

The Relation Between Short-Term Emotion Dynamics and Psychological Well-Being: A Meta-Analysis

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Not only how good or bad people feel on average, but also how their feelings fluctuate across time is crucial for psychological health. The last 2 decades have witnessed a surge in research linking various patterns of short-term emotional change to adaptive or maladaptive psychological functioning, often with conflicting results. A meta-analysis was performed to identify consistent relationships between patterns of short-term emotion dynamics—including patterns reflecting emotional variability (measured in terms of within-person standard deviation of emotions across time), emotional instability (measured in terms of the magnitude of consecutive emotional changes), and emotional inertia of emotions over time (measured in terms of autocorrelation)—and relatively stable indicators of psychological well-being or psychopathology. We determined how such relationships are moderated by the type of emotional change, type of psychological well-being or psychopathology involved, valence of the emotion, and methodological factors. A total of 793 effect sizes were identified from 79 articles ($N = 11,381$) and were subjected to a 3-level meta-analysis. The results confirmed that overall, low psychological well-being co-occurs with more variable (overall $\hat{\rho} = -.178$), unstable (overall $\hat{\rho} = -.205$), but also more inert (overall $\hat{\rho} = -.151$) emotions. These effect sizes were stronger when involving negative compared with positive emotions. Moreover, the results provided evidence for consistency across different types of psychological well-being and psychopathology in their relation with these dynamical patterns, although specificity was also observed. The findings demonstrate that psychological flourishing is characterized by specific patterns of emotional fluctuations across time, and provide insight into what constitutes optimal and suboptimal emotional functioning.

Keywords: psychological well-being, psychopathology, emotional variability, emotional instability, emotional inertia

A fundamental feature of our emotions and feelings is that they change over time. The patterns of emotional fluctuations reflect how people deal with changes in the environment and how they regulate their emotions (Larsen, 2000), and both contribute importantly to their psychological well-being. Indeed, a surge of research focusing on the time dynamic patterns of emotional experience has shown that, next to how people usually feel or how they feel on average, the patterns with which people's emotional expe-

riences change over time provide unique information that is relevant for psychological well-being. Here we present a meta-analysis of studies investigating the relation between on the one hand short-term dynamical patterns of emotions and on the other hand stable forms of psychological well-being and psychopathology, to identify the patterns of emotional change associated with general and specific forms of psychological health.

We define psychological well-being as a broad construct that involves either or both the presence of positive indicators of psychological adjustment such as positive emotionality, happiness, high self-esteem, or life satisfaction, and the absence of indicators of psychological maladjustment such as negative emotionality, psychopathological symptoms and diagnoses. This conceptualization captures several important distinctions relevant to psychological well-being. It involves both hedonic (experiencing high positive and low negative emotions) and eudaimonic (involving evaluations of functioning in life) aspects of well-being (Deci & Ryan, 2008). It encompasses the components of subjective well-being as proposed by Diener (involving high levels of positive emotions and life satisfaction and low levels of negative emotions; Diener, Suh, Lucas, & Smith, 1999). Finally, by including psychopathological symptoms and diagnoses, it applies to both the nonclinical and clinical range. Although psychological well-being and psychopathology are not simply two opposite ends of the same dimension, it is clear that variation in psychological well-being in nonclinical populations and in psychopathology

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are intricately tied (e.g., Bartels, Cacioppo, van Beijsterveldt, & Boomsma, 2013).

Emotions and Psychological Well-Being

A large amount of research has investigated how the experience of emotions relates to psychological well-being. This research has traditionally adopted a rather static perspective on emotions. With the term static perspective, we mean that emotions have traditionally been studied as either single monotone states that switch on and back off in response to an event (assessed with one measurement after, or one before and one after an eliciting stimulus), or as traits that characterize individuals in terms of a constant or average disposition to experience certain emotions. Research on this topic has taught us that the experience of positive emotions generally promotes well-being and other desirable outcomes (Fredrickson & Joiner, 2002; Lyubomirsky, King, & Diener, 2005), while the excessive experience of negative emotions is associated with undesirable outcomes, impaired mental health, and psychopathology (Watson, Clark, & Carey, 1988). In sum, experiencing relatively high levels of positive and relatively low levels of negative emotions (within boundaries) constitutes a key aspect of mental health.

Although this research has indisputably produced important insights, it has largely neglected the inherent time-dynamic nature of emotions. Indeed, emotions are not constant and unchanging over time, but continuously fluctuate as a result of internal or external events (Frijda, 2007). In fact, the very function of emotions lies in their time-dynamic nature, namely to alert us to important changes in the environment and motivate us to deal with these changes (Frijda, 2007; Scherer, 2009). The traditional approach linking emotions as static entities to psychological well-being has therefore provided only a limited perspective. With as much as we have learned about emotions, it is as if we have been taking still photos of a dance.

Studying emotions from a dynamic perspective, by examining how they change across time, offers a unique and complementary window on emotional functioning (Larsen, 2000). Several prominent theorists (e.g., Davidson, 2003; Larsen, Augustine, & Prizmic, 2009; Lewis, 2005; Scherer, 2009) have therefore called for a paradigm shift in the study of emotions, changing the focus from studying emotions as static entities to studying emotions as dynamic processes. Perhaps as a result, the past decades have seen a steep increase in studies looking at the temporal dynamics of emotions.

Emotion Dynamics and Psychological Well-Being

The term emotion dynamics refers to the patterns and regularities characterizing the changes and fluctuations in people's emotional and affective states over multiple points in time across seconds, hours, or days (Kuppens, in press). This definition is meant to capture the types of changes that bestow emotions with the function to allow an individual to respond to and cope with internal or external challenges, but clearly distinguishes emotion dynamics from developmental changes which take place across larger time scales.

The idea that patterns of emotional change are linked to psychological well-being is not new. For example, in Ancient Greece, Hippocrates formulated the existence of the choleric temperament

type, characterized by proneness to mood swings, aggression, and tension (Chamorro-Premuzic & Furnham, 2005). In modern psychology, emotional instability features prominently in theories of personality under the name of neuroticism (Cattell, 1946; Eysenck & Eysenck, 1975), and is considered a hallmark of several forms of psychological maladjustment (Barlow, Sauer-Zavala, Carl, Bullis, & Ellard, 2014; Lahey, 2009).

Indeed, time-dynamic patterns of emotions convey how people generally emotionally respond to events and regulate their emotions (Chow, Ram, Boker, Fujita, & Clore, 2005; Larsen, 2000), which play an essential role in adjustment (Gross & John, 2003; Gross & Muñoz, 1995) and psychopathology (Aldao, Nolen-Hoeksema, & Schweizer, 2010; Linehan, 1993; Peeters, Berkhof, Rottenberg, & Nicolson, 2010). As such, emotion dynamics have been considered to be part of the emotional phenomenology associated with psychological well-being and psychopathology, even in the form of criteria for psychiatric diagnoses (e.g., in the case of bipolar disorder or borderline personality disorder; American Psychiatric Association, 2013). Emerging evidence even suggests that such patterns of emotional microdynamics may lie at the base of differences in psychological well-being. Smaller short-term perturbations in emotions may accumulate to create adverse consequences for psychological health and risk for affective disorders (Wichers, 2014). In support of such claims, emotion dynamic patterns have been found to precede and prospectively predict changes in psychological well-being or psychopathology across longer periods of time (Kuppens et al., 2012; van de Leemput et al., 2014).

Emotion dynamic patterns. Over the years researchers have come up with many different ways of operationalizing patterns of emotion dynamics based on time-series data. Among the most often used are measures of emotional variability, instability, and inertia.

Emotional variability refers to the range or amplitude of someone's emotional states across time. An individual characterized by higher levels of emotional variability experiences emotions that reach more extreme levels and shows larger emotional deviations from his or her average emotional level. It is most often calculated as the within-person standard deviation (*SD*) or variance of emotional states across time (e.g., Eid & Diener, 1999). To illustrate, the left two panels of Figure 1 display possible patterns of emotional change characterized by low (showing less deviations from the mean) versus high (showing larger deviations from the mean) variability based on simulated data.

Emotional instability, in turn, refers to the magnitude of emotional changes from one moment to the next. An individual characterized by high levels of instability experiences larger emotional shifts from one moment to the next, resulting in a more unstable emotional life. It is typically calculated as the mean squared successive difference between consecutive emotion scores (MSSD) or a related metric (von Neumann, Kent, Bellinson, & Hart, 1941). In contrast to measures of variability, MSSD and related metrics capture the temporal aspects of changes over time by quantifying changes from one moment to the next instead of over an entire period of time. This is illustrated by the middle panels of Figure 1, which show simulated data patterns characterized by low versus high instability. While both time series have the same variance (thus the same level of dispersion from the average emotional state), the pattern showing high instability clearly shows stronger emotional ups and downs over time.

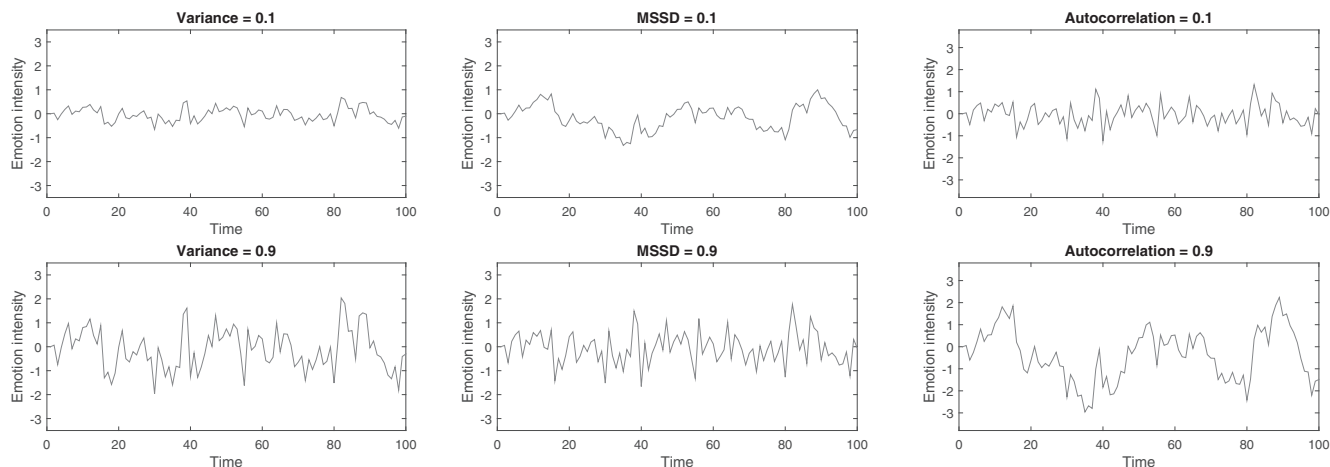


Figure 1. Simulated data illustrating time-series characterized by low versus high levels of variability (expressed in terms of variance; left panels), instability (expressed in terms of mean square successive difference or MSSD; middle panels), and inertia (expressed in terms of autocorrelation; right panels).

Emotional inertia refers to how well the intensity of an emotional state can be predicted from the emotional state at a previous moment (Kuppens, Allen, & Sheeber, 2010; Suls, Green, & Hillis, 1998). An individual characterized by high levels of emotional inertia experiences emotions that are more self-predictive and self-perpetuating across time, and therefore carry over more from one moment to the next, resulting in emotional fluctuations that linger and show relatively little homeostatic return to a baseline level. Emotional inertia is usually calculated as the autocorrelation of emotions across time. To illustrate, Figure 1 displays simulated data patterns characterized by low versus high levels of autocorrelation or inertia. As can be seen, a higher autocorrelation implies emotions that carry over more across time, that linger, and show less homeostatic recovery compared with low autocorrelation.

From the outset, it is important to point out that these patterns (as they are most often studied and as they are defined here) are described and studied without taking into consideration the context or situations in which the emotions unfold. They are used simply to describe how people's emotions change across time, regardless of whether their reactions are appropriate or contingent upon events that people encounter. In spite of this, they say something meaningful about a person's emotional life. Indeed, research is accumulating evidence that such patterns of emotional change are a fundamental feature of people's personality (Eid & Diener, 1999), and, indeed, are intricately tied to their overall psychological well-being (Ebner-Priemer et al., 2007; Ebner-Priemer & Trull, 2009; Trull et al., 2008).

Need for synthesis. Empirical research on dynamic aspects of emotions in relation to psychological well-being has burgeoned in the last decades, aided by technological advances that facilitate the repeated assessment of emotions in the lab and in daily life (Shiffman, Stone, & Hufford, 2008; Smyth, & Stone, 2003; Trull & Ebner-Priemer, 2013). The resulting body of research harbors a large number of findings linking patterns of emotion dynamics to a wide range of indicators of psychological well-being and psychopathology. Yet, the findings are scattered across different (non-clinical and clinical) literatures and are methodologically diverse,

making it difficult to formulate general conclusions about the exact relationships between emotion dynamic patterns and different forms of psychological well-being. Yet, a synthesis of this literature would be valuable and timely for a number of reasons.

First, with emotions being fundamentally dynamic phenomena, such a synthesis would complement the static perspective with a dynamic perspective that will together provide a much richer and more nuanced picture of the role of emotions in psychological well-being.

Second, identifying the specific associations between emotion dynamic patterns and different forms of psychological well-being would significantly help to understand the common or transdiagnostic versus possibly distinct forms of emotional (dys)regulation involved in different forms of psychological well-being and psychopathology. Moreover, by including studies involving both non-clinical and clinical manifestations of variations in psychological well-being, the findings can help to inform the discussion whether clinical diagnosis involves qualitative or rather quantitative differences with symptoms observed in the nonclinical range (Brown & Barlow, 2005; Kraemer, 2007), and help to build bridges between nonclinical and clinical literatures. As such, a synthesis of this domain would directly respond to initiatives (such as the Research Domain Criteria formulated by the National Institutes of Mental Health; Insel et al., 2010) that emphasize the need to obtain more insight into the emotional mechanisms at play in mental health and disorders.

Third, growing online access and portable technologies are rapidly increasing the possibilities to track people's ongoing affective, behavioral, and cognitive conditions in daily life (Myin-Germeys et al., 2009), and is generating large interest for the development of online or mobile mental health research and applications. Solid knowledge of the role of emotion dynamics in psychological well-being would be of great value for detection, diagnosis, prognosis, and treatment assessment purposes in this context (e.g., van de Leemput et al., 2014).

Finally, such a synthesis could also help to shed light on a theoretical ambiguity involving the adaptive or maladaptive nature

of emotional change. Implicitly or explicitly, two contradictory viewpoints seem to exist on whether or not changing emotions are adaptive. In one view, emotional fluctuations and changes are seen as indications of emotional lability, characteristic of low psychological well-being. Emotions that change too strongly or abruptly signal dysregulation and therefore maladjustment (see, e.g., the use of the term emotional instability as a synonym for neuroticism). In another view, emotional fluctuations and changes emanate from their adaptive function and reflect flexibility in emotional responding, which is considered a hallmark of psychological health (Hollenstein, Lichtwarck-Aschoff, & Potworowski, 2013; Kashdan & Rottenberg, 2010). The result is the simultaneous coexistence of the notions that changing emotions can on the one hand be destructive and impair normal functioning and on the other hand can be adaptive as flexibility is required for normal functioning. While the current synthesis of literature, focusing on emotion dynamics independent of the context in which they occur, cannot speak to whether emotional change is appropriate or contingent on events, it can nevertheless inform this debate by establishing which emotion dynamical patterns are adaptive or maladaptive in terms of their association with psychological well- and ill-being.

Methodological diversity. A synthesis of this literature would also allow us to conclude to what extent findings are generalizable across different research methods, and to what extent methodological factors shape conclusions.

As mentioned above, emotion dynamics have been operationalized in different ways, but mostly in terms of measures of variability (e.g., *SD* or variance), instability (e.g., *MSSD*), or inertia (e.g., autocorrelation) or variants thereof, although less common measures such as for instance pulse and spin (e.g., Kuppens, Van Mechelen, Nezlek, Dossche, & Timmermans, 2007; Timmermans, Van Mechelen, & Kuppens, 2010), spikiness and irregularity (e.g., Pincus, Schmidt, Palladino-Negro, & Rubinow, 2008), and so forth have also been studied. Although the different measures show conceptual and mathematical overlap¹ (e.g., Jahng, Wood, & Trull, 2008; Koval, Pe, Meers, & Kuppens, 2013), each measure still expresses decidedly different facets of emotional change across time (see above and Figure 1). Distinguishing between the different types of patterns of emotional change is tantamount to understanding the precise ways in which psychological well-being is related to emotion dynamics.

Next, there are indications that aging is associated with greater emotional stability (e.g., Carstensen et al., 2011), and that gender differences exist in emotion regulation (e.g., Nolen-Hoeksema, 2012). However, it remains unknown whether or how the relation between emotion dynamics and psychological well-being is a function of age and gender.

Emotion dynamics have also been studied on varying time scales, ranging from rapid fluctuations across seconds or minutes to mood changes observed over the course of days. As the processes underlying emotional change on shorter and longer time scales may be different (Ebner-Priemer & Sawitzki, 2007), the time scale on which emotional change is observed may be crucial to consider.

Different methods have been used to collect data for measuring emotional change across time. Emotion dynamics have been studied with experience sampling or diary methods, using paper-and-pencil or electronic tools (Green, Rafaeli, Bolger, Shrout, & Reis, 2006), with daily reconstruction methods or with other methods. It

is important to establish to what extent findings generalize across data collection methods or are moderated by them (e.g., Green et al., 2006). Moreover, emotion dynamics have been studied as naturally occurring in daily life or in the lab, or in response to standardized emotional stimuli. Distinguishing between these would allow some insight in the extent to which emotion dynamics are endogenous or driven by the events people encounter or elicit.

Finally, although most studies have focused on negative emotions, a subset of studies also examined positive emotion dynamics (e.g., Eid & Diener, 1999; Gruber et al., 2013; Kuppens, Allen et al., 2010; Stein, 1996). While positive and negative emotions are characterized by opposite valence, they are more than simply opposite ends of the same dimension. Positive emotions do not simply arise in the absence of negative emotions and vice versa, and they are characterized by qualitatively different appraisal patterns (e.g., Roseman, Spindel, & Jose, 1990), by different patterns of neural activity (e.g., Northoff et al., 2000), and are differently regulated (Webb, Miles, & Sheeran, 2012). Dynamic patterns of positive and negative emotions may not be identically linked to forms of psychological well-being and should therefore be distinguished.

The Present Study

The aim of this study is to provide a comprehensive meta-analysis identifying the relations between different patterns of short-term changes in emotional experience over the course of seconds, hours, or days and relatively stable indicators of psychological well-being, both in the typically developing and psychopathological range. Such a meta-analysis will allow us to formulate consistent conclusions about the relation between psychological well-being and emotion dynamics. Moreover, we will investigate how this relation varies as a function of the type of psychological well-being, the valence of the emotions under study, as well as various methodological characteristics. This will allow us to pinpoint exactly which patterns of emotional change are linked to different types of psychological well- or ill-being, and how such relations may be qualified by moderating factors.

Method

We tracked down and selected all possible relevant articles that report data on the relation (in various forms, e.g., correlations, regression coefficients, differences between group means, etc., see more below) between emotion dynamic measures on the one hand, and indicators of psychological well-being and psychopathology on the other hand, coded the articles for relevant variables, and analyzed the resulting meta-analytic dataset. In what follows, we detail the search strategy that was used, the inclusion and exclusion criteria that were applied to identify relevant studies, explain the coding schemes and procedure, and describe the statistical methods used to analyze the data.

¹ For example, higher variance tends to be associated with higher *MSSD* for constant levels of autocorrelation (see Figure 1, left panel). Moreover, a higher *MSSD* tends to be associated with a lower autocorrelation, for constant levels of variance (see Figure 1, middle panel). Similarly, a higher autocorrelation is associated with higher variance, for constant levels of *MSSD* (see Figure 1, right panel).

Literature Search

To maximize exhaustiveness, several complementary approaches were used to search for relevant articles. First, a systematic literature search was done in PsycInfo to identify empirical articles, published through the end of December 2013 in peer reviewed journals. The combinations of the following search terms were entered: (“affect*” OR “emotion*” OR “mood” OR “feel*”) AND (“variability” OR “stability” OR “instability” OR “inertia” OR “autocorrelation” OR “flexibility” OR “inflexibility” OR “change” OR “dynamics” OR “lability” OR “volatility”). Terms referring to psychological well-being were not included as search terms as it was deemed difficult to exhaustively capture the intended broad domain of psychological well-being and psychopathology. It was of course explicitly represented in the inclusion and exclusion criteria (see below). The search yielded 2,380 articles, which were subsequently checked for their relevance based on the inclusion and exclusion criteria (see below).

In addition, requests for published articles, in press articles, and unpublished data were sent out to electronic listservs of societies that were deemed relevant for the topic under study and that were accessible to researchers working in this research field (the *International Society for Research on Emotion*, the *Society for Ambulatory Assessment*, and the *Society for Personality and Social Psychology*). The addition of unpublished data and in press articles in the meta-analysis is important in an attempt to counterbalance possible reporting and publication bias (Lipsey & Wilson, 2001; Sutton, 2009). In response to our requests, we received 29 possibly relevant articles, and six unpublished datasets/articles.

As a third search strategy, reference lists of review articles that address the topic of the meta-analysis as well as all articles included in the meta-analysis that resulted from the two other search strategies were reviewed to check for additional relevant articles that were possibly missed in the previous steps.

Inclusion and Exclusion Criteria

First, articles were included if they reported empirical data involving a measure of intraindividual emotion dynamics that reflects patterns of change in one emotion or a composite of several emotions over a certain period of time. As stated in the Introduction, we define emotion dynamics as the patterns and regularities characterizing the changes and fluctuations that occur in people’s emotional and affective states over multiple time points across the time scales of seconds, hours, or days. Consistent with this definition, all included studies involved measures of emotion dynamics based on at least three consecutive time points (going beyond mere emotional level—as measured with one time point—and single emotional reactivity—as often measured with two time points). Furthermore, a maximum time interval of 1 week between consecutive measurements was chosen to exclude studies that focus on very long-term or developmental changes and pure treatment/intervention studies with follow-ups (see our definition of emotion dynamics).

Second, because our investigation focuses on the experiential component of emotions, only studies that reported data reflecting emotional experience, either as rated by self-report, or as observed and coded by others (as an other-reported source of subjective experience) were included. Note that studies in which only behavioral coding of emotional behavior was reported, such as for

instance aggression, were not included. Studies involving only other components of emotions such as for instance (neuro)physiological aspects of emotions, direct behavioral components as measured by behavioral tasks, or multiperson emotions (e.g., emotional states defined by multiple actors) were not included.

Third, only articles that reported data on indicators of psychological well-being in association with one or more measures of emotion dynamics as defined above were retained. Psychological well-being was broadly defined, and included both the presence of positive indicators of psychological well-being, including positive emotionality and aspects of eudaimonic well-being, but also the absence of negative indicators of well-being such as negative emotionality, and indicators of psychopathology symptoms or diagnoses (see our definition of psychological well-being). Indicators of physical health, cognitive abilities, developmental improvements, or the use of certain coping or emotion regulation strategies were not considered as indicators of psychological well-being. Also measures reflecting peripheral phenomena of psychological well-being such as aspects of interpersonal behavior, social support or job satisfaction were excluded.

Fourth, in a few studies, the repeated emotion scores were used not only to calculate one or more measures of emotion dynamics but also to calculate a measure of overall or average emotionality as an indicator of psychological well-being (i.e., average positive or negative affectivity). In such cases, both the indicator of psychological well-being and the measure of emotion dynamics were calculated from the same data or sampled at the same time points. This may result in a possible a priori dependency between the two (due to shared method variance, floor or ceiling effects, etc.), may artificially affect effect sizes, and thus confound the true relationship between psychological well-being and emotion dynamics. To rule out such confounding factors, such effect sizes were excluded from the meta-analysis.

Fifth, the meta-analysis was limited to studies pertaining to human subjects. Finally, only studies that were published or communicated in English were included.

Selected Studies

All 2,380 articles resulting from the PsycInfo search, 35 articles/datasets resulting from the listservs requests, and all articles listed in reference lists of included articles and review articles related to the topic were evaluated on the above mentioned inclusion and exclusion criteria. The selection followed a two-step process. In the first step, an initial broad selection was performed, excluding articles that clearly did not meet selection criteria based on the title and/or abstract. More specifically, during the initial search, articles were excluded in case they were not empirical studies, if they focused on nonhuman participants, if they only focused on physiological measures of emotions, if they only used a retrospective questionnaire to assess emotion dynamics, if they only reported on longitudinal studies assessing emotions every few months/years, and if they clearly didn’t measure any indicator of psychological well-being in the study. Next, selected articles were thoroughly inspected to ascertain they met all inclusion and exclusion criteria. A final 79 articles/datasets were selected for inclusion in the meta-analysis, of which 54 articles resulted from the PsycINFO search, 12 (of which six unpublished datasets) from the requests to list serves, and 13 from reviewing reference lists. A brief look at

the distribution of selected research across the years shows that the first studies on this topic (and that met our criteria) only started to appear in the 1980s (with a few articles per year), after which there is an increase in published research on the topic.

To investigate the reliability of the selection process, a second independent rater (a doctoral-level student working as a researcher in the field of emotion dynamics) judged the relevance of 201 (approximately 8%) of the original collection of 2,380 articles based on the inclusion and exclusion criteria. Interrater agreement was lacking for only one of the 201 articles (resulting in a Kappa equal to .95). After discussion, perfect agreement was obtained.

Data Coding Categories

Each selected paper reported one or more associations between measures of emotion dynamics and indicators of psychological well-being, as defined in the inclusion criteria. Different forms of associations could be reported for example, correlations, regression coefficients, difference between group means, and so forth. From the 79 articles/datasets, we collected a total of 793 such associations, with the average paper reporting 10.04 associations ($SD = 12.56$, range = 1–66). Every association was coded separately on variables pertaining to features of the dynamic measure, methodological factors, emotion related factors, and the type of psychological well-being. An overview of all coded variables is shown in Table 1.

Dynamic measure. A first variable that was coded is (a) the type of pattern captured by the emotion dynamic measure, involving four categories reflecting the three types of measures of emotion dynamics that are most prevalent in the reviewed articles, and a fourth other-category. The first category refers to measures of variability (such as within-person standard deviation (SD) or vari-

ance); the second category refers to instability measures (including MSSD, mean absolute successive difference (MASD), and the square root of the mean square successive differences [RMSSD]); the third category refers to measures of inertia or auto-dependency of emotions (such as autocorrelations or autoregressive slopes). Finally, the fourth category combined all other infrequently used measures that all reflect some kind of emotional change over time. Examples are spin (representing how much a person moved between different angles in the core affect space), pulse (reflects how much an individual varies between experiencing more and less intense core affect), absolute velocity (the speed of change in emotion ratings), frequency of mood change, probability of acute change, proportion of difference scores higher than a certain threshold, and so forth. While this category might be more difficult to interpret, and as a consequence might be less meaningful, it is included to safeguard the comprehensiveness of the meta-analysis and included studies.

Sample characteristics. For each effect size, the corresponding (b) total sample size, (c) mean age of participants, (d) total percentage of male participants in the sample, and (e) whether or not data was collected in clinical populations, was recorded.

Article characteristics. For each effect size, (f) the publication year of the article, (g) the impact factor of the journal in which the article appeared, and (h) whether or not the article was published, were recorded.

Sampling protocol. Each effect size was coded for (i) the average time interval between two consecutive measurements, and (j) the number of emotion measurements per day.

Data collection. The (k) data collection method per effect size was coded using following categories: paper-and pencil diaries, portable electronic devices in daily life such as palmtop comput-

Table 1
Overview of Coded Variables in the Meta-Analytic Dataset Organized According to Higher Order Categories, With Reference to the Tables and/or Figures Where Results Can Be Found for Each Variable

Category and coded variable	Results
Dynamic measure	
a. Type of emotion dynamics	Table 2; Figure 2
Methodological factors	
Sample Characteristics	
b. Total sample size	In text; Figure 6
c. Mean age of participants	Table 3; Table 4
d. Total percentage male participants	Table 3; Table 4
e. Clinical versus nonclinical populations	Table 9
Article characteristics	
f. Publication year	Table 3; Table 4
g. Impact factor	Table 3; Table 4
h. Publication status	Table 10
Sampling protocol	
i. Average time interval between two consecutive measurements	Table 3; Table 4
j. Number of emotion measurements per day	Table 3; Table 4
Data collection	
k. Data collection method	Table 5
l. Standardized stimuli versus naturally occurring events	Table 5
Emotion related features	
m. Valence of the emotion	Table 6; Figure 3, 4, 5
Psychological well-being categorization	
n. Theoretical categorization of psychological well-being	Table 7; Figure 3a, 4a, 5a
o. Empirical categorization of psychological well-being	Table 8; Figure 3b, 4b, 5b

ers/smartphones, desktop computers (online questionnaires or software), and other data collection methods such as oral reporting using telephones or observation. Next, (l) whether emotional change was recorded in response to naturally occurring events (such as in daily life or ecological interactions in the lab) versus standardized stimuli in the lab, was recorded.

Emotion related features. Each effect size was coded for (m) valence of the emotion(s) under study, indicating whether higher scores on the emotion variable reflect higher positive or negative valence, using a positive emotion category, a negative emotion category, and a mixed/no valence category (which was applied when the dynamic measure was for instance based on composite measures of nonreverse coded positive and negative emotions, or on emotional states without explicit valence, like for instance arousal).

Psychological well-being categorization. Regarding psychological well-being, a wide range of different indicators of psychological well-being and psychopathology was reported across studies. To enable an informative and comprehensive reporting of the meta-analytic results across different types of psychological well-being, we categorized them according to both (n) a theoretically and (o) an empirically informed (e.g., most prevalent) criterion and report results for both categorizations. Summarizing the meta-analytic results for both a theoretically and empirically informed categorization of psychological well-being will allow to report results both in terms of theoretically meaningful higher order concepts while at the same time reporting results for relatively specific but often studied categories.

Theoretical categorization. As suggested by our definition, psychological well-being involves hedonic (focusing on the experience of positive feelings and pleasure, and the relative absence of negative feelings or displeasure) and eudaimonic (focusing on satisfaction with the self and finding purpose in life) aspects (Deci, & Ryan, 2008; Diener et al., 1999; Ryan, & Deci, 2001). Clinically, psychological well-being also involves the absence of psychiatric diagnoses or symptoms. In this respect, several psychopathological conditions are specifically relevant as they have emotion dysregulation at their core, such as depression, bipolar disorder and mania, anxiety disorders, borderline personality disorder, and externalizing disorders/behaviors (American Psychiatric Association, 2013).

Following the above distinctions, in the theoretically informed classification, we constructed the following subcategories of psychological well-being (for a recent example of a similar categorization of subtypes of psychological well-being, see Schmitt, Branscombe, Postmes, & Garcia, 2014). Two categories represent the two aspects of hedonic well-being. A first category is *positive emotionality*, including measures that focus on the experience of positive emotions, such as positive affectivity, extraversion², happiness, and subjective well-being; the second category is *negative emotionality* (which is negatively related to hedonic well-being) and reflects the experience of negative emotions, including measures of negative affectivity, negative affective symptoms and neuroticism. A third category refers to general indicators of *eudaimonic well-being* (focusing on satisfaction and functioning in life) such as satisfaction with life, satisfaction with day, self-esteem, and optimism. The fourth category contains measures related to *depression* diagnosis and symptom severity, also including suicidal symptoms, duration of a depressive episode, occur-

rence/recurrence of depressive episodes, premenstrual (dysphoric) disorder, recurrent brief depressive disorder, subthreshold depressive disorder diagnosis, dysthymia, and depressive adjustment reaction. The fifth category relates to *bipolar/mania symptoms*, such as hyperthymia symptoms, cyclothymia symptoms, hypomania symptoms, mania symptoms, and (hypo)manic episodes. The sixth category consists of *anxiety* symptoms and anxiety disorder diagnoses, also including social anxiety and fear for negative evaluations, anxious-fearful personality disorder symptoms, and posttraumatic stress disorder symptoms and diagnosis. The seventh category includes measures related to *borderline personality disorder* symptoms and diagnosis. The eighth category includes measures related to *externalizing behavior*, and includes conduct problems, problem behavior, and aggressive behavior. Last, the ninth category includes all psychological well-being measures that are not included in one of the previous eight categories. This theoretical categorization serves the purpose of informing conclusions about theoretical distinctions of psychological well-being, and is also comprehensive as it involves all the effect-sizes from the meta-analytic dataset.

Empirical categorization. We also constructed an empirically driven categorization based on the most frequently occurring types of psychological well-being reported in the literature. After coding each effect size for the specific type of psychological well-being as defined in the respective study, we selected those types for which at least two effect sizes were available for each dynamic pattern separately (variability, instability, and inertia), and counted at least 10 effect sizes in total. This resulted in the following empirically informed subcategories. The first category contains measures of *positive affectivity (PA)*; the second measures of *self-esteem*; the third measures of *satisfaction with life*; the fourth measures of *extraversion*; the fifth measures of *negative affectivity (NA)*; the sixth measures of *neuroticism*; the seventh refers to *minor depression diagnosis*, including diagnosis of dysthymia, depressive adjustment reaction, and sub threshold major depressive disorder; the eighth category contains measures of *depressive symptoms* in nonclinical or clinical populations; the ninth category refers to *major depressive disorder diagnosis*; the tenth category contains measures of *anxiety symptoms* in nonclinical and clinical populations; the eleventh measures of *borderline personality disorder (BPD) symptoms* in nonclinical and clinical populations; the twelfth category refers to *BPD diagnosis*. Moreover, a last category contains all other indicators of psychological well-being that are not included in one of the previous 12 categories.

Data Coding Reliability

To investigate the reliability of the coding process, a selection of 20 articles which corresponded to 176 effect sizes (25% of the total selection of included articles, 22% of the total number of included effect sizes) was randomly drawn from the total number of included articles that was already coded by the principal investigator, and was coded by two additional independent raters (Rater 1 and Rater 2, one of which was a doctoral-level student and one a research assistant, both working as researchers in affective sciences with spe-

² It could be argued that the experience of positive emotions is only one aspect of extraversion. For effect sizes that relate to positive affectivity and extraversion separately, we refer to the empirical categorization.

cific focus on emotion dynamics). Interrater reliability was examined by calculating Pearson correlation coefficients for variables coded on a continuous scale (e.g., number of measurement occasions, age, etc.), and Kappa coefficient for categorical variables (e.g., dynamic measure, psychological well-being category, etc.).

Across variables that were coded on a continuous scale, the average reliability correlation between the principal coder and Rater 1 was 0.98 ($SD = 0.03$), with all correlations being higher than 0.90. The average reliability correlation between the principal coder and Rater 2 was 0.99 ($SD = 0.01$), with all correlations being larger than .98. Moreover, the reliability between Rater 1 and Rater 2 for the continuous variables averaged .98 ($SD = 0.04$, $min = .90$). For the categorical variables, the mean Kappa between the principal coder and Rater 1 was .99 ($SD = 0.03$, $min = 0.84$), and .97 with Rater 2 ($SD = 0.04$, $min = 0.87$). Reliability between the two raters was .98 ($SD = 0.04$, $min = .80$). Combined, these results strongly show that high interrater agreement was obtained for all variables, suggesting high reliability of the coding process. Cases of disagreement were discussed between the raters on the one hand and the principal and senior investigator on the other hand until full agreement was obtained and resolved for use in the final analysis.

Preparation of Effect Sizes

Because the reported associations between emotion dynamics and psychological well-being took many different forms across studies (e.g., correlations, regression coefficients, difference between group means, etc.), it was necessary to align these on a same scale and make them directly comparable. Each association was converted into a common effect size, the Pearson's correlation coefficient (following methods and formulas proposed by Borenstein, Hedges, Higgins, & Rothstein, 2009; Lipsey & Wilson, 2001, and Rosenthal, 1994). In cases where essential statistical information was missing, requests for more statistical information were sent to the authors. We sent requests for a total of 11 articles, and received responses for eight articles. If the exact associations or p values were not reported or obtained and only the (in)significance of the association was available, a conservative approach was used by setting p values $> \alpha$ to .99, and p values $\leq \alpha$ to α .

The resulting set of correlations included different and not directly comparable directions of the relationship between emotion dynamics and psychological well-being. For example, one correlation may reflect the relation between variability (i.e., within-person SD) of an emotion and self-esteem (an indicator of high psychological well-being), while another correlation may reflect the association between variability of an emotion and depression (an indicator of low psychological well-being). To compare and interpret effect sizes across multiple studies, it is necessary that all correlations reflected the relation between emotion dynamics and psychological well-being in the same direction. Therefore, where necessary, the direction of each correlation coefficient was changed, so that each effect size reflected the relationship between a type of dynamic measure (variability, instability, inertia, or other dynamic measures) and higher levels of psychological well-being (e.g., higher levels of positive emotionality, extraversion, self-esteem, or happiness; absence of psychopathological diagnoses; lower levels of negative emotionality, neuroticism, psychopathological symptom severity, etc.). To line up all effect sizes concerning other dynamic measures, the direction of these correlation

coefficients was changed to reflect the relationship between a dynamic measure as indicating more emotional change and higher levels of psychological well-being. Finally, all correlations were Fisher's Z transformed to approximate a normal sampling distribution (Lipsey & Wilson, 2001).

Statistical Analysis

Random effects models were used to perform the meta-analysis (Raudenbush, 2009). Traditional random effects models assume that the observed effect sizes may not only vary because of sample variation (possibly unique for each effect size), but also because of differences between studies, resulting in two-level models. In the current meta-analysis, most studies reported more than one effect size (see higher). It is plausible that effect sizes from the same study are in general more similar than effect sizes from different studies, for instance because the effect sizes may be based on the same (type of) participants or because data are collected using the same methods. Therefore, we performed a three-level meta-analysis that adds another level that allows the effect sizes to be correlated within a study (Cheung, 2014). More specifically, to also take the dependency between effect sizes from the same study into account, we used three-level models to analyze the data, dealing with three sources of variance: variance between studies, variance between correlations from the same study, and sampling variance of the observed correlations (Hox, 2002; Van Den Noortgate, López-López, Marín-Martínez, & Sánchez-Meca, 2013; Cheung, 2014). The resulting models therefore include three residuals, each assumed to be normally distributed with zero mean:

$$T_{jk} = \theta + v_k + u_{jk} + e_{jk}$$

An observed effect size in study k , T_{jk} , is assumed to be equal to an overall population effect size, θ , plus a random deviation of the mean population effect size in study k from this overall population effect size, v_k , plus a random deviation of the j -th population effect in study k from the mean effect in this study, u_{jk} , plus a random error deviation of the observed effect size from the population effect, e_{jk} . All three residuals are assumed to follow a normal distribution with zero mean. Parameters that are estimated in the analysis are the overall effect size, and the variance of the population and study effect sizes, σ_v^2 and σ_u^2 . Typically, the sampling variance, σ_e^2 , is not to be estimated anymore in the meta-analysis but is considered as known, as for commonly used effect size measures it can be derived based on for example, the sample size. For Fisher's Z , for instance, it has been shown that the sampling variance is equal to $1/(N - 3)$, with N equal to the sample size (Lipsey & Wilson, 2001). Because individual effect sizes are analyzed, rather than the average effect size per study, the three-level approach allows for studying the size of variation between effect sizes from the same study, and to look for moderator variables that can explain this variation within studies. To that end, the model can easily be extended by including not only characteristics of the studies, but also characteristics of the effect sizes within studies as moderators. At the same time, the three-level analysis accounts for the overlap in information that is contributed by the effect sizes from the same study, and therefore avoids an artificial inflation of the power, and an increased Type I error rate. All analyses used the restricted maximum likelihood procedure implemented in PROC MIXED from SAS.

The different types of dynamic measures included in this meta-analysis (variability, instability, inertia, and other dynamic measures) convey qualitatively different information about patterns of emotional change. As a consequence, the measures cannot be aligned with each other. Therefore, we performed separate meta-analyses per type of dynamic measure.

Results

Overall Relation Between Emotion Dynamics and Psychological Well-Being

Before turning to the results from the multilevel meta-analysis, Figure 2 shows a graphical representation of all included effect-sizes in the meta-analytic dataset with corresponding 95% confidence intervals in the form of a caterpillar plot. In this caterpillar plot, for each type of dynamic measure all effect sizes with corresponding 95% confidence intervals are shown in ascending order, illustrating the rang of reported correlations between psychological well-being and each type of dynamic measure. Although there is clearly variability in the magnitude of the correlations for each dynamic measure, the majority of the correlations point to a negative relationship with psychological well-being. This is mainly the case for variability (i.e., *SD*), instability (i.e., *MSSD*), and inertia (i.e., autocorrelation) measures. For the category with other dynamic measures, effect sizes are more mixed.

Next, separately for each type of dynamic measure, we first estimated the overall correlation effect size based on empty (intercept-only) three-level models, quantifying the magnitude of the relationship between each type of dynamic measure and psychological well-being overall. The overall estimated correlations and the number of correlations included in each dynamic measure category are listed in Table 2. Note that all correlations mentioned

Table 2

Estimated Overall Fisher's Z Effect Size Correlations (Z_r) for the Relation Between Psychological Well-Being and Variability (i.e. Standard Deviation), Instability (i.e. Mean Square Successive Difference), Inertia (i.e. Autocorrelation), and Other Dynamic Measures

Dynamic measure	<i>N</i>	Z_r (<i>SE</i>)	<i>t</i> (<i>df</i>)	<i>p</i> -value
Variability	414	-.180 (0.028)	-6.41 (41.2)	<.001
Instability	146	-.208 (0.037)	-5.62 (19.9)	<.001
Inertia	120	-.152 (0.038)	-4.04 (18.6)	<.001
Other measures	113	-.096 (0.038)	-2.50 (6.93)	.041

in the tables are Fisher's Z transformed. For ease of interpretation, all correlations mentioned in the text are backward transformed to the normal correlation scale (denoted as $\hat{\rho}$). Results showed a significant negative association between variability ($\hat{\rho} = -.178$), instability ($\hat{\rho} = -.205$), and inertia ($\hat{\rho} = -.151$) on the one hand, and psychological well-being on the other hand, indicating that the more variable, unstable, but also the more self-predictive or inert one's emotions are, the lower one's psychological well-being is. The results from the other-category of dynamic measures reflecting less commonly used measures of emotional change also showed a significant negative relationship between more changeable emotions and psychological well-being ($\hat{\rho} = -.096$). The results imply that each pattern separately is related to psychological well-being.

In addition to the three-level hierarchical analyses reported above, we also performed more traditional analyses in which we first computed the mean effect size per study and used these as input for two-level models to compute the mean effect size across studies for each type of dynamic measure. Results show highly

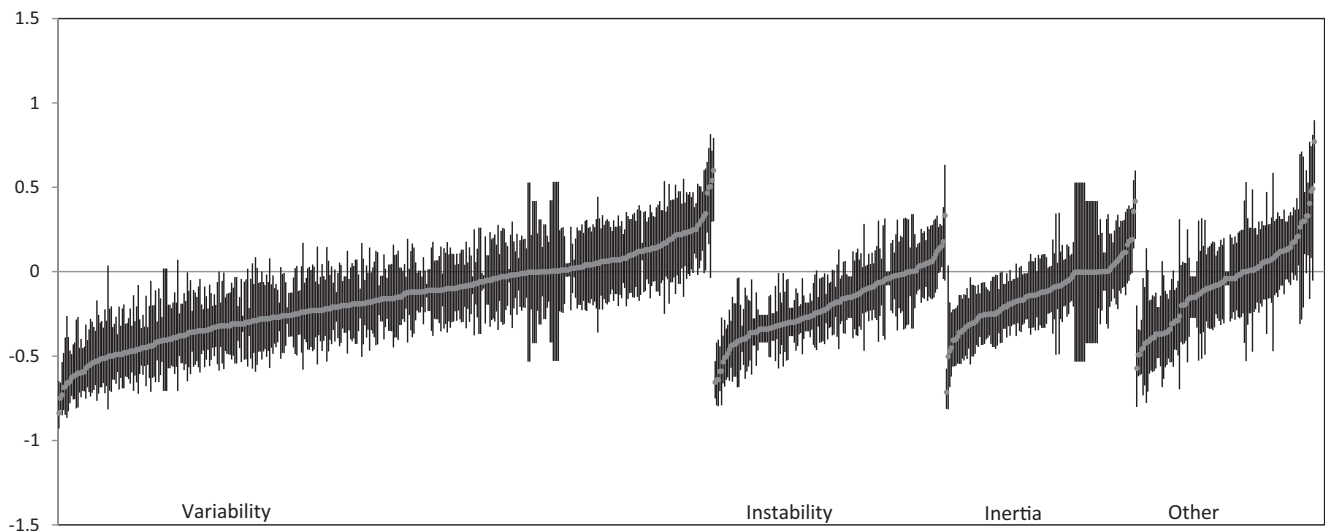


Figure 2. Caterpillar plot showing the magnitude of all effect sizes included in the meta-analysis with corresponding 95% confidence intervals (CI), backward transformed to the normal correlation scale, in ascending order, separately for effect sizes pertaining to the relation between psychological well-being and variability (i.e., standard deviation), instability (i.e., mean square successive difference), inertia (i.e., autocorrelation), and other dynamic measures.

similar results. For variability, the estimated mean effect size was $-.176$ ($SE = 0.028$, $t(44.2) = -6.19$, $p < .001$; $\hat{\rho} = -.174$). For instability, mean effect size was $-.208$ ($SE = 0.038$, $t(20.8) = -5.48$, $p < .001$; $\hat{\rho} = -.205$). For inertia, mean effect size was $-.154$ ($SE = 0.038$, $t(17.3) = -4.05$, $p = .001$; $\hat{\rho} = -.153$). For other dynamic measures, mean effect size was $-.127$ ($SE = 0.038$, $t(10.1) = -3.35$, $p = .007$; $\hat{\rho} = -.126$).

Heterogeneity in Effect Sizes

Next, based on variance estimates from the empty models, we examined the heterogeneity in effect sizes, both between studies and between effect sizes from the same study for each type of dynamic measure. Quantifying the variation between effect sizes between studies and within studies will give us clues to whether it is useful to add potential moderators to subsequent models to explain observed variation in effect sizes. For variability measures, significant variation between studies was found ($\hat{\sigma}^2 = 0.033$, $\chi^2(1) = 87.2$, $p < .001$) as well as between effect sizes from the same study ($\hat{\sigma}^2 = 0.024$, $\chi^2(1) = 474.3$, $p < .001$). Variance at level-1, the sampling variance, depends on the sample size of the study. Therefore, we looked at the median estimated value, which was 0.014. Together, this implies that for the median study, approximately 46% of the total variance in observed effect sizes is accounted for by variance between studies, approximately 34% by variance between effect sizes of the same study, and approximately 20% by random sampling variance.

For instability measures, significant variation between studies ($\hat{\sigma}^2 = 0.024$, $\chi^2(1) = 57.8$, $p < .001$) and between effect sizes from the same study was found ($\hat{\sigma}^2 = 0.008$, $\chi^2(1) = 39$, $p < .001$). The estimated sampling variance was 0.011. Consequently, 56% of the total variance in effect sizes was accounted for by variance between studies, approximately 19% by variance between effect sizes of the same study, and approximately 26% by random sampling variance.

For inertia measures, significant variation between studies ($\hat{\sigma}^2 = 0.024$, $\chi^2(1) = 65.1$, $p < .001$) but almost no variation between effect sizes from the same study was found ($\hat{\sigma}^2 = 0.001$, $\chi^2(1) = 0.5$, $p = .480$). The estimated sampling variance was 0.011. Consequently, 67% of the total variance was accounted for by variance between studies, 3% by variance between effect sizes of the same study, and approximately 31% by random sampling variance.

Finally, for other dynamic measures, significant variation between studies ($\hat{\sigma}^2 = 0.014$, $\chi^2(1) = 7$, $p = .008$) and between effect sizes from the same study was found ($\hat{\sigma}^2 = 0.025$, $\chi^2(1) = 76.1$, $p < .001$). The estimated sampling variance was 0.017. Consequently, 25% of the total variance was accounted for by variance between studies, 45% by variance between effect sizes of the same study, and approximately 30% by random sampling variance.

In conclusion, in most cases considerable variance is observed between effect sizes within and/or between studies. This points to substantial differences in observed effect sizes both within studies and/or between studies. In a next series of models, we investigated how such differences in observed effect sizes might be moderated by additional variables.

Methodological Factors

We investigated whether and how methodological factors affect the relation between the different dynamic measures and psychological well-being by including these factors as covariates in the three-level models.

Sample characteristics. Descriptive statistics for mean age of the sample and percentage males in the sample for each type of dynamic measure across studies are shown in Table 3. Separate models were estimated that examined the effect of mean age of the sample and percentage males in the sample on the overall effect size for each type of dynamic measure. The results are presented in Table 4.

Mean age of the sample showed no significant effect on the relationship between emotion dynamics and psychological well-being for any of the measures. Percentage of males in the sample positively moderated the effect size only for variability measures, in the sense that less negative correlations were found between variability and psychological well-being as the study sample consisted of more males.

Article characteristics. Descriptive statistics of publication year of the article and impact factor of the journal in which the data was published are shown in Table 3. The effects of each of these factors on the overall correlation for each dynamic measure separately are shown in Table 4. Neither publication year nor impact factor was significantly related to the correlation between any type of dynamic measure and psychological well-being.

Sampling protocol. The effect of two characteristics related to the sampling protocol was investigated: average time interval between consecutive emotion ratings and number of emotion measurements per day. Descriptive statistics for the average time interval between consecutive measurements and the number of measurements per day are shown in Table 3. Analyses revealed that neither the average time interval between consecutive measurements nor the number of measurements per day had a significant effect on the relationship between any of the dynamic measures and psychological well-being (see Table 4).

Data collection. Last, we investigated the effect of different data collection methods such as paper-and-pencil versus electronic diaries and so forth, and the use of standardized stimuli to investigate emotional change over time, versus the examination of naturalistic occurrence of emotions (either in the lab or daily life).

Overall tests for variability, instability, inertia, and other dynamic measures indicated that there were no significant effects of data collection method on the correlation between each type of dynamic measure and psychological well-being, $F(3, 67.5) = 1.38$, $p = .256$; $F(2, 26.2) = 0.18$; $p = .839$; $F(3, 39.4) = 0.97$; $p = .416$; $F(3, 11.1) = 0.98$; $p = .439$, respectively. Table 5 shows the estimated correlation between each type of dynamic measure and psychological well-being for each type of data collection method, and the number of correlations included for each category. Note that no data were available for instability measures based on other data collection methods such as oral emotional ratings. Despite the overall nonsignificant effects of data collection method for variability, instability, and inertia, we found significant relationships with psychological well-being in case data was collected using paper diaries, using portable electronic devices in daily life, or using other data collection methods such as oral reporting using telephones or observation, but only marginally significant or non-

Table 3
Descriptive Statistics for all Quantitative Methodological Factors in Studies Pertaining to the Relation Between Psychological Well-Being and Variability (i.e. Standard Deviation [SD]), Instability (i.e. Mean Square Successive Difference), Inertia (i.e. Autocorrelation), and Other Dynamic Measures

	Variability			Instability			Inertia			Other measures						
	Mean	Median	SD	Range	Mean	Median	SD	Range	Mean	Median	SD	Range				
Sample characteristics																
Mean age	29.07	27.00	13.20	12.67–82.80	27.96	28.21	9.36	13.37–55.91	25.59	24.31	8.07	12.47–42.40	31.38	30.99	9.11	20.25–46.45
Percentage males	29.52	35.28	21.22	0–100	30.83	32.33	20.40	0–77.77	35.29	37.37	27.68	0–100	25.18	22.22	20.64	0–61.19
Article characteristics																
Publication year		2002.50				2009.50				2007.00				2004.50		
Impact factor	3.21	3.00	1.90	0.58–12.76	4.05	3.34	2.73	1.67–12.76	3.20	2.52	2.69	0.98–12.76	3.83	3.01	3.21	0.96–12.76
Sampling protocol																
Mean time interval between measurements (hours)	14.08	9.56	15.48	0.00–84	8.09	1.75	9.97	0.05–24	6.07	2.00	9.03	0.00–24	12.70	12.00	11.80	0–34
Measurements per day	4.95	3.33	5.25	1–30	8.07	6.00	11.12	1–54	8.14	7.50	6.94	1–27	5.34	4.00	7.23	1–30

Note. The results are based on values that were first aggregated within studies in case multiple effect sizes were reported per study.

Table 4
The Effect of Quantitative Methodological Factors on Correlation Effect Size for the Relation Between Psychological Well-Being and Variability (i.e. Standard Deviation [SD]), Instability (i.e. Mean Square Successive Difference), Inertia (i.e. Autocorrelation), and Other Dynamic Measures

	Variability			Instability			Inertia			Other measures		
	Estimate (SE)	t-value (df)	p-value	Estimate (SE)	t-value (df)	p-value	Estimate (SE)	t-value (df)	p-value	Estimate (SE)	t-value (df)	p-value
Sample characteristics												
Mean age	-0.001 (0.003)	-0.55 (26.4)	.584	0.006 (0.004)	1.55 (16.9)	.139	0.009 (0.005)	1.67 (30.8)	.104	-0.006 (0.007)	-0.94 (7.26)	.376
Percentage males	0.002 (0.001)	2.32 (273)	.021	0.001 (0.002)	0.84 (42.6)	.405	0.001 (0.002)	0.69 (25.9)	.494	-0.001 (0.001)	-0.81 (79.6)	.420
Article characteristics												
Publication year	-0.003 (0.004)	-0.68 (45.6)	.497	0.006 (0.008)	0.79 (17)	.440	-0.006 (0.005)	-1.31 (15.4)	.208	0.001 (0.006)	0.19 (7.03)	.852
Impact factor	-0.008 (0.016)	-0.50 (37.2)	.622	-0.011 (0.016)	-0.64 (17.2)	.530	0.000 (0.018)	0.02 (16.8)	.985	0.008 (0.016)	0.52 (10.1)	.615
Sampling protocol												
Mean time interval between measurements	0.000 (0.002)	0.30 (86.4)	.768	-0.004 (0.004)	-0.96 (16.6)	.353	-0.002 (0.004)	-0.53 (20.2)	.605	0.001 (0.003)	0.33 (27.1)	.744
Measurements per day	0.002 (0.002)	1.05 (358)	.296	-0.001 (0.003)	-0.36 (29)	.725	-0.003 (0.003)	-0.96 (112)	.341	-0.000 (0.002)	-0.26 (86.9)	.796

Table 5
Estimated Fisher's Z Correlations (Z_r) for the Relation Between Psychological Well-Being and Variability (i.e. Standard Deviation [SD]), Instability (i.e. Mean Square Successive Difference), Inertia (i.e. Autocorrelation), and Other Dynamic Measures as a Function of Data Collection Method, and as a Function of Whether the Emotional Change Was Measured in Response to the Presentation of Standardized Stimuli in the Lab, or Nonstandardized Stimuli in the Lab or in Daily Life

Data collection method	Variability			Instability			Inertia			Other measures						
	N	Z _r (SE)	t (df)	p-value	N	Z _r (SE)	t (df)	p-value	N	Z _r (SE)	t (df)	p-value				
Paper diaries	239	-.200 (0.033) _a	-6.00 (49.5)	<.001	46	-.225 (0.051) _a	-4.41 (28.8)	<.001	43	-.114 (0.047) _a	-2.41 (28.3)	.023	50	-.107 (0.056) _a	-1.92 (8.85)	.088
Portable elect devices	88	-.144 (0.064) _a	-2.25 (57.7)	.028	67	-.206 (0.053) _a	-3.90 (27.3)	<.001	69	-.177 (0.048) _a	-3.66 (23.6)	.001	36	-.042 (0.083) _a	-0.50 (4.04)	.644
Computer	45	-.097 (0.057) _a	-1.69 (91)	.095	29	-.161 (0.101) _a	-1.60 (16.2)	.129	2	-.178 (0.177) _a	-1.01 (18.1)	.326	21	-.070 (0.065) _a	-1.09 (11.1)	.300
Other	30	-.274 (0.119) _a	-2.30 (37.5)	.027	0				6	-.247 (0.073) _a	-3.39 (57.6)	.001	2	-.420 (0.216) _a	-1.95 (21.8)	.065
Type of stimuli																
Standardized	2	-.211 (0.226) _a	-0.94 (60.2)	.353	2	-.106 (0.185) _a	-0.58 (24)	.570	2	-.178 (0.177) _a	-1.01 (18.8)	.327	0			
Nonstandardized	412	-.179 (0.029) _a	-6.28 (40.3)	<.001	144	-.213 (0.038) _a	-5.53 (18.9)	<.001	118	-.150 (0.039) _a	-3.81 (17.7)	.001				

Note. Effect sizes in the same column (separate for data collection methods, and type of stimuli) that do not share subscripts differ at $p < .05$, after Bonferroni correction for multiple comparisons.

significant relationships in case data was collected using computers (e.g., online questionnaires or software; Table 5). However, pairwise comparisons indicated no significant differences between the estimated effect sizes for different data collection methods (Table 5, subscripts). For other dynamic measures, only marginally significant or nonsignificant relationships with psychological well-being were found, for all methods of data collection.

Table 5 shows the estimated effect sizes for the relation between psychological well-being and variability, instability and inertia if data were collected in response to standardized stimuli versus in naturalistic settings. Overall tests indicated no significant effect for variability measures, $F(1, 59.8) = 0.02$; $p = .890$; instability measures, $F(1, 23.7) = 0.32$; $p = .578$; and inertia measures, $F(1, 18.8) = 0.02$; $p = .880$. Note that for other dynamic measures there was no data available to investigate the effect of this moderator. While not many effect sizes based on standardized stimuli were available, these results nonetheless indicate that based on the available evidence, effect sizes do not dramatically differ when the type of context in which emotion dynamics are observed is controlled or not.

Valence of Emotions

We next investigated per dynamic measure whether negative and positive emotion dynamics are differently related to psychological well-being. Table 6 lists the estimated correlations between each type of dynamic measure and psychological well-being, as a function of the valence of the emotion, and the number of correlations included in each category.

For variability measures, valence showed a strong significant main effect $F(2, 348) = 39.61$, $p < .001$. While results indicate a significant negative association between variability and psychological well-being for both positive and negative emotions, and also for mixed/no valence states (see Table 6), pairwise comparisons with Bonferroni correction for multiple testing indicated that the relationship between variability and psychological well-being was significantly stronger when based on negative emotions, compared with positive emotions and mixed/no valence states (Table 6, subscripts).

For instability and inertia measures, valence also showed a strong significant main effect ($F(2, 86.6) = 15.56$, $p < .001$ for instability; $F(2, 117) = 10.73$, $p < .001$ for inertia). For both measures, while a significant negative relationship with psychological well-being was found for both positive and negative emotions, but not for the mixed/no valence category, pairwise comparisons with Bonferroni correction for multiple testing indicated that both for instability and inertia, the relationship with psychological well-being was significantly larger when based on negative emotions, compared with positive emotions (Table 6, subscripts). No significant differences were found with mixed/no valence category.

For the other dynamic measures, valence had no effect on the overall correlation with psychological well-being, $F(2, 60.9) = 0.18$, $p = .838$. For these less commonly used measures of emotion dynamics, no significant relationships were found with psychological well-being for any of the valence categories (see Table 6).

Table 6
Estimated Fisher's Z Correlations (Z_r) for the Relation Between Psychological Well-Being and Variability (i.e. Standard Deviation [SD]), Instability (i.e. Mean Square Successive Difference), Inertia (i.e. Autocorrelation), and Other Dynamic Measures as a Function of Valence of the Emotion

Valence	Variability			Instability			Inertia			Other measures						
	N	$Z_r(SE)$	t (df)	p-value	N	$Z_r(SE)$	t (df)	p-value	N	$Z_r(SE)$	t (df)	p-value				
Positive	194	-.103 (0.029) _a	-3.53 (50.9)	<.001	61	-.145 (0.038) _a	-3.81 (24.1)	<.001	55	-.107 (0.040) _a	-2.70 (22.1)	.013	39	-.095 (0.055) _a	-1.74 (11.4)	.109
Negative	167	-.284 (0.030) _b	-9.51 (54.6)	<.001	81	-.270 (0.037) _b	-7.27 (21.7)	<.001	59	-.196 (0.039) _b	-5.01 (21.1)	<.001	11	-.157 (0.111) _a	-1.42 (41.4)	.163
Mixed/no	52	-.086 (0.043) _a	-2.01 (171)	.046	4	-.062 (0.101) _{a,b}	-0.61 (66.2)	.542	6	-.037 (0.092) _{a,b}	-0.40 (117)	.691	63	-.088 (0.051) _a	-1.74 (7.29)	.125

Note. Effect sizes in the same column that do not share subscripts differ at $p < .05$, after Bonferroni correction for multiple comparisons.

Psychological Well-Being Categories

Next, we examined for each type of dynamic measure how the effect sizes differ as a function of the specific type of psychological well-being being considered. This was done separately for the theoretically informed categorization of types of psychological well-being as the empirically informed categorization.

The results showed a strong main effect of both types of psychological well-being categorizations for variability measures ($F(8, 287) = 10.49, p < .001$ for theoretical psychological well-being categories; $F(12, 273) = 7.87, p < .001$ for empirical psychological well-being categories) and for instability measures ($F(8, 78.4) = 5.04, p < .001$ for theoretical psychological well-being categories; $F(12, 73.8) = 4.80, p < .001$ for empirical psychological well-being categories). The estimated correlations between each type of dynamic measure and each category of psychological well-being (and the number of correlations in each category) are shown in Table 7 for the theoretical categorization of psychological well-being and Table 8 for the empirical categorization of psychological well-being.

When considering the theoretical categorization of psychological well-being (see Table 7), for both variability and instability, a significant negative correlation with psychological well-being was found for all different psychological well-being categories, except for positive emotionality, and only a marginally significant relationship was found between instability and bipolar/mania symptoms. This means that both variability and instability are positively related to negative emotionality, externalizing behavior, depression, bipolar/mania symptoms (only marginally for instability), anxiety symptoms, borderline personality disorder, and negatively related to eudaimonic well-being and other indicators of high psychological well-being. Pairwise comparisons with Bonferroni correction for multiple testing did indicate that for variability, the correlation with positive emotionality was significantly weaker than the correlations with all other psychological well-being categories, except for externalizing behavior and bipolar/mania symptoms. For instability, the correlation with positive emotionality was also significantly weaker than the correlation with all other psychological well-being categories, with the exception of eudaimonic well-being, externalizing behavior, and bipolar/mania symptoms (Table 7, subscripts).

When considering the empirical categorization of psychological well-being (see Table 8), we found that variability and instability showed (marginally) significant associations with all psychological well-being categories, except for PA and extraversion. Variability and instability are positively related to NA, neuroticism, minor depression diagnosis, depressive symptoms and diagnosis, anxiety symptoms, BPD symptoms and diagnosis, and are negatively related to self-esteem (only marginally for instability measures), satisfaction with life, and other indicators of high psychological well-being. Pairwise comparison tests for variability showed that the correlation with PA was significantly lower than the correlation with NA. Moreover, the correlation with extraversion was significantly lower than the correlations with all other psychological well-being categories, with the exception of PA, satisfaction with life, depressive diagnosis, and BPD diagnosis (Table 8, subscripts). For instability, pairwise comparison tests showed that the correlation with PA was significantly lower than the correlation with NA, depressive symptoms, anxiety symptoms,

Table 7
Estimated Fisher's Z Correlations (Z_r) for the Relation Between Psychological Well-Being and Variability (i.e. Standard Deviation [SD]), Instability (i.e. Mean Square Successive Difference), Inertia (i.e. Autocorrelation), and Other Dynamic Measures as a Function of Type of Psychological Well-Being According to the Theoretical Categorization

Psychological well-being	Variability				Instability				Inertia				Other measures			
	N	Z_r (SE)	t (df)	p-value	N	Z_r (SE)	t (df)	p-value	N	Z_r (SE)	t (df)	p-value	N	Z_r (SE)	t (df)	p-value
Positive emotionality	71	.018 (0.034) _b	0.53 (105)	<.001	14	-.020 (0.047) _b	-0.43 (51.9)	.668	8	-.184 (0.052) _a	-3.53 (42.2)	.001	29	-.046 (0.054) _a	-0.85 (17.8)	.408
Negative emotionality	84	-.201 (0.032) _a	-6.22 (89.9)	<.001	17	-.231 (0.046) _a	-5.00 (53.2)	<.001	14	-.152 (0.048) _a	-3.17 (35.4)	.003	24	-.126 (0.058) _a	-2.15 (20.7)	.043
Eudaimonic well-being	44	-.120 (0.037) _a	-3.25 (137)	.002	13	-.134 (0.046) _{a,b}	-2.89 (53.7)	.006	20	-.169 (0.047) _a	-3.59 (33)	.001	22	-.080 (0.062) _a	-1.29 (21.5)	.211
Depression	92	-.233 (0.035) _a	-6.74 (103)	<.001	55	-.233 (0.036) _a	-6.46 (26.5)	<.001	33	-.179 (0.044) _a	-4.05 (25.4)	<.001	11	.010 (0.077) _a	0.13 (46.6)	.895
Bipolar/mania symptoms	3	-.314 (0.116) _{a,b}	-2.71 (290)	.007	3	-.193 (0.110) _{a,b}	-1.75 (137)	.082	0				3	-.298 (0.125) _a	-2.38 (65.7)	.020
Anxiety	31	-.250 (0.044) _a	-5.69 (205)	<.001	20	-.234 (0.043) _a	-5.47 (44.9)	<.001	8	-.091 (0.055) _a	-1.66 (48.5)	.103	1	-.128 (0.180) _a	-0.71 (49.7)	.479
Borderline personality disorder	26	-.262 (0.051) _a	-5.12 (229)	<.001	8	-.310 (0.066) _a	-4.71 (83)	<.001	20	-.104 (0.053) _a	-1.95 (38.3)	.058	9	-.376 (0.122) _a	-3.10 (47)	.003
Externalizing behavior	7	-.285 (0.094) _{a,b}	-3.04 (328)	.003	8	-.205 (0.051) _{a,b}	-4.03 (55)	<.001	0				0			
Other psychological well-being	56	-.196 (0.038) _a	-5.18 (141)	<.001	8	-.205 (0.053) _a	-3.86 (75.8)	<.001	17	-.163 (0.052) _a	-3.12 (41.8)	.003	14	-.084 (0.081) _a	-1.03 (44.3)	.310

Note. Effect sizes in the same column that do not share subscripts differ at $p < .05$, after Bonferroni correction for multiple comparisons. Note that all Fisher's Z correlations reflect the relationship between each type of dynamic measure and high psychological well-being. As a consequence, the interpretation of the direction of the correlation should be reversed for all indicators of low psychological well-being and psychopathology.

BPD symptoms, and other indicators of high psychological well-being. Moreover, the correlation with extraversion was significantly lower than the correlation with NA, neuroticism, depressive symptoms, anxiety symptoms, BPD symptoms, and other indicators of high psychological well-being (Table 8, subscripts).

In contrast to variability and instability measures, no significant effect of the type of psychological well-being was found for inertia measures, using either the theoretically informed categorization ($F(6, 42) = 1.06, p = .401$) or the empirically informed one, ($F(12, 41.4) = 0.99, p = .477$).

From the theoretical categorization (see Table 7), results showed that inertia is positively related to negative emotionality and depression, marginally positively related to borderline personality disorder, and negatively related to positive emotionality, eudaimonic well-being, and other indicators of high psychological well-being. Note that no data were available concerning the relationship between inertia, and externalizing behavior and bipolar/mania symptoms. Pairwise comparison tests with Bonferroni correction showed that the correlations for different psychological well-being categories were not significantly different from each other (Table 7, subscripts), which is in line with the nonsignificant overall test.

Considering the empirical categorization of psychological well-being (see Table 8), inertia was positively related to neuroticism, depressive symptoms and diagnosis, and BPD diagnosis, and marginally positively related to NA. Additionally, it was negatively related to PA, self-esteem, satisfaction with life, extraversion, and other indicators of high psychological well-being. Pairwise comparisons again showed that correlations for different psychological well-being categories did not significantly differ from each other (Table 8, subscripts).

Last, for other less commonly used dynamic measures we found a marginally significant effect of type of psychological well-being for only the theoretical categorization of psychological well-being ($F(7, 73.3) = 2.02, p = .064$ for theoretical categorization of psychological well-being; $F(10, 75.5) = 1.45, p = .177$ for empirical categorization of psychological well-being). Note that for some psychological well-being categories, no data were available (see Table 7 and Table 8).

Based on the theoretical categorization of psychological well-being, for less commonly used operationalizations of emotional change, significant positive associations were found between emotions that are more changeable, as measured by several heterogeneous indicators, and negative emotionality, bipolar/mania symptoms, and borderline personality disorder (see Table 7). However, pairwise comparisons indicated no significant differences between the correlations with different psychological well-being categories (Table 7, subscripts).

For the empirical categorization of psychological well-being (see Table 8), significant associations between more changeable emotions and NA, BPD diagnosis, and a marginally significant association with other indicators of high-psychological well-being were found, as the correlations showed that more changeable emotions were related to higher NA and BPD diagnosis, and marginally related to lower psychological well-being, as indicated by various measures of high psychological well-being. Again, no significant differences were found between correlations with different psychological well-being categories (Table 8, subscripts).

Table 8
Estimated Fisher's Z Correlations (Z_r) for the Relation Between Psychological Well-Being and Variability (i.e. Standard Deviation [SD]), Instability (i.e. Mean Square Successive Difference), Inertia (i.e. Autocorrelation), and Other Dynamic Measures as a Function of Type of Psychological Well-Being, According to the Empirical Categorization

	Variability				Instability				Inertia				Other measures			
	N	Z _r (SE)	t (df)	p-value	N	Z _r (SE)	t (df)	p-value	N	Z _r (SE)	t (df)	p-value	N	Z _r (SE)	t (df)	p-value
Psychological well-being	20	-.054 (0.051) _{ab}	-1.07 (247)	.288	4	.020 (0.065) _{b,c,d}	0.30 (96.1)	.761	4	-.195 (0.059) _a	-3.30 (46.3)	.002	8	-.019 (0.087) _a	-0.21 (49.9)	.831
Positive affectivity	26	-.136 (0.044) _{bc}	-3.07 (178)	.003	4	-.109 (0.065) _{ab,b,c}	-1.68 (96.1)	.096	14	-.155 (0.050) _a	-3.13 (40.6)	.003	13	-.080 (0.084) _a	-0.95 (31.6)	.351
Self-esteem	14	-.129 (0.053) _{abc}	-2.45 (222)	.015	8	-.185 (0.049) _{ab,b,c}	-3.77 (55.1)	<.001	6	-.151 (0.054) _a	-2.78 (47.7)	.008	6	-.085 (0.093) _a	-0.91 (56.2)	.369
Satisfaction with life	44	.062 (0.040) _b	1.55 (147)	.124	9	.004 (0.056) _{b,c}	0.07 (70.7)	.942	4	-.139 (0.061) _a	-2.27 (43.3)	.028	16	-.023 (0.071) _a	-0.32 (27.3)	.748
Extraversion	21	-.248 (0.049) _c	-5.06 (230)	<.001	4	-.358 (0.065) _a	-5.51 (96.1)	<.001	4	-.114 (0.059) _a	-1.92 (46.3)	.061	8	-.201 (0.087) _a	-2.32 (49.9)	.024
Negative affectivity	61	-.179 (0.036) _{ac}	-4.91 (113)	<.001	13	-.177 (0.049) _{ad}	-3.59 (59.4)	.001	10	-.149 (0.050) _a	-3.00 (41.8)	.005	16	-.070 (0.071) _a	-0.98 (27.3)	.335
Neuroticism	16	-.302 (0.074) _{bc}	-4.07 (322)	<.001	4	-.306 (0.086) _{ab,b,c}	-3.56 (133)	.001	4	-.087 (0.081) _a	-1.07 (107)	.289	0			
Minor depression diagnosis	38	-.244 (0.041) _{bc}	-5.98 (156)	<.001	26	-.237 (0.039) _a	-6.09 (34)	<.001	12	-.189 (0.048) _a	-3.92 (37.2)	<.001	4	-.078 (0.103) _a	-0.76 (61.7)	.450
Depressive symptoms	29	-.157 (0.058) _{ab,b,c}	-2.69 (194)	.008	8	-.237 (0.068) _{ab,b,c}	-3.48 (121)	.001	13	-.139 (0.053) _a	-2.63 (42.8)	.012	1	.300 (0.263) _a	1.14 (102)	.257
Depression diagnosis	13	-.242 (0.056) _{bc}	-4.34 (225)	<.001	15	-.244 (0.042) _a	-5.79 (41.9)	<.001	6	-.061 (0.056) _a	-1.09 (45.9)	.281	1	-.154 (0.183) _a	-0.84 (50.2)	.404
Anxiety symptoms																
Borderline personality disorder symptoms	13	-.278 (0.059) _{bc}	-4.70 (258)	<.001	2	-.310 (0.077) _a	-4.05 (80.5)	<.001	4	-.053 (0.062) _a	-0.85 (36.3)	.399	0			
Borderline personality disorder diagnosis	13	-.237 (0.095) _{ab,b,c}	-2.50 (267)	.013	6	-.321 (0.104) _{ab,b,c}	-3.08 (51.2)	.003	16	-.205 (0.076) _a	-2.68 (40.4)	.011	9	-.391 (0.124) _a	-3.15 (66.5)	.003
Other psychological well-being	106	-.222 (0.032) _{bc}	-6.93 (82.6)	<.001	43	-.217 (0.037) _a	-5.90 (28)	<.001	23	-.156 (0.046) _a	-3.40 (35.9)	.002	31	-.103 (0.059) _a	-1.74 (21.5)	.096

Note. Effect sizes in the same column that do not share subscripts differ at $p < .05$, after Bonferroni correction for multiple comparisons. Note that all Fisher's Z correlations reflect the relationship between each type of dynamic measure and high psychological well-being. As a consequence, the interpretation of the direction of the correlation should be reversed for all indicators of low psychological well-being and psychopathology.

Use of Clinical Sample

We examined whether the overall relationship between each type of dynamic measure and psychological well-being differed depending on whether the study involved clinical or nonclinical populations. Correlations for clinical populations versus nonclinical populations and number of correlations in each category are presented in Table 9. Analyses indicated significant relationships between variability, instability and inertia on the one hand, and psychological well-being on the other hand, both for clinical and nonclinical populations. Additionally, for instability and inertia measures, the estimated difference between the correlations for the two populations was nonsignificant (estimated difference = 0.056, SE = 0.047, $p = .233$ for instability; estimated difference = 0.000, SE = 0.039, $p = .997$ for inertia; also see Table 9, subscripts). However, it was significant for variability measures (estimated difference = 0.104, SE = 0.048, $p = .030$; also see Table 9, subscripts), indicating that the association between variability and psychological well-being was stronger when the data were collected in clinical populations. For other dynamic measures, the effect sizes were nonsignificant for both clinical and nonclinical groups, and the difference between the two was also nonsignificant (estimated difference = -0.045, SE = 0.093, $p = .644$).

In the next step, we examined whether clinical populations showed a significant interaction with psychological well-being categories, as the difference between the use of nonclinical versus clinical samples may be particularly relevant for some of the psychological well-being categories only. Results indicated no significant interactions for instability measures ($F(3, 130) = 0.08, p = .973$ for theoretical categorization; $F(2, 130) = 1.33, p = .269$ for empirical categorization), for inertia measures ($F(2, 85.8) = 1.88, p = .159$ for theoretical categorization; $F(1, 16.7) = 0.64, p = .437$ for empirical categorization), and for other dynamic measures ($F(2, 69) = 1.32, p = .275$ for theoretical categorization; F could not be estimated for empirical categorization).

For variability measures, we did see a (marginally) significant interaction between psychological well-being categories and the use of clinical versus nonclinical population ($F(5, 318) = 2.11, p = .064$ for theoretical categorization; $F(1, 399) = 5.02, p = .026$ for empirical categorization). When investigating this interaction in closer detail, we found that for the theoretical categorization, effect sizes for negative emotionality, depression, bipolar/mania symptoms, and anxiety were higher in clinical compared with nonclinical groups. For other indicators of psychological well-being and borderline personality disorder, the opposite holds. However, when using pairwise comparisons with adjusted Bonferroni correction, the difference between clinical and nonclinical populations was only meaningful for bipolar/mania symptoms.

For the empirical categorization, the interaction seemed to be driven by the estimated effect sizes for depressive symptoms and other indicators of psychological well-being being stronger for clinical than nonclinical populations. However, pairwise comparisons with Bonferroni correction indicated that only the difference for depressive symptoms was significant.

Table 9
Estimated Fisher's Z Correlations (Z_r) for the Relation Between Psychological Well-Being and Variability (i.e. Standard Deviation [SD]), Instability (i.e. Mean Square Successive Difference), Inertia (i.e. Autocorrelation), and Other Dynamic Measures as a Function of the Use of Clinical Populations

Population	Variability			Instability			Inertia			Other measures						
	N	Z_r (SE)	t (df)	p-value	N	Z_r (SE)	t (df)	p-value	N	Z_r (SE)	t (df)	p-value				
Clinical	92	-.257 (0.045) _a	-5.75 (92.4)	<.001	39	-.242 (0.046) _a	-5.22 (38.7)	<.001	41	-.152 (0.045) _a	-3.34 (32.9)	.002	27	-.064 (0.080) _a	-0.80 (11.2)	.443
Nonclinical	318	-.153 (0.030) _b	-5.16 (47.1)	<.001	107	-.185 (0.041) _a	-4.52 (24.8)	<.001	79	-.152 (0.040) _b	-3.77 (22.3)	.001	86	-.108 (0.048) _a	-2.27 (6.22)	.062

Note. Effect sizes in the same column that do not share subscripts differ at $p < .05$.

Dynamic Signature of Psychological Well-Being Categories

Finally, it may be informative for researchers in the domain to have a detailed picture of the meta-analytic effect sizes of how specific emotion dynamic measures relate to specific types of psychological well-being as a function of valence of the emotions. Figures 3–5 graphically report the effect sizes as a function of valence and psychological well-being category (both for the theoretical and empirical categorizations), separately for each type of dynamic measure (excluding the other category as this is less informative). Results based on the theoretical categorization are shown in Figures 3a–5a, and results for the empirical categorization are shown in Figures 3b–5b. While it is not our intention to discuss these results at length here, these estimates provide researchers with reference values for research into emotion dynam-

ics and psychological well-being (for instance for use in power calculations or as a basis for comparison). However, we will next report a test of the interaction between the valence of the emotion under study and psychological well-being categories per dynamic measure, which speaks to the specificity of the findings, and briefly indicate, if significant, what is driving the interaction.

Emotional variability. Overall, the interaction between valence and psychological well-being was significant for variability measures ($F(13, 289) = 3.07, p < .001$ for theoretical categorization; $F(21, 264) = 4.00, p < .001$ for empirical categorization), meaning that effect sizes differed as a function of a combination of psychological well-being category and valence of the emotions examined. Figure 3 displays the overall Fisher's Z correlation estimates between variability and psychological well-being as a function of psychological well-being type and valence. The results

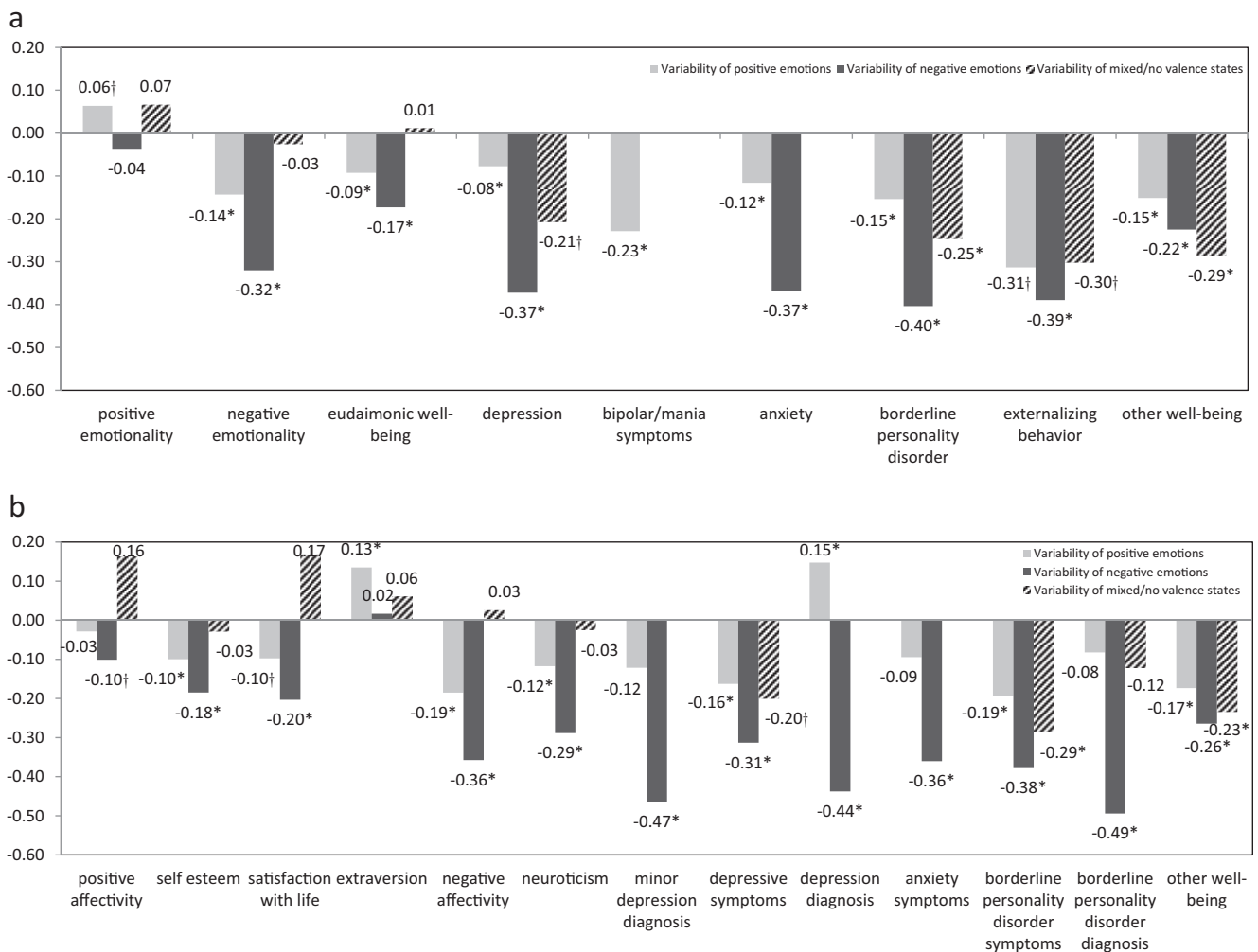


Figure 3. Bar graphs showing the estimated Fisher's Z correlations for the relations between variability (i.e., standard deviation) measures and psychological well-being, as a function of different valence and different psychological well-being categories. (a) shows results for the theoretical categorization of psychological well-being, (b) the results for the empirical categorization. Note that all Fisher's Z correlations reflect the relationship between variability and high psychological well-being. As a consequence, the interpretation of the direction of the correlation should be reversed for all indicators of low psychological well-being and psychopathology. * $p < .05$. † $p < .10$.

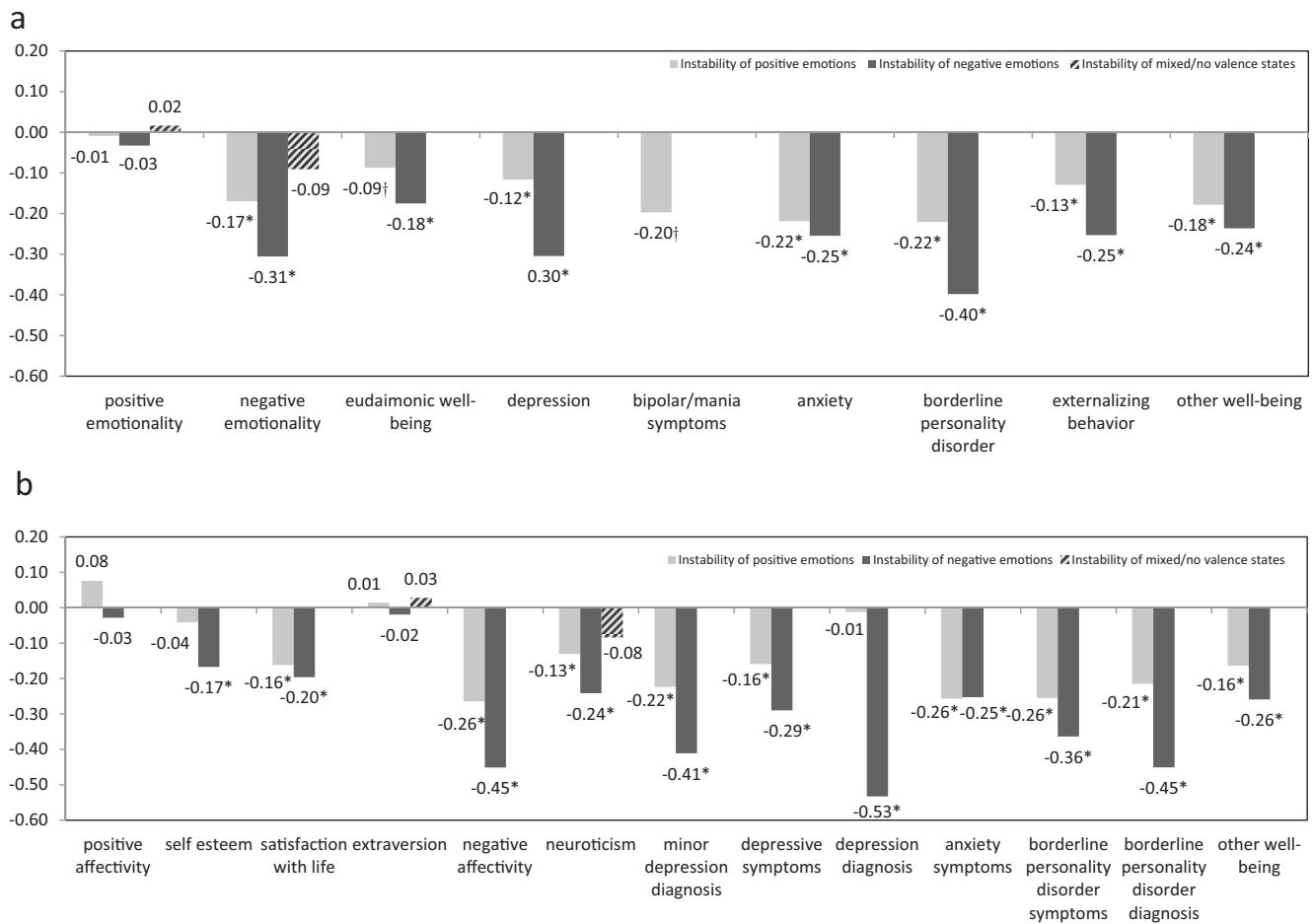


Figure 4. Bar graphs showing the estimated Fisher's Z correlations for the relations between instability (i.e., mean square successive difference) measures and psychological well-being, as a function of different valence and different psychological well-being categories. (a) shows results for the theoretical categorization of psychological well-being, (b) the results for the empirical categorization. Note that all Fisher's Z correlations reflect the relationship between instability and high psychological well-being. As a consequence, the interpretation of the direction of the correlation should be reversed for all indicators of low psychological well-being and psychopathology. * $p < .05$. † $p < .10$.

for the theoretical categorization indicated that positive emotionality was the only category of psychological well-being that was not significantly related to variability for any of the valence categories under study. However, a trend toward a significant positive association could be found with variability of positive emotions. Similarly, the results based on the empirical categorization showed that most psychological well-being categories were related in the same direction to variability of positive and/or negative emotions. However, some exceptions were observed. PA was not significantly related to variability, although a trend could be observed for negative emotions. For extraversion, however, a positive association with variability of positive emotions was observed, which is inconsistent with the results for all other psychological well-being categories. Finally, also for depressive diagnosis, an aberrant pattern of findings was found; depressive diagnosis was found to be related to higher variability of negative emotions, but to lower variability of positive emotions.

Emotional instability. The overall interaction between valence and psychological well-being was nonsignificant for instability measures based on the theoretical categorization, $F(8, 75.4) = 1.62, p = .133$, but was significant based on the empirical categorization of psychological well-being, $F(13, 46.6) = 3.03, p = .003$. This indicates that the type of psychological well-being, at least to some extent (when categorized based on the most prevalent subtypes of psychological well-being), qualified its relation with dynamics of positive or negative emotions. Figure 4 shows the correlations between instability and psychological well-being as a function of valence and psychological well-being category. The interaction between valence and psychological well-being category (according to the empirical categorization) can mainly be explained by PA and extraversion being unrelated to instability, independent of the valence of the emotion under study.

Emotional inertia. For inertia measures, the overall interaction between valence and psychological well-being was nonsignif-

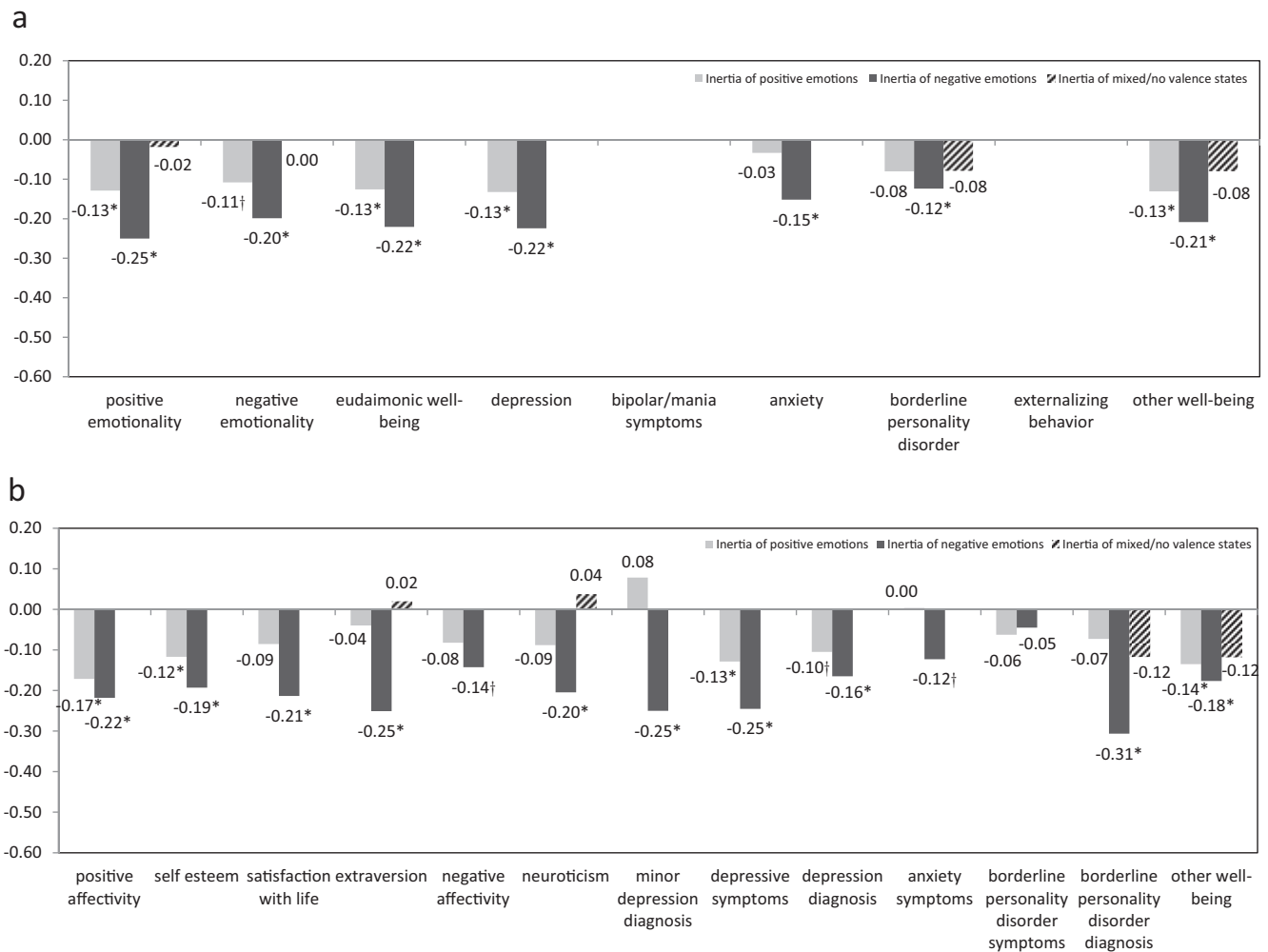


Figure 5. Bar graphs showing the estimated Fisher's Z correlations for the relations between inertia (i.e., autocorrelation) measures and psychological well-being, as a function of different valence and different psychological well-being categories. (a) shows results for the theoretical categorization of psychological well-being, (b) the results for the empirical categorization. Note that all Fisher's Z correlations reflect the relationship between inertia and high psychological well-being. As a consequence, the interpretation of the direction of the correlation should be reversed for all indicators of low psychological well-being and psychopathology. * $p < .05$. † $p < .10$.

icant: $F(9, 102) = 0.17, p = .996$ for theoretical categorization; $F(15, 90) = 0.80, p = .677$ for empirical categorization. **Figure 5** displays the different correlations between inertia and psychological well-being as a function of psychological well-being type and valence.

Explained Heterogeneity in Effect Sizes

To examine how much of the variance both between and within studies could be explained by the included moderator variables, we compared the estimated between-studies variance and within-studies variance from statistical three-level models including all moderators used in this meta-analysis, with variance estimates from models without moderators (i.e., empty intercept only models). Note that the models including all moderators can only consider effect sizes that have valid data for all moderators. To

make a correct comparison, variance estimates from these models were compared with those from empty models that only included the same (number of) effect sizes. For variability measures, inclusion of moderators explained 4% of variance between studies, and 72% of variance within study. For instability measures, it explained 100% of between-study variance, and 41% of within-study variance. For inertia measures, 89% of between-study variance could be explained by including all moderators. Explained within-study variance could not be estimated (likely due to the small amount of within-study variance, see higher). Last, for other dynamic measures, 100% of between-study variance, and 77% of within-study variance could be explained. These numbers indicate that the observed variability in effect sizes could be explained relatively well by the included moderators. Across all analyses, the type of psychological well-being and the valence of the emotion

under study are among the moderators accounting for most of the explained variance (see higher).

Publication Bias

Although we attempted to minimize possible publication bias by soliciting and adding unpublished data, it is nevertheless important to investigate whether such a bias is possibly present in the effects examined in this meta-analysis, and whether such a bias possibly affected the conclusions drawn from this meta-analysis. We used several approaches to investigate the possibility of publication bias.

Publication status and sample size. We compared the mean effect size for published versus unpublished studies for each type of dynamic measure. This comparison gives us an indication of the magnitude of the publication bias, as the actual bias is unlikely to be higher than the difference between these two effect sizes (Lipsey & Wilson, 2001). We compared the mean effect size between published and unpublished studies by estimating and testing for each type of dynamic measure the moderating effect of a binary variable coding for published versus unpublished correlations. Table 10 shows the estimated correlation for published and unpublished data. For none of the dynamic measures, significant differences between correlations for published and unpublished studies were found (estimated difference = -0.050, SE = 0.100, $p = .618$ for variability measures; estimated difference = 0.091, SE = 0.091, $p = .332$ for instability measures; estimated difference = 0.028, SE = 0.093, $p = .770$ for inertia measures; estimated difference = -0.117, SE = 0.127, $p = .384$ for other dynamic measures), and the resulting estimated magnitude of publication bias is small.

We also investigated whether sample size moderated the correlation between emotion dynamics and psychological well-being. Sample size had no significant effect on this correlation for variability measures ($B = 0.000$, SE = 0.000, $p = .214$), for instability measures ($B = 0.000$, SE = 0.000, $p = .471$), for inertia measures ($B = -0.000$, SE = 0.001, $p = .782$), and other dynamic measures ($B = 0.000$, SE = 0.000, $p = .422$) meaning that the magnitude of the effect size does not vary as a function of sample size.

Funnel plots. Next, we examined funnel plots to visually investigate the relationship between the estimated correlations and the sample size that was used in the study in which the effect size was reported, separate for each type of dynamic measure. A funnel plot visualizes the relationship between the magnitude of effect sizes and the sample sizes of the studies included in the meta-analysis. If the collection of effect sizes included in a meta-analysis is unbiased, larger variability in the magnitude of effect sizes should be observed for studies with a smaller sample size, and thus a funnel shaped plot is expected (Borman & Grigg, 2009). Figure 6 shows such plots between correlations and respective sample sizes in this meta-analysis, separately for each type of dynamic measure. For variability, instability, and other dynamic measures, sample size was first log transformed, as some studies used exceptionally large sample sizes (e.g., N s of 2,391 and 1,383). Funnel shapes can indeed be detected in these plots as greater variability can be observed among effect sizes reported in studies with smaller sample sizes compared with studies with larger sample sizes. This confirms that studies with smaller correlations are not

Table 10
Estimated Fisher's Z Correlations (Z_r) for the Relation Between Psychological Well-Being and Variability (i.e. Standard Deviation [SD]), Instability (i.e. Mean Square Successive Difference), Inertia (i.e. Autocorrelation), and Other Dynamic Measures as a Function of Publication Status

Status	Variability			Instability			Inertia			Other measures						
	N	Z_r (SE)	t (df)	p -value	N	Z_r (SE)	t (df)	p -value	N	Z_r (SE)	t (df)	p -value				
Published	356	-.175 (0.030) _a	-5.92 (41.5)	<.001	92	-.227 (0.042) _a	-5.42 (20.6)	<.001	66	-.158 (0.044) _a	-3.61 (19.1)	.002	103	-.083 (0.043) _a	-1.93 (7.34)	.094
Unpublished	58	-.226 (0.095) _a	-2.37 (30.4)	.025	54	-.136 (0.081) _a	-1.67 (14.9)	.115	54	-.130 (0.082) _a	-1.58 (13.9)	.136	10	-.201 (0.120) _a	-1.67 (8)	.133

Note. Effect sizes in the same column that do not share subscripts differ at $p < .05$.

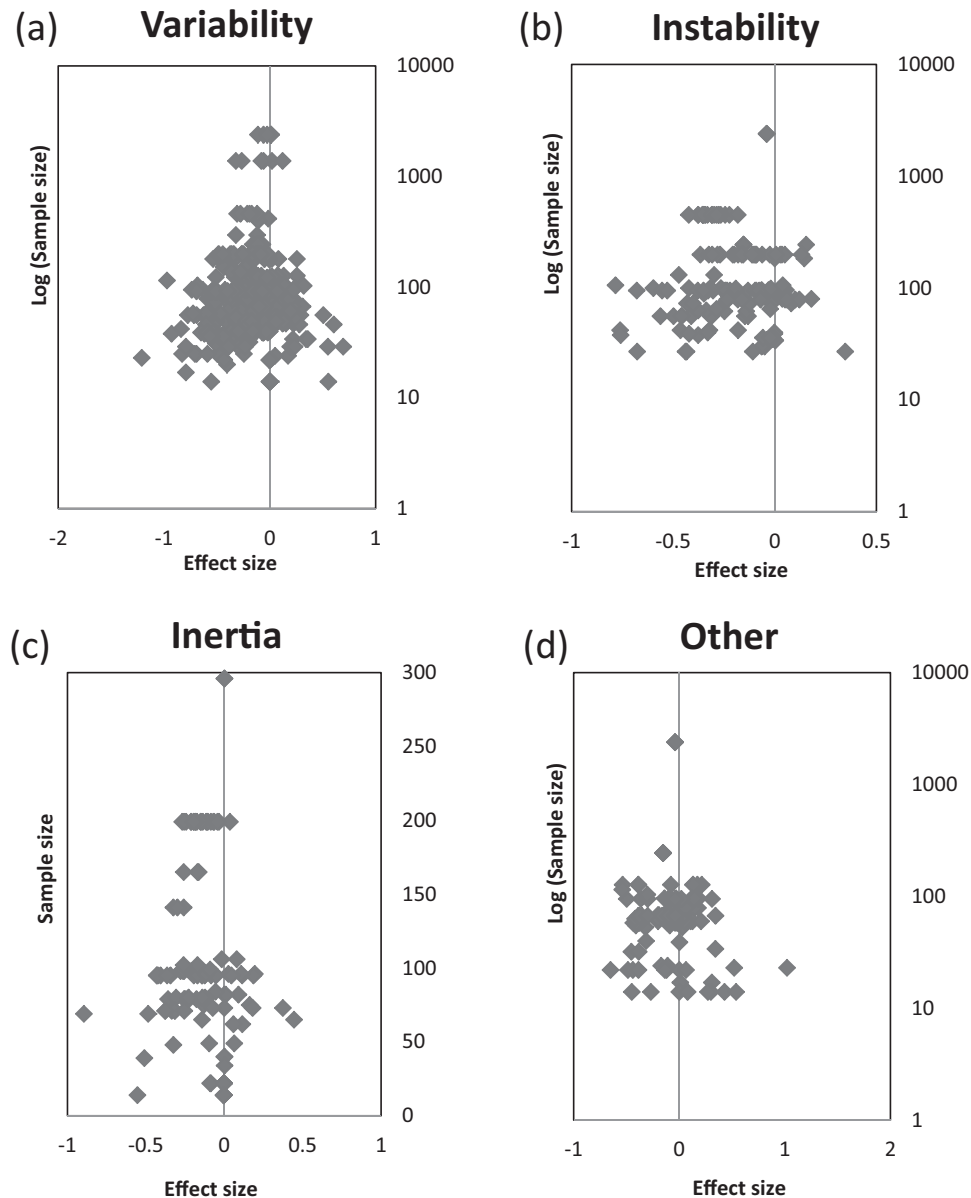


Figure 6. Funnel plots showing the relation between sample size of the study in which the effect size was reported and the estimated Fisher's Z correlations quantifying the magnitude of the relation between psychological well-being and (a) variability (i.e., standard deviation); (b) instability (i.e., mean square successive difference); (c) inertia (i.e., autocorrelation); and (d) other dynamic measures.

underrepresented in this meta-analysis. There is no indication for the underreporting of particular effect sizes in the analyzed studies.

Sensitivity analyses. Finally, we performed a sensitivity analysis to investigate whether the estimated overall effect sizes may be due to single influential (outlying) studies included in the meta-analysis. For each type of dynamic measure, we re-analyzed the data without moderators, estimating the overall correlation, each time leaving out one study. In general, the impact of leaving out one of the studies was small. For variability measures, the estimated overall correlations between

variability and psychological well-being ranged between $-.17$ (when Bauer et al., 2011 was left out) and $-.19$ (without Nezlek & Plesko, 2001). For instability measures, estimated overall correlations ranged between $-.19$ (without Bowen, Clark, & Baetz, 2004) and $-.22$ (without Carstensen et al., 2011). For inertia measures, estimated overall effects ranged between $-.13$ (without Sadikaj, Russell, Moskowitz, & Paris, 2010) and $-.17$ (without Bylsma, Peeters, & Rottenberg, 2013). Moreover, all correlations remained highly significant. We can conclude that no single study had a disproportionately strong effect on the overall estimated correlations between variability, instability,

and inertia on the one hand, and psychological well-being on the other hand.

For other dynamic measures, estimated overall effect sizes ranged between $-.08$ (without Bauer et al., 2011) and $-.11$ (without Pincus et al., 2008). All effect sizes remained significant, with some exceptions in which the p value changed up to $.07$, or even to $.153$ when the study by Kuppens, Oravecz, and Tuerlinckx (2010) was left out. However, the effect sizes were still comparable with other effect sizes.

Discussion

The study of emotion dynamics in relation to psychological well-being is a rapidly expanding domain of research, with important implications for the understanding of the type of emotional (dys)functioning characteristic of different forms of psychological well-being and psychopathology. The goal of this meta-analysis was to identify consistent relationships between patterns of short-term emotional change and different forms of psychological well-being and psychopathology based on this literature, and identify moderators of this relationship. A literature search yielded 793 effect sizes from 79 different studies that were coded with respect to how emotion dynamics were operationalized, the type of emotions and psychological well-being under study, and methodological factors such as sample characteristics and factors related to measurement protocol. On the basis of these data, three-level analyses were performed to establish the size of the relation between emotion dynamics and psychological well-being and obtain insight into which moderators affect the link between the two.

Overall Relations Between Patterns of Emotion Dynamics and Psychological Well-Being

In general, lower levels of psychological well-being, be it in terms of general affectivity, eudaimonic well-being, or several forms of psychopathology symptom severity or diagnosis, were found to be characterized by more variable (in terms of higher SD), more unstable (in terms of higher MSSD), but also more self-predictive or inert (in terms of higher autocorrelation) emotions. Higher levels of psychological well-being were found to be characterized by less variable, less unstable, but also less inert emotions.

To illustrate how these different patterns combine, Figure 7 shows simulated data depicting a typical pattern of emotional change that is indicative of higher psychological well-being, showing low variability, instability and inertia (Figure 7, upper panel) versus a typical pattern of emotional change that is indicative of lower psychological well-being, showing higher variability, instability, and inertia (Figure 7, lower panel). The middle panel in Figure 7 shows a pattern that is in between these two extremes.

As can be seen in Figure 7 (upper panel), an adaptive pattern of emotional change is characterized by emotions that have less extreme deviations from their mean level (located around 0) and make smaller consecutive jumps from one point to the next, but at the same time are not very self-predictive, as evidenced by less lingering emotions around the same intensity levels and a strong homeostasis toward a baseline level. If we were to speculate about what underlies such a pattern, we would hypothesize that it reflects moderate emotional reactivity to events, in combination with

strong emotion regulatory skills to facilitate emotional recovery, resulting in smaller deviations that reach fewer or less extreme values.

The less adaptive pattern from Figure 7 (lower panel), in turn, reflects an emotional life that reaches more extreme emotional intensities and involves relatively large moment-to-moment fluctuations, but at the same time shows a stronger self-predictive lingering effect that makes the emotion slower to recover or be pulled back to a normative state. If we were to speculate what underlies such a pattern, we would hypothesize that it reflects high emotional reactivity to events that take place, combined with a lack of regulatory control that allows the emotions to reach more extreme values and prevents them from recovering and returning to baseline.

While the overall effect sizes of these relations were modest in size (respectively $\hat{\rho} = -.178$, $\hat{\rho} = -.205$, $\hat{\rho} = -.151$), they are nevertheless comparable with (e.g., DeNeve & Cooper, 1998) or only slightly lower (Kashdan, 2007; Watson, Wiese, Vaidya, & Tellegen, 1999) than observed relationships between average levels of emotionality and psychological well-being, representative of the more traditional static approach to the role of emotions in psychological well-being. In other words, next to how people feel on average, it is equally important to study and pay attention to how people's feelings change for understanding and evaluating their psychological well-being.

The observed overall pattern of results is informative in understanding the theoretical ambiguity surrounding the (mal)adaptive nature of changing emotions. On the one hand, emotions that vary more and are less stable are associated with a host of maladaptive outcomes, which is in line with the view that large emotional changes across time are generally indicative of psychological ill-health. On the other hand, we also found consistent evidence that psychological maladjustment is characterized by emotions that are more inert, self-predictive, and linger more instead of being homeostatically regulated. Together, this evidence paints a picture of emotion dynamics characteristic of maladjustment in which emotions undergo larger changes and reach more extreme values, in the absence of strong homeostatic tendencies to return to baseline levels. Conversely, healthy psychological well-being is characterized by smaller, more stable emotional changes that are more homeostatically tied to baseline levels. Adaptive emotional functioning therefore seems to consist of emotional shifts that are smaller in size, but less self-predictive and more homeostatically regulated, reminiscent of, for instance, the smaller back and forth jumps a tennis player makes when preparing to counter a serve, or the constant small adjustments we make to remain standing upright. This lower self-predictiveness may enable the potential to respond to unpredictable events and circumstances, which is something that may be missing in those with low psychological well-being.

However, we want to emphasize again that as information about context is not incorporated in the used measures of emotion dynamics, it is not warranted to make statements about the extent to which the observed patterns reflect individual differences in the events people encounter or in how they respond to them. Comparing effect sizes from a small number of reviewed studies that used standardized stimuli to elicit emotions in the lab with those from studies that observed naturalistically occurring emotions (either in the lab or daily life) revealed no significant difference for vari-

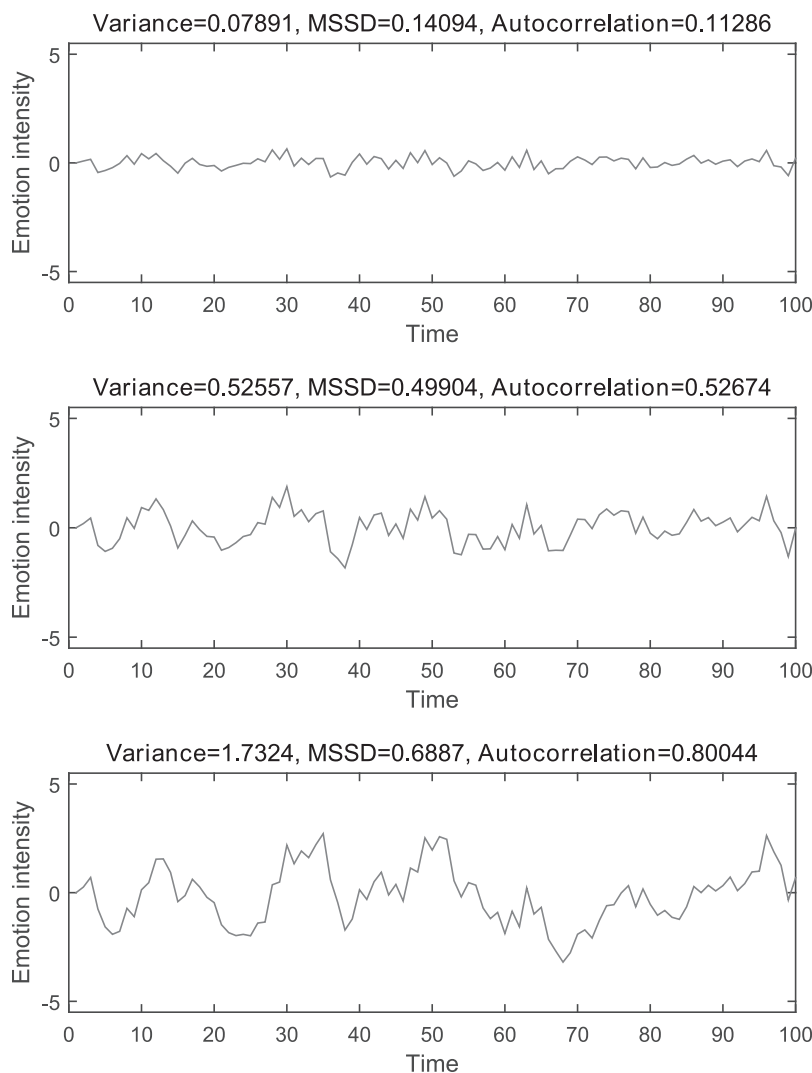


Figure 7. Simulated data illustrating time series characterized by low (upper panel), medium (middle panel), and high (lower panel) levels of variability (in terms of variance), instability (in terms of mean square successive difference or MSSD), and inertia (in terms of autocorrelation), indicative of respectively high, medium, and lower levels of psychological well-being.

ability, instability and inertia measures. This indicates that the results are not entirely driven by the context in which emotion dynamics occur, but instead say something about endogenous processes involved in emotional responding. Likewise, the included measures say nothing about the extent to which observed emotional changes are appropriate or contingent upon the events. Emerging research on flexibility and resilience of emotional responding (e.g., Hollenstein et al., 2013; Hollenstein & Lewis, 2006) are starting to make the important bridge between patterns of emotional change and the context in which they occur.

A related critical challenge for future research in emotion dynamics lies in pinpointing the exact (causal) role of these dynamics for psychological well-being. On the one hand, the ways in which a person's emotions fluctuate across time may be a concomitant or a consequence of psychological well-being or forms of maladjustment. On the other hand, specific patterns of emotion dynamics may reflect

an early form of emotional dysregulation that accumulatively creates vulnerability to disorders and maladjustment, or may help to maintain or create psychological well-being (see, Kuppens et al., 2012; van de Leemput et al., 2014; Wichers, 2014). More longitudinal research is needed to determine the exact role of emotion dynamics for psychological well-being.

A second important finding was that the associations between patterns of emotional change and psychological well-being were strongly moderated by the valence of the emotion studied: effect sizes were stronger for negative compared with positive emotions. While variability, instability, and inertia of positive emotions were also found to be related to lower psychological well-being (see also recently Gruber et al., 2013), such dynamic patterns of negative emotions were more predictive of psychological well-being. This has two important implications. First, it demonstrates that disruptions in the functioning and dynamics of negative emotions

are more indicative of psychological (mal)adjustment than those of positive emotions. As far as emotion dynamics may present risk factors for the development of psychopathology, therapeutic efforts to make people's emotions less variable, unstable, and inert should primarily focus on negative emotions. A second implication is that despite the importance of the message of positive psychology (which is also supported by the associations with dynamics of positive emotions), a larger part of the emotional flourishing encountered in different forms of high psychological well-being is reflected in the dynamics of negative emotions, rather than positive emotions.

Methodological Factors Moderating the Relation Between Emotion Dynamics and Psychological Well-Being

In general, methodological factors were found to moderate the observed relationships only to a limited extent. One exception was that emotional variability, as measured by *SD* measures, was more indicative of psychological well-being for females than for males, as we found the correlation to be lower as a function of the percentage males in the sample. At this point, and without targeted studies, it is not straightforward to provide a clear-cut interpretation of this finding. Some studies have shown that compared with men, women are more emotionally responsive to both positive and negative stimuli in the lab (e.g., Grossman & Wood, 1993), and score higher on neuroticism than men in several countries (Lynn & Martin, 1997) suggesting that women may be more labile in their emotions. Still, to precisely understand gender differences in the link between emotional variability and psychological well-being more targeted research is needed.

The mean age of the sample was found to be unrelated to the estimated effect sizes for all dynamic measures. However, we should note that, with the exception of variability measures, the range of included age groups was rather limited, as the maximum mean age pertaining to effect sizes for instability measures was 55.91, and 42.40 for inertia measures. This indicates that the findings only speak to age groups up to middle aged samples, and the generalizability to older samples is limited, although findings for variability measures, based on data of participants up to 82.80 years of age, suggest that findings might be similar for older samples.

Most surprising in our opinion was the finding that the time scale on which emotion dynamics was considered did not moderate their relationship with psychological well-being. Our meta-analysis included studies that examined emotional change on different time scales, ranging from change over the course of seconds to change over the course of days. However, the obtained relationships did not seem to be affected by this large variation. Although one cannot conclude from these findings that the same mechanisms underlie the second-to-second emotional changes observed, for instance, during interactions or lab tasks and the larger mood shifts observed across days, these findings nevertheless point to a certain self-similarity of emotion dynamics across time scales (Guastello & Liebovitch, 2009; Kuppens, Oravecz et al., 2010). It should be mentioned, however, that the reviewed literature contained relatively few studies looking at the very short, second-to-second time scale, and relatively more studies looking at changes across hours and days. This gap should be addressed in future

research to allow for a complete evaluation of the role of time scale in the relation between emotion dynamics and psychological well-being.

Regarding method of data collection, results showed that effect sizes did not differ if data were collected with electronic devices or paper diaries (see also Green et al., 2006), but that effect sizes were somewhat lower (and nonsignificant) when data were collected using computer ratings as compared with portable (electronic or paper) diaries, although the differences were not significant. These results seem to suggest that computers at home or in the lab may be less useful for the investigation of emotion dynamics.

Interestingly, we also did not find strong evidence for large differences in results or effect sizes if studies involved clinical samples versus samples from the general population (with some exceptions, however, see below). Moreover, the differences that were found were mainly a matter of degree (Rather than quality), with effect sizes for emotional variability—as measured by *SD* measures—being stronger in clinical compared to nonclinical samples. When taking psychological well-being type into account, this difference seemed to be most prominent for depressive symptoms and bipolar/mania symptoms. This is an important finding. First, it supports the notion that individual differences in psychological well-being and psychopathology may be more of a gradual or dimensional rather than categorical (or taxonic) nature (see also, Haslam, Holland, & Kuppens, 2012). Second, it implies that studies involving variation in nonclinical populations can be informative for understanding processes in the clinical range, and vice versa. Although it remains necessary to study emotional processes in both the nonclinical and the clinical range, the current findings suggest that both domains of inquiry can be used to inform one another, and that indications of low psychological well-being in the nonclinical range may extend to psychopathological ranges without major qualitative differences. As such, our findings suggest a natural bridge between a literature that is traditionally more clinically oriented, and the basic affective science literature that is involved with understanding the processes and mechanisms underlying variation in emotional functioning in typically developing populations.

Different Forms of Psychological Well-Being and Emotion Dynamics

An important aim of this meta-analysis was to identify distinct patterns of emotion dynamics characteristic of different forms of psychological well-being or psychopathology. Such findings could aid in sharpening diagnostic criteria for psychopathology and possibly identify markers of specific forms of (mal)adjustment, as well as provide clear indications for targeted therapeutic efforts.

Our findings indicated that type of psychological well-being moderated effect sizes in a number of instances. For variability and instability measures, a significant effect of type of psychological well-being was found. This was driven by the fact that only for positive emotionality, PA and extraversion, no or less significant associations were found, while high psychological well-being, as indicated by other psychological well-being categories including various indicators of subjective psychological well-being or the absence of various indicators of psychopathology, was consistently characterized by less variable or less unstable emotions. When taking valence into account, again significant interactions were

found for variability and instability measures. Again, these were mainly driven by nonsignificant (or sometimes even slightly positive) relationships with positive emotionality, PA, or extraversion. Despite these differences in size, however, it is most important to emphasize that (with some exceptions) different types of psychological well-being were consistently linked to a similar set of emotion dynamical patterns, namely lower level of variable, unstable, and inert emotions, albeit in varying strength of effect sizes. This commonality across the diverse types of psychological well-being studied suggests that there may be a core of emotional functioning that, at least when it comes to its dynamics, shows similar forms of dysregulation in relation to different forms of maladjustment. It has indeed been argued elsewhere that there might be large overlap between the processes and mechanisms underlying different forms of psychological well-being or mood disorders (e.g., Barlow et al., 2014; Judge, Erez, Bono, & Thoresen, 2002; Schmitz, Kugler, & Rollnik, 2003). It should be kept in mind, however, that the different indicators of psychological well-being may show considerable overlap or comorbidity themselves, and that this may partly account for the consistency in the findings (see also below).

Next to this consistency of the findings, subtle differences in findings could also be observed, in that some types of psychological well-being or psychopathology were characterized by distinctive emotion dynamic signatures. We highlight some of the most noteworthy instances.

As mentioned above, positive emotionality and positive affectivity were not so much related to more or less variable or unstable emotions, but were mostly characterized by low levels of inertia. Similarly, extraversion was characterized by less inert negative emotions. These results underscore the importance of less self-predictive positive and/or negative emotions for the tendency to experience more positive emotions in general (e.g., Hollenstein et al., 2013). Additionally, more variable positive emotions were also one of the dynamic features of extraversion. This relationship is opposite to what is found for most other psychological well-being categories. This finding could reflect that as extraverted people tend to have more elevated positive emotions during the day, this also results in a larger range of positive emotional intensities.

Borderline personality disorder, in general, was mainly characterized by more variable and unstable emotions. This fits with the clinical manifestation of borderline personality disorder, which indicates that it is characterized by instability and impulsivity (American Psychiatric Association, 2013). Borderline personality disorder symptoms were not consistently characterized by more inert emotions, however clinical borderline personality disorder diagnosis was (from the empirical categorization, see Figure 5b). The latter may indicate that only in clinical cases of borderline personality disorder, emotions have become more self-predictive and are slower to return to baseline levels (see also Ebner-Priemer et al., 2015). This is consistent with theoretical thinking about borderline personality disorder, which argues that a slow return to baseline for negative emotions is a feature of the emotion dysregulation found in borderline personality disorder (Linehan, 1993).

Depression, in turn, is characterized by more variable, more unstable, and more inert positive and negative emotions. Clinical levels of depression (depression diagnosis; see empirical categorization Figure 3b–5b), however, are characterized by these patterns of particularly negative emotions, and are additionally char-

acterized by lower variability of positive emotions. This is one of the notable instances in which less variable emotions are associated with ill-being. While anomalous, this result is not surprising when taking into account the fact that decreased positive affect and lack of pleasure is one of the main clinical criteria for depression diagnosis (American Psychiatric Association, 2013), which indeed will result in a low level of variability for experiencing such states across time.

Limitations

As with all meta-analyses, one cannot fully discount the possibility that our sample of studies is not completely representative of all studies conducted on the subject, or that the included effect sizes may be biased in one or the other direction. Yet, we tried to minimize this possibility by undertaking efforts to perform a systematic literature search and to obtain nonpublished findings. The fact that our data did not show any apparent indications of publication bias is reassuring in this respect, and gives confidence in the validity of our findings.

An important limitation of the reported results is the fact that we examined zero-order associations between measures of emotion dynamics and psychological well-being. Different measures of emotion dynamics show mathematical and empirical overlap (e.g., Jahng et al., 2008), average levels of emotionality are often related to both emotion dynamic patterns as well as to psychological well-being, and different indicators of psychological well-being can be expected to be intercorrelated to varying degrees. This implies that the effect sizes reported here may not always be independent of one another, such that, for instance, a found association between *SD* (i.e., variability) and depression may be partly due to the association between *MSSD* (i.e., instability) and depression, or between *SD* (i.e., variability) and neuroticism, and so forth. Similarly, average levels of emotionality might partially account for the relationship between emotion dynamics and psychological well-being. Yet, most studies do not systematically report effect sizes while controlling for overlapping dynamic measures, average levels of emotionality, overlapping psychological well-being measures, or other variables that could be deemed relevant. Moreover, it would be impossible to obtain such controlled-for associations in the same way from all studies. Therefore, the only option was to focus on zero-order associations in the present meta-analysis. Nevertheless, this is an important caveat to keep in mind when interpreting the results.

Another limitation of this meta-analysis is that it pertains only to linear relations between emotion dynamics and psychological well-being. It is plausible that nonlinear relations may be equally or perhaps better suited to characterize the relation between emotion dynamics and psychological well-being, with for instance both very low and very high levels of variability, instability, or inertia being indicative of dysregulated emotional functioning and therefore implicated in decreased levels of psychological well-being. Yet, with the vast majority of the research domain focusing on linear relations (for a recent exception in the domain of physiological emotion dynamics, however, see Kogan, Gruber, Shallcross, Ford, & Mauss, 2013), more work is needed to obtain such a more nuanced picture of optimal levels of emotion dynamics in relation to psychological well-being.

Conclusions

We formulate the following general conclusions based on a meta-analysis of the relation between patterns of emotional change across time and psychological well-being: (a) how people's emotions change across time is related to their psychological well-being or maladjustment; (b) emotions that are less variable, more stable, or less inert across time are indicative of higher psychological well-being, while more variable, unstable, and more inert emotions are indicative of psychological maladjustment; (c) the relationship between emotion dynamics and psychological well-being is stronger for negative compared with positive emotions; and (d) similar patterns hold across several different forms of psychological well-being and psychopathology, although subtle differences between for instance psychiatric categories can be discerned.

References

References marked with an asterisk indicate studies included in the meta-analysis.

- Aldao, A., Nolen-Hoeksema, S., & Schweizer, S. (2010). Emotion-regulation strategies across psychopathology: A meta-analytic review. *Clinical Psychology Review, 30*, 217–237. <http://dx.doi.org/10.1016/j.cpr.2009.11.004>
- American Psychiatric Association. (2013). *Diagnostic and statistical manual of mental disorders* (5th ed.). Arlington, VA: American Psychiatric Publishing.
- *Anestis, M. D., Selby, E. A., Crosby, R. D., Wonderlich, S. A., Engel, S. G., & Joiner, T. E. (2010). A comparison of retrospective self-report versus ecological momentary assessment measures of affective lability in the examination of its relationship with bulimic symptomatology. *Behaviour Research and Therapy, 48*, 607–613. <http://dx.doi.org/10.1016/j.brat.2010.03.012>
- Barlow, D. H., Sauer-Zavala, S., Carl, J. R., Bullis, J. R., & Ellard, K. K. (2014). The nature, diagnosis, and treatment of neuroticism: Back to the future. *Clinical Psychological Science, 2*, 344–365. <http://dx.doi.org/10.1177/2167702613505532>
- Bartels, M., Cacioppo, J. T., van Beijsterveldt, T. C., & Boomsma, D. I. (2013). Exploring the association between well-being and psychopathology in adolescents. *Behavior Genetics, 43*, 177–190. <http://dx.doi.org/10.1007/s10519-013-9589-7>
- *Bauer, M., Glenn, T., Alda, M., Grof, P., Sagduyu, K., Bauer, R., . . . Whybrow, P. C. (2011). Comparison of pre-episode and pre-remission states using mood ratings from patients with bipolar disorder. *Pharmacopsychiatry, 44*, S49–S53. <http://dx.doi.org/10.1055/s-0031-1273765>
- *Beal, D. J., & Ghandour, L. (2011). Stability, change, and the stability of change in daily workplace affect. *Journal of Organizational Behavior, 32*, 526–546. <http://dx.doi.org/10.1002/job.713>
- Borenstein, M., Hedges, L. V., Higgins, J. P., & Rothstein, H. R. (2009). *Introduction to meta-analysis*. Chichester, UK: Wiley. <http://dx.doi.org/10.1002/9780470743386>
- Borman, G. D., & Grigg, J. A. (2009). Visual and narrative interpretation. In H. Coopers, L. V. Hedges, & J. C. V. Valentine (Eds.), *The handbook of research synthesis and meta-analysis* (pp. 497–519). New York, NY: Russell Sage Foundation.
- *Bowen, R., Baetz, M., Hawkes, J., & Bowen, A. (2006). Mood variability in anxiety disorders. *Journal of Affective Disorders, 91*, 165–170. <http://dx.doi.org/10.1016/j.jad.2005.12.050>
- *Bowen, R., Clark, M., & Baetz, M. (2004). Mood swings in patients with anxiety disorders compared with normal controls. *Journal of Affective Disorders, 78*, 185–192. [http://dx.doi.org/10.1016/S0165-0327\(02\)00304-X](http://dx.doi.org/10.1016/S0165-0327(02)00304-X)
- *Bowen, R. C., Mahmood, J., Milani, A., & Baetz, M. (2011). Treatment for depression and change in mood instability. *Journal of Affective Disorders, 128*, 171–174. <http://dx.doi.org/10.1016/j.jad.2010.06.040>
- Brown, T. A., & Barlow, D. H. (2005). Dimensional versus categorical classification of mental disorders in the fifth ed. of the diagnostic and statistical manual of mental disorders and Beyond: Comment on the special section. *Journal of Abnormal Psychology, 114*, 551–556.
- *Bylsma, L. M., Peeters, F., & Rottenberg, J. (2013). *High positive affective variability in everyday life predicts depression remission*. Manuscript in preparation.
- *Campbell, J. D., Chew, B., & Scratchley, L. S. (1991). Cognitive and emotional reactions to daily events: The effects of self-esteem and self-complexity. *Journal of Personality, 59*, 473–505. <http://dx.doi.org/10.1111/j.1467-6494.1991.tb00257.x>
- *Carstensen, L. L., Turan, B., Scheibe, S., Ram, N., Ersner-Hershfield, H., Samanez-Larkin, G. R., . . . Nesselroade, J. R. (2011). Emotional experience improves with age: Evidence based on over 10 years of experience sampling. *Psychology and Aging, 26*, 21–33. <http://dx.doi.org/10.1037/a0021285>
- Cattell, R. B. (1946). *The description and measurement of personality*. New York, NY: World Book.
- Chamorro-Premuzic, T., & Furnham, A. (2005). *Personality and Intellectual Competence*. Hillsdale, NJ: Erlbaum.
- *Champagne, N., Erbas, Y., Houben, M., Koval, P., Meers, K., Pe, M. L., & Kuppens, P. (2013). [Longitudinal study on emotion dynamics, well-being, and cognition: Wave 1]. Unpublished raw data.
- *Chandler, M. M. (2012). *The antecedents and consequences of core affect variability at work* (Doctoral dissertation) The University of Akron, Akron, Ohio. Retrieved from <https://etd.ohiolink.edu/>
- Cheung, M. W. L. (2014). Modeling dependent effect sizes with three-level meta-analyses: A structural equation modeling approach. *Psychological Methods, 19*, 211–229. <http://dx.doi.org/10.1037/a0032968>
- Chow, S. M., Ram, N., Boker, S. M., Fujita, F., & Clore, G. (2005). Emotion as a thermostat: Representing emotion regulation using a damped oscillator model. *Emotion, 5*, 208–225. <http://dx.doi.org/10.1037/1528-3542.5.2.208>
- *Congard, A., Dauvier, B., Antoine, P., & Gilles, P. Y. (2011). Integrating personality, daily life events and emotion: Role of anxiety and positive affect in emotion regulation dynamics. *Journal of Research in Personality, 45*, 372–384. <http://dx.doi.org/10.1016/j.jrp.2011.04.004>
- *Cowdry, R. W., Gardner, D. L., O'Leary, K. M., Leibenluft, E., & Rubinow, D. R. (1991). Mood variability: A study of four groups. *The American Journal of Psychiatry, 148*, 1505–1511. <http://dx.doi.org/10.1176/ajp.148.11.1505>
- Davidson, R. J. (2003). Darwin and the neural bases of emotion and affective style. *Annals of the New York Academy of Sciences, 1000*, 316–336. <http://dx.doi.org/10.1196/annals.1280.014>
- Deci, E. L., & Ryan, R. M. (2008). Hedonia, eudaimonia, and well-being: An introduction. *Journal of Happiness Studies, 9*, 1–11. <http://dx.doi.org/10.1007/s10902-006-9018-1>
- *Delespaul, P. A. E. G., & deVries, M. W. (1987). The daily life of ambulatory chronic mental patients. *Journal of Nervous and Mental Disease, 175*, 537–544. <http://dx.doi.org/10.1097/00005053-198709000-00005>
- DeNeve, K. M., & Cooper, H. (1998). The happy personality: A meta-analysis of 137 personality traits and subjective well-being. *Psychological Bulletin, 124*, 197–229. <http://dx.doi.org/10.1037/0033-2909.124.2.197>
- Diener, E., Suh, E. M., Lucas, R. E., & Smith, H. L. (1999). Subjective well-being: Three decades of progress. *Psychological Bulletin, 125*, 276–302. <http://dx.doi.org/10.1037/0033-2909.125.2.276>
- *Eaton, L. G., & Funder, D. C. (2001). Emotional experience in daily life: Valence, variability, and rate of change. *Emotion, 1*, 413–421. <http://dx.doi.org/10.1037/1528-3542.1.4.413>

- Ebner-Priemer, U. W., Houben, M., Santangelo, P., Kleindienst, N., Tuerlinckx, F., Oravecz, Z., . . . Kuppens, P. (2015). Unraveling affective dysregulation in borderline personality disorder: A theoretical model and empirical evidence. *Journal of Abnormal Psychology*. Advance online publication. <http://dx.doi.org/10.1037/abn0000021>
- *Ebner-Priemer, U. W., Kuo, J., Kleindienst, N., Welch, S. S., Reisch, T., Reinhard, I., . . . Bohus, M. (2007). State affective instability in borderline personality disorder assessed by ambulatory monitoring. *Psychological Medicine*, *37*, 961–970. <http://dx.doi.org/10.1017/S0033291706009706>
- *Ebner-Priemer, U. W., & Sawitzki, G. (2007). Ambulatory assessment of affective instability in borderline personality disorder: The effect of the sampling frequency. *European Journal of Psychological Assessment*, *23*, 238–247. <http://dx.doi.org/10.1027/1015-5759.23.4.238>
- Ebner-Priemer, U. W., & Trull, T. J. (2009). Ecological momentary assessment of mood disorders and mood dysregulation. *Psychological Assessment*, *21*, 463–475. <http://dx.doi.org/10.1037/a0017075>
- *Eid, M., & Diener, E. (1999). Intraindividual variability in affect: Reliability, validity, and personality correlates. *Journal of Personality and Social Psychology*, *76*, 662–676. <http://dx.doi.org/10.1037/0022-3514.76.4.662>
- *Emmons, R. A. (1987). Narcissism: Theory and measurement. *Journal of Personality and Social Psychology*, *52*, 11–17. <http://dx.doi.org/10.1037/0022-3514.52.1.11>
- *Engel, S. G., Boseck, J. J., Crosby, R. D., Wonderlich, S. A., Mitchell, J. E., Smyth, J., . . . Steiger, H. (2007). The relationship of momentary anger and impulsivity to bulimic behavior. *Behaviour Research and Therapy*, *45*, 437–447. <http://dx.doi.org/10.1016/j.brat.2006.03.014>
- Eysenck, H. J., & Eysenck, S. B. G. (1975). *Eysenck personality questionnaire manual*. San Diego, CA: EdITS.
- *Farmer, R. F., Nash, H. M., & Dance, D. (2004). Mood patterns and variations associated with personality disorder pathology. *Comprehensive Psychiatry*, *45*, 289–303. <http://dx.doi.org/10.1016/j.comppsy.2004.03.009>
- Fredrickson, B. L., & Joiner, T. (2002). Positive emotions trigger upward spirals toward emotional well-being. *Psychological Science*, *13*, 172–175. <http://dx.doi.org/10.1111/1467-9280.00431>
- Frijda, N. H. (2007). *The laws of emotion*. Hillsdale, NJ: Erlbaum.
- *Gable, S. L., & Nezlek, J. B. (1998). Level and instability of day-to-day psychological well-being and risk for depression. *Journal of Personality and Social Psychology*, *74*, 129–138. <http://dx.doi.org/10.1037/0022-3514.74.1.129>
- *Golier, J. A., Yehuda, R., Schmeidler, J., & Siever, L. J. (2001). Variability and severity of depression and anxiety in post traumatic stress disorder and major depressive disorder. *Depression and Anxiety*, *13*, 97–100. <http://dx.doi.org/10.1002/da.1022>
- Green, A. S., Rafaeli, E., Bolger, N., Shrout, P. E., & Reis, H. T. (2006). Paper or plastic? Data equivalence in paper and electronic diaries. *Psychological Methods*, *11*, 87–105. <http://dx.doi.org/10.1037/1082-989X.11.1.87>
- Gross, J. J., & John, O. P. (2003). Individual differences in two emotion regulation processes: Implications for affect, relationships, and well-being. *Journal of Personality and Social Psychology*, *85*, 348–362. <http://dx.doi.org/10.1037/0022-3514.85.2.348>
- Gross, J. J., & Muñoz, R. F. (1995). Emotion regulation and mental health. *Clinical Psychology: Science and Practice*, *2*, 151–164. <http://dx.doi.org/10.1111/j.1468-2850.1995.tb00036.x>
- Grossman, M., & Wood, W. (1993). Sex differences in intensity of emotional experience: A social role interpretation. *Journal of Personality and Social Psychology*, *65*, 1010–1022. <http://dx.doi.org/10.1037/0022-3514.65.5.1010>
- *Gruber, J., Kogan, A., Quoidbach, J., & Mauss, I. B. (2013). Happiness is best kept stable: Positive emotion variability is associated with poorer psychological health. *Emotion*, *13*, 1–6. <http://dx.doi.org/10.1037/a0030262>
- Guastello, S. J., & Liebovitch, L. S. (2009). Introduction to nonlinear dynamics and complexity. In S. J. Guastello, M. Koopmans, & D. Pincus (Eds.), *Chaos and complexity in Psychology: Theory of nonlinear dynamics* (pp. 1–40). New York, NY: Cambridge University Press.
- Haslam, N., Holland, E., & Kuppens, P. (2012). Categories versus dimensions in personality and psychopathology: A quantitative review of taxometric research. *Psychological Medicine*, *42*, 903–920. <http://dx.doi.org/10.1017/S0033291711001966>
- *Hepburn, L., & Eysenck, M. W. (1989). Personality, average mood, and mood variability. *Personality and Individual Differences*, *10*, 975–983. [http://dx.doi.org/10.1016/0191-8869\(89\)90062-7](http://dx.doi.org/10.1016/0191-8869(89)90062-7)
- Hollenstein, T., & Lewis, M. D. (2006). A state space analysis of emotion and flexibility in parent-child interactions. *Emotion*, *6*, 656–662. <http://dx.doi.org/10.1037/1528-3542.6.4.656>
- Hollenstein, T., Lichtwarck-Aschoff, A., & Potworowski, G. (2013). A model of socioemotional flexibility at three time scales. *Emotion Review*, *5*, 397–405. <http://dx.doi.org/10.1177/1754073913484181>
- Hox, J. (2002). *Multilevel analysis. Techniques and applications*. Mahwah, NJ: Erlbaum.
- Insel, T., Cuthbert, B., Garvey, M., Heinszen, R., Pine, D. S., Quinn, K., . . . Wang, P. (2010). Research domain criteria (RDoC): Toward a new classification framework for research on mental disorders. *The American Journal of Psychiatry*, *167*, 748–751. <http://dx.doi.org/10.1176/appi.ajp.2010.09091379>
- *Jacobs, N., van Os, J., Derom, C., Thiery, E., Delespaul, P., & Wichers, M. (2011). Neuroticism explained? From a non-informative vulnerability marker to informative person-context interactions in the realm of daily life. *British Journal of Clinical Psychology*, *50*, 19–32. <http://dx.doi.org/10.1348/014466510X491397>
- Jahng, S., Wood, P. K., & Trull, T. J. (2008). Analysis of affective instability in ecological momentary assessment: Indices using successive difference and group comparison via multilevel modeling. *Psychological Methods*, *13*, 354–375. <http://dx.doi.org/10.1037/a0014173>
- Judge, T. A., Erez, A., Bono, J. E., & Thoresen, C. J. (2002). Are measures of self-esteem, neuroticism, locus of control, and generalized self-efficacy indicators of a common core construct? *Journal of Personality and Social Psychology*, *83*, 693–710. <http://dx.doi.org/10.1037/0022-3514.83.3.693>
- *Kardum, I. (1998). Affect intensity and frequency: Their relation to mean level and variability of positive and negative affect and Eysenck's personality traits. *Personality and Individual Differences*, *26*, 33–47. [http://dx.doi.org/10.1016/S0191-8869\(98\)00157-3](http://dx.doi.org/10.1016/S0191-8869(98)00157-3)
- Kashdan, T. B. (2007). Social anxiety spectrum and diminished positive experiences: Theoretical synthesis and meta-analysis. *Clinical Psychology Review*, *27*, 348–365. <http://dx.doi.org/10.1016/j.cpr.2006.12.003>
- Kashdan, T. B., & Rottenberg, J. (2010). Psychological flexibility as a fundamental aspect of health. *Clinical Psychology Review*, *30*, 865–878. <http://dx.doi.org/10.1016/j.cpr.2010.03.001>
- *Kashdan, T. B., Uswatte, G., Steger, M. F., & Julian, T. (2006). Fragile self-esteem and affective instability in posttraumatic stress disorder. *Behaviour Research and Therapy*, *44*, 1609–1619. <http://dx.doi.org/10.1016/j.brat.2005.12.003>
- Kogan, A., Gruber, J., Shallcross, A. J., Ford, B. Q., & Mauss, I. B. (2013). Too much of a good thing? Cardiac vagal tone's nonlinear relationship with well-being. *Emotion*, *13*, 599–604. <http://dx.doi.org/10.1037/a0032725>
- *Koval, P., & Kuppens, P. (2012). Changing emotion dynamics: Individual differences in the effect of anticipatory social stress on emotional inertia. *Emotion*, *12*, 256–267. <http://dx.doi.org/10.1037/a0024756>
- *Koval, P., Pe, M. L., Meers, K., & Kuppens, P. (2013). Affect dynamics in relation to depressive symptoms: Variable, unstable or inert? *Emotion*, *13*, 1132–1141. <http://dx.doi.org/10.1037/a0033579>

- Kraemer, H. C. (2007). DSM categories and dimensions in clinical and research contexts. *International Journal of Methods in Psychiatric Research, 16*, S8–S15. <http://dx.doi.org/10.1002/mpr.211>
- Kuppens, P. (in press). It's about time: A special issue on affect dynamics. *Emotion Review*.
- *Kuppens, P., Allen, N. B., & Sheeber, L. B. (2010). Emotional inertia and psychological maladjustment. *Psychological Science, 21*, 984–991. <http://dx.doi.org/10.1177/0956797610372634>
- *Kuppens, P., Oravecz, Z., & Tuerlinckx, F. (2010). Feelings change: Accounting for individual differences in the temporal dynamics of affect. *Journal of Personality and Social Psychology, 99*, 1042–1060. <http://dx.doi.org/10.1037/a0020962>
- *Kuppens, P., Sheeber, L. B., Yap, M. B. H., Whittle, S., Simmons, J. G., & Allen, N. B. (2012). Emotional inertia prospectively predicts the onset of depressive disorder in adolescence. *Emotion, 12*, 283–289. <http://dx.doi.org/10.1037/a0025046>
- *Kuppens, P., Timmermans, T., Dossche, D., & Van Mechelen, I. (2007). [Core affect and well-being]. Unpublished raw data.
- *Kuppens, P., Van Mechelen, I., Nezelek, J. B., Dossche, D., & Timmermans, T. (2007). Individual differences in core affect variability and their relationship to personality and psychological adjustment. *Emotion, 7*, 262–274. <http://dx.doi.org/10.1037/1528-3542.7.2.262>
- Lahey, B. B. (2009). Public health significance of neuroticism. *American Psychologist, 64*, 241–256. <http://dx.doi.org/10.1037/a0015309>
- Larsen, R. J. (2000). Towards a science of mood regulation. *Psychological Inquiry, 11*, 129–141. http://dx.doi.org/10.1207/S15327965PLI1103_01
- Larsen, R. J., Augustine, A. A., & Prizmic, Z. (2009). A process approach to emotion and personality: Using time as a facet of data. *Cognition and Emotion, 23*, 1407–1426. <http://dx.doi.org/10.1080/02699930902851302>
- *Larson, R., Csikszentmihalyi, M., & Graef, R. (1980). Mood variability and the psychosocial adjustment of adolescents. *Journal of Youth and Adolescence, 9*, 469–490. <http://dx.doi.org/10.1007/BF02089885>
- *Larson, R. W., Raffaelli, M., Richards, M. H., Ham, M., & Jewell, L. (1990). Ecology of depression in late childhood and early adolescence: A profile of daily states and activities. *Journal of Abnormal Psychology, 99*, 92–102. <http://dx.doi.org/10.1037/0021-843X.99.1.92>
- *Lawton, M. P., Parmelee, P. A., Katz, I. R., & Nesselroade, J. (1996). Affective states in normal and depressed older people. *The Journals of Gerontology: Series B: Psychological Sciences and Social Sciences, 51B*, 309–316. <http://dx.doi.org/10.1093/geronb/51B.6.P309>
- Lewis, M. D. (2005). Bridging emotion theory and neurobiology through dynamic systems modeling. *Behavioral and Brain Sciences, 28*, 169–194. <http://dx.doi.org/10.1017/S0140525X0500004X>
- Linehan, M. M. (1993). *Cognitive behavioural treatment of borderline personality disorder*. New York, NY: Guilford Press.
- *Links, P. S., Eynan, R., Heisel, M. J., Barr, A., Korzekwa, M., McMain, S., & Ball, J. S. (2007). Affective instability and suicidal ideation and behavior in patients with borderline personality disorder. *Journal of Personality Disorders, 21*, 72–86. <http://dx.doi.org/10.1521/pepi.2007.21.1.72>
- Lipsey, M. W., & Wilson, D. B. (2001). *Practical meta-analysis*. Thousand Oaks, CA: Sage.
- Lynn, R., & Martin, T. (1997). Gender differences in extraversion, neuroticism, and psychoticism in 37 nations. *The Journal of Social Psychology, 137*, 369–373. <http://dx.doi.org/10.1080/00224549709595447>
- *Lyubomirsky, S. (1994). *The hedonic consequences of social comparison: Implications for enduring happiness and transient mood* (Unpublished doctoral dissertation). Stanford University, Stanford, California.
- Lyubomirsky, S., King, L., & Diener, E. (2005). The benefits of frequent positive affect: Does happiness lead to success? *Psychological Bulletin, 131*, 803–855. <http://dx.doi.org/10.1037/0033-2909.131.6.803>
- *McConville, C., & Cooper, C. (1992). Mood variability and personality. *Personality and Individual Differences, 13*, 1213–1221. [http://dx.doi.org/10.1016/0191-8869\(92\)90257-P](http://dx.doi.org/10.1016/0191-8869(92)90257-P)
- *McConville, C., & Cooper, C. (1996). Mood variability and the intensity of depressive states. *Current Psychology, 14*, 329–338. <http://dx.doi.org/10.1007/BF02686921>
- *McConville, C., & Cooper, C. (1998). Personality correlates of variable moods. *Personality and Individual Differences, 26*, 65–78. [http://dx.doi.org/10.1016/S0191-8869\(98\)00139-1](http://dx.doi.org/10.1016/S0191-8869(98)00139-1)
- *Meier, L. L., Orth, U., Denissen, J. J., & Kühnel, A. (2011). Age differences in instability, contingency, and level of self-esteem across the life span. *Journal of Research in Personality, 45*, 604–612. <http://dx.doi.org/10.1016/j.jrp.2011.08.008>
- *Miller, D. J., Vachon, D. D., & Lynam, D. R. (2009). Neuroticism, negative affect, and negative affect instability: Establishing convergent and discriminant validity using ecological momentary assessment. *Personality and Individual Differences, 47*, 873–877. <http://dx.doi.org/10.1016/j.paid.2009.07.007>
- Myin-Germeys, I., Oorschot, M., Collip, D., Lataster, J., Delespaul, P., & van Os, J. (2009). Experience sampling research in psychopathology: Opening the black box of daily life. *Psychological Medicine, 39*, 1533–1547. <http://dx.doi.org/10.1017/S0033291708004947>
- *Neumann, A., van Lier, P. A. C., Frijns, T., Meeus, W., & Koot, H. M. (2011a). Emotional dynamics in the development of early adolescent psychopathology: A one-year longitudinal study. *Journal of Abnormal Child Psychology, 39*, 657–669. <http://dx.doi.org/10.1007/s10802-011-9509-3>
- *Newton, T. L., & Ho, I. K. (2008). Posttraumatic stress symptoms and emotion experience in women: Emotion occurrence, intensity, and variability in the natural environment. *Journal of Psychological Trauma, 7*, 276–297. <http://dx.doi.org/10.1080/19322880802492237>
- *Nezelek, J. B., & Plesko, R. M. (2001). Day-to-day relationships among self-concept clarity, self-esteem, daily events, and mood. *Personality and Social Psychology Bulletin, 27*, 201–211. <http://dx.doi.org/10.1177/0146167201272006>
- Nolen-Hoeksema, S. (2012). Emotion regulation and psychopathology: The role of gender. *Annual Review of Clinical Psychology, 8*, 161–187. <http://dx.doi.org/10.1146/annurev-clinpsy-032511-143109>
- Northoff, G., Richter, A., Gessner, M., Schlagenhaut, F., Fell, J., Baumgart, F., . . . Heinze, H. J. (2000). Functional dissociation between medial and lateral prefrontal cortical spatiotemporal activation in negative and positive emotions: A combined fMRI/MEG study. *Cerebral Cortex, 10*, 93–107. <http://dx.doi.org/10.1093/cercor/10.1.93>
- *Oosterwegel, A., Field, N., Hart, D., & Anderson, K. (2001). The relation of self-esteem variability to emotion variability, mood, personality traits, and depressive tendencies. *Journal of Personality, 69*, 689–708. <http://dx.doi.org/10.1111/1467-6494.695160>
- *Palmier-Claus, J. E., Ainsworth, J., Machin, M., Dunn, G., Barkus, E., Barrowclough, C., . . . Lewis, S. W. (2013). Affective instability prior to and after thoughts about self-injury in individuals with and at-risk of psychosis: A mobile phone based study. *Archives of Suicide Research, 17*, 275–287. <http://dx.doi.org/10.1080/13811118.2013.805647>
- *Palmier-Claus, J. E., Taylor, P. J., Gooding, P., Dunn, G., & Lewis, S. W. (2012). Affective variability predicts suicidal ideation in individuals at ultra-high risk of developing psychosis: An experience sampling study. *British Journal of Clinical Psychology, 51*, 72–83. <http://dx.doi.org/10.1111/j.2044-8260.2011.02013.x>
- *Pe, M. L., Ogrinz, B., Koval, P., & Kuppens, P. (2011). [Executive functioning, heart rate variability, and emotional functioning in the lab and in daily life]. Unpublished raw data.
- *Peeters, F., Berkhof, J., Delespaul, P., Rottenberg, J., & Nicolson, N. A. (2006). Diurnal mood variation in major depressive disorder. *Emotion, 6*, 383–391. <http://dx.doi.org/10.1037/1528-3542.6.3.383>
- Peeters, F., Berkhof, J., Rottenberg, J., & Nicolson, N. A. (2010). Ambulatory emotional reactivity to negative daily life events predicts remission from major depressive disorder. *Behaviour Research and Therapy, 48*, 754–760. <http://dx.doi.org/10.1016/j.brat.2010.04.008>

- *Pincus, S. M., Schmidt, P. J., Palladino-Negro, P., & Rubinow, D. R. (2008). Differentiation of women with premenstrual dysphoric disorder, recurrent brief depression, and healthy controls by daily mood rating dynamics. *Journal of Psychiatric Research, 42*, 337–347. <http://dx.doi.org/10.1016/j.jpsychires.2007.01.001>
- Raudenbush, S. W. (2009). Analyzing effect sizes: Random-effects models. In H. Cooper, L. V. Hedges, & J. C. Valentine (Eds.), *The handbook of research synthesis and meta-analysis* (pp. 295–315). New York, NY: Russell Sage Foundation.
- *Rhodewalt, F., Madrian, J. C., & Cheney, S. (1998). Narcissism, self-knowledge organization, and emotional reactivity: The effect of daily experiences on self-esteem and affect. *Personality and Social Psychology Bulletin, 24*, 75–87. <http://dx.doi.org/10.1177/0146167298241006>
- *Roberts, J. E., & Gotlib, I. H. (1997). Temporal variability in global self-esteem and specific self-evaluation as prospective predictors of emotional distress: Specificity in predictors and outcome. *Journal of Abnormal Psychology, 106*, 521–529. <http://dx.doi.org/10.1037/0021-843X.106.4.521>
- *Röcke, C., Li, S. C., & Smith, J. (2009). Intraindividual variability in positive and negative affect over 45 days: Do older adults fluctuate less than young adults? *Psychology and Aging, 24*, 863–878. <http://dx.doi.org/10.1037/a0016276>
- Roseman, I. J., Spindel, M. S., & Jose, P. E. (1990). Appraisals of emotion-eliciting events: Testing a theory of discrete emotions. *Journal of Personality and Social Psychology, 59*, 899–915. <http://dx.doi.org/10.1037/0022-3514.59.5.899>
- Rosenthal, R. (1994). Parametric measures of effect size. In H. Cooper & L. V. Hedges (Eds.), *The handbook of research synthesis* (pp. 231–244). New York, NY: Russell Sage Foundation.
- *Russell, J. J., Moskowitz, D. S., Zuroff, D. C., Sookman, D., & Paris, J. (2007). Stability and variability of affective experience and interpersonal behavior in borderline personality disorder. *Journal of Abnormal Psychology, 116*, 578–588. <http://dx.doi.org/10.1037/0021-843X.116.3.578>
- Ryan, R. M., & Deci, E. L. (2001). On happiness and human potentials: A review of research on hedonic and eudaimonic well-being. *Annual Review of Psychology, 52*, 141–166. <http://dx.doi.org/10.1146/annurev.psych.52.1.141>
- *Sadikaj, G., Russell, J. J., Moskowitz, D. S., & Paris, J. (2010). Affect dysregulation in individuals with borderline personality disorder: Persistence and interpersonal triggers. *Journal of Personality Assessment, 92*, 490–500. <http://dx.doi.org/10.1080/00223891.2010.513287>
- Scherer, K. R. (2009). The dynamic architecture of emotion: Evidence for the component process model. *Cognition and Emotion, 23*, 1307–1351. <http://dx.doi.org/10.1080/02699930902928969>
- Schmitt, M. T., Branscombe, N. R., Postmes, T., & Garcia, A. (2014). The consequences of perceived discrimination for psychological well-being: A meta-analytic review. *Psychological Bulletin, 140*, 921–948. <http://dx.doi.org/10.1037/a0035754>
- Schmitz, N., Kugler, J., & Rollnik, J. (2003). On the relation between neuroticism, self-esteem, and depression: Results from the National Comorbidity Survey. *Comprehensive Psychiatry, 44*, 169–176. [http://dx.doi.org/10.1016/S0010-440X\(03\)00008-7](http://dx.doi.org/10.1016/S0010-440X(03)00008-7)
- *Schulberg, D., & Gottlieb, J. (2002). Dynamics and correlates of microscopic changes in affect. *Nonlinear Dynamics, Psychology, and Life Sciences, 6*, 231–257. <http://dx.doi.org/10.1023/A:1015063927555>
- *Schwerdtfeger, A., & Friedrich-Mai, P. (2009). Social interaction moderates the relationship between depressive mood and heart rate variability: Evidence from an ambulatory monitoring study. *Health Psychology, 28*, 501–509. <http://dx.doi.org/10.1037/a0014664>
- *Shea, T., & Fisher, B. E. (1996). Self-ratings of mood levels and mood variability as predictors of junior I-6 impulsivity and ADHD classroom behaviors. *Personality and Individual Differences, 20*, 209–214. [http://dx.doi.org/10.1016/0191-8869\(95\)00164-6](http://dx.doi.org/10.1016/0191-8869(95)00164-6)
- Shiffman, S., Stone, A. A., & Hufford, M. R. (2008). Ecological momentary assessment. *Annual Review of Clinical Psychology, 4*, 1–32. <http://dx.doi.org/10.1146/annurev.clinpsy.3.022806.091415>
- *Silk, J. S., Forbes, E. E., Whalen, D. J., Jakubcak, J. L., Thompson, W. K., Ryan, N. D., . . . Dahl, R. E. (2011). Daily emotional dynamics in depressed youth: A cell phone ecological momentary assessment study. *Journal of Experimental Child Psychology, 110*, 241–257. <http://dx.doi.org/10.1016/j.jecp.2010.10.007>
- *Silk, J. S., Steinberg, L., & Morris, A. S. (2003). Adolescents' emotion regulation in daily life: Links to depressive symptoms and problem behavior. *Child Development, 74*, 1869–1880. <http://dx.doi.org/10.1046/j.1467-8624.2003.00643.x>
- Smyth, J. M., & Stone, A. A. (2003). Ecological momentary assessment research in behavioral medicine. *Journal of Happiness Studies, 4*, 35–52. <http://dx.doi.org/10.1023/A:1023657221954>
- *Stein, K. F. (1996). Affect instability in adults with a borderline personality disorder. *Archives of Psychiatric Nursing, 10*, 32–40. [http://dx.doi.org/10.1016/S0883-9417\(96\)80084-7](http://dx.doi.org/10.1016/S0883-9417(96)80084-7)
- *Suls, J., Green, P., & Hillis, S. (1998). Emotional reactivity to everyday problems, affective inertia, and neuroticism. *Personality and Social Psychology Bulletin, 24*, 127–136. <http://dx.doi.org/10.1177/0146167298242002>
- *Suls, J., Martin, R., & David, J. P. (1998). Person-environment fit and its limits: Agreeableness, neuroticism, and emotional reactivity to interpersonal conflict. *Personality and Social Psychology Bulletin, 24*, 88–98. <http://dx.doi.org/10.1177/0146167298241007>
- Sutton, A. J. (2009). Publication bias. In H. Coopers, L. V. Hedges, & J. C. V. Valentine (Eds.), *The handbook of research synthesis and meta-analysis* (pp. 435–452). New York, NY: Russell Sage Foundation.
- *Thompson, R. J., Mata, J., Jaeggi, S. M., Buschkuhl, M., Jonides, J., & Gotlib, I. H. (2012). The everyday emotional experience of adults with major depressive disorder: Examining emotional instability, inertia, and reactivity. *Journal of Abnormal Psychology, 121*, 819–829. <http://dx.doi.org/10.1037/a0027978>
- *Timmermans, T., Van Mechelen, I., & Kuppens, P. (2010). The relationship between individual differences in intraindividual variability in core affect and interpersonal behavior. *European Journal of Personality, 24*, 623–638. <http://dx.doi.org/10.1002/per.756>
- *Tobacyk, J. (1981). Personality differentiation, effectiveness of personality integration, and mood in female college students. *Journal of Personality and Social Psychology, 41*, 348–356. <http://dx.doi.org/10.1037/0022-3514.41.2.348>
- *Tolpin, L. H., Gunther, K. C., Cohen, L. H., & O'Neill, S. C. (2004). Borderline personality features and instability of daily negative affect and self-esteem. *Journal of Personality, 72*, 111–137. <http://dx.doi.org/10.1111/j.0022-3506.2004.00258.x>
- Trull, T. J., & Ebner-Priemer, U. (2013). Ambulatory assessment. *Annual Review of Clinical Psychology, 9*, 151–176. <http://dx.doi.org/10.1146/annurev-clinpsy-050212-185510>
- Trull, T. J., Solhan, M. B., Tragesser, S. L., Jahng, S., Wood, P. K., Piasecki, T. M., & Watson, D. (2008). Affective instability: Measuring a core feature of borderline personality disorder with ecological momentary assessment. *Journal of Abnormal Psychology, 117*, 647–661. <http://dx.doi.org/10.1037/a0012532>
- van de Leemput, I. A., Wichers, M., Cramer, A. O., Borsboom, D., Tuerlinckx, F., Kuppens, P., . . . Scheffer, M. (2014). Critical slowing down as early warning for the onset and termination of depression. *Proceedings of the National Academy of Sciences of the United States of America, 111*, 87–92. <http://dx.doi.org/10.1073/pnas.1312114110>
- Van den Noortgate, W., López-López, J. A., Marín-Martínez, F., & Sánchez-Meca, J. (2013). Three-level meta-analysis of dependent effect sizes. *Behavior Research Methods, 45*, 576–594. <http://dx.doi.org/10.3758/s13428-012-0261-6>

- *Vestre, N. D. (1984). Irrational beliefs and self-reported depressed mood. *Journal of Abnormal Psychology, 93*, 239–241. <http://dx.doi.org/10.1037/0021-843X.93.2.239>
- von Neumann, J., Kent, R. H., Bellinson, H. R., & Hart, B. I. (1941). The mean square successive difference. *Annals of Mathematical Statistics, 12*, 153–162. <http://dx.doi.org/10.1214/aoms/1177731746>
- Watson, D., Clark, L. A., & Carey, G. (1988). Positive and negative affectivity and their relation to anxiety and depressive disorders. *Journal of Abnormal Psychology, 97*, 346–353. <http://dx.doi.org/10.1037/0021-843X.97.3.346>
- Watson, D., Wiese, D., Vaidya, J., & Tellegen, A. (1999). The two general activation systems of affect: Structural findings, evolutionary considerations, and psychobiological evidence. *Journal of Personality and Social Psychology, 76*, 820–838. <http://dx.doi.org/10.1037/0022-3514.76.5.820>
- Webb, T. L., Miles, E., & Sheeran, P. (2012). Dealing with feeling: A meta-analysis of the effectiveness of strategies derived from the process model of emotion regulation. *Psychological Bulletin, 138*, 775–808. <http://dx.doi.org/10.1037/a0027600>
- *Weinstein, S. M., & Mermelstein, R. J. (2013). Dynamic associations of negative mood and smoking across the development of smoking in adolescence. *Journal of Clinical Child and Adolescent Psychology, 42*, 629–642. <http://dx.doi.org/10.1080/15374416.2013.794698>
- *Weiss, H. M., Nicholas, J. P., & Daus, C. S. (1999). An examination of the joint effects of affective experiences and job beliefs on job satisfaction and variations in affective experiences over time. *Organizational Behavior and Human Decision Processes, 78*, 1–24. <http://dx.doi.org/10.1006/obhd.1999.2824>
- *Wenze, S. J., Gunthert, K. C., Forand, N. R., & Laurenceau, J. P. (2009). The influence of dysphoria on reactivity to naturalistic fluctuations in anger. *Journal of Personality, 77*, 795–824. <http://dx.doi.org/10.1111/j.1467-6494.2009.00565.x>
- Wichers, M. (2014). The dynamic nature of depression: A new micro-level perspective of mental disorder that meets current challenges. *Psychological Medicine, 44*, 1349–1360. <http://dx.doi.org/10.1017/S0033291713001979>
- *Wichers, M., Peeters, F., Geschwind, N., Jacobs, N., Simons, C. J. P., Derom, C., . . . van Os, J. (2010). Unveiling patterns of affective responses in daily life may improve outcome prediction in depression: A momentary assessment study. *Journal of Affective Disorders, 124*, 191–195. <http://dx.doi.org/10.1016/j.jad.2009.11.010>
- *Witte, T. K., Fitzpatrick, K. K., Warren, K. L., Schatschneider, C., & Schmidt, N. B. (2006). Naturalistic evaluation of suicidal ideation: Variability and relation to attempt status. *Behaviour Research and Therapy, 44*, 1029–1040. <http://dx.doi.org/10.1016/j.brat.2005.08.004>
- *Woyshville, M. J., Lackamp, J. M., Eisengart, J. A., & Gilliland, J. A. M. (1999). On the meaning and measurement of affective instability: Clues from chaos theory. *Biological Psychiatry, 45*, 261–269. [http://dx.doi.org/10.1016/S0006-3223\(98\)00152-8](http://dx.doi.org/10.1016/S0006-3223(98)00152-8)
- *Zeigler-Hill, V., & Abraham, J. (2006). Borderline personality features: Instability of self esteem and affect. *Journal of Social and Clinical Psychology, 25*, 668–687. <http://dx.doi.org/10.1521/jscp.2006.25.6.668>

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