

**Understanding the dynamic nature of well-being: A multilevel SEM framework to capture
intra- and inter-individual associations across multiple timescales and levels of analysis**

by

Jonathan Rush
MSc, University of Victoria, 2010
BA, Brock University, 2007

A Dissertation Submitted in Partial Fulfillment of the Requirements for the Degree of

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Supervisory Committee

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Abstract

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The study of well-being has a long history of investigation from a nomothetic (between-person) perspective that aimed to understand characteristic levels of well-being and individual difference variables that account for stable differences across people. Recent investigations have demonstrated that levels of well-being have the capacity to rapidly fluctuate within people over short intervals and also exhibit slower changes over longer intervals, highlighting the importance of considering the ideographic (within-person) nature of well-being. The aim of this dissertation was to help build on such within-person understanding by demonstrating how theories of well-being may be empirically evaluated using innovative research designs (e.g., intensive repeated measurement designs) and analytic techniques (e.g., multilevel structural equation models [MSEM]) that can fully capture the complexity and dynamic nature of well-being. Three distinct research studies employing intensive repeated measurement designs and an MSEM analytic framework addressed a variety of research questions concerning intra- and inter-individual predictors of well-being. Study one (Chapter 2) simultaneously examined the multilevel moderation and mediation effects of cognitive interference on stress reactivity estimated in a 14-day daily diary design. Study two (Chapter 3) utilized measurement burst data from a large U.S. sample of adults, assessed across multiple time-scales, to examine long-term changes in short-term within-person associations. Random within-person slopes were specified as exogenous predictor variables of individual differences in global levels of psychological well-being. Study three (Chapter 4) used simulation data to examine the conditions where specifying within-person measurement scales as latent variables compared to unit-weighted composite scores optimized detection of within-person effects. This dissertation demonstrates the importance of innovative design and analysis to appropriately model and understand the complex, dynamic associations that operate within and across individuals in predicting their experiences of well-being.

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Chapter 1

General Introduction

In this dissertation, I illustrate how advances in longitudinal methodology can be applied to diverse issues of interest and advance well-being research. The intention is to evaluate and address conceptual and methodological issues surrounding the need for a) study designs that link information at different levels of analysis; b) innovative methodological approaches that are sensitive to complex dynamic relationships; and c) valid and reliable measures suitable to reflect true within-person change and variation, as well as between-person differences. Progress on these issues, in turn, requires a greater understanding of within-person processes. The aim of this dissertation is to help build such understanding by demonstrating how theories of well-being may be empirically evaluated using innovative research designs (e.g., intensive repeated measurement designs) and analytic techniques (e.g., multilevel structural equation models) that can fully capture the complexity and dynamic nature of well-being.

The study of well-being has a long history of investigation from a nomothetic (between-person) perspective that aimed at understanding characteristic levels of well-being (e.g., Diener, 1984; Ryff, 1989) and individual difference variables that could account for stable differences across people. The nomothetic approach has produced extensive insights into the many contextual, social, and individual factors that are predictive of levels of well-being (e.g., Dolan, Peasgood, & White, 2008; Diener, Diener, & Diener, 1995). However, recent investigations have demonstrated that levels of well-being have the capacity to fluctuate considerably within people over short intervals of time and may also exhibit changes over longer intervals (e.g., Mroczek & Spiro, 2005; Rush & Grouzet, 2012; Rush & Hofer, 2014). That well-being levels vary considerably within individuals highlights the importance of considering the ideographic (within-

person) nature of well-being. Conclusions based solely on nomothetic research that do not consider ideographic information have the potential to be misleading (Nesselroade, 1991).

Accessing insights into the ideographic elements of well-being requires research designs that repeatedly assess individuals to capture variations and changes. A variety of research designs, including decisions about the number, frequency, and types of measurements, are used to understand developmental and health-related processes. Various statistical models can be applied to answer specific questions regarding stable individual differences, population average patterns of change, individual differences in level and rate of change, and multivariate dynamics of within-person variation. Each observed score carries many sources of variation that influence our models. When participants are measured on only one occasion, the inter-individual variability in the measurements can reflect three different sources: 1) stable differences among people; 2) intra-individual variability; and 3) temporal measurement error. These three possible sources of variation are inextricably confounded when data are obtained on only one occasion, and it is impossible to separate them (Nesselroade, 1991).

Sampling Time: Issues with Single Occasion Measurements

Cross-sectional and widely spaced longitudinal measures fail to account for the potential variability around trait levels. When measures vary both within-person across time as well as between people, measuring only once forces all systematic within-person variations to be grouped together and treated as random measurement error. As a result, the cross-sectional measure carries both between person information (i.e., characteristic individual level) and within-person information (i.e., deviations from individual level) with no possibility of disentangling the two primary sources of variation with only a single measurement (e.g., Curran & Bauer, 2011; Hoffman & Stawski, 2009). For example, an individual could be higher than

others on a measure of well-being because they are a generally a happier person, or their well-being level could be affected by them having a particularly good day, which elevates their score above their typical level (Schwarz & Strack, 1999). Assuming that a construct is stable can be problematic when the construct does indeed systematically vary over time and can lead to conclusions about individual differences that are confounded with within-person variance (e.g., Rush & Hofer, 2014).

Many constructs in psychological research are captured via recall of behaviors, attitudes, or experiences within a delimited period of time (e.g., well-being, victimization, substance use). These measures typically rely on self-report recall, or the recall of other informants (e.g., friends, family, teachers; Allen, Chango, Szwedlo, Schad, & Marston, 2012; Jordan & Graham, 2012; Ladd & Kochenderfer-Ladd, 2002). The retrospective time-range of cross-sectional measures can vary widely from the previous months or years, to asking about global levels. When measures are derived solely from a single occasion there are a number of biases that distort the true level of the construct. Global measures are susceptible to retrospection bias, particularly when the assessment period is farther removed from the period of recall (Schwarz, Kahneman, & Xu, 2009). A potentially more problematic issue with global measures are social desirability biases, which include 1) impression management, where individuals purposefully attempt to present themselves more favorably; and 2) deceptive self-enhancement, where individuals unintentionally respond according to their self-image, rather than actual behaviors/experiences (Barta, Tennen, & Litt, 2012). An inability to accurately recall the events of the distant past (e.g., months/year) often results in the responses being based on a top-down approach of relying on a global self-perception of themselves and how someone who fits that self-perception would act (Schwarz, 2012). For example, parents who rated the enjoyment they experience while spending

time with their children via a global self-report consistently rank it as among the most enjoyable things they do (Juster, 1985). However, when rating their enjoyment with their children on a particular day, through an end-of-day reconstruction, they rated it as among the least enjoyable events of the day (Kahneman, Krueger, Schkade, Schwarz, & Stone, 2004). Reporting globally that one does not enjoy time with their children would likely be in stark contrast to their self-perception as a loving parent, however reporting that on this one day they did not enjoy time with their children does not preclude them as quality parents. Aggregating across multiple daily reports would therefore reflect the parents' actual enjoyment during this time period and individual differences among parents would be based on actual differences in enjoyment rather than differences in global self-perception. Research on other undesirable behaviors have found similar patterns. In a study of unsafe sexual practices, it was found that participants underreported the number of unsafe sexual behaviors in general cross-sectional measures compared to daily reports (McAuliffe, DiFranceisco, & Reed, 2007).

Contrary to undesirable behaviors, global measures of life satisfaction are often negatively skewed (Diener, 2000), with most people considering themselves to be generally quite satisfied with their life. However, these responses are more likely based on their perception of themselves as a happy person, rather than on actual accounts of how satisfied they are day in and day out. Thus, aggregating over many closely spaced assessments may provide an account of an individual's true level of a construct that is less dependent on retrospection and social desirability biases. Indeed, comparing a cross-sectional measure of life satisfaction to a daily measure aggregated over 14 days revealed that the two measures are only moderately correlated ($r = 0.58$). Additionally, individuals rated their general level of life satisfaction higher than their average daily life satisfaction ($t(146) = 11.71, p < .001$). Figure 1.1 shows the comparison of the

cross-sectional and daily measures of ten participants. Each participant had higher levels on the cross-sectional life satisfaction measure than the aggregated daily measure. More than 85% of the sample overestimated their global life satisfaction relative to their daily mean, providing support for the upward bias of cross-sectional measures. When reporting on typical level of life satisfaction, participants were likely using a top-down approach where they perceived themselves as more satisfied to a greater extent than was actually the case if asked to assess day-by-day. It is important to note that global perceptions of life satisfaction may be of substantive interest, however, global reports have been demonstrated to differ from individual-averaged experiences of life satisfaction as they occur on a daily basis.

Methodologies to Capture Dynamic Associations

Intensive Repeated Measurement Designs

In order to capture individual experiences as they change and fluctuate over relatively short periods of time, researchers now regularly implement intensive repeated measurement research designs (e.g., Bolger & Laurenceau, 2013; Hoffman, 2007; Nesselroade, 1991; Rast, MacDonald, & Hofer, 2012; Salthouse & Nesselroade, 2010; Sliwinski, 2008; Walls, Barta, Stawski, Collyer, & Hofer, 2012). Intensive repeated measurement designs consist of frequent closely-spaced assessments repeated within individuals over many measurement occasions. The structure of these research designs may differ across studies based on number of repeated assessments, frequency of sampling, types of measures obtained (e.g., self-report, physiological data, activity). The most commonly used types of intensive measurement designs include daily diaries, where participants are sampled once per day over many days or weeks (e.g., 14 days), and ecological momentary assessment (EMA), where participants are sampled on a quasi-random schedule multiple times per day, repeated over many days or weeks.

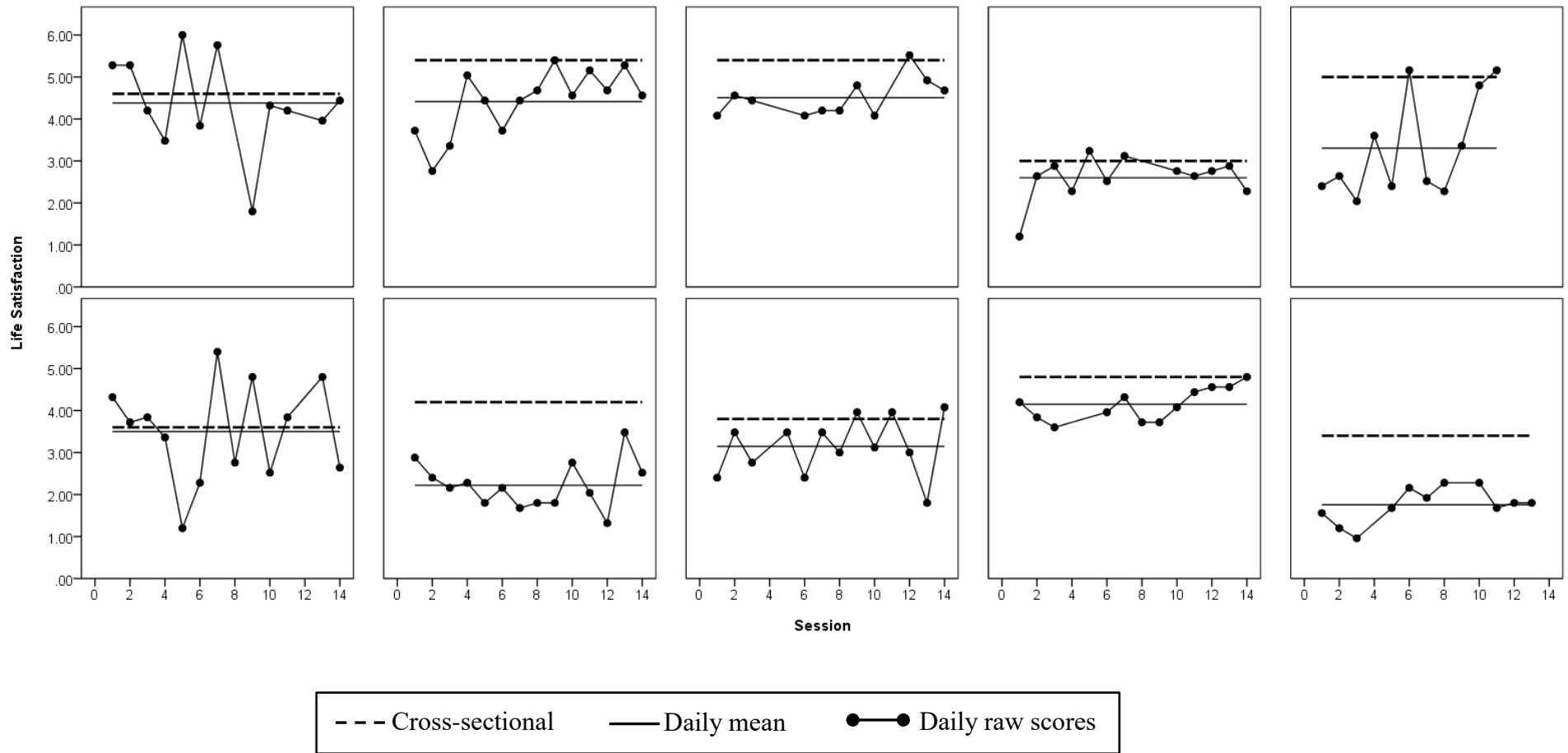


Figure 1.1. Reported life satisfaction values from ten random participants displaying differences in cross-sectional, aggregated daily mean, and daily raw score measures.

Repeatedly sampling many points in time addresses a number of the issues that plague cross-sectional designs. Intensive measurement designs enable within-person variation to be disaggregated from between-person differences. Furthermore, the lag-time between the experiencing and the reporting can be reduced to the point where retrospection bias is largely eliminated and reports are based more on a bottom-up report of actual events rather than a top-down representation of perceived self-image. In comparison with traditional longitudinal panel designs, intensive measurement designs allow researchers to observe processes of *short-term* change and fluctuation. Incorporating several measurement bursts that are repeated at more widely spaced intervals (e.g., one year), enables change to be measured on multiple time scales to allow short-term fluctuations to be disaggregated from long-term changes (e.g., Gerstorf, Hoppmann, & Ram, 2014) and permit an evaluation of changes in these within-person dynamics.

The growing availability of mobile assessment tools (e.g., smartphones, tablets, accelerometers) allows for the study of the determinants and consequences of changes in well-being within people's everyday lives. The short time intervals between events and self-reports improves accuracy and reduces bias. In addition to these improvements in measurement precision, repeated assessments of the same person over time addresses a serious problem in inference that plagues research in this area. Variables that predict differences between people on an outcome like well-being may have no effect or even the opposite effect on the same outcome when measured as a change within the person observed over time (Martin & Hofer, 2004; Tennen & Affleck, 1996; Sliwinski, 2008). Only careful studies that evaluate changes over time in both the independent and dependent variable can safely make such assertions.

Multilevel Structural Equation Modeling Framework

In addition to designing studies of change and variation, one critical aspect of testing theories of dynamic associations is fitting appropriate statistical models of change to empirical data. In this section, we describe an analytic framework that affords many opportunities when used in conjunction with intensive repeated measurement designs. Multilevel structural equation models (MSEM) are a flexible system of models that combines features of standard multilevel models and structural equation models to allow for the ideographic and nomothetic information to be simultaneously modeled together. The MSEM framework integrates a multilevel measurement and structural model that has many advantages over a traditional multilevel modeling approach. Specifically, MSEM permits the specification of latent variables at both the within- and between-person levels of analysis, which disattenuates unsystematic measurement error from reliable true-score variance. In addition, MSEM permits variables to be specified as either exogenous or endogenous across levels of analysis allowing for a more thorough multivariate investigation of dynamic associations across levels of analysis.

A key question in the understanding of well-being is whether the covariance structure that has been identified at the between-person level with cross-sectional designs is equivalent in structure and magnitude within individuals, measured repeatedly over time. That is, are the multivariate associations structured the same way within an individual as they are across individuals? Within the MSEM framework a multilevel measurement model can be employed on intensive repeated measurement data to simultaneously examine both a within-person and between-person factor structure. The within-person factor structure reflects common covariance in the indicators at each specific occasion, pooled across occasions and individuals. The between-person factor structure reflects common covariance in individual levels of indicators

aggregated across time (i.e., person-mean level). The multilevel measurement model can be expressed by the following equation (Muthén, 1991; Preacher, Zyphur, & Zhang, 2010):

$$Y_{ij} = \nu + \lambda_w \eta_{ij} + \varepsilon_{ij} + \lambda_b \eta_i + \varepsilon_i, \quad (1.1)$$

where Y_{ij} is a p -dimensional vector of observed variables for individual i on occasion j , where p is the number of observed indicators; ν is a p -dimensional vector of intercepts; λ_w is a $p \times q$ within-person factor loadings matrix, where q is the number of latent variables; λ_b is a $p \times q$ between-person factor loadings matrix; η_{ij} and η_i are q -dimensional vectors of within-person and between-person latent variables, respectively; and ε_{ij} and ε_i are p -dimensional vectors of within-person and between-person specific factors (i.e., residuals), respectively. At the between-person level, the indicators are person means of each within-person indicator that are aggregated in order to adjust for unreliability in sampling error (see Lüdtke et al., 2008 for further details), such that the between-person indicators are represented as latent means.

Figure 1.2 provides an example of a multilevel confirmatory factor analysis (MCFA) for an adapted version of the Satisfaction with Life Scale (SWLS), measured daily for 14 consecutive days. In this case, a single factor at both the within- and between-person level fit the data extremely well, with all five items loading onto this single factor. These five items reliably covary within a person across occasions (i.e., on occasions when one item deviated from typical levels, the other four items also deviated in the same direction) and between people (i.e., individuals who were higher on one item relative to others were also higher on the other items). The within-person structure will not always match the between-person structure. For example, Rush and Hofer (2014) found that positive affect (PA) and negative affect (NA) were best represented by two inversely related factors (PA and NA) at the within-person level, but independent PA and NA factors at the between-person level.

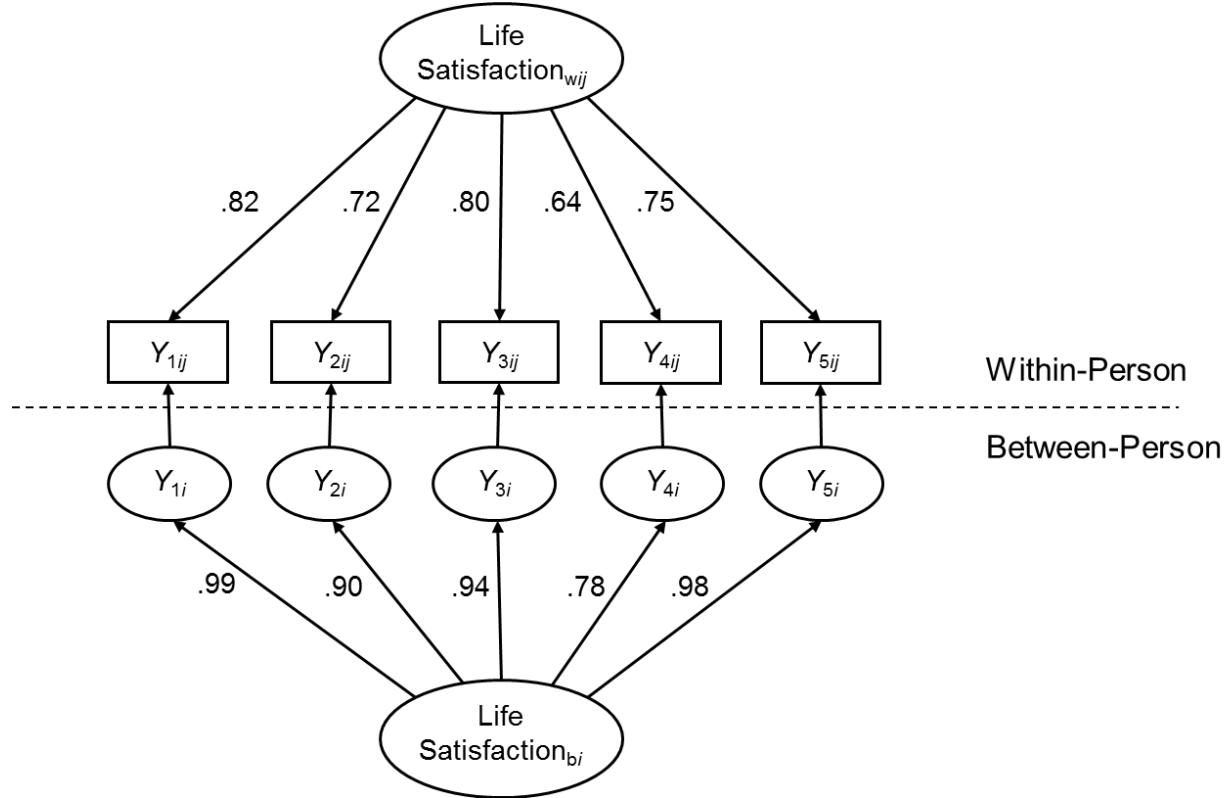


Figure 1.2. Multilevel confirmatory factor model of life satisfaction with one within-person factor and one between-person factor. Results are based on 1644 observations ($N = 147$); $\chi^2(10) = 15.83$, $p = .10$, CFI = .997, SRMR(WP) = 0.01, SRMR(BP) = 0.02, RMSEA = 0.02.

In addition to the multilevel measurement model, the MSEM framework also permits a structural model across levels of analysis. Within this framework, hierarchical data can be represented in a manner where observed variables can be specified as either exogenous or endogenous across levels of analysis, permitting simultaneous modeling of intra-individual and inter-individual mediation and moderation effects (see Chapter 2; Preacher et al., 2010; Preacher, Zhang, & Zyphur, 2016). Furthermore, the latent variables that are specified from the multilevel measurement models reflecting common covariance at the within- or between-person level, disattenuated from measurement error, can be modeled as either endogenous outcome variables, exogenous predictor variables, or both (see Chapter 4). Critically, the random effects from one level (e.g., within-person level) can be specified as a latent variable (e.g., estimated individual intercept or slope) at subsequent levels (e.g., between-person level) and simultaneously modeled as either an exogenous or endogenous individual difference variable (see Chapter 3). The very flexible nature of the structural side of MSEM can be represented in the following equations (Muthén & Asparouhov, 2009; Preacher et al., 2010):

$$\text{Level 1: } \eta_{ij} = \alpha_i + \beta_i \eta_{ij} + \zeta_{ij} \quad (1.2)$$

$$\text{Level 2: } \eta_i = \mu + \gamma \eta_i + \zeta_i, \quad (1.3)$$

where α_i is q -dimensional vector of intercepts, β_i is $q \times q$ matrix of regression coefficients for individual i ; ζ_{ij} represents level 1 residuals; μ is a q -dimensional vector of level 2 coefficient means; γ represents a $q \times q$ matrix of level 2 regression slopes; and ζ_i is a vector of level 2 residuals. Of note, η_{ij} and η_i appear on both sides of their respective equations. η_{ij} represents a vector of within-person latent variables, whereas η_i represents a vector of between-person latent variables. This vector of between-person latent variables could include latent person means aggregated from observed within-person variables, latent between-person variables representing

common covariance among indicators, or latent random slopes or intercepts representing individual differences in within-person associations and levels, respectively. The ability to include the latent variables on either side of the equation¹ permits these variables to be specified as endogenous outcomes, exogenous predictors, or both allowing a thorough examination of multivariate associations among fixed and random variables across levels of analysis. Many possible models can be incorporated within an MSEM framework in conjunction with intensive burst designs to address complex questions surrounding the dynamic nature of well-being and its intra- and inter-individual associations with other key variables.

Dissertation Structure

This dissertation consists of three distinct research studies that employ intensive repeated measurement designs and an MSEM analytic framework to address a variety of research questions concerning intra- and inter-individual predictors of well-being. Each study relies on a distinct form of sample data and applies the MSEM framework in a different way that highlights the flexibility and utility of this system of models for examining the study specific research questions. Study one (Chapter 2) simultaneously examined the multilevel moderation and mediation effects of cognitive interference on stress reactivity estimated in a 14-day daily diary design. Study two (Chapter 3) utilized measurement burst data from a large U.S. sample of adults, assessed across multiple time-scales, to examine long-term changes in short-term within-person associations. Random within-person slopes were specified as exogenous predictor variables of individual differences in global levels of psychological well-being. Finally, study three (Chapter 4) relied on simulation data to examine the conditions where specifying within-

¹The same latent variable is not predicting itself. Rather, η_i represents a vector of latent variables that vary across people and can be specified in numerous combinations with other latent variables as endogenous or exogenous.

person measurement scales as latent variables compared to unit-weighted composite scores optimized detection of within-person effects. By relying on multiple forms of sample data collected through various types of intensive measurement designs and applying different analytical approaches within the MSEM framework, this dissertation demonstrates the importance of innovative design and analysis to appropriately model and understand the complex, dynamic associations that operate within and across individuals in predicting their experiences of well-being.

Chapter 2

The Moderating and Mediating Effects of Cognitive Interference on Stress Reactivity: Intra- and Inter-Individual Associations across Levels of Analysis Using Multilevel SEM

2.1 Abstract

Cognitive interference has been shown to play a role in the day-to-day link between stressor exposure and emotional well-being and may be an underlying mechanism that either explains or moderates this association. A fourteen-day intensive measurement study examined daily levels of cognitive interference as a possible mediator or moderator of the relationship between daily stress severity and emotional well-being. A series of multilevel structural equation models simultaneously estimated the effects at both the within-person and between-person levels of analysis. Results revealed that daily levels of cognitive interference moderated the relationship between stressor severity and negative affect at the within-person level and fully mediated this relationship at the between-person level of analysis. An application of the Johnson-Neyman technique indicated that the daily effect of stress severity on negative affect was exacerbated on days when cognitive interference was higher than usual, but non-significant on days when cognitive interference was more than one SD lower than personal mean levels. The research helps clarify the differing role that cognitive interference plays as a mechanism to explain (i.e., mediate) or alter (i.e., moderate) the relationship between stressor severity and emotional well-being across multiple levels of analysis.

Keywords: Multilevel structural equation modeling, stress reactivity, cognitive interference, daily diary, Johnson-Neyman technique

2.2 Introduction

The presence of stressful experiences has consistently been related to detrimental effects on mental, physical, and emotional well-being. Major life stressors, such as job transitions, death of family members, or being diagnosed with an illness take a toll on our ability to sustain our well-being (Schneiderman, Ironson, & Siegel, 2005). Much research has been devoted to understanding the processes that enable us to be resilient in the face of major life stressors (Calhoun & Tedeschi, 2014; Hefferon, Greal, & Mutrie, 2009). Though these major life stressors have a large impact on our lives, they are relatively rare and do not afflict all of us. More recently, research has focused on understanding the impact that minor daily hassles can have on the quality of our daily experiences and emotional well-being. Negative affect has consistently been shown to be higher in the presence of daily stressors (e.g., Almeida, 2005; Rast, Hofer, & Sparks, 2012; Sliwinski, Almeida, Smyth, & Stawski, 2009; Stawski, Mogle, & Sliwinski, 2011). It has further been demonstrated that the degree of emotional reactivity to daily stressors can have detrimental effects both in the short term and over longer periods of time (e.g., Charles, Piazza, Mogle, Sliwinski, & Almeida, 2013; Mroczek et al., 2015; Piazza, Charles, Sliwinski, Mogle, & Almeida, 2013; Sin, Graham-Engeland, Ong, & Almeida, 2015). For example, individuals who consistently reported higher levels of negative affect in response to a daily stressful experience had poorer health outcomes and increased risk of morbidity up to ten years later, relative to individuals who were less emotionally reactive to daily stressors (Charles et al., 2013). Sin and colleagues (2015) found that individual differences in emotional reactivity to a daily stressor predicted levels of inflammation. Therefore, the strength of the within-person relationship between daily stress and affect is informative beyond the momentary association and a concerted effort to understand the mechanisms of this relationship is warranted. However, there

still lacks a thorough understanding of the processes that lead to this relationship. Moreover, it is unclear how individual and contextual factors exacerbate or mollify the impact of daily stress on emotional well-being (i.e., negative and positive affect).

The short-term response to stress can be adaptive and necessary to our development. Physiologically, we are designed to handle acute stressors, as it activates a response and propels our body into action to alleviate the stressor (Selye, 1956), provided that an appropriate response is activated. Indeed, short-term exposure to acute stressors has been shown to be beneficial to physiological development and functioning (Dhabhar & McEwen, 1997).

However, daily stressors may be detrimental to emotional well-being because we have the potential to carry them with us throughout our daily experiences, in our thoughts and attention, and often long after the stressor itself has been removed. The consistent focus on past stressors or possible future events may be a process through which daily stressors impact mood. Acute daily stressors may only be as harmful as the extent that they linger in our thoughts and awareness and interfere with our ability to attend to and engage with current tasks and experiences in the present moment. It has been shown that an elevated focus on negative events of the past or future can be detrimental to daily experiences of psychological and emotional well-being (Rush & Grouzet, 2012), whereas a greater engagement and attention to the present moment consistently relates to greater experiences of well-being (Brown & Ryan, 2003; Rush & Grouzet, 2012).

Stressful experiences can make it more challenging to remain attentive to the present moment. In the face of stressors, there is the tendency to perseverate on these stressors, which interrupts our present-moment attention and pulls our mind into focusing on the past or future. As the severity of the stressor increases, it may be even more difficult to not be influenced by

intrusive thoughts, and the effect may be amplified. Cognitive interference, which is the presence of intrusive, off-task thoughts that interfere with normal task-oriented thinking, has been found to be directly related to both stress and negative affect (Stawski et al., 2011). Whereas, chronic prolonged stressors contribute to the wear and tear on our system and overall deterioration (Brownley, Hurwitz, & Schneiderman, 2000; Segerstrom & Miller, 2004; Selye, 1956), it has also been proposed that repeated activation of cognitively intrusive thoughts (i.e., perseverative cognition) underlies a prolonged stress response that leads to poorer health and well-being (Brosschot, Gerin, & Thayer, 2006).

The chronic activation of perseverative or intrusive thoughts is a likely mechanism through which daily stressors impact emotional well-being as this process diminishes the potential to focus on and engage in the present moment. Cognitive interference has been examined primarily as a mediator that is believed to explain the relationship between stress and health and well-being (Brosschot et al., 2006). Specifically, intrusive thoughts increase in the presence of stressful experiences and it is these intrusive thoughts that are one potential reason for why daily stressors negatively impact health and well-being. This hypothesis was proposed from a between-person perspective, implying individual differences in tendencies to be afflicted by perseverative cognitive interference relative to others. The nature of these relationships may be theoretically and empirically distinct at the within-person (i.e., day-to-day) level that evaluates variation over time relative to one's own typical pattern.

2.2.1 Integrating Intra-Individual and Inter-Individual Processes

A common approach to understanding emotional experiences and factors that influence mood is to examine individual differences in these constructs and their interrelationships at a between-person level. The between-person approach examines whether individuals who

experience greater stress in general also experience higher levels of negative affect on average, relative to others, and what stable characteristics of the individual may explain (i.e., mediate) or alter (i.e., moderate) this relationship. Though this nomothetic approach is valuable and informative, it ignores situational and contextual influences that operate within each individual. Therefore, it is also important to understand how individuals change and vary over time based on contextual influences, and the dynamic interrelationships that unfold within individuals. This ideographic approach provides valuable insights into intra-individual processes that guide individual behaviour in the presence of varying daily exposures.

The pattern, magnitude, or direction of intra-individual (within-person) relationships do not need to be the same as inter-individual (between-person) relationships. How experiences deviate and interrelate within an individual over time, relative to what is typical of them, is not necessarily the same as how individual's average experiences interrelate relative to other individuals (Hoffman & Stawski, 2009). Furthermore, the between-person pattern of results are often confounded by within-person variability and a failure to properly disaggregate within-person variations from between-person differences can obscure results at both levels of analysis (see Curran & Bauer, 2011; Hoffman & Stawski, 2009; Rush & Hofer, 2014, 2017).

The interpretation of cognitive interference as a mediator in the relationship between stress and emotional well-being would differ depending on examining from a between-person analysis or a within-person analysis. From a between-person perspective, it would imply that individuals who experience greater stress on average also experience more intrusive thoughts on average relative to others, and it is the elevated intrusive thoughts that is the reason why these individuals also experience poorer emotional well-being relative to others. Previous research has supported this pattern of results (e.g., Nolen-Hoeksema et al., 2008; Michl et al., 2013).

On the other hand, a within-person mediation would imply that on days when an individual is exposed to stressful experiences they also experience more cognitive interference than is typical for them, and it is the elevated cognitive interference that is the reason why they experience poorer emotional well-being relative to their levels of emotional well-being on a typical day. There has been some empirical support for this pattern of results. For example multiple studies have found that rumination, a form of perseverative cognition, partially mediated the within-person link between self-report of negative daily events and negative mood (Genet & Siemer, 2012; Jose & Lim, 2015; Moberly & Watkins, 2008). However, other research has failed to detect a within-person mediation effect (e.g., Ruscio et al., 2015).

An alternative hypothesis is that cognitive interference moderates the relationship at the within-person level. A moderation model implies that individuals do not necessarily experience cognitive interference in concert with perceived stress. However, when they do report intrusive thoughts, the effect of stress severity on negative affect is exacerbated. Thus, the strength of the within-person association between stress severity and affect depends on the degree of cognitive interference. Research that has examined similar constructs to cognitive interference (e.g., rumination) as an effect modifier of the within-person relationship between negative daily events and negative mood has found some support for this hypothesis (Connolly & Alloy, 2017; Genet & Siemer, 2012). There is currently no empirical evidence for cognitive interference as a moderator of the between-person relationship between stress and emotional well-being.

To date, research has typically examined either within-person relationships or between-person relationships when examining the mechanism of perseverative cognitions as either a mediator or moderator in the link between stress and emotional well-being. The present study examined both within-person and between-person processes simultaneously through a series of

multilevel structural equation models (MSEM). Simultaneous modeling of within-person and between-person relationships permits the intra-individual variance to be disaggregated from the inter-individual variance and enables a more appropriate examination of both levels of analysis (Curran & Bauer, 2011; Hoffman & Stawski, 2009; Preacher et al., 2010, 2016).

Furthermore, much of the research examining daily stressors have looked at the effect of experiencing a stressor compared to non-stress days, or has looked at the number of negative daily events. The present research examines these interrelationships upon exposure to one or more stressors. Because cognitive interference may be particularly influential in moments of stress, looking at the role of cognitive interference in the presence of exposure to a stressor isolates the situations that may be most useful to understand. Thus, the current research examines the overarching question: when exposed to a stressor, how does the severity of the stressor impact affect and what is the role of cognitive interference in explaining or altering this relationship.

2.2.2 Present Study

The present study utilized an intensive repeated measurement design to examine the effects of daily stress severity and cognitive interference on negative and positive affect over 14 days. To date, research has examined the unique effects of stress and cognitive interference on negative affect and have found that each uniquely accounts for negative affect over and above what the other explains (Stawski et al., 2011). However, it has yet to be examined whether cognitive interference interacts with stress severity to differentially predict emotional well-being. The present study extends previous research in several important ways. First, cognitive interference was examined as a mediator and moderator at both the within-person and between-person level simultaneously within the same statistical models, permitting an unconfounded

examination at both levels of analysis. Second, the pattern of relationships were examined upon exposure to naturally occurring daily stressors. This approach provides insight into the importance of cognitive interference under varying conditions of daily stress severity. It is in these situations of heightened stressful experiences where the role of cognitive interference is likely to be the most informative as a mechanism to understand the relationship between stress and emotional well-being. Finally, the present study examined both negative and positive affect as an outcome of emotional well-being. Most research to date has only examined the associations between stress and negative affect. Less is known about the within- and between-person associations between stress, cognitive interference and positive affect. There is recent evidence to suggest that the within-person association between stress and positive affect is also an informative indicator of the individual and is predictive of health outcomes (e.g., Mroczek et al., 2015; Sin et al., 2015). Therefore, investigating the mechanisms underlying the association between stress severity and positive affect could also provide valuable insights.

It is expected that the disaggregation of within-person and between-person effects will clarify the mediating and moderating role of cognitive interference. Daily variations in cognitive interference are hypothesized to moderate the within-person relationship between daily levels of stress severity and emotional well-being. The strength of the association between an individual's daily stress severity and daily negative affect will be higher on days when their cognitive interference is higher than their personal mean level, but weakened if their cognitive interference is lower than their personal mean level. Thus, even when exposed to daily stressors if individuals are able to remain focused on the present moment and engaged in their current tasks, then the increased severity of stressors are not expected to have as detrimental an impact on their daily negative affect compared to when they are disrupted by intrusive, off-task cognitions.

Average levels of cognitive interference across the fourteen days are hypothesized to mediate the between-person relationship between average levels of stress severity and average levels of negative affect. Based on previous research it is reasonable to expect that individuals who typically experience greater stress severity relative to others also experience more cognitively intrusive thoughts relative to others, and higher levels of negative affect relative to others. It is hypothesized that the consistently high levels of cognitive interference will fully account for why these individuals also experience higher levels of negative affect than those with less average stress severity. Similar patterns of within- and between-person relationships are expected for positive affect. However, because exposure to stressors tends to be more strongly related to negative affect, it is anticipated that the magnitude of the effects will be smaller when examining positive affect as the outcome.

2.3 Method

2.3.1 Participants and Procedure

One hundred forty-seven undergraduate students (87% female; $M_{age} = 19.9$, $SD = 3.2$) were recruited through a university-based participant pool in exchange for extra credit in a psychology course. Participants were invited to an instruction session where they completed a preliminary web-based questionnaire consisting of demographic information and were informed of the protocol for completing the daily diary portion of the study. Beginning on the following day, participants completed a daily web-based questionnaire each evening for 14 consecutive days between the hours of 6:00 pm and 2:00 am. Daily questionnaires that were not completed during that period were considered missing. Each questionnaire consisted of daily measures of positive and negative affect, cognitive interference, and stressors. Of a possible 2,058 daily questionnaires (147 participants X 14 days), data for 1,644 complete days were obtained (80%;

$M_{occasions} = 11.2$). Given that the research question was focused on the severity of stressful days, only days where a stressful event had been reported were retained for the analyses, leaving data for 972 days from 144 participants.

2.3.2 Measures

Positive and Negative Affect. Positive and negative affect were assessed using the Positive and Negative Affect Schedule (PANAS; Watson, Clark, & Tellegen, 1988). Participants were presented with a list of 20 emotions and asked to indicate to what extent they had felt each emotion in the past 24 hours. Responses ranged from 1 (*very slightly or not at all*) to 5 (*extremely*). Daily negative and positive affect scores were computed by averaging across the respective items ($M_{NA} = 1.70$, $SD = 0.65$ and $M_{PA} = 2.70$, $SD = 0.74$). To eliminate order effects, the order of the items was randomly presented at each occasion. Both within-person and between-person reliability estimates were good for negative affect ($\omega = .82$ and $.97$, respectively) and positive affect ($\omega = .84$ and $.96$, respectively).

Cognitive interference. Cognitive interference (CI) was measured using the short cognitive interference measure (SCIM; Stawski et al., 2011). This six-item measure assessed the frequency of experiencing intrusive thoughts (e.g., “In the last 24 hours, how often did you think about something you didn’t mean to?”) and attempts to avoid thinking about certain thoughts (e.g., “In the last 24 hours, how often did you try to avoid certain thoughts?”). Participants responded on a 1 (*never*) to 10 (*constantly*) scale. A daily cognitive interference score was computed by averaging across the six items ($M = 3.96$, $SD = 1.28$). Reliability was high at both within-person and between-person level ($\omega = .84$ and $.96$, respectively).

Stress severity. Daily stressors were assessed using the Daily Inventory of Stressful Events (DISE; Almeida, Wethington, & Kessler, 2002). The inventory consisted of six questions

inquiring whether certain types of stressors had been experienced in the last 24 hours (e.g., “In the past 24 hours, did you have an argument or disagreement with anyone?”). When a stressor was reported, participants then indicated the severity of the stressor from 1 (*not at all*) to 4 (*very stressful*). A daily stress severity score was computed by averaging the severity of any stressors reported ($M = 2.73$, $SD = 0.80$), as has been done previously (see Stawski, Sliwinski, Almeida, & Smyth, 2008).

2.3.3 Data Analytic Strategy

Multilevel structural equation modeling analyses were used to handle the hierarchical structure of the data in which daily measurement occasions were nested within people. Multilevel models allow the intra-individual variability to be systematically modeled at the day-level (Level 1) and the inter-individual variability to be modeled at the person-level (Level 2). That is, within-person fluctuations (i.e., daily deviations from their personal mean) across days and between-person differences can be estimated and accounted for in a systematic manner. Furthermore, MSEM permits variables at both levels of analysis to be treated as both endogenous and exogenous, enabling explicit examination of cognitive interference as a moderating or mediating variable at the within- and between-person levels (Preacher et al., 2016, 2010).

The daily within-person fluctuations enable a thorough understanding of the day-to-day processes of stress, cognitive interference, and their relationship with NA and PA. The use of within-person coupling procedures (Hoffman & Stawski, 2009), in which daily fluctuations in affect are accounted for by daily fluctuations in stress and cognitive interference gives an indication that the variables travel (i.e., covary) together, such that a deviation in one variable is

reliably associated with a deviation in the other. The daily (within-person) and average (between-person) moderation of CI on the effect of stress severity on affect can be displayed as follows:

$$\text{Level 1: } \text{Affect}_{ij} = \beta_{0i} + \beta_{1i}(\text{Stress}_{ij}) + \beta_{2i}(\text{CI}_{ij}) + \beta_{3i}(\text{Stress}*\text{CI}_{ij}) + r_{ij} \quad (2.1a)$$

$$\text{Level 2: } \beta_{0i} = \gamma_{00} + \gamma_{01}(\text{pm_Stress}_i) + \gamma_{02}(\text{pm_CI}_i) + \gamma_{03}(\text{pm_Stress}*\text{pm_CI}_i) + u_{0i} \quad (2.1b)$$

$$\beta_{1i} = \gamma_{10} + u_{1i} \quad (2.1c)$$

$$\beta_{2i} = \gamma_{20} + u_{2i} \quad (2.1d)$$

$$\beta_{3i} = \gamma_{30} + u_{3i} , \quad (2.1e)$$

where Affect_{ij} is the affect (negative or positive affect) score for person i on day j . β_{0i} refers to the predicted affect score for an average occasion of stress severity and CI for person i ; β_{1i} and β_{2i} represent the slope coefficients for daily stress severity and CI (i.e., the within-person relationship), respectively; β_{3i} is the within-person daily interaction effect; Stress_{ij} and CI_{ij} represent the person-mean centered stress severity and CI scores for person i on day j , respectively; $\text{Stress}*\text{CI}_{ij}$ represents the daily interaction term of stress severity and CI for person i on day j ; and r_{ij} represents the within-person residual variance in daily affect. At Level 2, γ_{00} represents the average intercept; γ_{10} and γ_{20} represent the average within-person effect of stress severity and CI on affect, respectively; γ_{30} is the average within-person interaction of CI on the effect of stress severity on affect; γ_{01} and γ_{02} represent the between-person association between average daily affect and average stress severity and CI, respectively; γ_{03} is the between-person interaction of CI on the effect of stress severity on affect; and u_{0i} to u_{3i} , represent individual deviations from average intercepts and slopes (i.e., random effects).

In order to appropriately model the within-person moderation, both the stress severity and cognitive interference variables were person-mean centered prior to creating the interaction term (i.e., $\text{Stress} * \text{CI}_{ij}$). This approach removes the between-person variance from the within-person interaction term and permits both the within- and between-person moderation to be examined without conflating the combined within- and between-person effects (Preacher et al., 2016). As a result, the within-person interaction term indicates how the effect of daily deviations in stress severity (from one's personal mean level) on daily affect is dependent on their daily deviations in cognitive interference. Whereas, the between-person interaction term indicates how the effect of an individual's average stress severity on their average level of affect is dependent on their average level of cognitive interference.

Significant moderations were further probed using the Johnson-Neyman technique that examines the effects of stress severity on affect continuously across the full range of cognitive interference (the moderating variable) in order to identify the regions of statistical significance, that is, the exact boundary values where the moderator elicits an effect. This approach is advantageous compared to the typical pick a point approach to probe interactions, which rely on arbitrary values of the moderating variable (Bauer & Curran, 2005; Rast, Rush, Piccinin, & Hofer, 2014).

Finally, multilevel SEMs were used to examine the role of cognitive interference as a mediating variable in the relationship between stress severity and affect across levels of analysis. This was accomplished by including cognitive interference as both an endogenous variable, predicted by stress severity, and an exogenous variable predicting affect. In order for cognitive interference to act as a mediator, the relationship between stress severity and affect would have to be reduced following the inclusion of cognitive interference into the model. Furthermore, the

indirect effect of stress severity on affect through cognitive interference would need to be statistically significant (Preacher et al., 2010; Hayes, 2013). Multilevel SEM allowed for the within- and between-person mediation and moderation model to be estimated simultaneously. Mplus v7 software (Muthén & Muthén, 2012) was used to fit all models, which were estimated using full information maximum likelihood with robust standard errors (MLR).

2.4 Results

A series of multilevel SEMs were carried out with each model building upon the previous (see Table 2.1). Model 1 tested the empty model, which partitioned the variance in NA and PA into within-person (WP) and between-person (BP) variability. Calculation of the intraclass correlation coefficient (ICC) indicated that the percentage of within-person variance in NA and PA was approximately 57% and 58%, respectively.

2.4.1 Within- and Between-Person Relationships

Model 2 included daily stress severity, which was person-mean centered on each individual's mean to control for individual differences in mean level (Hoffman & Stawski, 2009), as a WP predictor and person-mean stress severity (centered at the grand mean) as a BP predictor. As can be seen in Tables 2.1 and 2.2, stress severity predicted NA and PA at both the WP and BP level. On days when stress severity was higher than usual (i.e., higher than an average day), participants reported higher NA (*estimate* = 0.26, *SE* = .02, *p* < .001) and lower PA (*estimate* = -0.14, *SE* = .03, *p* < .001). Similarly, individuals who had higher stress severity on average over time relative to others also reported higher NA on average (*estimate* = 0.29, *SE* = .09, *p* = .001) and lower PA on average (*estimate* = -0.19, *SE* = .08, *p* = .02). Pseudo- R^2 revealed that stress severity accounted for 14% of the within-person variance in daily NA and 4% in daily PA.

Table 2.1

Multilevel SEM analyses of the effects of daily stress severity and cognitive interference on negative affect.

Variable	Model 1	Model 2	Model 3	Model 4
	Estimate (<i>SE</i>)	Estimate (<i>SE</i>)	Estimate (<i>SE</i>)	Estimate (<i>SE</i>)
Fixed Effects				
Within-person variables				
Intercept (γ_{00})	1.699 (.040)***	1.695 (.037)***	1.672 (.031)***	1.617 (.031)***
Stress (γ_{10})	—	0.258 (.024)***	0.180 (.021)***	0.174 (.020)***
CI (γ_{20})	—	—	0.161 (.012)***	0.154 (.012)***
Stress X CI (γ_{30})	—	—	—	0.080 (.024)***
Between-person variables				
Mean Stress (γ_{01})	—	0.292 (.090)**	0.106 (.064)	0.100 (.065)
Mean CI (γ_{02})	—	—	0.229 (.034)***	0.220 (.031)***
Mean Stress X Mean CI (γ_{03})	—	—	—	0.102 (.068)
Random effects				
Within-person (σ_e^2)	0.240 (.022)***	0.206 (.019)***	0.155 (.015)***	0.141 (.015)***
Between-person				
Intercept (σ_0^2)	0.182 (.049)***	0.165 (.040)***	0.104 (.024)***	0.094 (.020)***
Stress (σ_1^2)	—	0.006 (.014)	0.006 (.010)	0.003 (.010)
CI (σ_2^2)	—	—	0.005 (.002)*	0.005 (.002)
Stress X CI (σ_3^2)	—	—	—	0.023 (.010)*

Note. Results are based on 972 daily assessments ($N = 144$). CI = cognitive interference; Stress = stressor severity.

* $p < .05$. ** $p < .01$. *** $p < .001$.

Table 2.2

Multilevel SEM analyses of the effects of daily stress severity and cognitive interference on positive affect.

Variable	Model 1	Model 2	Model 3	Model 4
	Estimate (<i>SE</i>)	Estimate (<i>SE</i>)	Estimate (<i>SE</i>)	Estimate (<i>SE</i>)
Fixed Effects				
Within-person variables				
Intercept (γ_{00})	2.698 (.045)***	2.701 (.044)***	2.717 (.031)***	2.730 (.047)***
Stress (γ_{10})	—	-0.144 (.028)***	-0.101 (.029)***	-0.101 (.030)***
CI (γ_{20})	—	—	-0.087 (.018)***	-0.086 (.018)***
Stress*CI (γ_{30})	—	—	—	-0.010 (.031)
Between-person variables				
Mean Stress (γ_{01})	—	-0.194 (.083)*	-0.140 (.097)	-0.141 (.089)
Mean CI (γ_{02})	—	—	-0.059 (.037)	-0.055 (.036)
Mean Stress*Mean CI (γ_{03})	—	—	—	-0.053 (.058)
Random effects				
Within-person (σ_e^2)	0.320 (.021)***	0.309 (.021)***	0.281 (.021)***	0.280 (.022)***
Between-person				
Intercept (σ_0^2)	0.233 (.034)***	0.226 (.033)***	0.220 (.032)***	0.219 (.032)***
Stress (σ_1^2)	—	0.002 (.011)	0.004 (.011)	0.005 (.014)
CI (σ_2^2)	—	—	0.009 (.004)*	0.009 (.004)*
Stress*CI (σ_3^2)	—	—	—	0.002 (.035)

Note. Results are based on 972 daily assessments ($N = 144$). CI = cognitive interference; Stress = stressor severity.

* $p < .05$. ** $p < .01$. *** $p < .001$.

Model 3 added to Model 2 by including daily cognitive interference (person-mean centered) as a WP predictor and mean cognitive interference (grand-mean centered) as a BP predictor, which enabled for the unique effects of stress severity and CI to be identified after accounting for the other. Stress severity remained a significant predictor of both NA and PA at the WP level after accounting for daily CI (see Tables 2.1 and 2.2). Furthermore, CI also uniquely predicted daily NA and PA, such that on days when CI was higher than usual, NA was also higher ($estimate = 0.16, SE = .01, p < .001$) and PA was lower ($estimate = -0.09, SE = .02, p < .001$). The inclusion of CI accounted for 25% of the WP variability in NA over and above what stress severity accounted for, and 9% of the WP variability in PA. At the BP level, average stress severity was no longer a significant predictor of NA or PA after adjusting for the effects of average CI. Conversely, average CI did uniquely predict NA after adjusting for average stress severity. Individuals who reported greater CI on average over time also reported greater NA. Average CI did not uniquely predict PA.

Multilevel Mediation and Moderation Models. Model 4 simultaneously estimated the daily (within-person) and average (between-person) moderation of CI on the effect of stress severity on affect. The daily effect of stress severity on NA was moderated by daily CI ($estimate = 0.08, SE = .02, p < .001$). However, the between-person effect of stress severity was not found to be moderated by average CI ($estimate = 0.10, SE = .07, p = .13$). There was no moderating effect of CI on the relationship between stress severity and positive affect at either the within- or between-person level.

Model 4 was extended to simultaneously test the role of cognitive interference as a mediator of the relationship between stress severity and affect at both the within-person and between-person levels (see Figure 2.1). Results revealed that CI fully mediated the relationship

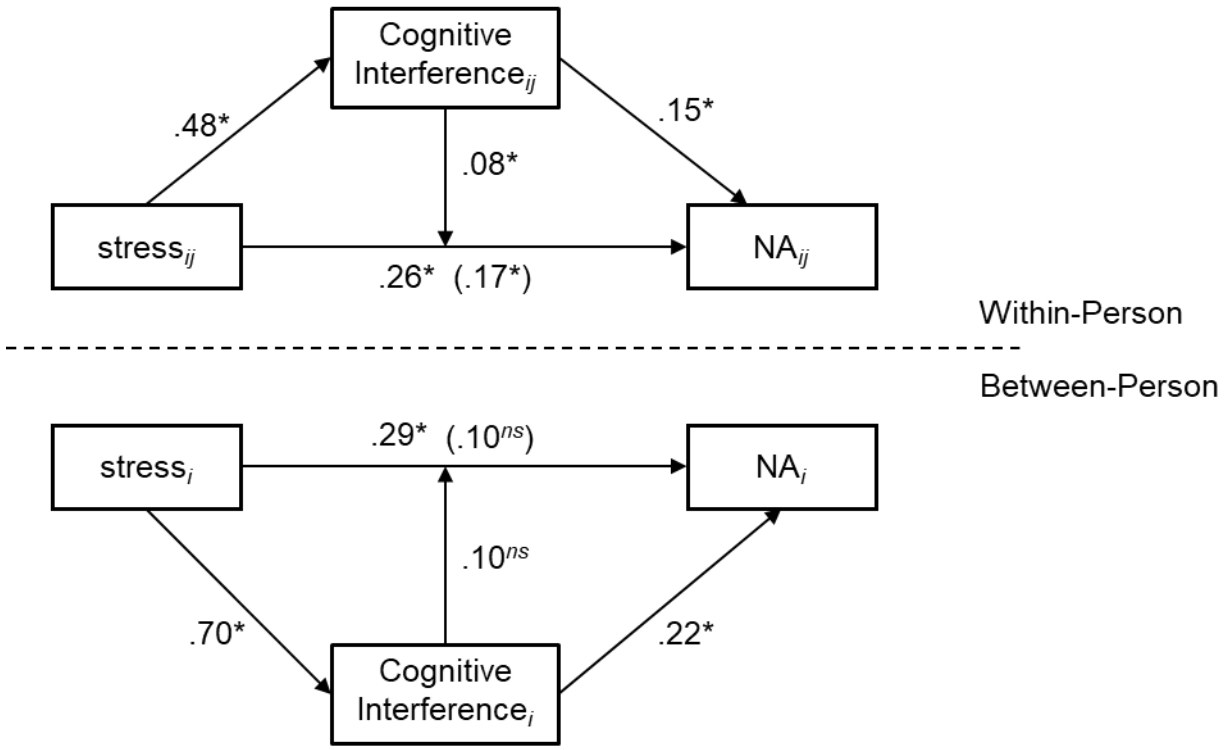


Figure 2.1. Multilevel SEM of within-person moderation and between-person mediation. Note. Values are unstandardized parameter estimates. Values in parentheses are path coefficients after including the effect of the mediator. Indirect pathway from stress severity to NA through cognitive interference was significant at both the within-person and between-person levels (estimate = 0.08, SE = .01, $p < .001$ and estimate = 0.16, SE = .06, $p = .004$, respectively). * $p < .001$; ns = $p > .10$. Model fit indices: $\chi^2(2) = 6.86$, $p = .03$; RMSEA = .05; CFI = .98; SRMR_{within} = .040, SRMR_{between} = .049.

between stress severity and NA at the between-person level. That is, the relationship between an individual's average amount of stress severity and average NA was fully accounted for by individual differences in average levels of cognitive interference. Average amounts of stress severity were significantly related to average levels of NA on their own, however, when cognitive interference was entered into the model the direct effect of stress severity on NA was no longer significant, whereas cognitive interference uniquely predicted NA over and above the effects of stress severity. Furthermore, the indirect effect of stress severity on NA through cognitive interference was statistically significant (*estimate* = 0.16, *SE* = .06, *p* = .004). To formally examine if the direct effect of stress severity on NA was reduced, an additional model was run that constrained the between-person pathway of stress severity and NA to zero. A chi-square difference test revealed that constraining this pathway to zero did not significantly reduce the model fit when compared to the model that freely estimated the pathway ($\Delta\chi^2(1) = 3.23, p = .07$). Therefore, it can be concluded that the between-person effect of stress severity on NA is essentially reduced to zero and this effect is fully explained through cognitive interference.

At the within-person level, daily cognitive interference partially mediated the daily relationship between stress severity and negative affect. Though the direct effect of stress severity on NA was still significant after including cognitive interference in the model, it was slightly reduced (from .26 to .17) and the indirect effect of daily stress severity predicting NA through daily cognitive interference was statistically significant (*estimate* = .08, *SE* = .01, *p* < .001). Daily cognitive interference also partially mediated the within-person effect of stress severity on positive affect. The indirect effect of daily stress severity on PA through daily cognitive interference was statistically significant (*estimate* = -0.04, *SE* = .01, *p* < .001) and the

direct effect of stress severity on PA was slightly reduced from -0.14 to -0.10 , though still statistically significant.

In sum, cognitive interference moderated the effect of stress severity on NA at the within-person, but not at the between-person level, and fully mediated the effect at the between-person level, but only partially mediated at the within-person level. The moderating and mediating role of cognitive interference on the effect of stress severity on PA was minimal, only partially mediating the within-person effect.

Probing Within-Person Moderation using the Johnson-Neyman Technique. In order to further understand the moderating role of cognitive interference on the daily (within-person) effect of stress severity on NA, the Johnson-Neyman technique was employed (Bauer & Curran, 2005; Preacher, Curran, & Bauer, 2006; Rast et al., 2014). This technique allows for the identification of the specific values of cognitive interference where stress severity is significantly related to negative affect. Figure 2.2 reveals that on days when individuals report higher stress severity than usual and typical levels of cognitive interference, their negative affect is higher (*simple slope* = 0.17, *SE* = 0.02, $p < .001$, when *CI* = mean). This effect is exacerbated when the individual also experiences higher levels of daily cognitive interference than usual (*simple slope* = 0.28, *SE* = 0.04, $p < .001$, when *CI* = +1 SD). Conversely, on days when *CI* is lower than usual, the effect of stress severity on negative affect is mollified (*simple slope* = 0.07, *SE* = 0.04, $p = .05$). Indeed, results from the Johnson-Neyman technique revealed that when cognitive interference was more than 1 SD below an individual's typical level, the effect of stress severity on negative affect was no longer statistically significant (see Figure 2.3). Thus, the impact of stress severity on NA worsened on days when *CI* was higher than usual. However, greater stress

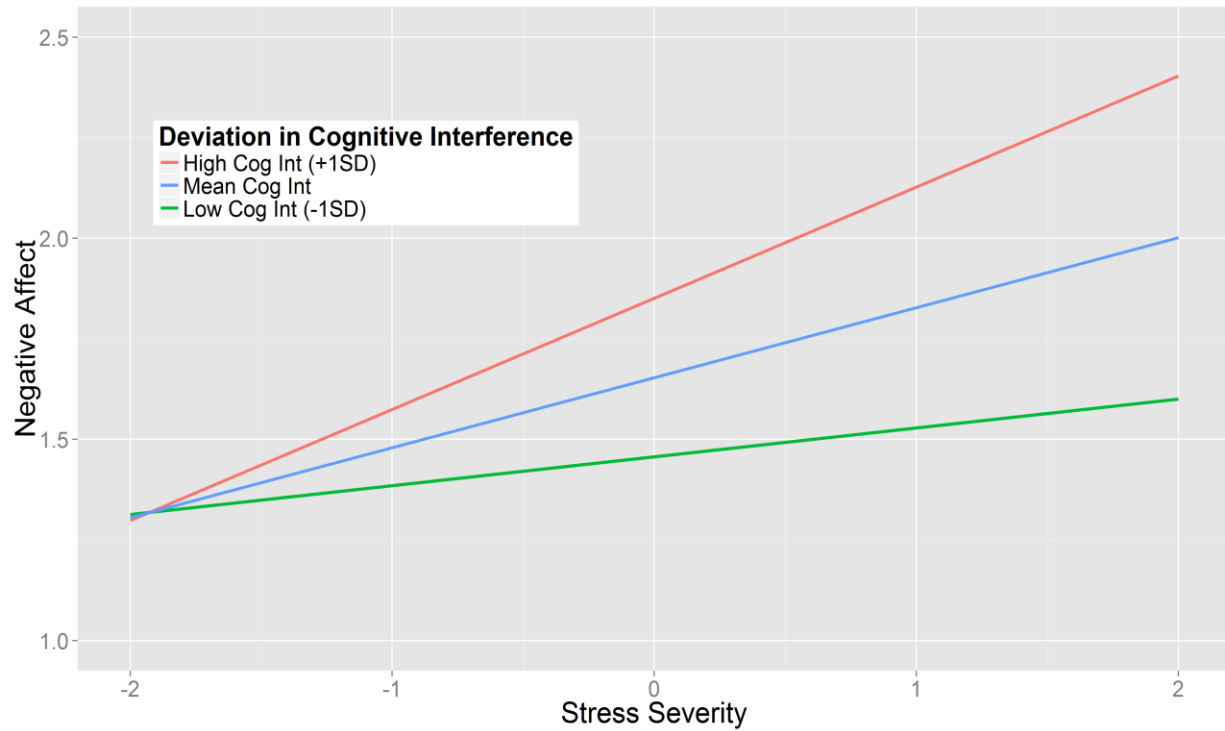


Figure 2.2. Simple slope of the within-person effect of stress severity on negative affect at high (+1 SD), mean, and low (-1 SD) levels of daily cognitive interference. All lines are statistically different from zero ($p \leq .05$).

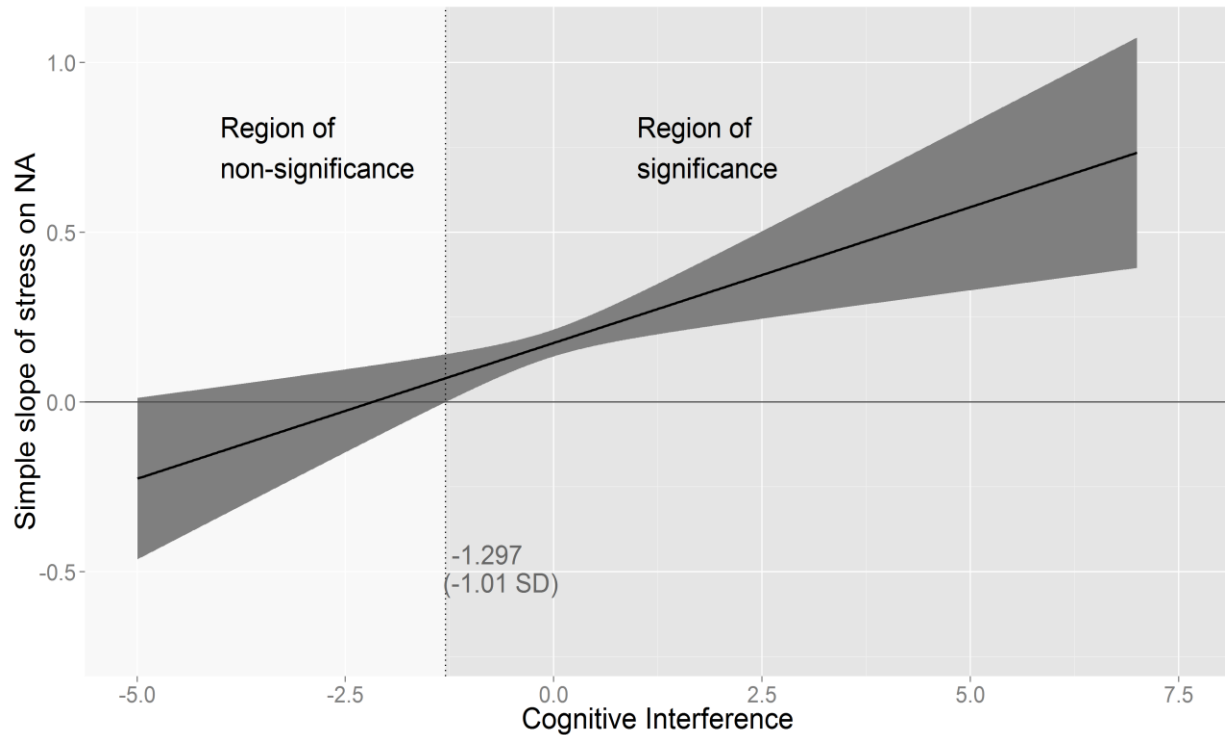


Figure 2.3. Johnson-Neyman technique to identify regions of significance. The simple slope of the within-person effect of stress severity on negative affect (NA) is shown across varying levels of cognitive interference (thick black line). The gray bands represent the 95% confidence interval that can be used to infer statistical significance. When the horizontal zero line is included in the confidence bands, the simple slope is not statistically significant at that value of cognitive interference. The vertical hatched line denotes the boundary value of cognitive interference where the effect of stress severity on NA is no longer statistically significant.

severity did not significantly influence NA on days when cognitive interference was more than one SD below mean levels.

2.5 Discussion

The present research examined the extent to which cognitive interference explains (i.e., mediates) or alters (i.e., moderates) the relationship between stress severity and emotional well-being in the context of naturally occurring stressors during daily life. These relationships were simultaneously examined at both the within-person and between-person levels of analysis through the application of a series of multilevel structural equation models employed on intensive repeated measurement data. Results revealed that the role of cognitive interference differed when examined at the intra-individual (within-person) or inter-individual (between-person) level of analysis. At both levels, however, cognitive interference emerged as an important mechanism for understanding the link between stress severity and emotional well-being.

2.5.1 Intra-Individual Relationships

As had been demonstrated in previous research, the severity of daily stressors predicted negative and positive affect at the within-person level (see Tables 2.1 & 2.2, Model 2). That is, on days when individuals reported a stressor to be more severe than on a typical stress day, their level of negative affect was higher and positive affect was lower compared to days when the stressor(s) were rated as less severe. Furthermore, daily levels of cognitive interference were also related to negative and positive affect (see Tables 2.1 & 2.2, Model 3). On days when an individual experienced more intrusive thoughts than was typical for them, they also experienced greater NA and less PA compared to days when they experienced fewer intrusive thoughts. These within-person associations are consistent with what is known about the link between daily

stressful experiences, cognitive interference, and emotional well-being (e.g., Almeida, 2005; Stawski et al., 2009, 2011).

Within-person moderation. Daily cognitive interference was shown to moderate the within-person relationship between stress severity and negative affect. On a day-to-day basis, when faced with a daily stressor, the severity of that stressor predicted the level of negative affect, where days that had more severe stressors than typical resulted in higher negative affect than usual. However, the level of cognitive interference altered the relationship between stress severity and negative affect. That is, when the individual experienced more cognitive interference than was typical for them, the severity of the stressor had a stronger impact on the level negative affect experienced. Conversely, on days when the individual was able to limit the degree of cognitive interference to a level that was less than typical (i.e., more than 1 SD below their personal average daily level), then the severity of the stressor was no longer indicative of the amount of negative affect experienced on that day (see Figures 2.2 & 2.3). The within-person moderation effect is consistent with previous research that has examined other forms of perseverative cognitions, such as rumination, as a moderator of the relationship between daily stress and negative mood (Connolly & Alloy, 2017; Genet & Siemer, 2012; Jose & Lim, 2015). A clear picture is emerging from the research that the strength of the within-person relationship between stress and negative affect is dependent on the co-occurrence of intrusive thoughts. Therefore, reducing the amount of cognitive interference that occurs when faced with a daily stressor appears to be an effective strategy to mollify the detrimental effect that stress severity has on emotional well-being (specifically, negative affect).

Within-person mediation. Daily cognitive interference partially mediated the within-person relationship between stress severity and both negative and positive affect. When stress

severity was higher within an individual than their typical day, there was a tendency for them to also report more intrusive thoughts than their average day, and the greater level of cognitive interference partially accounted for their higher levels of NA and lower levels of PA on those days. Though this mediation effect was minimal, it does corroborate previous research that has shown perseverative cognitions to partially explain the link between stress and affect (Genet & Siemer, 2012; Jose & Lim, 2015; Moberly & Watkins, 2008).

2.5.2 Inter-Individual Relationships

At the between-person level, individuals who reported stressors as more severe on average across the fourteen days also experienced higher NA and lower PA on average relative to individuals who reported stressors as less severe on average (see Tables 2.1 & 2.2, Model 2). Similar to the within-person effect, individuals who experienced more cognitive interference on average also experienced more NA and less PA on average across the fourteen days, relative to individuals who experienced less cognitive interference on average. Furthermore, stress severity was directly related to cognitive interference. Individuals who consistently reported stressors that were perceived to be more severe had a tendency to have more intrusive thoughts than individuals who reported less severe stressors.

Between-person mediation. The between-person relationship between average stress severity and negative affect was fully mediated by an individual's average level of cognitive interference. That is, those who experienced greater stress severity on average also experienced greater cognitive interference on average and adjusting for individual differences in cognitive interference accounted fully for higher negative affect in these individuals. Evidence of the between-person mediation effect supports the perseverative cognition hypothesis proposed by Brosschot and colleagues (2006) that persistent intrusive thoughts prolong the stress response

and it is this tendency to carry the stressor with us in our thoughts and attention that accounts for the detrimental link between minor daily hassles and emotional well-being. This mediation effect is also consistent with cross-sectional research that has found similar constructs (i.e., rumination) to mediate the links between stress and mood (Nolen-Hoeksema, 1991).

The current research extends these previous findings by examining the severity of stressors, rather than merely the occurrence of stressors, and how cognitive interference explains the impact of greater stress severity. The current results reveal cognitively interfering thoughts are particularly problematic as stress severity increases and individuals who experience greater stressor severity on average are particularly prone to greater cognitive interference. Furthermore, upon exposure to a daily stressor, the extent that one is inundated with intrusive, off-task thoughts alters the relationship between the severity of the stressor and coinciding negative affect. Results from the Johnson-Neyman technique suggest that if an individual can limit their daily cognitive interference, then the severity of the stressor no longer relates to the higher levels of negative affect.

This research has important implications for targeting interventions to reduce the detrimental consequences that elevated stress reactivity may bring about. It has become evident that the strength of the daily within-person relationship between stress and emotional well-being is indicative of a number of concurrent and future health and well-being outcomes (Charles et al., 2013; Piazza et al., 2013; Sin et al., 2015). Identifying processes that attenuate this detrimental relationship could help improve health and well-being over both short and long-term periods of time. Cognitive interference appears to be a process that both explains and alters the stress-affect relationship within the individual on a daily level. Rather than attempting to reduce the severity of the stressor (or perceptions of its severity), a more effective strategy could be to target the

extent that the individual is cognitively pulled away from the present moment and obstructed from engaging in their current tasks. There is some evidence suggesting that increasing levels of mindfulness successfully reduces emotional reactivity in randomized control trials (Britton, Shahar, Szepsenwol, & Jacobs, 2012).

It is important to note the distinction between the within-person and between-person patterns of results. Even though on average, individuals who perceived their stressors to be more severe generally have higher levels of cognitive interference on average, and it is the higher CI that fully accounts for why they experience greater NA on average relative to individuals who report less severe stressors. When examining these patterns on a day-to-day basis from a within-person perspective, there are days when individuals, who on average are relatively low in cognitive interference compared to others, still experience greater cognitive interference relative to their own average level. Conversely, there are days when individuals, who on average are relatively high in cognitive interference compared to others, still experience less cognitive interference relative to their own average level. These daily variations in cognitive interference (relative to the individual's average level) are moderating the association between daily stress severity and NA. On any given day, if the individual is experiencing fewer intrusive, off task thoughts than is typical for them, then their negative affect will be less impacted by the severity of the stressors they report. Whereas, when the individual experiences more intrusive thoughts, their negative affect on that day will more strongly relate to the severity of the stressor. Therefore, this research also highlights that the experience of cognitive interference is not only a problem for people who are chronically afflicted, but can also impact those low on average, but high on a particular day. By modeling the within- and between-person effects simultaneously within the same multilevel SEM, the two levels of analysis were disaggregated from each other

and have clear interpretations. As a result, the models allowed for a proper examination of the pattern of results at both the within- and between-person levels, revealing the role that cognitive interference plays within individuals over time, as well as across individuals.

2.5.3 Limitations and Future Directions

A limitation of the present study was the use of a university student sample. There is evidence that the nature of emotional experience differs between young and older adults (Carstensen, Isaacowitz, & Charles, 1999). Older adults have been shown to be less variable in their day-to-day affect than younger adults and may not be as reactive to stressors (Röcke, Li, & Smith, 2009). Furthermore, age has been shown to moderate the within-person association between daily stress exposure and cognitive interference in older adults (Stawski et al., 2011). It is possible that younger adults, particularly students, will be differentially affected by cognitive interference. The demands of university life may require differential amounts of daily cognitive effort, and being pulled away from the moment through intrusive, off-task cognitions may be particularly agitating (emotionally disruptive) in their attempt to deal with their cognitive load. The nature and perceptions of stress severity may also be systematically different in this population. Though the pattern of results observed in the present research are not expected to differ much across populations, it is unclear to what extent the magnitude of the effects would generalize across populations. The pattern of these relationships should be further investigated empirically by examining non-student populations that vary in educational and occupational backgrounds, as well as across different age groups and cohorts.

Additionally, it will be important for future research to investigate specific contextual factors that lead to daily levels of cognitive interference. There is potential to examine the specific conditions that may interact to reduce cognitive interference in the face of stressors (e.g.,

physical activity, meditation, etc.). This would require analyzing an additional layer of interacting contextual variables that co-occur within each individual's day-to-day experiential environment. A better understanding of these contextual variables will be important in guiding interventions designed to reduce the degree of cognitive interference.

Evidence from mindfulness-based interventions have shown promise as an approach to enhance present-moment awareness to help mitigate the prevalence of intrusive thoughts (Ainsworth, Bolderston, & Garner, 2017) and also to reduce emotional reactivity to stressors (Britton et al., 2012). Further research into the implementation and evaluation of interventions that aim to reduce intrusive thoughts in response to naturally occurring stressful experiences will be an important practical application of the current research. If reducing cognitive interference effectively mollifies the stress-mood relationship, then it should also attenuate the impact on health outcomes. Extending research to examine the impact of daily cognitive interference on physical manifestations of stress exposure, such as physical symptoms, blood pressure, and heart rate will help to elucidate the role of cognitive interference and the prolonged stress response has on physiological outcomes.

Finally, it is also important to note that these models represent a pattern of relationships from which we cannot infer a causal direction. Though the pattern is consistent with both previous research and a coherent theoretical direction, it is still plausible that the direction of results operates in a different ordering. A more fine-tuned temporal sequencing of experiences could help to elucidate the causal pattern by establishing whether intrusive thoughts follow the stressful experience, which ultimately leads to changes in emotional well-being. However, in the absence of true experimental designs, the direction of the causal relationship will remain unclear.

2.5.4 Conclusions

Cognitive interference is an important variable to consider when investigating the relationship between stress and emotional well-being. Results indicate that the increased presence of cognitive interference serves to exacerbate the impact that daily stressors have on negative emotions. Therefore, the ability to minimize these intrusive, off-task thoughts (by continuing to engage in and attend to the present moment) may be an effective strategy to mitigate the impact of stressors on our experiences of negative affect. It is in the face of greater stress severity that this task becomes more challenging as the tendency to experience cognitive interference on days with severe stressors is heightened. Nevertheless, it is in these situations where it is even more beneficial to remain engaged with the current tasks rather than being pulled away through intrusive, off-task cognitions.

The current study also highlights the importance to consider how patterns of relationships may differ across levels of analyses. The mediating role of cognitive interference at the between-person level and the moderating role at the within-person level indicate the importance of disaggregating the two sources of variation to reveal an unconfounded set of results. The manner in which individuals operate relative to themselves need not be the same as how individuals differ relative to others. A better understanding of the differing patterns of results across levels of analyses will be important for appropriately targeting such variables for interventions and health promotion.

Chapter 3

Modeling Long-Term Changes in Daily Within-Person Associations:

An Application of Multilevel SEM

3.1 Abstract

Short-term within-person associations are considered to reflect unique dynamic characteristics of an individual and are frequently used to predict distal outcomes. These effects are typically examined with a two-step statistical process. The present research demonstrates how long-term changes in short-term within-person associations can be modeled simultaneously within a multilevel structural equation modeling framework. We demonstrate the utility of this model using measurement burst data from the National Study of Daily Experiences (NSDE) embedded within the Midlife in the United States (MIDUS) longitudinal study. Two measurement bursts were separated by ten years, with each containing daily measures of stress and affect across eight consecutive days. Global measures of psychological well-being were also assessed across the ten-year period. Three-level structural equation models were fit to simultaneously model short-term within-person associations between stress and negative affect and long-term changes in these associations over the ten-year period. Individual differences in long-term changes of the short-term dynamics between stress and affect predicted global well-being levels. We highlight how characterizing an individual based on the strength of their within-person relationships across multiple time scales can be important predictors of distal outcomes, as well as the utility of employing multilevel structural equation models in conjunction with measurement burst designs.

Keywords: Multilevel structural equation modeling, stress reactivity, psychological well-being, measurement burst, daily diary

3.2 Introduction

As research methods continue to evolve and further our insights into how to best understand developmental processes, it is becoming clear that there is a need to capture better the complex dynamic processes that operate within an individual's lived experiences. As many individual characteristics are likely to vary and develop over multiple temporal frequencies, intensive measurement designs are being deployed to better capture characteristics of the individual that represent informative aspects about their health and well-being. Indeed, recent research designs have moved beyond the traditional cross-sectional approach of measuring individuals at a single point in time and widely spaced longitudinal designs that provide multiple "snapshots" of an individual across years. While an individual's average level and rate of change is certainly informative and has been fruitful in gaining insights into the typical characteristics that are predictive of health and well-being relative to others, it is increasingly more common to consider how individuals vary, change, and respond to exposures over short intervals and how these dynamics change over longer periods of time.

3.2.1 Capturing Characteristics of the Individual

Developmental research into the analysis of change have taken aim at understanding how measures of short-term variability may capture characteristics of the individual not represented by measures of central tendency (e.g., Charles, Piazza, Mogle, Sliwinski, & Almeida, 2013; Hedeker, Mermelstein, Berbaum, & Campbell, 2009; Hultsch, Strauss, Hunter, & MacDonald, 2008; Hülür, Hoppmann, Ram, & Gerstorf, 2015; Piazza, Charles, Sliwinski, Mogle, & Almeida, 2013; Rast, Hofer, & Sparks, 2012; Röcke & Brose, 2013; Röcke, Li, & Smith, 2009; Sliwinski, Almeida, Smyth, & Stawski, 2009; Stawski et al., 2017). The increased prevalence of measurement burst designs, where frequent closely-spaced assessments (e.g., across hours or

days) are repeated over longer intervals (e.g., months, years) enables an investigation into how short-term intra-individual variability (i.e., person-specific deviations in responses across repeated assessments) informs us about unique characteristics of the individual (Martin & Hofer, 2004; Nesselroade, 1991; Sliwinski, 2008). As this burgeoning area of research continues to develop, it is becoming clear that intra-individual variability is not merely unreliable measurement error, but rather carries systematic information about the context, individual, or both.

Short-term variability has been used in a variety of ways to capture unique aspects of the individual. One approach has been to measure the amount of variability an individual displays over short intervals of time (e.g., across days, hours, or trials). Though there have been numerous quantifications of intra-individual variation (see Stawski et al., 2017), the conceptual idea remains that the amount of short-term variability an individual displays can be an informative metric that furthers our understanding of that individual. Individual differences in the amount of intra-individual variability has been shown to be predictive in a number of psychological domains. For example, higher amounts of trial-to-trial variability in reaction time tasks have been predictive of cognitive performance and declines (Bielak, Hultsch, Strauss, MacDonald, & Hunter, 2010; MacDonald, Hultsch, & Dixon, 2003; MacDonald, Li, & Bäckman, 2009). Intra-individual variability in daily self-esteem has predicted depression (Gable & Nezlek, 1998). Daily variability in positive affect has been associated with daily cortisol levels (Human et al., 2015), whereas daily variability in negative affect has been associated with neuroticism and cross-sectional age differences (Röcke et al., 2009).

While the raw amount of intra-individual variability may be informative in some areas of research, it is often the context that coincides with the intra-individual deviations that are of

primary interest. For example, day-to-day variations in negative affect (NA) can be understood in more depth if we also examine the context (e.g., amount of daily stress) that is contributing to the intra-individual deviations. The short-term covariation (i.e., coupling) of constructs within individuals further accounts for the systematic intra-individual variations. Similar to how individuals may differ in the amount of intra-individual variability they display, so too can individuals differ in the strength of their within-person (coupled) associations. This has been applied most frequently in the area of stress and affect, where individuals differ in the degree that their NA increases in response to a stressful experience (i.e., their stress reactivity).

Characterizing an individual based on the strength of their within-person association moves beyond amount of stress or NA and toward a conceptualization of the magnitude of the contextual influence. Importantly, the magnitude of the contextual influence (i.e., the strength of the within-person association) can differ across individuals or across longer intervals of time within individuals. Understanding individual differences and developmental changes in the magnitude of contextual influences could provide a unique account of how to characterize the individual.

To date numerous research studies have used individual differences in the magnitude of within-person associations as a between-person predictor variable. Hülür and colleagues (2015) found that individual differences in the within-person correlation of positive affect (PA) and NA accounted for differences in cognitive decline. Research has also used individual differences in stress reactivity, the within-person association of daily stress and NA, to effectively predict a variety of physical and mental health outcomes, such as risk of morbidity (Piazza et al., 2013), mortality (Mroczek et al., 2015), inflammation (Sin, Graham-Engeland, Ong, & Almeida, 2015), sleep efficiency (Ong et al., 2013), and affective disorders (Charles et al., 2013). Each of these

research has examined within-person associations from a single measurement burst. Few studies have examined if people change over longer periods in their short-term within-person association. Sliwinski and colleagues (2009) found that there were long-term increases in the daily association of stress severity and NA. In addition, they found that burst level perceived stress was predictive of the magnitude of stress reactivity within the same burst. However, no study to our knowledge has examined if long-term changes in stress reactivity is predictive of other distal outcomes.

Stress reactivity research has primarily focused on predicting physical health outcomes (e.g., inflammation, morbidity, mortality, sleep quality). There has yet to be an examination of stress reactivity as a between-person predictor of psychological well-being (PWB) and life satisfaction. Furthermore, no research has examined if long-term changes in the short-term stress reactivity association further explains global levels of PWB. Given the detrimental health effects of stress reactivity, it is expected that they will also be detrimental to the experiences of PWB and life satisfaction. Changes in stress reactivity could also indicate a downward shift in life quality and an inability to manage adverse situations. Individuals undergoing such a change are expected to report lower levels of PWB and life satisfaction than those who are stable or are becoming less reactive to stressors over time.

3.2.2 Statistical Approaches to Modeling Within-Person Variability

Intra-individual variability, when treated as an individual difference predictor variable, has most commonly been examined through a two-step procedure. A multilevel model provides estimates of person-specific deviations in either the amount of intra-individual variability or random effects in the strength of the within-person covariation between two time-varying variables (e.g., NA and stress). These person-specific deviations from the fixed effect are then

extracted for each individual and entered as a time-invariant individual difference predictor into a separate statistical model to predict some other outcome (e.g., cognitive performance, mental health, mortality). Though this approach is frequently applied throughout the literature, it is unclear the impact the additional step has on the variance components of the final model. Analogous to the slopes-as-outcomes model that ignores variance across levels and treats each individual equally regardless of data points contributed (Hoffman, 2015; Singer & Willett, 2003), the two-step approach may carry similar concerns.

An alternative approach is to model all effects simultaneously within a single statistical model using a multilevel structural equation modeling (MSEM) framework (Muthén & Asparouhov, 2009; Preacher, Zyphur, & Zhang, 2010; Rush, Ong, Hofer, & Horn, 2017). Multilevel SEM combines features of multilevel modeling and structural equation modeling. It handles hierarchically structured data and time-varying effects (that are present in measurement burst designs) while permitting a multivariate examination of time-varying relationships across levels of analysis. An important feature of the MSEM approach is that random effects at each level can be modeled as either exogenous or endogenous variables at subsequent levels of analysis. That is, the latent random slopes can be specified to represent individual differences in the within-person associations, and these individual differences can be included as predictors of concurrent or distal outcomes. Furthermore, measurement burst designs that assess individuals across multiple time-scales can now be modeled in a manner that examines random effects of the random effects. An example of this is an examination of short-term intraindividual associations change within individuals over longer intervals of time and an evaluation of whether individual differences in this change in within-person dynamics are predictive of other outcomes. The flexibility of the MSEM framework in concert with measurement burst designs permit numerous

innovative questions about the utility of short-term variability and within-person associations to characterize an individual during a given period, as well as the long-term changes in these within-person dynamics.

3.2.3 Present Study

The present study utilized data from the Midlife in the United States (MIDUS) project that embeds intensive measurement burst data within a longitudinal panel design. Through this form of study design, it was possible to examine how short-term (i.e., daily) within-person associations changed over longer intervals of time (i.e., 10 years). Furthermore, individual differences in the degree of change was then used to account for between-person differences in general levels of psychological well-being and life satisfaction. Multilevel SEMs were employed to simultaneously model these effects across multiple time-scales and levels of analysis. The present study extends previous research in several important ways. First, the study examined long-term changes across ten years in the daily within-person association of stress and negative affect. Second, individual differences in the within-person association of daily stress and affect, and long-term changes in this within-person association, were used to predict between-person differences in general levels of psychological well-being. Finally, research to date has primarily used a two-step approach to examine individual differences and patterns of change among short-term within-person associations. The present study models individual differences in both the within-person association, as well as individual differences in the degree that the within-person association changes over time, simultaneously as random slopes within an MSEM framework. This approach permits the random effects of within-person associations to be modeled as latent slopes that can then act as either exogenous or endogenous variables across levels of analysis. By modeling these effects simultaneously within a single statistical model, the variability within and

across levels of analysis can be accounted for more appropriately (see Lüdtke et al., 2008; Marsh et al., 2009 for a full discussion).

3.3 Method

3.3.1 Participants and Procedure

Participants were from the MIDUS project, a publicly available data set that consists of multiple sub-projects aimed at collecting a large representative sample of Americans assessed during midlife (age 24 – 74 at baseline). The MIDUS project incorporates a large-scale longitudinal panel design, where participants complete a comprehensive survey on many aspects of their health and well-being at ten-year intervals. In addition, a subset of participants were also invited to participate in the National Study on Daily Experiences (NSDE) sub-project, where they responded to end of day telephone interviews for 8 consecutive days that assessed daily levels of stress and affect. The NSDE data collection burst was repeated approximately 10 years later, providing two measurement bursts of the daily diary data (see Almeida, 2005; Almeida, McGonagle, & King, 2009 for detailed description of data collection). The present study made use of the first two waves of the MIDUS survey (MIDUS I and II), as well as the two bursts of the NSDE data collection (NSDE I and II; see Figure 3.1). The current research made use of all available data from respondents who participated in the NSDE I or II and MIDUS I and II survey studies ($N = 2485$; # daily assessments = 23,592). Previous studies have demonstrated that participants who completed both of the NSDE bursts did not significantly differ from those who only complete burst 1 in terms of age, sex, and education (see Charles et al., 2013).

3.3.2 NSDE Daily Diary Measures (Burst 1 and 2)

Negative Affect. Daily negative affect was assessed during bursts one and two of the NSDE data collections. Participants were presented with a list of six emotions (*fidgety, nervous,*

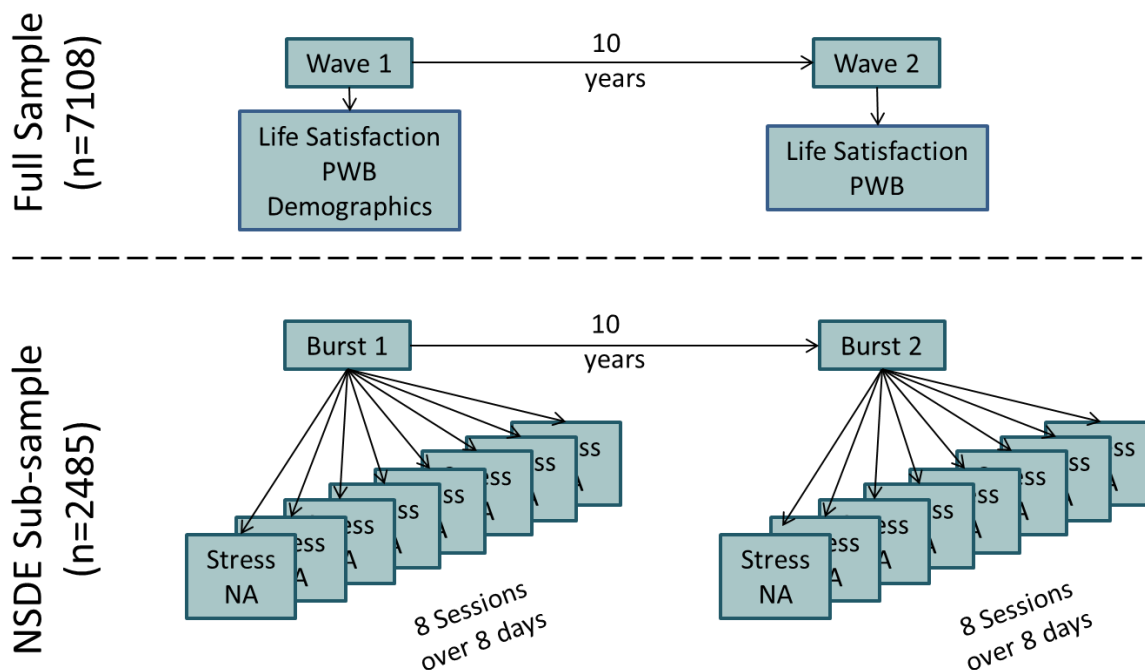


Figure 3.1. Midlife in the United States (MIDUS) study design. All participants completed Wave 1. A sub-sample completed the National Study of Daily Experiences (NSDE) daily assessments (2,485 participants completed either Burst 1 or Burst 2). *Note.* PWB = psychological well-being. NA = negative affect.

worthless, so sad that nothing could cheer you up, everything was an effect, and hopeless) and asked to indicate how frequently they felt each emotion in the past 24 hours. Responses ranged from 0 (*none of the time*) to 4 (*all of the time*). Daily negative affect scores were computed by averaging across the items.

Daily stressors. Daily stressors were assessed using the Daily Inventory of Stressful Events (DISE; Almeida, Wethington, & Kessler, 2002). The inventory consisted of six questions inquiring whether certain types of stressors had been experienced in the last 24 hours (e.g., “In the past 24 hours, did you have an argument or disagreement with anyone?”). A dichotomous variable was used to characterize days as either stress days (at least one stressor was reported) or non-stress days (no stressor reported).

3.3.3 MIDUS Longitudinal Panel Measures (Wave 1 and 2)

Life satisfaction. Participants rated their satisfaction across five life domains (work, health, relationship with partner, relationship with children, and overall) on a scale from 0 (worst possible) to 10 (best possible). The scores for relationship with partner and relationship with children were averaged to create a single item. This item was averaged with the remaining items to create an overall mean score (Prenda & Lachman, 2001).

Psychological well-being. Six dimensions of psychological well-being were measured at wave 1 and wave 2. The six dimensions included: *autonomy*, *environmental mastery*, *personal growth*, *positive relations*, *purpose in life*, and *self-acceptance* (Ryff & Keyes, 1995). Each PWB dimension was measured using a three-item scale with responses to each item ranging from 1 (*strongly disagree*) to 7 (*strongly agree*). A total score for each dimension was computed by summing across the three items with higher scores representing higher levels of PWB (range = 3 to 21).

Covariates. Participant age at wave 1, sex, and education were included as covariates to adjust for sample heterogeneity. Age was centered at the grand mean in all statistical models. Sex was coded with males as the reference category. Education was measured on a 4 point scale, (1=*less than high school*, 2=*high school degree*, 3=*some college*, 4=*graduated college*) and was centered on the median response of 3. Descriptive statistics for all study variables are included in Table 3.1.

Table 3.1. Means and Standard Deviations of Study Variables

Variable	Wave 1 / Burst 1		Wave 2 / Burst 2	
	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>
Demographics				
Age	47.02	12.60	56.15	12.31
Sex	0.55 ^a	0.50	—	—
Education	2.94	0.94	—	—
Global Well-being				
Life Satisfaction	7.78	1.23	7.82	1.20
Autonomy	16.36	3.31	16.57	3.05
Environmental Mastery	16.24	3.44	16.89	3.24
Personal Growth	18.00	3.09	17.26	3.25
Positive Relations	16.25	4.08	16.90	3.83
Purpose in Life	16.74	3.51	16.43	3.34
Self-Acceptance	16.72	3.52	16.42	3.79
Burst-level variables				
Daily NA	0.19 ^b	0.29	0.21 ^b	0.28
Daily Stressor	0.40 ^c	0.26	0.40 ^c	0.27

Note. NA = negative affect. ^a Proportion of female participants. ^b Aggregated across daily assessments. ^c Proportion of stress days.

3.3.4. Data Analytic Strategy

Multilevel structural equation modeling analyses were used to permit a multivariate examination of stress reactivity and well-being across time-scales and levels of analysis. These models handle the hierarchical structure of the data and allow random slope coefficients to be simultaneously modeled as either exogenous predictor variables or endogenous outcome variables across levels of analysis. Daily measurement occasions were nested within measurement bursts and measurement bursts were nested within people, resulting in three-levels of analysis. Model specification for each level of analysis is described next (see Figure 3.2).

Level 1 (daily measurements within burst). At the within-burst level, daily stress exposure_{ijk} was included as a predictor of daily levels of NA_{ijk}. The subscript *ijk* in Figure 3.2 indicates that both stress exposure and NA could vary across days (*k*), measurement bursts (*j*), and individuals (*i*). The daily within-person association between stress exposure and NA (i.e., stress reactivity) was modeled as a random slope and was permitted to vary across bursts and individuals. That is, the strength of the daily stress-NA association could differ across bursts within an individual, as well as across individuals.

Level 2 (within-person, between-bursts). At the second level of analysis, the random stress reactivity_{ij} slope was modeled as a latent endogenous variable that varies across bursts and individuals. Burst-level NA_{ij} was also modeled as a latent endogenous variable that represents the mean NA for person *i* during burst *j*. A dichotomous Burst_{ij} variable (0=burst 1; 1=burst 2) was included as a predictor of both burst-level NA_{ij} and stress reactivity_{ij} to examine if there was a within-person change from burst 1 to burst 2 in the level of NA or the strength of the daily stress-NA association, respectively. The change in stress reactivity from burst 1 to burst 2 was modeled as a random slope, permitting individual differences in the degree of change in the daily

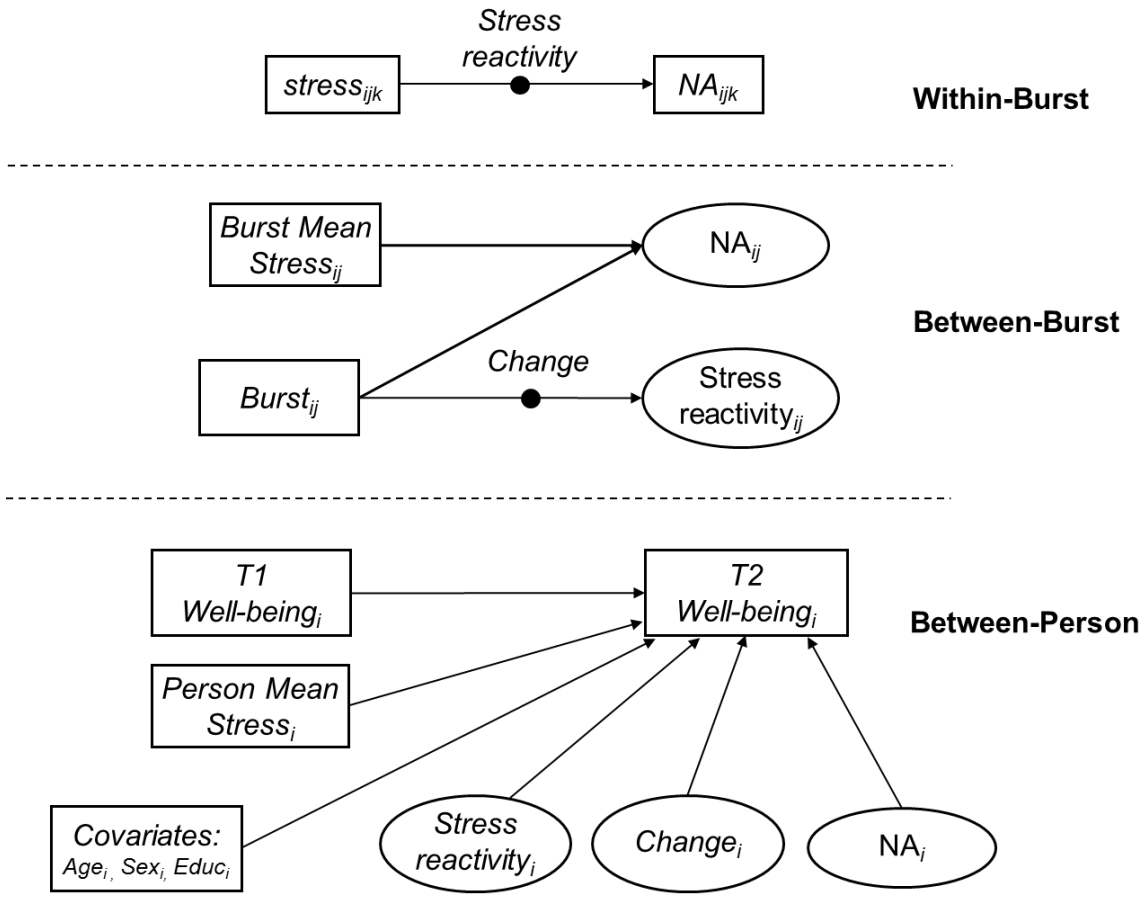


Figure 3.2. Three-level structural equation model. Daily assessments are nested within-bursts and bursts of measurements are nested within people. Black dots indicate that pathway was modeled as a random slope. Note. NA = negative affect; stress = stress day; Educ = highest education level obtained.

WP association of stress and NA across bursts. That is, modeling if some individuals differed in the amount that their stress reactivity changed from burst 1 to burst 2. Burst mean stress, which is the proportion of burst-specific stress days for individual i during burst j , was also included as a predictor of burst-level NA_{ij} to adjust for differences in burst-level stress exposure.

Level 3 (between-person). Individual differences in stress reactivity $_i$ and changes in stress reactivity (i.e., $change_i$) were modeled as latent slopes, indicating that they are estimated from the model and reflect strength of the daily stress reactivity association and amount of change in stress reactivity, respectively, across bursts for individual i . NA_i was modeled as a latent mean that reflects average levels of NA for individual i across days and bursts. Individual differences in stress reactivity, changes in stress reactivity, and mean levels of NA were used to predict individual differences in global well-being (PWB and life satisfaction) measured at wave 2. A set of covariates were included to adjust for the effects of age (centered at the grand mean), sex, education, corresponding wave 1 well-being, and person mean stress (i.e., the proportion of days where at least one stressor was reported across days and bursts) on wave 2 well-being. All effects were estimated simultaneously using full information maximum likelihood with robust standard errors (MLR), which makes use of all available data and adjusts for non-normality. Mplus version 8 software (Muthén & Muthén, 2017) was used to fit all models.

3.4 Results

Table 2 presents the findings from the full MSEMs. Each of the wave 2 global well-being outcomes (i.e., six dimensions of PWB and life satisfaction) were examined in separate models.

3.4.1 Daily Within-Person Associations over Time

Stressor exposure was associated with NA within-bursts. On days when individuals were exposed to a stressor their NA was higher than days when they did not report a stressor. This

Table 3.2. Three-Level Structural Equation Modeling Analyses of the Effects of Daily Stress Reactivity on Well-Being

Variable	Life Satisfaction	Environmental Mastery	Personal Growth	Purpose in Life	Relatedness	Self-Acceptance
	Estimate (<i>SE</i>)	Estimate (<i>SE</i>)	Estimate (<i>SE</i>)	Estimate (<i>SE</i>)	Estimate (<i>SE</i>)	Estimate (<i>SE</i>)
Fixed Effects						
Within-person variables						
NA Intercept	0.053 (.007)***	0.052 (.007)***	0.052 (.007)***	0.053 (.007)***	0.053 (.007)***	0.053 (.007)***
Wave 1 Stress Reactivity	0.132 (.008)***	0.134 (.008)***	0.132 (.008)***	0.131 (.008)***	0.131 (.008)***	0.133 (.008)***
Between-burst variables						
NA Change	0.001 (.006)	0.002 (.006)	0.001 (.006)	0.000 (.006)	0.000 (.006)	0.001 (.006)
Burst-mean Stress	0.178 (.018)***	0.178 (.018)***	0.181 (.018)***	0.181 (.018)***	0.180 (.018)***	0.180 (.018)***
Stress Reactivity Change	0.037 (.009)***	0.036 (.009)***	0.036 (.009)***	0.038 (.009)***	0.037 (.009)***	0.036 (.009)***
Between-person variables predicting Wave 2 Well-being						
Intercept	5.539 (.339)***	14.288 (.648)***	10.618 (1.04)***	12.942 (1.24)***	11.358 (1.422)***	10.31 (.791)***
Sex	0.114 (.044)*	-0.074 (.124)	0.553 (.129)***	-0.021 (.134)	0.364 (.146)*	0.126 (.140)
Education	0.103 (.025)***	0.232 (.068)**	0.211 (.073)**	0.291 (.078)***	0.152 (.079)†	0.249 (.080)**
Wave 1 Age	0.007 (.002)**	0.025 (.005)***	0.003 (.005)	-0.028 (.006)***	0.016 (.006)**	0.011 (.006)†
Wave 1 Well-being	0.439 (.024)***	0.339 (.021)***	0.486 (.024)***	0.378 (.022)***	0.511 (.019)***	0.557 (.023)***
Person-mean NA	-2.496 (.693)***	-8.833 (2.10)***	-4.145 (1.476)**	-3.172 (1.253)*	-6.049 (1.679)***	-5.593 (1.574)***
Person-mean Stress	-0.443 (.102)***	-0.900 (.267)**	0.046 (.267)	-0.094 (.288)	-0.766 (.296)**	-0.464 (.289)
Stress Reactivity	-0.325 (.583)	0.687 (1.335)	-0.914 (1.449)	-2.520 (1.955)	0.563 (2.003)	-1.244 (1.585)
Stress Reactivity Change	-23.674 (7.67)**	-61.55 (10.04)***	-58.405 (30.43)†	-61.024 (36.94)†	-67.552 (41.230)	-75.22 (17.11)***

Random effects						
Within-person NA	0.047 (.002)***	0.047 (.002)***	0.047 (.002)***	0.047 (.002)***	0.047 (.002)***	0.047 (.002)***
Between-burst						
NA Intercept	0.013 (.003)***	0.013 (.003)***	0.013 (.003)***	0.013 (.003)***	0.013 (.003)***	0.013 (.003)***
Stress Reactivity	0.023 (.005)***	0.023 (.005)***	0.023 (.005)***	0.023 (.005)***	0.023 (.005)***	0.023 (.005)***
Between-person						
NA Intercept	0.016 (.004)***	0.017 (.004)***	0.016 (.004)***	0.017 (.004)***	0.016 (.004)***	0.016 (.004)***
Stress Reactivity	0.020 (.006)**	0.020 (.006)**	0.020 (.006)**	0.019 (.006)**	0.019 (.006)**	0.020 (.006)**
Stress Reactivity Change	0.001 (.000) [†]	0.001 (.000)**	0.001 (.000)	0.001 (.001)	0.001 (.000)	0.001 (.000)*
Residual Variance						
Wave 2 Well-being	0.507 (.429)	2.167 (2.580)	5.656 (3.028) [†]	6.410 (3.832) [†]	6.382 (5.120)	4.068 (3.845)

Note. Results are based on 23,592 daily assessments ($N = 2,485$). NA = negative affect. Results from Autonomy model not displayed due to non-convergence of model. [†] $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

effect was significant during both burst 1 ($estimate = 0.13, p < .001$) and burst 2 ($estimate = .17, p < .001$). Furthermore, there was evidence of person-specific and burst-specific variations in the strength of the daily association between stress and NA as indicated by the amount of variability around the burst-level and person-level fixed effects of stress reactivity (residual variances = .02 and .02, $ps < .001$, respectively). Figure 3.3 depicts the individual differences in strength of the daily association. The black line represents the average within-person effect (i.e., the fixed effect), while the dotted coloured lines demonstrate the person-specific deviations in this effect for five individuals (i.e., the random effects). Some individuals are more emotionally reactive to stressors and others are less reactive. Furthermore, these individual deviations are present in both burst 1 and burst 2.

Stress reactivity changed from burst 1 to burst 2. Individuals displayed higher levels of stress reactivity during burst 2 than burst 1 ($\Delta stress\ reactivity = .04, p < .001$). That is, the strength of the daily association between stress and NA was significantly stronger during burst 2 than it was during burst 1, indicating that on average individuals were more reactive to daily stressors. In addition, there were also individual differences in the degree of change in stress reactivity across bursts. Figure 3.4 displays the average (fixed) change in stress reactivity (thick black line), as well as individual deviations in the degree of stress reactivity change (coloured dotted lines) for five individuals. Figure 3.4 also highlights the multiple levels of random slopes, wherein there are individual deviations in stress reactivity during both bursts of measurement (depicted in the balloons) as well as individual deviations in the degree of stress reactivity change across bursts.

Burst 1



Burst 2

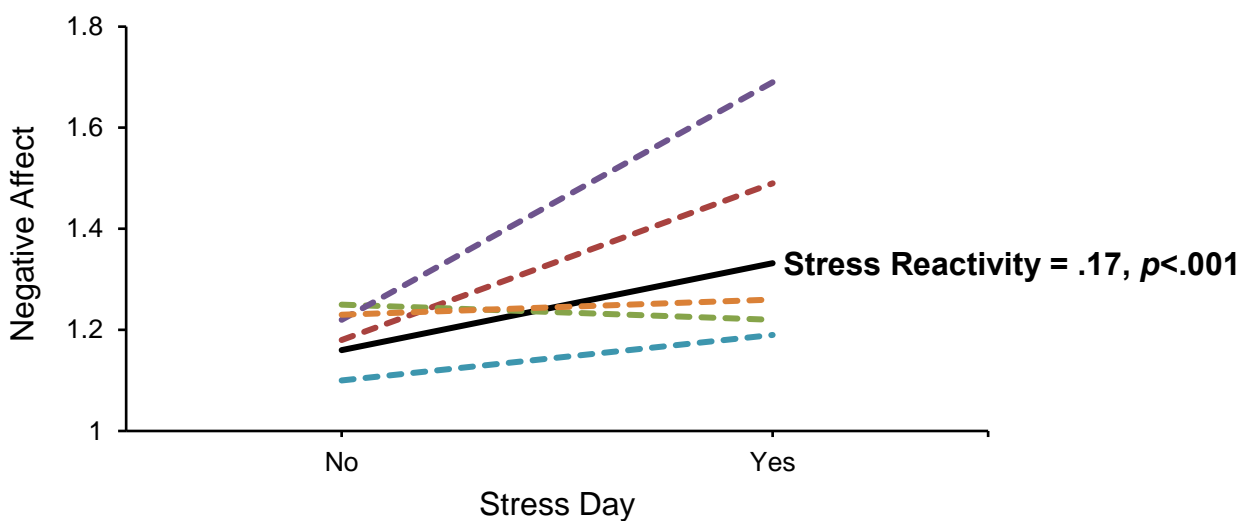


Figure 3.3. Individual differences in within-person association of stress and negative affect. Top panel represents the within-person association between stress and NA (i.e., stress reactivity) at burst 1 (stress reactivity = .13, $p < .001$). Bottom panel represents within-person association between stress and NA (i.e., stress reactivity) at burst 2 (stress reactivity = .17, $p < .001$). Black line represents average within-person association between stress and NA. Colored dotted lines represent individual participants with varying strengths of within-person association within each measurement burst.

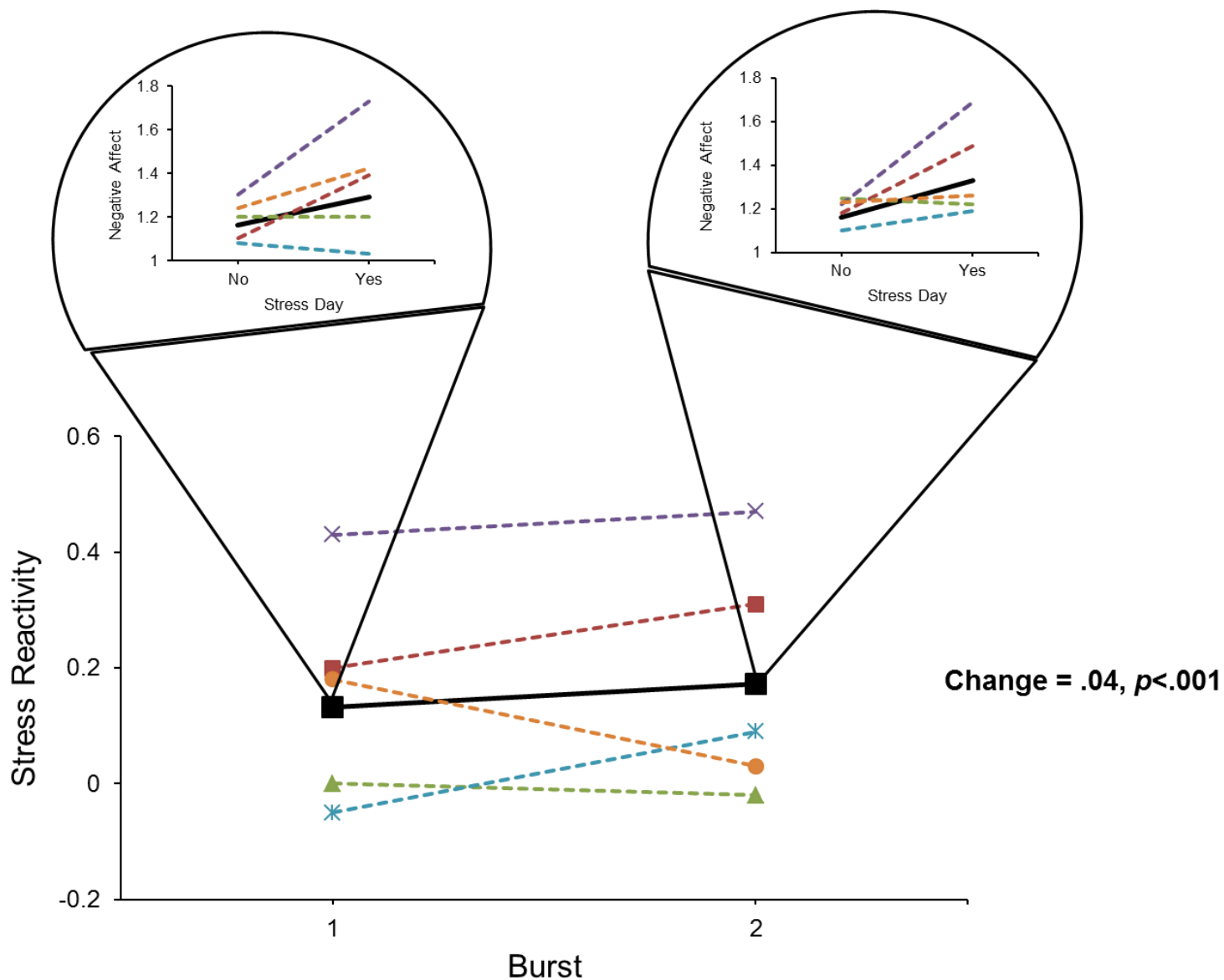


Figure 3.4. Change in within-person association between stress and NA (i.e., stress reactivity) across bursts. Black square (line) represents average within-person association between stress and NA and change in average within-person association across bursts (Δ stress reactivity = .04, $p < .001$). Colored dotted lines represent individual participants with varying strengths of within-person association within and across bursts.

3.4.2 Predicting Wave 2 Well-Being

The primary effect of interest was whether individual differences in changes in stress reactivity was predictive of global well-being at wave two. Results revealed that changes in stress reactivity significantly accounted for individual differences in life satisfaction at wave 2. Individuals who became more reactive to stressors over time relative to others had lower levels of life satisfaction at wave 2 (*estimate* = -23.67 , *SE* = 7.67 , $p < .01$). This result was present after adjusting for age, sex, average stress reactivity, average levels of NA, amount of stress exposure, and wave 1 life satisfaction. Furthermore, higher average levels of NA and a greater proportion of stress day exposure was reliably related to lower levels of life satisfaction (*estimates* = -2.50 and -0.44 , $ps < .001$, respectively). Figure 3.5 displays the unstandardized estimates from the three-level SEM predicting life satisfaction.

Similar patterns were found for each of the dimensions of psychological well-being. Individuals who became more reactive over time relative to others had lower levels of psychological well-being at wave 2. Individual differences in changes in stress reactivity were significant predictors of environmental mastery and self-acceptance (*estimates* = -61.55 and -75.22 , $ps < .001$, respectively), however results only approached statistical significance when predicting personal growth, purpose in life, and positive relations with others (ps range from .055 to .101). Individuals with higher average levels of negative affect also had reliably lower levels of all dimensions of PWB. Greater proportion of stress day exposure was reliably related to lower levels of environmental mastery and positive relations (*estimate* = -0.90 and -0.77 , $ps < .01$, respectively). Average levels of stress reactivity across bursts were not predictive of PWB at wave two after adjusting for the effects of other variables of interest.

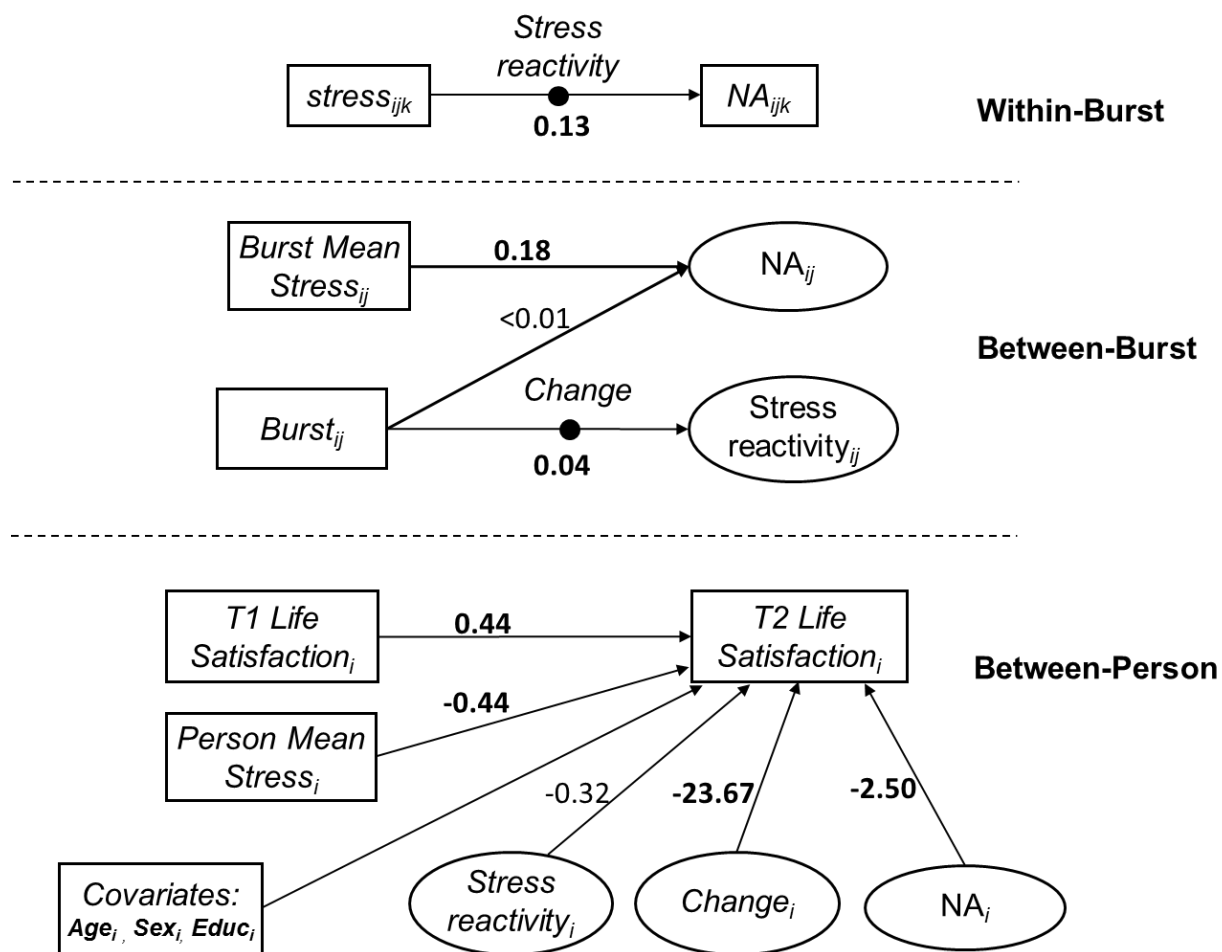


Figure 3.5. Estimated three-level structural equation model predicting between-person differences in life satisfaction. Note. Values are unstandardized coefficients. Bold values are statistically significant, $p < .01$. Black dots indicate that pathway was modeled as a random slope. NA = negative affect. stress = stress day. Educ = education.

3.5 Discussion

The present study examined the potential to characterize the individual through short-term (daily) WP associations. Longitudinal changes in the short-term WP associations of daily stress and NA were modeled across time. Individual differences in longitudinal changes of these WP associations were further examined to predict global levels of PWB and life satisfaction. All effects were modeled simultaneously through an innovative multilevel SEM framework, rather than the two-step approach that is most prevalent in the literature.

Consistent with previous findings, on average individuals were emotionally reactive to daily stressors across both measurement bursts. That is, the tendency was to report higher levels of NA on days when they were exposed to a stressor relative to non-stress days. However, despite a significant average within-person association between daily stress and NA, there was considerable person-specific variability in the strength of the association both within and across bursts (see Figure 3.3). These individual differences in stress reactivity within and across bursts highlight the importance of considering multivariate dynamics to capture individual processes.

Extending previous research that has examined the role of stress reactivity during a single measurement burst, the current research demonstrated that on average individuals tend to change in their level of stress reactivity over longer periods of time. The strength of the daily association increased over time as individuals became more emotionally reactive to daily stressors. It is unclear why there was a tendency for individuals to become more reactive at ten-year follow-up than they were initially. Given that the study sample follows individuals through midlife, it is plausible that the demands and strains of midlife (e.g., changes in health, occupational responsibilities, family strain, etc.; Lachman, 2004) are contributing to changes in the level of stress reactivity. In a sample of older adults from the Cognition, Health, and Affect Project,

Sliwinski and colleagues (2009) found that individuals on average became more reactive to stressors as they aged. This finding appears to be at odds with Carstensen and colleagues' (1999) theory of socioemotional selectivity, which posits that older adults tend to become more accepting of life and their emotional experience improves and becomes more stable as they age. Research examining longitudinal changes in momentary levels of affect across three measurement bursts found that average levels of affect did improve over a ten-year period (Carstensen et al., 2011). Furthermore, Röcke and colleagues (2009; 2013) have found support that older adults are less variable in NA than are younger adults. Of note, is that these results are based on average levels and raw amount of affect and does not consider how individuals are impacted by contextual influences (e.g., daily stressors). Charles' (2010) strength and vulnerability integration (SAVI) theory proposes that as individuals age they are better able to maintain higher levels of emotional well-being by relying on aging-related strengths (e.g., experience, emotional dampening) to reduce or avoid negative situations. However, when faced with negative events (i.e., stressors) age-related strengths are attenuated and their age-related vulnerabilities (e.g., difficulties regulating sustained physiological arousal – elevated blood pressure, cortisol, etc.) are magnified, resulting in a more adverse response. The SAVI model is consistent with the results of the current research. On average, cross-sectional differences in age was related to higher levels of global well-being. However, there was a tendency over time for individuals to become more reactive to daily stressors, demonstrating a reduced ability to regulate their negative emotions in response to the stressor.

Importantly, not all individuals increased in their stress reactivity over the ten-year period. Individual differences in changes in stress reactivity emerged (see Figure 3.4), where some individuals became more reactive to daily stressors and others remained stable or became

less reactive. Person-specific variation in changes in stress reactivity is also consistent with the SAVI model, as individuals are expected to vary in the balance of strengths and vulnerabilities they possess in dealing with stressful experiences (Charles, 2010). Furthermore, these individual differences in changes in stress reactivity were reliable predictors of global levels of well-being. Individuals who demonstrated greater increases in their stress reactivity from burst 1 to burst 2 had lower global levels of well-being than individuals who did not change as much in their stress reactivity. This pattern was consistent across dimensions of well-being, but was only statistically significant when predicting life satisfaction, environmental mastery, and self-acceptance.

Greater levels of stress reactivity have consistently been shown to relate to a number of detrimental outcomes, including chronic health conditions (Charles et al., 2013), mental disorders (Piazza et al., 2013), mortality (Mroczek et al., 2015), inflammation (Sin et al., 2015), and sleep quality (Ong et al., 2013). Each of these previous studies examined daily stress reactivity during a single measurement burst. This study adds to this literature by demonstrating that stress reactivity changes over long intervals (i.e., ten years) and that individual differences in the degree of change accounts for between-person differences in levels of global PWB and life satisfaction. It is clear that greater NA levels in response to daily stressors represent an adverse characteristic of the individual that is associated with poorer health and well-being across a number of life domains. The current results reveal that not only levels of stressor reactivity, but also changes in stress reactivity over time are particularly concerning. That changes in stress reactivity was uniquely predictive of global well-being over and above the effects of average levels of NA, stress exposure, and wave 1 well-being, further demonstrates that the WP association of stress and NA is capturing an element of the individual that is not captured by NA or stress exposure on their own.

The current approach to model each of the effects simultaneously across levels of analysis and time-scales provides an important methodological extension to previous research in the area of intra-individual variability and covariation. Nearly all research examining individual differences in WP associations as a predictor variable has used a two-step approach. Within-person estimates from multilevel models are first exported and then subsequently entered into regression models (or univariate growth models) to predict outcomes (e.g., Charles et al., 2013; Hülür et al., 2015; Mroczek et al., 2015; Piazza et al., 2013; Sin et al., 2015; Stawski et al., 2017). In contrast, the current research utilized an MSEM framework, where the variance components are decomposed within a single model that adjusts for variance across levels of analysis and permits random slopes to be integrated as both exogenous predictor variables and endogenous outcome variables. This extension opens a number of possibilities in how we conceptualize the complex developmental relationships across time-scales. By permitting the random slopes of within-person associations to be either predictor or outcome variables, pathways that link short-term and long-term processes can be specified to enable a thorough investigation of developmental changes in the impact of contextual influences. Furthermore, moderator variables can be included to evaluate changes in within-person dynamics relative to life events (e.g., child birth) and developmental periods (e.g., midlife, retirement). These extensions will have important ramifications for how we characterize the individual and how we attempt to capture the slower and more rapidly developing influences at each stage of the lifespan.

3.5.1 Limitations and Future Directions

The MIDUS study design consisting of multiple daily measurement bursts within a longitudinal panel design on a large representative national sample provides unique opportunities

to examine and statistically model the complex relationships across multiple time-scales that were under investigation. Despite these clear strengths, there are still a number of limitations that should be addressed with future research. First, further investigation is needed into the number and spacing of short-term measurement occasions necessary to reliably estimate within-person associations as a stable individual difference variable. It is unknown how many measurement occasions (e.g., daily assessments) are needed for the within-person association to be an accurate and valid characterization of the individual. Because the estimates are a measure of variance based on random effects, they are likely to be more volatile than measures of central tendency. Some research has suggested that within-person associations based on fewer than seven measurement occasions have low reliability (Estabrook, Grimm, & Bowles, 2012; Mejía, Hooker, Ram, Pham, & Metoyer, 2014; Wang & Grimm, 2012). However, this is likely to depend on the quality and temporal spacing of the measures in addition to the number of occasions. The within-person associations of the current study are based on measurement bursts of eight daily assessments, which have been used frequently throughout the literature. Nevertheless, a thorough empirical investigation into this issue is warranted to establish best practices that will optimize study designs and analyses. Second, the current statistical models are computationally demanding and often require large sample sizes to converge. The strengths of the MIDUS data collection permitted these models to converge in nearly all cases (the model did not converge when predicting autonomy). In addition to understanding the measurement design requirements to appropriately model person-specific variations in within-person associations, it will be important for future research to understand the person-level sample size requirements to permit stable estimates and model convergence.

Finally, the ten-year interval between measurement bursts makes it difficult to interpret what the change in the strength of the within-person stress reactivity association truly represents. It is impossible to determine the processes that are unfolding during this period that are contributing to the changes in stress reactivity. Furthermore, it is unknown if the change is occurring linearly or is in response to more slowly occurring contextual factors. In the same way that NA varies daily based on contextual factors (e.g., stressful experiences), so too could stress reactivity change be dependent on slower occurring contextual processes (e.g., life transitions – parenthood, occupational commitments, family strain, etc.) that are accounting for why some individuals are becoming more reactive to daily stressors than others over longer intervals of time. More frequent measurement bursts assessed at shorter intervals (e.g., annually) would permit a better understanding of the nature of change in stress reactivity within each individual. The MIDUS project is ongoing and additional measurement waves and bursts continue to be collected. The multilevel SEM framework outlined in the current study provides opportunities to examine additional complex questions of change and development across time-scales. The current study examined individual differences in global measures of well-being assessed at wave 2. Future research could also investigate how long-term changes in daily relationships coincide with long-term changes in global well-being to understand how these processes unfold together.

3.5.2 Conclusions

The current study presents a novel approach for simultaneously modeling short-term within-person relationships and long-term changes in these short-term relationships. We further demonstrated how characterizing an individual based on the strength of their within-person relationships across multiple time scales can be important predictors of distal outcomes. Individuals who became more reactive to daily stressors over a ten-year period consistently

reported lower global levels of well-being relative to those who did not become more reactive. These effects were present over and above the effects of person-mean levels of NA and stress exposure. This approach provides new opportunities to capture the informative characteristics of the individual across various periods of the lifespan and to better understand how the impact of contextual influences change and impact concurrent and future individual states.

Chapter 4

Optimizing Detection of True Within-Person Effects: A Comparison of Multilevel SEM and Unit-Weighted Scale Scores

4.1 Abstract

Intensive repeated measurement designs are frequently used to investigate within-person variation over relatively brief intervals of time. The majority of research utilizing these designs rely on unit-weighted scale scores, which assume that the constructs are measured without error. An alternative approach makes use of multilevel structural equation models (MSEM), which permit the specification of latent variables at both WP and BP levels. These models disattenuate measurement error from systematic variance, which should result in less biased WP estimates and larger effect sizes. Differences in power, precision, and bias between multilevel unit-weighted and MSEM models were compared through a series of Monte Carlo simulations. Results based on simulated data revealed that precision was consistently poorer in the MSEM models than the unit-weighted models, particularly when reliability was low. However, the degree of bias was considerably greater in the unit-weighted model than the factor model. Although the unit-weighted model consistently underestimated the effect of a covariate, it generally had similar power relative to the MSEM model due to the greater precision. Considerations for scale development and the impact of within-person reliability are highlighted.

Keywords: Multilevel modeling, within-person effects, power, multilevel structural equation modeling, composite scores

4.2 Introduction

Intensive repeated measurement designs (e.g., daily diary, ecological momentary assessment) are frequently used in well-being research to investigate within-person variation over relatively brief intervals of time (e.g., hours, days, or weeks). These designs allow variance to be partitioned into within-person (WP) and between-person (BP) sources of variability, enabling differential effects to be estimated at the WP and BP level of analysis (e.g., Curran & Bauer, 2011; Hoffman & Stawski, 2009; Sliwinski, 2008). Much research has examined within-person covariation of time-varying constructs to identify how variables travel dynamically together across time. These covariations have been examined in a variety of domains to identify reliable short-term within-person associations. For example, Hoppmann and Klumb (2006) examined daily variations in personal goals as within-person predictors of daily mood and cortisol levels. Webster and Hadwin (2015) found that within-person fluctuations in positive emotions covary with goal attainment during study sessions. Rush and Grouzet (2012) examined how fluctuations in daily temporal focus accounted for daily levels of psychological well-being.

Research examining within-person associations often investigate constructs (e.g., affect, stress, working memory, rumination, etc.) that are measured through self-report scales assessed repeatedly over many occasions. These measurement scales consist of multiple items that are assumed to reflect a single construct that varies within an individual across measurement occasions. When developing measures for use in within-person intensive measurement research, a primary motivation is to limit the participant burden that results from repeatedly responding to the same questions day after day. It has become common practice to use short-form scales that have been adapted from existing cross-sectional measures. Often these shortened scales consist of just three or four items, and sometimes fewer (e.g., Kashdan et al., 2013; Morelli, Lee, Arn, and

& Zaki, 2015; Reynolds, Robles, & Repetti, 2016). Of concern, is that these measures have been designed and evaluated for identification of between-person differences rather than within-person fluctuations. As a result, many of the within-person measures used lack a proper investigation into the within-person psychometric properties and factor structure, and the reporting of within-person reliabilities are often omitted.

Furthermore, the common analytic approach of research utilizing intensive measurement designs to examine within-person associations rely on unit-weighted scale scores (i.e., composite scores), where all of the items reflecting a construct are summed (or averaged) to create a total score. This approach weights each item of the scale equally and assumes that the constructs are measured without error. The composite score is then included as a time-varying predictor (X_{ij}) in a multilevel modeling (MLM) analysis to account for occasion specific covariation with an outcome (Y_{ij}). The following equations display a common MLM approach to estimate a within-person effect (γ_{10}):

$$\text{Level 1: } Y_{ij} = \beta_{0i} + \beta_{1i}(X_{cij} - X_{c\cdot i}) + e_{ij} \quad (4.1a)$$

$$\text{Level 2: } \beta_{0i} = \gamma_{00} + \gamma_{01}(X_{c\cdot i}) + u_{0i} \quad (4.1b)$$

$$\beta_{1i} = \gamma_{10} + u_{1i} \quad (4.1c)$$

where Y_{ij} is the outcome variable for person i on occasion j . β_{0i} and β_{1i} refers to the intercept and within-person association for person i , respectively; X_{cij} is the composite score for person i on occasion j ; $X_{c\cdot i}$ is the person-mean of X_{cij} for person i ; and e_{ij} represents the within-person residual variance. At Level 2, γ_{00} represents the average intercept; γ_{10} represents the average within-person effect of X on Y ; γ_{01} represents the between-person association between X and Y ;

and u_{0i} and u_{1i} , represent individual deviations from average intercepts and slopes (i.e., random effects).

The unit-weighted composite score consists of both systematic WP variability (i.e., true score variance) and unsystematic WP variability (i.e., measurement error). When a composite score is computed, it cannot be determined how much variability is due to measurement error and how much is due to systematic occasion-to-occasion WP fluctuations. The true systematic fluctuations are of substantive interest to understand the contextual circumstances when individuals are deviating from their typical levels. However, the unsystematic WP variations that are due to measurement unreliability add noise to statistical models attempting to capture true within-person associations.

Variance over time in the same measure has long been an indicator of measurement unreliability. Indices of test-retest reliability treats all within-person variations as scale measurement error under assumptions of stable true scores and no learning effects. Extensive research now clearly demonstrates that many constructs can systematically vary within an individual over either short or longer periods of time. However, from a measurement perspective, it is often unclear how much of the within-person variability over time is due to true systematic variance in the construct and how much is due to measurement error. Unreliable WP measures may give the appearance of considerable WP variability, but are really just scale unreliability. Therefore, it is important when examining WP effects to consider how much scale unreliability is influencing our ability to detect true WP associations based on systematic covariation. Failing to account for such error has the potential to downwardly bias our estimates and may decrease the sensitivity to identify true WP effects.

An alternative analytic approach, multilevel structural equation modeling (MSEM), permits the specification of latent variables at both WP and BP levels in order to disattenuate measurement error from systematic variance. Multilevel SEM combines a measurement model and structural model across levels of analysis. This allows for the within-person variance to be disaggregated from the between-person variance, while still attenuating for measurement error at both levels. The multilevel measurement model can be expressed by the following equation (Muthén, 1991; Preacher et al., 2010):

$$X_{ij} = \nu + \lambda_w \eta_{ij} + \varepsilon_{ij} + \lambda_b \eta_i + \varepsilon_i, \quad (4.2a)$$

where X_{ij} is a p -dimensional vector of observed variables (i.e., scale items) for individual i on occasion j , where p is the number of observed indicators; ν is a p -dimensional vector of intercepts; λ_w is a $p \times q$ within-person factor loadings matrix, where q is the number of latent variables; λ_b is a $p \times q$ between-person factor loadings matrix; η_{ij} and η_i are q -dimensional vectors of within-person and between-person latent variables, respectively; and ε_{ij} and ε_i are p -dimensional vectors of within-person and between-person uniqueness factors (i.e., residuals), respectively.

At the BP level, the indicators are person means of each WP indicator that are aggregated in order to adjust for unreliability in sampling error (see Lüdtke et al., 2008; Marsh et al., 2009 for further details), such that the BP indicators are represented as latent means. Both the BP and WP parts of the model are estimated simultaneously with the WP factor structure representing common covariance in the indicators at each specific occasion across time and BP factor structure representing common covariance in the person-mean indicators across people.

The structural model permits latent variables from the measurement model to be specified as exogenous or endogenous variables within and across levels of analysis. A reduced form of

the within-person (Level 1) and between-person (Level 2) structural models can be expressed by the following equations (Muthén & Asparouhov, 2009; Preacher et al., 2010):

$$\text{Level 1: } \eta_{ij} = \alpha_i + \beta_i \eta_{ij} + \zeta_{ij} \quad (4.2b)$$

$$\text{Level 2: } \eta_i = \mu + \gamma \eta_i + \zeta_i, \quad (4.2c)$$

where α_i is q -dimensional vector of intercepts, β_i is $q \times q$ matrix of regression coefficients for individual i ; ζ_{ij} represents level 1 residuals; μ is a q -dimensional vector of level 2 coefficient means; γ represents a $q \times q$ matrix of level 2 regression slopes; and ζ_i is a vector of level 2 residuals. Within this framework, multiple latent variables can be specified as exogenous or endogenous to one another. Specifically, latent variables at the WP level can be included as a time-varying predictor of endogenous outcomes.

An important distinction between the multilevel UW and MSEM approach is how they deal with unsystematic WP variations. With the specification of latent variables at the WP level, the MSEM approach removes the occasion to occasion variability in the scale items that are not common across items. Common WP covariance reflects occasion specific variations that are common across the scale indicators. That is, on occasions when an individual deviates from their average on one scale item, it reflects the extent that they also deviate from their average in the other scale items. The remaining occasion specific variability that is not common across the scale items is estimated as item uniqueness factors (i.e., unsystematic measurement error). Therefore, the WP latent variable contains only occasion-to-occasion variability in the construct and not random error variance. As a result, using the true score variance to account for WP deviations in an outcome variable should result in larger effect sizes due to a reduction in the noise and an increase in the signal. Of note, it has been shown that latent models often result in poorer precision (i.e., increased standard errors) of estimated mediation effects than observed score

models (Ledgerwood & Shrout, 2011). The degradation of precision in latent models can result in less power than observed score models, despite the larger effect sizes.

4.2.1 Present Study

The goal of the present study was to compare the multilevel unit-weighted composite score approach typically used in MLM with a latent variable modeling approach of MSEM. We compared these two different modeling approaches in their ability to effectively capture true within-person effects. Differences in power, precision, and bias between multilevel unit-weighted (UW) and multilevel structural equation models (MSEM) were examined through a series of Monte Carlo simulations carried out in Mplus.

We expected that the within-person latent variable should better capture true systematic within-person variation and would result in less biased WP estimates of a time-varying covariate (i.e., within-person association) and larger estimated effects. It was further hypothesized that the larger estimated effects from the MSEM would result in greater power to detect a within-person effect than the UW multilevel model. However, as has been found previously, the use of latent variables often results in poorer measurement precision than manifest variables (Ledgerwood & Shrout, 2011), which reduces power. Given the two counteracting influences of larger effect sizes and poorer precision, it was plausible that the MSEM would not result in greater power than the UW models.

4.3 Method

4.3.1 Simulation Data

Data were generated to examine the two modeling approaches under varying conditions. Monte Carlo simulations with 5000 replications were carried out using Mplus v7 software (Muthén & Muthén, 2012). Three factors were manipulated, including the number of

measurement occasions, scale reliability of the predictor variable, and cluster size, resulting in a 2 (*Model*: Unit-Weighted vs. MSEM) \times 2 (*Reliability*: High [0.9] vs. Low [0.5]) \times 3 (*Measurement Occasions*: 4 vs. 7 vs. 10) simulation design. The WP effect of a time-varying predictor was the focus of these simulations, thus the BP population parameters were held constant across conditions to isolate the WP effects. The WP effect size of the predictor was also held constant at 0.2 across conditions. The predictor variable consisted of a four-item scale. Reliability of this scale was computed as the ratio of true-score variance to total variance (ω ; see McDonald, 1999; Geldhof, Preacher, & Zyphur, 2014) and was derived by varying the amount of error in population parameters of each of the scale indicators. Within-person factor variance was set to 0.4 and unstandardized population loadings were set to 1 for each of the four items². Cluster sizes were varied from $N = 25$ to 200. Population parameter values were selected to be within plausible range of values commonly found in well-being research examining within-person effects.

4.3.2 Data Analytic Strategy

Unit-weighted multilevel models and MSEMs were both fit to the simulated data. Figure 4.1 displays the specification of the two models. Power, precision, and bias in detecting the effect of a WP covariate (γ_{10}) was examined across conditions. Power was assessed as the proportion of replications (out of 5000) that yielded a statistically significant within-person effect, based on $\alpha = .05$. Precision was assessed as the average estimated standard error of the within-person effect, where smaller standard errors indicate better precision. The accuracy in estimating the within-person effect was assessed with proportion of bias, which was computed as

² Additional population parameters with heterogeneous factor loadings were also considered, however these results did not differ much from the homogenous factor loading condition, so are not presented here.

the difference of the mean estimated within-person effect across 5000 replications from the true population value, all divided by the population value (Muthén & Muthén, 2002).

The unit-weighted MLM was specified within an MSEM framework with constraints rather than the traditional composite score predictor included in an MLM as a time-varying covariate. In order to produce the equivalent model to the typical MLM (Equation 4.1), the factor loadings of each item was fixed to 1 and the item uniquenesses (i.e., specific error factors) were fixed to 0 (see Figure 4.1A). This specification asserts that the items are equally weighted in their contributions to the common factor (η_{wij}) and that the construct is measured without error. This is the equivalent model to the traditional MLM investigating the WP effect of a time-varying covariate that was measured as a composite variable (Equation 4.1). By specifying the UW MLM in this manner, it permitted a direct comparison with the freely estimated latent variable MSEM approach.

The MSEM approach specified the time-varying predictor as a latent variable at both the WP and BP levels, which disattenuated for measurement error at both levels (see Figure 4.1B). Both the WP and BP parts of the model were estimated simultaneously with the WP latent variable (i.e., η_{wij}) representing common covariance in the indicators at each specific occasion across time (i.e., X_{1ij} to X_{4ij}) and the BP latent variable (i.e., η_{bij}) representing common covariance in the person-mean indicators across people (i.e., X_{1i} to X_{4i}). Item-specific measurement error variance (i.e., variance not shared with the common factor) was freely estimated at the WP (i.e., ε_{w1ij} to ε_{w4ij}) and BP levels (i.e., ε_{b1i} to ε_{b4i}). Therefore, the WP latent variable reflected occasion-specific deviations from person-mean levels (i.e., WP variation) that were common across the four scale items.

4.4 Results and Discussion

A number of findings emerged from the simulation studies. Independent of modeling approach, there were consistent main effects of cluster size and number of occasions on power and precision of the estimated WP effect. Figures 4.2 and 4.3 clearly demonstrate that larger cluster sizes and more measurement occasions resulted in greater power to detect the WP effect and more precise estimates (i.e., smaller SEs) for both modeling approaches. Conversely, accuracy of the estimated effect did not vary based on cluster size nor measurement occasions (see Figure 4.4). The high reliability condition ($\omega = .90$) consistently resulted in higher power than the low reliability condition ($\omega = .50$) across conditions. The influence of cluster size and number of occasions did not vary based on scale reliability, as these patterns were consistent for low or high reliability.

A comparison of the MSEM and multilevel UW modeling approaches revealed that both performed comparably in power to detect WP effects across conditions (see Figure 4.2). However, the standard errors were consistently higher in the MSEMs than the unit-weighted models, particularly when reliability was low (see Figure 4.3). Finally, the UW models were much less accurate in detecting the WP effect compared to the MSEM approach (see Figure 4.4). The UW models consistently underestimated the true effect across conditions, whereas, the MSEM approach estimated the true WP effect with minimal bias. Differences in the degree of bias between the two modeling approaches were exacerbated when the scale reliability was low. Even with low scale reliability, the MSEM approach produced minimal bias (< 1%). However, the degree of bias in the UW model increased from around 3% when scale reliability was high to over 20% when scale reliability was low.

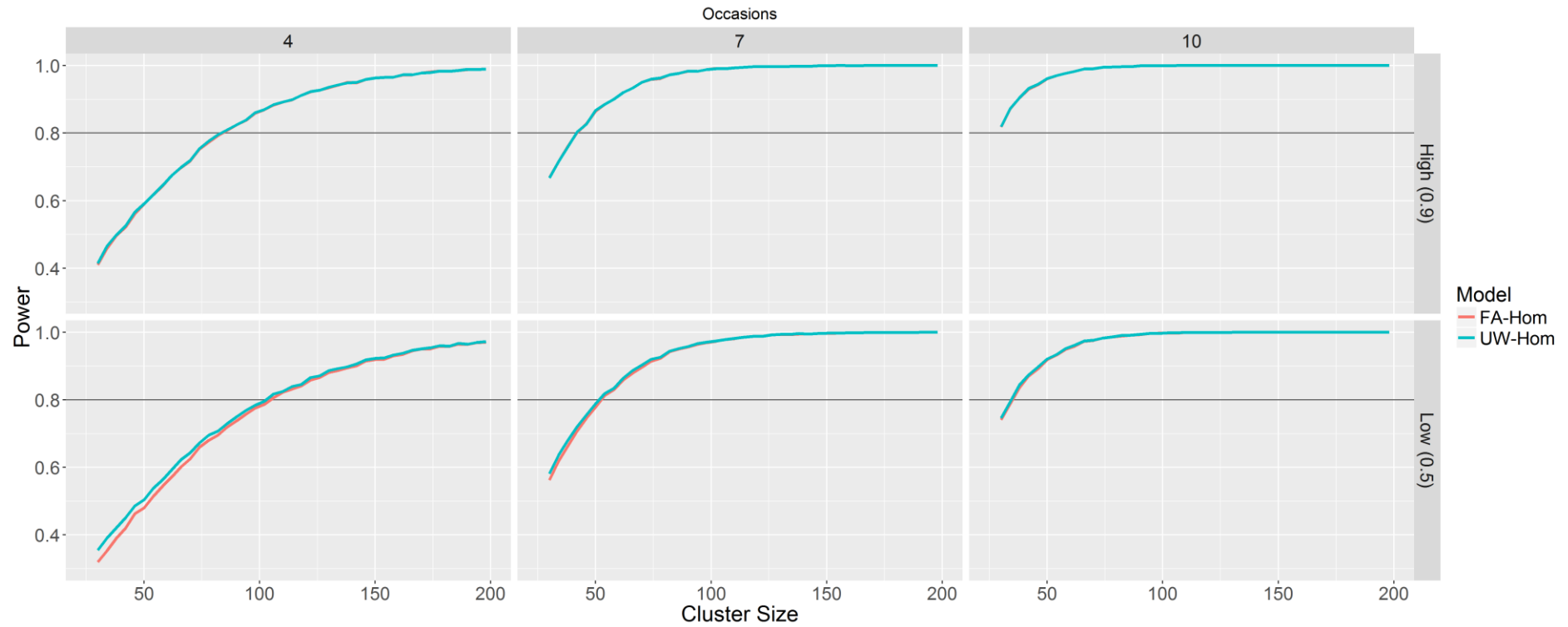


Figure 4.2. Power to detect a within-person effect across varying conditions. *Note.* Based on Monte Carlo simulation of 5000 replications. FA = MSEM factor model; UW = unit-weighted model.

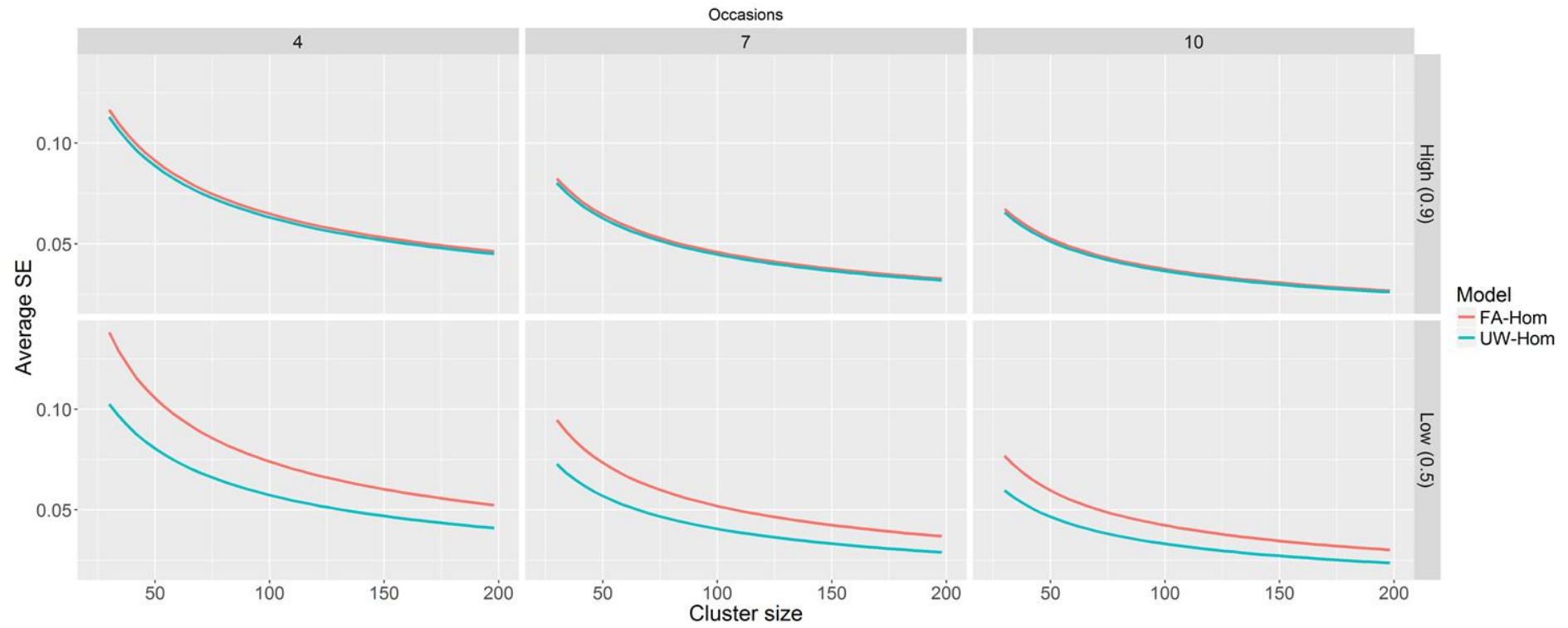


Figure 4.3. Precision of within-person estimate across varying conditions. *Note.* Based on Monte Carlo simulation of 5000 replications. FA = MSEM factor model; UW = unit-weighted model.

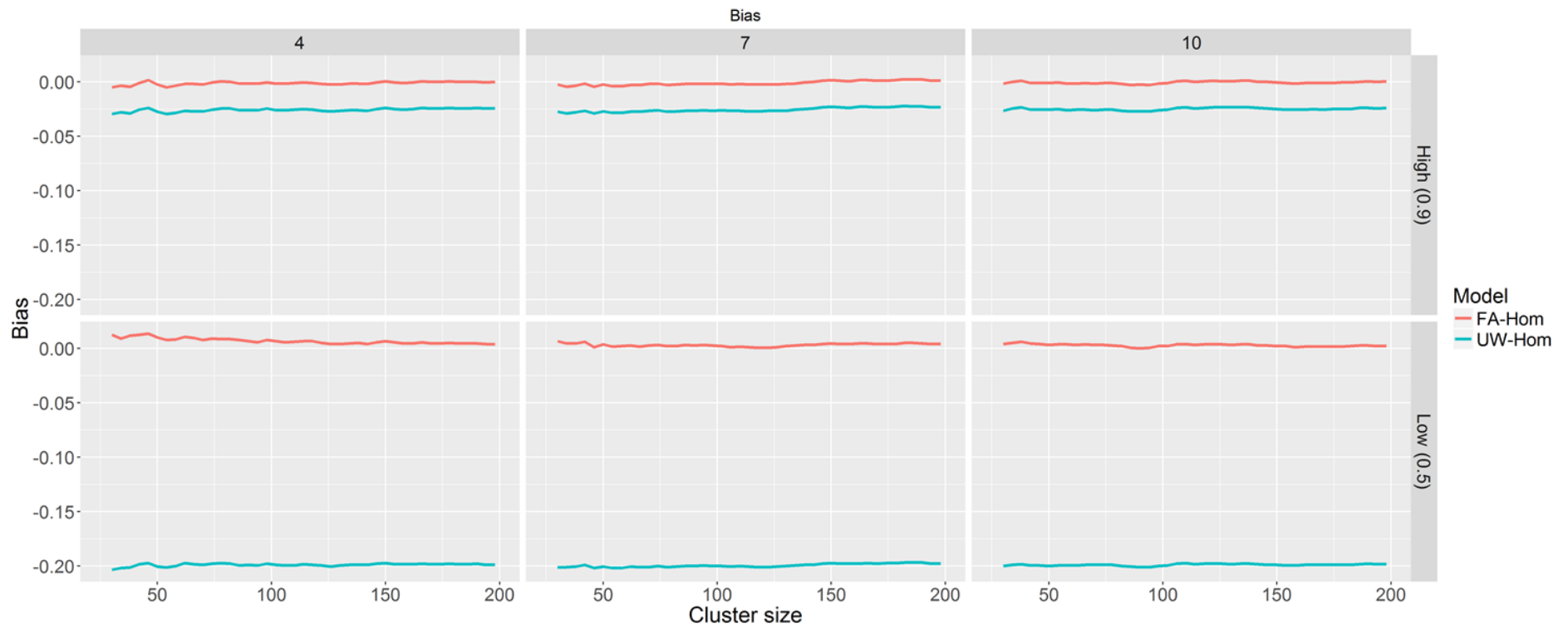


Figure 4.4. Bias in within-person estimates across varying conditions. *Note.* Based on Monte Carlo simulation of 5000 replications. Bias = (mean estimated value – population value) / population value. FA = MSEM factor model; UW = unit-weighted model.

To further inspect the impact of scale reliability on power, precision, and accuracy additional simulations were conducting that held cluster size and number of occasions constant at 75 and 7, respectively³, but varied the scale reliability semi-continuously from 0 to 1. As scale reliability emerged as one of the most influential elements to consider when comparing MSEM and UW models, these series of simulations permitted a thorough examination of the impact of poor reliability of WP measures on the two modeling approaches. Figure 4.5 displays the results of varying the reliability. When reliability of the WP predictor variable was low ($< .70$) the bias of the WP effect was unacceptably high when estimated using a UW approach (bias $> 10\%$; see Figure 4.5b). Furthermore, the 95% coverage of the true population parameter was consistently low with the UW modeling approach (see Figure 4.5d). Whereas, the MSEM approach acceptably recovered the true population parameter with minimal bias ($< 1\%$) regardless of reliability levels. Conversely, the precision of the WP estimate was dramatically poorer for the MSEM model compared to the UW models in situations when reliability was less than $.70$ (see Figure 4.5c). The competing elements of underestimated effects combined with more precise estimates in the UW models resulted in nearly identical levels of power between the MSEM and UW approaches (see Figure 4.5a). Ledgerwood and Shrout (2011) demonstrated similar trade-offs between using a latent variable model versus an observed score model (i.e., unit-weighted) in between-person mediation analyses. The latent model improved accuracy (i.e., produced less biased estimates), but also yielded poorer precision (i.e., higher standard errors) relative to the unit-weighted model. Although the latent variable model produced larger estimates, the reduction in precision typically resulted in lower power to detect the effect.

³ These values were chosen for the cluster size and measurement occasions because a) they represent design characteristics that are commonly used in intensive measurement designs; and b) this appeared to be a point where the two modeling approaches began to diverge.

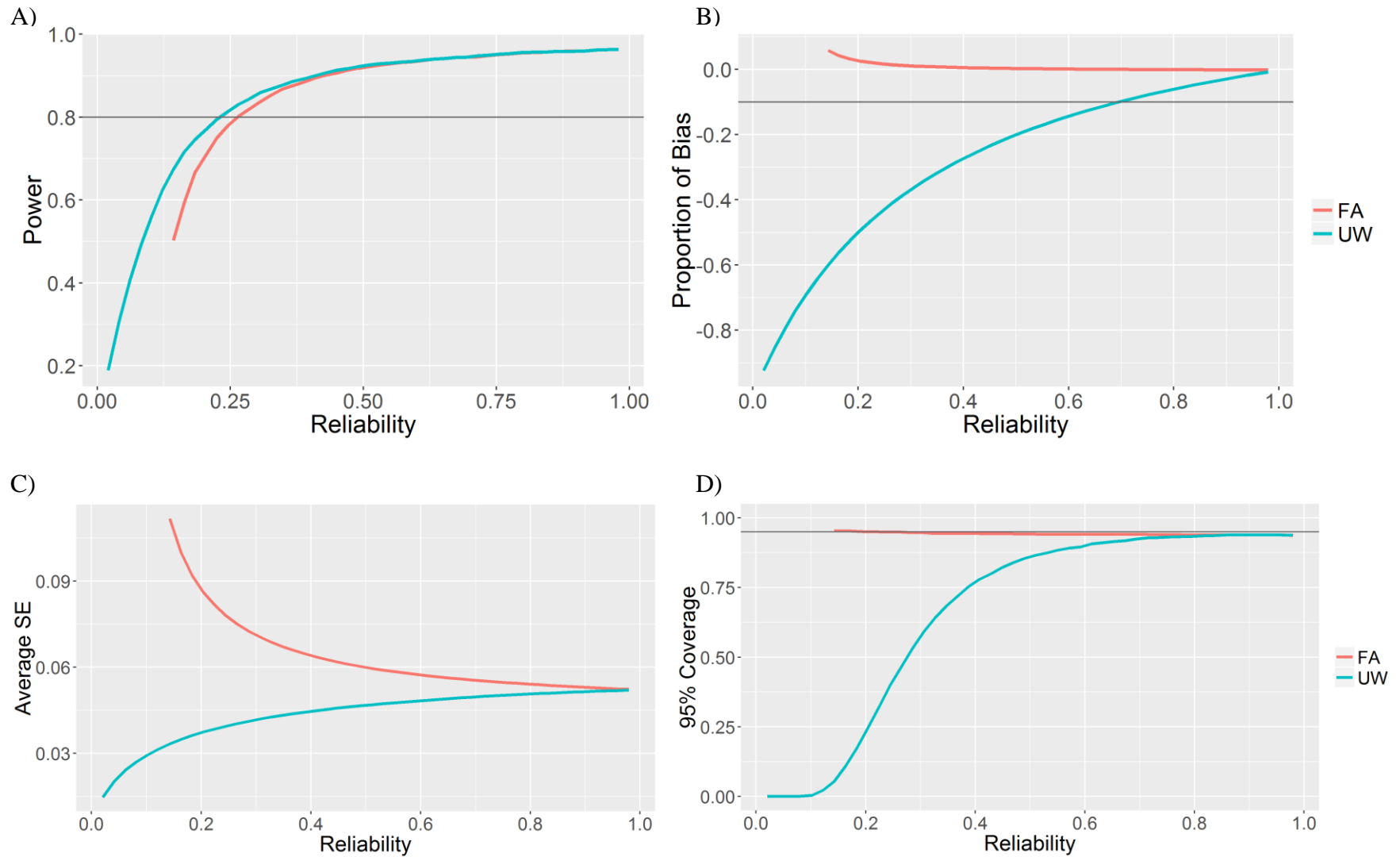


Figure 4.5. Power, precision, bias, and coverage across varying reliability of within-person predictor ($n = 75$; occasions = 7).
Note. Based on Monte Carlo simulation of 5000 replications. Bias = (mean estimated value – population value) / population value.
 FA = MSEM factor model; UW = unit-weighted model.

Due to the considerable proportion of bias at moderate to low reliability, WP effects based on unit-weighted composite scores are likely underestimated. Given that the reliability of WP measures are often not considered and rarely reported, it is difficult to gauge the extent of the issue. Many measures created to capture WP dynamics emphasize face validity and participant burden as the primary considerations and neglect within-person reliability and measurement properties (e.g., factor structure). Computing a composite score from these items obfuscates the potential multidimensionality or poor reliability of the measure. As a result, the WP effects reported throughout the literature, which tend to be small, may be a poor representation of the true magnitude of effects (e.g., 20% bias would reduce $r = .40$ to $r = .32$).

Despite the many advantages, an MSEM approach may not always be the most appropriate choice. Multilevel SEM estimates many more parameters and fluctuations across samples appear to lead to less consistency from one sample to the next in the estimated WP effect (as indicated by the larger SEs). Even though on average across the 5000 replications, the MSEM approach resulted in a considerably less biased WP estimate, in any given sample the estimate may not be as accurate. Precision was particularly concerning when reliability was low and cluster sizes were small. Larger cluster sizes are typically required to produce stable estimates within an SEM framework using latent variables compared to models that rely solely on observed variables (Kline, 2011). Therefore, it may be advantageous at times to continue to use a UW composite score approach, but only under certain conditions and with the specific limitations in mind. First, a UW composite score should only be used after the WP factor structure and reliability of the scale have been established. In the same way that we devote much effort to establishing acceptable measurement properties for cross-sectional between-person scales, so too should such effort be devoted to establishing measures designed to capture

systematic WP fluctuations within intensive measurement studies. It is not sufficient to assume that measures designed and validated for between-person assessment will be suitable and maintain their psychometric properties when used for within-person assessment. Research devoted to establishing and replicating the multilevel factor structure and measurement properties of WP measurement scales should be more normative (e.g., Rush & Hofer, 2014). After establishing that the measure represents a single construct at the WP level and possesses adequate reliability (i.e., $> .75$) to capture WP fluctuations then it may be reasonable to treat these measures as a composite score and employ it in cases with smaller cluster-level sample size where model complexity and convergence may be a concern. In these cases, however, it should be noted that the WP estimates based on composite score predictors will likely be smaller than their true value.

4.4.1 Limitations and Future Directions

Despite the straightforward goals and strengths of the current study, there are a number of limitations that should be addressed with future research. First, the study was solely focused differences in detecting true WP effects. In order to isolate the WP effect, all BP population parameters were held constant across conditions. Future research could benefit from examining the impact of these conditions on BP effects in hierarchically structured data by varying BP population parameters (e.g., BP scale reliability). Furthermore, cross-level effects could be examined to determine how unsystematic WP variance impacts BP estimates. Second, the size of the WP effect was held constant. Though varying effect size may seem warranted, additional analyses examining large versus small effect sizes revealed that the pattern of results did not interact with effect size. Finally, the current study held the number of scale items constant at four. It could be useful to examine how fewer or more scale items impacts results. Similar to

cluster size and number of occasions, it is expected that there will be main effects of number of items, where adding more items will improve power and precision. However, it is less clear if the influence of number of items would differ across modeling frameworks.

4.4.2 Conclusions

The magnitude of short-term WP effects reported throughout psychological research tends to be quite small in general. This is likely exacerbated by the frequent use of a UW composite scores modeling approach in conjunction with scales that possess moderate to low reliability. It is important to examine scale reliability and to design measures that reflect true WP variability in the construct of interest. In doing so, it may be reasonable to utilize a UW modeling approach, as bias may be minimal and precision improved, particularly in situations when sample sizes are small and estimating a latent measurement model in addition to a structural pathway leads to convergence issues. However, the MSEM approach is a more accurate modeling approach when estimating the effect of a WP covariate and could provide a clearer picture of the true magnitude of WP effect sizes. Furthermore, the reliability of the predictor variable is less of a concern in capturing the magnitude of the true effect compared to the UW modeling approach. Nevertheless, the reduced precision of these estimates does warrant some consideration when the goal is to reliably detect a true WP effect.

Chapter 5

Summary and Conclusions

This dissertation advanced a multilevel SEM framework for optimized measurement and analysis of intensive repeated measurement designs with application to the examination of dynamic multivariate associations across multiple time-scales and levels of analysis. The scientific study of well-being requires the application of carefully planned designs and measurements to capture dynamic subjective human experiences and both external and internal factors that impact these experiences. Well-being is a multidimensional construct that fluctuates considerably within individuals over short intervals of time (e.g., hours, days) while potentially changing over longer periods (e.g., years or decades). Both the long-term changes and short-term variations are impacted by a variety of individual and contextual factors. In order to appropriately measure and model well-being, and its antecedents and consequences, research designs must have the capacity to accurately capture the temporal variations that exist within each individual, as well as an analytic approach that synergistically accounts for intra-individual variations and inter-individual differences.

Each of the three studies presented examined distinct research questions, which showcased the utility of intensive repeated measurement designs, as well as the flexibility of the MSEM framework within the context of well-being research. The first study, *'The Moderating and Mediating Effects of Cognitive Interference on Stress Reactivity: Intra- and Inter-individual Associations across Levels of Analysis using Multilevel SEM'*, illustrated how the role of cognitive interference differed within people over time than between people on average in understanding the process of how stress impacts emotional well-being. The ability to analyze cognitive interference as a moderator and mediator simultaneously at both the within-person and

between-person levels extended previous research approaches and produced new findings. The results of this study further emphasized how the pattern of results need not be the same when examining associations within an individual over time as they are between individuals. Careful investigations and theoretical development into the varying patterns of associations at different levels of analysis are required to fully explain, anticipate, and modify the interacting influences that play a role in an individual's ongoing experience of well-being.

The second study, '*Modeling Long-Term Changes in Daily Within-Person Associations: An Application of Multilevel SEM*', extended the approaches that examine individual differences in within-person associations as a predictor of between-person outcomes. Past research has predominantly analyzed these models through a two-step analytic approach. The flexibility of the MSEM framework permitted these individual differences in within-person associations (i.e., random slope effects) to be estimated simultaneously within a single model. Specifying the random slopes at the within-person level as exogenous predictors at the between-person level enabled for an investigation into these processes across time-scales that adjusted for variability across levels. The three-level SEM employed in this study further extended previous approaches by examining long-term changes in the short-term within-person association between stress and affect, and modeling individual differences in these changes as a significant predictor of between-person differences in psychological well-being. Characterizing an individual based on the strength of their within-person associations across multiple time scales was shown to be an important predictor of distal outcomes that has much potential to expand our theoretical conceptualizations about the influence of the individual's current state and their dynamic responses to varying contextual influences.

Finally, the third study, '*Optimizing Detection of True Within-Person Effects: A Comparison of Multilevel SEM and Unit-Weighted Scale Scores*', highlighted the importance of carefully considering the design features and psychometric properties of the measurement scales that are used to capture within-person fluctuations applied to intensive repeated measurement designs. A comparison of an MSEM approach that specified latent variables to reflect the within-person construct to the more common approach that uses unit-weighted composite scores revealed that scale reliability of the within-person measure was critical in distinguishing the two modeling approaches. Applying the MSEM approach with latent variables dramatically reduced bias in the magnitude of a within-person effect compared to the unit-weighted approach, particularly when scale reliability was poor. The MSEM latent variable modeling approach emerged as a useful method that more accurately captured the true magnitude of within-person effect sizes. Nevertheless, the composite score modeling approach still has merit as a method for identifying within-person effects under certain circumstances.

Future Outlook

The collection of research studies presented in this dissertation highlight the benefits of examining and appropriately accounting for patterns of associations across levels of analysis, utilizing designs that link multiple time-scales, and considering the impact of measurement concerns. While these advances are informative in advancing the current state of knowledge and providing exemplars for developing future research, there are still a number of areas that require attention to further advance our understanding of intra-individual processes related to well-being and other psychological and health outcomes. Additional work into optimal design is needed. Study three highlighted the importance of considering within-person reliability when making design and modeling decisions, however further investigations into how we assess the reliability

of within-person processes is warranted. If short-term within-person associations are to be treated as reliable individual difference variables then a better understanding of the sensitivity of design features to within-person effects is needed to have confidence in these estimates and their replicability. Currently, it is often unknown if the constructs under investigation are fundamentally different when measured on different time-scales. As the time-scale varies, the process that is being measured may also change in terms of quantitative or qualitative shifts (Birren & Schroots, 1996; Martin & Hofer, 2004) and therefore cannot be assumed that constructs are equivalent across occasions or levels of analysis. This is both an empirical and theoretical question and should receive consideration as such, with careful theoretical developments that are supported or refuted through extensive empirical investigations. Accordingly, the measures that are designed to capture the constructs across time-scales should be given adequate attention to ensure they possess sufficient validity and reliability to support the statistical conclusions. Measures designed to capture stable between-person differences may not possess suitable sensitivity to accurately capture small increments in within-person variation. In addition, most research to date in this area has been purely observational that at best, has identified patterns of multivariate associations and modifiers. Though many theoretical models imply causal influences and directionality, the empirical results remain correlational. More frequent assessments across multiple time-scales should provide opportunities to more closely approximate the temporal sequencing of causal variables. Introducing interventions into these measurement intensive designs would be an important step in the direction of identifying causal patterns in these complex dynamic associations.

The advancements in mobile data collection technologies (e.g., smartphone apps, wearable devices) are drastically enhancing the ease of data collection for both researchers and

participants. As concerns of researcher costs (financial and time commitments) and participant burden move to the periphery, the primary concerns should focus on how to validly and reliably measure the constructs at the time-scales under investigation and to appropriately model the complex patterns of associations across levels of analysis. Integrating intensive repeated measurement burst designs that sample across numerous time-scales place us in a better position to empirically investigate how these constructs, and their associations with key predictor and outcome variables, may depend on the underlying time-frame, helping us to evolve our theoretical understanding of the processes at play. Applying an MSEM analytic approach permits the researcher to 1) appropriately investigate the construct validity and reliability of the measures used at each level of analysis through multilevel measurement models; 2) account for variations that occur across levels of analysis; and 3) simultaneously investigate multivariate associations that unfold within and across levels of analysis, permitting a more complete examination of the influencing processes that vary over multiple time-scales. Given the research design and analytical tools available, it is no longer reasonable to assume that the nomothetic approach is sufficient to fully explain the complex, dynamic experience of well-being.

Closing Statement

An increasing number of research studies demonstrate the remarkable intra-individual variability that is present in cognitive, behavioral, and physical functioning across different time scales. The results from the current studies, and that of several studies using short-term repeated assessments, provides evidence that single assessments do not usually provide optimal estimates of an average or typical value of a person's functioning, and adversely affect results from between-person and within-person analysis. We have highlighted the strengths of measuring individuals more often than typical widely-spaced longitudinal designs in order to better sample

the contextual and intrinsic variation of individual experiences and functioning. We demonstrated how intensive repeated measurement designs can improve the discrimination of between-person differences by disentangling true between-person differences in typical level from contextual factors and intrinsic intra-individual variation. Applying appropriate analytical models further permits the researcher to disaggregate the multiple sources of variation and to integrate effects that operate across varying temporal scales.

As intensive measurement designs become less burdensome and costly for participants and researchers, the benefits will clearly outweigh the costs. However, in order to ensure that these designs are utilized to their potential, a greater focus must be placed on developing theories that adequately and appropriately account for both within-person variation and between-person differences. There is a need for our methods of research design to match our research questions. Theoretical models should not be limited to our current research designs. Rather, our research designs should evolve to appropriately evaluate theoretical models and expand the evidence base for alternative designs and frequency of temporal sampling for different measurements. Though many areas of investigation will (and should) be empirically driven, it will still ultimately be that our theoretical models guide where in the data we look, how we aggregate, and what patterns are meaningful. It is not sufficient to merely collect as much data as possible, on a near continuous timeline, and assume that the patterns of greatest importance will simply reveal themselves to the researcher. Theoretical models remain necessary and it is the development of these models that will benefit the most from flexible research designs and analyses that will be able to accommodate and evaluate their complexities.

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