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Affect Dynamics or Response Bias? The Relationship Between Extreme Response Style and Affect Dynamics in a Controlled Experiment

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Intensive longitudinal data (ILD) have become a popular data format to capture people's momentary affect in everyday life. Besides describing persons' average affect over time, ILD are also often used to describe affect dynamics—that is, how affect changes over time—such as intraindividual variability or moment-to-moment temporal dependencies. Given that ILD studies mostly use self-report rating data, there is an increasing concern that response biases, such as extreme responding, might impact the estimates of affect dynamics. In this study, we assessed the relationship between extreme responding and affect dynamics in a controlled experiment. In a highly powered sample with $N = 1{,}398$ persons, we measured extreme responding using background questionnaires and repeatedly induced affect using a probabilistic reward task with $T = 140$ trials per person. Our results suggest that people with high extreme response style trait levels show substantially higher measures of affect variability. However, extreme responding is neither associated with moment-to-moment temporal dependencies nor with participants' reactivity to affective stimuli. We conclude with a discussion on the importance of evaluating measurement in ILD for psychological assessments and outline potential areas for future research to improve assessments of affect dynamics.

Public Significance Statement
We investigate whether extreme response style is associated with affect dynamics in intensive longitudinal data. Our results show that extreme response style is associated with greater affect variability, but not with moment-to-moment temporal dependencies or reactivity to affective stimuli. Our study emphasizes the importance of evaluating measurement biases in psychological assessments.

Keywords: affect dynamics, intensive longitudinal data, measurement, response biases, extreme response style

Supplemental materials: https://doi.org/10.1037/pas0001370.supp

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Intensive longitudinal data (ILD)—data that consist of many observations within a same person across time—have become a popular data structure in psychological research and with good reason, as these data allow researchers to uncover the dynamical processes that guide a person's behavior and mental states. Through understanding the dynamics of psychological processes, researchers are able to better understand how and why people develop psychopathological disorders such as depression or bipolar disorder,

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Data were originally published in Vanhasbroeck et al. (2024). Data collection has been preregistered, and the data are publicly available (see https://osf.io/ce87p/ and https://gitlab.kuleuven.be/ppw-okpiv/researchers/u0123135/affective-consistency in Vanhasbroeck et al., 2024). Analysis scripts are publicly available (see https://osf.io/w2kvp/; Henninger et al., 2024b). A preprint is available on the PsyArxiv (see https://osf.io/preprints/psyarxiv/vk5sh; Henninger et al., 2024a).

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Mirka Henninger played a lead role in conceptualization, formal analysis, visualization, and writing–original draft and an equal role in methodology and writing–review and editing. Niels Vanhasbroeck played a lead role in data curation and an equal role in conceptualization, methodology, visualization, and writing–review and editing. Francis Tuerlinckx played an equal role in conceptualization, methodology, visualization, and writing–review and editing.

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what characterizes these disorders, and how to describe and explain subclinical affective processes (e.g., McKone & Silk, 2022; Röcke & Brose, 2013; Russell et al., 2007).

One field in which ILD have shaped research is affect dynamics, which investigates how affective experiences change over time. These fluctuations are often thought to reflect how a person responds to external events and are considered important indicators of psychological functioning and well-being (Hedeker & Mermelstein, 2020; Koval et al., 2016; Kuppens et al., 2007; Röcke & Brose, 2013). Characteristics of affect dynamics, such as affect variability, are crucial in clinical research and have been associated with clinical outcomes, such as suicidal ideation (Palmier-Claus et al., 2012), mental health and borderline symptoms (Jenkins et al., 2024; Russell et al., 2007), or substance abuse (Mohr et al., 2015).

Within this domain, researchers typically make use of different types of measures to investigate affect dynamics (see, e.g., Dejonckheere et al., 2019; Jahng et al., 2008; Wang et al., 2012; Wendt et al., 2020, for overviews). One often-investigated dynamical characteristic of affect is its intraindividual variability (also sometimes called dispersion), which refers to the degree to which an individual's affective states fluctuate over time. Intraindividual variability captures how much a person's momentary affect deviates from their baseline affective state (i.e., one's own average affect). Affect variability is commonly operationalized as the within-person standard deviation of repeated affect measures across multiple measurement occasions (see, e.g., Eid & Diener, 1999; Kuppens et al., 2007; Price et al., 2023). In other words, it reflects the amplitude of fluctuations while ignoring the temporal dependencies of responses (e.g., Eid & Diener, 1999; Hedeker & Mermelstein, 2020; Kuppens et al., 2007; Larsen & Diener, 1987; Wichers et al., 2015).

Another measure of how affect changes over time is the first-order autoregressive effect, which captures temporal relations between adjacent time points. The first-order autoregressive effect, also called moment-to-moment predictability or inertia, indicates how strongly an affective state at a certain time point predicts the affective state at the following time point. It hence reflects how much a person's affective state persists from one moment to the next. In other words, it can be considered as the resistance to changes in affect over time, such that high levels of inertia might indicate a lack of affective flexibility (Bos et al., 2019; Hedeker & Mermelstein, 2020; Koval et al., 2013, 2016; Wang et al., 2012; Wichers et al., 2015).

Through the use of such measures of affect dynamics, researchers have been able to characterize people's affective lives. For example, research shows that both characteristics of affect dynamics reflect how a person adapts to their environment and that the strength of affect dynamics remains relatively consistent over time (Bos et al., 2019; Carver, 2015; Kuppens & Verduyn, 2017; Panksepp, 2012; Smit et al., 2023). Additionally, research has associated increased affect variability with an increase in depressive symptoms, a higher probability of depression relapse, an overall lower well-being, lower emotional flexibility, and a lower self-esteem (Bos et al., 2019; Czyz et al., 2021; Franck & De Raedt, 2007; Hamaker et al., 2016; Hedeker, Mermelstein, et al., 2009; Houben et al., 2015; Koval et al., 2016; Maher et al., 2019; Piasecki et al., 2016; Trull et al., 2015). Thus, ILD have helped researchers gain new insights into the emotional system, as well as into differences in how this system works across individuals (Ernst et al., 2021; Scott et al., 2020; Wang et al., 2012).

However, most of the discussed studies rely on self-report data to investigate measures of affect dynamics (e.g., using experience sampling methodology or ecological momentary assessments). These measures might therefore be prone to influences by how participants use and interact with the measurement instrument, for instance, the rating scale. This means that these measures might not only capture affect dynamics but might also be systematically impacted by a person's response styles (e.g., Adams et al., 2019; Baumgartner & Steenkamp, 2001; Bolt & Johnson, 2009). Examples of such response styles are the preference for extreme categories (i.e., extreme response style [ERS]) or the middle category (i.e., midscale response style) and the tendency to agree with an item independent of the item content (i.e., acquiescent response style; e.g., Couch & Keniston, 1960; Hamilton, 1968; Henninger & Meiser, 2020a; Paulhus, 1991; Van Vaerenbergh & Thomas, 2013).

Among these response styles, ERS seems to be the most ubiquitous and prominent in self-report rating data and can have a substantial impact on the measures derived from this type of data. For instance, when response styles are examined in an exploratory manner, ERS tends to be omnipresent, while midscale response style and acquiescent response style are found to be less influential (e.g., Bolt et al., 2014; Falk & Cai, 2016; Henninger, 2021; Henninger & Meiser, 2020b, 2022; Plieninger & Heck, 2018). Furthermore, response styles have been shown to be stable over content domains and over time (Van Vaerenbergh & Thomas, 2013; Weijters et al., 2010a; Wetzel et al., 2013). ERS can therefore be considered as an additional variance component that is not related to the characteristic being measured and carries the risk to bias estimates of trait scores, variability, and correlations (e.g., Adams et al., 2019; Böckenholt & Meiser, 2017; Bolt et al., 2014; Bolt & Johnson, 2009; De Jong et al., 2008; Plieninger, 2017). For these reasons, the awareness that controlling for the effects of response styles is crucial to safeguard data quality in self-report measures has increased in recent years.

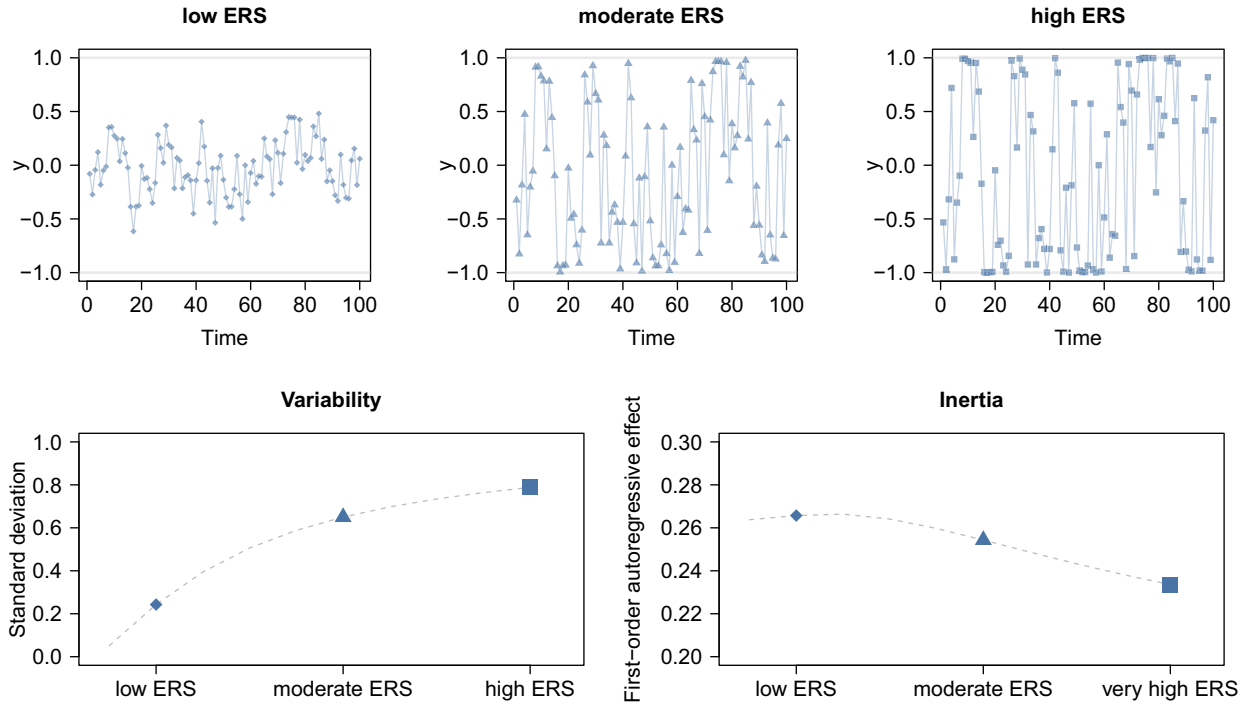
In the context of ILD, response tendencies such as ERS might impact measures of variability. People with high ERS levels tend to overselect the extreme categories and be thus assigned higher variability values—not because their affective states vary more strongly over time but because of the way they use the rating scale. In contrast, people with low ERS levels tend to prefer the intermediate categories, hence provide responses at the center of the rating scale, which might result in reduced measured intraindividual variability. Unlike intraindividual variability, the relationship between ERS and inertia is more difficult to predict and may be less pronounced.

We use simulated, artificial data to illustrate potential effects of ERS on affect dynamics in Figure 1. In the top row, we show how affect measures in ILD may differ for different levels of ERS (assuming that the average person's affect location is 0). We can see that when ERS is low, the responses lie in the center and never reach the limits of the possible range of the scale (y-axis ranging from −1 to 1). When ERS is moderate, fluctuations are more easily visible, sometimes reaching the limits of the scale. When ERS is high, the full range of the scale is used, and many responses are located at the extremes of the scale. The bottom row of Figure 1 shows the standard deviation (variability; left panel) and the first-order autoregressive effect (inertia; right panel) of the time series as a function of different ERS levels. In this simulated data, we observe that variability increases with higher ERS, while inertia decreases,

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Figure 1

llustration of How Extreme Responding (ERS) Influences Measures in a Time Series (Top Row; for Low, Moderate, and High ERS) as Well as Variability and Inertia (Bottom Row)



Note. The time series y is generated as an autoregressive process of order 1 with the autoregressive parameter $\rho = 0.3$. The series is transformed using the hyperbolic tangent function y_t to map the series to the interval ([−1, 1]). The dashed line in the bottom row additionally reflects the continuum of ERS levels based on a single artificial, simulated time series. More information about the data generating process is given in Supplemental Appendix A. ERS = extreme response style. See the online article for the color version of this figure.

albeit to a lesser extent. Please note that this simulation illustrates *potential* effects of ERS on affect dynamics. In empirical data, the majority of participants will most likely have moderate levels of ERS, with smaller fractions of participants having low and high levels of ERS.

The relationships between ERS and different measures of affect dynamics in ILD have not been the focus of methodological studies yet—to the best of our knowledge, only two studies have examined the relationship between ERS and variability, and we have not encountered any studies addressing its relationship with inertia.

First, Baird et al. (2017) asked participants to rate to which extent 10 adjectives could describe cartoon characters from the Simpson television show. Because the cartoon characters are identical for each person, interindividual differences in variability are considered as response styles by the authors. Their results show that indeed the variability of the cartoon character ratings correlates moderately with measures of within-scale variability using personality self-reports. These results indicate that variability might be a person-specific response tendency that is stable across domains and might reflect components different from the measures of interest.

One limitation of this study is that it did not make use of a longitudinal data: Intraindividual variability was measured using the average standard deviation in personality self-reports across the Big Five traits or across different contexts (friends, family member, partner, student). In a second study, however, the authors did employ a daily diary design over a period of 3 weeks. The results of this study suggested that intraindividual variability of different constructs is associated with each other. Unfortunately, however, this study only included a limited number of measurement occasions ($T = 14$). Additionally, variability and response bias were both operationalizing through the standard deviation, which may potentially confound these measures and lead to an overestimation of the association between intraindividual variability and ERS. It would hence be desirable to be able to clearly separate the measurement of affect dynamics and response biases, such as ERS.

Second, Deng et al. (2018) examined the relationship between ERS and intraindividual variability in positive and negative affect based on 10 measurement occasions dispersed over an 8-week period. Using a psychometric modeling approach, the authors showed that the biasing effect of ERS on affect measures was highest for people with moderate values of positive and negative affect. The authors also highlighted the need to control for the biasing effects of ERS on affect variability using psychometric models.

A limitation of this study is that the measurements of affect were skewed and, thus, showed a restriction of range in the observed intraindividual variability. As a consequence, measures of variability are likely to be associated with a person's mean value, potentially limiting the conclusions that can be drawn from the study

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(Bos et al., 2019; Koval et al., 2013; Mestdagh et al., 2018; Wagenmakers & Brown, 2007). Hence, it would be important to separate affect location from intraindividual variability. In addition, both ERS and affect variability were measured using the same items (i.e., items measuring positive and negative affect), making it very likely that the ERS measure is confounded with the affect measures. High ERS naturally leads to higher proportions of choices in the extreme categories. When the distribution of affect is skewed (e.g., more people report high rather than low levels of positive affect), it becomes difficult to distinguish whether a response in the "strongly agree" category is driven by high ERS or high levels of affect. To fully separate the measurement of ERS from affect measures, it would be desirable to clearly disentangle affect location from variability, for instance, by experimentally controlling affect location through affective stimuli and measuring ERS by a separate set of items.

The Present Study

In this study, we assess the relationship between ERS and different types of affect dynamics in a controlled experimental setting. By means of an experimental study, we can address the limitations in the studies by Baird et al. (2017) and Deng et al. (2018) mentioned above: (a) We obtain ERS trait scores from a psychometric model using items that are independent from the affect measures in the experiment, thereby avoiding a confound of ERS with affect measurement, (b) we use experimental stimuli of wins and losses to induce affect levels and disentangle location from variability, and (c) we aim at a high power using a large sample and a high number of measurement occasions to study multiple types of affect dynamics simultaneously. In the remainder of this section, we discuss how we address each of these points in more detail.

First, to obtain valid ERS trait scores, we use item responses that are separate from the affect measures collected during the experimental trials. This procedure follows the recommendations to use separate items in order to avoid confounding effects of trait and ERS measurement (e.g., Bolt et al., 2014; Henninger et al., 2023; Paulhus, 1991; Wetzel & Carstensen, 2017) and is based on the assumption that ERS is stable over content domains and time (Weijters et al., 2010b; Wetzel et al., 2016). Furthermore, we will apply state-of-the-art response style modeling using a so-called *IRTree* model (Böckenholt, 2012; De Boeck & Partchev, 2012; Jeon & De Boeck, 2019; Meiser et al., 2019). This approach allows us to obtain latent estimates of ERS levels that can be used as person-specific predictors for a person's intraindividual variability and inertia.

Second, instead of controlling for average affect levels when computing or assessing intraindividual variability scores (as, e.g., Baird et al., 2017; Bos et al., 2019), we use data in which person levels of affect show intermediate values, thereby avoiding floor and ceiling effects. This property of the data has been achieved by directly inducing affect levels through experimental stimuli using a probabilistic reward task (Vanhasbroeck et al., 2024; see also Koval et al., 2016, for another laboratory approach to induce affect). In this task, participants are exposed to wins and losses as stimuli in each experimental trial. Affect ratings are collected after the amount of win or loss has been revealed to the participant. This experimental induction of affect solves the confound between intraindividual variability and average affect location. Because the obtained distribution of affect measures is approximately uniform, we avoid that persons show low or high affect locations resulting in floor or ceiling effects and reduced variability (see Baird et al., 2017; Deng et al., 2018). Thus, using controlled experimental stimuli for affect, we are able to observe affect ratings over the whole response range for all participants.

Third, modeling affect dynamics requires a larger sample size compared to solely modeling affect location (see Wang et al., 2012, for a discussion). In this study, we used data from $N = 1{,}398$ persons and $T = 140$ trials. This large sample size with a high number of measurement occasions allows us to employ a latent variable modeling approach to study intraindividual variability and inertia simultaneously (Hedeker & Mermelstein, 2020; Wang et al., 2012) and to include additional random effects to study the relationship between ERS and reactivity to affective stimuli.

Research Questions

Our main interest lies in exploring whether persons with high ERS levels exhibit higher intraindividual variability in affect measures after controlling for the previous affect rating and the stimulus strength (Research Question [RQ] 1). To study this question, we will assess the extent to which the stable person-specific tendency to give extreme responses is associated with intraindividual variability in affect. If it is the case that some of the variability in affect measurement in ILD is due to a general tendency to provide extreme responses, this result might suggest that researchers who associated affect variability measures with, for example, psychopathological development, tap into explaining ERS rather than affect variability. Thus, implications based on research findings with regard to affect variability might be limited when ERS is not accounted for.

Second, we will examine the relationship of ERS and inertia (RQ2), which, to our knowledge, has not yet been examined in previous studies. Intraindividual variability and inertia capture two different aspects of affect dynamics with low intercorrelations (Wang et al., 2012). We will explore whether and how ERS is associated to inertia (i.e., the retraction to the average affect level) operationalized by the first-order autoregressive parameter.

Third, we will explore whether ERS levels are associated with participants' reactivity to affective stimuli. A preference for extreme categories has been shown to be associated with intensified judgments (Böckenholt, 2012; He & van de Vijver, 2016; Mourali et al., 2007; Weijters et al., 2016). Other studies have suggested relationships of ERS and personality or cultural characteristics, suggesting that different ERS levels may be due to differential perception of the environment (He & van de Vijver, 2013; Hoffmann et al., 2013; Plieninger, 2020; Ulitzsch et al., 2024). We will explore whether people with high ERS show higher reactivity to affective stimuli (i.e., wins and losses in the probabilistic rewards task). Such a finding could suggest that people with high ERS do not merely use the rating scale differently but may actually react distinctively to affective stimuli.

Method

This study relies on publicly available experimental data that were collected by Vanhasbroeck et al. (2024). In their study, the authors

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investigated the reliability of several single-item measures of affect by means of an online experiment. We summarize the key aspects of the experimental study here and refer to the original article for a full description of the data and methods.

Sample Characteristics and Procedure

A total of 1,398 participants were recruited through the online data collection platform Prolific (https://www.prolific.co/).[1] Sixty percent of the participants identified as male. Twenty-six percent indicated having a high school degree, 45% indicated having a bachelor's degree, 23% indicated having a master's degree, and the remaining 6% indicated an education level that was not covered by the provided categories ("other"). Participants were on average 34 years old (SD = 13, range = [18, 76]). Participants were told that they would receive their total task earnings as a reward for their participation. Unbeknownst to them, this total was predetermined and set to £5. Participants spent on average 23 min 59 s (SD = 9 min 6 s, range = [11 min 21 s, 79 min 39 s]) on the task.

After giving consent, participants completed a self-paced probabilistic reward task (see Vanhasbroeck et al., 2024). In each of the T = 140 trials, they were presented with four doors (see Panel A in Figure 2). They were told that two of these doors hid a monetary reward while the other two doors hid a monetary loss. On each trial, participants had to choose one of the doors, and then the door lit up for 500 ms and finally opened, displaying the stimulus, that is, the monetary outcome (between −£0.5 and £0.5) for 2 s. While participants were told that they had an equal probability of winning on each trial, the monetary outcomes were in reality predetermined, though the order in which participants received them varied between participants.

Next, participants were asked to report their affective state using a rating scale of a specific format (see Panel B in Figure 2 and below). Participants were asked to indicate the "position on the scale [which] provides information on how positive (blue) and/or negative (red)" a participant feels (exact wording in quotes). Responses of the participants remained visible on screen as a red dot. Participants could move on to the next trial by pressing the spacebar. The red dot disappeared at the start of the next trial.

At the end of the study, participants were asked to fill out two questionnaires, namely, a questionnaire about how they experienced the study that we used to estimate an ERS score for each person, as outlined in detail further below, and a depression questionnaire that is not used in our analyses and, hence, is not discussed any further. After filling out both questionnaires, participants were debriefed and given a diligence question ("In your honest opinion, should we use your data?"), to which they could respond with "yes" or "no." People who answered "no" are not included in this data set (see Footnote 1 and Vanhasbroeck et al., 2024, for more details).

Materials

Measurement of Affect

Vanhasbroeck et al. (2024) were interested in the reliability with which participants report on their momentary affective states. For this reason, the authors varied the visual layout of the rating scale (referred to as a format) and whether it could either be answered in a continuous or discrete manner (referred to as continuity) randomly between-participants (see Panel B in Figure 2 and Vanhasbroeck et al., 2024). Since Vanhasbroeck et al. (2024) did not find any indication that these response formats influenced measurement consistency (see also Henninger et al., 2023, for similar results for the effect of response formats on response scale use), we did not further consider the variation between the response formats in our study (apart from robustness checks).

Note that positive and negative affect (PA/NA) were measured with two types of scales (evaluation space grid, and two-dimensional visual analogue scale, 2D VAS), while valence was directly measured using one scale (one-dimensional visual analogue scale), and indirectly measured using the other two scales.[2] In line with Vanhasbroeck et al. (2024) and to be able to consider the responses on all scales together, we calculated a one-dimensional valence score for the evaluation space grid and two-dimensional visual analogue scale response formats as:

$$\text{valence}_t = 0.5 \times (\text{PA}_t - \text{NA}_t + 1), \tag{1}$$

where the values of valence are high when PA is high and NA is low and vice versa. For instance, when PA = 1 and NA = 0, valence = 1, when PA = 0 and NA = 1, valence = 0, and when PA = NA, valence = 1/2. Note that this derived measure also falls within the range of 0 and 1 and that this calculation implies that measurements from the evaluation space grid and two-dimensional visual analogue scale are included in our analyses for positive and negative affect, and additionally for the derived valence scores.

Questionnaire Used to Measure ERS

To estimate ERS trait scores, we use measurements of how participants experienced the experiment assessed by a separate set of items. Vanhasbroeck et al. (2024) asked participants to fill out a self-designed, unvalidated questionnaire at the end of the study. The questions targeted the extent to which participants were influenced by the stimuli of the experiment (Q1–Q4), how motivated participants were to complete the study (Q5–Q9), and the ease and accuracy with which participants felt they could report their feelings (Q10–Q17). Participants had to answer each of these questions on a 7-point Likert scale from "strongly disagree" to "strongly agree." The questions were presented in the same order to all participants, and item wording together with descriptive statistics of the items is presented in Supplemental Tables S1 and S2.

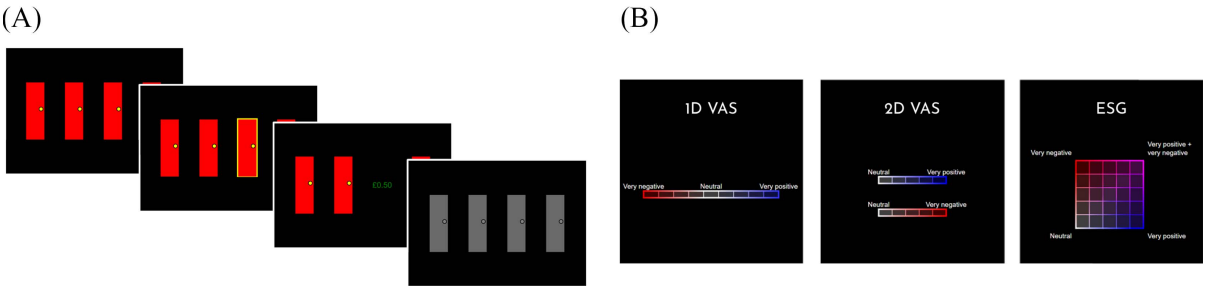
Analysis Approach

We employ a joint modeling approach to assess the influence of ERS on affect dynamics. Herein, we modeled the latent ERS trait using a psychometric modeling approach for response styles,

[1] Of the original 1,416 participants, who completed the experiment on Prolific, eight participants were not included in the analyses because their data were not (four participants) or not fully (four participants) registered in the database (see Vanhasbroeck et al., 2024). Another 10 participants indicated that they preferred that their data would not be used. They were therefore excluded from the analyses. Of these 10 participants, eight were men and two were women, they were on average 23.6 years old (SD = 4, range = [21, 35]), eight indicated they had a bachelor's degree, one had a master's degree, one had a high school degree, and one indicated "other."

[2] Note that all measurements that were obtained through these measures fall in the range from 0 to 1.

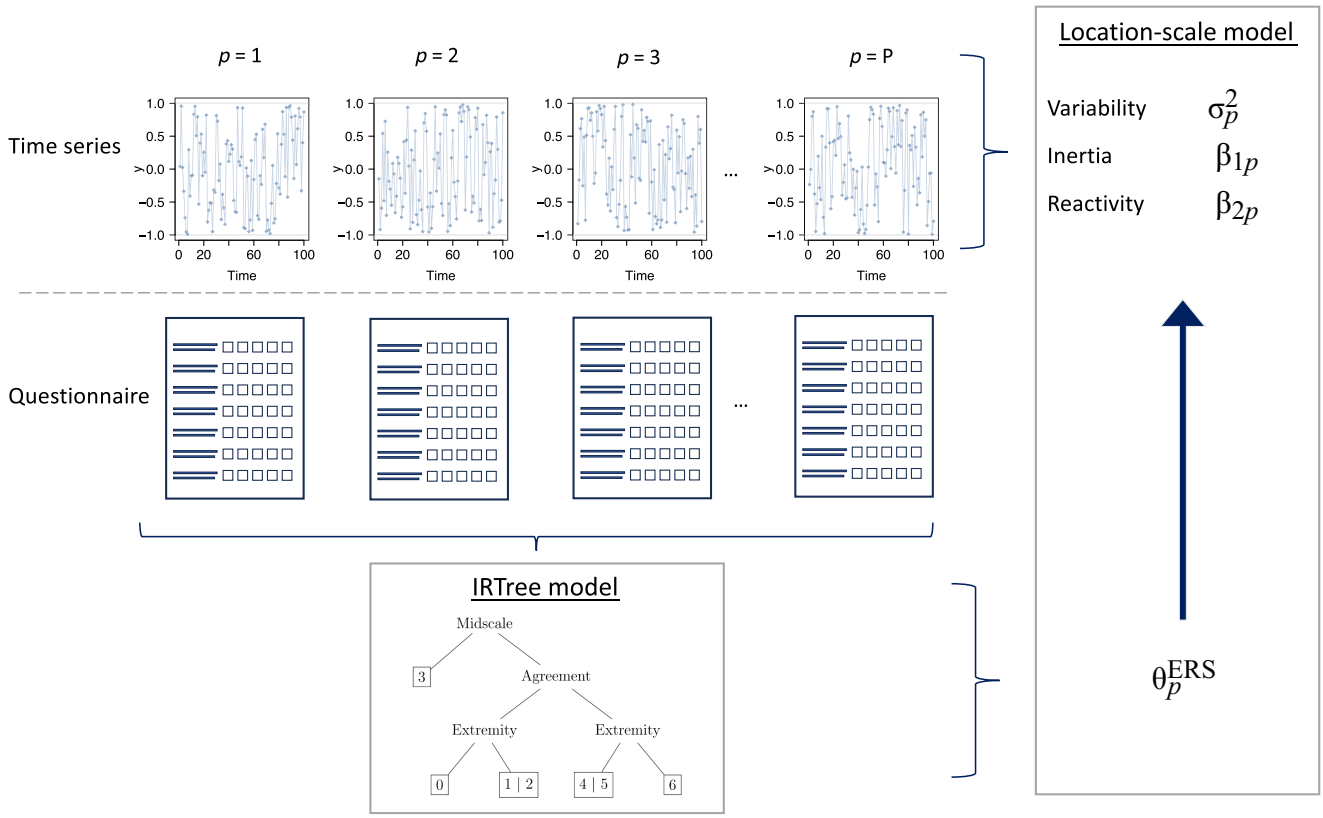
Figure 2
Illustration of the Experimental Procedure



Note. Panel A shows the sequence in each trial: (a) choosing a door, (b) the choice is being displayed through a yellow frame around the door, (c) the door opens and the monetary outcome is displayed, (d) the doors become inactive until the participant has rated their affective state. Panel B shows the different rating scale formats that were used to measure affect. Note that rating scale formats were varied between individuals in the original study, but this variation was not considered in this study. 1D VAS = one-dimensional visual analogue scale; 2D VAS = two-dimensional visual analogue scale; ESG = evaluative space grid. See the online article for the color version of this figure.

namely, a two-parameter IRTree model (Böckenholt, 2012). Within the same modeling approach, we use this latent ERS trait estimates as a predictor in a multilevel location-scale regression model to explain interindividual levels of intraindividual variability, of inertia, and of the influence of the experimental stimuli on affect (Hedeker, Demirtas, & Mermelstein, 2009; Hedeker & Mermelstein, 2020; McNeish, 2021). Figure 3 illustrates our analysis approach graphically.

Figure 3
Illustration of Our Analysis Approach

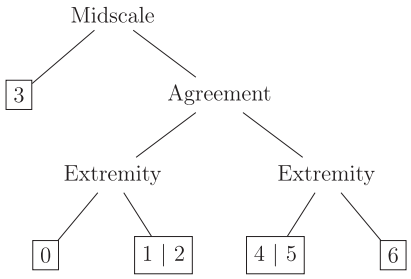


Note. ERS trait scores of participant *p* are estimated from questionnaire responses using an IRTree model. They serve as a predictor in a location-scale model to explain affect dynamics. ERS = extreme response style. See the online article for the color version of this figure.

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Figure 4

IRTree Structure for 7-Point Rating Items With Midscale, Agreement and Extremity Response Processes



Psychometric Model for ERS (IRTree)

Response styles can be modeled using extensions to modeling approaches from item response theory that incorporate them as additional latent dimensions (see Böckenholt & Meiser, 2017; Henninger & Meiser, 2020a, 2022, for reviews). A popular family of response style models are IRTree models. They decompose the responses to rating scale items into distinct response processes (Böckenholt, 2012; De Boeck & Partchev, 2012; Khorramdel & von Davier, 2014; Meiser et al., 2019; Plieninger & Meiser, 2014). For a 7-point item with response categories 0–6, the responses can be decomposed into a midscale response process (midscale response style; responses in the middle category 3 vs. non-mid responses in categories 0–2 and 4–6), an agreement response process (responses in the disagreement categories 0–2 vs. the agreement categories 4–6), and an extremity response process (ERS; responses in the extreme categories, 0 and 6 vs. the intermediate categories 1, 2, 4, 5). Figure 4 illustrates the decomposition of the observed response on a 7-point Likert-type scale into the midscale, agreement, and extremity response processes using an IRTree.

We used the IRTree modeling approach to obtain a latent estimate of the ERS trait scores. These factor scores of the extremity response process serve as the ERS predictor variable θ_p^{ERS} in the location-scale model. Supplemental Appendix C provides more information about the specification of the IRTree model and the model equations as well as the results for the IRTree model in terms of the item parameters and the variance–covariance matrix of the three response processes (midscale, agreement, and extremity). We fit the IRTree model to the self-reported measures based on the questionnaire about participants' experience with the experiment. Note that we conducted different types of robustness checks for the IRTree model that are presented in Supplemental Appendix D and the additional online material on the Open Science Framework (OSF; https://osf.io/w2kvp/). More details on the IRTree model are provided by Böckenholt (2012) and De Boeck and Partchev (2012), its validity is discussed by Plieninger and Meiser (2014), its interpretation by Plieninger (2020), and its comparison to alternative modeling strategies by Henninger and Meiser (2022).

Location-Scale Model Using ERS as a Predictor Variable

Our main analysis model is a multilevel location-scale model for longitudinal data (Hedeker & Mermelstein, 2020; McNeish, 2021; Wang et al., 2012). This model allows us to model not only interindividual differences in mean levels of affect but also their intraindividual variability (RQ1), inertia (RQ2), and reactivity to affective stimuli (RQ3). The model is specified on two levels, where Level 1 represents the experimental trials and Level 2 represents the participants of the experiment.

On Level 1, we explain affect measures (y_{tp}) for trial t and person p by specifying an autoregressive effect (inertia, β_{1p}) and an effect of participants' reactivity to the affective stimuli (i.e., the amount of win or loss in each experimental trial, β_{2p}):

$$\text{Level-1}: \; y_{tp} = \beta_{0p} + \beta_{1p} \cdot y_{(t-1)p} + \beta_{2p} \cdot \text{stimulus}_{tp} + \varepsilon_{tp}. \quad (2)$$

We allow the Level-1 variance to be specific for each person p, therewith obtaining a measure of intraindividual variability σ_p^2:

$$\varepsilon_{tp} \sim N(0, \sigma_p^2). \quad (3)$$

We model between-person differences in intraindividual variability (σ_p^2) as a function of a fixed intercept (ω_0) and a random effect capturing the residual interindindividual differences in intraindividual variability (u_{3p}). In addition, we explain intraindividual variability through a fixed effect of the latent ERS trait variable (ω_1):[3]

$$\begin{aligned} &\text{Level-2 model for variability/scale (RQ1)}: \\ &\sigma_p^2 = \exp(\omega_0 + \omega_1 \cdot \theta_p^{ERS} + u_{3p}). \end{aligned} \quad (4)$$

On Level 2, we specified random effects for the intercept (β_{0p}), the slope of the autoregressive effect (β_{1p}), and the slope of the stimulus variable (β_{2p}). This means that the locations of the affect variables, inertia, and reactivity to affective stimuli are allowed to vary between persons. We used the latent ERS trait variable (θ_p^{ERS}) as a predictor variable for the between-person intercept and the between-person slopes of inertia and stimulus:

$$\begin{aligned} &\text{Level-2 model for location}: \\ &\text{Between-person intercept}: \; \beta_{0p} = \gamma_{00} + \gamma_{01} \cdot \theta_p^{ERS} + u_{0p} \\ &\text{Between-person slope of inertia (RQ2)}: \; \beta_{1p} = \gamma_{10} + \gamma_{11} \cdot \theta_p^{ERS} + u_{1p} \\ &\text{Between-person slope of stimulus (RQ3)}: \; \beta_{2p} = \gamma_{20} + \gamma_{21} \cdot \theta_p^{ERS} + u_{2p}. \end{aligned} \quad (5)$$

The variance components (random intercept and slopes, and intraindividual variability) follow a multivariate normal distribution with means fixed to 0 and a variance–covariance matrix Σ_τ:

$$\begin{bmatrix} u_{0p} \\ u_{1p} \\ u_{2p} \\ u_{3p} \end{bmatrix} \sim MVN\left(\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \tau_{00} & & & \\ \tau_{01} & \tau_{11} & & \\ \tau_{02} & \tau_{12} & \tau_{22} & \\ \tau_{03} & \tau_{13} & \tau_{23} & \tau_{33} \end{bmatrix} \right). \quad (6)$$

We estimate the latent ERS trait variable and affect dynamics in a joint modeling approach. Such a one-step approach is advantageous because it takes uncertainty in the estimation of latent person parameters into account when regressing ERS trait scores on intraindividual variability, inertia, and reactivity to affective stimuli

[3] Note that the exponential function ensures that the variance σ_p^2 is positive and that when u_{3p} follows a normal distribution, σ_p^2 is lognormally distributed at the level of the person (Hedeker, Demirtas, & Mermelstein, 2009; Hedeker et al., 2008). Also note that θ_p^{ERS} is not explicitly centered, but—as a latent trait estimate from the IRTree model—is expected to have a symmetric distribution around 0.

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(Hedeker, Demirtas, & Mermelstein, 2009; Hedeker & Mermelstein, 2020; Wang et al., 2012). Due to the complexity of the modeling approach with four random components and their covariance matrix, we estimated separate models for positive affect, negative affect, and valence. Importantly, we do not account for the visual layout of the rating scales in our analyses, as they were shown to have no effect on the data characteristics (see Vanhasbroeck et al., 2024). However, we conducted robustness checks to assess the impact of the visual layout of the rating scales for our main analyses showing that the results are largely unaffected (see Supplemental Appendix D).

Model Estimation

We estimated the models using Mplus 8.6 (L. K. Muthén & Muthén, 2017).[4] We used Bayesian estimation using the default uninformative prior distributions of Mplus in combination with prior sensitivity analyses (see Asparouhov & Muthén, 2023; Gelman & Hill, 2006; Guo et al., 2019; Leckie et al., 2014; Lin et al., 2018; B. Muthén & Asparouhov, 2012; Rast et al., 2012).[5]

The final models were fit using 12 chains each with dispersed starting values using 5,000 iterations, with half of them as burn-in (B. Muthén, 2010). We assessed model convergence by inspecting overlaid Bayesian traceplots of the multiple chains (see additional online material on OSF at https://osf.io/w2kvp/) and the potential scale reduction (PSR) which was PSR = 1.009 in the model for positive affect, PSR = 1.009 in the model for negative affect, and PSR = 1.017 in the model for valence, indicating that the chains mixed well (Brooks & Gelman, 1998; Gelman & Rubin, 1992).

Transparency and Openness

The experimental design, tasks, procedures, and measures have been preregistered,[6] and the data are publicly available.[7]

For the present study, the research questions and data analysis scripts have not been preregistered. Mplus output files, Markov Chain Monte Carlo traceplots, and results of the robustness checks are available on OSF (https://osf.io/w2kvp/).

Results

Results for the IRTree model are presented in Supplemental Appendix C and the additional online material on OSF (https://osf.io/w2kvp/).

Descriptive Distributions of Positive Affect, Negative Affect, and Valence

Figure 5 shows the distribution of affect measures on Level 1 in the top row and the distribution of affect person means in the bottom row. As expected, the full range of the response scale has been used by the participants in the experiment when providing responses on the affect measures (top row). Furthermore, the distribution of person means (bottom row) is peaked and symmetric around the center of the scale. This distribution reflects the fact that affect was manipulated through the probabilistic reward task in a balanced manner, effectively reducing the variability of person-specific affective means. However, the data show substantial variability for Level-1 measures of affect, as one can see in the top row of this figure. Both characteristics of the affect distributions—lower variability in the means of affect and high intraindividual variability—are advantageous for the current analysis as discussed above.

Fixed Effects on Location in the Location-Scale Model

Figure 6 shows the fixed effects on a participant's locations of affective states throughout the experiment. The results across the three affective measures are very consistent and could be precisely estimated (small 95% credible intervals) because of the high power in the present study. The interested reader is also referred to Supplemental Appendix E for the exact parameter estimates together with their 95% credible interval.

The results for the intercept, inertia, and stimulus are presented mainly for plausibility checking and to ensure comparability to previous studies. The fixed intercepts for the locations of all three affective variables lie around .5 which is plausible given the affect scale that ranged from 0 to 1 and we induced affect in a balanced manner. The fixed effect of inertia lies around .3 for all three affective variables, which is a typical estimate for inertia in affect research (e.g., Koval et al., 2016). The predictor variable stimulus (i.e., amount of win or loss in each trial; reactivity) was associated with the affective variables in the expected direction (positively for positive affect and valence, negatively for negative affect).

Interindividual differences in the levels of ERS have no effect on interindividual differences in the location of affect. This result was to be expected, since we manipulated average affect levels in the experiment resulting in a reduced variability in person means of affect (see Figure 5).

Effect of ERS on Affect Dynamics in the Location-Scale Model

Figure 7 summarizes the effect of ERS on the affect dynamical measures. First and foremost, we can see that ERS has a positive effect on log affect variability (RQ1). Respondents with higher ERS levels as measured by the background questionnaire tend to show larger variability of affect (i.e., within-person variances of affect) across trials (positive affect: $\hat{\omega}_1 = 0.09$, CI [0.004, 0.18]; negative affect: $\hat{\omega}_1 = 0.10$, CI [0.01, 0.19]; Valence: $\hat{\omega}_1 = 0.13$, CI [0.05, 0.21]). Regarding the second and third research questions, ERS does

[4] We furthermore used the R packages MplusAutomation (Hallquist & Wiley, 2018) for integrating model results into R, mirt (Chalmers, 2012), for marginal maximum likelihood estimation of the IRTree model to derive data-dependent priors for prior sensitivity analysis and ggplot2 (Wickham, 2016) for plotting.

[5] In the IRTree model, we used normal prior distributions with mean 0 and standard deviation 5 for discrimination and difficulty parameters α_i and δ_i and inverse-Wishart priors for variances and covariances, that is, $IW(1, 4)$ and $IW(0, 4)$, respectively. In the location-scale model, we used uninformative, univariate normal prior distributions with mean 0 and standard deviation 10^{10} for the regression parameters γ and ω. For variances and covariances of random intercepts and slopes in the location-scale model, we used an improper inverse-Wishart prior $IW(0, -5)$ (Asparouhov & Muthén, 2023). We conducted prior sensitivity analyses for the inverse-Wishart priors and observed consistent parameter estimates across prior specifications, indicating the robustness of model estimates against prior specifications (see Supplemental Appendix D and the additional online material on OSF at https://osf.io/w2kvp/ for more details).

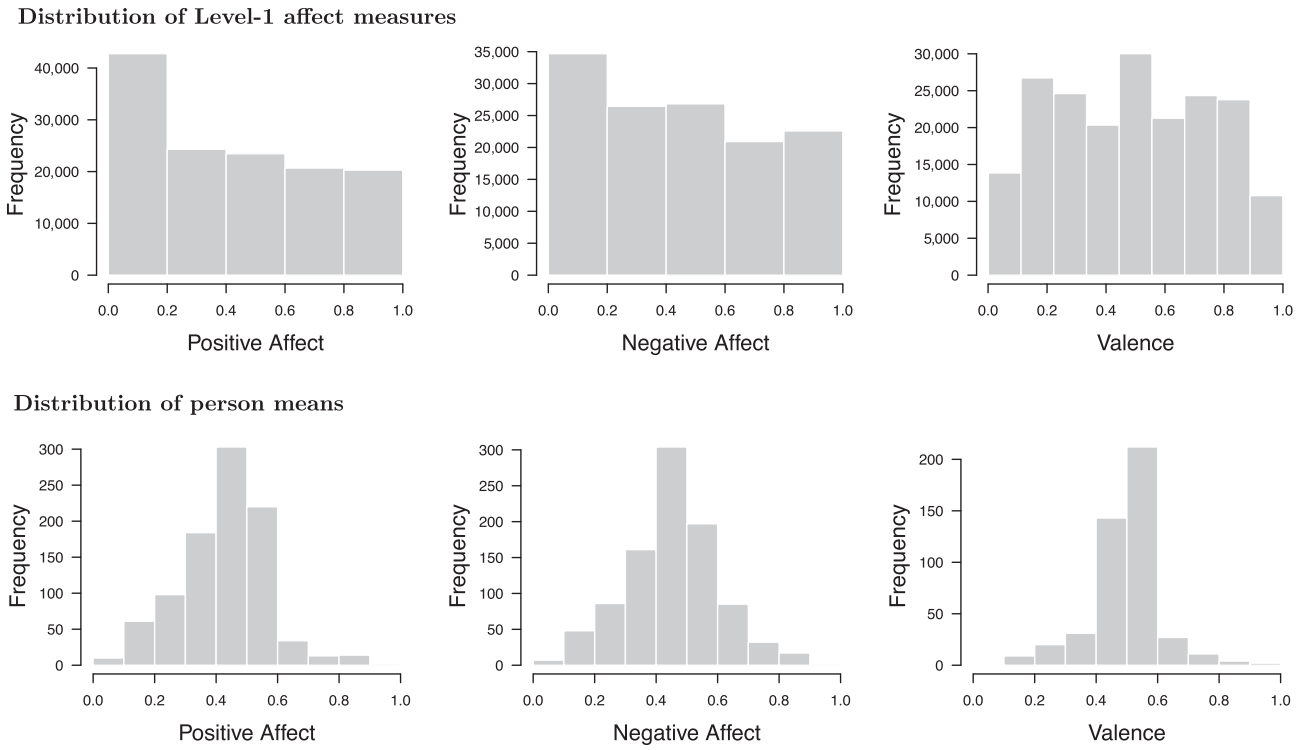
[6] By Vanhasbroeck et al. (2024): https://osf.io/ce87p/

[7] By Vanhasbroeck et al. (2024): https://gitlab.kuleuven.be/ppw-okpiv/researchers/u0123135/affective-consistency

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Figure 5

Distribution of Affect Measures at the Trial and Person Level



Note. In the top row, the distribution of all affect measures at the trial level is shown. In the bottom row, the distributions of the person means are displayed. The bins of the histograms in the top row are chosen in accordance to the response format (see Figure 2). Positive and negative affect were measured using five response categories and are, thus, presented in five bins. The valence measure, in contrast, is based on a computed score (see Equation 1) resulting in nine bins.

not seem to be consistently associated with between-person differences in inertia (RQ2) neither with reactivity to affect stimuli as reflected in the effect of ERS on the slope of the stimulus (RQ3).

Proportional Change in Affect Variability as a Function of ERS

Because variability is estimated on the log scale (see Equation 4), its interpretation is more challenging. In this case, the exponential of the regression coefficient of ERS on variability reflects the proportional change in the dependent variable and can serve as an effect size for the relationship between affect variability and ERS (see, e.g., Hedeker et al., 2008; Lo & Andrews, 2015). This means that $\sqrt{\exp(\hat{\omega}_1)}$ is the proportional change that we expect in the standard deviation of affect for a one-unit increase in ERS. Hence, if ERS increases by 1 (which is a plausible change given that the estimated ERS levels range from −1.2 to 1.56 in our data), the expected proportional change in the standard deviation of affect amounts to 8.98% for positive affect, 10.19% for negative affect, and 13.43% for valence.

Figure 8 further quantifies the magnitude of the association between ERS and affect variability (as specified in Equation 4) in the present sample. The *x*-axis shows the model-predicted proportional change in affect variability for one person given their ERS trait score; the *y*-axis shows the frequency of occurrence of this effect size in the analysis sample. For instance, for valence, we can see that approximately 100 participants show a reduced variability by −10% to −15% due to their low ERS levels, while approximately 110 participants show an increased variability by 10%–15% due to their high ERS levels in the analyzed data set.

Affect Response Distributions for Different ERS Levels

We further descriptively illustrate the relationship between ERS and the self-reported ratings (i.e., raw data) of positive affect, negative affect, and valence in Figure 9. We show the frequency distributions of the three affective variables as a function of ERS levels. The columns in the figure show these frequency distributions for participants with low (lowest 20%), moderate (middle 60%), and high (highest 20%) in the left, middle, and right panel, respectively. For all three affect variables, the proportion of responses in intermediate bins decreases, and the proportion of responses in the extreme bins increases from the left over the middle to the right panel. In the right panel depicting affect measures for the 20% of the sample with the highest ERS level, most affect responses are given in the extreme bins at the lower and upper end of the scale.

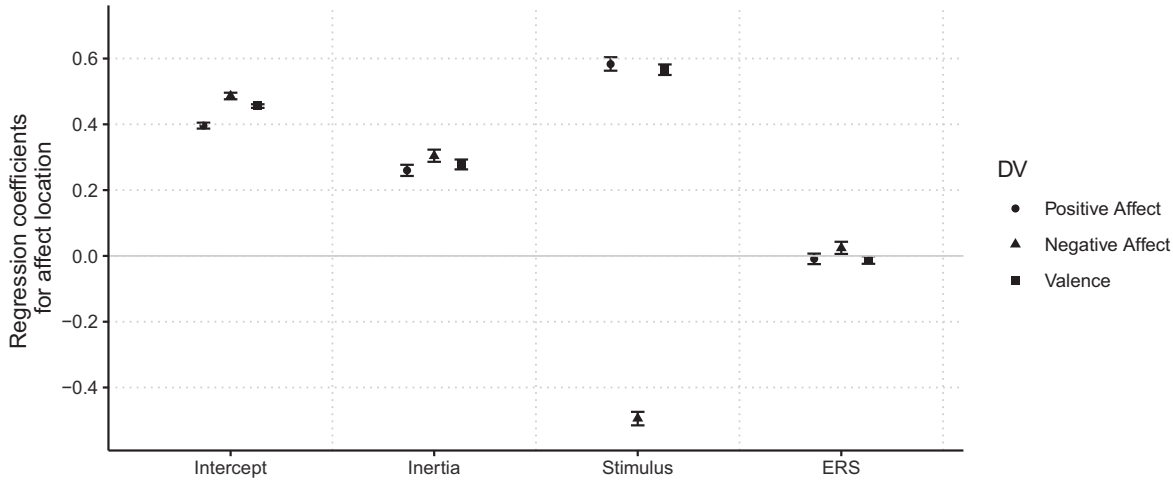
Random Effects in the Location-Scale Model

Lastly, in Table 1, we present the variances and covariances between the random effects in the location-scale model as specified in Equation 6. As expected from a controlled experiment with

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Figure 6

Fixed Effect Regression Coefficients for Affect Locations



Note. Error bars reflect 95% credible intervals (see Supplemental Appendix E for exact values). DV = dependent variable; ERS = extreme response style.

balanced stimuli, the intercepts of affect show essentially no variation across individuals. In contrast to the residual variance of the intercept, the residual variance of variability is much more pronounced indicating that there are substantial differences between persons in how much their affect varies over trials, followed by the residual variance of inertia and the effect of the stimulus.

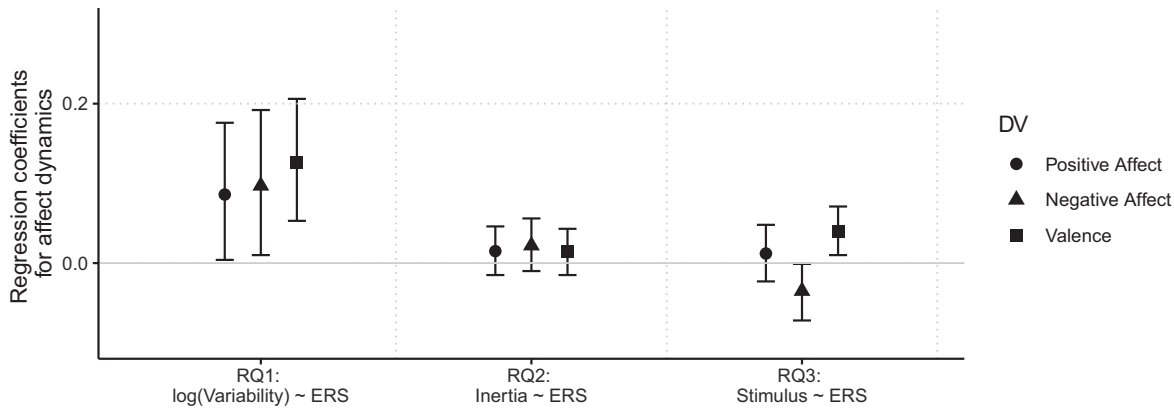
Table 1 furthermore illustrates associations between the different measures of affect dynamics. First, residual variability is negatively correlated with residual variability in inertia. This means that people with higher affective variability tended to take longer to return to their baselines. Second, residual variability is associated with more positive residual slopes of the stimulus for positive affect and valence and more negative residual slopes of the stimulus for negative affect. This means that people with higher intraindividual variability also showed more pronounced effects of the experimental stimulus in the probabilistic reward task on affect. Third, participants with higher residual autoregressive effects showed less pronounced residual effects of the stimulus (less positive for positive affect and valence, less negative for negative affect). This correlation indicates that participants with higher inertia were less reactive to the stimuli, that is, the monetary outcome, of the current trial.

Discussion

In this study, we examined the association between ERS and different measures of affect dynamics in a controlled experiment. Using a location-scale model, our results suggest that people with higher ERS levels also exhibit higher intraindividual variability in affect (RQ1). However, ERS is not associated with interindividual differences in inertia (RQ2) nor with participants' reactivity to the

Figure 7

Fixed Effect Regression Coefficients for Affect Dynamics: Effect of ERS on Variability (RQ1), Inertia (RQ2), and the Stimulus (i.e., Reactivity to Affective Stimuli; RQ3)

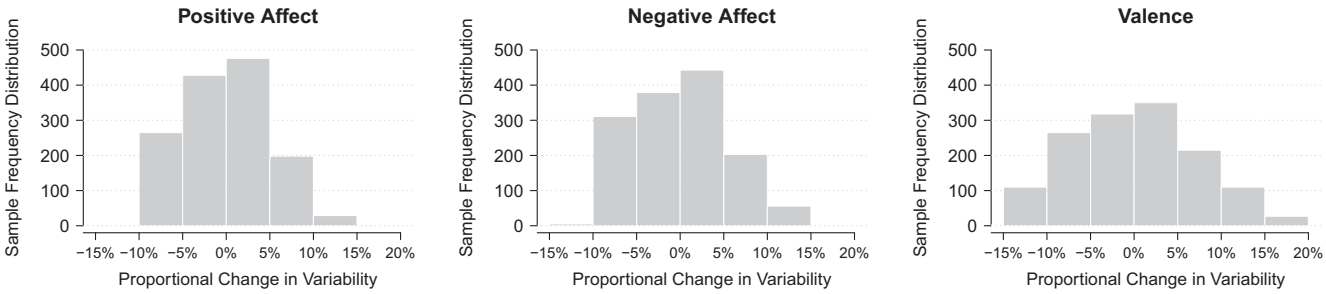


Note. Error bars reflect 95% credible intervals (see Supplemental Appendix E for exact values). DV = dependent variable; RQ = research question; ERS = extreme response style.

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Figure 8

Sample Frequency Distribution of the Model-Predicted Proportional Change in Affect Variability

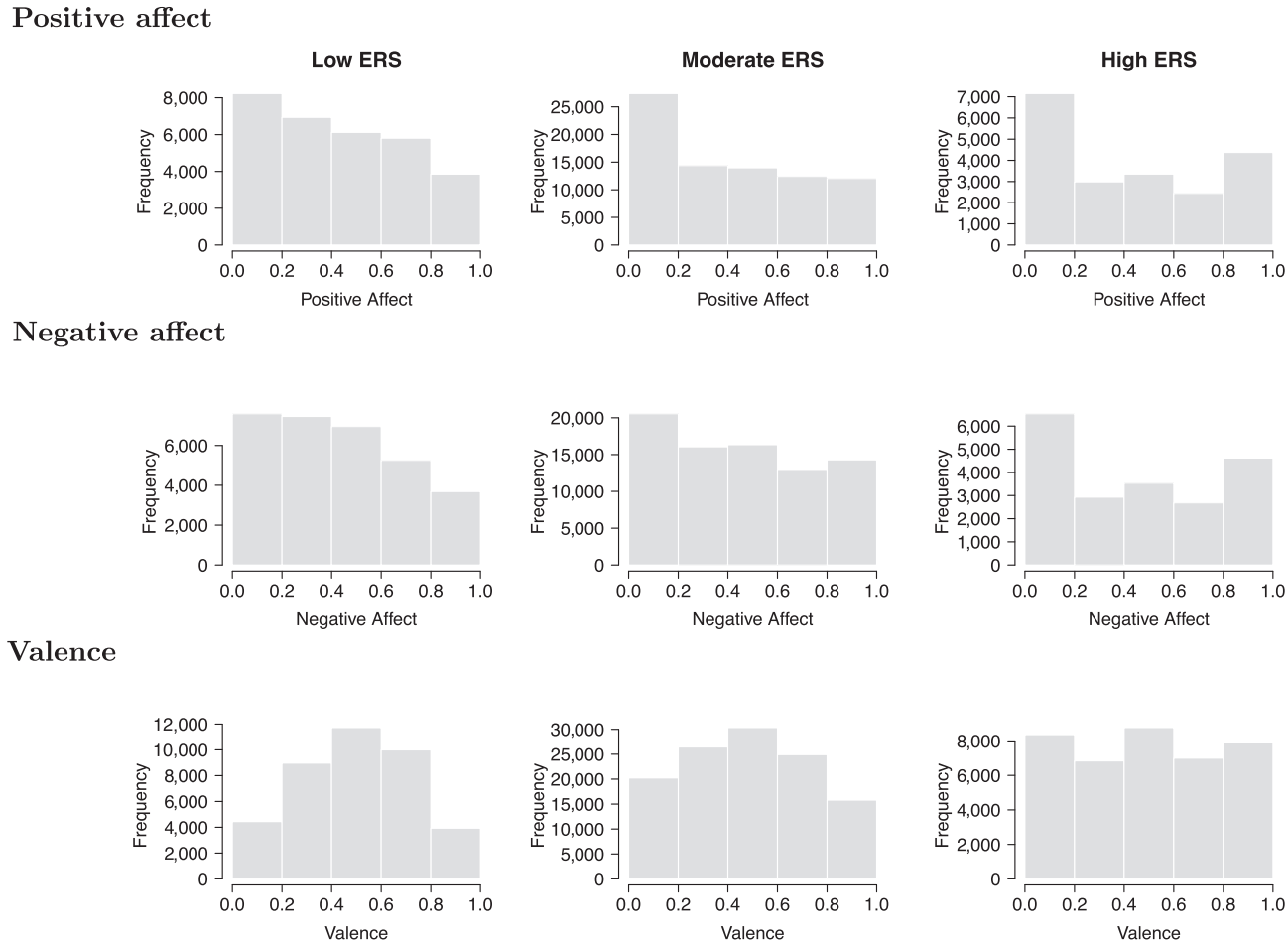


affective stimuli they encountered during the study (RQ3). Our study is the first highly powered study assessing the influence of response biases in ILD using unconfounded measurement of ERS and various measures of affect dynamics simultaneously.

Our findings have several implications. First, we have seen that the propensity for extreme categories was associated with higher variability in affect measures. In addition, we saw descriptively that those participants who showed high ERS in a questionnaire that was

Figure 9

Affect Response Distribution for Low, Medium, and High Extreme Responding (ERS) Levels



Note. The affect response distribution for positive and negative affect visually differs from the distribution for valence. Because valence is a composite score of positive and negative affect (see Equation 1), the distribution of valence measures is approximately normal compared to the distribution of positive and negative affect, with more responses in the center of the scale (around 0.5). As a consequence, the distribution under high ERS (rightmost column) also shows more responses in the center of the scale for valence compared to positive and negative affect. ERS = extreme response style.

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Table 1

Residual Variances (Diagonals) and Correlations Σ_τ of Random Effects (Off-Diagonals) for Negative and Positive Affect and Valence (See Equation 6)

Residual variance and correlation of random effect	1	2	3	4
Positive affect				
1. Intercept	.02			
2. Inertia	−.20	.10		
3. Stimulus	.31	−.70	.07	
4. Variability	.15	−.37	.66	.54
Negative affect				
1. Intercept	.02			
2. Inertia	.23	.10		
3. Stimulus	−.11	.61	.08	
4. Variability	.17	−.38	−.45	.61
Valence				
1. Intercept	.01			
2. Inertia	−.28	.09		
3. Stimulus	.08	−.68	.08	
4. Variability	−.12	−.35	.50	.55

Note. Credible intervals for variance and correlation estimates are presented in Supplemental Appendix E.

filled out at the end of the study also displayed a higher propensity to respond in the extreme categories in their affective responses throughout the experiment (see Figure 9). This result implies that a part of the variability in ILD may not be due to "true" variability in the construct that is measured. This is an important observation, as ERS has been shown to be consistent across content domains and over time (Van Vaerenbergh & Thomas, 2013; Weijters et al., 2010a; Wetzel et al., 2013), meaning our results may not be limited to the affective domain, but that ERS is likely to impact data that we obtain through our measures in various ILD domains in psychological and clinical research.

Interestingly, however, we did not find evidence that a participant's ERS influences the conclusions one reaches through the use of a typical autoregressive or multilevel model. In other words, neither inertia nor the slope of the stimuli, that is, the monetary outcomes, seems to be related to ERS. One explanation for this result may be that the potential range of statistical effects of ERS on these characteristics is small, as was also suggested for inertia in our simulated illustration presented in Figure 1.

Another interesting result pertains to the negative residual correlation that we observed between inertia and variability, which stands in contrast to previous studies that reported small to moderate positive correlations between these two measures (e.g., Bos et al., 2019; Wang et al., 2012). There might be several reasons for this difference in sign. One explanation might be that the skewed distribution of affect variables in previous studies exerted an impact on between-person correlation that was eliminated in our study with non-skewed distribution of affect variables. Another explanation might be the conceptual meaning of inertia or the moment-to-moment predictability, which might be different in real-world settings compared to an artificial experimental setup with short time interval between measurements (see also Bringmann et al., 2022, for a critical discussion on conceptual clarity).

Our results should be interpreted in light of several strengths and limitations. First, in contrast to previous studies (e.g., Baird et al., 2017) who used the same items to measure affect and ERS, we used a distinct background questionnaire to extract ERS indicators. This procedure allowed us to disentangle the measurement of affect dynamics from the measurement of ERS, which is corroborated by the low correlations between the ERS indicators and affect. Second, we induced affect levels in each experimental trial through varying the amount of wins and losses in a probabilistic reward task. As a consequence, affect measures in our study were approximately uniformly distributed without skewness and floor or ceiling effects, which—in contrast to previous studies—provided us with unconfounded measures of affect dynamics (see Baird et al., 2017; Bos et al., 2019; Deng et al., 2018; Koval et al., 2016). Lastly, this study was highly powered with $T = 140$ measurement occasions and $N = 1{,}398$ persons. This large sample allowed us to study affect variability, inertia, and reactivity to affect stimuli (see Wang et al., 2012).

While our experimental setup yielded many advantages, including high internal validity, a limitation of our study is the potential lack of generalizability to other contexts, such as real-world settings or different scales. The data collection setting differs substantially from typical ILD settings, such that the intervals between measurement points are extremely short and affect was only influenced by the stimulus, that is, the outcome of the probabilistic reward task, and not by external situational factors. Hence, participants may be more prone to fatigue effects over the 140 consecutive trials or to adapt their responses in accordance to the experimenter's intentions (e.g., responding positively to "win" trials compared to "loss" trials) in our study compared to an ILD study. In a real-world ILD study, various external factors may influence responses differently across measurement occasions and participants. These factors could also affect the association between ERS and variability, which needs to be studied in further detail. In addition, because response styles have been shown to be stable across time (e.g., over the course of 8 years; see Wetzel et al., 2016), it seems reasonable to assume that they would also be stable across experimental trials and in ILD studies. It may, however, be an interesting avenue for future research to assess how response styles may vary in shorter timescales (e.g., over the course of responding to a questionnaire; see Merhof & Meiser, 2023; Weijters et al., 2010a, for first results) or over the course of an ILD study, highlighting the need for future research.

Another limitation of our study is that the data used in this study were not primarily collected for the purpose of this article; hence, the sample characteristics of this study depend on the choices made by Vanhasbroeck et al. (2024). Unfortunately, they did not include several demographic variables that might have been informative with regard to generalizability to a broader population, of which we are therefore uncertain.

Furthermore, Vanhasbroeck et al. (2024) used different visual layouts to assess affect. While we did not find that the visual layout of the response scales had an impact on our results (see Supplemental Appendix D and the additional online material on OSF at https://osf.io/w2kvp/), we cannot rule out that the association between ERS and affect dynamics might be different when using other scale formats. Besides, the background questionnaire that we used to measure ERS was unvalidated, and items may form several facets instead of a unidimensional latent content trait (see Supplemental Appendices B and C for more details). To rule out potential threats to our conclusions, we have conducted several robustness checks which have shown that the measurement of ERS was robust against different

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types of psychometric modeling approaches (e.g., a single ERS factor model or alternative IRTree model specifications; see Supplemental Appendix D).

Thus, our study also points toward some interesting avenues for future research. Besides varying the response and measurement formats, future research should particularly focus on investigating the influence of ERS in daily-life settings. Future research may, for instance, investigate to what extent response styles, in general or ERS in particular, are present in ILD and other daily-life settings, measure them with validated questionnaires, assess to what extent response styles change between scale formats (e.g., scale formats that are popular in ILD, such as slider scales), or over time, and whether participants adapt their responses as a function of responses given at previous measurement occasions. Lastly, while we showed that variability was associated with ERS, there also is substantial residual variability that was not explained. Hence, affect variability may be an interesting subject of study in ILD and should be investigated further to learn more about interindividual processes and dynamics (e.g., Hedeker, Demirtas, & Mermelstein, 2009; Hedeker & Mermelstein, 2020; Wang et al., 2012).

We studied the association between ERS and affect variability, but did not assess to what extent ERS might be associated to measures of other constructs, such as mood, distress, or specific clinical symptoms. Because response styles have been shown to be stable across content domains (e.g., Wetzel & Carstensen, 2017; Wetzel et al., 2013), we expect that our findings would generalize to the measurement of other constructs, but this expectation needs to be corroborated by future studies. In addition, ERS has been studied extensively in the general, healthy population (e.g., Hamilton, 1968; Van Vaerenbergh & Thomas, 2013; Wetzel & Carstensen, 2017), but much less is known about how ERS manifests itself in clinical samples. ERS has been found to be associated with different personality traits, such as uncertainty avoidance (e.g., De Jong et al., 2008), intolerance of ambiguity and simplistic thinking (e.g., Naemi et al., 2009), and extraversion (e.g., Austin et al., 2006; Couch & Keniston, 1960; Harzing, 2006; Hibbing et al., 2019), indicating that ERS may be even more pronounced in clinical samples compared to the general population. Several studies found that ERS is associated with depression relapse (e.g., Brouwer et al., 2019; Teasdale et al., 2001) or with the likelihood of transitions from depressive to manic episodes (Stange et al., 2013). The main assumption underlying these results is that depression and mania is associated with a more pronounced dichotomous thinking style, manifesting itself in more extreme responses in questionnaires. It is hence possible that in clinical samples, ERS may additionally be confounded with dichotomous thinking, and it may be even more difficult to disentangle thinking style from rating scale usage.

When aiming at investigating ERS is clinical samples, it may be thus necessary to first develop specific methods to disentangle black-and-white thinking from rating scale usage before assessing to what extent ERS is associated to variability. Such an investigation is much needed because the hallmark of some psychological disorders is the presence of extreme responses. It is therefore crucial to being able to disentangle response styles from genuine extreme responses that are indicative of the presence of underlying psychological dysfunction.

More generally, the broad topics of measurement quality and measurement reliability have only recently gained more attention in ILD research (see, e.g., Calamia, 2019; Cloos et al., 2023; Ringwald et al., 2022; Scott et al., 2020; Wright & Zimmermann, 2019). At the moment, standard procedures and clear guidelines how to evaluate data quality and control for potential confounding factors in ILD studies are missing. Our study has demonstrated that the magnitude of response biases may also vary between persons, corroborating the necessity to develop person-specific measures of data quality. Developing such standard procedures for self-report measures in ILD but also passive measures is thus an essential next step to improve psychological and clinical assessments (Langener et al., 2024; Vize & Wright, 2024).

Lastly, modeling ERS using latent measurement models, such as item response theory or structural equation modeling, may oftentimes not be feasible for empirical researchers, for instance, due to sample size restrictions. It would be desirable for everyday research practice to control for ERS using an approach which could be more easily integrated into the main analysis model. Future research may assess the effectiveness of such simplified approaches using manifest ERS trait levels that can be used in latent regressions as a control variable in contrast to more complex modeling approaches and derive guidelines for statistical analyses of ILD data.

Assessing intraindividual variability has become more and more important in clinical studies (e.g., Jenkins et al., 2024; Mohr et al., 2015; Palmier-Claus et al., 2012; Russell et al., 2007). Our study is the first showing the association between response strategies and measures of affect variability in a controlled experimental setup. Recently, researchers have started to be interested in comparing measures of affect variability between regular and clinical samples or age groups or use affect variability to detect transitions from regular to clinical states (e.g., Röcke et al., 2009; Schreuder et al., 2024; Trull et al., 2008). Our study provides the basis for developing more directed procedures to account and control for extreme responding and other response biases in measures of affect dynamics that will then allow researchers to conduct more robust analyses on clinically relevant affect dynamics. Our study is thus of foundational importance for all applied and clinical applications with measures of affect variability and is a stepping stone to improved measures of affect dynamics in psychological and clinical assessments.

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