Examining the Dynamic Nature of Worker Subjective Well-Being: The Application of Idiographic Approaches

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Abstract

Our theoretical understanding of subjective well-being in the workplace is incomplete without a dynamic understanding of antecedents and outcomes of SWB. While between-person differences provide useful information about employee outcomes, these differences do not provide information about the relationships between subjective well-being and employee outcomes that evolve over time and across situations. In this paper, we review specific statistical methods within the nomothetic and idiographic perspectives that can support dynamic research on subjective well-being in the workplace and outline unanswered contemporary questions regarding structure, processes, and dynamics of subjective well-being that may be addressed for each; some of which were proposed in early research but progressed slowly due to a lack of adequate methods. This discussion highlights how idiographic methods from outside organizational psychology can be applied to the study of worker subjective well-being to strengthen this dynamic approach in a way that addresses limitations associated with reliance on between-person models.

keywords: subjective well-being; workplace; emotions; satisfaction; idiographic

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Today's organizations place great value on the subjective well-being (SWB) of their workers because happy workers (i.e., with high SWB) are more likely to show up, invest effort, and excel at work (Myers & Diener, 1997), while unhappy workers (i.e., low SWB) are more likely to engage in absenteeism and turnover (Tenney, Poole, & Diener, 2016). A worker's SWB is defined by level of satisfaction with their job (or life; i.e., cognitive component) and their daily experiences of negative and positive emotions (i.e., affectivity; Diener, Sandvik, & Pavot, 1991). A worker is said to have high SWB when they are satisfied with their job (studied as job satisfaction, engagement, and involvement), and experience high-levels of positive emotions (e.g., enjoyment, happiness) and low-levels of negative emotions (e.g., frustration, anger; Bakker & Oerlemans, 2011; Diener, 2000; Diener et al., 1991; Fisher, 2010). Given the importance for both employees and organizational survival (Spreitzer & Porath, 2012), SWB has been a popular topic in organizational and psychological research (e.g., Danna & Griffin, 1999; Robertson & Cooper, 2010).

The majority of organizational research on SWB has adopted a trait approach (Wood & Beckmann, 2006) that examines antecedents and outcomes of between-person differences (i.e., rank-order differences) in SWB, and explains these between-person differences in terms of environmental (e.g., working conditions) and individual (e.g., personality) differences (e.g., Weiss, Bates, & Luciano, 2008). Yet, SWB is not a static entity. Instead, it ebbs and flows across hours, days, weeks, and even situations. Scholars have pointed to inconsistencies in between-person relationships among employee characteristics, SWB, and behavior across situations (e.g., Nezlek, 2008) as evidence for the need to adopt a within-person, dynamic approach that can take into account these ebbs and flows of SWB across time (e.g., Ilies, Schwind, & Heller, 2007;

Xanthopoulou, Bakker, & Ilies, 2012). While between-person differences in SWB provide useful information about employee outcomes (e.g., turnover, organizational commitment; Lyubomirsky, King, & Diener, 2005), between-person research cannot account for weak correspondence between between-person SWB and momentary work performance or behaviors, why the relationships between SWB and employee outcomes evolve over time and across situations, and whether within-person relationships are a result of a systematic increase or decrease on the antecedent variable. However, the study of within-person variability (i.e., absolute estimate of deviations from an average), alone, cannot do this either because variability itself does not examine time as a critical factor beyond the observation that variability in SWB occurs over time and does vary. Timing is an important consideration for both measuring and modeling psychological processes.

Our theoretical understanding of SWB in the workplace is incomplete without a *dynamic* understanding of antecedents and outcomes of SWB, as well as the construct itself. Dynamics refer to relationships among psychological processes (e.g., expectations, goals), considered in continuous time, and how psychological processes of encoding, perception, motivation, etc. are linked together over time, pushing and pulling one another toward new momentary states of SWB. The study of SWB needs to shift towards a more dynamic approach that focuses on within-person differences (e.g., variability; un-sequenced estimates of how much SWB tends to vary around a point of central tendency) *and* micro-level processes (i.e., affects, cognitions, attention) that underlie such variability. These within-person processes offer a better lens to understand how the components of SWB (i.e., positive affect, negative affect, life/job satisfaction) are linked to one another, in continuous time, as well as why (and for how long) outside forces, such as situational features or stress, have an impact on SWB in the workplace.

For instance, within-person changes in negative affect associated with stress may predict within-person changes in life satisfaction, and vice versa. Understanding these dynamic relationships is not only theoretically important, but practically important because it is crucial to understand whether increases in a worker's stress relative to their previous stress (rather than relative to other peoples') is likely to be associated with decreases in well-being or not.

Studying dynamics of SWB is not only useful for understanding change (or variability) in the various facets of SWB (e.g., job satisfaction) following workplace events, but also for linking such variability to individual differences in the psychological processes (e.g., cognition, attention) underlying subsequent outcomes. For instance, let us say two salespeople, Joan and Jannen, who joined the same sales team a year ago, were just passed over for a promotion, despite both exceeding their sales goals this quarter. If we had gathered information on their negative affect before and after the event, and displayed it in a time series like in Figure 1, we study sheer variability and see that both Joan and Jannen experienced an increase in negative affect after being passed over (the dashed vertical line), or even that Joan experienced a larger increase in negative affect. However, a dynamic approach could show for how long Joan's versus Jannen's negative affect persisted, and the micro-processes (e.g., cognitions, past experiences) that explain how the increase in negative affect relates to variability in job performance. As shown by the gray boxes around portions of their time series in Figure 1, we might find that Joan's negative affect persisted over three days, while Jannen's only persisted until the end of the workday; and that, while Jannen's performance dipped severely the day after being passed over for promotion, Joan's performance showed larger variability over weeks so she failed to meet her sales goals that quarter. A dynamic approach could also examine how previous events influenced perceptions of being passed over for promotion, such that, because the sales manager covered for Jannen with a client when her daughter was sick, Jannen did not perceive the promotion incident as negatively as Joan, and this is why the increase in negative affect did not persist for as long as for Joan. Studying the dynamics of SWB to understand these differences between Joan and Jannen allows researchers to identify the unique patterns of perception, cognition, and emotion experienced by Joan versus Jannen, and their implications for important outcomes.

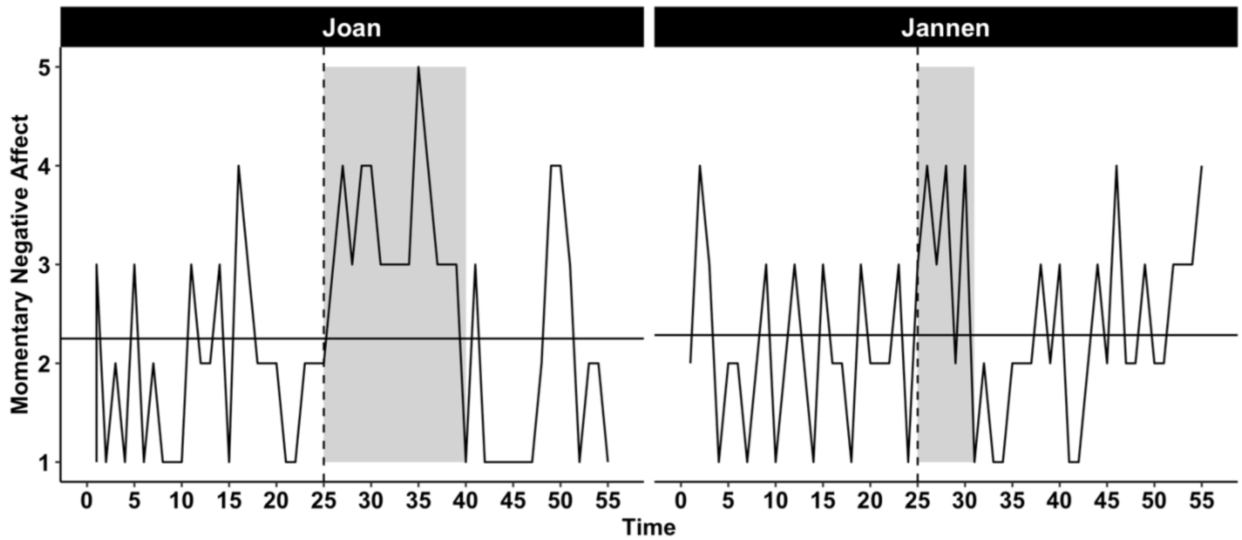

Figure 1. Example time series for two hypothetical employees, Joan and Jannen, sampled twice daily over four weeks. The x-axis indicates the survey measurement since the beginning of the measurement period, the y-axis indicates their self-ratings of negative affect on a 1 to 5 scale. The dashed vertical line indicates when each was passed over for a promotion. The gray shaded box indicates the period during which each experienced heighted negative affect after being passed over.

Our aim is to discuss advances in statistical modelling that can be applied by researchers to investigate the dynamics of worker SWB. Below we introduce statistical methods and detail their benefits as a dynamic approach, contrasting them with the typical between-person approaches to studying worker SWB. Towards this end, we review specific statistical methods within the idiographic perspectives that can support dynamic research on SWB in the workplace. The current paper suggests that idiographic statistical methods from outside organizational psychology can be applied to the study of worker SWB to address limitations associated with reliance on between-person models.

Thinking Dynamically about Subjective Well-Being

Although between-person differences in SWB provide useful information about employee outcomes (e.g., turnover, organizational commitment; Lyubomirsky, King, & Diener, 2005), our understanding of worker SWB is incomplete without more research adopting a dynamic approach. This is because SWB is inherently dynamic, such that it is defined as people's evaluations "both at the moment and for long periods such as the last year'' (Diener, Oishi, & Lucas, 2003, p. 404). Not only that, but SWB is dynamic in its composition, as emotional evaluations (two of the three recognized components of SWB) are short-lived reactions to *external cues* that accumulate over time to influence satisfaction (the cognitive component of SWB; Fisher, 2010). However, the emphasis on between-person approaches in studying SWB has left a great deal of dynamic propositions undertested, or even untested.

Affective Events Theory (AET; Weiss & Cropanzano, 1996) has helped researchers to start thinking dynamically about SWB by incorporating situational, environmental, and affective components into a dynamic framework of affect and attitudes. AET states that workers have immediate emotional responses to work events, which are important predictors of short-term behavior and more persistent job attitudes, like satisfaction (Weiss & Cropanzano, 1996). Research has applied recent methodological advances, like experience sampling methodology (ESM) to collect within-person data to test AET propositions. In doing so, these efforts have underscored the importance of dynamic processes for a worker's SWB, in real time. For instance, Verduyn and colleagues (2009) found that emotional responses can be prolonged by physical, or even imagined reappearance of the emotion-eliciting circumstances. This means that the influence of work situations on SWB could be reoccurring, depending on whether employees encounter physical or psychological reminders of the initial event.

AET also acknowledges that specific events are embedded within broader, environmental features (e.g., pay, promotion opportunities, autonomy, social support) that can influence how events are perceived. So emotional responses to events are not only influenced by the interaction of person and event variables, but also broader environmental features. For instance, if Joan's husband lost his job during the pandemic, her pay, an environmental feature of the job, was particularly salient and/or important to her, which influenced how she perceived being passed over for promotion and the intensity of her emotional reaction (i.e., negative affect). The intensity of Joan's negative affect is important, as the duration for which work situations impact SWB may vary according to the intensity of workers' initial emotional responses, as well as the perceived importance of the emotion-eliciting circumstances; both of which translate into longer emotional responses to work situations (Frijda, Mesquita, Sonnemans, & Van Goozen, 1991; Sonnemns & Frijda, 1995; Verduyn et al., 2009). This means that events may be more impactful on long term SWB depending on its impact on short term SWB (defined by intensity of change in negative affect, positive affect, and job satisfaction). As such, the greater perceived importance of the potential promotion due to the loss of her husband's salary not only cultivated a more intense negative emotional response for Joan, but it could mean more severe long-term consequences for Joan's SWB and related work behavior.

In addition, the intensity and duration of fluctuations in worker SWB following affective events may vary depending on individual differences, such as personality. Personality traits have been linked to people's emotional reactivity (Brief & Weiss, 2002), as well as the way people encode and perceive situational features and the goals by which people judge the benefit or harm of a situation (Mischel & Shoda, 1999; Sherman, Nave, & Funder, 2013). Going back to our example, due to their shared conscientiousness, we might see that Jannen and Joan experience similar levels of negative affect in response to not getting the promotion, but because Joan is higher on neuroticism, the two differ in how long their negative affect persists, which could have different consequences for personal, social, and work behaviors. This is all to say that, given the dynamic nature and composition of SWB, studying within-person dynamics is critical for testing theory around the SWB of workers, as well as gaining broader insight into the functioning of people at work on a momentary and day-to-day basis. Below we discuss methodological advances and how they can be applied to benefit research focused on understanding worker SWB and its components dynamically.

Understanding the Dynamics of Worker SWB: Idiographic Methods

While there are existing techniques appropriate for testing within-person processes (e.g., multilevel modeling), several researchers have laid out evidence suggesting the use of predominantly between-person models to investigate within-person processes, which is often misleading because psychological phenomena tend to be non-ergodic (i.e., when the results of between-person and within-person models are different). Ergodicity exists if the between-person factor structure of a construct and relationships are the same as they are within a person. Although comparisons of between- and within-person mood processes are sparce (c.f. Zevon & Tellegen, 1982), ergodicity has not been supported within personality research (e.g., Beck & Jackson, 2020a; Molenaar, 2004). Without ergodicity, it is difficult to draw strong, or even accurate conclusions about within-person processes from between-person approaches (Borsboom et al., 2003; Molenaar, 2004; Fisher et al., 2018). Unfortunately, multilevel modeling, which is often used for examining dynamic data from ESM studies, is not immune to this. Most focus on aggregated within-person effects, which assume some degree of commonality in how a process unfolds within an individual that rarely holds in practice. Given that many between- and within-person approaches are not adequate to capture the processes and dynamics of psychological phenomena, some have advocated for idiographic approaches as an alternative approach to traditional, between-person, nomothetic models that assess what is common across people (e.g., Beck & Jackson, 2020a; Molenaar, 2004). Idiographic models emphasize what is unique to the person, both in terms of the content of a psychological construct (e.g., SWB), and processes that are relevant to them and how those unfold over time (Beck & Jackson, 2020a). Idiographic models are uniquely suited to examine within-person processes by measuring and modeling individuals relative to themselves. Thus, rather than trying to capture those components of SWB that most people share, an idiographic approach seeks to understand what experiences or components make up an individual's unique, dynamic experience of SWB. Such a proposition aligns well with perspectives that suggest SWB is inherently a subjective experience, meaning that each person knows best whether (and to what degree) he or she is happy (Luhmann, 2016).

The quantitative shift to idiographic methods would allow for this, and the opportunity to expand our conceptualization and measurement of SWB to include idiosyncratic structures, or personalized models of SWB. Instead of relying on the assumption that assessments of SWB are equally applicable to everyone, idiographic models can be interpreted as the relative standing of relevant SWB variables within a person. For example, although positive affect is important for task performance for both Joan and Jannen, the experience of positive affect may be quite different for each person, requiring unique models. Maybe for Joan, the primary positive-affect related experience in the workplace is pride, but for Jannen it may be a variety of positive affect-related experiences, like happiness and excitement. And even if they have similar levels of positive affect-related experiences, how those experiences manifest may differ. Therefore, we argue that, because SWB is experienced and lived by each person differently, we need idiographic models that incorporate dynamics and this uniqueness.

Below, we draw from the existing literature on affective dynamics and integrate additional components like job satisfaction to introduce useful idiographic approaches for studying SWB, which are briefly summarized in Table 1. Of course, the utility of these idiographic methods is not limited to the study of affect and SWB. Rather these dynamic models are applicable to examining the functioning of any (theoretically appropriate) construct (e.g., job performance). For instance, idiographic models can be applied to understand how manifestations of personality and vocational interests unfold uniquely within a person in ways that highlight differences between people. The application of idiographic methods to organization research can expand the methodological toolkit available to organizational researchers for studying dynamic models of worker SWB.

Table 1

Examples of Commonly Used Idiographic Methods

Technique	Description of Technique	Exemplar Paper
Within-Person Variability	Intraindividual standard deviations of an observed variable. Often tested using multilevel models, which are not idiographic.	Gadermann & Zumbo, 2006
Inertia	Simple lagged correlations or regressions of a target variable meant to capture spillover effects.	Yang et al., 2016
P-Technique Factor Analysis / Principle Components Analysis	An exploratory factor analysis for one individual.	Molenaar, 2004; Spain et al., 2010
Vector Autoregressive (VAR) Models	Show contemporaneous and lagged paths among observed variables.	Beck & Jackson, 2020a
Change-as-Outcome Models	Dynamic models linking levels of an observed variable with change in that variable.	Danvers et al., 2020

P-technique. The earliest form of idiographic quantitative modeling is *P-technique* factor analysis. According to Cattell (1957), and as shown in Figure 2, data can be factored into three dimensions: people (P_1 to P_N), variables (X_1 to X_p), and occasions, or time (T_1 to T_t). Traditional investigations of between-person differences (i.e., *R-technique*) examine the person (P) and variable (X) dimensions and collapse across the occasion (T) dimension (e.g., examining each person's (P) average levels (across occasions) of SWB (X)). However, instead of collapsing across occasions, one could adopt a dynamic approach by studying the SWB variable (X) on multiple occasions (T) and fixing the person (P) dimension to capture the unique structure of SWB for a single person, across occasions – that is, the within-person idiographic structure of SWB. Cattell described this procedure as the *P-technique* and is the first method to explicitly incorporate time, while being person specific.

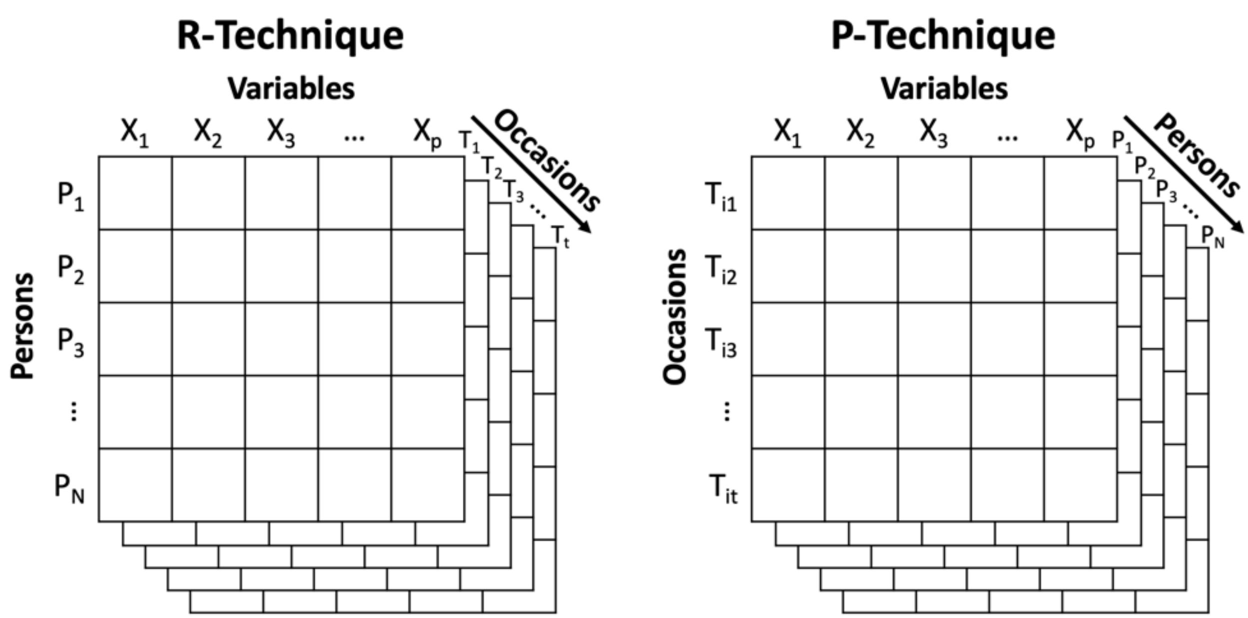

Figure 2. Two ways to "slice" the Cattell's data box to produce R-technique (nomothetic) and P-technique (idiographic) factor analytic structures. In R-technique, one collapses across or slices across the occasions dimension (T) to get the common structure of variables across people, perhaps solely applicable to a particular time or population. In P-technique, one slices across individuals to find the unique structure of variables within a particular person across time.

Although not often used, there are a few examples of *P-technique* within organizational sciences (cf. Fuller et al., 2003; Spain et al., 2010). Using the *P-technique,* Fuller and colleagues (2003) found that the idiographic factor structure of worker strain was different from the between-person factor structure. These results exemplify why the use of between-person models to model within-person, dynamic processes is often misleading: different within- and between-person structures indicate that a phenomena is non-ergodic. Without ergodicity, within-person processes and/or causal relationships cannot be inferred from between-person data, and importantly, a growing body of evidence suggests that most psychological phenomena are non-ergodic (Borsboom, Mellenbergh, & Van Heerden, 2003; Molenaar, 2004; Fisher, Medaglia, & Jeronimus, 2018). As such, future research on worker SWB should apply the *P-technique* to examine the structure and relationships amongst facets of SWB.

While a great deal of research has examined the relationships between negative affect, positive affect, and life evaluations (e.g., satisfaction, engagement; the facets of SWB) at the between-person level (Thoresen, Kaplan, Barsky, Warren, & de Chermont, 2003), there is evidence that these relationships may look different when studied at the within-person level. For instance, when measured at the trait level (i.e., between-person difference), job demands negatively predicts engagement (an indicator of SWB; e.g., Bakker et al., 2007a), but when measured at the state level (i.e., momentary experience) job demands positively predicts worker engagement (Bakker et al., 2007b). As such, there are still questions surrounding what factors influence state level experiences of SWB facets. Given the importance of event-related affect for broader job attitudes (e.g., job satisfaction; Mignonac & Herrbach, 2004) it is likely that momentary emotional experiences are important for fluctuations in cognitive evaluations associated with SWB (e.g., job satisfaction, engagement; Weiss & Cropanzano, 1996). Research has found that within-person fluctuation explains a significant amount of variance in indicators of both cognitive (e.g., job satisfaction, work engagement; Ilies & Judge, 2002; Judge & Ilies, 2004; Xanthopoulou & Bakker, 2012) and affective (i.e., emotional experiences; e.g., Garbriel et al., 2014) components of SWB.

One potential hurdle to studying within-person SWB is that scale items used to assess the facets are general, and not contextualized within a particular experience. It is thus unclear whether the factor structure of general assessments of SWB correspond to the lived life of a person. Stated differently, research can apply *P-technique* to determine (1) whether between-person differences in SWB show up in average within-person SWB measures and (2) whether all indicators of SWB are relevant to each individual. The former would confirm whether the structure of self-reported trait SWB actually corresponds to momentary or daily self-reports of SWB, and the latter would determine the degree to which certain facets of SWB are important for SWB, across different workers. However, a major weakness of the *P-technique* is that it is not inherently dynamic because it does not measure any *changes* in SWB. Instead, it collapses across time to get a single metric of how experiences tend to cluster together within a person. While this does capture reliable clusters of in-the-moment relationships, it does limit the questions one can address. Its ultimate goal as form of factor analysis is data reduction. As a result, the indicators of SWB that go into a *P-technique* factor analysis are reduced to a factor and error, thus potentially losing out on information that is unique to the person.

Moving beyond *P-technique*. There are important fluctuations in both affect and attitudes (i.e., work engagement or job satisfaction; Heller & Watson, 2005; Ilies, Scott, & Judge, 2006) across time which are missed when using *P-technique*. These important time indices are metrics of oscillation (momentary changes), fluctuation (changes over longer periods of time, like weeks or days), and inertia (speed of momentary changes).

Oscillations and fluctuations signify how the timescale of change can have differing impacts. As applied to our example, Jannen's negative affect after being passed over for promotion might be relatively acute (i.e., short-term oscillation) because of the appreciation she still feels for her manager's help when her daughter was sick (i.e., another oscillation), so the negative affect may or may not have long-term consequences for productivity (i.e., fluctuations). In contrast, it is likely that prolonged demands in Joan's life, such as having to work longer hours to make-up for lost salary of a spouse, prompts longer-term changes in SWB over weeks (i.e., fluctuations). Continuing oscillations and fluctuations of negative affect and performance may have long-term consequences for productivity. Such fluctuations could also shape future situations encountered or the quality of their relationships, which are important for satisfaction. Indeed, Lyons and Scott (2011) found that affective states predicted the receipt of help and harm from colleagues, such that positive emotional states were associated with the receipt of help and negative emotional states were associated with the receipt of harm.

Inertia can help capture features of oscillations and fluctuations in worker SWB. Like in physics, inertia refers to the tendency to stay consistent within a particular state. Inertia is defined as the autoregressive (lagged) correlation from one time (t-1) to the next (t). Going back to our example, imagine being passed over for a promotion that you have been working for, would the emotions you experienced spill over into your experience of the next meeting? Within-person dynamics are important in understanding inertia, as the inertia of emotional responses to events is influenced by dynamic processes (e.g., goals, perceptions). For instance, your emotional response to not getting the promotion may be more likely to carry over (as it did for

Joan) if the event or situation is perceived as important, or it is relevant to an important goal (e.g., status striving). People also vary (between- and within-themselves) in the ability to shake things off and return to their baseline, or general level of negative affect, such that emotional experiences can spillover more into short-term behaviors for certain people (e.g., Yang et al., 2016). For instance, within the psychopathology literature, there is evidence that individuals with higher depressive symptoms also have higher inertia of negative emotion experiences (Hohn et al., 2013). Extending this to SWB, given that employees predisposed towards negative affect are more likely to experience negative affect, which spills over to how they appraise their work (Connolly & Viswesvaran, 2000), future research could draw from these metrics to examine if workers with low SWB find it more difficult to bounce back after an upsetting meeting or interaction with a supervisor or colleague.

Vector AutoRegressive (VAR) models. In recent years there has been a proliferation of tools that move beyond P-technique, to allow dynamic investigations and more explicitly test idiographic questions. One of the most basic is the lagged, or vector autoregressive (VAR) model (e.g., Bringmann et al., 2016; Epskamp et al., 2017; Gates & Molenaar, 2012, Wild et al., 2010), which can examine the simultaneous and temporal relationships between multiple variables for a single individual. In so doing, VAR models do a better job of tackling the complexities of multivariate times series data, which consists of multiple variables assessed multiple times. At the most basic level, one needs to account for (1) bidirectional relationships between lagged and concurrent predictors (e.g., does Joan's negative affect at time t and time t-1 predict her job performance at time t ?), (2) autoregressive relationships among lagged predictors (e.g., is Joan's job performance at time t-1 associated with higher or lower job performance at time t?), and (3) the structure of lagged and concurrent relationships among all variables in the model (e.g., is anger a key component of negative affect for Joan, while sadness a key component of negative affect for Jannen?). It may be the case that Jannen does not experience much anger, or if she does, anger is not related to job performance.

Cross-lagged VAR models have several advantages. First, they account for relationships at both the within-(contemporaneous) and across- (lagged) time levels. Contemporaneous relationships signify probabilistic relationships at one timepoint – for instance, the probability of state-level negative and positive affect co-occurring, at the same time point (t) (calculated by correlating two variables collected repeatedly together from time 1 to t). Lagged relationships, in contrast, estimate probabilistic within-person, cross-time point (or cross-lagged) relationships that can be thought of as *if…then* relationships. For instance, the tendency for state-level negative affect at the previous timepoint ($t – 1$) to predict lower job satisfaction at time t , across measurement occasions; otherwise stated as *if* the person has high state-level negative affect at time $t - 1$ then they will likely have lower job satisfaction at time t.

Second, by including a larger set of predictors and using pruning techniques to prevent multicollinearity (e.g., graphical LASSO; Friedman, Hastie, & Tibshirani, 2008), they capture the unique relationships among diverse phenomena that influence manifestations of SWB embedded within the workplace. Third, they can test complex sets of relationships embedded within a changing environment. Such relationships are complex not only in that they can include a large number of predictors, but also in what those predictors are (e.g., shifts in the environment). For example, multiple markers of positive and negative affect can be included, along with life satisfaction, job satisfaction and job performance. The relationship among all of these variables can be examined at the individual, $N = 1$ level. The sample procedure for doing so can be seen in Figure 3. Using this procedure may reveal, for example, that a model of Joan's experiences shows a relationship between frustration (after being passed over for promotion) and task performance, such that negative affect, through frustration, drives much of Joan's task performance. In contrast, Jannen's model may demonstrate that frustration is wholly unpredictive of her task performance either contemporaneously or lagged. Instead, Jannen's driver of task performance may be positive affect markers, such as excitement, which may be associated with both contemporaneous and future task performance. Although a similar model could be estimated by a multilevel model, if some subset of participants showed different patterns of positive affect-performance relationships and negative affect-performance relationships (e.g., some show positive affect-performance relationships while another subset showed only negative affect-performance relationships), the model would say there was no effect of either positive or negative affect, which is not true for the subsets of the sample, just for the sample as a whole. Without idiographic models these types of differences between people are left as residual error.

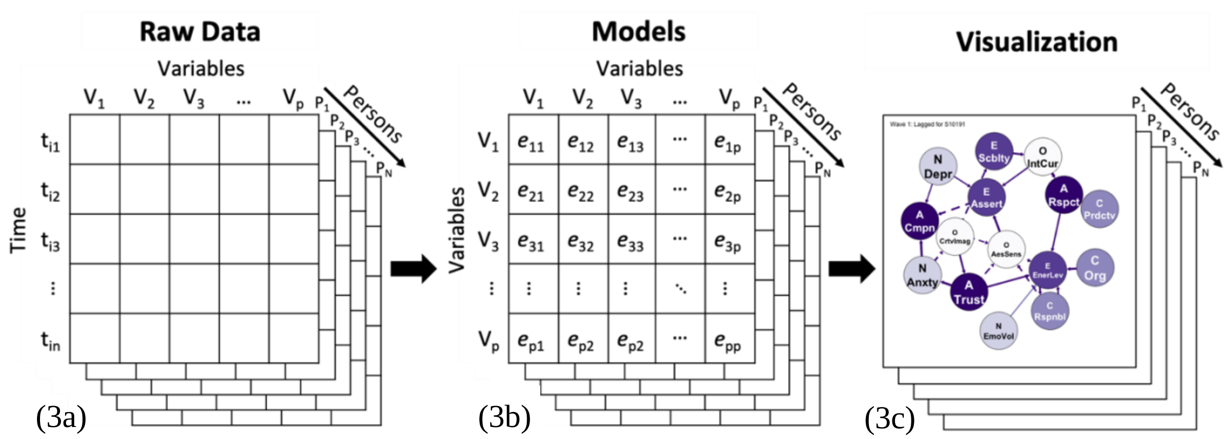

Figure 3. A simplified analytic procedure for using network tools on idiographic time series data from raw data (3a) to modeling relationships among variables (V_1 to V_p) and formatting them as a matrix (3b) to visually displaying them as a network or profile of relationships (3c).

Cross-lagged VAR models also allow researchers to test timing effects of SWB. Timing effects occur when fluctuations of a variable, or its relationship with another variable, depend on the passage of time or point in time that one or both variables are measured. Such effects can be focused on either short (e.g., hours, weeks) or long (e.g., year, ten years, career stages) time frames. Timing effects play a role for testing within person processes. It may be the case that SWB is not associated with task performance in the moment that hard work is occurring, but is over some slightly longer timespan. As such, testing different timing effects can provide stronger evidence for antecedents and outcomes (Sonnentag et al., 2010) by considering temporal order and acknowledging specific aspects of positive and negative work experiences for one worker. Timing is an important consideration for both measuring and modeling psychological processes. Dynamic models, such as cross-lagged VAR models, at the idiographic level are better able to evaluate potential causal effects that occur over different timeframes.

In terms of modeling these effects, timing plays an equally large role. One practical difficulty is dealing with missing data. Ideally, a researcher would have assessments for all constructs at all times of the day. But between monetary, time, practice, and learning constraints (not to mention sleep), 24-7 assessment is not possible for self- or other-reported data. As a result, data will always be "missing." Depending on the timing of data collection, missing data may not be too prevalent, outside of what is known as the day-night problem—where the lag between the last assessment in the day and the first in the morning is much larger than the lags between remaining assessments. If this lag issue is ignored, it may increase error in the model and make it more difficult to capture signal, as one is inadvertently creating unequal measurement intervals between lags. These unequal lags also occur if one's timing of assessments is semi-random and not at prespecified times. These semi-random prompts are often seen as beneficial due to the inability of participants to know *when* an assessment prompt is coming and allows for better sampling of a variety of participants' experiences. However, it creates a number of quantitative challenges, as it creates unequal lags by definition. Unequal lags entail modeling processes under the assumption that the influence of variables does not depend on time lag, an assumption that is likely wrong.

Currently there exist a number of techniques to deal with unequal lags, including cubic spline interpolation (Fisher et al., 2017) and multiple imputation (see Piccirillo et al., 2019) for a more thorough discussion). However, both of these are merely work arounds to a problem, rather than a way to directly address whether time between lags affect parameter estimates. In other words, these techniques try to make sure that unequal lags do not bias results too much. What they do not allow for are tests of whether lag time matters. As a result, they cannot directly capture the optimal lag between measurements.

Continuous time models. New techniques, like the continuous time vector autoregressive (CVAR; Haan-Rietdijk, Voelkle, Keijsers, & Hamaker, 2017) model, help to correct this issue by treating the variables (or the relationship between variables) as a function of a continuous time variable. Continuous time models assume that the variables being modeled vary continuously over time – that is, their associations may not be the same across the measured sampling period. In CVAR models, time is explicitly incorporated into the model to avoid conflating different time intervals as the same. This is useful so that timing effects can be defined by either short (e.g., hours, weeks) or long (e.g., year, ten years, career stages) time frames. For instance, when examining if velocity (i.e., rate of change in models with continuous time variable) in SWB matters for turnover, one can ask if it matters at the moment, a week later, or months later. It is important to be able to consider these questions simultaneously with other metrics of SWB given evidence that people's in-situ versus retrospective (a few days later) ratings of positive affect, negative affect, and subjective experience of events not only significantly differ from one another, but also seem to differ in their importance; with the former important for estimating experiences and the latter important for predicting future choices (Wirtz, Kruger, Scollon, & Diener, 2003).

Continuous time models have a number of advantages. First, and as described above, continuous time models can deal with unequal lags between measurement occasions. Second, the way that variables are modeled in continuous time models comes closest to conceptual definitions of how dynamic processes influence one another and outcomes (Cattell, 1947; 1957). Dynamic processes (i.e., the way variables relate to one another over time) do not influence one another at standard lag intervals, they do so through continuous associations over time. Continuous time models provide the means to model time-sensitive dynamic processes, as well as test potential timing effects. Timing effects can also be important for long-term outcomes of SWB. For instance, at the lifespan level, general SWB may be less important for turnover intention of workers closer to retirement because other factors, such as being fully vested in their retirement, are more important than for workers who are far from retirement.

Third, CVAR models can better estimate the processes between two constructs. By incorporating time directly into the model, continuous time models can better estimate true autoregressive and cross-lagged relationships and estimate the strength of relationships at different time intervals; so unequal time intervals become useful and desirable, rather than a problem. That is, when measures are collected at different intervals, then CVAR and other methods for continuous time modeling can examine the strength of relationships at different time intervals. CVAR models could examine the contemporaneous relationship between Joan's frustration and task performance immediately after being passed over for promotion, and then again 2 days after and 2 weeks after. Using CVAR models we could examine whether the relationship between frustration and task performance was strongest immediately after before returning to pre-promotion pass over levels. CVAR models can also help identify antecedents and outcomes of fluctuations in worker SWB, which can inform organizational strategies for supporting the happiness and productivity of their workers on a day-to-day basis. Seeing how the relationship between variables change over time is an important consideration for both measuring and modeling psychological processes.

Fourth, similar to the standard VAR models, the complexity of CVAR models almost always require idiographic modeling, and, as such, can be used to examine whether the (1) average association between two variables within a person varies across people and (2) whether the association between two variables within a person varies across both time and people. Again, going back to our example, we might find that both Joan and Jannen have a weak lagged association between their negative affect at time $t - 1$ and their task performance at time t using standard VAR models. Thus, Joan and Jannen would be indistinguishable using standard VAR models, as the models would indicate they have the same autoregressive relationship between negative affect and task performance. However, a CVAR model can compare the strength of this relationship over time, and if the results of the models are collected together, across people. Doing so, we might find that the association between negative affect and task performance for Jannen is weak, but consistent over time, while for Joan, this relationship showed a steep increase at the beginning of the observation periods and then a decrease halfway through the study period. Based on this, we may hypothesize that major disruptors in Joan's life, like not getting a promotion, may nudge the association between frustration and performance upward, ensuring poorer performance after disruptions. And we might hypothesize that Jannen's performance is less likely to change much as a function of frustration, and that any increase in frustration is not expected to spiral, such that frustration leads to worse performance that leads to more frustration and so on as it does for Joan. As an example, this shows that for both Joan and Jannen, frustration and task performance are related, but that the processes through which frustration influences task performance plays out over different timescales for each person.

These types of individual differences demonstrate the impact of model choice on the ability to make inferences about a single person and the types of inferences that can be made. Even though VAR and CVAR models are both idiographic, they make different assumptions. The former assumes that time operates similarly for each construct, while the latter allows these restrictions to be relaxed. The appropriateness of each depends on the research question and the data available. VAR may be appropriate if data are collected using a fixed interval schedule and variability of the constructs and/or relationships of interest vary around that fixed interval schedule. Such data may be best suited to answer contemporaneous questions, controlling for cross-time phenomena. In contrast, CVAR may be most appropriate when data are collected using a random or semi-random schedule or when violations of ergodicity occur (i.e., the relationship is thought to vary over time so cannot be modelled by between-person models).

An important takeaway here is that there are many types of idiographic models and many forms each of those models can take. Not all types of idiographic models are equivalent, just as not all people are the same. Even though VAR models are idiographic, a standard VAR might treat people similarly, just as a simple between person questionnaire might. It is not until CVAR models are employed that some processes can be disentangled, and the individual differences brought to light.

Dynamic Dynamic models. Treating time continuously to understand how psychological processes unfold over gets us one step closer to the ultimate goal of knowing how psychological processes unfold or change over time (i.e. their dynamics) and how their change relates to changes of other processes.

These models are important tools for testing the validity of between-person relationships at the within-person, dynamic level. As stated earlier, relationships with antecedents and outcomes established at the between-person level may not look the same at the within-person level (Chen, Bliese, & Mathieu, 2005). For instance, between-person research suggests that two employees with the same level of job satisfaction (i.e., cognitive component of worker SWB) will have the same likelihood for turnover. However, when studying this effect at the within-person level, it is important to consider if the employees' current level of job satisfaction is a result of a systematic increase or decrease from before (Chen, Ployhart, Thomas, Anderson, & Bliese, 2011). As such, it is important to test the same psychological mechanisms of SWB at different levels of analysis. This is demonstrated by findings regarding the relationship between job demands and worker engagement (a common metric for the cognitive component of workplace SWB), such that job demands were positively associated with engagement at the within-person level, but negatively associated with engagement at the between-person level (Halbesleben, 2010; Xanthopoulou & Bakker, 2013).

If the psychological mechanisms and correlates of a construct at the within-person level do not mirror those at that at between-person level, research must refine the surrounding theory to acknowledge the unique functioning at the different levels of analysis (Gable & Reiss, 1999; Pitariu & Ployhart, 2010). Given that the effect of worker SWB may not look the same at the between- and within-person levels, our research must move beyond our understanding of SWB at the between-person level and consider dynamic relationships at the within-person level (e.g., how do the behaviors, attitudes, and health of workers change when they are happier than they were the day before? How do specific situational features, like conflict, influence SWB, and for how long?).

While CVAR models are useful for this task, they require a large amount of data, and have trouble incorporating a lot of variables simultaneously. Additionally, calculating continuous change is difficult, analytically. A good illustration of the complexity of the required calculations comes from physics. As a field, physics has a trove of tools for understanding how objects move as well as forces that may impact such movement. So let us say that we are trying to calculate how fast a car would have to go to travel a mile in 60 seconds. A simple calculation shows that it would require a velocity of 60 miles / hour to travel 1 mile in a minute. But, what if the car is starting from a stopped position? When a car moves from a stop (i.e. zero miles / hour), the answer is not so simple because it cannot go from zero miles / hour to 60 miles / hour instantly. As such, the velocity of the car will also be changing across distance. So in this case, not only will the distance of the car change, but its velocity will also change across such distance, which in physics is the acceleration of the car. Thus, to travel one mile in one minute, the car would need to have an average velocity of 60 miles per hour, but in the early distance it moves, its velocity will be below 60 miles per hour, and it will ultimately have to have a velocity above 60 miles / hour at some point in the full one mile distance in order to achieve an average of 60 miles / hour. So we need to try to understand what its velocity is as a function of its distance from the origin, which can be achieved by taking the first derivative of an equation modeling the car's distance from the origin.

Analogously, for psychological phenomena, like SWB, we typically ask participants to self-report their current level of the phenomena on a Likert-like scale, which are akin to distance. Although levels have been demonstrated to predict a number of outcomes, many of the questions we ask have more to do with the nature of changes in those levels (e.g., are rapid changes in negative affect worse for performance than slower changes), which are questions of velocity or acceleration rather than level. Thus, the use of derivatives and differential equations offers new opportunities to fit idiographic models of SWB. Change across time (i.e., velocity) is found through taking a derivative with respect to time (those that repressed or skipped calculus can imagine a simple slope, with time on the x axis). While the velocity of SWB in the workplace captures how one person's SWB increases or decreases – changes – over time, the acceleration (i.e. the rate of change of velocity, the second derivative of level with respect to time) captures the rate of a worker's change in SWB. Much like a car beginning to move, changes in psychological phenomena do not happen monotonically, or the same rate. For example, getting passed over for promotion may influence negative affect differently as you move further from the event. For some, there may be a quick increase (i.e., both velocity and acceleration are strong and positive). For others, change may be more gradual, first listening through the decision given before getting upset (i.e., velocity may be weakly positive, and acceleration may be weakly positive or even zero). Both groups may end up equally upset but get there in very different ways that could conceivably have social or behavioral consequences.

Analytic techniques well suited to address these concepts include differential equation models that describe the relationship between the level of variable and its derivatives with respect to time (Boker, Neale, & Rausch, 2004). Although models that directly incorporate time, like VAR and CVAR models, allow psychological scientists to disentangle changes due to time, they do not incorporate all elements of differential equations that are the underpinning of dynamic systems models. One of the fundamental features of dynamic systems models that are not directly captured in VAR and CVAR models is equilibria. dynamic systems models study how systems move. The movement of systems is modeled in terms of movement towards or away from its steady, preferred state, called equilibria. As such, dynamic systems models capture how and where the system moves toward and away from equilibria points. Because VAR and CVAR models are not able to directly capture systems' equilibria they are not truly *dynamic*, dynamic models.

Sometimes, forces will pull a state toward a specific equilibrium (this is called an attractor), while in other situations a current force will push a state toward a different point (this is called a repeller). These attractors and repellers are not directly assessed but are dynamic features of processes that unfold over. For example, looking at Figure 4, you see two change as outcome plots for Joan and Jannen's positive affect. In the Figure, their level at any point is on the x-axis, while their time normalized change (per hour) is on the y-axis. The points at which each of the lines intersect with the x-axis (i.e. y-intercept of 0), then change is zero and they are at an equilibria. Both have more than one equilibria. Thus, looking at the left panel which captures Joan's positive affect, she has two equilibria, one at one on a 1-5 scale and one at four, which indicates that when she reports being around a 1.5 or 4, she is likely to stay there for some time. The equilibria at 4 is an attractor (velocity is positive, so level is increasing), meaning that if she is not at a four at the current moment, she is likely to be pulled toward 4 in the next moment. If 4 is an attractor, the next equilibria must be a repeller, which we see at a 1.5. Although Joan is typically pulled toward higher positive affect, if a situational push pushes her too low, she will remain with low positive affect. In that way, the system does not want to be at a level of 1.5, and thus repels her if she is in that state. The result of these attractors and repellers is that Joan is likely to stay in an attractor state (4 in this example), while not likely to stay long in a repeller state (1.5 in this example) by either moving downward to a 1 or pushed upward to four.

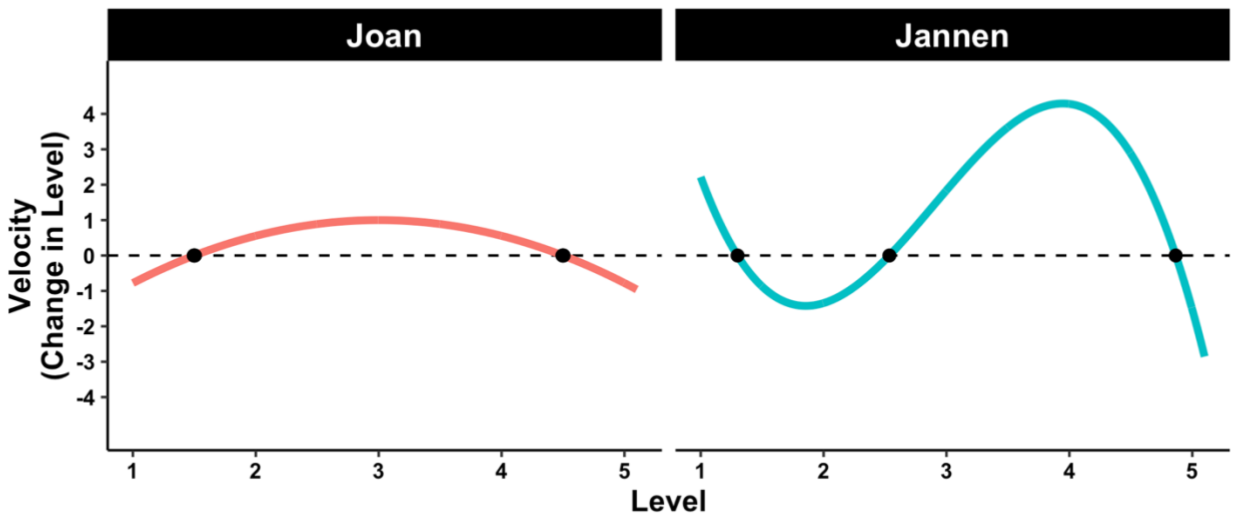

Figure 4. Hypothetic change-as-outcome models of change in positive affect as a function of its current level for two hypothetical people, Joan and Jannen. Points where the lines intersect with the x-axis (small black points in the figure), indicate equilibria. In the left panel, there are two equilibria, one repeller at 1.5 and one attractor at around 4. In the right panel, there are three equilibria, two attractors at around 1 and 5 and one repeller around 2.5.

Jannen, who is represented in the right side of Figure 4, in contrast, shows a cubic relationship between level and change. In this instance, she has three equilibria, two attractors (1 and 5) and one repeller (2.5). Thus, she prefers to have either relatively high or low positive affect. When situational experiences push her toward the middle she will be pushed away by the repeller and pulled toward one of the attractors, depending on whether she is experiencing positive affect above or below about 2.5. Thus, Jannen might be expected to have more consistently low or high positive affect than Joan who is typically being pulled toward high levels. If conceptualized like magnets these attractors and repellers can push people around depending on their current state. Thus, if one can model such attractors and repellers, it is possible to better estimate future states. In this way, attractors and repellers help to explain why dynamics occur. This model can extend to more than one construct. Adding additional main effects to the model can change the location of the equilibria (Butner et al., 2014). Together, these serve as ways to incorporate other constructs/situations that one wants to control for or that may moderate the association (see Danvers et al,. 2020 for a broader discussion). For example, one can look at whether feeling stressed does or does not impact the dynamics of happiness. Or does someone's dynamics change as a result of training.

Concluding Remarks

Our theoretical understanding of SWB in the workplace is incomplete without a *dynamic* understanding of antecedents and outcomes of SWB, as well as the structure of the construct itself. The current paper suggests that idiographic statistical methods from outside organizational psychology can be applied to the study of worker SWB to address limitations associated with reliance on between-person models and limited focus on within-person variability. Towards this end, we reviewed four idiographic techniques: the *P-technique,* vector autoregressive (VAR) models, continuous time models, and dynamic, dynamic models. We encourage researchers to apply the methods described in this paper to their own research to study worker SWB idiographically, rather than just as individuals within populations. This, coupled with models optimized for including a larger number of predictors and incorporating time explicitly into models, offers a path for testing the dynamic processes and structure of SWB in the workplace.

Both trait (i.e., between-person) and state (i.e., within-person, dynamic) qualities of SWB are important, but neither, alone, can provide a dynamic understanding of worker SWB. While the trait level defines an employee's baseline, it is the state level experiences that initiate dynamic psychological processes that shape worker SWB and attitudes (George, 1991; Weiss & Cropanzano, 1996). Even though between-person, trait differences influence state level changes, states are the more proximal predictors of immediate work experiences and behavior. As such, supplementing between-person findings with dynamic, within-person investigations will not only support the utility of trait differences, but delineate the function of dynamic processes (Cervone, 2005). For the same reason, our understanding of the structure and dynamic nature of SWB can benefit from a dynamic approach to the structure or facets of SWB. Given the importance of event-related affect for broader job attitudes (e.g., job satisfaction) it is likely that momentary emotional experiences are important for fluctuations in cognitive evaluations associated with SWB (Weiss & Cropanzano, 1996).

We described a number of overlooked advantages of state level inquiry, highlighting additional ways to push these lines of research even farther. Even though between-person, trait differences influence the probability of being in any one state level, states are the more proximal predictors of immediate work experiences and behavior (Roberts & Jackson, 2008). As such, supplementing between-person findings with within-person, state level investigations can support the utility of between person SWB differences, delineate dynamic processes, and explore idiographic structures. Doing so will help the field avoid falling prey to ecological fallacy (Robinson, 1950), and push beyond standard methods that make a lot of assumptions about how SWB is measured and operates dynamically in the workplace.

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