The Attitude-Engagement Model Within-Persons: An Experience Sampling Study of Job Attitudes and Behavioral Engagement

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THE ATTITUDE-ENGAGEMENT MODEL WITHIN-PERSONS: AN EXPERIENCE SAMPLING STUDY OF JOB ATTITUDES AND BEHAVIORAL ENGAGEMENT

by

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ABSTRACT

Although a large body of research has attempted to answer the question, “Is a happy worker a more productive worker?” by examining the relationship between job attitudes and behaviors, results are often inconsistent. Drawing upon Fishbein and Ajzen’s (1974) compatibility principle as well as theory on job attitude change and dynamic performance, the current study sought to answer this question by examining the attitudes-performance relationship at the within-persons level of analysis. Specifically, an Attitude-Engagement Model that specifies a broad conceptualization of job attitudes and behavioral engagement should exhibit the strongest relationship between job attitudes and job behaviors (Harrison, Newman, & Roth, 2006; Newman, Joseph, & Hulin, 2010) within-persons. Although relationships between these two domains have been theorized and examined within a between-subjects framework, no attempts have been made to examine these broad factors at the within-subjects level. Using experience sampling methodology (ESM), job attitudes and job behavior data were collected from 52 hairdressers, cosmetologists, and barbers across 1,438 observations. Using intensive longitudinal methods (Bolger & Laurenceau, 2013), evidence for large within-persons variability in both job attitudes and behavioral engagement was found. Evidence for the Attitude-Engagement model at the within-persons level of analysis was also provided, even after introducing a one “moment” and one “day” time lag. Furthermore, in order to provide evidence for the construct validity of the A-Factor and the E-Factor within-persons, evidence for the within-persons reliability of the assessment of change was established employing a generalizability framework. The findings have both research and practical implications for the study of attitudes and behaviors in the workplace and suggest several interesting avenues for future research.
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CHAPTER ONE: INTRODUCTION

Success is not the key to happiness; happiness is the key to success. A happy worker is a productive worker. These maxims are often proclaimed by organizational stakeholders and the general public to suggest that employee performance is at least in some part attributable to employee satisfaction and happiness. Indeed, the relationship between job attitudes and job performance has often been referred to as the holy grail of organizational psychology and organizational behavior (Landy, 1989). To test this age-old adage, a plethora of theoretical and empirical studies have been conducted that examine the relationship between job attitudes and behaviors in an attempt to build the case for utilizing employee satisfaction to predict performance.

For example, an initial meta-analysis in 1984 suggested that the corrected correlation between job satisfaction and job performance was .31 ($r = .23$; Petty, McGee, & Cavender, 1984). However, a meta-analysis published the following year which incorporated a larger base of studies found that this relationship was much weaker ($\hat{\rho} = .17, r = .15$; Iaffaldano & Muchinsky, 1985). This relatively weak relationship led Iaffaldano and Muchinsky (1985) to deem the relationship between job satisfaction and job performance an “illusory correlation” (p. 270; see also Chapman & Chapman, 1969). Their finding of a weak relationship also echoed the most influential early review of the job satisfaction-performance relationship (Brayfield & Crockett, 1955) which stated that there was “minimal or no relationship” between job satisfaction and performance (p. 405).

Notably, Judge, Thoresen, Bono, and Patton (2001) conducted a meta-analytic review of the relationship between job satisfaction and job performance over a decade after the Iaffaldano and Muchinsky (1985) meta-analysis. They estimated the corrected correlation between job
satisfaction and performance to be .30 ($r = .23$ uncorrected). In doing so, they improved upon many methodological limitations in the prior meta-analyses by including unpublished studies and correcting for unreliability (Judge et al., 2001). Additional meta-analyses have since explored moderator variables such as culture (Ng, Sorensen, & Yim, 2009) and situational strength (Bowling, Khazon, Meyer, & Burrus, 2015) on the satisfaction-performance relationship as well as collective conceptualizations of job satisfaction and their effects on overall performance (Whitman, Van Rooy, & Viswesvaran, 2010).

Although Judge et al.’s (2001) finding suggests a moderate relationship between satisfaction and performance, Harrison, Newman, and Roth (2006) have found that the conceptualization of the predictor and criterion domains as broad (i.e., overall, general constructs) or narrow (i.e., specific, facet-level constructs) has an effect on the job attitudes-performance relationship. Drawing upon Fishbein and Ajzen’s (1974) compatibility principle, Harrison et al. (2006) found support for their “attitude-engagement model” in which overall job attitudes (i.e., the A-Factor, or a broad factor subsuming several job attitudes, including job satisfaction and organizational commitment) predicted an overall individual effectiveness factor (i.e., the E-Factor, or a broad factor subsuming task performance, organizational citizenship behavior (OCB), and withdrawal) using meta-analytic structural equation modeling ($\gamma_{\text{standardized}} = .59$; see also Newman, Joseph, & Hulin, 2010). The revised version of the attitude-engagement model (Newman et al., 2010) can be found in Figure 1 and includes job involvement as an element of the A-Factor. In summary, although initial evidence suggested weak support for the “happy worker is a productive worker” hypothesis (e.g., Iaffaldano & Muchinsky, 1985), more recent work suggests a moderate relationship between job satisfaction and job performance (e.g.,
Judge et al., 2001) and a robust relationship between broad job attitudes and broad performance (Harrison et al., 2006).

Another underdeveloped focus of the prior meta-analytic research concerning the satisfaction-performance relationship has been on the nature of the within-persons relationship. Most of the prior meta-analytic research has examined the satisfaction-performance relationship at the between-persons level, rather than over time, within-persons. An initial sojourn into exploring the role and meaningfulness of within-person variation in job satisfaction as a predictor of job performance can be found in Judge et al. (2001). They found that type of design did moderate the satisfaction-performance relationship, with longitudinal designs ($\hat{\rho} = .23$, $r = .14$) exhibiting much smaller correlations than cross-sectional designs ($\hat{\rho} = .31$, $r = .18$).
Furthermore, in a meta-analysis of panel studies on job satisfaction, organizational commitment, and job attitudes, Riketta (2008) found through meta-analytic regression that the relationship between attitudes and performance was stronger for prospective designs (job attitudes preceding performance; $\beta = .06, p < .001$) rather than for retrospective designs (performance preceding job attitudes; $\beta = .00$, n.s.). The prospective relationship was significant for the 1-6 month time lag, and not for the other, longer time lags. The component relationships between satisfaction and commitment with performance suggests that this prospective relationship was slightly stronger in magnitude for commitment than satisfaction ($\beta = .08$ vs. $\beta = .03$, respectively). The selection of time lags as well as a broad vs. narrow conceptualization (e.g., job attitudes vs. organizational commitment and job satisfaction) is important for the within-persons understanding of the satisfaction-performance relationship.

So is a happy worker a productive worker? As can be seen from the prior meta-analytic research, job satisfaction is modestly related to job performance (Judge et al., 2001). However, most of this prior research is cross-sectional in nature or considers only prospective / retrospective longitudinal designs. Although the relationship between task satisfaction and task performance at the within-persons level has been found in some prior research to be fairly strong ($r = .57$, Fisher, 2003), additional research is needed on the within-persons relationship of job attitudes and behavioral engagement (i.e., attitudes and behaviors conceptualized broadly). Prior research suggests that when the attitude and performance domains are both are conceptualized as broad factors (see Figure 1, Harrison et al., 2006; Newman et al., 2010), the relationship is stronger than correlations between broad and narrow conceptualizations (e.g., job satisfaction and overall performance). Drawing on Fishbein and Ajzen’s (1974) “compatibility principle”,

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when the predictor and criterion space are broadened (e.g., to overall attitudes and performance), a happy worker may very well be a productive worker.

As such, the purpose of this study is to fill the gap in prior research on the relationship between job attitudes and organizational outcomes to examine the often neglected within-persons nature of job attitudes and its role in the attitudes-performance relationship. Generally speaking, this study constitutes a broad, within-persons analysis of the “is a happy worker a productive worker” adage. Although well-established theory and empirical work suggests the daily experience of job events and perceptions of the work environment contribute to cumulative job attitudes and performance behavior (Weiss & Cropanzano, 1996), the extent to which the “is a happy worker a productive worker” adage generalizes to the individual level remains unknown (i.e., it remains unclear whether individuals work harder during periods of happiness in their jobs). Thus, experience sampling methodology (ESM) was utilized to examine the relationship between job attitudes and job behaviors at the within-persons level of analysis.

This study attempts to contribute to the organizational sciences in three ways. First, the variability of the broad A-Factor and E-Factor constructs was tested at the within-persons level of analysis. Second, the relationship between the A-Factor and E-Factor was tested at the within-persons level of analysis. Third, the reciprocal relationship between the E-Factor and the A-Factor was tested at the within-persons level of analysis. Overall, this study is the first exploration of the Attitude-Engagement model (Harrison et al., 2006; Newman et al., 2010) at the within-persons level of analysis.

The A-Factor

Job attitudes have been the focus of a wide array of published empirical and theoretical work in the organizational sciences; in fact, Judge and Kammeyer-Mueller (2012) identified over
33,348 records pertaining to this topic. As of the time of this writing (2015), this number has increased by nearly 10,000 records (i.e., 44,048 – using Judge and Kammeyer-Mueller’s search criteria). Along with this vast amount of literature, a number of psychological constructs pertaining to job attitudes have emerged in attempt to characterize the content domain of job attitudes. Job attitudes refer to “a relatively stable evaluative disposition toward a specific person, situation, or other entity, which varies in intensity and favorability and tends to guide an individual’s responses to that object” (Schleicher, Hansen, & Fox, 2010, p. 137). Of these job attitudes, the most common have been job satisfaction, organizational commitment, job involvement, and work engagement (Harrison et al., 2006; Hulin & Judge, 2003; Judge, Hulin, & Dalal, 2012; Judge & Kammeyer-Mueller, 2012; Newman et al., 2010; Schleicher et al., 2010). In this section, I review the prior definitions of these common job attitudes and research that suggests that they are related. Secondly, I discuss prior literature on within-persons variability in specific job attitudes to suggest that there is significant within-persons variability in the A-Factor and this structure persists at the within-persons level of analysis.

One pervasive problem in the organizational sciences concerns the appropriate explication and differentiation of constructs, especially within the area of job attitudes (Le, Schmidt, Harter, & Lauver, 2010; Morrow, 1983). Notably, there is conceptual and empirical overlap between common job attitudes constructs including job satisfaction, organizational commitment, and job involvement (Harrison et al., 2006; Hulin, 1991; Newman et al., 2010). Multiple definitions for job satisfaction (Fritzsche & Parrish, 2005; Hulin & Judge, 2003; Locke, 1969; Weiss, 2002) have emerged over the years, although they primarily focus on a combination of affective and cognitive evaluations of one’s job (Hulin & Judge, 2003; Schleicher et al., 2010). Organizational commitment (Allen & Meyer, 1990; Meyer & Allen,
1991) refers to a job attitude “reflected in a combination of affect (emotional attachment, identification), cognition (identification and internalization of [organizational] goals, norms, and values), and action readiness (a generalized behavioral pledge to serve and enhance the organization’s interests)” (Solinger, van Olffen, & Roe, 2008, p. 80). Lastly, most definitions of job involvement (Kanungo, 1982; Keller, 1997; Lodahl & Kejner, 1965) represent the “degree of psychological involvement one is experiencing with one’s current job, with aspects of one’s job, or with work in general” (Schleicher et al., 2010, p. 160). These definitions of job attitudes (especially organizational commitment and job satisfaction) share an affective evaluation component; notably, Hulin (1991) suggests that the only clear difference is between targets of the job and organization for satisfaction and commitment, respectively. However, even this distinction has been diminished in recent years with the forwarding of “target-free” approaches to job attitudes in which more generalized forms of the constructs are forwarded without explicit targets (Klein, Cooper, Molloy, & Swanson, 2014; Klein, Molloy, & Brinsfield, 2012).

The conceptual overlap among job attitudes has been substantiated by empirical research on the topic. First, although some early empirical studies have provided evidence for the discriminant validity of the three job attitudes constructs (Brooke, Russell, & Price, 1988; Mathieu & Farr, 1991), these prior studies failed to account for the full range of measurement artifacts in their factor analytic models (e.g., transient error). A more recent empirical study correcting for additional forms of measurement error provided a very large estimate of the latent correlation between job satisfaction and organizational commitment ($\varphi = .91$, Le et al., 2010). Second, prior meta-analytic research tends to suggest strong correlations between satisfaction, commitment, and involvement. For example, strong positive manifold has been found between
job satisfaction and organizational commitment ($\rho = .60$, Harrison et al., 2006); between job satisfaction and job involvement ($\rho = .45$, Brown, 1996); and between organizational commitment and job involvement ($\rho = .50$, Brown, 1996; $\hat{\rho} = .52$, Cooper-Hakim & Viswesvaran, 2005; $\rho = .44$, Mathieu & Zajac, 1990; $\hat{\rho}_{\text{affective}} = .53$, Meyer, Stanley, Herscovitch, & Topolnytsky, 2005). Third, recent research using meta-analytic structural equation modeling and confirmatory factor analysis provides evidence for an A-Factor, or a latent factor consisting of several discrete job attitudes (see Figure 1, Harrison et al., 2006; Newman et al., 2010). This evidence for substantial overlap among satisfaction, commitment, and involvement has even led to the proliferation of new constructs, including “core work evaluation” which essentially represents the “A-Factor” as a “summary psychological evaluation of the elements of the work environment” (Webster, Adams, & Beehr, 2014, p. 28). Across three studies, Webster and colleagues ruled out the threat of common method variance, provided evidence for the discriminant validity with other constructs (i.e., individual differences and general environmental evaluations), and provided evidence for criterion-related validity of this core work evaluation construct.

**Within-Person Variation in Job Attitudes.** Interestingly, although a substantial amount of evidence has been provided for the A-Factor at the between-persons level of analysis, very little work has been conducted on the factor structure of job attitudes at the within-persons level.

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1 The Harrison et al. (2006) corrected correlation estimate is based on a composite of prior meta-analytic correlations from Mathieu and Zajac (1990) as well as from Meyer et al. (2002).

2 Only correlations between job attitudes and either overall organizational commitment or affective organizational commitment are reported. Prior research has criticized the Three Component Model of organizational commitment (Allen & Meyer, 1990) as not representing a general organizational commitment model (cf. Meyer & Herscovitch, 2001)—only affective commitment represents an attitude toward the organization whereas the other two (i.e., normative and continuance commitment) represent specific attitudes toward behavior or turnover (Solinger et al., 2008). Further representing this empirical distinction, affective commitment has been referred to as “attitudinal commitment” in prior research (Riketta, 2002) and meta-analytic research has provided evidence for the discriminant validity of the commitment dimensions (Meyer et al., 2002).
of analysis. One exception can be found from a previously mentioned study (Le et al., 2010), however, this analysis only incorporated two time points which is not sufficient enough to capture the longitudinal unfolding of job attitudes over time (Ployhart & Vandenberg, 2010). Furthermore, individual explorations of the within-person variability of component job attitudes have suggested that a large proportion of the variance in job attitudes exists within-persons (i.e., 76% of the variance in task satisfaction, Fisher, 2003; 36% of the variance in job satisfaction, Ilies & Judge, 2002; 35% of the variance in job satisfaction, Ilies, Scott, & Judge, 2006).

However, research has only recently suggested what might be driving changes in job attitudes. One could expect the A-Factor structure to be recapitulated over time within-persons for a variety of reasons. A recently forwarded theoretical framework for job satisfaction change can be especially informative in describing how the structure of job attitudes likely stays the same over time (Chen, Ployhart, Thomas, Anderson, & Bliese, 2011). Chen et al. (2011) drew primarily on four theories to describe reasons behind job satisfaction change: 1) Prospect Theory (Kahneman & Tversky, 1979, 1984), 2) Conservation of Resources (COR; Hobfoll, 1989), 3) Within-Person Spirals Theory (Lindsley, Brass, & Thomas, 1995), and 4) Sensemaking Theory (Louis, 1980). In combination with Prospect Theory, theory on counterfactuals (Folger, 1986, 1987; Folger & Martin, 1986; Kahneman & Miller, 1986; Kahneman & Tversky, 1982) may also help explain why job satisfaction can change through the consideration of ad-hoc, hypothetical alternatives.

First, Prospect Theory (Kahneman & Tversky, 1979, 1984) suggests that gains or losses from a person’s reference point of job attitudes (depending upon their magnitude) can make the gain or loss experience more salient, and thus alter or change the job attitudes. As applied to research on job attitudes, the Comparison Level Model of Satisfaction suggests that derivations
in a person’s outcomes experienced in a focal role from those experienced or witnessed in prior roles (i.e., a comparison level) contribute directly to satisfaction, such that larger, positive discrepancies are more satisfying. These theories mirror the theoretical mechanism suggested by prospect theory in that reference points are directly affected by comparisons with positions and jobs from focal others. Similar to Prospect theory, Kahneman’s work on counterfactuals suggests that conceiving of alternative experiences with the target that are constructed ad hoc may also affect or emotional and cognitive responses (Kahneman & Miller, 1986; Kahneman & Tversky, 1982). Drawing on this prior work, Folger forwarded Referent Cognitions Theory to suggest that people make fairness attributions in a similar fashion by considering what might have been (Folger, 1986, 1987; Folger & Martin, 1986). Empirical research suggests that counterfactual thinking can affect both emotional (Spencer & Rupp, 2009) and attitudinal experiences (Ersner-Hershfield, Galinsky, Kray, & King, 2010). The work of Kahneman and Folger suggests that not only are direct comparisons with previously experienced or witnessed reference points meaningful; but those that are counterfactual, hypothetical, or ad hoc matter as well in attitude formation and change.

These theories pave the way for Conservation of Resources Theory (Hobfoll, 1989), where decrements in job attitudes can lead to “loss spirals” (p. 519) as we are motivated to protect and conserve personal resources (continuous decrements in job attitudes lead to compounding use and replenishment of resources). Relatedly, within-person spirals theories (Lindsley et al., 1995) suggest that positive or negative trends in job attitudes can lead employees to believe that they no longer have control over their trajectory and they may in turn alter their experiences and expectations to align with their own perceived lack of control. Finally, dynamic sense making (Louis, 1980) is another process that may facilitate job attitude change as
employees have a need to make sense of and interpret their experiences. They may look to prior work experiences in order to make sense of their current experiences and may dynamically shape job attitudes as a result.

As additional evidence for change in job attitudes, research on organizational commitment change suggests that affective commitment is subject to within-individual variation as based in psychological contracts theory: changes in the employment relationship (i.e., relational aspects of psychological contracts; Greenbaum, Folger, & Ford, 2011; Rousseau, 1989; Rousseau, & McLean Parks, 1993) resulting in breaches of social exchange obligations can lead to changes in affective or attitudinal commitment (Bentein, Vandenbarghe, & Stinglhamber, 2005; Morrison & Robinson, 1997). When applied to general job attitudes, we may expect sudden breaches to adversely affect satisfaction, commitment, and involvement at the within-persons level as these forms of attitudes contain affective and cognitive components. This proposition is further grounded in recent theory concerning the dynamic microstructure of organizational commitment (Solinger, Hofmans, & van Olffen, 2015). Solinger et al. (2015) recognize the traditional approach to conceptualizing attitudes as consisting of affective, cognitive, and behavioral components (Rosenberg & Hovland, 1960). Drawing on prior theories of social intuitionism (Haidt, 2001), cognitive dissonance (Festinger, 1957), and social cognitive neuroscience (Cunningham & Zelazo, 2007; Cunningham, Zelazo, Packer, & Van Bavel, 2007); affective, behavioral, and cognitive elements of prior attitudes are expected to facilitate change in future behavioral and cognitive elements of the same attitudes. As such, we may expect prior experiences as well as the current experience to contribute to a dynamically constructed overall job attitude.
Despite the prior research that suggests there is meaningful within-person variation in job attitudes, alternative theories do exist that suggest variation in job attitudes is not as large as one would assume. The primary theory drawn upon to suggest that affect and attitudes are relatively stable is the “Hedonic Treadmill” theory (Brickman & Campbell, 1971). This theory suggests that although people accrue experiences that slightly improve or diminish their happiness, they still remain relatively stable in their satisfaction over time. The “Hedonic Treadmill” is also grounded in Adaptation Level theory (Helson, 1964) which suggests that our perceptions are not absolute, but rather relative to a set point—in turn, we habituate to new circumstances and fall back to base line levels of satisfaction. Although these theories might suggest that within-person variation in job attitudes are minor, the “Hedonic Treadmill” theory has recently been clarified to suggest that set points can change over time and that our adaptation levels can also vary across people (Diener, Lucas, & Scollon, 2006). The latter point is especially important, concerning that adaptation levels likely have a direct effect on variability in job attitudes. Furthermore, recent research does suggest that frequent and minor events (e.g., exercise, religious service attendance, etc.) actually can have an impact on long-term happiness and well-being (Mochon, Norton, & Ariely, 2008). As such, given the prior empirical and theoretical research that supports change in job attitudes (Bentein et al., 2005; Boswell, Shipp, Payne, & Culbertson, 2009; Chen et al., 2011; Ilies & Judge, 2002; Liu, Mitchell, Lee, Holtom, & Hinkin, 2012; Solinger et al., 2015); one might suggest that there is a large proportion of variability in job attitudes relative to between-persons variability that exists within-persons. In other words, the employee experience of job attitudes varies from moment-to-moment and day-to-day in addition to their average experiences of job attitudes (Iida, Shrout, Laurenceau, & Bolger, 2012).
Hypothesis 1: A significant proportion of the variance in broadly-defined job attitudes (i.e., the A-Factor) is within-person.

The E-Factor

Since the 1950s and earlier, industrial/organizational psychologists have decried the ambiguous and tedious nature of criterion selection as evident in the “criterion problem” (Austin & Villanova, 1992; Schmidt & Kaplan, 1974; Wallace & Weitz, 1955; Wildman, Bedwell, Salas, & Smith-Jentsch, 2010). Nagle (1953) posits three issues that surround the selection of criteria: criterion relevance, reliability, and combination with other criteria. The latter facet of the criterion problem is arguably the most important of the three and has been the foundation of a great debate that still rages to this day. Should multiple criteria be grouped together to form a generalized, global criterion? Should criteria be treated separately as isomorphic indicators of success? These questions constitute the crux of the criterion specificity component of the “criterion problem.” Schmidt and Kaplan (1974) conclude that “criterion elements can be, and, in fact, at some point must be, weighted into a composite irrespective of their intercorrelations” also adding that if they are all considered to be bidirectional indicants of a success construct than they should be weighted together as such (p. 431). This highlights the practical use of criteria but some would argue that examinations at a narrower level of abstraction may also be valuable depending upon the purpose. In this section, I outline previous research justifying the grouping of behavioral criteria (i.e., a behavioral engagement factor). Furthermore, I suggest that there is meaningful within-persons variation in the E-Factor at the within-persons level of analysis and provide evidence for the variability in the components of behavioral engagement (e.g., job performance, OCB, and withdrawal).
A similar extension of the “criterion problem” can be seen in the realm of research on job attitudes. For example, as previously mentioned, early research on the relationship between job attitudes and job performance was considered inconclusive and lamentable; however, research was improved through enlargement of the criterion domain (Harrison et al., 2006). Harrison et al. (2006) referred to their supported model involving expanded predictors and expanded criteria as the “attitude-engagement model” (see Figure 1). Their findings support theory forwarded by Fishbein and Ajzen’s (1974) “compatibility principle,” in which broad predictor domains should predict broad behavioral outcomes. Newman et al. (2010) re-conceptualized the supported attitude-engagement model from Harrison et al. (2006) to include some additional components (e.g., job involvement and a 2\textsuperscript{nd} order withdrawal factor, see Figure 1). They differentiated the unified job attitude predictor domain and the unified job behavior domain, referring to the former as the “A-Factor” and to the latter as the “E-Factor.” The E-Factor, or behavioral engagement, contained focal job performance, organizational citizenship behavior (OCB), and withdrawal behaviors (lateness, absence, and turnover). Focal job performance, or task performance, refers to “the total expected value to the organization of the discrete behavioral episodes that an individual carries out over a standard period of time” (Motowidlo & Kell, 2013, p. 96). OCB, or contextual performance, refers to “contributions to the maintenance and enhancement of the social and psychological context that supports task performance” (Borman & Motowidlo, 1993; Organ, 1988, 1997, p. 91). Finally, withdrawal behaviors (Hom, 2010; Johns, 2001) refer to lateness (i.e., arriving after work starting times), absenteeism (i.e., failure to report for duty), and turnover (i.e., “movement across the membership boundary of a social system”, Price, 1977, p. 4). This was nearly identical to the Harrison et al. (2006) conceptualization, except for the fact that a second-order withdrawal component was added and there was no “progression of
withdrawal” in the model in which lateness causes absenteeism, which causes turnover. This re-conceptualization of the attitude-engagement model is preferable to that used by Harrison et al. (2006) as it represents a more complete picture of the job attitudes domain with the inclusion of job involvement as well as the theoretically sound inclusion of the second order withdrawal component.

Although Harrison et al. (2006) was the first to specify a broad behavioral engagement construct, they were not the first to consider a general enlargement of the criterion domain (see also Hulin, 1982); for example, Viswesvaran has explored the possibility of a general factor of performance (p-factor; Viswesvaran, 1993; Viswesvaran & Ones, 2000; Viswesvaran, Schmitt, & Ones, 2005). Viswesvaran (1993) drew on the lexical hypothesis to propose that the whole job performance domain could be captured by collecting 486 prior measures of performance; after 10 dimensions were derived from the prior measures, over 300 studies were collected and meta-analyzed with all dimensions demonstrating positive manifold (see also Viswesvaran & Ones, 2000). Notably, Viswesvaran and colleagues were able to provide meta-analytic evidence for the existence of a general factor of performance not attributable to halo error that accounted for 60% of the variance (Viswesvaran et al., 2005). The reason for this positive manifold across performance ratings is perhaps due to the notion that OCBs or contextual performance (Borman & Motowidlo, 1993) actually affect ratings on all performance dimensions (Orr, Sackett, & Mercer, 1989). Furthermore, they also suggest that individual differences such as general mental ability and conscientiousness may contribute to performance ratings across all dimensions (Motowidlo, Borman, & Schmit, 1997; Ones & Viswesvaran, 1996; Viswesvaran et al., 2005).

In general, the relationships among the performance criteria have been supported by prior meta-analytic research (especially for convergence between performance and OCB):
performance and OCB ($\hat{\rho}_{OCB-I} = .74$, $\hat{\rho}_{OCB-O} = .74$, Hoffman, Blair, Meriac, & Woehr, 2007; $\hat{\rho}_{OCB-I} = .47$, $\hat{\rho}_{OCB-O} = .54$, Podsakoff, Whiting, Podsakoff, & Blume, 2009); performance and withdrawal behaviors ($\hat{\rho}_{absenteeism} = -.29$, Bycio, 1992; $\hat{\rho}_{turnover} = -.15$, Griffeth, Hom, & Gaertner, 2000; $\hat{\rho}_{lateness} = -.17$, Koslowsky, Sagie, Krausz, & Singer, 1997; $\hat{\rho}_{absenteeism} = -.33$, Viswesvaran, 2002); and OCB and withdrawal behaviors ($\hat{\rho}_{turnover intentions} = -.22$, $\hat{\rho}_{turnover} = -.14$, $\hat{\rho}_{absenteeism} = -.16$, Podsakoff et al., 2009; $\hat{\rho}_{turnover} = -.26$, Williams & Livingstone, 1994).³ The convergence between performance and OCB with withdrawal constructs is not as strong, with small-to-moderate, negative correlations. However, this could be due to the lack of studies representing the higher-order withdrawal construct and its correlations with performance and OCB (cf., Harrison et al., 2006; Newman et al., 2010). Regardless, the accumulated meta-analytic evidence tends to suggest the existence of a behavioral engagement factor at the between-persons level of analysis.

**Within-Persons Variability in Behavioral Engagement.** There are a variety of reasons one might expect the E-Factor to exist not only between-persons, but also at the within-persons level of analysis (Dalal, Bhave, & Fiset, 2014). Drawing on the integrative model of within-person variability in performance (Minbashian & Luppino, 2014), fluctuations in performance in the short term stem from variability in situational cues. Their integrative framework is based largely on the Cognitive-Affective Personality System (CAPS; Mischel & Shoda, 1995) and suggests a link between situational cues and the activation of if-then profiles of behavior. In support, the episodic process model also conceptualizes performance as collections of

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momentary behaviors varying from occasion to occasion which are rife with situational cues (Beal, Weiss, Barros, & MacDermid, 2005).

Minbashian and Luppino (2014) also outline “resource allocation processes” (Beal et al., 2005) and “task characteristics” (Alvares & Hulin, 1972; Wood, 1986) as primary reasons for why we might expect short-term fluctuations in performance. Specifically, when confronted with a given situation, we may divert resources away from a given task towards another and engage in cognitive processes to determine resource allocation (Kanfer, 1987). This also aligns with the strength model of self-control (Baumeister, Vohs, & Tice, 2007) wherein employees are expected to manage their resources in order to focus their attention on task-relevant requirement, as opposed to non-work distractions. Furthermore, we may expect there to be changes in both inputs and outputs in a given task over time—these contextual factors related to the inputs and outputs of a task and increase the complexity and demands of the task in any given situation (Minbashian & Luppino, 2014). The task structure is theorized to change with increasing practice (Alvares & Hulin, 1972) as the set of abilities needed to perform the task also changes (e.g., dynamic criteria, Ghiselli, 1956). Relatedly, Murphy (1989) also emphasizes that transition (i.e., a period of work involving substantial changes in responsibility) and maintenance phases (i.e., a period of work in which there is automaticity in fulfillment of tasks and responsibilities) account for longer term variation in job performance. Utilizing performance data from 393 tennis players, Minbashian and Luppino (2014) found support for their propositions regarding situational cues and their impact on short-term performance variability. Given their theoretical framework, we may expect behavioral engagement to fluctuate at the within-persons level in a similar way.
Short term cues may cause resources to be diverted away from performance, OCB, or withdrawal-based behaviors depending on the eliciting cue. For example, mind wandering (McVay, Kane, & Kwapił, 2009; Randall, Oswald, & Beier, 2014; Smallwood, 2013; Smallwood & Schooler, 2006, 2015; Thomson, Besner, & Smilek, 2015) and interruptions (Baethge, Rigotti, & Roe, 2015; Ziljstra, Roe, Leonora, & Krediet, 1999) from the context can perhaps cause within person-variability in behavioral engagement. The resource allocations as generally conceptualized can be expended toward general behavioral engagement or “disengagement” (e.g., towards OCB and task performance or towards withdrawal cognitions and behavior). This process mirrors the construct of “psychological quit” (March & Simon, 1958) in which dissatisfied employees (from an eliciting cue) withhold contributions as a result of their situation.

Longitudinal research on the nature of job performance, OCB and, withdrawal over time also suggests that there should be meaningful within-persons variation in behavioral engagement. In the job performance domain, research on dynamic criteria (Ghiselli, 1956) has focused on examining trends in job performance data as an indicator of successful performance over time. Hofmann, Jacobs, and Baratta (1993) use random coefficients modeling to explore trends in employee quarterly sales performance metrics and found that the linear growth trend accounted for 25% of the variance in sales. A later study exploring the effect of cognitive ability on growth trends in performance of sewing machine operators found that much of the variation (45%) in performance was at the within-persons level (Deadrick, Bennett, & Russell, 1997). Other ESM studies have demonstrated similar levels of within-persons variance in performance (63.2% in Study 2, Dalal, Lam, Weiss, Welch, & Hulin, 2009; 77% in Study 2, Fisher, 2003; 59%, Trougakos, Beal, Cheng, Hideg, & Zweig, 2015). As another piece of evidence suggesting job performance changes over time, Zyphur, Chaturvedi, and Arvey (2008) modelled these
trajectories using latent growth curve modeling (see also Alessandri, Borgogni, & Truxillo, 2015; Ployhart & Hakel, 1998) and also drew on prior theory that prior performance can affect future performance through autocorrelation. This effect is likely due to the nature of performance feedback (Locke, 1967) and the forces of self-regulation theory or control theory (Carver & Scheier, 1981) and goal-setting theory (Locke & Latham, 1990). Features of prior performance have been demonstrated to have an impact on performance ratings of supervisors as well (Reb & Greguras, 2010). Recent theory has also drawn upon self-regulation approaches to suggest that there may be within-person variation in OCB or contextual performance domains (Bolino, Harvey, & Bachrach, 2012). In a series of diary studies, evidence for within-person variation in OCB has been found (45% in Study 1, 44-52% for all forms of OCB in Study 2, Dalal et al., 2009; 29%, Ilies et al., 2006; 38% in Study 2, 33-41% for all forms of OCB in Study 3, Spence, Brown, Keeping, & Lian, 2014; 57% in OCB-I, Trougakos et al., 2015).

Similarly, longitudinal theory has been at the forefront of turnover and withdrawal research for some time (Hulin, 1991; Lee, Holtom, McDaniel, & Hill, 1999; Lee & Mitchell, 1994; Mobley, 1982; Steel & Lounsbury, 2009). However, typical research in this domain involves survival analyses with typically arbitrarily chosen predictor measurements at one point in time (Kammeyer-Mueller, Wanberg, Glomb, & Ahlburg, 2005). Although recent research has helped to alleviate this concern by measuring turnover and turnover antecedents over time (Holtom, Tidd, Mitchell, & Lee, 2013; Kammeyer-Mueller et al., 2005; Lee, Gerhart, Weller, & Trevor, 2008; Weller, Holtom, Matiaske, & Mellewigt, 2009), these studies have typically examined static, dichotomous outcomes (e.g., leaving vs. staying) and have not historically examined psychological perceptions of withdrawal. An exception is a recent ESM study by Scott and Barnes (2011), which found that 15.1% of the variance within psychological perceptions of
work withdrawal was within-person. Although the percentage of psychological work withdrawal that exists at the within-persons level is smaller than that of other criteria, it is still large enough in magnitude to suggest that there is within-persons variation. Given the similar justifications for variability in the behavioral engagement facets at the within-persons level via control theory (Carver & Scheier, 1981), dynamic criteria (Ghiselli, 1956), and goal-setting theory (Locke & Latham, 1990); a broad conceptualization of behavioral engagement would be expected to be preserved at the within-persons level of analysis.

The prior empirical and theoretical research support variability in behavioral engagement (Bolino et al., 2012; Carver & Scheier, 1981; Dalal et al., 2009, 2014; Deadrick et al., 1997; Ghiselli, 1956; Ilies et al., 2006; Minbashian & Luppino, 2014; Spence et al., 2014; Trougakos et al., 2015; Scott & Barnes, 2011); as such, one might suggest that there is a large proportion of variability in behavioral engagement that exists within-persons, relative to the between-persons and that the dynamic factor structure of the E-Factor is preserved over time. In other words, the employee experience of behavioral engagement varies from moment-to-moment and day-to-day in addition to their average experiences of behavioral engagement (Iida et al., 2012).

**Hypothesis 2:** A significant proportion of the variance in broadly-defined behavioral engagement (i.e., the E-Factor) is within-person.

**The Attitude-Engagement Model at the Within-Persons Level**

So what of the causal link between job attitudes and job performance? How does the relationship between job attitudes and job performance unfold at the within-persons level of analysis? In this section, I review prior research on the assessment of the within-person job attitudes and behavioral criteria relationship. I suggest that Affective Events Theory (AET, Weiss & Cropanzano, 1996) provides a strong, general theoretical framework to support the
recapitulation of behavioral engagement within-persons (suggesting a happy worker is a more productive worker), over time and that experience sampling methodology can be used to examine the unfolding of job attitudes and behavioral engagement. Lastly, I draw on the social psychology and behavioral decision-making literatures to suggest that the relationship between the A-Factor and the E-Factor should be preserved at the within-persons level of analysis.

Prior research on variability in job attitudes and performance has tended to focus on longer time lags of monthly to yearly intervals of measurement (Riketta, 2008). When examining changes in job attitudes, these time intervals may not be the most appropriate in positions with variable, discrete performance episodes (e.g., retail staff, wait staff, hairdressers, etc.). As such, research in this domain may benefit from a finer within-subjects analysis of the job performance and job attitudes relationship. The lack of granularity may help facilitate the progression of these relationships over time without arbitrary time lag distinctions even when such an analysis samples from a relatively short time period. I argue that the within-day interval of measurement is the most appropriate interval to study the within-persons relationship between job attitudes and performance, as affect-driven attitudinal fluctuations are based on mood congruent memory (Altmann & Gray, 2002; Rusting & DeHart, 2000). As these memories (and the moods associated with them) decay rather quickly, the two should be assessed concomitantly and frequently (Judge & Ilies, 2004). Furthermore, recent ESM research suggests that daily affect is related to the within-person formation of daily beliefs and attitudes about the influence of work demands (Harris & Daniels, 2005). This concern in longitudinal research has been echoed by Ployhart and Vandenberg (2010), who emphasize the criticality of selecting the appropriate time lag for repeated measurements. Prior research has studied between-subjects variation in the relationship between job attitudes and job behaviors. Examination of this relationship at the
within-persons level has been nascent in the research literature (cf., Chen et al., 2011; Solinger et al., 2015).

Weiss and Cropanzano’s (1996) Affective Events Theory (AET) theory posits that on-the-job events impact affective reactions. In turn, these reactions impact attitudes and behaviors. In essence, Weiss and Cropanzano (1996) propose that affective reactions mediate the relationship between job characteristics/events and job attitudes/behaviors (see also Judge et al., 2012). What implications does AET have for the examination of the relationship between job attitudes and behaviors? For one, it makes the shortfall in research on this relationship at the within-subjects level apparent. Much of the previous research has been an analysis at the between-subjects level. Furthermore, it brings to light the notion that attitudes and behaviors may share common antecedents (events and organizational structural characteristics acting through the mechanism of affective reactions) that may drive their correspondence. In support of this assertion, Ohly and Schmitt (2015) have forwarded a taxonomy of affective work events and demonstrated that these distinct clusters were associated with affective states and attitudes. As such, AET is a strong theoretical framework from which to substantiate the proposed relationship between attitudes and behaviors at the event level.

In a critical review and analysis of the insufficient findings from earlier research on the specificity of the criterion and predictor domains, Fisher (1980) posited that there should be a linkage between broad attitudes and broad behaviors as well as a linkage between specific attitudes and specific behaviors. Previous studies did not ensure alignment between the levels of analysis for the criterion and predictor domains and therefore did not provide evidence for a strong relationship between attitudes and job behaviors. Furthermore, Fisher (1980) drew upon the “congruence” or “compatibility principle” in relating the nature of the attitude-behavior
“criterion problem.” Fishbein and Ajzen (1974) in their review of the behavioral criterion in attitudes research, noted that “a person’s attitude towards an object need not be related to any single behavior that may be performed with respect to the object…it should be related to the overall pattern of…behaviors” (p. 61). Harrison et al. (2006) notes that the terminology used to describe this relationship has shifted from “congruence” to “compatibility.” In examining the relationship between attitudes and behaviors, the various job attitudes that are often assessed (job satisfaction, affective commitment, etc.) imply a broad target and are, in essence, a broad level of analysis. As such, this broad level of attitudes should predict a broad level of behaviors.

Within the domains of affect and AET, a major research directive has been to temporally separate the discrete events that employees experience throughout their work days and examine their affective reactions and corresponding attitudes/behaviors. This has been done so through the use of “experience sampling methods” (ESM), also known as “event signal methods” or “ecological momentary assessments” (EMA). These methods have been used in psychology since the 1980s and were incorporated into the realm of organizational psychology in the 1990s (Beal & Weiss, 2003). AET has been incorporated into a large number of ESM studies examining the temporality of job satisfaction and job performance (Dalal et al., 2009; Fisher, 2002; Fuller et al., 2003; Ilies et al., 2006; Judge, Scott, & Ilies, 2006; Miner, Glomb, & Hulin, 2005). Judge et al. (2012) would argue that the incorporation of within-person analyses into the study of job attitudes and behaviors is of optimal importance as this source of variance would normally be considered error in traditional, between-subjects examinations of these relationships.

Should one expect the aforementioned relationships between job attitudes and job behaviors at the between-subjects level to be mirrored at the within-subjects level? Judge et al. (2012) note that “no inferences about the within-person level should be made solely on the basis
of data collected at the between-person level” (p. 41). Their argument against this level of generalization appears to hearken to the notion of an “ecological fallacy,” or “ecological correlation” as originally introduced by Robinson (1950). An ecological fallacy limits the generalization of conclusions drawn from statistical analyses at the between-subjects level; generalization to other levels of analysis (i.e., the within-persons level of analysis) may be problematic. Although this may be a valid criticism, one might expect the support of the attitude-engagement model of Harrison et al. (2006) and its subsequent revision by Newman et al. (2010) to extend to the within-subjects level of analysis.

Theory regarding the within-persons nature of the relationship between events, attitudes, and behaviors has been around for quite some time; for example, Hirschman (1970) notes the cognitive interplay between attitudes and withdrawal in his seminal work, *Exit, Voice, and Loyalty: Responses to Decline in Firms, Organizations, and States*. Here, he argues that in response to organizational decline events, which could be a deterioration of the quality or quantity of goods (e.g., in an employment context, the provisions the organization provides to its employees), employees are confronted with a unique combination of “voice” and “exit” responses that vary as a function of attitudes (e.g., loyalty). Here, employees either engage in withdrawal behaviors (e.g., exit) or act out through decreasing task-related inputs or otherwise engaging in proactive behaviors (e.g., voice) to correct the organizational decline. The behavioral disengagement from work roles that occurs when employees experience low job satisfaction is also consistent with March and Simon’s (1958) inducements-contributions theory and Adams’ (1965) equity theory. Here, employees are induced to contribute based on a psychological contract stipulating what the employee will contribute and what he/she should expect to receive in return (March & Simon, 1958). If the employer is not fulfilling their part of the contract, the
employee may begin to withhold their own contributions. Furthermore, these contributions and expected outcomes are a function of comparisons with similar others in which employees strive for equity between the ratios of their outcomes to inputs and those of relational others (Adams, 1965).

With regard to prior empirical research, the relationship between momentary task satisfaction and concurrent perceived task performance has been found in prior research to be fairly strong \( (r = .57, \text{Fisher, 2003}) \). In the following section, I provide support for the existence of the Attitude-Engagement model at the within-persons level of analysis.

Further theoretical support for the Attitude-Engagement model within-persons can be drawn from the social psychology and behavioral decision making literatures. These literatures further explicate the within-persons relationship between job attitudes and behavioral engagement within an Affective Events Theory (Weiss & Cropanzano, 1996) framework. Overall, theories from these literatures suggest events that happen on the job lead to the formation of job attitudes, which in turn lead to behavioral engagement: 1) Endowment/Contrast model (Cheng, 2004; Tversky & Griffin, 1991; Winkler, König, & Kleinmann, 2012), 2) Social Information Processing model (SIP; Salancik & Pfeffer, 1978; Zalesny & Ford, 1990), and 3) Theory of Planned Behavior (TPB, Ajzen, 1991, 2001; Ajzen & Fishbein, 1980, 2005; Schleicher et al., 2010). All of these theories provide support for the within-persons attitude-engagement relationship as they specify a causal process for the formation of attitudes from experiences and specify how these attitudes are related to behaviors. Given the outlined process mechanisms in these theories, our attitudes are dynamically shaped by our experiences and interactions with the environment and our attitudes, in turn, affect our behavior. As such, these
theories can serve to support and inform the within-persons application of the attitude-engagement model.

First, the Endowment/Contrast model is a theoretical mechanism which might explain the within-persons relationship between job attitudes and behavioral engagement (Cheng, 2004; Tversky & Griffin, 1991; Winkler et al., 2012). According to this model, events or stimuli have a direct contribution to the current happiness or satisfaction of an individual (i.e., an endowment effect). However, repeated events of the same stimulus can lead to habituation of the effect, and thus the magnitude of satisfaction or happiness elicited is reduced as the stimulus becomes less salient (i.e., a contrast effect). As such, there should be large, meaningful variability at the within-persons level for job attitudes and behavioral engagement as well as persistent effects of job attitudes on behavioral engagement over time, as contingent upon the variability or stability in valence of workplace events (Winkler et al., 2012). Given the variability in experiences and valences during the work day for many positions (Beal et al., 2005; Ohly & Scmitt, 2015), one might expect there to be more of a pronounced and consistent endowment effect as opposed to a contrast effect (especially in customer service positions with continuous, discrete performance episodes).

Second, the SIP model (Salancik & Pfeffer, 1978; Zalesny & Ford, 1990) suggests that we take in social information from the surrounding context (including dynamism in work events and situational characteristics) leading to the encoding of information as strong (weak) perceptions and attitudes. This information is then used to inform subsequent behaviors and vice versa. Furthermore, if the attitudes that are reinforced are strong, we also may engage in routine, scripted behavior. As such, we may expect the structure of the Attitude-Engagement model to be generally preserved over time.
Third, and perhaps the most widely acknowledged theory explicating the link between attitudes and behavior is the TPB (Ajzen, 1991, 2001; Ajzen & Fishbein, 1980, 2005; Schleicher et al., 2010). TPB states that attitudes toward behavior, norms, and behavioral control perceptions influence behavioral intentions, and in turn, behaviors. Given that the behavior in question, norms regarding that behavior, and the control perceptions are likely in fluctuation from task-to-task and moment-to-moment due to variation in affect and episodic attentional pulls and demands (Beal et al., 2005); one might expect behavioral engagement and job attitudes to vary within-persons and be related to one another in causal correspondence. A wide variety of research also supports the tenants of TPB including meta-analyses and reviews (Ajzen & Fishbein, 2005; Armitage & Conner, 2000; Glasman & Albarracín, 2006; Kraus, 1995; Sutton, 1998). Overall, these theories from the social psychology and behavioral decision making literatures suggest that there should be a link between attitudes and behavioral engagement at the within-persons level.

Out of all of the ESM studies reviewed, only a few have “bridged the gap” between attitudes and behavioral engagement/performance (Bakker & Xanthopoulou, 2009; Judge et al., 2006; Ilies et al., 2006; Xanthopoulou, Bakker, Demerouti, & Schaufeli, 2009). For example, Ilies et al. (2006) examined the impact of traits and affective/attitudinal states on OCB. Among other findings, they found that OCBs were predicted over time by both positive affect and job satisfaction (to a lesser degree). The relationship between job satisfaction and OCBs were not moderated by personality, as positive affect was (for agreeableness). Furthermore, Judge et al. (2006) found that a great deal of the total variance in CWBs was accounted for by state hostility, job satisfaction, and interpersonal justice. They found that job satisfaction added incremental validity to a model including interpersonal justice and state hostility in predicting CWBs ($\Delta R^2 =$}
This suggests that given a narrow conceptualization of attitude-behavior relations, job satisfaction predicts CWBs at the within-persons level. Bakker and Xanthopoulou (2009) as well as Xanthopoulou et al. (2009) examined “work engagement,” which is a statistical analog to “job involvement” (Newman et al., 2010). In both studies, attitudinal engagement and task performance were studied concurrently with the focus of the former study on engagement crossover to co-workers and in the latter study on the utilization of persona and job resources. Bakker and Xanthopoulou (2009) found that crossover occurred on days with frequent interactions and that an actor’s job involvement had an effect on the partner’s work performance. Xanthopoulou et al. (2009) objectively operationalized performance as daily financial returns and found that “work engagement” did affect financial returns. These findings, together, provide support for specific instances in which narrow conceptualizations of attitudes predict narrow conceptualizations of behaviors within-persons.

None of the aforementioned studies concurrently examined the components of the A-Factor (job satisfaction, job involvement, and affective commitment) and the E-Factor (performance, OCB, and withdrawal behaviors). However, some of the later studies have examined subcomponents of these factors and have begun to “bridge the gap.” The current research would add to the literature by incorporating the A-Factor and E-Factor into an ESM analysis of the within-persons variance of attitudes and performance. As such, all relevant constructs may be incorporated into the predictor and criterion domains and may provide a better fitting model. Hearkening back to Fishbein and Azjen’s (1974) compatibility principle, broad conceptualizations of attitudes (A-Factor) are likely to predict broad conceptualizations of behavioral engagement (E-Factor; Harrison et al., 2006; Newman et al., 2010). Furthermore, the tenants of AET (Weiss & Cropanzano, 1996), the endowment/contrast effect (Cheng, 2004;
Tversky & Griffin, 1991; Winkler et al., 2012), SIP (Salancik & Pfeffer, 1978; Zalesny & Ford, 1990), and TPB (Ajzen, 1991, 2001; Ajzen & Fishbein, 1980, 2005; Schleicher et al., 2010) support the proposed relationship between the A-Factor and the E-Factor, within-persons. In other words, job attitudes predict behavioral engagement from moment-to-moment and day-to-day.

Hypothesis 3: The A-Factor will significantly predict the E-Factor, within-persons: the A-Factor will be positively related to present E-Factor, next-moment E-Factor, and next-day E-Factor.

What comes first? The attitude or the behavior?

Although support may be provided for the relationship between the A-Factor and the E-Factor at the within-persons level of analysis, a reciprocal relationship may also be plausible. However, there has been little examination of whether the E-Factor affects the A-Factor at the within-persons level of analysis (leaving the question of whether a person is more productive when he/she is happy unknown, cf. Riketta, 2008). Beyond affect-driven explanations for within-persons attitude-behavior relations, motivation theories such as the expectancy-based theories, also posit that behavioral outcomes such as rewards can produce changes in job attitudes (Lawler & Porter, 1967; Naylor, Pritchard, Ilgen, 1980; Vroom, 1964). Furthermore, cognitive dissonance theory (Festinger, 1957) and self-perception theory (Bem, 1972) suggest that employees strive for consistency in their rationalizations for their actions, and as a result, adjust their own attitudes to be in alignment with their behavior. Riketta (2008) attempted to examine these causal relationships between job attitudes and job performance (and vice versa) through a meta-analysis of the job attitudes and job performance panel studies. He concluded that there was some weak support for the notion that job attitudes predict performance ($\beta = .06$) and no
support for a reciprocal relationship between the two ($\beta = .00$). He also found that it appears as if the relationship between job attitudes and job performance are stronger with shorter time lags between measurement of attitudes and performance.

However, Riketta’s (2008) meta-analytic tests were on studies with relatively granular intervals of measurement (i.e., 1-6 months, 7-12 months, or more than 13 months). As argued earlier, these intervals of measurement may not be fine enough to adequately assess within-persons variability in job attitudes and behavioral engagement (Harris & Daniels, 2005; Ilies & Judge, 2002; Judge & Ilies, 2004; cf., Bowling, Beehr, & Lepisto, 2006; Dormann & Zapf, 2001). Furthermore, Riketta (2008) only examined job performance as the outcome, and did not include other forms of behavioral engagement (e.g., OCB, withdrawal cognitions) as suggested by the Attitude-Engagement model (Harrison et al., 2006; Newman et al., 2010).

As such, an additional test of the causal direction of the attitudes-behavior relationship is needed that corrects for these limitations by employing a finer, episodic time lag for measurement and that includes other forms of behavioral engagement. One might expect a reciprocal or cyclical relationship given the strength of prior theories suggesting a relationship between the A-Factor and E-Factor at the within-persons level (see the prior section) as well as theories supporting reverse-causality: Expectancy theories (Lawler & Porter, 1967; Naylor et al., 1980; Vroom, 1964), Cognitive Dissonance theory (Festinger, 1957), and self-perception theory (Bem, 1972). In other words, job attitudes predict behavioral engagement (and vice versa) from moment-to-moment and day-to-day.

**Hypothesis 4:** The E-Factor will significantly predict the A-Factor, within-persons: the E-Factor will be positively related to present A-Factor, next-moment A-Factor, and next-day A-Factor.
CHAPTER TWO: METHOD

Design

Experience sampling methods (ESM) provide a unique technique for assessing within-person variability. These methods seek to capture the attitudes, behaviors, affect, or other dynamic traits for individuals at various moments over a period of time. This differs from more traditional techniques that attempt to assess general traits or attitudes cross-sectionally or longitudinally over a limited span of time lags (Beal & Weiss, 2003). Kane and Lawler (1979) originally suggested that performance measurement often ignores within-person variability which is a major detriment to the assessment and analysis of individuals (as cited in Beal & Weiss, 2003). Despite its limitations, studies using ESM have the potential to make substantial contributions to the field of applied research in psychology and may provide evidence that furthers human resources initiatives.

This data collection method utilizes samples from psychological, behavioral, or physiological indicators by “pinging” individuals at various points throughout a day (often through stopwatches, beepers, or other forms of notification alerts) over the course of several weeks (Alliger & Williams, 1993). The prompts that individuals receive, or “signals”, are programmed to activate at various times and signal the participant to take the momentary assessments of the study (Alliger & Williams, 1993, p. 527; Wheeler & Reis, 1991). By sampling data using this method, individuals are able to be assessed at a very fine granularity compared to traditional measurement methods. This has enabled researchers to study affect,

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4 In this manuscript, “moments” and “signals” are used interchangeably when referring explicitly to time points. This is because signals are sent to participants at particular moments. However, the use of moments more precisely reflects within-day variability in the tests of hypotheses 3 and 4 (e.g., when referring to a lagged momentary effect). Signals, on the other hand, refer to the explicit text messages that the participants receive in order to alert them to complete a survey.
experiences, motivation, and other dynamic psychological constructs that have the capacity to fluctuate. These methods of data collection have largely evolved over the last several decades and have paralleled technological enhancements and developments in communication and data transmission. Further advances in technology including the advent of the internet and the increasing accessibility of application creation methods may provide even more flexibility and customization in implementing ESM designs. Given the benefits to ESM studies, this was selected as the best design to test the hypotheses in question.

However, despite the benefits of the ESM approach, it is not a panacea. Namely, a variety of limitations to the method include participant burden or fatigue, adopting careless response styles or sets, and instrumentation (Beal, 2015; Shadish, Cook, & Campbell, 2002). Wherever possible, care was taken to rule out these concerns by using shortened scales and automating processes in order to reduce participant burden and fatigue (Black, Harel, & Matthews, 2012); to screen responses for careless response patterns by including periodic attention checks (Gosling & Mason, 2015; Oppenheimer, Meyvis, & Davidenko, 2009) and examining the data after it is collected for invariant or distinct response patterns (Meade & Bartholomew Craig, 2012); or by specifying the proper error covariance matrix structure in order to reduce the impact of autocorrelation (Braun, Kuljanin, & DeShon, 2013; Singer & Willett, 2003).

**Apparatus**

In this study, SurveySignal (Hofmann & Patel, 2015) was used to administer the surveys associated with each signal. SurveySignal is an ESM data collection platform that operates as a “software as a service” (SAS) which enables one to manage, administer, and distribute surveys at various schedules to research participants’ smartphones. SurveySignal was designed to interface with common survey administration services (e.g., Qualtrics, Survey Monkey, etc.) to enable
ESM data collection. After participants registered their phones with the system, SurveySignal coordinated the submission of a text message to the participant which contains a link to the ESM survey. Once they completed the survey, that participant’s data was retained (along with their other surveys) and organized by time point in the study, time-stamped, and stored under a unique identifier in the Qualtrics survey administration system. The service also includes other features such as response reminders, response monitoring, and follow-up survey invitations. Furthermore, there was a two-way flow of communication with SurveySignal and Qualtrics which enabled embedded data to be passed freely between the two services, enabling signal-contingent display of text and items, depending upon the survey each participant received and its context. For example, Qualtrics would send each participant taking the survey all questions, but only some may display according to the relevant SurveySignal data (e.g., if the survey was being sent in the evening or final signal for the day, they would receive the end-of-day interactions survey).

**Procedure**

Hairdressers, hairstylists, and cosmetologists in the southeastern United States were contacted during the period of December 2015 and March 2016 and a survey link was distributed to each participant containing the initial orientation survey. Flyers and other recruitment material were distributed to management in tandem so that the hairdressers can be notified of the study. Recruitment occurred through a variety of methods, largely, word-of-mouth; the distribution of electronic and paper flyers (see Appendix A); contacting organizations and businesses directly through e-mail, social media messaging, phone, and face-to-face media; and broad postings in professional social media groups on Facebook, Reddit, and LinkedIn. As a last sampling method, upon conclusion of the study and administration of study payment, participants were encouraged to notify anyone they may think may be interested in the study by distributing a flyer to them.
Upon accessing the orientation survey, participants first read a brief overview of the study and the informed consent, and proffered their consent to participate in the study. Supervisor and Subordinate dyads interested in participating were encouraged to enroll at the same time as a “cohort” in order to properly progress through the study. In order to align the signals between subordinates and supervisors, supervisors and up-to-three of their subordinates needed to register on the same day so that their surveys could be sent at around the same times.

A “captcha” was included toward the beginning of the survey in order to discourage spam or fraudulent responses. Participants went through a pre-screening process that automatically redirected them away from the study if they did not meet study requirements. Participants were pre-screened for position, age, and mobile capabilities before being permitted to participate in the study. Furthermore, as a part of a separate research endeavor, participants completed the Big Five Inventory (BFI, scored from 1 to 5; John, Donahue, & Kentle, 1991) personality survey following the pre-screening questionnaire. The participant’s scores on the Big 5, although not used to test study hypotheses, were used as auxiliary variables in all study analyses in order to facilitate the performance of the full information maximum likelihood estimation procedure (FIML). The BFI was scored on a scale from 1 to 5.

Next the participants completed the contact information and demographics form. They were then provided with a registration guide outlining how to register their phones for SurveySignal, which they could read and download at their convenience (see Appendix B). After reading the registration guide, participants were automatically redirected to SurveySignal and immediately sent a welcoming e-mail to the study, outlining next steps and what they could expect over the next couple of days. The registration
process involved entering phone information on the SurveySignal website and proceeding through a text message phone verification process. Following registration, the mobile phase was set to automatically begin 2 days later.

The mobile phase of data collection began with signal-contingent experience sampling (see Wheeler and Reis, 1991) that assessed participants at 3 points a day (e.g., once during the morning, between the hours of 9:00AM and 1:00PM; once during the afternoon, between the hours of 1:00PM and 5:00PM; and once during the evening, between the hours of 5:00PM and 9:00PM). This time frame of between 9:00AM and 9:00PM was chosen as this best approximated the schedule business hours held by barbers, hairdressers, and cosmetologists at major chains. Signals were then sent as text messages that contained a link to the momentary survey. Participants had a 2 hour window following the text message to respond to the survey. The decision to allot 2 hours of response time constitutes a trade-off between assessment immediacy and the problematic intrusiveness that may arise from expecting participants to abandon their interaction with clients to respond to the surveys. Participants were also sent a reminder message 1 hour after receiving the signal via a text message. Furthermore, individuals were contacted via e-mail to inquire about 3 days’ worth of missed signals in order to determine if they were experiencing any technical difficulties and to otherwise provide accommodation for any difficulty experienced. On Days 2 and Day 13, check-in e-mails were sent to participants asking them whether or not they were experiencing any technical difficulties or if they otherwise had any questions about the mobile surveying process.

The repeated individual self-report assessments that the hair dressers completed (as outlined in the measures section) during the mobile phase consisted of the job satisfaction, affective commitment, job involvement, and working time surveys. Participants were asked
questions about their shift schedules for the day in order to best approximate the time spent working (or not working) each day in the study. On working days, participants received the behavioral engagement surveys along with the attitude surveys if they worked at all during the prior signal. Supervisors participating in the study also completed a form of the working time survey, a question asking whether or not they supervised each one of their participating subordinates since the last signal, and finally, were given the behavioral engagement scales for each subordinate they had an opportunity to participate. After completing each survey, the ESM data was then transmitted from the mobile devices and compiled through the Qualtrics survey software. According to the SurveySignal service, participants took an average of 15.08 minutes ($SD = 3.50$) to respond to receiving each signal (e.g., approximately 15 minutes to open each survey) and an average of 15.47 minutes ($SD = 3.50$) to complete each signal. Due to study technical difficulties, 9 morning signals on the day of 2/27/16 were not sent. Participants were informed of this discrepancy and received payment for this missed signal. Furthermore, two participants were not sent signals for one full day due to unknown technical issues that were verified by SurveySignal. These participants received payment for their missed signals as well.

After receiving the last signal, participants were invited to complete the full, unmodified (non-state) versions of the job attitudes for a chance to earn an additional five dollars. They were reminded to take this survey exactly 1 day and 3 days following the initial administration of the survey and were given 1 week to complete it. Also included as a part of this survey, the Extended Range Vocabulary Test (ERVT) and the Diagramming Relations Test (DRT) from the ETS Kit of Factor Referenced Tests were included as a part of a separate research endeavor (The two tests were combined into an average GMA score, which was represented as a proportion of 1.00, with 1.00 being a perfect score on the test or combined tests).
This cognitive ability information, although not used to test study hypotheses, were used as auxiliary variables in all study analyses in order to facilitate the performance of the full information maximum likelihood estimation procedure (FIML). 2 participant’s elongated survey data at this phase was not included in the analyses due to a failed attention check. Upon completion of the study (after a 2-4 week period), the participants were thanked, compensated, and asked if they would like to participate in future research studies. Participants were also asked to notify others who may be interested in the study via flyering and word-of-mouth.

**Participants**

Participants were comprised of a sample of hairdressers, hair stylists, and cosmetologists from Florida ($n = 52$) who participated in the study during the range of four months between December 2015 and March 2016. The sample was limited to internet-enabled cell phone owners with a data plan as the study requires internet connectivity and the ability to receive text messages. Hairdressers were targeted as the sample in this design as they experience discrete performance episodes, OCBs, and withdrawal behaviors. Although supervisors were actively recruited to participate in the study, only 2 supervisors agreed to provide signal-contingent performance ratings of 6 of the 32 hairdressers in order to mitigate the threat of common source bias and impression management. However, this data was not used in the final analyses given the low number of responses. Participants were at least 18 years of age. Participants were enticed to participate in the study through compensation of $1.25 for each completed survey (the ESM period lasted 15 business days for each participant) or $4.00 for each day of fully completed surveys (a quarter bonus). Furthermore, they received $5.00 for completing the orientation survey and $5.00 for completing the elongated job attitudes survey (see Measures and Procedure sections for more detail regarding these surveys and their administration). The maximum amount
of earnings an individual garnered by fully participating in the study was $75.00 (including an additional $5.00 bonus for completing every survey).

Of the 104 organizations that were directly contacted, 11 (10.58%) indicated that they would be willing to distribute the flyers to potential participants and 21 (20.19%) declined to participate in the study. Furthermore, 8 beauty schools in the Central Florida area were contacted, with 3 (37.5%) agreeing to distribute flyers among hairdresser, barber, and cosmetologist stakeholders. The rest did not respond to the inquiries.

Of the 204 participants who opened the survey link to participate in the study, 59 (28.92%) of the responses were identified as spam through the survey administration filter, via examining geographical locations beyond the bounds of the sampling frame, as well as the provision of inconsistent demographics information (i.e., inconsistent response location, area code, zip code, etc.). 56 (27.45%) participants opened the survey link and did not progress pass the informed consent stage, with only 2 of these participants formally and explicitly declining to participate in the study. Of the remaining participants, 15 (7.35%) were removed from the study as a result of the pre-screening process and did not progress to the mobile phase. 1 of the 15 participants who failed the pre-screening process completed the entire orientation survey, but did not proceed to the mobile phase as they registered with an iPad (which is not supported by SurveySignal). 6 responses were removed as they were duplicate entries (2.94%). Lastly, 14 (9 participants and 5 supervisors) participants dropped out at some point during the orientation phase (6.86%) and 6 participants (3 participants and 3 supervisors) dropped out after completing the orientation survey (2.94%). The 3 dropout participants were included in the between-persons dataset in order to facilitate differential attrition analyses and following missing data case retention guidelines (Newman, 2009, 2014). Also worthy of mentioning, one of the participants
who dropped out enrolled from the Washington, DC, area. Otherwise, the remaining participants were all from Florida. The remaining 54 participants (including the 2 supervisors, 26.47%) enrolled in the mobile, ESM phase of the study.

A differential attrition analysis (Shadish et al., 2002) was conducted as this phase to determine whether or not the participants who enrolled in the mobile phase differed on any major characteristics or individual differences for the 9 who dropped out of the study. None of the individual differences or demographic variables measured in the study were related to dropout. The partial response rate from those who accessed the orientation survey but dropped out of the study was 4.41%. Of the 52 participants that did register for the mobile phase, they largely did so with the use of iPhones (73.1%) and Android phones (25.0%), although 1 participant used a Windows phone (1.9%).

With regards to the sample description of those with valid responses to the orientation survey (including the 14 dropout participants), 45.6% of the sample consisted of cosmetologists, 27.9% of the sample consisted of hairdressers/hairstylists, and 1.5% of the sample consisted of barbers (1 participant). 7 participants (10.3%) indicated that they were supervisors, although only 2 supervisors ended up participating in the mobile phase of the study. 10 participants (14.7%) explicitly marked “other”. Lastly, 13 people clarified in an entry blank their “other” response with some also clarifying their prior position response. Here, 2 participants indicated that he/she was a nail technician. All of the others mentioned that they held some supervisory role: 1 indicated that he/she was a salon owner / hairdresser whereas 4 indicated that they held some form of supervisory position, while participating as hairdressers/stylists. 6 participants indicated that they were cosmetology school students.
Of the non-dropout, non-supervisor participants, 32.7% were self-employed and 84.6% worked full time. They worked an average of 4.50 days a week, 38.80 hours a week, and 8.79 hours per day. Self-employed participants generally rented spaces within a hair or beauty salon—they saw their own clients, but still built relationships with coworkers and the owners and otherwise worked in an organization-like setting. Interestingly, most of the participants in the study came from separate organizations, with the exception of seven organizations which accounted for 8 (15.4%), 7 (13.5%), 4 (7.7%), 3 (5.8%), and three organizations with 2 (3.80%) participants, respectively. This precludes the use of multilevel analyses nested within organizations due to the small within-class cell sizes. Furthermore, 5 participants (9.6%) indicated that they worked at more than one location as a hairdresser, cosmetologist, or barber. Participants indicated that they tended to take on freelance work or work at multiple locations and that it was a common practice both in this industry and within this job category.

The participants were 84.6% female and 15.4% male. Although participants were given the option to select “other” or “do not wish to specify”, none of the participants did so. Participants were also between 18 and 51 years of age ($M = 30.40, SD = 8.30$) and worked at their location from between 2 to 240 months ($M = 43.42, SD = 50.18$), or 20 years. With regard to race, participants indicated that they were 71.2% Caucasian/White (Not Hispanic), 7.7% African American/Black (Not Hispanic), 5.8% Asian/Pacific Islander, 9.6% Hispanic. One participant (1.9%) indicated that he/she was “Latin Brazilian” in the “Other” category. Lastly, 3.8% of the sample indicated that they did not wish to specify their race.

Overall, survey responses for hairdresser participants across 1,438 signals were provided with 56 possible data points per signal. 6 (<0.01%) consisted of responses for which only supervisor reports were available (e.g., the supervisor responded but the “focal” hairdresser did
not). The other 10 received supervisor reports were combined with each signal response provided by the hairdresser study participants, as they occurred during the same time point period. Given the extremely low representation for supervisor reports in the study, their analysis was omitted and only self-reports from the cases were analyzed.

Not counting data points from the 27 partially completed signals, there were 79,016 data points from fully completed signals included in the study (out of a possible 131,040 data points from 2,340 signals). 1,438 signals were received out of the 2,340 signals that were sent via SurveySignal to the hairdresser study participants (not including supervisors). This suggests an overall study signal response rate of 61.45%. The average study participant response rate during the mobile phase was also 61.45% ($SD = 30.50\%$, $MIN = 4.44\%$, $MAX = 100.00\%$). This response rate was consistent with if not slightly lower than that which is typically found in prior ESM research (i.e., 70-90%, Fisher, 2012). Of these 1,438 responses, 538 (37.4%) of the responses were explicitly during work periods. However, 840 (58.4%) of the responses occurred on days in which the participants were scheduled to work. Furthermore, although only 37.4% of responses were during actual working periods, 767 (53.3%) of the responses captured some degree of behavioral engagement ratings. This suggests that approximately 15.9% of responses occurred after the participants’ shifts had ended, although they were still able to reflect on the behavioral engagement since the last signal or since the beginning of their shift. As such, overall there was a roughly equivalent distribution of sampled experiences of work and non-work/missing periods.

Lastly, all 52 study participants were invited to complete the elongated survey, and 34 (65.38%) of contacted participants fully completed this survey. 4 participants opened the link but did not complete the survey at all (7.69%). 3 provided partial responses, but did not fully
complete the survey (5.77%). 21.15% did not respond to the elongated survey at all. As with the orientation survey, a differential attrition analysis was conducted in order to determine whether or not those who completed the elongated survey differed from those who did not on individual characteristics. None of the characteristics measured during the orientation survey had an effect on dropout rates.

Measures

**Demographics and Individual Characteristics.** Several demographics variables and individual characteristics were collected during the orientation survey. First, a series of work characteristics were collected including the employee’s “primary position” at the organization, self-employed status, full or part-time status, the number of days worked per week, the number of hours worked per week, and the number of hours worked per day. Next, contact information was collected along with a series of demographics variables. The demographics included the type of phone, information about the organization the participant belonged to, the age (in years), gender (male, female, other, do not wish to specify), race [African American/Black (Not Hispanic), Asian/Pacific Islander, Caucasian/White (Not Hispanic), Hispanic, Native American / American Indian, other, do not wish to specify ), organizational tenure (in months), and whether or not the participant worked at any other businesses during the study, which were collected as control variables and as auxiliary variables to include in the random coefficients models and variance decomposition analyses (see the data analysis strategy section). These items were self-reported from the hairdressers and supervisors from the orientation survey.

**Job Satisfaction.** The 5-item shortened version of the Brayfield and Roth (1951) overall job satisfaction scale was used to assess job satisfaction (Judge, Locke, Durham, & Kluger, 1998). Participants were instructed to indicate the extent to which they agreed with each item,
thinking of their job and organization even if they were not working at the moment. These items were altered to assess current job satisfaction perceptions by adding the stem, “at this moment.” These 5 items are “At this moment, I feel fairly well satisfied with my present job,” "At this moment, I am enthusiastic about my work," "At this moment, each minute at work seems like it will never end" (reverse coded), "At this moment, I am finding real enjoyment in my work," and "At this moment, I consider my job rather unpleasant" (reverse coded). The response scale ranges from 1 (strongly disagree) to 5 (strongly agree). The 5 items were averaged to produce a single score for overall job satisfaction at each experience sample. The items were also averaged with the Affective Commitment and Job Involvement scales to create an overall, A-Factor scale. These items were self-reported from the hairdressers and collected at each signal 3 times a day for 15 days. As recommended by Shrout and Lane (2012), the Cronbach’s Alpha (Cronbach, 1951) for each scale administered during the mobile phase of the study was computed for all 45 time points in the study. The average α for momentary job satisfaction was .89 (SD = 0.04) and ranged from .69 to .96.

The full version of this measure (18 items) was administered to the participant following the ESM phase for the purposes of establishing convergent validity between the short and full forms of the measure (α = .85). Convergent validity between the full job satisfaction scale and the reduced scale was, indeed, established by fitting a random coefficients model regressing momentary job satisfaction onto the grand mean centered elongated form of the survey at level 2 (γ10 = 0.89, SE = 0.13, p < .05). This model represents the pure, cross-level relationship between the full job satisfaction scale and the shortened job satisfaction scale (accounting for between- and within-subjects error).
**Affective Commitment.** The 6-item shortened version of the Allen and Meyer’s (1990) Affective Commitment Scale was used to assess Affective Organizational Commitment (Eisenberger, Armeli, Rexwinkel, Lynch, & Rhoades, 2001). Participants were instructed to indicate the extent to which they agreed with each item, thinking of their job and organization even if they were not working at the moment. These items were altered to assess current affective commitment perceptions by adding the stem, “at this moment.” These 6 items are “At this moment, working here has a great deal of personal meaning to me,” “At this moment, I feel a strong sense of belonging to this place” “At this moment, I would be proud to tell others I work here,” “At this moment, I feel emotionally attached to this place,” “At this moment, I would be happy to work here until I retire,” and “At this moment, I would enjoy discussing my job with people who do not work here.” The response scale ranges from 1 (strongly disagree) to 5 (strongly agree). The 6 items were averaged to produce a single score for overall affective commitment at each experience sample. The items were also averaged with the Job Satisfaction and Job Involvement scales to create an overall, A-Factor scale. These items were self-reported from the hairdressers and collected at each signal 3 times a day for 15 days. As recommended by Shrout and Lane (2012), the Cronbach’s Alpha (Cronbach, 1951) for each scale administered during the mobile phase of the study was computed for all 45 time points in the study. The average α for momentary affective commitment was .86 (SD = 0.03) and ranged from .79 to .92.

The full version of this measure (18 items; α = .86) and the Affective Commitment subscale (6 items; α = .83) were administered to the participants following the ESM phase for the purposes of establishing convergent validity between the short and full forms of the measure. Convergent validity between the full affective commitment scale and the reduced scale was, indeed, established by fitting a random coefficients model regressing momentary affective
commitment onto the grand mean centered elongated form of the organizational commitment survey at level 2 ($\gamma_{01} = 0.78$, SE = 0.15, $p < .05$) as well as the affective commitment subscale at level 2 ($\gamma_{01} = 0.69$, SE = 0.08, $p < .05$).

**Job Involvement.** 6 items from Reeve and Smith’s (2001) reduction of the Job Involvement Scale (JI, Lodahl & Kejner, 1965) were utilized for this study. Participants were instructed to indicate the extent to which they agreed with each item, thinking of their job and organization even if they were not working at the moment. These items were altered to assess current job involvement perceptions by adding the stem, “at this moment.” These 6 items include “At this moment, the major satisfaction in my life comes from my job;” “At this moment, the most important things that happen to me involve my work;” “At this moment, I have other activities more important than my work” (reverse coded); “At this moment, my work is only a small part of who I am” (reverse coded); “At this moment, I am very much involved personally in my work;” and “At this moment, most things in life are more important than work” (reverse coded). 3 items were excluded from the original scale as they were not suited for the momentary assessment context. These items included “I’ll stay overtime to finish a job, even if I’m not paid for it”; “Sometimes, I lie awake at night thinking ahead to the next day”; and “I live, eat, and breathe my job” (Lodahl & Kejner, 1965; Reeve & Smith, 2001). Nevertheless, the 6 remaining items all performed satisfactorily on at least 3 of a series of psychometric analyses by Reeve and Smith (2001) on the JI, including a qualitative content analysis, classical item analyses, item response theory analyses, partial confirmatory factor analyses, and discriminant validity analyses. The response scale ranges from 1 (strongly disagree) to 5 (strongly agree). The 6 items were averaged to produce a single score for overall job involvement at each experience sample. The items were also averaged with the Job Satisfaction and Affective Commitment scales to
create an overall, A-Factor scale. These items were self-reported from the hairdressers and collected at each signal 3 times a day for 15 days. As recommended by Shrout and Lane (2012), the Cronbach’s Alpha (Cronbach, 1951) for each scale administered during the mobile phase of the study was computed for all 45 time points in the study. The average $\alpha$ for momentary job involvement was $0.87$ ($SD = 0.03$) and ranged from $0.79$ to $0.92$.

The full version of this measure (20 items; Lodahl & Kejner, 1965) was administered to the participant following the ESM phase for the purposes of establishing convergent validity between the short and full forms of the measure ($\alpha = 0.88$). However, convergent validity between the full job involvement scale and the reduced scale was not established, as fitting a random coefficients model regressing momentary job involvement onto the grand mean centered elongated form of the survey at level 2 was not significant ($\gamma_01 = 0.26$, $SE = 0.24$, n.s.). This may be because the Reeve and Smith (2001) revision of the original Lodahl and Kejner (1965) measure was a substantial improvement over the original scale; many of the additional items that were not retained in the shortened form had very poor construct and content validity evidence across their series of psychometric and validation studies. Across a series of 4 studies including a content validation study, classical test theory item analyses, item response theory analyses, and confirmatory factor analysis evidence. Indeed, nearly half (45%) of the original Lodahl and Kejner (1965) items did not perform well across all 4 studies (i.e., items 2, 4, 5, 8, 9, 13, 16, 17, and 20) and were not included in the Reeve and Smith updated scale. Notably, many of these items were deemed to inadequately represent the content of the job involvement construct (Reeve & Smith, 2001).

**A-Factor.** The 17 items from the Job Satisfaction, Affective Commitment, and Job Involvement scales at the within-persons level were averaged to create an overall, A-Factor
scale. As recommended by Shrout and Lane (2012), the Cronbach’s Alpha (Cronbach, 1951) for each scale administered during the mobile phase of the study was computed for all 45 time points in the study. The average α for the A-Factor within-persons was .92 (SD = 0.01) and ranged from .88 to .95.

Regardless of the disparity between job satisfaction, organizational commitment, and job involvement on convergent validity across within- and between contexts; combining all of the scales at the between-persons and within-persons level of analysis, respectively, and regressing the momentary A-Factor onto the grand mean centered elongated form of the survey (56 items; α = .93) at level 2 was significant (γ₀₁ = 0.97, SE = 0.11, p < .05).

Working Time and Characteristics. In order to determine the nature of work on a given signal for a participant, they were asked a series of questions which were then used to construct the working schedule and elapsed time on shift. At each signal, participants were asked whether or not they were working at the moment, to provide the name of the organization they were working for at the moment, how many surveys had been completed in the study so far that day, whether or not they were scheduled to work on that day, and the start and end times for their shift in 15 minute intervals.

Task Performance. Williams and Anderson’s (1991) 7-item measure of in-role performance was used to measure task performance. These items were altered to assess current task performance perceptions by adding the stem, “since the beginning of my shift” or “since the last signal” as contingent on the time of administration. These 7 items include, for example, “since the last signal, I adequately completed assigned duties,” “since the last signal, I fulfilled responsibilities specified in my job description,” “since the last signal, I performed tasks that were expected of me,” “since the last signal, I met formal performance requirements of the job,”
“since the last signal, I engaged in activities that directly affected my performance evaluation,”
“since the last signal, I neglected aspects of the job I was obligated to perform” (reverse-scored),
and “since the last signal, I failed to perform essential duties” (reverse-scored). An item
assessing global performance similar to that which was included in Dalal et al. (2009) was also
administered: “since the last signal, my overall performance was very good”. The response scale
ranges from 1 (strongly disagree) to 5 (strongly agree).

Furthermore, the items were averaged to produce a single score for overall task
performance at each experience sample. These items were self-reported from the hairdressers
and collected at each signal 3 times a day for 15 days. The items were also averaged with the
OCB scale and withdrawal scale (reverse-coded) to create an overall, E-Factor scale.

As recommended by Shrout and Lane (2012), the Cronbach’s Alpha (Cronbach, 1951)
for each scale administered during the mobile phase of the study was computed for all 45 time
points in the study. The average α for momentary task performance was .89 ($SD = 0.07$) and
ranged from .51 to .98. An investigation of the within-person reliability on Day 5, Signal 3 (α =
.51) demonstrated a relatively poor internal consistency estimate. Upon further investigation of
this case, if the item concerning whether or not “engaged in activities that directly affected”
his/her “performance evaluation” was deleted, the reliability would have increased to a more
acceptable level (e.g., .70 or above, Nunnally & Bernstein, 1994). However, given that this poor
reliability estimate was obtained on only one occasion, the item was retained in the scale.

**Organizational Citizenship Behavior.** The full, 8-item Organizational Citizenship
Behavior Scale utilized in Dalal et al. (2009, Study 1) was administered during the mobile phase.
Although only a sub-set of these items were utilized for each signal in the original study, the full
scale was administered in the current endeavor given that on average, 53% of OCB items were
endorsed in Study 1 of Dalal et al. (2009) suggesting that the occurrence of these sorts of behaviors is fairly common between signals (cf. 10% of counterproductive work behavior items in the same study, which tend to have a lower base rate). The 8 items are followed by the leading phrases “since the beginning of my shift” or “since the last signal, I…” and include “went out of my way to be a good employee,” “was respectful of other people’s needs,” “praised or encouraged someone”, “volunteered to do something that was not required”, “showed genuine concern for others,” “tried to be considerate to others”, “displayed loyalty to my organization”, and “tried to uphold the values of my organization”. “The response scale was changed from a yes/no indicator of behavior to a response scale that ranged from 1 (strongly disagree) to 5 (strongly agree). The 8 items were averaged to produce a single score for OCB at each experience sample. These items were self-reported from the hairdressers and collected at each signal 3 times a day for 15 days. The items were also averaged with the task performance scales and withdrawal scale (reverse-coded) to create an overall, E-Factor scale.

As recommended by Shrout and Lane (2012), the Cronbach’s Alpha (Cronbach, 1951) for each scale administered during the mobile phase of the study was computed for all 45 time points in the study. The average $\alpha$ for momentary organizational citizenship behavior was .88 ($SD = 0.08$) and ranged from .65 to .98. An investigation of the within-person reliabilities on Day 4, Signal 2 ($\alpha = .67$); Day 5, Signal 2 ($\alpha = .65$); Day 5, Signal 3 ($\alpha = .68$); and Day 11, Signal 2 ($\alpha = .69$) demonstrated somewhat poor internal consistency estimates. Upon further investigation of these cases, if the item concerning whether or not one sought to “volunteer to do something that was not required” of his/her organization was deleted, the reliability increased to more acceptable levels (e.g., .70 or above, Nunnally & Bernstein, 1994). However, given that
these poor reliability estimates were obtained in only 8.89% of occasions, the item was retained in the scale.

**Perceptions of Withdrawal.** The modified version of Lehman and Simpson’s (1992) psychological work withdrawal scale (Scott & Barnes, 2011) was used to assess work withdrawal. The 5 items are followed by the leading phrases “since the beginning of my shift, I…” or “since the last signal, I…” and include “spent work time on personal matters,” “thought about being absent,” “put less effort into the job than I should have,” “thought about leaving my current job,” and “daydreamed.” The response scale ranged from 1 (strongly disagree) to 5 (strongly agree). These 5 items were averaged to produce a single score for withdrawal at each experience sample. These items were self-reported from the hairdressers and collected at each signal 5 times a day for 15 days. The items were also averaged with the task performance scale and the OCB scale to create an overall, E-Factor scale.

As recommended by Shrout and Lane (2012), the Cronbach’s Alpha (Cronbach, 1951) for each scale administered during the mobile phase of the study was computed for all 45 time points in the study. The average $\alpha$ for momentary psychological withdrawal was $.78$ ($SD = 0.09$) and ranged from .41 to .93. An investigation of the within-person reliabilities across the 45 signals demonstrated somewhat poor internal consistency estimates on 5 occasions, or roughly 11.11% of the measurement occasions: Day 2, Signal 1 ($\alpha = .63$); Day 6, Signal 1 ($\alpha = .68$); Day 11, Signal 1 ($\alpha = .68$); Day 11, Signal 2 ($\alpha = .41$); Day 14, Signal 3 ($\alpha = .66$). Upon further investigation of these cases, it was difficult to pinpoint problematic items, although in 3 of the 5 cases, if the item “I spent work time on personal matters” was deleted the alphas rose to acceptable levels (e.g., .70 or above, Nunnally & Bernstein, 1994).
**E-Factor.** The 21 items from the Task Performance, Organizational Citizenship Behavior, and Withdrawal (reverse-coded) scales were averaged to create an overall, E-Factor scale. As recommended by Shrout and Lane (2012), the Cronbach’s Alpha (Cronbach, 1951) for each scale administered during the mobile phase of the study was computed for all 45 time points in the study. The average α for the self-reported E-Factor within-persons was .92 ($SD = 0.04$) and ranged from .76 to .97. There were supervisor-reported E-Factor ratings for 11 given signals across the 6 participants. As such, the supervisor ratings were not utilized in the study given the extremely low response rate for working observations.

**End of Day Interactions Assessment.** In order to determine the nature and quality of the interaction with clients throughout the course of the shift, an end of day interactions assessment was administered along with the third signal for each day. This survey included a question eliciting the average number of minutes spent with each client, the number of hours spent working on job-related tasks during that day, and the number of hours the individual was at work.

**Data Analysis Strategy**

To handle missing data, the compounded, construct-level missingness rate was calculated (Newman, 2009). Due to the nature of attrition in intensive longitudinal designs, this value is almost always greater than the criterion of 10% (Newman, 2014) and as such full information maximum likelihood (FIML) estimation was used to estimate and impute missing data, as recommended in prior research on missing data, multilevel modelling, and ESM methods (Beal, 2015; Black et al., 2012; Graham, 2009; Newman, 2009, 2014; Schafer & Graham, 2002). As consistent with best practices regarding missing data handling, any case with at least one observation during the mobile phase was used for the within-persons analyses (Hox, 2010;
Indeed, the FIML technique exhibits unbiased parameter estimates and accurate statistical power under conditions of missingness at random and completely at random (Newman, 2009). Simulation research suggests that the FIML technique is generally the best (along with multiple imputation, MI) performing technique for handling longitudinal missing data [cf., listwise deletion, pairwise deletion, mean substitution, stochastic regression imputation, the expectation-maximization (EM) algorithm] for both random coefficients models and structural equation models (Black, Harel, & Betsy McCoach, 2011; Cheung, 2007, Newman, 2003). Furthermore, demographic and individual differences variables were included into the model as auxiliary variables wherever possible to, in essence, “convert an MNAR missingness mechanism into an MAR missingness mechanism”, a best practice when utilizing FIML (Newman, 2014, p. 391). In the results section, upon reviewing the between and within-subjects correlations, theoretical and empirical rationales for the selection of auxiliary variables are included.

Although a multilevel, dynamic confirmatory factor analysis (CFA) was proposed to be conducted in order to confirm the factor structure of the attitude and behavioral engagement constructs, given the small between-subjects sample size ($n = 52$), factor analytic provision for construct validity evidence would be inadmissible given the data. As Mehta and Neale (2005) note, in multilevel CFA, “the appropriate sample size comparable to the conventional SEM sample size is the total number of clusters” (p. 280). Although a CFA could be conducted on all of the scales at the within-persons level (across 1,438 measurement occasions), in several simulation studies this practice is discouraged in favor of a multilevel CFA approach given adequate sample sizes at each level of analysis (Pornprasertmanit, Lee, & Preacher, 2014). This is because ignoring clustering or aggregating to the class level increases model misfit, especially
when the ICC is high (Pornprasertmanit et al., 2014). Furthermore, Jackson, Voth, and Frey (2013) suggest that for a study with similar factors (3) and parameters (7 per factor) to be estimated, in order for the model to satisfactorily converge (at either level of analysis), a sample size of 100 is required for either the detection of low (.40) or high (.80) population loading values. Regardless, the psychometrics of daily experiences is a bourgeoning field (Bolger & Laurenceau, 2013), and in an attempt to provide construct validity evidence beyond multilevel CFA for the momentary scales utilized in this study, the variance decomposition of sources of variance in daily experiences was carried out. By decomposing the variance into items, people, and times using a generalizability theory framework; reliability coefficients that characterize the ability of the job attitudes and behavioral engagement measures to properly capture within-persons variation were calculated to provide construct validity evidence (Bolger & Laurenceau, 2013; Cranford et al., 2006; Shrout & Lane, 2012).

Procedures for longitudinal growth modeling (Bliese & Ployhart, 2002; Singer & Willett, 2003) and intensive longitudinal methods (Bolger & Laurenceau, 2013) were used to test the hypotheses. The first two hypotheses was tested through random coefficients models to calculate the intraclass correlation coefficient, ICC(1), as well as to examine the proportion of variance in the A-Factor and E-Factor that exists at the within-persons level,

\[
\rho = \frac{\sigma^2}{\sigma^2 + \sigma^2_{u_0}}
\]

(1)

where \(\rho\) is a form of the ICC(1), \(\sigma^2_e\) refers to within-person variation, and \(\sigma^2_{u_0}\) refers to between-person variation (Bliese & Ployhart, 2002; Singer & Willett, 2003; Bolger & Laurenceau, 2013). A significance test (Wald Test) was employed to determine whether or not the within-persons
variability was statistically significant, using the Satterwhaite (1946) degrees of freedom approximation, a procedure which improves the performance of the Wald test in small numbers of groups or classes (Manor & Zucker, 2004).5

The next two hypotheses concerned the reciprocal relationship between the A-Factor and E-Factor at the within-persons level. This was tested by constructing hierarchical linear models: one that regresses the E-Factor onto the A-Factor (i.e., Equation 2) and one that regresses the E-Factor onto the A-Factor separately (i.e., Equation 3). This would allow for a test of the appropriateness of the A-Factor and E-Factor as well as their relationship at the within-persons level. As an additional test of the within-persons relationship, lagged versions of the predictors in Equations 2 and 3 will be incorporated, both at the moment and day level of analysis. Although not a part of the study hypotheses, as an additional component of the growth model building procedure (Bliese & Ployhart, 2002), trajectories in the growth of the A-Factor or the E-Factor over time were tested for their contribution to the model by using change in deviance tests.

In order to handle unequal intervals between measurement occasions, as is an issue with experience sampling method designs, the spatial power structure was implemented using SAS PROC MIXED (Bolger & Laurenceau, 2013). This structure is comprised of an autocorrelation parameter that incorporates each person’s total elapsed time in the mobile phase in minutes as measured from the SurveySignal service for any given answered signal in the study. This parameter adjusts the unequal spaces between measurements, effectively reflecting what would be expected if all intervals within the study were equal, which is especially helpful in terms of

5 Given that the Satterwhaite (1946) method adjusts the degrees of freedom based on the values of the residual variances (Hox, 2010; Manor & Zucker, 2004), the degrees of freedom should not be similar across reciprocal models (e.g., regressing the A-Factor onto the E-Factor and vice versa). This is because the residuals that are estimated should vary as a function of which variables are entered into the random coefficients model.
handling missing data and meeting the assumption that there are equal intervals between
time measures (Bolger & Laurenceau, 2013). For example, if a participant answered the Day 3,
Signal 1 survey but did not respond again until the Day 3 Signal 3 survey, the time interval in
between these points (and all other points in the model) as well as their autocorrelation were
adjusted as if they were equivalent. In essence, this procedure adjusts for unequal time intervals
in the variance-covariance matrix of the random part of the random effects model (Bolger &
Laurenceau, 2013).

Various demographic variables were also used as auxiliary variables in all hypothesis
tests to facilitate the performance of the FIML algorithm (Newman, 2009, 2014). The list of
these variables include: self-employment status, full-time status, age, gender, race, organizational
tenure, the Big 5 personality traits, and GMA. Furthermore, the impact of time-varying
covariates (e.g., number of minutes spent with clients, shift length) was explored for their effect
on the A-Factor and the E-Factor respectively for the tests of hypotheses 3-4. The final random
coefficients models that were tested (excluding the aforementioned auxiliary variables and
covariates, which are included or excluded based on the relevance to the analyses at hand) are as
follows:

\[
\text{Level-1 Model (within-persons)} \]

\[
E - Factor = \beta_0 + \beta_1(A - Factor) + e_{ij} \tag{2}
\]

\[
\text{Level-2 Model (between-persons)} \]

\[
\beta_0 = \gamma_{00} + u_{0j} \]

\[
\text{Level-1 Model (within-persons)} \]
\[ A - Factor = \beta_0 + \beta_1 (E - Factor) + e_{ij} \]

**Level-2 Model (between-persons)**

\[ \beta_0 = \gamma_{00} + u_{0j} \]
CHAPTER THREE: RESULTS

Descriptive Statistics

**Between-subjects level of analysis.** The means, standard deviations, and correlations at the between-subjects level of analysis are presented in Table 1. The demographics, work characteristics, and study measures obtained during the orientation survey and the elongated follow up survey at the end of the study are included in this table. The between and within-subjects analyses were separated as shortened forms of the measures were used at the within-subjects level. As can be seen from Table 1, agreeableness ($r = .44$, $p < .05$) and extraversion ($r = .44$, $p < .05$) appeared to be moderately-to-strongly related to the A-Factor. As evidence for the validity of the A-Factor, the A-Factor was strongly and positively correlated to its subscales of job involvement ($r = .90$, $p < .05$), job satisfaction ($r = .82$, $p < .05$), and affective organizational commitment ($r = .78$, $p < .05$). There was also strong, positive manifold between the A-Factor facets (correlations ranging from .51 to .75) providing strong evidence for the A-Factor.
Table 1: Means, Standard Deviations, Reliabilities, and Correlations at the Between-subjects Level for Non-Supervisor Participants

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Note: Coefficient Alphas presented on the diagonal of the matrix where appropriate. Sample size ranges from 33 to 52 across all analyses. Gender (Female=0, Male=1), Self-Employed (No=0, Yes=1), Full-time (Part-time=0, Full-Time=1), Working at More Than one Location (No=0, Yes=1). BFI traits and GMA scores provided for descriptive purposes only.

*p < .05, two-tailed.
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<tr>
<td>15. General Mental Ability</td>
<td>0.48 (0.19)</td>
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<td>16. Diagramming Relationships Test</td>
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<tr>
<td>17. Extended Range Vocabulary Test</td>
<td>0.53 (0.18)</td>
<td>0.09</td>
<td>-0.19</td>
<td>0.91*</td>
<td>0.64*</td>
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<td>(Crystallized Intelligence)</td>
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<tr>
<td>18. A-Factor</td>
<td>3.67 (0.55)</td>
<td>-0.22</td>
<td>-0.01</td>
<td>-0.13</td>
<td>-0.22</td>
<td>-0.04</td>
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<tr>
<td>19. Job Satisfaction</td>
<td>4.15 (0.55)</td>
<td>-.43*</td>
<td>-0.07</td>
<td>-0.10</td>
<td>-0.16</td>
<td>-0.03</td>
<td>0.82*</td>
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<tr>
<td>20. Job Involvement</td>
<td>3.45 (0.68)</td>
<td>-0.21</td>
<td>0.16</td>
<td>-0.13</td>
<td>-0.22</td>
<td>-0.05</td>
<td>0.90*</td>
<td>0.75*</td>
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<tr>
<td>21 Organizational Commitment</td>
<td>3.37 (0.70)</td>
<td>-0.01</td>
<td>-0.19</td>
<td>-0.08</td>
<td>-0.14</td>
<td>-0.01</td>
<td>0.73*</td>
<td>0.31</td>
<td>0.44*</td>
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<tr>
<td>22. Affective Commitment</td>
<td>3.73 (0.97)</td>
<td>-0.17</td>
<td>-.36*</td>
<td>0.01</td>
<td>-0.10</td>
<td>0.10</td>
<td>0.78*</td>
<td>0.57*</td>
<td>0.51*</td>
<td>0.82*</td>
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*Correlation is significant at the .05 level (2-tailed).
<table>
<thead>
<tr>
<th>Variable</th>
<th>$M$ (SD)</th>
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<th>14</th>
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<th>21</th>
<th>22</th>
<th>23</th>
<th>24</th>
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<tbody>
<tr>
<td>23. Normative Commitment</td>
<td>3.59 (1.00)</td>
<td>-0.08</td>
<td>-0.28</td>
<td>-0.09</td>
<td>-0.18</td>
<td>0.00</td>
<td>.68*</td>
<td>.38*</td>
<td>.39*</td>
<td>.88*</td>
<td>.78*</td>
<td>(.88)</td>
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<tr>
<td>24. Continuance Commitment</td>
<td>2.79 (0.91)</td>
<td>0.24</td>
<td>0.25</td>
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<td>-0.04</td>
<td>-0.12</td>
<td>0.13</td>
<td>-0.29</td>
<td>0.05</td>
<td>.48*</td>
<td>-0.01</td>
<td>0.10</td>
<td>(.78)</td>
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</table>
The distributions of all continuous and interval-level variables from the orientation survey were also examined for departures from normality, as one of the assumptions of parametric statistics. Although the Shapiro-Wilk tests for days worked per week, \( W(33) = 0.85, p < .05 \); age, \( W(33) = 0.92, p < .05 \); organizational tenure, \( W(33) = 0.73, p < .05 \); agreeableness, \( W(33) = 0.93, p < .05 \); and neuroticism, \( W(33) = 0.93, p < .05 \) were significant suggesting that the distributions were non-normal, an examination of their standardized skewness and kurtosis statistics revealed that only age, organizational tenure, agreeableness and neuroticism variables were substantially skewed or kurtotic. However, as the variables were not a part of the main analyses and in order to refrain from substantially changing the interpretation of the nature of these variables, they were retained in their original form. Furthermore, in the elongated survey, none of the measured variables violated the assumption of normality except for the Diagramming Relationships Test of fluid intelligence, \( W(33) = 0.89, p < .05 \). However, in examining its standardized skewness and kurtosis values, it appears as if the deviations from normality are not severe and not significant.

**Within-subjects level of analysis.** At the within-persons level, the overall construct missingness rate depends upon which variables may be considered psychological constructs given the data and varies between 38-40% (38.55% fully missing cases and 1.15% partial responses). Only 1.88% of all received responses were partial. This meets Newman’s (2014) threshold of not surpassing 10% for partial responses and not falling below 30% for a person-level response rate with regard to the handling of missing data. As such, no sensitivity analysis was needed, although FIML estimation along with auxiliary variables was still utilized as recommended (Newman, 2009, 2014).
The means, standard deviations, and correlations at the Within-subjects level of analysis are presented in Table 2, consisting of the momentary assessments compiled from the mobile phase of the study and separated by time-related variables and A-Factor and E-Factor scales. As can be seen in Table 2, whether or not one is working at the moment is related to a variety of time-related variables, most likely because the items for the most part only appear if one is working at the moment or had an opportunity to reflect on their prior behavioral engagement, since the last signal. Participants seem to respond to working signals to a slightly lesser degree as the study progresses ($r = -.08, p < .05$). Otherwise, working for more than one organization, whether or not one was scheduled to work, time spent with each client in minutes, and time spent working were relatively unrelated. Participants tended to take less time to respond to the signals ($r = -.22, p < .05$) and the surveys themselves ($r = -.20, p < .05$) when they were working, perhaps given the strength of the situation and the requirement to return back to work.
Table 2: Means, Standard Deviations, Reliabilities, and Correlations at the Within-subjects Level for Non-Supervisor Participants

<table>
<thead>
<tr>
<th>Variable</th>
<th>$M$</th>
<th>$SD$</th>
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<tr>
<td><strong>Time-Related Variables</strong></td>
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<tr>
<td>1. Working at the Moment</td>
<td>.38</td>
<td>(.49)</td>
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<tr>
<td>2. Work for more than one Organization</td>
<td>.07</td>
<td>(.26)</td>
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<tr>
<td>3. Scheduled to Work</td>
<td>.59</td>
<td>(.49)</td>
<td>.63*</td>
<td>-.03</td>
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<tr>
<td>4. Time Spent With Each Client (Minutes, Daily)</td>
<td>55.38</td>
<td>(36.95)</td>
<td>.07</td>
<td>-.11</td>
<td>.02</td>
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<tr>
<td>5. Time Spent Working (Hours, Daily)</td>
<td>6.96</td>
<td>(2.69)</td>
<td>.23*</td>
<td>.11</td>
<td>-.07</td>
<td>-.01</td>
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<tr>
<td>6. Time Spent at Work (Hours, Daily)</td>
<td>7.86</td>
<td>(2.15)</td>
<td>.33*</td>
<td>-.06</td>
<td>-.09</td>
<td>-.07</td>
<td>.70*</td>
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<tr>
<td>7. Shift Length (Minutes)</td>
<td>490.25</td>
<td>(161.13)</td>
<td>.28*</td>
<td>-.05</td>
<td>.03</td>
<td>-.03</td>
<td>.54*</td>
<td>.70*</td>
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<tr>
<td>8. Elapsed Time at Work (Minutes)</td>
<td>330.36</td>
<td>(211.09)</td>
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<td>.03</td>
<td>-.04</td>
<td>-.11</td>
<td>.35*</td>
<td>.34*</td>
<td>.18*</td>
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<tr>
<td>9. Time Point</td>
<td>22.03</td>
<td>(13.05)</td>
<td>-.08*</td>
<td>-.05</td>
<td>-.04</td>
<td>.00</td>
<td>-.05</td>
<td>-.07</td>
<td>-.05</td>
<td>.05</td>
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<td><strong>A-Factor and E-Factor Scales</strong></td>
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<tr>
<td>10. A-Factor</td>
<td>3.64 (.72)</td>
<td>-.03</td>
<td>.09*</td>
<td>-.04</td>
<td>.24*</td>
<td>-.26*</td>
<td>-.20*</td>
<td>-.10*</td>
<td>-.05*</td>
<td>(.92)</td>
<td></td>
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<tr>
<td>11. Job Satisfaction</td>
<td>4.17 (.82)</td>
<td>-.05</td>
<td>.04</td>
<td>-.06*</td>
<td>.27*</td>
<td>-.23*</td>
<td>-.18*</td>
<td>-.11*</td>
<td>-.10*</td>
<td>-.03</td>
<td>.83*</td>
<td>(.89)</td>
<td></td>
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<tr>
<td>12. Job Involvement</td>
<td>2.85 (.86)</td>
<td>-.01</td>
<td>.08</td>
<td>.01</td>
<td>.17*</td>
<td>-.20*</td>
<td>-.15*</td>
<td>-.04</td>
<td>-.05*</td>
<td>.77*</td>
<td>.38*</td>
<td>(.87)</td>
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<tr>
<td>13. Affective Commitment</td>
<td>3.97 (.88)</td>
<td>-.03</td>
<td>.11*</td>
<td>-.05</td>
<td>.18*</td>
<td>-.25*</td>
<td>-.18*</td>
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<td>.76*</td>
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<tr>
<td>14. E-Factor</td>
<td>4.14 (.63)</td>
<td>.19*</td>
<td>.05</td>
<td>.00</td>
<td>.30*</td>
<td>-.12</td>
<td>-.12</td>
<td>-.05</td>
<td>.09*</td>
<td>-.12*</td>
<td>.53*</td>
<td>.55*</td>
<td>.32*</td>
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<tr>
<td>15. Task Performance</td>
<td>4.32 (.67)</td>
<td>.18*</td>
<td>.08</td>
<td>.05</td>
<td>.30*</td>
<td>-.17*</td>
<td>-.14*</td>
<td>-.03</td>
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<td>-.13*</td>
<td>.41*</td>
<td>.46*</td>
<td>.22*</td>
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<tr>
<td>16. OCB</td>
<td>4.21 (.70)</td>
<td>.16*</td>
<td>.08</td>
<td>-.03</td>
<td>.25*</td>
<td>-.08</td>
<td>-.14*</td>
<td>-.08*</td>
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<td>-.08*</td>
<td>.49*</td>
<td>.47*</td>
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<tr>
<td>17. Psychological Withdrawal</td>
<td>2.24 (.91)</td>
<td>-.13*</td>
<td>.03</td>
<td>.00</td>
<td>-.20*</td>
<td>.06</td>
<td>.01</td>
<td>.01</td>
<td>-.04</td>
<td>.10*</td>
<td>-.47*</td>
<td>-.50*</td>
<td>-.28*</td>
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</table>

Note: Average Within-Person Coefficient Alphas presented on the diagonal of the matrix where appropriate. Blank cells indicated correlations where one or more variables were constant. Sample size ranges from 101 to 1,438 across all analyses. Working at this Moment, Work for more than one organization, scheduled to work, (No=0, Yes=1). OCB=Organizational Citizenship Behavior. Psychological Withdrawal is coded so that larger values indicated higher amounts of psychological withdrawal. For each time-related variable, the frequency of assessment and the unit of measurement are included in parentheses next to the variable label.
<table>
<thead>
<tr>
<th>Variable</th>
<th>M (SD)</th>
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<th>14</th>
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<th>16</th>
<th>17</th>
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<tr>
<td>13. Affective Commitment</td>
<td>3.97</td>
<td>(.86)</td>
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<td>(0.63)</td>
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<tr>
<td>15. Task Performance</td>
<td>4.32</td>
<td>.38*</td>
<td>.89*</td>
<td>(.89)</td>
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<td>(0.67)</td>
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<tr>
<td>16. OCB</td>
<td>4.21</td>
<td>.45*</td>
<td>.88*</td>
<td>.71*</td>
<td>(.88)</td>
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<td></td>
<td>(0.70)</td>
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<tr>
<td>17. Psychological Withdrawal</td>
<td>2.24</td>
<td>-.41*</td>
<td>-.78*</td>
<td>-.54*</td>
<td>-.50*</td>
<td>(.78)</td>
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<td></td>
<td>(0.91)</td>
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In terms of the associations between the time-related scales and the momentary assessments, working for more than one organization tends to have a slightly positive impact on affective commitment ($r = 11, p < .05$) and the A-Factor as a whole ($r = .09, p < .05$). However, this variable was not included as a momentary covariate given that it was already included as a demographic auxiliary variable in the forthcoming analyses. Participants tended to report slightly less job satisfaction when working ($r = -.06, p < .05$). As can be seen in Table 2, participants tended to experience a significantly small-to-moderate boost in all job attitudes and behavioral engagement variables when spending more time on average with each client. As such, this variable was considered as a covariate in the construction of random coefficients models when testing Hypotheses 3 and 4. Interestingly, there also appeared to be a negative effect of time-spent working on job-related tasks ($r = -.26, p < .05$), time spent at work ($r = -.20, p < .05$), scheduled shift length ($r = -.10, p < .05$), and elapsed time at work ($r = -.08, p < .05$) on the A-Factor. Paradoxically, time spent at work appeared to have a negative effect on job involvement ($r = -.15, p < .05$). Given that time spent working on job-related tasks affected the A-Factor and its facets uniformly, it was included as a time-varying covariate in Hypothesis 4 tests. Although time spent at work was also related to the A-Factor, it was highly multicollinear with time-spent...
on working on job-related tasks (\(r = .70, p < .05\)) and was not included in the model as a time-varying covariate. Although the overall shift length had no effect on the E-Factor, the elapsed time at work in minutes did have a moderate effect on the E-Factor (\(r = .09, p < .05\)). Given that this variable affected both the A-Factor and the E-Factor, it was also considered as a time-varying covariate for the Hypothesis 3 and 4 tests.

As a final element of Table 2, support for the positive manifold of the A-Factor was provided via a strong within-persons correlation between job satisfaction and affective commitment (\(r = .76, p < .05\)), although the evidence was less strong for job involvement and its relationships with job satisfaction and affective commitment. These correlations (i.e., with job satisfaction \(r = .38\); affective commitment, \(r = .49\)) however, are of similar magnitude to the corrected correlations found in Brown’s (1996) meta-analysis of job involvement with job satisfaction (.45) and organizational commitment (.50). Regardless, the A-Factor was strongly correlated with job satisfaction, job involvement, and affective commitment. Evidence for strong positive manifold of behavioral engagement was more clear-cut, with correlations ranging from an absolute value of .50-.71 across task performance, psychological withdrawal, and OCB. Similarly, the E-Factor was also strongly correlated with its facets. Also worthy of noting, the A-Factor and E-Factor were strongly correlated at the within-persons level of analysis (\(r = .53, p < .05\)). For both the A-Factor and E-Factor, this correlation was much stronger than each general factor’s correlation with narrower criteria or predictors in all but one case (the correlation between job satisfaction and behavioral engagement was only .02 higher, \(r = .55, p < .05\)), providing mostly complete support for the compatibility principle (Ajzen & Fishbein, 1980).

Although not a part of the correlation matrix, in order to determine whether or not there were time of day characteristic effects on particular variables at the within-subjects level of
analysis, the dummy-coded signal period (i.e., morning, afternoon, and evening) variables were correlated with a selection of the within-persons variables of interest. Although time of day had no effect on job attitudes, it appeared that the time of day did have a small effect on the provision of organizational citizenship behaviors during the morning ($r = .17, p < .05$) and evening ($r = -.16, p < .05$) signals, perhaps providing evidence for a resource depletion perspective on organizational citizenship behavior (Trougakos et al., 2015) or a bounded rationality perspective on helping behavior (Folger et al., 2013; Kouchaki & Smith, 2014). However, these “time of day” effects were not controlled for in the extant analyses as these effects did not uniformly generalize to task performance or psychological withdrawal, which together ultimately comprise the E-Factor. However, it should be noted that there was a weak, positive effect of morning responses on the E-Factor ($r = .14, p < .05$), most likely driven by the strong effect of the morning time period on OCB (the other two behavioral engagement facets were not significant).

The distributions of all continuous and interval-level variables from the orientation survey were also examined for departures from normality, as one of the assumptions of parametric statistics. All Shapiro-Wilk tests for the within-persons time-related variables and momentary assessments were significant suggesting that the distributions were non-normal. However, with the time-related variables this was expected, given that many of the values “increased” as the study progressed. With regards to the momentary assessment scales, an examination of their standardized skewness and kurtosis statistics revealed that the A-Factor and E-Factor scales were significantly skewed. However, an examination of the Normal Q-Q plots as well as their histograms suggested that they approximated normality, with a restriction of range in the lower part of the scoring distribution that might account for the deviations from normality. In order to refrain from substantially changing the interpretation of the nature of these variables,
they were retained in their original form. Skewed distributions are quite common for attitude and behavior ratings across a variety of industries and the use of a normal distribution is coming into question with regard to its application to the world of work, with distributions obscuring the emergence of star performers amongst poor or average performers, or conversely, those who perform very poorly amongst those that normally perform well (Aguinis & O’Boyle, 2014; O’Boyle & Aguinis, 2012). Regardless, the true normality assumption to be met in random coefficients modeling is that the residuals in any given random coefficients model with a fixed effect are normally distributed, such as those employed in the tests of Hypothesis 3 and 4 (Hox, 2010). For both of those tests and across all lagged tests, this assumption was met (along with evidence for a lack of heteroscedasticity).

**Selecting Auxiliary Variables.** Regarding the use of auxiliary variables in missing data estimation, an unfortunate side effect of the employment of the FIML technique is that it incorporates any of the auxiliary variables utilized into the substantive model itself (Newman, 2009). Furthermore, recent guidelines on the incorporation of control variables in statistical models (Becker, 2005; Bernerth & Aguinis, 2016) suggest that the incorporation of control variables should move beyond the mere inkling that the variables may matter for the analyses at hand. Given this requirement for the incorporation of control variables, before conducting the hypothesis tests the following individual differences were selected given pre-established empirical relationships with job attitudes, behavioral engagement, or both. Beyond the incorporation of personality and general mental ability due to the mostly consistent, substantial literature (Barrick, Mount, & Judge, 2001) regarding their relationships with job attitudes (Borman, Penner, Allen, & Motowidlo, 2001; Brown, 1996; Choi, Oh, & Colbert, 2015; Judge, Heller, & Mount, 2002; Bruk-Lee, Khoury, Nixon, Goh, & Spector, 2009) and behavioral
engagement (Barrick & Mount, 1991; Chiaburu, Oh, Berry, Li, & Gardner, 2011; Gonzales-Mulé, Mount, & Oh, 2014; Hunter, 1986; Judge, Rodell, Klinger, Simon, & Crawford, 2013; Kluemper, McLarty, & Bing, 2015; Schmidt & Hunter, 1998, 2004; Zimmerman, 2008); a review of the relationships between the other proposed auxiliary variables with job attitudes and behavioral engagement follow.

For one, the self-employment status variable was demonstrated to be related to the A-Factor at the between subjects level of analysis (see Table 1). Some support for this relationship has been provided through empirical research suggesting that self-employment reduces work-to-family conflict and spillover and ultimately improves job attitudes (Hundley, 2001). Furthermore, self-employed individuals have been shown to exhibit both heightened work engagement (a psychological construct that is conceptually redundant with the A-Factor, Newman et al., 2010) and task performance (Gorgievski, Bakker, & Schaufeli, 2010). With regard to behavioral engagement, self-employment status has been shown to improve task performance (see also, Gorgievski et al., 2010) to the extent that it facilitates a pursuit of learning regarding professional development of the job as well as whether or not one has positive person-job fit perceptions for self-employed positions (Niessen, Binnewies, & Rank, 2010). Furthermore, Pfeifer (2013) found that self-employed workers displayed less withdrawal behaviors (e.g., reported sick days, absences) than their employed private sector and public sector counterparts, as they are expected to have higher job attitudes and also have more to lose if they are absent (e.g., foregone income).

Second, some meta-analytic evidence supports the notion that full-time workers have higher job involvement than part-time workers, although there appears to be no difference between the two on job satisfaction, organizational commitment, or withdrawal cognitions.
(Thorsteinson, 2003). He cites a variety of reasons why part- and full-time employees may differ on job attitudes, including different perceptions of person-job fit and varying equity frames of reference (Thorsteinson, 2003). Furthermore, some evidence suggests that those who work full-time are more prone to engage in helping organizational citizenship behaviors (Stamper & Van Dyne, 2001). Most importantly, however, partial inclusion theory (Miller & Terborg, 1979) suggests that full-time employees are more holistically included within an organizational social system, whereas part-time employees do not have that kind of holistic support. As such, full-time employees are more likely to be happier and more productive given their inclusion and belongingness experienced as being a part of a social system. Regardless, as seen in Table 1, full-time status has a strong impact on organizational commitment and a moderate effect on job involvement and the A-Factor as a whole at the between-persons level (although the latter two were not significant), so it was retained as an auxiliary variable.

Third, demographics variables such as age, gender, race, and organizational tenure were included as auxiliary variables for both the A-Factor and the E-Factor. Overall, prior research has integrated these characteristics in a model that links surface- and deep-level characteristics to job attitudes as well as behavioral engagement and performance outcomes (Guillaume, Brodbeck, & Riketta, 2012). In these models, although deep-level dissimilarity is more important, surface-level dissimilarity does have an effect on social integration and ultimately, job attitudes and behaviors (Guillaume et al., 2012). In a review of the meta-analytic literature on job attitudes, Schleicher et al. (2010) reported that age was moderately related to organizational commitment. Indeed, these results were corroborated across all job attitudes in a more recent, updated meta-analysis (Ng & Feldman, 2010) on the relationship between age and job attitudes, suggesting that age is moderately, positively, and significantly related to job attitudes (all elements comprising...
the A-Factor). However, the meta-analytic relationship between age and behavioral engagement, including task performance, OCB, and withdrawal behaviors is decidedly lower, although still significant (Ng & Feldman, 2008a). Given the relationships with job attitudes, and to a lesser degree behavioral engagement, age was retained as an auxiliary variable.

Although prior meta-analytic research suggests that gender is primarily unrelated to job attitudes (Aven, Parker, & McEvoy, 1993; Tait, Youtz Padgett, & Baldwin, 1989) there is evidence that there are slight, but significant differences in overall, supervisor, and objective ratings of job performance between genders in field research in favor of females (Roth, Purvis, & Bobko, 2012). As such, gender was retained as a covariate, given that supervisor ratings of performance were included in the composite calculations of the E-Factor.

Although there is not much research on racial differences in job attitudes (cf., Koh, Shen, & Lee, in press; slight black-white meta-analytic differences in job satisfaction), a large literature on racial or ethnic differences in performance suggests that there are racial differences on a variety of measures of performance (Bobko & Roth, 2013; Roth, Huffcutt, & Bobko, 2003).

Finally, although tenure has not been shown to be meta-analytically related to behavioral engagement, it has been suggested that longer tenure leads to diminished job attitudes and heightened perceptions of boredom (Ng & Feldman, 2013). Notably, affective commitment (one of the components of the A-Factor), has been meta-analytically demonstrated to be moderately, positively correlated with organizational tenure (Meyer et al., 2002). Furthermore, Brown (1996) found that job involvement was meta-analytically related to organizational tenure and age, although these relationships were notably small. As such, all of the previously mentioned demographics variables and individual differences listed were retained as auxiliary variables in the model.
As a final note, in the within-persons descriptive statistics section, time in minutes spent with clients was determined to be a potential covariate for the A-Factor whereas shift length was determined to be a potential covariate for the E-Factor. These covariates are theoretically important to the models at hand for a variety of reasons. First, longer periods of time spent with each client increases the potential for customer affiliative behavior, which has been shown in prior research to be related to employee well-being and happiness (Holman, in press; Humphrey, Nahrgang, Morgeson, 2007) due to its tendency to conserve energy (Dormann & Zapf, 2004) and protect resources (Hobfoll, 1989). However, the longer period of time spent with clients could just as easily permit a certain number of negative events to occur, leading to negative attitudinal reactions. Regardless of the direction of the effect, this variable should be retained as a time-varying covariate. Second, shift length is theoretically expected to be related to behavioral engagement according to the integrative model of Social Identity and Commitments at Work (Meyer, Becker, & Van Dick, 2006; Ng & Feldman, 2008b). Here, when the organization becomes a significant part of one’s social identity, individuals are more likely to spend longer hours at work and become behaviorally engaged. Shift length has been shown to be meta-analytically related to absenteeism, although its relationship with job performance is not significant (Ng & Feldman, 2008b). However, given the theoretical reason for its relationship along with its association with the E-Factor within-persons in this study, it was retained as a time-varying covariate. Lastly, Ng and Feldman (2008b) demonstrated that longer working hours is related to organizational pressures for performance, job demands, role overload, and interpersonal conflict—they also found that it can result in increased job stress, mental strain, and work-to-family conflict. As such, there is reason to expect that longer hours at work and
more time spent working on job-related tasks will have a negative effect on job attitudes, thus suggesting it be retained as a time-varying covariate for job attitudes.

**Using Generalizability Theory to Examine the Reliability of the A-Factor and the E-Factor**

Interestingly, guidance on how to examine the psychometrics of emotional states and within-persons phenomenon is in its nascence; an idea which is surprising given the extent to which longitudinal phenomena have been of interest to psychologists. (Bolger & Laurenceau, 2013). Recent research has since provided guidance to researchers employing experience sampling or intensive longitudinal methods in order to examine the psychometric properties of their measured phenotype, beyond coefficient alpha and CFA. Notably, psychometricians have introduced generalizability theory as a way to decompose measurement variation into sources of relevant variance and error variance, in order to make inferences about whether or not constructs are measured reliably (Cronbach, Gleser, Nanda, & Rajaratnam, 1972; Cronbach & Meehl, 1955; Shavelson & Webb, 1991).

Notably, some suggest that the use of generalizability theory is one way to provide construct validity evidence for the constructs of interest in one’s study (Kraiger & Teachout, 1990; Lakes & Hoyt, 2008). Furthermore, many suggest that it should be used in conjunction with CFA in order to provide construct validity evidence for experience sampling method designs (Bolger & Laurenceau, 2013; Shrout & Lane, 2012). Using a generalizability theory approach, Cranford et al. (2006) were the first to suggest that in an ESM study, construct ratings can be decomposed into the following latent (see Bolger & Laurenceau, 2013) sources of variance: time, person, item, time*person, time*item, person*item, person*time*item. However, given the sizes of the fully crossed person*time*item datasets for the A-Factor (24,446) and E-Factor (30,199), conducting this form of analysis would be untenable and too computationally
intensive. As such, the decomposition of variance of the A-Factor and E-Factor items for each of the six scales is presented in Table 3, instead of for the entire A- and E-Factor scales.\textsuperscript{6}

Furthermore, the reliability coefficients for each scale will be based on the average variance component estimates across each set of three scales, to provide an estimate of the reliability of change in the A- and E-Factors.

\textsuperscript{6} It is important to note that the variance decomposition procedure here primarily concerns measurement error and does not reflect uncovering relevant sources of variation in the A-Factor and the E-Factor. Time as a source of variance here does not reflect within-person variation in the A- or E-Factor as is explored in the hypothesis tests of this study; rather, it reflects each time point explicitly as a source of variation in attitudes or behaviors. For example, in a daily diary study of job satisfaction, a small variance component of time would suggest that Day 1, Day 2, and Day 3 in a three day study design exhibit little between-day variation across all people and items on levels of job satisfaction. A large variance component of time would suggest that, in general, Day 1 has much higher estimates than Day 2 and slightly more than Day 3. So it is not that within-person variation is being assessed by the variance component. Instead, it is between-time point variation. In fact, a small variance component of time would minimize the extent to which specific time points have an effect on the measurement of the construct of interest, as would be the case if people were generally happier on the first day or last day of the study.
Table 3: Generalizability Theory: Variance Partitioning of the A-Factor and E-Factor Scales

<table>
<thead>
<tr>
<th>Source of Variance</th>
<th>Job Satisfaction</th>
<th>Affective Commitment</th>
<th>Job Involvement</th>
<th>A-Factor Average</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Variance Component</td>
<td>% of Total Variance</td>
<td>Variance Component</td>
<td>% of Total Variance</td>
</tr>
<tr>
<td>Time</td>
<td>0.000</td>
<td>0.00</td>
<td>0.000</td>
<td>0.00</td>
</tr>
<tr>
<td>Person</td>
<td>0.432</td>
<td>40.08</td>
<td>0.589</td>
<td>34.73</td>
</tr>
<tr>
<td>Items</td>
<td>0.021</td>
<td>1.95</td>
<td>0.181</td>
<td>10.70</td>
</tr>
<tr>
<td>Time * Person</td>
<td>0.187</td>
<td>17.37</td>
<td>0.091</td>
<td>5.37</td>
</tr>
<tr>
<td>Time * Item</td>
<td>0.001</td>
<td>0.08</td>
<td>0.002</td>
<td>0.10</td>
</tr>
<tr>
<td>Person * Item</td>
<td>0.092</td>
<td>8.55</td>
<td>0.450</td>
<td>26.56</td>
</tr>
<tr>
<td>Time * Person * Item</td>
<td>0.000</td>
<td>0.00</td>
<td>0.000</td>
<td>0.00</td>
</tr>
<tr>
<td>Error</td>
<td>0.344</td>
<td>31.97</td>
<td>0.382</td>
<td>22.55</td>
</tr>
<tr>
<td>Total</td>
<td>1.077</td>
<td>100.00</td>
<td>1.695</td>
<td>100.00</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Source of Variance</th>
<th>Task Performance</th>
<th>OCB</th>
<th>Withdrawal</th>
<th>E-Factor Average</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Variance Component</td>
<td>% of Total Variance</td>
<td>Variance Component</td>
<td>% of Total Variance</td>
</tr>
<tr>
<td>Time</td>
<td>0.029</td>
<td>3.53</td>
<td>0.026</td>
<td>2.89</td>
</tr>
<tr>
<td>Person</td>
<td>0.232</td>
<td>28.30</td>
<td>0.252</td>
<td>27.64</td>
</tr>
<tr>
<td>Items</td>
<td>0.028</td>
<td>3.43</td>
<td>0.036</td>
<td>3.95</td>
</tr>
<tr>
<td>Time * Person</td>
<td>0.159</td>
<td>19.48</td>
<td>0.164</td>
<td>17.99</td>
</tr>
<tr>
<td>Time * Item</td>
<td>0.000</td>
<td>0.00</td>
<td>0.006</td>
<td>0.63</td>
</tr>
<tr>
<td>Person * Item</td>
<td>0.091</td>
<td>11.10</td>
<td>0.170</td>
<td>18.61</td>
</tr>
<tr>
<td>Time * Person * Item</td>
<td>0.000</td>
<td>0.00</td>
<td>0.000</td>
<td>0.00</td>
</tr>
<tr>
<td>Error</td>
<td>0.280</td>
<td>34.17</td>
<td>0.258</td>
<td>28.28</td>
</tr>
<tr>
<td>Total</td>
<td>0.818</td>
<td>100.00</td>
<td>0.911</td>
<td>100.00</td>
</tr>
</tbody>
</table>

*Note.* MIVQUE(0) estimation procedure was utilized in order to estimate the variance components (as recommended by Bolger & Laurenceau, 2013). Using this estimation procedure, negative variance components can be obtained as there are no non-zero constraints, as in Maximum Likelihood Estimation. Any negative estimates obtained were close to zero, or otherwise normally treated as statistical error (i.e., in time * person * item effects, Bolger & Laurenceau, 2013). As such, any negative variance components were treated as if they were zero, as recommended (SAS User’s Guide, 2009).
Each variance component presented in Table 3 is meaningful in that it characterizes the variance sources of the A-Factor and E-Factor. The variance component associated with time suggests that there are little differences between moments or time points associated in the measurement of the A-Factor or E-Factor. This suggests that there is not one predictable pattern of change that occurs across people and items from each specific moment to moment. Furthermore, the relatively large person component suggests that there are substantial between-persons differences in job attitudes that exist across items and that are stable over time. The large items component for the A-Factor suggests that there are substantial differences between the items regarding their tendency to elicit either positive or negative responses. This would be expected, given the highly skewed nature of the data as is typical with attitude and behavior ratings. Of the variance components, Bolger and Laurenceau (2013) note that person * time variance component is of particular interest as it represents “the extent to which people differ in how they change over time (averaging across items)” (p. 132). This element is critical to the calculation of the reliability of within-subjects changes from study-to-study.

In order to provide evidence for the reliability of within-persons change assessed within the current study, a series of 3 reliability coefficients were calculated using the variance components obtained from Table 3 for both the A-Factor and the E-Factor (Bolger & Laurenceau, 2013; Cranford et al., 2006; Shrout & Lane, 2012). These reliability coefficients operate in much of the same way as g coefficients (Cronbach et al., 1972; Cronbach & Meehl, 1955; Shavelson & Webb, 1991) and can be interpreted in a similar fashion as other reliability coefficient, such as Cronbach’s Alpha. In the following calculations, given that all momentary assessments were not explicitly fixed in time (e.g., they randomly varied from person to person and moment-to-moment), the random versions of all formulas were used. The first reliability
coefficient, $R_c$, is perhaps the most important (Bolger & Laurenceau, 2013), and represents the reliability of moment-to-moment changes in the A-Factor and E-Factor,

$$R_c = \frac{\sigma_{T^*P}^2}{\sigma_{T^*P}^2 + [(\sigma_e^2 + \sigma_{T^*P^*I}^2)/k]}$$  \hspace{1cm} (4)

Where $\sigma_{T^*P}^2$ refers to the variance component associated with the time by person interaction, $\sigma_e^2$ refers to within-person variation, $\sigma_{T^*P^*I}^2$ refers to the variance component associated with the person by time by item interaction, and $k$ refers to the number of items. Both estimates for the A-Factor ($R_c = .89$) and the E-Factor ($R_c = .88$) were very good, suggesting that the design reliably captures moment-to-moment changes in both the A- and the E-Factor. However, the estimates for the A-Factor subscales were somewhat smaller and more unreliable (job satisfaction, $R_c = .73$; affective commitment, $R_c = .59$; and job involvement, $R_c = .67$) than those from the E-Factor (task performance, $R_c = .82$; OCB, $R_c = .84$; and psychological withdrawal, $R_c = .63$).

Second, the $R_{1R}$, is the reliability coefficient that considers the ability of the A- or the E-Factor to differentiate between people on a single random moment during the course of the study,

$$R_{1R} = \frac{\sigma_P^2 + (\sigma_{P^*I}^2/k)}{\sigma_P^2 + (\sigma_{P^*I}^2/k) + \sigma_T^2 + \sigma_{T^*P}^2 + [(\sigma_e^2 + \sigma_{T^*P^*I}^2)/k]}$$  \hspace{1cm} (5)

Where $\sigma_P^2$ refers to the variance component associated with between-person differences, $\sigma_{P^*I}^2$ refers to the variance component associated with the person by item interaction, $k$ refers to the
number of items, $\sigma_T^2$ refers to the variance component associated with differences associated with each unique time point, $\sigma_{T*P}^2$ refers to the variance component associated with the time by person interaction, $\sigma_e^2$ refers to within-person variation, and $\sigma_{T*P*I}^2$ refers to the variance component associated with the person by time by item interaction. Although the estimate for the A-Factor was acceptable ($R_{IR} = .75$), unfortunately, the estimate for the E-Factor was not ($R_{IR} = .64$). This suggests that the E-Factor does not necessarily differentiate between people on behavioral engagement very well at a single random time point during the course of the study. The implication here is that if the E-Factor scale is used to differentiate between people at a given time point, it may not be as effective (perhaps due to the constraints of these ratings during working periods and working days, as well as the affective events which happen during these shifts, which vary from person-to-person across the study time points). The estimates for the subscales were also poor for the most part, with the exception of affective commitment and job involvement (job satisfaction, $R_{IR} = .64$; affective commitment, $R_{IR} = .81$; and job involvement, $R_{IR} = .79$; task performance, $R_{IR} = .52$; OCB, $R_{IR} = .55$; and psychological withdrawal, $R_{IR} = .59$). A better reliability measure would assess the ability to differentiate between people on attitudes and engagement across all time points.

Lastly, the $R_{KR}$, is the reliability coefficient that considers the reliability of the A- or the E-Factor across all time points (e.g., the reliability of the A- or E-Factor not on a single random time point, but across all 45, virtually randomly occurring time points; Shrout & Lane, 2012)

$$
R_{KR} = \frac{\sigma_P^2 + (\sigma_{P*I}^2/k)}{\sigma_P^2 + (\sigma_{P*I}^2/k) + (\sigma_T^2/m) + (\sigma_{T*P}^2/m) + [(\sigma_e^2 + \sigma_{T*P*I}^2)/(k*m)]}
$$

(6)
Where $\sigma_p^2$ refers to the variance component associated with between-person differences, $\sigma_{p*I}^2$ refers to the variance component associated with the person by item interaction, $k$ refers to the number of items, $\sigma_T^2$ refers to the variance component associated with differences associated with each unique time point, $m$ refers to the number of time points in the study, $\sigma_{T*P}^2$ refers to the variance component associated with the time by person interaction, $\sigma_e^2$ refers to within-person variation, and $\sigma_{T*P*I}^2$ refers to the variance component associated with the person by time by item interaction. The estimates for both the A-Factor ($R_{KR} = .99$) and the E-Factor ($R_{KR} = .99$) were excellent, suggesting that the momentary assessments reliably assess what they are intended to assess across all study time points. The estimates for the A-Factor subscales (job satisfaction, $R_{KR} = .99$; affective commitment, $R_{KR} = .99$; and job involvement, $R_{KR} = .99$) and the E-Factor subscales (task performance, $R_{KR} = .98$; OCB, $R_{KR} = .98$; and psychological withdrawal, $R_{KR} = .98$) were also excellent.

**Testing Within-Persons Variation in the A-Factor and the E-Factor**

In order to test Hypothesis 1 (i.e., there is significant, within-person variation in the A-Factor), random coefficients modeling was utilized to calculate an intraclass correlation coefficient reflecting the percentage of total variation in the A-Factor that is within-persons. As mentioned in the Analysis Strategy section, a model employing FIML missing data estimation, incorporating all relevant individual differences variables assessed during the orientation and elongated surveys, using the spatial power structure for handling autocorrelation and unequal intervals in measurement, and employing the Satterthwaite degrees of freedom estimation method was utilized to model the variation in the A-Factor attributable to between- and within-persons sources. Indeed, both the between-persons ($\sigma_{u0}^2 = 0.14$, SE=0.04, $z = 3.88$, $p < .05$) and within-persons ($\sigma_e^2 = 0.11$, SE=0.01, $z = 15.88$, $p < .05$) estimates were significantly different.
from zero, according to the Wald tests. The $ICC(1)$ was .56, suggesting that 44% of the variation in job attitudes as broadly defined, or the A-Factor, is within-persons. As such, Hypothesis 1 was supported.

In order to test Hypothesis 2 that there is significant, within-persons variation in the E-Factor, the same approach was employed. Again, both the between-persons ($\sigma^2_{u_0} = 0.06$, SE=0.02, $z = 3.22$, $p < .05$) and within-persons ($\sigma^2_e = 0.21$, SE=0.01, $z = 15.69$, $p < .05$) estimates were significantly different from zero according to the Wald tests, although the disparity amongst the between- and within-persons estimates was much larger this time. The $ICC(1)$ was .22, suggesting that 78% of the variation in behavioral engagement as broadly defined, or the E-Factor, is within-persons. As such, Hypothesis 2 was supported.

In order to visualize these within-persons changes in the A-Factor in E-Factor, time series plots are presented in Figures 2 and 3, respectively. In these figures, each individual’s time series for the A-Factor and the E-Factor are plotted. In Figures 2 and 3, there is little to be seen by way of trajectory for each of the participants, with much variation occurring from moment to moment and from day-to-day, although most individuals appear to have their own “baseline” of job attitudes and behavioral engagement, as in alignment with the Hedonic Treadmill Theory (Brickman & Campbell, 1971; Helson, 1964). This suggests that in conceptualizing the A-Factor or the E-Factor for any given interval, one should not assume that there will be uniform linear change in the same way that most would expect when studying “longitudinal” phenomena.
Figure 2: A-Factor series plot depicting each participant’s A-Factor scores over time
Modeling Growth of the A-Factor and E-Factor

Although not explicitly hypothesized, as a research question, the growth trajectories of the A-Factor and the E-Factor were explored. First, in an effort to visually examine the potential trajectories of the A-Factor and the E-Factor, spaghetti plots or graphs that plot each individual’s trajectory along with a scatterplot of their responses are included as Figures 4 and 5, respectively (Bolger & Laurenceau, 2013; Singer & Willett, 2003). As can be seen, the A-Factor does not appear to grow or decline in general as a function of time—however, there are several cases that appear to exhibit a consistent downward or upward trajectory throughout the course of the study. However, across all respondents, it appears that on average, participants do not predictably grow or decline over the course of the study. As a comparison point, examining Figure 2 demonstrates...
that although there is substantial within-person variation, it does not take the form of pure linear or quadratic growth. Notably, it appears as if cycles may be present in job attitudes and behavioral engagement. Furthermore, the low $R_{1R}$ reliability coefficient for behavioral engagement can perhaps be further understood by visualizing Figure 5, in which the predicted values for virtually any time point are clarified by low observed “out of character” or outlier data points for some participants. This suggests that on any given day, there may be deviations from what is predicted for each individual, given meaningful relevant variation caused by workplace events (Beal et al., 2003; Weiss & Cropanzano, 1996).
Figure 4: A-Factor spaghetti plot depicting each participant’s A-Factor trajectories against each participant’s scatterplot
To formally test the tenability of linear or quadratic growth trends for the A-Factor, Bliese and Ployhart’s (2002) model building procedure was followed. These models built off of those tested in hypotheses 1 and 2. The first step of the procedure is to calculate the intraclass correlation coefficient to determine if there is sufficient within-person variation to test for growth functions. This step was completed in the prior section, and a sufficient proportion of within-person variation exists to test growth in the A-Factor over time. As a second step, each fixed function of time starting with a linear effect and adding a quadratic effect was modelled and the change in deviance was tested in order to determine whether or not adding linear or quadratic parameters significantly contribute to the fit of the random coefficients model. As can be seen
from Table 4, although the intercepts in both models were significant, neither the linear nor the quadratic effects in the A-Factor were significant. Furthermore, the changes in deviance by adding the linear term, Δ deviance (1) = 0.9, n. s., and by adding the quadratic term, Δ deviance (1) = 0.0, n. s., were not significant for the A-Factor. Second, although the change in deviance by adding the linear term, Δ deviance (1) = 4.4, $p < .05$ was significant for the E-Factor; adding the quadratic term, Δ deviance (1) = 0.4, n. s., was not significant for the E-Factor. This suggests that there was no linear or quadratic growth in the A-Factor over time in this study. However, there is evidence for very slight, negative change in the E-Factor over time in this study. Considering that most of the E-Factor trajectories appear to be stable in Figure 5, it could be that a series of “outlying” trajectories are what is causing the effect of time point to be significant. Furthermore, after releasing the constraint on the variability of E-Factor growth, the fixed effect of growth is no longer significant ($\beta_1 = -0.003$, n.s.). Given that the significant growth parameter was small, contrary to expectation, ceased to be significant after releasing the growth variability constraint, and only slightly improved model fit after inclusion (see Table 4, Δ deviance = 14.0), it will not be modeled in the forthcoming analyses.

Table 4: Random Coefficients Growth Models of the A-Factor and the E-Factor

<table>
<thead>
<tr>
<th>Construct</th>
<th>Fixed Effect</th>
<th>Coefficient</th>
<th>SE</th>
<th>df</th>
<th>$t$</th>
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</thead>
<tbody>
<tr>
<td><strong>A-Factor</strong></td>
<td>Intercept</td>
<td>3.09</td>
<td>1.41</td>
<td>34.4</td>
<td>2.19*</td>
</tr>
<tr>
<td></td>
<td>Linear Trend</td>
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<td>&lt;0.01</td>
<td>180.0</td>
<td>0.94</td>
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<tr>
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<td>Quadratic Trend</td>
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<td>&lt;0.01</td>
<td>237.0</td>
<td>0.17</td>
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<tr>
<td><strong>E-Factor</strong></td>
<td>Intercept</td>
<td>1.33</td>
<td>1.06</td>
<td>35.4</td>
<td>1.25</td>
</tr>
<tr>
<td></td>
<td>Linear Trend</td>
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<td>&lt;0.01</td>
<td>276.0</td>
<td>2.10*</td>
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<tr>
<td></td>
<td>Quadratic Trend</td>
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<td>284.0</td>
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</table>

<table>
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<th>Variance Component</th>
<th>SE</th>
<th>Deviance</th>
<th>Δ Deviance</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>A-Factor</strong></td>
<td>Intercept Variance</td>
<td>0.14</td>
<td>0.04</td>
<td>200.4</td>
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</table>
The Attitude-Engagement Model, Within-Persons

To test the final hypotheses of the study, the Attitude-Engagement model was tested, within-persons. Random coefficients models regressing the A-Factor onto the E-Factor, and vice versa, were computed in order to test whether or not there is a significant effect of the A-Factor on the E-Factor (Hypothesis 3) and whether or not there is a significant effect of the E-Factor on the A-Factor (Hypothesis 4). Furthermore, the covariates identified in the within-persons descriptive statistics section were included as time-varying covariates in order to control for the impact of shift length on the E-Factor and for minutes spent with clients on the A-Factor (along with the auxiliary variables). The A-Factor and E-Factor scores were group-mean centered before entry into the random coefficients model, given that they did not have meaningful zeroes and in order to partial out between-persons variance so that a pure estimate of the within-persons relationship could be obtained (Dalal & Zickar, 2012; Hofmann & Gavin, 1998). As can be seen
in Table 5, the A-Factor has a significant within-persons effect on the E-Factor supporting Hypothesis 3, $\beta (139) = 0.49, SE = 0.06, 95\% CI LL = 0.38, 95\% CI UL = 0.60, t = 8.55, p < .05$.

Second, the E-Factor has a significant within-persons effect on the A-Factor supporting Hypothesis 4, $\beta (149) = 0.68, SE = 0.08, 95\% CI LL = 0.52, 95\% CI UL = 0.83, t = 8.78, p < .05$.

As the two models were non-nested, a comparison of their model fit by way of their AIC and their BIC values was warranted. Given that the values for AIC and BIC were smaller for the model regressing the A-Factor onto the E-Factor along with a slightly stronger beta weight (although the confidence intervals for each overlapped suggesting they were not significantly different), this appeared to be the more appropriate model. However, given all of the evidence, it appears that there is a reciprocal effect of the A-Factor on the E-Factor at the within-persons level.

Table 5: Random Coefficients Models Regressing the A-Factor onto the E-Factor and Vice-Versa, Within-Persons

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Fixed Effect</th>
<th>Coefficient</th>
<th>SE</th>
<th>df</th>
<th>t</th>
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<tr>
<td><strong>E-Factor</strong></td>
<td>Intercept</td>
<td>3.67</td>
<td>0.39</td>
<td>36.0</td>
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<td>0.49</td>
<td>0.06</td>
<td>139.0</td>
<td>8.55*</td>
</tr>
<tr>
<td></td>
<td>Shift Length</td>
<td>&lt;0.01</td>
<td>&lt;0.01</td>
<td>152.0</td>
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<td>Time Spent With Each Client</td>
<td>&lt;0.01</td>
<td>&lt;0.01</td>
<td>167.0</td>
<td>0.66</td>
</tr>
<tr>
<td><strong>A-Factor</strong></td>
<td>Intercept</td>
<td>3.73</td>
<td>0.47</td>
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<td>0.08</td>
<td>149.0</td>
<td>8.78*</td>
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<tr>
<td></td>
<td>Shift Length</td>
<td>&lt;0.01</td>
<td>&lt;0.01</td>
<td>157.0</td>
<td>0.65</td>
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<tr>
<td></td>
<td>Time Spent With Each Client</td>
<td>&lt;0.01</td>
<td>&lt;0.01</td>
<td>164.0</td>
<td>0.95</td>
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<tr>
<td></td>
<td>Hours Spent Working</td>
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<td>-0.01</td>
<td>171.0</td>
<td>1.81†</td>
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</table>

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<th>Variance Component</th>
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<th>AIC (BIC)</th>
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</table>

90
<table>
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<tr>
<th></th>
<th>Intercept</th>
<th>Variance</th>
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<th></th>
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</thead>
<tbody>
<tr>
<td>E-Factor</td>
<td>0.09</td>
<td>0.03</td>
<td>81.0</td>
<td>123.0</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(155.1)</td>
</tr>
<tr>
<td></td>
<td>0.06</td>
<td>0.01</td>
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<td></td>
</tr>
<tr>
<td>A-Factor</td>
<td>0.13</td>
<td>0.04</td>
<td>135.6</td>
<td>179.6</td>
</tr>
<tr>
<td></td>
<td></td>
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<td>(213.2)</td>
</tr>
<tr>
<td></td>
<td>0.08</td>
<td>0.01</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Note.* All auxiliary variables were included in the model. Both the A-Factor and the E-Factor were group-mean centered in accordance with best practices in random coefficients modeling (Dalal & Zickar, 2012; Hofmann & Gavin, 1998), given that the two did not have meaningful zero points. The three time-varying covariates that were identified as potential within-persons covariates of the A-Factor and the E-Factor were included here as well. *p < .05, †p < .10. All tests 2-tailed.*

As an additional test of the relationship, cross-lagged effects were introduced for each predictor on the relevant criterion. For example, The E-Factor was regressed upon to the A-Factor score at the preceding time point, two time points, day, and two days in order to permit a longitudinal, lagged test of the Attitude-Engagement Model within-persons across various time frames. One and two time points were chosen within days to capture the extent of within-day variation. One and two days were chosen to capture any sort of longer term effects job attitudes and behavioral engagement may have on one another. Models testing the cross-lagged relationship of the E-Factor on the A-Factor were also tested in order to provide further evidence for Hypothesis 4. In all analyses, the lagged effects (e.g., the effect of the prior A-Factor onto the preceding A-Factor) were controlled for. These lagged and cross-lagged effects are presented in Table 6.
Table 6: Lagged Random Coefficients Models (Moments and Days) Regressing the A-Factor onto the E-Factor and Vice-Versa, Within-Persons

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Lag</th>
<th>Fixed Effect</th>
<th>Coefficient</th>
<th>SE</th>
<th>df</th>
<th>t</th>
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<tbody>
<tr>
<td><strong>E-Factor</strong></td>
<td>Prior Moment</td>
<td>Intercept</td>
<td>3.69</td>
<td>0.41</td>
<td>34.2</td>
<td>9.06*</td>
</tr>
<tr>
<td></td>
<td></td>
<td>A-Factor (-1t)</td>
<td>0.26</td>
<td>0.09</td>
<td>106.0</td>
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<tr>
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<td>E-Factor (-1t)</td>
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<td>0.07</td>
<td>132.0</td>
<td>1.07</td>
</tr>
<tr>
<td></td>
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<td>&lt;0.01</td>
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<td>Time Spent With Each Client</td>
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<td>&lt;0.01</td>
<td>154.0</td>
<td>0.96</td>
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<tr>
<td><strong>A-Factor</strong></td>
<td>Prior Moment</td>
<td>Intercept</td>
<td>3.95</td>
<td>0.43</td>
<td>36.4</td>
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<td>0.08</td>
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<tr>
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<td>0.02</td>
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<td>1.45</td>
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<td><strong>E-Factor</strong></td>
<td>Prior Day</td>
<td>Intercept</td>
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<tr>
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<td>Time Spent With Each</td>
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</tr>
<tr>
<td><strong>A-Factor</strong></td>
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<td>Intercept</td>
<td>4.26</td>
<td>0.46</td>
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<td>&lt;0.01</td>
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<td>2.54*</td>
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<td></td>
<td>Hours Spent Working</td>
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<td>0.02</td>
<td>83.3</td>
<td>1.58</td>
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<td><strong>E-Factor</strong></td>
<td>2 Prior Days</td>
<td>Intercept</td>
<td>4.03</td>
<td>0.56</td>
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<td>7.22*</td>
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<td>1.32</td>
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<td>&lt;0.01</td>
<td>43.4</td>
<td>1.80†</td>
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<td>Time Spent With Each Client</td>
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<td>&lt;0.01</td>
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<td><strong>Intercept</strong></td>
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<td>0.49</td>
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<td>0.00</td>
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</tr>
<tr>
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<td>&lt;0.01</td>
<td>55.10</td>
<td>0.27</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time Spent With Each Client</td>
<td>&lt;0.01</td>
<td>&lt;0.01</td>
<td>32.80</td>
<td>0.67</td>
<td></td>
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</tr>
<tr>
<td>Hours Spent Working</td>
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<td>0.02</td>
<td>34.50</td>
<td>2.13*</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Note. -1t = At the prior signal or moment, -2t = 2 signals earlier, -3t = One day (or 3 signals) earlier, -6t = Two days (or 6 signals) earlier. All auxiliary variables were included in the model. Both the A-Factor and the E-Factor were group-mean centered in accordance with best practices in random coefficients modeling (Dalal & Zickar, 2012; Hofmann & Gavin, 1998), given that the two did not have meaningful zero points. The three time-varying covariates that were identified as potential within-persons covariates of the A-Factor and the E-Factor were included here as well. †p < .10, *p < .05. All tests 2-tailed.*
<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Lag</th>
<th>Random Effect</th>
<th>Variance Component</th>
<th>SE</th>
<th>Model Deviance</th>
<th>AIC (BIC)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>E-Factor</strong></td>
<td>Prior Moment</td>
<td>Intercept Variance</td>
<td>0.08</td>
<td>0.03</td>
<td>109.9</td>
<td>153.9 (186.2)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Within-Persons Variance</td>
<td>0.09</td>
<td>0.02</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>A-Factor</strong></td>
<td>Prior Moment</td>
<td>Intercept Variance</td>
<td>0.11</td>
<td>0.03</td>
<td>96.6</td>
<td>142.6 (176.4)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Within-Persons Variance</td>
<td>0.07</td>
<td>0.01</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>E-Factor</strong></td>
<td>2 Prior Moments</td>
<td>Intercept Variance</td>
<td>&lt;0.01</td>
<td>&lt;0.01</td>
<td>105.0</td>
<td>147.0 (177.8)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Within-Persons Variance</td>
<td>0.19</td>
<td>0.03</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>A-Factor</strong></td>
<td>2 Prior Moments</td>
<td>Intercept Variance</td>
<td>0.10</td>
<td>0.03</td>
<td>151.1</td>
<td>197.1 (230.8)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Within-Persons Variance</td>
<td>0.11</td>
<td>0.01</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>E-Factor</strong></td>
<td>Prior Day</td>
<td>Intercept Variance</td>
<td>&lt;0.01</td>
<td>&lt;0.01</td>
<td>58.4</td>
<td>100.4 (129.8)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Within-Persons Variance</td>
<td>0.16</td>
<td>0.03</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Intercept Variance</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>--------</td>
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<td>-------</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Within-Persons</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Variance</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>A-Factor</strong></td>
<td>Prior Day</td>
<td>0.06</td>
<td>0.03</td>
<td>106.5</td>
<td>152.5</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(184.8)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>E-Factor</strong></td>
<td>2 Prior Days</td>
<td>0.06</td>
<td>0.03</td>
<td>28.1</td>
<td>72.1</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(102.2)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>A-Factor</strong></td>
<td>2 Prior Days</td>
<td>&lt;0.01</td>
<td>0.07</td>
<td>81.5</td>
<td>127.5</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(159.0)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.12</td>
<td>0.02</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.06</td>
<td>0.02</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.18</td>
<td>0.07</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
The single moment, cross-lagged effect of the A-Factor on the E-Factor was positive and significant providing additional support for Hypothesis 3, $\beta (106) = 0.26$, $SE = 0.09$, 95% CI LL = 0.07, 95% CI UL = 0.44, $t = 2.76$, $p < .05$. However, there was no significant cross-lagged momentary effect of the E-Factor on the A-Factor, failing to provide support for Hypothesis 4, $\beta (161) = 0.08$, $SE = 0.06$, 95% CI LL = -0.04, 95% CI UL = 0.19, $t = 1.33$, n.s. A comparison of the AIC and BIC between these models suggests that the model predicting the A-Factor is a slightly better fit than the one predicting the E-Factor, when considering both the effects across 1 momentary time lag. However, the 95% Confidence Intervals of the beta weights overlap suggesting that they are not significantly different from one another in magnitude (given they are on the same scale).

The cross-lagged effect of the A-Factor on the E-Factor across two moments was negative and significant, failing to provide additional support for Hypothesis 3, $\beta (96.5) = -0.19$, $SE = 0.09$, 95% CI LL = -0.37, 95% CI UL = -0.007, $t = 2.06$, $p = 0.042$. However, given that the CI UL is very close to zero and that the parameter was barely significant, this effect should be interpreted with caution. There was no cross-lagged effect of the E-Factor on the A-Factor across two moments, failing to provide support for Hypothesis 4, $\beta (112) = 0.04$, $SE = 0.06$, 95% CI LL = -0.09, 95% CI UL = 0.16, $t = 0.59$, n.s. A comparison of the AIC and BIC between these models suggests that the model predicting the E-Factor is a better fit than the one predicting the A-Factor, when considering both the effects across 2 momentary time lags.

Four additional random coefficients models were computed in order to examine the extent to which the A-Factor or E-Factor scores had an impact across 1 and 2 day time lags. The single day, cross-lagged effect of the A-Factor on the E-Factor was positive and significant providing additional support for Hypothesis 3, $\beta (46.1) = 0.31$, $SE = 0.11$, 95% CI LL = 0.09,
95% CI UL = 0.52, \( t = 2.87, p < .05 \). However, there was no significant cross-lagged day effect of the E-Factor on the A-Factor, failing to provide support for Hypothesis 4, \( \beta \) (82) = -0.06, \( SE = 0.11 \), 95% CI LL = -0.29, 95% CI UL = 0.16, \( t = 0.56 \), n.s. A comparison of the AIC and BIC between these models suggests that the model predicting the E-Factor is a better fit than the one predicting the A-Factor, when considering both the effects across 1 momentary time lag. However, the 95% Confidence Intervals of the beta weights overlap suggesting that they are not significantly different from one another in magnitude (given they are on the same scale).

The cross-lagged effect of the A-Factor on the E-Factor across two days was not significant, failing to provide additional support for Hypothesis 3, \( \beta \) (26.1) = -0.14, \( SE = 0.10 \), 95% CI LL = -0.35, 95% CI UL = 0.08, \( t = 1.32 \), n.s. There was also no cross-lagged effect of the E-Factor on the A-Factor across two days, failing to provide support for Hypothesis 4, \( \beta \) (28.4) = <-0.01, \( SE = 0.19 \), 95% CI LL = -0.40, 95% CI UL = 0.40, \( t = <-0.00 \), n.s. A comparison of the AIC and BIC between these models suggests that the model predicting the E-Factor is a better fit than the one predicting the A-Factor, when considering both the effects across 2 momentary time lags.
CHAPTER FOUR: DISCUSSION

In this study, a test of the “is a happy worker a productive worker” adage using a broad conceptualization of job attitudes and behavioral engagement was employed. In a sample of Floridian hairdressers, barbers, and cosmetologists, evidence for the substantial within-persons variability of both job attitudes (i.e., the A-Factor) and behavioral engagement (i.e., the E-Factor) was provided. A descriptive analysis of the between- and within-persons correlations between the A-Factor and the E-Factor as well as their common correlates provided some construct validity evidence for their convergent and discriminant validity. Furthermore, extensive examinations of the psychometrics of the within-person emotional states were provided through the calculation of within-person reliability statistics, employing a generalizability theory framework. These assessments of the reliability of within-persons change in the job attitudes and behavioral engagement generally suggested that the assessments were reliable and adequately reflected within-persons variability across times, persons, and items.

In addition to establishing substantial within-persons variation in job attitudes and behavioral engagement that mirror or exceed magnitudes and findings from prior studies of component job attitudes (Ilies & Judge, 2002; Ilies et al., 2006) and behaviors (Dalal et al., 2009; Trougakos et al., 2015), evidence for the reciprocal relationship at the within-persons level of analysis was provided for the Attitude-Engagement model (Harrison et al., 2006; Newman et al., 2010) employing concurrent effects. However, a prospective attitude-engagement effect was found after introducing a one moment time lag and a one day time lag, controlling for lagged effects, perhaps giving some credence to the meta-analytic findings from prior panel research (Riketta, 2002). Lastly, although linear and quadratic growth curves were fitted in order to determine if there was an underlying trend of job attitudes or behavioral engagement across
people, evidence was not found for job attitudes, although weak evidence was found for a slight downwards trend in behavioral engagement. As such, there is weak evidence for linear or quadratic growth at the momentary level of analysis (e.g., throughout the day). These major findings regarding the Attitude-Engagement model hold a great deal of implications for research and practice concerning the functional, metric, and temporal form of job attitudes and behaviors.

**From Here—To There—and Back Again: Theoretical and Research Implications**

The findings of this study hold several theoretical and research implications concerning the study of job attitudes and performance in organizational behavior. First, evidence for the large within-persons variation of both job attitudes and behavioral engagement provides credence to the existence of the A-Factor and E-Factor at the within-persons level of analysis, providing support for the Attitude-Engagement model (Harrison et al., 2006; Newman et al., 2009). Furthermore, some support is provided for the Compatibility Principle, given that the within-persons associations between the A-Factor and its respective behavioral engagement outcomes (as well as between the job attitudes components and the E-Factor) tended to be smaller on average when compared to the A-Factor and E-Factor relationship (see Table 2). This estimate ($r = .53$, $\beta = 0.61$, $p < .05$) is very close to, if not slightly stronger than the relationship observed between the A-Factor and the E-Factor utilizing SEM ($\gamma_{\text{standardized}} = .59$, Harrison et al., 2006).

With regard to job attitudes within-persons, the finding that 44% of the variability in job attitudes is within-persons provides mirrors prior estimates of the within-persons variability in job satisfaction (36%, Ilies & Judge, 2002; 35%, Illies et al., 2006). Furthermore, this finding provides support for theory on job attitude change, including the job satisfaction change framework (Chen et al., 2011) as well as the dynamic microstructure of organizational
commitment (Solinger et al., 2015). Worthy of note, these frameworks are often drawn upon to explicitly provide theoretical support for linear or quadratic attitudinal change. However, when one considers a sample of these theories themselves (Prospect Theory, Kahneman & Tversky, 1979, 1984; Conservation of Resources, Hobfoll, 1989; Within-Persons Spirals, Lindsley et al., 1995; and Sensemaking, Louis, 1980), all for the most part can accommodate non-linear or cyclical change very well, as was evident in the study findings. For example, consider the idea that job attitudes may increase or decrease as a function of the depletion vs. replenishment of personal resources. Although explicit linear change may occur within a given time period as a result of some work event, it may taper off, or otherwise return to “normalcy” or otherwise assume a new form after some time has passed or a new event has occurred. As such, although these theories are drawn upon to suggest how people get from “here to there” over time, we can just as easily draw upon them to suggest how one may “get back again”. With regard to behavioral engagement, the finding that 78% of the variability in behavioral engagement was within-persons slightly exceeds and is not far off from some of the prior estimates from the research literature. For example, Dalal et al. (2009) found that 77% of the variance in job performance was within-persons and Trougakos et al. (2015) found that 57% of the variance in OCB was also within-persons. This finding provides support for prior theory on within-persons variability in performance that suggests that situational cues alter and elicit behaviors, and we allocate resources to address the situational cues (Beal et al., 2005; Dalal et al., 2014; Hobfoll, 1989; Minbashian & Luppino, 2014).

Finally, the support for the Attitude-Engagement model at the within-persons level of analysis provides support for Affective Events Theory (Weiss & Cropanzano, 1996), in which work events or situational cues affect our affective reactions, the formation of attitudes, and
eventually performance behaviors. Furthermore, the substantiated within-persons attitude-behavior relationship also provides potential support for or may have been caused by 1.) The effect of social information processing on the formation of attitudes which impact behaviors (Salancik & Pfeffer, 1978; Zalesny & Ford, 1990), 2.) Affect variability and episodic attention pulls which alter our job attitudes levels as a function of norms and control perceptions (Ajzen, 1991, 2001; Ajzen & Fishbein, 1980, 2005), and 3.) The elicitation of if-then profiles that influence cognitive-affective interpretations of experiences, influencing attitudes and behaviors (e.g., a hairdresser is commended for a great job, feels great about her job as a result, and strives to perform better later that day). With regard to empirical support for the linkage between job attitudes and behavioral engagement at the within-persons level, the relationship tended to be larger between the A-Factor and the E-Factor ($\beta = 0.61$) than found in prior studies (e.g., job satisfaction and OCB, $\beta = 0.15$, Ilies et al., 2006; $\beta = -0.09$, job satisfaction and CWB, Judge et al., 2006; $\beta = -0.05$, engagement and task performance, Bakker & Xanthopoulou, 2009). Despite the number of strengths associated with this study, a number of limitations and potential direction for future research to address those limitations should be mentioned.

Limitations

Although providing evidence for the Attitude-Engagement model within-persons, there are a number of limitations to the study. First, data on employee absenteeism, lateness, and actual turnover were unable to be collected in this study, although explicit components of the Attitude-Engagement model (Harrison et al., 2006; Newman et al., 2010). However, psychological withdrawal was assessed in its place, and most of the item content reflected turnover intentions. Second, a dynamic, multilevel confirmatory factor analysis (Song & Zhang, 2014; Wood & Brown, 1994) should be conducted in future research to determine whether or not
the structure of the attitude-engagement model changes over time. However, given the small sample size at level 2, this form of analysis could not be conducted. Furthermore, advancements in the estimation of these types of models are still in their nascence and little is known with regard to the performance of dynamic factor models within multilevel contexts as well as the appropriate fit indices to interpret (Song & Zhang, 2014). As such, even if there was an appropriate sample size in the current endeavor, the interpretation would be curtailed by much needed advancements in behavioral statistics.

Third, although attempts to collect supervisor reports on the behaviors of participants from moment to moment were made, supervisor report data was only available across 6 participants, with only 16 observations returned. Given that these responses were not used in the extant analyses due to the small sample size, common source bias (and common method bias due to the implementation of survey methods throughout the course of the study) still could have been operating. Despite concerns with these types of biases, Podsakoff, MacKenzie, Lee, and Podsakoff (2003) note that one way to reduce them is through the temporal separation of the predictor and criterion which serves to 1.) Reduce retrieval biases during the response process, 2.) Reduce the motivation to use previous answers on the current survey, and to 3.) Make retrieval of those prior responses less salient or relevant (see also Beal, 2015). Given that momentary and day-based lagged effects were tested in hypotheses 3 and 4, this could have reduced the extent to which common source bias was a threat to the validity of the findings, at least for the lagged tests of the final 2 hypotheses. Furthermore, given that participants completed the surveys on their phones in various conditions and circumstances, the threat of this type of bias may have been altered at each time point (Podsakoff et al., 2003). In addition to these benefits of common source bias reduction in temporally lagged designs, prior simulation
research suggests that the threat of common method and common source variance (i.e., the commission of Type I errors) can be reduced through the introduction of additional common method or source contaminated variables (Lai, Li, & Leung, 2013; Siemsen, Roth, & Oliveira, 2010). Given that nearly all random coefficients model analyses were run with a series of auxiliary variables to facilitate the FIML procedure (assessed via the same source and method), they may have had the added benefit of reducing the threat of this form of bias.

An additional limitation can be found in the unreliability of change in some of the study measures along with significant parameter estimates that may be due to chance. Furthermore, the $R_{ik}$ parameter estimate was very poor for the E-Factor, although (as previously mentioned) this may be due to the occasions in which participants drastically departed from their usual patterns of within-person variation of the course of the study, most likely in response to a serious, shock-related event (Lee et al., 1999). Also, as mentioned previously, perhaps the $R_{kr}$ reliability estimate was more appropriate given that not all participants had the same work schedule or opportunity for behavioral engagement ratings across all 45 study time points. Relatedly, there was some evidence for a slight, negative trend in behavioral engagement over the course of the study. However, this finding should be interpreted with caution given the small magnitude of the parameter, the small incremental contribution to model fit, and that it becomes non-significant once the linear growth parameter is freed to randomly vary. Lastly, the effect of job attitudes on behavioral engagement two moments later was, although significant, negative in direction. This finding is unexpected given the positive adjacent parameter estimates for the A-Factor at 1 moment and 1 day time lags. Given how close the confidence interval upper limit is to zero for this estimate along with the relatively large p-value, this estimate should also be taken with a grain of salt and interpreted cautiously.
Furthermore, given that respondents were given 2 hours to respond to each signal, they may have been prompted to reflect upon their experiences upon receipt of each signal, or otherwise given an opportunity to anticipate their future answers. This limitation is mitigated to some extent by the approximately 15 minute average response time (even when given 2 hours to respond) as well as the 15 minute average completion time, suggesting that most participants finished or otherwise accessed their surveys fairly soon after being signaled. In general, the vast majority of scales, composite scales, and their within-persons reliabilities were strong suggesting that the scales utilized in this study were for the most part reliable and accessed in a reasonable amount of time.

The final limitations of the study primarily reflect issues with external validity. As the sample consisted of mostly white, full-time, Floridian female hairstylists and cosmetologists; the extent to which the results generalize to other ethnicities, genders, and those of other individual difference characteristics is in question. Furthermore, the nature of discrete performance episodes experienced by hairstylists may be different from those experienced in other industries or occupations. Lastly, the hairstylist occupation is unique given that multiple opportunities for working full- or part-time, self-employment, and working with multiple organizations are available. Although multiple employees across these different working arrangements were included in the study, improving external validity, they for the most part came from a variety of working situations. Since there were not enough participants who shared the same organization, analyses of organization level effects or the application of multiple membership models (Beretvas, 2011) to those who worked at more-than-one organization were not able to be carried out. Furthermore, the self-employed and student participants may have perceived some of the items in the study differently, which could constitute a limitation to the findings. However,
Directions for Future Research

Despite the study limitations, a variety of exciting directions for future research may be realized to advance the within-persons study of job attitudes and behavioral engagement. First, and most importantly, forms of change in job attitudes and behavioral engagement beyond linear, quadratic, and cubic effects should be examined; namely cyclical patterns over time. West and Hepworth (1991) suggested the application of spectral analysis to uncover cyclical relationships in time series designs (Bowerman & O’Connell, 1979). Recently, Kubiak and Jonas (2007) have suggested the application of circular statistics to understanding cycles in mood or emotion data over time, converting continuous time based emotions data into a circular distribution of events (e.g., similar to the hands on a clock). A random coefficient modelling extension of a detection method for cyclical patterns in data similar to these would help advance the study of longitudinal phenomena. The previously mentioned methods are also limited in that they tend to require at least 50 within-persons observations in order to appropriately detect cyclical patterns (West & Hepworth, 1991). Furthermore, a technique enabling one to capture latent classes of cycles would be useful to determining whether or not some people tend to fall into attitude-behavior patterns that vary from person-to-person.

Furthermore, several improvements to the psychometrics and validity of the attitude-engagement model can be made through future research. First, Dormann and Griffin (in press) provide a method for calculating an optimal time lag in panel studies. This time lag refers to the time interval which maximizes the validity coefficient between a predictor and a criterion. Future research should examine the Attitude-Engagement model at a variety of different time lags
(beyond momentary and day lags, as were implemented in this study) in order to calculate the optimal time lag across several periods of time. Furthermore, future research should test for the time invariance of the error variance-covariance matrix in random coefficients models of job attitudes and behavioral engagement, which is caused by rater drift or unpredictable influences that impact the dynamic processes in play and can ultimately lead to Type I errors (Braun et al., 2013). However, as neither the A-Factor nor the E-Factor exhibited consistent, compelling growth over time (see Figures 4 and 5), there would perhaps be no need for a drift parameter in this study (Braun et al., 2013). However, future research assessing change in the A-Factor or E-Factor as a result of a specific event uniformly experienced by all participants should seek to incorporate the drift parameter and computer the Augmented Dickey-Fuller test procedures (Dickey & Fuller, 1979) to ensure that the error covariance matrix is time-invariant, or risk the occurrence of Type I errors (Braun et al., 2013). Lastly, computerized adaptive testing (CAT; Weiss & Kingsbury, 1984) driven by item response theory applications (IRT; Lord, 1980) and the generalized graded unfolding model for polytomous response options (GGUM; Roberts, Donoghue, & Laughlin, 2000) can be utilized in order to assess participants current job attitudes levels without the need for an undue number of items, perhaps reducing test fatigue and memorization of response processes in ESM contexts.

Future research should also attempt to differentiate the construct of employee engagement from overall job attitudes (Newman et al., 2010) at the within-persons level of analysis through dynamic factor analysis to determine whether or not the structural relations between employee engagement and job attitudes persists over time. Future research should also examine the relationship between emotional labor (Grandey, 2000; Hochschild, 1983) and job attitudes within-persons. The employment of deep acting vs. surface acting methods may
moderate the extent to which job attitudes are related to behavioral engagement and vice versa. Furthermore, job attitude strength (Krosnick & Petty, 1995; Schleicher, Smith, Casper, Watt, Greguras, 2015; Schleicher, Watt, & Greguras, 2004) can be assessed to see whether or not the strength of the A-Factor changes over time, and particularly whether or not it moderates the attitude-engagement relationship. Given these research implications for the nature and conceptualization of job attitudes in organizations and their impact on behavioral engagement, a number of practical and managerial implications follow.

**Practical Implications**

The finding that there is large within-person variability from moment to moment in job attitudes and behavioral engagement is especially important for practitioners who seek to improve or harness positive job attitudes in order to seek gains in behavioral engagement. As one assessment-related implication, evidence for the large within-person variation from moment to moment from this study and prior research further highlights the potential need for an evolution beyond the “big data” trend to one focusing on “fast data” (Hugg, 2014; Lorentz, 2013; Spencer, 2015). The “big data” paradigm suggests large amounts of data compiled and collected by organizations to guide business decisions. However, the recent trend toward fast data reflects the idea that constantly incoming, actionable data is more useful than large amounts or quantities of data, although the two may work best when in concert (Hugg, 2014). Given that job attitudes and behavioral engagement are important to organizations and impact the bottom line, the notion that they change so much from moment-to-moment suggests that developments in the assessment of job attitudes and behavioral engagement should reflect these changes so that they are administered moment-to-moment or perhaps even in real-time (if technological advancements allow).
As a related second practical implication, the current paradigm of annual or bi-annual job attitude and engagement surveys obscure important underlying fluctuations that could have a broad, emergent impact on organizational performance. If a manager’s goal is to improve productivity by bolstering job attitudes or engagement, than he/she needs to acknowledge the day-to-day and moment-to-moment situational influences on these factors and not only apply interventions that work broadly over time, but to apply those that are adaptive and address the moment-to-moment idiosyncrasies that arise in the world of work. For example, Laurano and Jacobsen (2014) suggest that through investing in technology to engage employees, leveraging the power of relationships, and through recognition of employee performance; organizations can adaptively move “beyond the annual engagement surveys” to drive organizational effectiveness.

Finally, if job attitudes and behavioral engagement change from moment-to-moment or in real-time, then so should attitude and performance improvement interventions. However, given that “we know we have to—or want to—change, but find ourselves moving around in circles”, implementing these kind of attitude or behavioral change initiatives can be very difficult (van Nistelrooij & de Caluwé, 2016, p. 153). But by recognizing the inconsistency in employee behaviors, fully understanding resistance to change, and understanding the change recipients themselves can perhaps help in developing these sorts of interventions (van Nistelrooij & de Caluwé, 2016). Furthermore, some may hold strong but inconsistent views about change interventions themselves, obscuring whether or not people actually adhere to attitude or skill-enhancing HR practices (Oreg & Sverdlik, 2011). In order to address this, it may be necessary to identify and dynamically address those who champion vs. doubt the change, and perhaps to understand the factors responsible for leading people to become converts vs. defectors, changing their stances on the intervention itself (Jansen, Shipp, & Michael, in press). So not only should
the attitudes or behavioral engagement interventions change, but also the approaches to managing change as well.

**Conclusion**

In a sample of over 50 hairdressers, barbers, and cosmetologists from Florida, evidence for the Attitude-Engagement model (Harrison et al., 2006; Newman et al., 2010) was provided within-persons. Large portions of variability in both the A-Factor and the E-Factor were uncovered, along with a significant reciprocal relationship between the two at the within-persons level of analysis, cross-sectionally. Support for the attitude-engagement model was provided after introducing a one moment and one day time lag. Support for the effect of behavioral engagement on job attitudes over time was not found, in general. In addition, support for the reliability of within-persons variation was provided for the job attitudes and behavioral engagement scales. However, no evidence was provided for linear or quadratic growth in job attitudes, although some weak evidence was provided for linear growth in behaviors. The findings provide support for the compatibility principle (Fishbein & Ajzen, 1974) within-persons as well as credence to integrative models of workplace events, job attitude change, and behavioral engagement variability. The implications for these findings are great, considering the primary assumption that attitudes such as job satisfaction are relatively stable and given that they are traditionally measured at one point in time. As such, future research and practice should revisit this assumption and consider the within-persons variability of this relationship when considering job attitudes and behavioral engagement in the workplace.
APPENDIX A:

HAIREDRESSER STUDY FLYER
Are you interested in participating in a UCF research study on hairdressers, barbers, and cosmetologists?

Details:
What you will do:

- First, you will complete a 35 minute survey as part of the registration process
- Then, you will answer 3, five-minute surveys per day for 15 days on your smartphone
- You will then complete a 10 minute survey via e-mail after the 15th day

Compensation for your time:

- If all 15 days' worth of surveys are completed, you will receive a $75.00 Amazon Giftcard
- Otherwise, you will be compensated $4.00 for each full day of fully completed surveys (or $1.25 per survey on each partial day of fully completed surveys), $5.00 for the initial survey, and $5.00 for the closing survey (all as Amazon Giftcards)

Eligibility Criteria:

- At least 18 years of age; work at least 3 days and 24 hours/week; work at least 6 hours/day
- Hairdresser, barber, cosmetologist, or a supervisor/manager
- Own an internet-ready phone
- Supervisors that wish to participate must coordinate with subordinates prior to participating

Study contacts:
Dr. Dana Joseph (faculty, UCF Psychology Department): dana.joseph@ucf.edu
Dave Gerum (UCF Psychology Department): dgerum@knights.ucf.edu

To participate, please visit the following link or the QR code on the upper right corner: http://ucf.qualtrics.com//SE/?SID=SV_bqGivhKByqs1Qq1
APPENDIX B:

SURVEYSIGNAL REGISTRATION GUIDE
Hair Dresser Study Registration Guide

You can register your phone for the Hair Dresser Study in 4 steps:

**USING A DESKTOP COMPUTER**

1. Upon completion of the initial orientation survey (Click FINISH below and select whether or not you are an employee or a supervisor), you should be redirected to the survey signal registration page.
   a. If you were not directed to this site, please contact glerumd@knights.ucf.edu for a registration link relevant to your position (either the supervisor/manager link or the employee link). It will look something like this: [http://www.surveysignal.com/RegParticipant.aspx?surveyid=xxxxxxxxxxxxx](http://www.surveysignal.com/RegParticipant.aspx?surveyid=xxxxxxxxxxxxx)

2. Then, fill in the information requested for registration on this page. When you have done this, click the ‘REGISTER’ button.

Welcome to the Hair Dresser Study registration page! Please complete the following information to register for the study. Thank you!

General Consent

I have read and understand the conditions of my participation in this research. My participation in this study is voluntary, and I understand that if at any time I wish to leave the study, I may do so by contacting the respective study administrator. Furthermore, I am also aware that the data gathered in this study are confidential. Providing my phone number and Email address in the fields below signifies that I consent to participate.
**NOTE: BE SURE TO CHANGE THE TIME ZONE TO EASTERN**

**ON YOUR PHONE**

3. At around the same time, you will be receiving a text message asking you to verify your phone (see left hand side of figure). Please click the link included in text message to verify your phone.

You will receive confirmation that you are verified by a completed registration page (see right hand side of figure)
4. You will then read a page with additional information after the registration process. You will need to verify that you have read the page by entering your e-mail address and clicking submit.

Within the 1-2 days after verifying your phone, you will begin receiving signals everyday over the course of a 15 day period. You will receive 3 per day: one in the morning/early afternoon, one in the afternoon, and one in the evening.

After completing your final surveys on the 15th day, you will be sent an elongated survey that you complete for an additional $5.00.

If you have further questions about the registration process, please feel free to contact Kate Ciarlante (kciarlante@Knights.ucf.edu) or Dave Glerum (glerumd@knights.ucf.edu).

Thank you, and we hope you enjoy participating!
APPENDIX C:

IRB APPROVAL LETTER
Approval of Human Research

From: UCF Institutional Review Board #1
FWA00000151, IRB00001128

To: David R. Glarum, Jr. and Co-PI: Donna Joseph

Date: November 20, 2015

Dear Researcher:

On 11/20/2015, the IRB approved the following human participant research until 11/19/2016 inclusive:

Type of Review: UCF Initial Review Submission Form
Project Title: Hair Dressers, Barbers, and Cosmetologists Study
Investigator: David R. Glarum Jr.
IRB Number: SBE-15-11746
Funding Agency:
Grant Title:
Research ID: N/A

The scientific merit of the research was considered during the IRB review. The Continuing Review Application must be submitted 30 days prior to the expiration date for studies that were previously explicated, and 60 days prior to the expiration date for research that was previously reviewed at a convened meeting. Do not make changes to the study (i.e., protocol, methodology, consent form, personnel, site, etc.) before obtaining IRB approval. A Modification Form cannot be used to extend the approval period of a study. All forms may be completed and submitted online at https://irbresearch.ucf.edu.

If continuing review approval is not granted before the expiration date of 11/19/2016, approval of this research expires on that date. When you have completed your research, please submit a Study Closure request in IRB so that IRB records will be accurate.

Use of the approved, stamped consent document(s) is required. The new form supersedes all previous versions, which are now invalid for further use. Only approved investigators (or other approved key study personnel) may solicit consent for research participation. Participants or their representatives must receive a copy of the consent form(s).

All data, including signed consent forms if applicable, must be retained and secured per protocol for a minimum of five years (six if HIPAA applies) past the completion of this research. Any links to the identification of participants should be maintained and secured per protocol. Additional requirements may be imposed by your funding agency, your department, or other entities. Access to data is limited to authorized individuals listed as key study personnel.

In the conduct of this research, you are responsible to follow the requirements of the Investigator Manual.

On behalf of Sophia Dzegalezewski, Ph.D., L.C.S.W., UCF IRB Chair, this letter is signed by:

[Signature]

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Signature applied by Joanne Muratori on 11/20/2015 09:31:29 AM EST.

IRB Manager
REFERENCES


Alliger, G. M., & Williams, K. J. (1993). Using signal-contingent experience sampling methodology to study work in the field: A discussion and illustration examining task


In J. C. Masters & W. P. Smith (Eds.), Social Comparison, Social Justice, and Relative


