantifications (e.g., net-
work graphs; Fair et al., 2008). The obtained summary measures (e.g., number of principal components with large eigenvalues) provide an indication of the structure of short-term change occurring across multiple variables—and can be used as an indicator of individuals’ dynamic characteristics. For example, Ong and Berge- man (2004) used P-technique analyses (intraindividual principal components) to quantify the intraindividual structure of day-to-day emotional experiences as an index of individuals’ capacity to distinguish between pleasant and unpleasant feeling states, emotional complexity (considered an indicator of adaptational effectiveness; for other applications, see Carstensen et al., 2000; Ram, Carstensen & Nesselroade, 2009; Quinn & Martin, 1999; Wess- man & Ricks, 1966). As the application of daily-diary methodologies reaches further up the adult life span and the duration of those studies increase, we see the application of P-technique as holding great promise for the measurement and quantification of dynamic characteristics that are expressed in a multivariate manner (see Jones & Nesselroade, 1990; Nesselroade & Ford, 1985; Nesselroade & Jones, 1991, for discussion of application to study of aging).

Aligning Constructs and Methods

In summarizing this section on the methods used to examine time-structured and net intraindividual variability, we highlight the need for care in the alignment of theoretical conceptions and the methods meant to render them operational (e.g. Bergeman & Wallace, 2006; Collins, 2006). Proceeding from Fiske and Rice’s (1955) footsteps, we have formulated distinct types of intraindividual variability on the basis of fundamental statistical principles about how the repeated-measures data of single individuals are structured or treated with respect to time. The distinction between net and time-structured intraindividual variability is a methodological one, wherein one set of measures and models requires or assumes that data conform to iid assumptions (time only being used as a categorical identifier) and the other set explicitly models data with time-related dependencies.

We have tethered this distinction to two sets of constructs, dynamic characteristics and dynamic processes. Formulaic calculation of the iSD and other measures of net intraindividual variability rests on the assumption that the observations are random draws from a single distribution. As a consequence, the use of such indices implies that the ordering of occasions is immaterial and that the same summary information would be obtained even when the data are reshuffled with respect to time. Thus, the constructs these measures represent are inherently about the possible range of behavior, not the progression of behavior. In contrast, when crucial aspects of the dynamic concept to be measured include, are defined by, or imply systematic progression or patterns of behavior, then models of time-structured intraindividual variability may be more appropriate. For example, negative feedback processes imply an ordering wherein discrepancies between current and preferred states reduce as time progresses (e.g. Ford & Lerner, 1992). Appropriate measures of such regulatory processes, in essence, require specificity of the time course and time-ordered patterning of short-term change—and imply specific models of time-structured intraindividual variability (e.g., damped oscillators; e.g., Bisconti et al., 2004).

As noted in the lists of measures and models previously discussed, there are many tools available for quantifying and studying both time-structured and net intraindividual variability. The same data can be analyzed in many ways, each of which invoke a particular set of assumptions and can be used to indicate one or more possible constructs. Said differently, there are many ways to divide one’s data stream into time-structured and unstructured (net) portions (multiple pieces of each also being possible). For example, in obtaining net intraindividual variability, the time-structured aspects of the data might be filtered out with sinusoidal functions (Fourier decomposition) or polynomial functions (Taylor-series expansion) or some combination of both. Each filter carries with it an implicit or explicit view on the various types of processes that contributed to the stream of observed behaviors. What is removed by one filter may be passed over by another. At the extremes, the researcher has the possibility to treat any set of intraindividual variability data as a manifestation of completely (in principle) deterministic processes (total intravar = time-structured intravar) or as completely (in principle) stochastic or random (total intravar = net intravar). Thus, theory plays an exquisitely crucial role in how researchers choose from among the many analytical possibilities.

So does study design—particularly the timing and spacing of observations. Kept in mind at all times must be the fact that the frequency and length of observation have severe implications on if and how the data may have been prefiltered during collection (see Adolph et al., 2008). With too few occasions, the study lacks reliability (see last section of Schmiedek, Lövden, & Lindenberg, 2009). With too many, the choice of filters becomes more difficult. With too small an interval between observations, one only sees stability; with too large an interval, one misses the phenomena (Boker & Nesselroade, 2002). The end result is that the study may lead one toward a set of measures and models that may or may not align with or indicate the intended dynamic characteristics or dynamic processes. See Boker, Molenaar, and Nesselroade’s (2009) comment for a cogent discussion of this problem.

Further, as with all research, the particular constructs and variables under examination must be considered as but one portion of a system, an incomplete model of an individual’s total functionality. Intraindividual variability measures and models must be interpreted within a broader framework of interindividual and contextual differences, historical changes, and so on (e.g., Baltes et al., 1977; Hofer & Shue, 2005; Sliwinski & Mogle, 2008). In sum, intraindividual variability research requires a lot of hard choices, many of which psychological researchers, as a field, are not yet in a particularly informed position to make.

Viewing these difficulties as part of the usual challenges faced in behavioral research, we wish to underscore the point that there are many measures and models that can be used to extract and describe short-term change. These methods offer the possibility to articulate and examine a multitude of conceptually interesting

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6 In addition, one needs to take great care to model the temporal dependencies appropriately. Although in some cases model misspecifica- tion is not detrimental for recovery of parameters that adequately represent the data (see Molenaar & Nesselroade, 2009), in many other cases (i.e., most cases outside the 1-lag state-space model), ignoring the time depen- dencies is very detrimental. Spurious structures (e.g., latent factors) and relations among variables appear without ever raising an alarm.
dynamic characteristics and processes. As the study of intraindividual variability proceeds and expands, and more concepts and methods are developed and used, researchers have the opportunity to outline precise definitions of the individual characteristics and processes of interest and to carefully tether them to the quantitative and qualitative assumptions on which the correspondent indices or models and inquiries are based. In our view, the tighter and more efficient the tie, the better.

Intraindividual Variability and Aging

Returning to the concepts introduced at the outset, the study of intraindividual variability is characterized by intensive repeated measurements at relatively fast, microtime scales (e.g., seconds, hours, days, weeks). It offers the possibility to measure and model dynamic characteristics and dynamic processes. In complement, the study of intraindividual changes that proceed on relatively slow, macrotime scales (e.g., years, decades) offers the opportunity to describe and examine long-term processes such as development, maturation, aging, or senescence.

At the microtime scale, researchers in many areas make use of methods wherein multiple reports or assessments are obtained over a relatively short span of time, including diary, ecological momentary assessment, multitrial (e.g., reaction-time tasks), ambulatory, (practically) continuous assessment, and other intensive longitudinal study designs (Bolger et al., 2003; Csikszentmihalyi & Larson, 1987; Hoppmann & Riediger, 2008; Shiffman, Stone, & Hufford, 2008; Walls & Schaffer, 2006). Those engaged in aging research in particular have been making good use of such designs to examine intraindividual variability in affect, activities of daily living, physical activities, social exchanges, cognitive and physiological function, and other variables (see Cain, Depp, & Jeste, 2008; Hultsch & Macdonald, 2004). But this is only part of the story of aging.

Combining microtime research designs with more macrotime designs for examining intraindividual change, researchers can examine questions about the aging of individuals’ dynamic characteristics and processes. Nesselroade (1991) suggested making use of a measurement-burst design that involves measuring individuals on multiple time scales. At the microtime level, observations are obtained from one or more individuals at closely spaced intervals (e.g., seconds, minutes, hours, weeks)—a “burst” of measurement. At the macrotime level, these same individuals are measured again at a wider interval (e.g., months, years), each time providing another burst of information from which measures of the individual’s dynamic characteristics and processes can be extracted. Thus, the multitime-scale repeated-measures design combines the benefits of short-term longitudinal studies and the study of net and time-structured intraindividual variability with those of long-term longitudinal studies and the study of aging.

To illustrate, consider the bursts of measurement depicted in the A circles of Figure 1. Both bursts of intraindividual variability were obtained from the same person. The burst on the left was obtained when the person was young and showed fluctuations characterized by low levels of dispersion. The burst on the right was obtained when the person was older, at which time the individual exhibited a more disperse set of short-term fluctuations in behavior. The long line connecting the bursts obtained from this individual implies intraindividual change—that is, aging—of the dynamic characteristic measured in the burst (e.g., age-related increases in inconsistency). In parallel, the bursts of measurement depicted in the B circles imply intraindividual, age-related change in the dynamic process indicated by the amplitude and frequency of oscillations captured by a sinusoidal model of time-structured intraindividual variability.

Reviewing and elaborating the potential of measurement-burst designs for investigating human behavior, Sliwinski (2008) highlighted that the design’s multiple-time-scale features augment the information obtained from conventional (single-time-scale) studies. These include improved precision and power for estimating long-term change (e.g., using intraindividual variability to distinguish and separate noise), greater capability to distinguish between changes and change processes that operate over different time scales (e.g., distinguishing short-term learning or forgetting processes from long-term aging processes), and the ability to track long-term changes (aging) in what we have called net intraindividual variability. In line with our presentation of the study of intraindividual variability as affording the opportunity to measure and model both net and time-structured intraindividual variability, we add that the measurement-burst design also provides the opportunity to track long-term changes in the dynamic processes that underlie behavior.

Of course, burst designs also come with problems. Sliwinski (2008) noted some of the drawbacks, including the complexity and cost of the infrastructures required for coordinating and collecting many, many repeated measures on multiple time scales, the heavy burdens on participants and the resulting difficulties in retaining them, and the tough issues and choices that must be made regarding the relative spacing of occasions and techniques for analysis. We see this last issue as one of the primary obstacles in designing a successful burst study. When, how often, and what should researchers measure? Good answers are not readily available beyond the advice to measure as often as possible for as long as possible (e.g., Adolph et al., 2008). Unable to conduct intensive measurements of all variables all the time (and still have a participant or two left), investigators are faced with the difficult task of making very specific predictions about when and how the constructs and processes of interest interact and manifest. Believing or acknowledging that human behavior is co-constructed (Baltes, Reuter-Lorenz, & Rössler, 2006; Li, 2003) by processes occurring at many levels and across multiple time scales in some senses demands a new level of theoretical precision. In many cases, researchers will be wrong and led astray by the data. But, with faith and a diligent accounting and reporting of how behavior manifests over micro-, macro-, exo-, and other time scales, they might just bring together some of the pieces of the puzzle needed for further understanding of the variety and complexities of development.

Synopsis

As a part of this collection of articles on intraindividual variability and aging, our purpose has been to introduce some concepts and indicate why and how the study of short-term intraindividual variability can be used as a tool to examine the aging of dynamic properties of human behavior. In doing so, we hope to have illustrated three points: (a) studying variability provides access to an individual’s capacities for change (dynamic characteristics) and
systematic transformations (dynamic processes), (b) such dynamic characteristics and processes can effectively be rendered operational by measures of net intraindividual variability and models of time-structured intraindividual variability, and (c) an integrated and combined study of multiple-time metrics obtained with measurement-burst designs allows researchers to examine the aging of dynamic characteristics and processes and other key developmental questions.

Across a wide variety of domains, the study of intraindividual variability is vibrant and is pushing forward understanding of the dynamic nature of individual functioning and its age-related change. Along with the ubiquitous multitrial and continuous recording of behavior obtained at faster time scales in many studies of cognitive or motor performance and psychophysiology, daily diaries and other studies of intraindividual variability take researchers many steps along what is hopefully a long avenue of inquiry that extends from rather static and stable representations—single-occasion still-photo pictures describing where individuals are in the world—to more dynamic representations—moving pictures that provide a rich and dynamic picture of how individuals can travel or are travelling through time and space. With diligence and planning, researchers might even then be able to splice those clips together to describe, explain, predict, and potentially modify the complex stories that unfold over a life span—development in process.

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