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Examining the Interplay of Processes Across Multiple Time-Scales: Illustration With the Intraindividual Study of Affect, Health, and Interpersonal Behavior (iSAHIB)

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Abstract

Human development is characterized by the complex interplay of processes that manifest at multiple levels of analysis and time-scales. We introduce the Intraindividual Study of Affect, Health and Interpersonal Behavior (iSAHIB) as a model for how multiple time-scale study designs facilitate more precise articulation of developmental theory. Combining age heterogeneity, longitudinal panel, daily diary, and experience sampling protocols, the study made use of smartphone and web-based technologies to obtain intensive longitudinal data from 150 persons age 18–89 years as they completed three 21-day measurement bursts ($t = 426$ bursts, $t = 8,557$ days) wherein they provided reports on their social interactions ($t = 64,112$) as they went about their daily lives. We illustrate how multiple time-scales of data can be used to articulate bioecological models of development and the interplay among more ‘distal’ processes that manifest at ‘slower’ time-scales (e.g., age-related differences and burst-to-burst changes in mental health) and more ‘proximal’ processes that manifest at ‘faster’ time-scales (e.g., changes in context that progress in accordance with the weekly calendar and family influence processes).

Keywords

emotion; family; depression; aging; ecological momentary assessment; multi-scale analysis

Most modern theories of development promote the idea that human functioning proceeds simultaneously on multiple levels (e.g., cells to society) and time-scales (e.g., seconds to decades). For example, developmental systems theory (e.g., Ford & Lerner, 1992), the lifespan developmental framework (e.g., Baltes, Lindenberger, & Staudinger, 2006), probabilistic epigenesis (Gottlieb, 2007), and the bioecological framework (Bronfenbrenner & Morris, 2006) all highlight that the structure and function of processes at any one level are

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influenced by the structure and function of processes at other levels. To the extent that there are reciprocal influences among processes manifesting across levels and time, the study of human functioning, and individual development in particular, calls for simultaneous observation and analysis of multiple levels and multiple time-scales (Li, 2003).

In this paper we introduce the Intraindividual Study of Affect, Health and Interpersonal Behavior (iSAHIB) as a model for how multiple time-scale study designs facilitate assessment and modeling of the interplay among processes that manifest at different time-scales. Our core thesis is that functional processes that manifest at one level of behavior (e.g., hour-to-hour) are influenced by processes that proceed at slower time-scales (e.g., month-to-month). Here, we specifically use iSAHIB to demonstrate how multiple time-scale studies can be used to articulate the complexity of behavior change.

Multiple Time-Scale Study Design

Within the lifespan developmental framework, Nesselroade (1991) highlighted the distinction between intraindividual change and intraindividual variability. *Intraindividual change* was conceptualized as directional change that manifests on a macro-time scale (e.g., years, decades) as a result of long-term processes such as development, maturation, aging, or senescence. In complement, *intraindividual variability*, was conceptualized as fluctuations, inconsistency, instability, oscillations, or “noise” that manifest on micro-time scales (e.g., minutes, hours, days, weeks) as the result of short-term processes such as regulation, reinforcement, or homeostasis. In practice, the study of *intraindividual change* and “slow” processes is typically characterized by repeated measurement of individuals’ attributes over a few or several relatively widely spaced occasions. Researchers interested in developmental processes, for instance, often make use of data collected at a macro time-scale; longitudinal panel study designs wherein multiple reports are obtained from multiple individuals at 6-month, yearly, or longer intervals (see e.g., Schaie, 1983). In contrast, the study of *intraindividual variability* and “fast” processes is characterized by repeated measurement of individuals’ attributes over many relatively closely spaced occasions. Multiple reports or assessments are obtained over a relatively short span of time using experience sampling, ecological momentary assessment, multi-trial assessment (e.g., reaction time tasks), ambulatory assessment, and other intensive longitudinal study designs (Bolger et al., 2003; Csikszentmihalyi & Larson, 1987; Hoppmann & Riediger, 2009; Mehl & Connor, 2012; Shiffman et al., 2008).

Along with making the distinction between time scales, Nesselroade (1991) suggested that ‘slower’ and ‘faster’ processes be examined simultaneously using *measurement-burst designs*, wherein individuals are measured repeatedly in accordance with both longitudinal panel and intensive longitudinal designs. Specifically, at the ‘faster’ time-scales, observations are obtained from one or more individuals at closely spaced intervals (e.g., seconds, minutes, hours, weeks) – “bursts” of intensive measurement. At the ‘slower’ time-scale, these same individuals are measured again at a wider interval (e.g., months, years), each time providing another ‘burst’ of information (see e.g., Carstensen et al., 2011; Ram, Rabbitt, Stollery & Nesselroade, 2005). The embedded nature of the measurement-burst design (faster time-scale nested within slower time-scale) provides opportunities for

examining relations between long-term change and short-term change processes (see Ram & Gerstorf, 2009).

Moving beyond the change/variability distinction (and purposively setting aside Nesselroade's accompanying distinction between enduring changes and reversible changes; see Ram & Grimm, in press), two time-scale measurement-burst study designs can be extended to *multiple time-scale study designs* wherein data are simultaneously collected at macro, meso, micro, nano, etc. time-scales. Making use of advances in technology, studies can now easily engage in longitudinal panel, daily diary, and experience sampling data collections at the same time with the same participants. For example, and portending the empirical example to follow, the Intraindividual Study of Affect, Health and Interpersonal Behavior (iSAHIB) invoked smartphone and web-based technology within a multiple time-scale study design that facilitated assessment and modeling of processes that manifest along four time-scales: decades, months, days, and hours. Such studies, where all these longitudinal designs are combined and integrated are providing unique opportunities to articulate and examine how the structure and function of processes at any one level of behavior (biological, psychological, cultural) are influenced by the structure and function of processes at other levels. Pushing a bit further, our contention is that the richness of data emerging from these study designs has the potential to catalyze more comprehensive and unified empirical articulations of human development, in particular, and behavioral change processes more generally. In the sections that follow we attempt, albeit in a cursory manner, to illustrate how consideration of multiple time-scale design, data and analysis can facilitate integration of multiple theories and perspectives. As the process of integration becomes more fluid, we hope that it may contribute to more robust understanding of the complexities of human development.

Operationalizing a Human Ecology

Systems theories of development (e.g., Baltes et al., 2006; Ford & Lerner, 1992; Gottlieb, 2007) highlight the interplay among multiple levels of organismic function and the environment. Central tenets are that individuals are embedded in ever-changing social and structural environments, and that biological and psychological processes are influenced by and influence behavioral, social, and cultural processes. We frame our illustration using the bioecological model of development (Bronfenbrenner & Morris, 2006). This model highlights that *proximal processes* – the primary processes producing human development – vary systematically as a function of the *person*, the *context*, and *time*. More specifically, proximal processes are the complex reciprocal interactions between an active human organism and the persons, objects, and symbols in its immediate environment. The form, content, power, timing, and effectiveness of these proximal processes is influenced by and influences the characteristics of the developing person, the immediate and more remote environments in which the processes are taking place, the nature of the outcomes under consideration, and the social continuities and changes occurring over time. For example, the proximal influence of family on an individual's behavior changes over time as the individual moves through different social environments and the life course (distal processes).

Of course, operationalizing the bioecological model requires research designs that represent all four key components of the model – process, person, context, and time – and that provide for detection of the kinds of synergistic interdependencies among these components that are posited by the theory. For example, the general model asserts that changes and events proceeding over the life course and across generations in *macrotime* (and periodicity over days and weeks in *mesotime*) influence the progression of proximal processes in *microtime* (Bronfenbrenner & Morris, 2006). Using portions of the iSAHIB data, we seek to operationalize such a model.

The Present Study

We develop a simple ‘bioecological system’ of processes, contexts, and personal characteristics to illustrate the utility of multiple time-scale designs for modeling how processes that manifest at one time-scale (e.g., hour-to-hour) are influenced by processes that manifest at other time-scales (e.g., decade-to-decade). Specifically, we consider a system where the *proximal processes* of interest are the set of processes through which family members influence individuals’ emotional states in *microtime*. These influences are placed within a set of periodic changes in *context* that manifest in *mesotime* in accordance with the normative weekly calendar (weekday/weekend). In turn, the proximal processes and ongoing changes in context are themselves embedded within on-going (burst-to-burst) changes in a *person’s* mental health and his or her location in *macrotime* – within the life course. Given our main purpose here is to illustrate the utility of multiple time-scale aspects of the study design, we purposively introduce the system under consideration in a very concise way.

Proximal process: Family influence on emotional state

The bioecological model posits that individual behavior emerges, in part, through exchange with a micro-context consisting of close others (e.g., family, peers). For example, work on emotional transmission highlights that individuals in the proximal environment, family members in particular, influence individuals’ emotional states in both positive and negative ways (Almeida, Wethington, & Chandler, 1999; Larson & Almeida, 1999). Following this line of work, we define the proximal process of interest as the influence that family members have on individuals’ happiness and/or sadness, as measured via self-report shortly after their social interactions with both family members and non-family others. Importantly, the proximal process is considered as one that proceeds on a relatively fast time-scale – *microtime*.

Context: Temporal location within the weekly calendar

Individuals’ emotional states are also influenced by temporal location within the normative social calendar. For example, differences in emotional states across the days of the week is well documented, with individuals, on average, reporting more positive and less negative emotions on weekend days compared to week days (e.g., Golder, & Macy, 2011; Helliwell & Wang, 2013; Ryan, Bernstein, & Brown, 2010; Sheldon, Ryan, & Reis, 1996; Stone, Hedges, Neale, & Satin, 1985; Stone, Schneider, Harter, 2012). The weekly calendar also influences the structure of individuals’ social lives, goals, and activities. This suggests that

the processes governing influence of family on emotional state may depend on the temporal location of those interactions within the weekly calendar. More specifically, we hypothesize that the slower time-scale processes progressing in accordance with the weekly calendar affect the progression of the faster time-scale family influence processes.

Person: Mental health

Mental health serves as an endogenous context in which faster time-scale processes operate. For example, emotional states, family-related processes, and weekly calendar-related processes may all be, in part, constrained by an individual's current level of depressive symptoms. Higher levels of depressive symptoms have been related to lower levels of positive and higher levels of negative emotion (e.g., Silk, Steinberg, & Morris, 2003), insensitivity to context (Bylsma, Morris, & Rottenberg, 2008; Rottenberg, Gross, & Gotlib, 2005), and blunted responses to feedback processes (Steele, Kumar, & Ebmeier, 2007). Together, such findings suggest that current mental health symptoms would both contribute to level of emotional state as well as influence the effect of more proximal, 'faster' time-scale processes (e.g., the weekly calendar) on those states. As a person's mental health changes (e.g., over a period of several months), the ways in which the 'faster' time-scale processes operate may also change.

(Macro-)Time: Aging-related processes

As noted above, the proximal process, context, and person components of our example bioecological model are each proceeding at specific time-scales – hours, days, months. In turn, age-related processes progress on a relatively slow time-scale – over decades – and influence a wide variety of functional processes. Relevant to the present illustration, socioemotional selectivity theory (Carstensen, 2006) suggests that as individuals get older, shifts in motivation change the ways in which individuals prioritize the role of close others, away from information seeking and towards more meaningful emotional experience. As such, temporal location with respect to chronological age should influence how family-related processes contribute to an individual's emotional states. Further, given age-related changes in entrainment to the weekend/week day distinction (e.g., reduction in influence of work-related processes with retirement), and evidence of differential weekend effects across the life span (Helliwell & Wang, 2013), we hypothesize age-related attenuation of processes associated with the weekly calendar.

With the metatheoretical, theoretical, and empirical considerations outlined above as a backdrop, we use the multiple time-scale design of iSAHIB to articulate and model how processes that manifest at slower time-scales (i.e., aging and mental health across decades and months) influence processes that manifest at faster time-scales (social calendar changes and family influence across days and hours).

Method

Participants

The iSAHIB worked with 150 adults (51% women) recruited from the Pennsylvania State University and surrounding community. Purposively stratified by gender and across the

adult life span in 18–24 ($n=22$), 25–34 ($n=27$), 35–49 ($n=30$), 50–64 ($n=41$), 65+ ($n=30$) year age-bins. Participants were between 19 and 89 years of age ($M_{Age} = 47.64$, $SD_{Age} = 18.85$), had obtained between 2 and 24 years of formal education ($M_{Educ} = 16.36$, $SD_{Educ} = 3.90$), and had between 0 and 6 children ($M_{Children} = 1.5$, $SD_{Children} = 1.41$). Participants self-identified as Caucasian (91%), African American (4%), Asian American (1%), and Mixed or Other (4%) ethnicity; and as heterosexual (93%) or bisexual, gay, or lesbian (6%), with less than 1% of the participants declining to indicate sexual orientation. Participants' yearly family income ranged from 'under \$20,000' to '\$200,000 and over' ($Median_{Income} = \$50,000 - \$74,999$, $Mode_{Income} = \$20,000 - \$49,999$), with 8.7% declining to answer.

Of the 150 participants, 136 (90.7%) completed the entire intensive protocol, and 14 withdrew after completing between a third ($n = 11$, 7.3%) and two-thirds ($n = 3$; 2.0%) of the total protocol. Reasons for withdrawal included relocation or loss of contact ($n = 10$), health problems ($n = 1$), and loss of interest or inability to complete protocol ($n = 3$). Participants who withdrew did not differ systematically from those who completed the entire protocol with respect to the measured demographics ($ps > .05$).

Procedure

In brief, after being recruited, explained the intensive nature of the assessments, and self-selecting into the study, participants completed a series of three 21-day “measurement bursts” spaced at about 4.5-month intervals ($M = 5.25$ months between Bursts 1 and 2; 4.25 months between Bursts 2 and 3). During each 21-day burst, individuals reported about their social interactions as they went about their daily lives, and provided end-of-day reports about their feelings, thoughts, and behaviors using a study-provided smartphone (Verizon XV6900) on which resided a customized ‘iSAHIB Surveys’ application. As well, prior to and after each 21-day burst, individuals visited the laboratory to receive training or debriefing, pick-up or drop-off smartphones, and complete web-based batteries of demographic, health, personality, and other questionnaires. Participants were compensated \$500 for completing the entire protocol.

Measures

The study was designed to enable measurement of constructs at four levels of ‘time’: *social interactions* (minutes to hours) nested within *days* (~9 weeks total) nested within *bursts* (~4.5 month intervals) nested within *persons* (between-person differences in age spanning 70+ years). Given the present report’s focus on illustrating how such studies can be used to examine the interplay of processes across multiple time-scales, we detail only the select set of variables used in the forthcoming illustration.

Social Interactions—Throughout each day, participants provided event-contingent reports of face-to-face social interactions that lasted longer than five minutes by completing 27 items on the smartphone survey application. These reports included descriptions of when and where the interaction occurred, who the interaction was with, perceptions of their and their partner’s behavior and how they felt ‘right now’. To facilitate compliance, the smartphones were programmed to, between 8 am and 8 pm, chime a prompt if the participant had not provided a report for two hours. When describing their most recent social

interaction, participants were asked to “Describe the person you interacted with ...” by clicking on 1 of 7 check-boxes: stranger, friend, co-worker, romantic partner, family, service professional, or other. Collapsing across categories, we created a binary variable indicating whether each social interaction was with ‘family’ (romantic partner or family) or ‘other’ (all other categories). Proportion of family interactions ranged from 0 to .85 with the prototypical participant interacting with family in 39.2% of reported interactions.

In the present analysis, we examine as separate outcome variables, individuals’ levels of *happy* and *sad* (selected as easily understood markers of positive and negative emotion/well-being states), as indicated in response to the items “How do you feel right now? HAPPY” and “How do you feel right now? SAD” via a ‘touch-point continuum’ (slider-type interface) that was digitally coded to a 0 (not at all) to 100 (strongly) scale (numbers were not visible to participants). Over the entire study period, participants provided, on average, $M_{numobs} = 427.4$ reports ($SD = 145.7$, range = 88 to 869) about their current happiness ($M_{happy} = 63.82$; $SD_{happy} = 22.00$) and sadness ($M_{sad} = 10.63$; $SD_{sad} = 15.50$). An illustrative collection of social interaction-level reports provided over the course of a single day by a randomly chosen individual are shown in the top panel within Figure 1. As can be seen, levels of happy (dots with solid lines) and sad (dots with dashed lines) fluctuated over time. Background shading indicates whether the report was provided after an interaction with a family member (darker shading) or other person (lighter shading).

Days—Day-level descriptions were provided shortly before participants went to bed through completion of a 52-item ‘end of day’ survey on the smartphone. In the present analysis, we make use of calendar information regarding whether reports were obtained on a week day (Mon – Fri) or *weekend* day (Sat, Sun = 28.0% of days within-person). The second panel within Figure 1 illustrates how the social interaction reports were embedded within a 21-day measurement burst. Day-level averages of happy (dots with solid lines) and sad (dots with dashed lines) are shown over a background indicating whether the reports were provided on a week day (white) or weekend day (shaded).

Bursts—Participants provided information about the endogenous and exogenous contexts in which they were functioning at each pre- or post-burst visit using web-based questionnaires. In the present analysis, we use burst-level measures of *depressive symptoms*, calculated as the average of responses to the 20-item Center for Epidemiologic Studies Depression scale (CESD; Radloff, 1977) provided at both pre- and post-burst visits. Across all persons and bursts, depression scores ranged from 0 to 48.5 ($M = 9.73$, $SD = 7.85$), with comparable sample-level averages and ranges across the three bursts. The third panel within Figure 1 illustrates how an individual’s burst-level averages of happy (bars with solid lines) and sad (bars with dashed lines) changed over time and in relation to their current level of depressive symptoms (density of diagonal shading).

Persons—Trait-like demographics and dispositions were measured periodically throughout the study (to reduce burden) using web-based questionnaires. In the present analysis, we make use of person-level differences in chronological *age*, computed specifically as the number of years between an individual’s birthdate and the day on which the study commenced (see sample demographics above). The bottom panel within Figure 1

illustrates the nesting of bursts within an individual and location within macrotime, as indicated by chronological age. As can be seen, the illustrative social interaction-, day-, and burst-level data were obtained from a unique, 49-year-old female participant represented by a ‘bar bell’ connecting person-level averages of happy (dots with solid line) and sad (dots with dashed line).

In total, cleaned data consisted of reports on 64,112 social interactions nested within 8,557 days, nested within 426 burst periods, nested within 150 persons.

Data Analysis

Our main interest in the present illustration was to examine if and how proximal processes influencing individuals’ happiness and sadness were influenced by changes in context that manifest on different time-scales. Variables from each time-scale were brought together within a multilevel modeling framework (e.g., Raudenbush & Bryk, 2002; Snijders & Bosker, 1999) where the emotion reports (*happy* and *sad*) were modeled as a function of social interaction-level (*family*), day-level (*weekend*), burst-level (*depressive symptoms*), and person-level (*age*) variables, and all possible interactions among those variables.

In a preliminary step, we sought to establish a hierarchical structure that would parsimoniously accommodate the complexity of the nesting and accurately represent the distribution of “error” variance. Unconditional means models (no predictors) indicated that total variance in the moment-to-moment reports of emotions was unevenly distributed across time-scales. For example, of the total variance embedded in the intensive repeated measures of *happy*, 42.16% were attributable to differences across social interactions, 0.79% to differences across days, 10.89% to differences across bursts, and 46.15% to differences across persons. Similarly, of the total variance embedded in the intensive repeated measures of *sad*, 55.44% were attributable to differences across social interactions, 0.74% to differences across days, 13.03% to differences across bursts, and 30.78% to differences across persons. The extremely low proportions of variance at the day-level (< 1%) indicated the utility (in terms of parsimony) of combining unexplained interaction-to-interaction and day-to-day differences in emotional state into a single error term. The resulting model (described below) provides a parsimonious, although still complex, accounting of how the interplay among family, weekly calendar, mental health, and age-related processes influenced individuals’ emotional state.

Following usual practice (see e.g., Bolger & Laurenceau, 2013), predictor variables assessed at lower levels were conceived as having time-varying (in some cases at multiple time-scales) and time-invariant components and split accordingly. For example, burst-level measures of depressive symptoms were split into *chronic depressive symptoms* (*CESDchronic_p*), a person-level time-invariant variable calculated as the arithmetic mean across the three repeated measures, and *burst-specific depressive symptoms* (*CESDburst_{bp}*), a time-varying variable calculated as the burst-level deviations from the person-specific means. Similarly, to examine (and control for) potential exposure differences across bursts and persons, the proportion of interactions during each burst that were with family members was calculated and split into *typical family exposure*, and *burst-specific family exposure* components.

The extended set of variables was then placed within the 3-level hierarchical model (social interaction and day combined, burst, person) and fit to the data using SAS 9.3 (proc mixed, Littell, Miliken, Stoup, & Wolfinger, 1996), with incomplete data ($\ll 1\%$) treated as missing at random. Burst-level and person-level predictors were sample- and/or person-centered to facilitate interpretation of model parameters as representing effects for the prototypical person (as described by the average demographics above). Social interaction-level and day-level predictors were kept binary with effects indicating changes in emotion associated with family (vs. other) and weekend day (vs. week day). An initial model included all possible main effects and interactions. However, an opportunity for parsimony emerged when none of the main or interaction effects associated with the typical and burst-specific family exposure variables were significant. These variables were then removed completely, and the model for became

$$Emotion_{tbp} = \beta_{0bp} + \beta_{1bp}(family_{tbp}) + \beta_{2bp}(weekend_{tbp}) + \beta_{3bp}(weekend_{tbp} \times family_{tbp}) + e_{tbp} \quad (1)$$

With burst level predictors incorporated via

$$\beta_{0bp} = \pi_{00p} + \pi_{01p}(CESDburst_{bp}) + u_{0bp} \quad (2)$$

$$\beta_{1bp} = \pi_{10p} + \pi_{11p}(CESDburst_{bp}) + u_{1bp} \quad (3)$$

$$\beta_{2bp} = \pi_{20p} + \pi_{21p}(CESDburst_{bp}) \quad (4)$$

$$\beta_{3bp} = \pi_{30p} + \pi_{31p}(CESDburst_{bp}) \quad (5)$$

and person-level variables incorporated via

$$\pi_{00p} = \gamma_{000} + \gamma_{001}(CESDchronic_p) + \gamma_{002}(age_p) + \gamma_{003}(age_p \times CESDchronic_p) + v_{00p} \quad (6)$$

$$\pi_{01p} = \gamma_{010} + \gamma_{011}(CESDchronic_p) + \gamma_{012}(age_p) + \gamma_{013}(age_p \times CESDchronic_p) + v_{01p} \quad (7)$$

$$\pi_{10p} = \gamma_{100} + \gamma_{101}(CESDchronic_p) + \gamma_{102}(age_p) + \gamma_{103}(age_p \times CESDchronic_p) \quad (8)$$

$$\pi_{11p} = \gamma_{110} + \gamma_{111}(CESDchronic_p) + \gamma_{112}(age_p) + \gamma_{113}(age_p \times CESDchronic_p) \quad (9)$$

$$\pi_{20p} = \gamma_{200} + \gamma_{201}(CESDchronic_p) + \gamma_{202}(age_p) + \gamma_{203}(age_p \times CESDchronic_p) \quad (10)$$

$$\pi_{21p} = \gamma_{210} + \gamma_{211}(CESDchronic_p) + \gamma_{212}(age_p) + \gamma_{213}(age_p \times CESDchronic_p) \quad (11)$$

$$\pi_{30p} = \gamma_{300} + \gamma_{301}(CESD_{chronic_p}) + \gamma_{302}(age_p) + \gamma_{303}(age_p \times CESD_{chronic_p}) \quad (12)$$

$$\pi_{31p} = \gamma_{310} + \gamma_{311}(CESD_{chronic_p}) + \gamma_{312}(age_p) + \gamma_{313}(age_p \times CESD_{chronic_p}) \quad (13)$$

where the t , b , and p subscripts denote social interaction, burst, and person, respectively, and *emotion* as outcome indicating that the same model was fit separately to *happy* and *sad*. Random effects (i.e., variance of e , u , and v residuals) were allowed to covary within-level, and, as usual, assumed orthogonal across levels. For additional parsimony, non-significant higher-order interactions were trimmed iteratively towards a 2-way interaction limit, always retaining the relevant lower-order interactions when any higher-order interactions remained. Upon reaching the most parsimonious model, non-significance of the family exposure variables and their interaction with other variables was re-checked. Significant 2-way and 3-way interactions (evaluated at $\alpha = .01$) were interpreted, in all cases, as evidence that processes manifesting at the ‘slower’ time-scale moderated the influence of the ‘faster’ time-scale process. Model parameter estimates were used to produce plots that might help with communication and interpretation of the results.

Results

Results from the final models examining how processes affecting individuals’ happiness and sadness were moderated by changes in context that manifest on different time-scales are shown in Table 1. We walk through effects on happy at each time-scale in turn, and briefly describe parallel results for sad without going into as much detail.

Happy

Results from the final model reported in the Happy column of Table 1 are compiled and plotted in Figure 2.

Social Interaction-level—For the prototypical person, in the prototypical burst, on the prototypical weekday, after the prototypical interaction outside the family, the expected level of happiness was $\gamma_{000} = 62.09$ (on the 0 to 100 scale). On average, interactions with family members boosted happiness by $\gamma_{100} = 1.16$ units ($p < .01$). Notably, the expected levels and family-related influence on happiness varied both within-persons across bursts (as indicated by the significant burst-level random effects, $\sigma^2_{u0bp} = 47.73$ and $\sigma^2_{u1bp} = 9.50$) and across persons (as indicated by the significant person-level random effects, $\sigma^2_{v00p} = 144.44$ and $\sigma^2_{v10p} = 13.12$). Prototypical expectations derived from the model are plotted in Figure 2. Specifically, points within the innermost Box A indicate the expected level of happiness following social interactions with non-family others ($= 62.09$) and with family members ($= 62.09 + 1.16 = 63.72$).

Day-level—For the prototypical person, weekend days provided a boost of $\gamma_{200} = 1.88$ units, but significantly attenuated the influence of family members, reversing the weekday boost ($\gamma_{100} = 1.16$) by $\gamma_{300} = -1.65$ units. Model-derived expectations are highlighted within slanted Box B in Figure 2. As apparent from the nonparallel slopes of the lines spanning

across week and weekend days, there was clear evidence that ‘slower’ day-level processes progressing in accordance with the weekly calendar moderated the ‘faster’ family-related processes manifesting across social interactions. In particular, the prototypical person is happier when interacting with family members vs. others on weekdays, but not on the weekend.

Burst-level—For the prototypical person, during bursts where depressive symptoms were higher than usual, happiness was lower, $\gamma_{010} = -0.74$ and weekend-related processes were accentuated, $\gamma_{210} = 0.12$. As shown by the pattern of within-person changes captured within the C panel of Figure 2, during bursts when an individual’s level of depressive symptoms was higher ($CESD_w + 1SD$) than usual or lower than usual ($CESD_w - 1SD$), the boost provided by weekends was larger or smaller (as indicated by the differences in the slopes of the lines connecting the open squares). Again, this was interpreted as evidence that ‘slower’ burst-to-burst changes in depressive symptoms moderated the influence of ‘faster’ weekend-related processes.

Person-level—At the person-level, we considered two sets of between-person differences. First, splitting depressive symptoms into chronic and burst-specific components provided for examination of how the faster processes were influenced by chronic (i.e., stable) differences in overall levels of depressive symptoms. Results, viewed as differences in the vertical direction across the D panels in Figure 2, indicated that between-person differences in depressive symptoms moderated faster processes in the same way as the within-person changes in depressive symptoms. Higher depression scores were associated with lower levels of happiness, $\gamma_{001} = -1.28$ and an accentuation of weekend-related processes, $\gamma_{201} = 0.05$. That is, individual with higher depression scores tended to get a bigger boost from the weekend, even through their overall level of happiness was lower.

Second, using between-person differences in age as a proxy for lifespan development, we indeed found evidence that age moderated the faster processes. In particular, as can be seen when looking at differences in the horizontal direction across the D panels in Figure 2, older age was associated with an attenuation of the weekend-related boost in happiness, $\gamma_{202} = -0.04$, and disattenuation of the extent to which the weekend-related processes attenuated family influence, $\gamma_{302} = 0.05$. That is, the macro time-scale results suggest that there are significant age-related differences in how weekend-related processes unfold and influence family-related processes occurring at even ‘faster’ time-scales.

Sad

Results from the final model reported in the sad column of Table 1 are compiled and (in slightly abbreviated form) plotted in Figure 3. In brief, there was again evidence at each time scale that the processes manifesting at ‘slower’ time-scales moderated the processes manifesting at ‘faster’ time-scales. At the fastest time scale, results indicated, as expected, significant family influence on sadness ($\gamma_{100} = 1.548$) that were not influenced directly by week/weekend processes. Within-person changes in depressive symptoms across bursts as well as between-person differences in depressive symptoms contributed both directly to sadness ($\gamma_{010} = 0.383$, $\gamma_{110} = 0.748$,) as well as moderated the interplay of the weekly

calendar and family influences (3-way interactions). At the slowest time-scale, differences in age moderated week/weekend day processes ($\gamma_{202} = -0.029$) as well as how differences in depressive symptoms moderated those processes ($\gamma_{203} = -0.004$). Overall, the results complement the findings for ‘happy’, with a bit of added complexity resulting from the 3-way interactions – as displayed in the additional panels in Figure 3.

Discussion

Systems theories of development (e.g., Baltes et al., 2006; Ford & Lerner, 1992; Gottlieb, 2007) posit development and behavior as emerging through interplay among processes at multiple levels of analysis and time-scales. In this paper, we introduced the Intraindividual Study of Affect, Health and Interpersonal Behavior (iSAHIB) as a model for how multiple time-scale study designs facilitate articulation and modeling of that complexity. The study used advances in mobile- and web-based technology to move a sample of 150 persons through an intensive protocol that combined four time-scales: decades, months, days, and hours. These data were then used to model how proximal processes that manifest at a relatively fast time-scale are influenced by changes in context, personal characteristics, and across age that manifested at slower time-scales. In doing so, we provided a concrete example for how a complex milieu of processes unfolding at multiple time-scales can be conceptualized, assessed, and modeled. To our knowledge, iSAHIB is the first study to systematically and simultaneously examine behavior at four time-scales.

Slower Processes Influence Faster Processes

Our empirical illustration made use of intensive repeated measures of self-reported intensity of the emotions *happy* and *sad* that were provided after social interactions with family members or others. Within-person changes in family influence processes across social interactions were modeled, using standard multilevel models, as a function of changes in context that accompany the (socially constructed) distinction between week days and weekend days, changes in level of depressive symptoms, and differences in chronological age. The results from models of ‘happy’ provided evidence of family influence on happiness at the social interaction-level, within-person changes in happiness across week day and weekend day context at the day-level and across levels of depressive symptoms at the burst-level, and stability of happiness across chronological age at the person-level. The pattern of cross-level interactions also provided surprisingly clear evidence that the proximal and ‘faster’ family influence processes were moderated by the ‘slower’ day-level (week/weekend day) processes that were themselves moderated by the even ‘slower’ burst-level differences in depressive symptoms. Finally, at the ‘slowest’ time-scale there was evidence of age-differences moderating the day-level processes and how those day-level processes, in turn, moderated the family influence processes manifesting at the social interaction-level. All together, the findings support theoretically and empirically-based hypotheses related to the importance of (a) close others for individual well-being, (b) weekend as a social context, (c) mental health as a personal context, and (d) age as a ‘macrotime’ context in which more proximal processes are embedded.

Multiple Time-Scale Design and Analysis

Generalizing from Nesselroade's (1991) distinction between intraindividual change and intraindividual variability and proposal for use of measurement-burst designs to examine long-term change in short-term change processes, iSAHIB was specifically designed to obtain simultaneous assessments at multiple time-scales. Note that the sample is small and select ($N = 150$). Focus was purposively shifted away from large-scale representative sampling of between-person differences and towards rich sampling of situations and time – within-persons (64,112 social interactions over 8,557 days during 426 burst periods). Possibilities for generalization are obtained through capture of processes embedded within data collected multiple times per day, daily, and at each burst for a total time spanning almost 23.5 years. The intensity of data collection was facilitated by use of smartphone- and web-based survey applications with real-time data transfer to a central server, technologies that both reduced participant burden and provided for efficient deployment of 'motivational calls' to maintain data flow. The volume and quality of the data evidence the participants' success in providing the types of data necessary for modeling within-person dynamic processes. We encourage new studies that make use of the very latest innovations in sensor technology, data storage, and data transfer to integrate additional data into the multiple time-scale paradigm.

Engaging participants in a combined longitudinal panel, daily diary, and experience sampling protocol facilitated simultaneous collection of multivariate data at macro, meso, and micro time-scales that could then be used to articulate theory acknowledging that human behavior is "co-constructed" by multiple processes occurring at many levels (Li, 2003). Our illustrative analysis structured the data as a set of nested time-scales defined by the collection protocol that could be placed in a pre-defined hierarchical structure (social interactions nested within days nested within bursts nested within persons). The multilevel modeling framework facilitated our examination of how a univariate outcome at the social interaction level (happy or sad) was influenced by 'faster' and 'slower' processes operationalized through repeated measurement of specific variables (family, weekend, CESD, chronological age). This set-up allowed for articulation of a process-person-context-time model (constructed following Bronfenbrenner & Morris, 2006), examining whether processes manifesting at faster time-scales were influenced by processes manifesting at slower time scales, and evidence for a set of theoretically and empirically derived hypotheses. The results are compelling, and the accompanying plots hopefully provide a framework for effective communication of the complex multilevel interactions supporting predictions.

Although we obtained a reasonably interpretable model and successfully tested a set of empirical hypotheses, we must highlight a potential mismatch between the analytical approach used here and the theoretical framework we seek to articulate. Systems theories of development (e.g., Baltes et al., 2006; Bronfenbrenner & Morris, 2006; Ford & Lerner, 1992; Gottlieb, 2007) all highlight the importance of *interplay* among levels and time scales. All of these theories specifically outline the existence of *bidirectional* influences. Processes at one level and time-scale are *influenced by and influence* processes at other levels and time-scales. The multilevel modeling framework we invoked for analysis portrays all effects

as moving from the ‘slower’ processes towards the ‘faster’ processes to eventually manifest in a single repeated measures outcome (e.g., ‘happy’). The analytical set-up does not allow for simultaneous modeling of multiple outcome variables at different levels (e.g., we were not able to articulate both social interaction-level ‘happy’ and burst-level ‘depressive symptoms’ as mutually interdependent outcomes) or interpretation of bidirectional influences between ‘faster’ and ‘slower’ processes. To more precisely articulate the bidirectional influence across time-scales, we foresee a shift in focus away from the analytical frameworks typically used to analyze longitudinal panel, daily diary, and experience sampling data (i.e., multilevel models) toward person-specific and multiscale analysis approaches used in other fields (see Molenaar & Campbell, 2009; Ram & Diehl, in press, Ram et al., 2014; Roche, Pincus, Hyde, Conroy, & Ram, submitted). Seeing similarities between the data introduced here and the ‘big data’ supporting multiple time-scale analysis in biology, physics, meteorology, and other fields, we encourage adaptation and use of alternative analytical paradigms for research in human development (Ram et al., in press).

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Figure 1. Multiple time-scale design of the Intraindividual Study of Aging, Health, and Interpersonal Behavior (iSAHIB). Four time-scales, illustrated with a select set of variables, zoom from ‘slower’ time-scales towards ‘faster’ time-scales (bottom panel to top panel). The *Persons* panel highlights age heterogeneity across 70 years of the life course (age 18 to 89), with each individual depicted as a unique ‘bar bell’ connecting their average levels of happy (dot with solid line) and sad (dot with dashed line). Zooming into the data provided by a single individual (a 49 year old woman), the *Bursts* panel shows average levels of happy and sad obtained during three bursts of intensive collection spaced over 12 months (here, from May 2010 to May 2011). As well, shaded bars indicate the individual’s CESD score (by quartile) at each burst. Zooming into the first burst of data, the *Days* panel shows fluctuations in happy and sad over 21 days, with week and weekend days indicated by shading. Zooming

into a specific day, the top *Social Interactions* panel shows changes in happy and sad over 24 *hours* as the individual had social interactions with different types of partners (family = vs. other).

Figure 2.

Expected scores for 'happy' derived from multiple time-scale analysis. Central panel indicates expected within-person changes across social interactions with family or others (Box A), on week days or weekend days (Box B), and burst-to-burst changes in depressive symptoms (Panel C). Surrounding panels (Panels D), separated by white space, indicate between-person differences associated with depressive symptoms (across the three horizontal vertical panels) and age (across the three horizontal panels). Moderation of the 'faster' processes by the 'slower' processes is apparent both within the central panel and across the panels through comparison of the slopes of the lines within and across panels.

Figure 3.

Expected scores for 'sad' derived from multiple time-scale analysis. Central panel indicates expected within-person changes across social interactions with family or others, on week days or weekend days, and burst-to-burst changes in depressive symptoms (open boxes and dashed lines). Surrounding panels, separated by white space, indicate between-person differences associated with age and depressive symptoms. Moderation of the 'faster' processes by the 'slower' processes is apparent both within the central panel and across the panels by changes in the slopes of the lines.

Table 1

Results from final models examining how ‘faster’ time-scale processes influencing individuals’ happiness and sadness were moderated by processes manifesting at ‘slower’ time-scales.

Parameters	Parameter Estimates (SE)			
	Happy		Sad	
Fixed Effects				
Intercept, γ_{000}	62.085 [*]	(1.045)	10.672 [*]	(0.619)
Family, γ_{100}	1.163 [*]	(0.380)	1.548 [*]	(0.312)
Weekend, γ_{200}	1.882 [*]	(0.194)	−0.241	(0.161)
Weekend x Family, γ_{300}	−1.645 [*]	(0.270)	−0.197	(0.225)
CESDburst, γ_{010}	−0.740 [*]	(0.134)	0.383 [*]	(0.106)
CESDburst x Family, γ_{110}	0.001	(0.063)	0.005	(0.071)
CESDburst x Weekend, γ_{210}	0.120 [*]	(0.042)	−0.243 [*]	(0.063)
CESDburst x Weekend x Family, γ_{310}	--		0.296 [*]	(0.088)
CESDperson, γ_{001}	−1.276 [*]	(0.145)	0.748 [*]	(0.093)
CESDperson x Family, γ_{101}	−0.020	(0.052)	0.158 [*]	(0.044)
CESDperson x Weekend, γ_{201}	0.052 [*]	(0.021)	0.011	(0.026)
CESDperson x Weekend x Family, γ_{301}	--		−0.120 [*]	(0.034)
CESDperson x CESDburst, γ_{011}	0.010	(0.013)	0.1790	(0.010)
CESDperson x CESDburst x Family, γ_{111}	--		−0.003	(0.007)
CESDperson x CESDburst x Weekend, γ_{211}	--		0.021 [*]	(0.007)
CESDperson x CESDburst x Weekend xFamily, γ_{311}	--		−0.029 [*]	(0.009)
Age, γ_{002}	−0.013	(0.056)	0.056	(0.033)
Age x Family, γ_{102}	−0.014	(0.022)	0.015	(0.017)
Age x Weekend, γ_{202}	−0.044 [*]	(0.010)	−0.029 [*]	(0.006)
Age x Weekend x Family, γ_{302}	0.051 [*]	(0.016)	--	
Age x CESDperson, γ_{003}	--		0.003	(0.005)
Age x CESDperson x Weekend, γ_{203}			−0.004 [*]	(0.001)
Random effects				
Social Interaction-level				
Residual variance, e_{tbp}	205.420 [*]	(1.158)	139.04 [*]	(0.785)
Burst-level				
Variance intercept, σ^2_{u0bp}	47.731 [*]	(4.370)	29.204 [*]	(2.693)
Variance family, σ^2_{u0bp}	9.499 [*]	(1.497)	5.962 [*]	(1.001)
Covariance intercept, family, $\sigma_{u0jbp\ u1bp}$	−3.273	(1.821)	−2.445	(1.193)
Person-level				
Variance intercept, σ^2_{v00p}	144.440 [*]	(19.08)	45.697 [*]	(6.838)
Variance family, σ^2_{v10p}	13.120 [*]	(2.417)	8.963 [*]	(1.637)

Parameters	Parameter Estimates (SE)	
	Happy	Sad
Covariance intercept, family, $\sigma_{v00p, v10p}$	-2.560 (4.823)	0.186 (2.414)
-2LL	522,648	496,563

*
 $p < .01$.

SE = standard error.

Data are reports on 64,112 social interactions nested within 8,557 days, nested within 426 burst periods nested within 150 persons. Processes, ordered from faster to slower, indicated by family, weekend, CESD, and age variables. Interaction terms indicate the extent to which slower processes moderate faster processes. Family exposure variables (e.g., proportion of social interactions with family members for a day, burst, or person) were considered as additional predictors but were not significant and thus removed for parsimony.